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Explaining the cyclical volatility of consumer debt risk using a heterogeneous agents model: The case of Chile☆

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ABSTRACT

Previous studies of consumer debt risk estimate low sensitivities to negative shocks, contradicting the historical data. This work proposes a heterogeneous agents model of household finances and credit risk. Families suffer labor income shocks and choose from a menu of loans contracts, defaulting on debt commitments when unable to finance minimum consumption standards. Using a variety of survey data I simulate household credit default for Chile over the last 20 years, replicating successfully the highs and lows of consumer delinquency. Some households are shown to be highly vulnerable to changes in interest rates, credit maturities and liquidity.

1. Introduction

Household debt is an asset of increased relevance in the balance sheets of financial institutions, reaching more than 100% of the GDP in several developed countries (Cecchetti et al., 2011). However, the last 5 years have shown a strong component of cyclical risk in consumer debt which was unaccounted for in current financial models. Banks' expenses with non-performing consumer loans from 2006 to 2009 increased more than 3 times in the USA and UK (Federal Reserve Board, Bank of England), appearing as a high risk asset class. Therefore measuring the sensitivity of consumer credit risk to aggregate shocks is relevant now as regulators discuss countercyclical macro-prudential tools, such as capital buffers and loan loss provisions, to curb financial risk (Laeven and Majnoni, 2003; Rubio and Carrasco-Gallego, 2016; Agénor and Silva, 2017).

This work proposes a cyclical model of consumer debt risk in which households' income shocks and the contractual terms offered by lenders explain default. Households are required to service their consumption needs and accumulated debt obligations using a budget composed of current income, past savings, plus new debt contracts available from banks and non-financial institutions. Lenders offer a menu of contracts according to the risk of households and banks' funding costs, with loans differing in terms of interest rates, maturity and the debt amount available. Families' income is subject to idiosyncratic shocks of labor income and unemployment spells, with some workers being more vulnerable to the economic cycle and to changes in credit conditions. It is the interaction between shocks to household income processes and the debt contracts available to them that leads some households to lose credit, become insolvent and unable to pay their debts. I then show how household finances and credit risk are affected in distinct phases of the business cycle by factors such as layoff risk, income volatility and unemployment benefits. Liquidity shocks are shown to be important, with increases in banks' funding costs, sudden credit rationing of debt amounts or a shortening of debt maturities having a great impact on default rates. Institutional factors such as interest rate ceilings also affect the volatility of repayment risk.

The model uses an heterogeneous distribution of households, which is calibrated with employment, finance and consumption

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survey datasets that are available in most developed countries (Eurosystem, 2009; Ampudia et al., 2016). Furthermore, the model assumes a simple behavioral rule for consumption based on demographics, permanent income, precautionary behavior regarding income volatility, and habit persistence, rather than full-optimization. Default decisions are also behaviorally determined by the inability to pay for both debt service and a minimum consumption level. The use of behavioral rules allows for a calibration with a large number of agents which is well-suited to study the sensitivity of financial institutions to different shocks. However, behavioral rules may hinder analysis of certain institutional shocks that drastically change agents' behavior, such as modifications to bankruptcy laws (Nakajima and Ríos-Rull, 2014). Using data from Chile the model replicates well the fluctuations of consumer loans' default rates observed in the period 1990 to 2012, including all its high risk episodes: the early 1990s, the Asian crisis of 1999–2001, and the recent international credit crisis of 2007–09. Chile presents a challenging empirical case for the study of consumer debt default, since unsecured consumer credit represents a large share of financial assets and mirrors the consumer credit expansion in the rest of Latin America (IMF, 2006).

The most relevant result is that consumer debt default and household insolvency are highly cyclical. Also, economic fundamentals such as unemployment, income and credit market shocks play a significant role in explaining consumer default fluctuations. Families are affected by liquidity risk, besides unemployment and high interest rates. Low liquidity and shorter loan maturities increase the financial charge due to amortization in the households' budget constraint, therefore making indebted households worse at an increased rate and giving them less time to fix their finances after negative shocks. Furthermore, I estimate that consumers' credit constraints imply a reduction in overall consumption between 0.5% and 1%, with worse effects during recessions.

The calibration of this structural model of household risk requires three components: (1) the distribution of income, expenditure and debt across agents, (2) families' income risk and default behavior, and, finally, (3) the structure of credit markets and how banks and retail institutions offer different types of credit conditional on households' risk profile.

To measure the debt distribution I consider the waves of the Chilean Household Finance (EFH) survey, which comprise a representative sample of 12,000 households, with detailed information on their income, labor status, assets, debt service charges and maturities, plus default behavior. I then simulate the non-durable expenditures' profiles of these families using the Household Expenditure Survey (EPF, 2007), which covers a sample of 10,000 urban households. Afterwards, households' working members suffer stochastic income shocks and unemployment spells, using a dynamic process estimated by Madeira (2015). This process is innovative in relation to previous literature such as Carroll and Samwick (1997) by explicitly considering the large income drops caused by transitions into and out of unemployment. Indebted households can then adjust their consumption commitments, but cannot experience too large consumption drops or consume below a minimum living standard for families with its profile. Families reach a status of insolvency when their income plus access to new credit is unable to pay past debts and minimum consumption.

Finally, the model incorporates a realistic credit market structure where heterogeneous families can access different amounts of credit by lenders, either banks or retail stores, with loan amounts depending on a multiple of households' income. The EFH survey provides a metric of repayment risk given by households' answers to whether the family "failed any loan payment over the last 12 months". Banks price the interest rate of each family according to the default probability based on its demographics and income risk. If the debtor's risk profile surpasses the legal limits on usury interest rates, then he is denied credit. Retail stores accept a wider range of debtors, but are limited to charging the same interest rate for all clients and to an "accept/reject" decision on loan applicants. The inability to discriminate loan terms leads retail stores to charge high interest rates.

The model's expected dynamics for household income, consumption and default are then simulated for each quarter of the last 23 years, considering the historical evolution of banks' funding costs and the labor market shocks experienced by each type of worker profile. Unemployment and income volatility dynamics are accurately measured over this period using the Chilean Income and Employment Survey (ENE), which covers a large sample of 45,000 workers at a quarterly frequency. The simulations replicate well the historical mean and volatility of consumer delinquency in Chile, implying the model can be taken as a serious tool for evaluating policy scenarios.

My study is closest in spirit to previous studies of bankruptcy and default (Chatterjee et al., 2007; Athreya et al., 2015; Livshits et al., 2016). Other studies show that countercyclical income risk in the US can explain the rise in credit spreads, foreclosures and consumer debt default during recessions (Luzzetti and Neumuller, 2016; Kaplan et al., 2017; Nakajima and Ríos-Rull, 2014) and that labor market shocks explain part of the surge in default during the Great Recession (Gerardi et al., 2015; Athreya et al., 2015). However, the high computational costs of these models limit their analysis to a world without aggregate shocks or to a small number of agents' types, hindering the study of the cyclical volatility of default. Other models have advanced on adding macro fluctuations by assuming that forecasting the aggregate equilibrium is independent of the heterogeneity of the agents (Krusell and Smith, 1998; Kaplan et al., 2017). My model limits these computational demands by using behavioral rules for the consumption and default decisions of the agents. Both assumptions have some empirical support. One, Chile is a small open economy, therefore the aggregate interest rate and credit are at least partly determined by international developments. Also, empirical evidence supports households' use of simple behavioral rules for both consumption (Carroll, 1994) and loan decisions (Agarwal and Mazumder, 2013; Einav et al., 2012), rather than complete optimization. However, since the model is based on behavioral assumptions estimated from past data, its results can be less accurate when analyzing large institutional shocks. One example could be the case of policies that promise to pardon past loans (such as educational loans) or delinquency, since such measures impact lenders and borrowers' expectations about future behavior (Lucas, 1976).

This paper is organized as follows. In Section 2 I portray the strong cyclical volatility of consumer default and how previous studies fail to explain it. Section 3 introduces the model's framework and how households and lenders interact, then Section 4 explains how to calibrate the model from survey data. Section 5 comments on how well the model explains the historical evolution of debt risk in Chile. Finally, Section 6 concludes with implications for policy and future research.

2. The cyclical volatility of consumer debt default

Consumer debt default has strong fluctuations over the business cycle. The most common definition of the delinquency rate measures the ratio of the value of loans in arrears after 90 days over the stock of overall loans (Botha and van Vuuren, 2009). The United States, Spain, and Chile have consumer delinquency statistics for a long history, although the USA series measures loan arrears after 30 days instead of the more recent standard of 90 days. Since arrears of only 30 days may overstate the true default rate I also analyze the ratio of banks' expenses with non-performing consumer loans

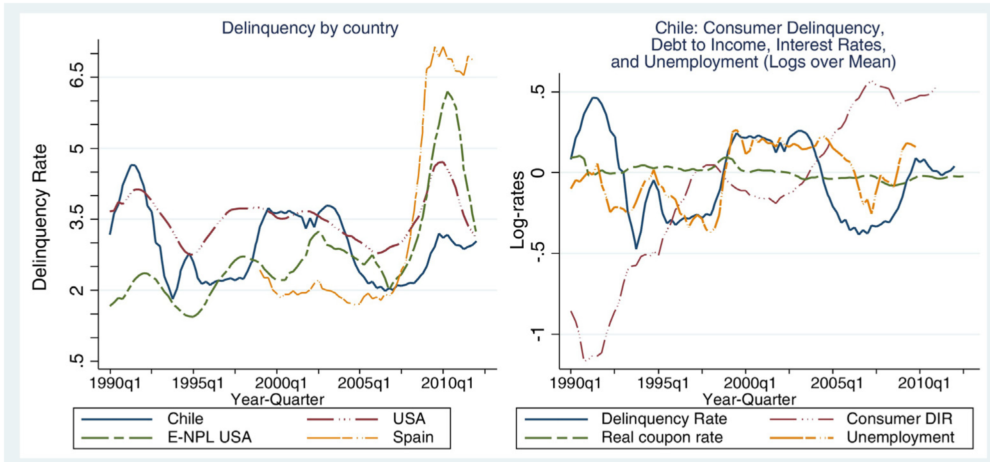

Fig. 1. Aggregate statistics of delinquency for Chile, Spain and the United States.

over total loans for the USA. Fig. 1 summarizes aggregate data from the Central Bank of Chile, Chilean Financial Authority (SBIF), Bank of Spain and Federal Reserve Board, showing that over the last 23 years consumer delinquency rates fluctuated between 2.76% and 4.71% in the USA and 1.82% to 4.65% in Chile, with strong fluctuations happening in all economic cycles. Measuring fluctuations as a peak-to-trough ratio, $\frac{delinquency(high)}{delinquency(low)}$, consumer delinquency during recessionary periods increased up to 171% (if using arrears over 30 days) or even 430% (if using banks' expenses) in the USA, 256% in Chile, and much more in Spain. Strong fluctuations in household delinquency were also observed in several eurozone countries since 1999 (Rinaldi and Sanchis-Arellano, 2006).

The second graph in Fig. 1 plots the consumer delinquency in Chile with other aggregate indicators: the aggregate consumer debt to income ratio, the unemployment rate, and a measure of the real cost of debt service, $\frac{i_t/12}{1-(1+i_t/12)^{-12}}$, which is the monthly cost of paying one unit of a one-year fixed coupon debt with i_t being the average real interest rate for consumer loans. All variables are standardized as the log over their mean, $\ln(\frac{x_t}{E[x_t]})$. In Chile consumer debt delinquency is positively correlated with unemployment and the variation in the real cost of debt service, but it shows much higher volatility than these indicators. The aggregate Consumer Debt relative to Household Income ratio shows a positive trend over the whole period of 1990 to 2010 and yet this ratio does not increase during periods of high consumer delinquency. Similarly, in time series for the USA and other OECD countries, the correlation between aggregate debt service to income and delinquency is close to zero (Girouard et al., 2007).

Default is driven by a small fraction of credit constrained households, leading several central banks to perform stress tests using micro survey data, but such stress tests often suggest that even significant increases in unemployment or in interest rates imply small changes in default rates (Ampudia et al., 2016). Micro-data stress tests for Finland (Herrala and Kauko, 2007) and Spain (Eurosystem, 2009) estimate that a 100 basis points increase in interest rates would represent a log-increase in debt default lower than 3%. From 2007 to 2009 an increase around 150 basis points in Spanish' government yields was associated with a consumer debt delinquency rate change from 1.96% to 7.14%, which is a log-change of 129% and a much bigger shock than these tests suggest.

A problem in these studies is that default is measured by limited statistics such as whether households' debt service to income ratio is below 40% or a simple probit model, ignoring important elements such as the loan amount and its maturity, families' income volatility, and the difficulty to reduce consumption or to gain access to new credit. Finally, these studies consider one-period unemployment spells, ignoring realistic income dynamics. The model of the next section provides a rich framework of how loan terms, income dynamics and access to new credit affect loan default.

3. A framework to analyze household debt risk

3.1. An empirical model of household default and consumption

Household risk is difficult to assess, since their major asset is given by future income which is hard to expropriate as collateral, creating asymmetric information between lenders and borrowers. Lenders react to the adverse selection of borrowers by capping loan size, interest rates, and debt maturities (Jaffee and Stiglitz, 1990). Since consumer loans have short maturities, amortization represents a larger component of the debt service than interests, making credit constrained households more sensitive to loan maturity than interest rates (Attanasio and Weber, 2010).

These factors can be represented using a simplified version of the contract pricing model of Einav et al. (2012). In each period t families with heterogeneous characteristics ζ receive a stochastic income y_t, accumulate assets A_t (which may include a vector of both liquid or illiquid instruments) and assume loan contracts ϕ_t (which are characterized by terms such as interest rate, loan amount, and maturity), with consumption, asset and loan decisions being subject to a budget constraint $B(y_t, \phi_t, A_t|\phi_{t-1}, A_{t-1}) \geq 0$. Loan terms affect debtors' repayment probability, therefore lenders offer contracts $\phi|y_t, \zeta, \Psi_t$ conditional on debtors' characteristics and a vector of global factors, Ψ_t, such as regulations and banks' funding costs. Households then choose to default or not, $Df_t \in \{0, 1\}$, by considering the consumption utility of paying their loans, $u(y_t, \phi_t)$, versus defaulting with some punishment cost and residual loans $\phi_t^{df}(\phi_t)$ (which need to be paid even after default), $u_d(y_t, \phi_t^{df}(\phi_t)$, plus their sequential value discounted by β:

$$\max_{Df_t \in \{0,1\}, \phi_t \geq 0, A_t \geq 0, \ s.t\ B(y_t, \phi_t, A_t|\phi_{t-1}, A_{t-1}) \geq 0} U_t(y_t, \phi_t) = \{u(y_t, \phi_t) + \beta E_t[U_{t+1}(y_{t+1}, \phi_{t+1})],$$

$$u_d(y_t, \phi_t^{df}(\phi_t)) + \beta E_t\left[\bar{U}(y_{t+1}, \phi_{t+1}^{df})\right]\}. \quad (1)$$

In this model shocks to income and future credit access play a role even if previous loan contracts ϕ_t are fixed. Suppose a household is able to amortize his debt only partially. Its liabilities are in a declining path, but the family remains solvent only with access to new credit in good terms.

Consumer debt default may happen with agents who fail to optimize their decisions completely (Einav et al., 2012), therefore I propose a simple empirical model of default and expenditure that approaches the main behavioral motivations of households, while using a rich framework for the households' budget constraint, income dynamics and loans. The behavioral rule assumes households choose an "informal default" or delinquency when faced with an extreme reduction in consumption. Some previous works (Benjamin and Mateos-Planas, 2013; Athreya et al., 2015) consider delinquency is the result of a bargaining option of debtors that may threaten lenders with bankruptcy procedures. Chile is a country with no bankruptcy and with full recourse contracts, implying that agents can be prosecuted until their debts are settled. However, lenders still face expensive collection procedures that may deter them from pursuing delinquent debtors.[1] Also, since Chile does not have a common credit register for all lenders, then it is possible a lender does not want to risk going to court and find out that other claims are ahead of his.

All households start in a state of no-default, $Df_t = 0$, at time t. The initial endowments of debt, liquid assets A_t, and income are heterogeneous across households, but for simplicity of notation I ommit the household identifier i for now. Let Y_t, C_t, DS_t represent the household income, consumption and debt service in period t, with $S_t = Y_t - C_t - DS_t$ being current savings. Households' initial consumption $C_t = c(\zeta, P_t, \sigma_t, \varepsilon^c)$ is a function of their demographic characteristics ζ, permanent income P_t, income volatility σ_t, and an idiosyncratic taste component in each household ε^c, as in Carroll and Samwick (1997). $B(.)$ denotes the budget constraint function, which determines whether a given expenditure is affordable $B(C_t) \geq 0$ or unaffordable $B(C_t) < 0$. At period $t+s$ households keep consumption constant if their last income was enough to pay past consumption and debt service (i.e., if savings $S_{t+s-1} \geq 0$). If savings are negative, $S_{t+s-1} < 0$, then households reduce their expenditure gradually by a fraction $\lambda \in (0, 1)$ each quarter until reaching a minimum living standard, $m(\zeta)$. If this smooth consumption plan $g(\zeta, C_{t+s-1}, S_{t+s-1})$ is unaffordable, then households decide to default, $Df_{t+s} = 1$, become excluded from credit, and consume their current income Y_{t+s} minus some debt service DS^{df}_{t+s} that cannot be reduced by default (such as mortgages):

$$\{Df_{t+s}, C_{t+s}\} = \{0, g(\zeta, C_{t+s-1}, S_{t+s-1})\}, \quad \text{if} \quad B(g(\zeta, C_{t+s-1}, S_{t+s-1})) \geq 0, \tag{2.1}$$

$$\{Df_{t+s}, C_{t+s}\} = \{1, Y_{t+s} - DS^{df}_{t+s}\}, \quad \text{if} \quad B(g(\zeta, C_{t+s-1}, S_{t+s-1})) < 0, \tag{2.2}$$

with (2.1) and (2.2) subject to $g(\zeta, C_{t+s-1}, S_{t+s-1}) = 1(S_{t+s-1} \geq 0)C_{t+s-1} + 1(S_{t+s-1} < 0)(C_{t+s-1} - \lambda|C_{t+s-1} - m(\zeta)|)$.

The budget constraint, $B(.)$, includes current savings S_t, liquid financial assets A_t, which pay the interest rate R_t, and positive new debt amounts contracted by the household, $ND_{v,t} \geq 0$, with each available lender v, $v = 1, 2, \ldots, V$. Negative savings require using either liquid assets or new debt contracts. The feasible consumption budget function $B(C_t)$ is now defined as:

$$B(C_t) = Y_t - C_t - DS_t + (A_t(1 + R_t) - A_{t+1}) + \sum_{v=1}^{V} ND_{v,t} = 0, \quad \text{subject to} \quad C_t, A_{t+1}, ND_{v,t} \geq 0. \tag{3}$$

Each lender v offers differentiated contracts with a fixed maturity, m_v, interest rates $i_{v,t} = i(.|CF_t, X_{v,t})$ priced for the cost of funds CF_t plus the borrowers' default risk conditional on lender v's information set, $X_{v,t}$, and a top debt limit $dc_{v,t} = dc_v(P_t, Y_t, \zeta)$ as a function of their demographics, ζ, plus permanent P_t and current income Y_t. Lenders with different information sets can coexist as long as there are frictions in borrowers' choices, due to travel costs, marketing or even decision inertia (Pagano and Jappelli, 1993). Besides consumer debt some households also have a mortgage debt, MD_{t+1}, with payment, MG_{t+1}, which for simplicity is exogenous and with no default due to collateral. If households decide not to default, $Df_t = 0$, then they accept to satisfy their total debt service (DS_{t+1}) and legal liabilities ($D_{t+1} = MD_{t+1} + \sum_{v=1}^{V} D_{v,t+1}$) defined as:

$$DS_{t+1} = MG_{t+1} + \sum_{v=1}^{V} DS_{v,t+1}, \tag{4.1}$$

with debt amount and service for each lender v given by $DS_{v,t+1} = \sum_{j=0}^{m_v-1} ND_{v,t-j} \frac{i_{v,t}}{1-(1+i_{v,t})^{-m_v}}$ and $D_{v,t+1} = \sum_{j=0}^{m_v-1} ND_{v,t-j} \frac{1-(1+i_{v,t})^{j-m_v}}{1-(1+i_{v,t})^{-m_v}} \leq dc_{v,t}$, for $v = 1, \ldots, V$. If households decide to default I assume for simplicity that they default on all consumer debts, but not on its mortgage:

$$DS^{df}_{t+1} = MG_{t+1}, \quad D_{t+1} = MD_{t+1}, \quad DS_{v,t+1} = 0, \quad D_{v,t+1} = 0, \quad \text{for} \quad v = 1, \ldots, V, \tag{4.2}$$

For each household several income paths are simulated based on a stochastic process, $Y_{t+s} = F(|\zeta, Y_t, \sigma_t)$, dependent on their demographic characteristics ζ, current income Y_t, and with income volatility σ_t. The model's stochastic simulations of the default behavior of each household i at time $t+s$, Df_{t+s}, are then aggregated for all the households and used to estimate the non-performing loans (NPL_t), the expenses with non-performing loans ($ENPL_t$), and the consumption reduction made by households due to credit frictions (CC_t), at a specified horizon of s quarters:

$$NPL_t(s) = \frac{1}{\sum_{i=1}^{N} W_{i,t}} \sum_{i=1}^{N} W_{i,t} Pr(Df_{i,t+s} = 1|\zeta_i, Y_{i,t}), \tag{5.1}$$

$$ENPL_t(s) = \frac{1}{\sum_{i=1}^{N} W_{i,t}} \sum_{i=1}^{N} W_{i,t} E\left[\frac{(Df_{i,t+s} \times D_{i,t+s})}{D_{i,t}}|\zeta_i, Y_{i,t}\right], \tag{5.2}$$

$$CC_t(s) = \frac{1}{\sum_{i=1}^{N} W_{i,t}} \sum_{i=1}^{N} W_{i,t} E\left[-\ln\left(\frac{C_{i,t+s}}{C_{i,t}}\right)|\zeta_i, Y_{i,t}\right], \tag{5.3}$$

where $W_{i,t}$ is a weight measure, which can be either a population weight (f_i) representing the number of households in each strata, an income weight ($f_i Y_{i,t}$) giving the proportion of household i in terms of the national income or a debt weight ($f_i D_{i,t}$) representing the share of household i in the aggregate consumer debt. Non-performing loan rates (NPL, $ENPL_t$) use debt weights to measure the risk of loan portfolios. For the cost of consumption (CC_t) I apply either a standard population weight (which gives the consumption cost of the average family) or an income weight (giving the consumption cost in terms of its impact on the national disposable income). The horizon parameter s is calibrated to be $s = 8$ quarters, which is the average maturity of consumer loans in Chile. There is a random sampling treatment of households. A household that has finished repaying its debts is replaced by another household with the same characteristics ζ from the data sample of households. In the same way households in default stay in the sample for 8 quarters without credit and then are randomly replaced by

[1] Accounting standards for the Chilean banks recommend that consumer loans should expect losses of 60%, 90% and 100%, after a period of respectively 4, 5 and 6 months in arrears (Matus, 2015), therefore banks prefer to assume default on consumer loans as a loss. Accounting standards for mortgages assign a loss of 20% even after more than 6 months in arrears, therefore the model does not consider mortgage default since their capital can be recovered.

Table 1
Calibrated and estimated parameters.

Parameters and exogenous shocks	Source
Population distribution and endowments (Income, assets, debts $\|\zeta$)	EFH 2007–2011 ζ = {Region, Sex, Age, Education, Industry, Quintile(Y_t), Number of household Members}
Shocks to Initial Debt Endowments	Mean Debt and Interests Growth (SBIF)
Income dynamic shocks (540 types)	Y_t, σ_t (Madeira, 2015, ENE 1990–2012)
Expenditure choice	$C_t = c(\zeta, P_t, \sigma_t, \varepsilon^c)$ (EPF, 2007) $m(\zeta) = Q_1(C_0\|\zeta)$, $\lambda = 0.15$
Default decisions	Budget kink: $B(g(\zeta, C_{t+s-1}, S_{t+s-1})) < 0$
Credit Market, 2 lenders ($\nu = 1, 2$)	Banks, Retail: $D_{\nu,t+1} \le dc_{\nu,t+1}$(lender ν)
Loan terms: $i_{\nu,t} = i(.\|CF_t, X_{\nu,t})$	EFH: $X_{\nu,t} = \{\zeta, D_t, P_t, Y_t, Pr(U_t), DS_t\}$
$m_t = \{m_{1,t}, m_{2,t}\}$	$m_t = \{8, 4\}$ (EFH data, MMFS, 2011)
$dc_t = \{dc_{1,t}, dc_{2,t}\}$	$\{dc_1(P_t, Y_t, \zeta), dc_2(P_t, \zeta)\}$
Maximum Legal Interest Rate	$i_{\nu,t} \le 1.50 \times E[i_{2,t}]$
Banks' fundraising real interest rates, i_t	Central Bank of Chile (1990Q1–2012Q4)

another household with the same characteristics ζ.[2] The length of this punishment period does not overly affect the results because in each quarter the percentage of households in default is small relative to the overall stock of debtors.[3]

The data sources used to calibrate the default model are summarized in Table 1. The distribution of families with demographic characteristics ζ and their initial endowments of assets, debts, and income in period t is calibrated using the EFH household finance survey. Furthermore, in each period t I adjust the initial endowments for each family i to reflect aggregate growth in the mean financial assets, loan amount and debt service.[4] The stochastic income dynamics are calibrated using permanent and transitory labor shocks estimated from the Chilean Employment Survey (ENE).

[2] Accounting standards for banks recommend that loans in arrears are written-off (erased from the balance sheet) after 24–36 months (Matus, 2015), therefore 8 quarters corresponds to the period in which lenders expect repayment. This random sample replacement of households after their loans are repaid or after a default plus a limited punishment period has two motivations: (1), it limits the horizon over which each agent's simulation is kept and this avoids complex decisions that occur over the lifetime (such as when to have more children or when to buy a new home, see Attanasio and Weber, 2010) and that may affect both loans and risk; (2), this gradual random replacement of households with similar ones in the original data insures a long-run steady-state equilibrium with an heterogeneous distribution of agents which is given by the empirical data sources and demographic changes (estimated from the Chilean Employment Survey (ENE)). A previous version of the model also simulated marriage, children, plus the decision of a new loan and its amount conditional on ζ, and such results are available from the author upon request. In the current model, households appear with their assets, loans and are followed for a short period, therefore it concentrates on the repayment risk period and it is agnostic about loan decisions and the life cycle.

[3] Another important aspect is that the model considers that default comes purely from economic stress due to households being unable to keep paying both a minimum consumption and their debts when they suffer large income shocks. However, the length of the punishment period could matter substantially for models that consider bankruptcy or default is a strategic decision of the agents regarding explicit punishment costs (Nakajima and Ríos-Rull, 2014).

[4] The initial debt endowments in period t for each family are adjusted for mean debt growth and interest rate changes: $D_{i,t} = D_{i,EFH} \frac{MCD_t}{MCD_{t(EFH)}}$, $DS_{i,t} = \frac{MCD_t}{MCD_{t(EFH)}} \sum_d DS_{d,i,t} \frac{i_{t-m}/(1-(1+i_{t-m})^{-M})}{i_{t(EFH)-m}/(1-(1+i_{t(Efh)-m})^{-M})}$, where MCD_t is the Mean Value of Consumption Debt per Debtor, $DS_{d,i,t}$ is the debt service of household's debt d and i_t the average interest rate for consumer loans in period $t-m$. The quarterly series for MCD_t and i_t are obtained from the Central Bank of Chile and the Chilean Financial Authority (SBIF). Also, survey expansion factors are adjusted over time based on heterogeneous demographic population growth estimates $P_t(\zeta_i)$ from the ENE: $f_{i,t} = f_{i,EFH} \frac{P_t(\zeta_i)}{P_{t(EFH)}(\zeta_i)}$.

The initial consumption function $C_t = c(.)$ and the minimum consumption $m(\zeta)$ are estimated using the non-durables expenditures of the Chilean Expenditure Survey. The consumption habit parameter is set as $\lambda = 0.15$, following studies for the United States which estimate that even families with large income falls only reduce consumption by 12.1% (Gruber, 1997) or 14% (Chetty and Szeidl, 2007), suggesting it is hard to cut consumption by more than 15%. Finally, the credit market model considers two types of lenders, banks and retail stores, that lend with maturities of 8 and 4 quarters respectively, which are the mean loan maturities for these lenders in Chile (see Table 3 in the next section, plus Marinovic et al., 2011, hence on MMFS, 2011). Lenders price interest rates based on the repayment risk of each household and a maximum legal interest rate.

4. Calibration data

4.1. Sample population

Measuring default risk requires a large sample to provide accuracy, therefore I use the five EFH survey waves (collected from 2007 to 2011) as a single pooled sample of 12,264 households, with the expansion factors of each wave being adjusted according to their respective share in the total sample. These surveys have a highly detailed measure of income, assets, and debts, including mortgage and consumer loans with their respective terms (debt service, loan amount, maturity).

The model in this work depends on several datasets, including imputed values and simulations. However, all the results are continuous statistics, therefore valid asymptotic confidence intervals and standard-errors can be obtained through a bootstrap procedure in which replica samples are built with replacement for each one of the EFH, ENE and EPF datasets, with all the household's members sampled in each observation unit. All the model's coefficients and random simulations are re-made on each bootstrap sample. Gourinchas and Parker (2002) provide a valid asymptotic GMM variance matrix for a model estimated from different datasets, but their derivation ignores imputations, simulation error and it is cumbersome for a large number of parameters.

4.2. Workers' stochastic income process

Worker's earnings are simulated with a dynamic income process estimated by Madeira (2015), using the Chilean Employment Survey which covers 35,000 households per quarter. Each labor force member k of household i at time t has a simulated income $Y_{k,i,t}$, and suffers unemployment transitions ($U_{k,i,t} = 1$ if unemployed, 0 if working) plus permanent $P_{k,i,t}$ and transitory income shocks $L_{k,i,t}$ (as in Carroll and Samwick, 1997). Workers' income shocks and unemployment transitions with layoff and job-finding probabilities, $layoff_{k,i,t} = \Pr(U_{k,i,t+1} = 1|t,\ U_{k,i,t} = 0,\ x_{k,i})$ and $job_{k,i,t} = \Pr(U_{k,i,t+1} = 0|t,\ U_{k,i,t} = 1,\ x_{k,i})$, are both time-varying due to the business cycle (t) and heterogeneous for 540 different worker types ($x_{k,i}$) given by $x_{k,i}$ = Santiago Metropolitan city or Outside, Industrial Activity (primary, secondary, tertiary sectors), Gender, Age (3 brackets, ≤ 35, 35–54, ≥ 55), Education (less than secondary schooling, secondary school or technical education, college), and Household Income quintile. This income process accounts for recessions having both more layoffs and longer unemployment spells (Shimer, 2012) and is summarized as:

$$P_{k,i,t+s} = G_{k,i,t+s} P_{k,i,t+s-1} \eta_{k,i,t+s}, \tag{6}$$

$$L_{k,i,t+s} = \zeta_{k,i,t+s} RR_{k,i,t+s}^{U_{k,i,t+s}}, \tag{7}$$

$$Y_{k,i,t+s} = P_{k,i,t+s} L_{k,i,t+s}, \quad \text{for} \quad s = 1, \ldots, M. \tag{8}$$

Table 2
Log-consumption semi-parametric estimates of $\ln(c_{i,t}) - g(z_i)$, EPF (2007).

Independent variables	Non-durables	Durables	Total expenditures
Permanent income, $P_{i,t}$	0.485 (0.006)***	0.856 (0.015)***	0.569 (0.007)***
Labor income risk, $\bar{\sigma}_{i,t}$	−0.719 (0.029)***	−1.079 (0.069)***	−0.733 (0.031)***
R-square	0.417	0.284	0.446

10,092 observations, standard-errors from 10,000 bootstrap replicas.
*** 1% statistically significant.

Permanent income[5], $P_{k,i,t}$, is affected by an heterogeneous drift, $G_{k,i,t} = \frac{E(Y_{k,i,t}|t,x_{k,i})}{E(Y_{k,i,t-1}|t-1,x_{k,i})}$, which represents mean income growth, plus a log-normal random shock $\ln(\eta_{k,i,t}) \sim N(0, \sigma_\eta(\chi_{k,i,t}))$. Transitory income is affected by a continuous log-normal shock, $\ln(\zeta_{k,i,t}) \sim N(0, \sigma_\zeta(\chi_{k,i,t}))$, plus an extra shock when workers change employment status, $RR_{k,i,t+1}^{U_{k,i,t+1}}$. $RR_{k,i,t}$ is defined as the replacement ratio of unemployment benefits relative to their working income and it ranges from as low as 3% to as high as 40% (Madeira, 2015), depending on the worker's type $x_{k,i}$. One then obtains the simulated household current and permanent income levels as the sum of their working members' incomes, $Y_{i,t+1} = a_i + \sum Y_{k,i,t+1}$ and $P_{i,t} = a_i + \sum_k P_{k,i,t}(1-u_{k,i,t}) + P_{k,i,t}RR_{k,i,t}(u_{k,i,t})$, plus non-labor household income, a_i. I then obtain the household's income weighted unemployment risk and income volatility, $\bar{u}_{i,t} = \sum_k \frac{P_{k,i,t}}{P_{i,t}-a_i} u_{k,i,t}(x_{k,i})$ and $\bar{\sigma}_{i,t} = \sum_k \frac{P_{k,i,t}}{P_{i,t}-a_i}(\sigma_\zeta(\chi_{k,i,t}) + \sigma_\zeta(\chi_{k,i,t}))$.

4.3. Consumption

The initial expenditure of households at time t is a stochastic function of their demographics, z_i, permanent income $P_{i,t}$, income volatility $\bar{\sigma}_{i,t}$ and an idiosyncratic consumption preference ε_i:

$$\ln(c_{i,t}) = g(z_i) + \beta[\ln(P_{i,t}), \bar{\sigma}_{i,t}] + \varepsilon_i, \quad \text{with} \quad \varepsilon_i \sim N(0, \sigma_i = v(z_i)). \tag{9}$$

For $c_{i,t}$ I focus on non-durable expenditures, since previous studies show households smooth non-durable expenditures even during unemployment events while durable goods are easy to postpone (Attanasio and Weber, 2010). Consumption is truncated above a minimum living standard given by the 20th percentile conditional on family characteristics, $m(z_i) = p_{20}(c_i|\zeta)$. This model is estimated with Robinson's (1988) two-step procedure using the EPF data. The EPF contains no wealth information (Attanasio and Weber, 2010), although wealth is correlated with demographics z_i, but model estimates that include current income $y_{i,t}$ and an estimated value of the financial wealth according to the sex, age and education of the household members give similar results. These results are available from the web Data in Brief or from the author upon request.

Table 2 shows the results of the regression (9) for non-durables, durables, and total household expenditures, and with the demographic vector z_i = home-ownership, employment status and age of the household head, Metropolitan Area, number of adults, minors, and senior members in the family. Household consumption is shown to be increasing in permanent income and decreasing in labor income risk ($\bar{\sigma}_{i,t}$) for both durables and non-durable goods. Consumption of durables is more sensitive to both permanent income and income risk, confirming that it is easier to reduce.

4.4. Borrowers' profiles, credit access and interest rates

In Table 3 I summarize the debt of households in three different situations: those with loans just in banks or just in retail stores, and those with loans in both lenders. Almost 50% of the Chilean families in the EFH sample hold a loan with one of these lenders. Banks make larger loans than retail stores, at lower interest rates, longer maturities and have lower delinquency rates (defined as a late payment for at least one month in the last year). Bank loans are also more related to the purchase of durable goods, which is relevant since such loans could be partially collateralized. Households in the survey sample also report that some of their current loans are being used to repay past debts, which is a signal that lenders and borrowers may engage in future renegotiation of defaulted debts. "Pay Previous Debts" is more reported for bank loans, which may indicate that since such loans are much larger than the ones in retail stores, then borrowers take larger efforts to renegotiate them. Furthermore, Table 4 shows that debtors in banks have higher permanent income ($\bar{P}_{i,t}$), lower unemployment ($\bar{u}_{i,t}$) and layoff risk ($\bar{\lambda}_{i,t}^{EU}$) than retail store customers.

Each lender v adjusts its loans to their expected delinquency risk for each borrower i at time t, $Pr(Dl_{v,i,t})$, conditional on an observed set of information $X_{i,t}^v$. The cost of providing a loan equals its capital plus the lenders' cost of funds CF_t, which equals 7% of loan administration costs plus the 1-year deposit interest rate. In case of delinquency lenders lose a portion LGD of their capital. By equating loan costs with expected revenues, lender v obtains its competitive interest rate:

$$(1+CF_t) = E\left[revenues_{v,t}(i)|X_{i,t}^v\right] = (1+i_{v,t}(i)) \times [(1-Pr(Dl_{v,i,t})) + (1-LGD)Pr(Dl_{v,i,t})] \Leftrightarrow i_{v,t}(i) = \frac{CF_t + (LGD \times Pr(Dl_{v,i,t}))}{1-(LGD \times Pr(Dl_{v,i,t}))}, \tag{10}$$

with $v = 1$ (for banks) and 2 (for retail stores). The loss-given-default portion of the loan, LGD, is fixed at 0.50, which is similar to US estimates (Botha and van Vuuren, 2009). Borrowers' risk, $Pr(Dl_{v,i,t})$, is estimated by a probit model of whether households missed any loan payment over the last 12 months, conditional on lender v's restricted information set, $X_{i,t}^v$:

$$Pr(Dl_{v,i,t}) = Pr(Delinquency_{i,t} = 1|X_{i,t}^v) = \Phi(\theta_v z_i^v + \beta_v x_{i,t}^v), \tag{11}$$

with Φ being the standard normal cdf. $X_{i,t}^v = \{z_i^v, x_{i,t}^v\}$ includes a vector of fixed demographic characteristics, z_i^v, plus a set of continuous time-varying risk-factors, $x_{i,t}^v$, which induce heterogeneous time shocks to interest rates. The empirical estimation uses z_i^v = *Santiago Metropolitan resident or not*, *number of household members*, *gender*, *marriage status*, *age an deducation dummies of the household head* and $x_{i,t}^v$ = household log-income $y_{i,t}$, lender's consumer debt to permanent income ratio $\frac{D_{i,t}^v}{12 \times P_{i,t}}$, debt service to income ratio $\frac{DS_{i,t}^v}{Y_{i,t}}$, and the household's unemployment probability $\bar{u}_{i,t}$. $\frac{D_{i,t}^v}{12 \times P_{i,t}}$ and $\frac{DS_{i,t}^v}{Y_{i,t}}$ are measures of household solvency and liquidity risk of high immediate payments. Some variables (such as financial assets) may affect default behavior but are excluded from the information set $X_{i,t}^v$ because those factors are unobserved by lenders (since in Chile

[5] The initial unemployment status $U_{k,i,t}$ at time t is randomized according to the unconditional unemployment probability, $u_{k,i,t} = \Pr(U_{k,i,t} = 1|t, _{k,i})$. The initial income is equal to the reported survey income at time t^*, Y_{k,i,t^*}, adjusted for nominal income growth in the workers' industry between time t and t^*, $Y_{k,i,t} = Y_{k,i,t^*} \frac{E(Y_{k,i,t}|t,x_{k,i})}{E(Y_{k,i,t^*}|t^*,x_{k,i})}$, and the permanent income is given by $P_{k,i,t} = Y_{k,i,t}\exp(-\zeta_{k,i,t})RR_{k,i,t}^{-(U_{k,i,t}-U_{k,i,t^*})}$, using a random log-normal $\zeta_{k,i,t}$.

Table 3
Loan terms, durable purchases and delinquency rates across lenders (mean values).

Debtor type	Households (% of population)	Maturity (months)	Amount[a]	Interest rate	Durables expenses	Pay Previous Debts	Delinquency[b] (30 days or more)
Bank (only)	7.8%	25.3	2549	19%	21.1%	14.9%	10.2%
Bank + Retail	12.9%	20.5	3015	24%	15.7%	16.9%	21.3%
Retail store (only)	28.9%	12.2	492	47%	6.8%	7.6%	19.0%

[a] Thousands of pesos. Bank + Retail corresponds to the total debt with both lenders.
[b] Delinquency in the EFH survey refers to a late payment over the last 12 months.

Table 4
Unemployment, income risk and log-permanent income across lenders (mean values).

Debtor type	$\bar{u}_{i,t}$	$\bar{\lambda}^{EU}_{i,t}$	$\bar{\lambda}^{UE}_{i,t}$	$\ln(\bar{P}_{i,t})$	$\bar{\sigma}_{i,t}$	$\bar{R}_{i,t}$
Bank (only)	4.8%	2.0%	33.8%	13.56	18.4%	25.8%
Bank + Retail	5.3%	2.3%	35.4%	13.46	18.2%	25.5%
Retail store (only)	5.5%	2.6%	36.6%	13.01	16.5%	23.5%

All the table values are means of each group.

Table 5
Consumer delinquency probit model (EFH pooled sample).

Explanatory variables	Full information	Banks	Retailers
$y_{i,t} = \ln(Y_{i,t})$	−0.144 (0.024***)	−0.188 (0.030***)	−0.115 (0.028***)
$\frac{D^v_{i,t}}{12\times P_{i,t}}$	0.915 (0.132***)	1.621 (0.215***)	0.620 (0.187***)
$\frac{DS^v_{i,t}}{Y_{i,t}}$	0.439 (0.151***)	0.181 (0.109*)	0.476 (0.202**)
College degree	−0.202 (0.062***)	−0.174 (0.064***)	−0.277 (0.065***)
Unemployment risk, $\bar{u}_{i,t}$	2.073 (0.488***)	1.811 (0.501***)	2.056 (0.495***)
Nr of household members	0.104 (0.013***)	0.103 (0.013***)	0.097 (0.013***)
Pseudo *R*-square	0.069	0.086	0.075
Nr of observations	5696	5696	5696

Standard-errors in () using 1000 bootstrap replicas. Other control variables: dummies for year, high income town (over 80% of population is above median national income), gender, marriage status, education and age of family head.
* 10% statistical significance.
** 5% statistical significance.
*** 1% statistical significance.

the largest financial asset managers are pension funds, which are non-bank related).

Table 5 shows the estimated delinquency probit model for banks, retailers, and a counterfactual lender which would have full information on both banking and retail debt loans of the borrower. Delinquency is correlated with lower education and larger families, lower income, higher debt amounts and debt service, and unemployment risk. Banks and retailers seem to have similar risk models, but banks are more averse to high debt levels, $\frac{D^v_{i,t}}{12\times P_{i,t}}$, while retailers are more averse to high debt service $\frac{DS^v_{i,t}}{Y_{i,t}}$. Fig. 2 plots the simulated population distribution of interest rates for bank debtors in the year 2006. This pdf distribution realistically replicates three features of the banking consumer credit, with one mode around 18% (consistent with credit cards and lines of credit), a second mode around 25–32% (consistent with contractual credits), and very few values above 45% (consistent with Chile's maximum legal interest rate).

Retail stores discriminate loans just by accepting or rejecting applicants, but offer the same interest rate to all borrowers, $i_{2,t} = E[i_{2,t}(i)]$. Lenders reject loan applications if the family's competitive interest rate does not satisfy the maximum legal interest rate, $i_{v,t}(i) \leq 1.50E[i_{1,t}(i)]$.

Lenders have debt ceilings based on a multiple of borrowers' permanent and transitory incomes (similarly to the credit-constrained representative agent model of Ludvigson (1999)). Banks' loan ceiling is calibrated as $b_{1,i,t} = 1(P_{i,t} \geq 70UF)(2P_{i,t} + 1Y_{i,t}) + 1(P_{i,t} \in (7, 70UF))(1P_{i,t} + \frac{1}{3}Y_{i,t})$, with UF being a Chilean real monetary unit value (one UF corresponds roughly to 45 US Dollars). Retail stores gather information less frequently, therefore their ceiling is a simple multiple of permanent income, $b_{2,i,t} = 1(P_{i,t} \geq 70UF)(2P_{i,t}) + 1(P_{i,t} \in (7,\ 70UF))(1P_{i,t})$. Since some families have more access to credit, the debt ceiling of the lender is given by the maximum of the income-based borrowing abilities, the family's current debt, and the 75th quantile of debt of families with similar characteristics z_i: $dc_{v,i,t} = \max(b_{v,i,t}, D_{v,i,t-1}, Q_{75}(D_{v,t-1}|z_i))$.

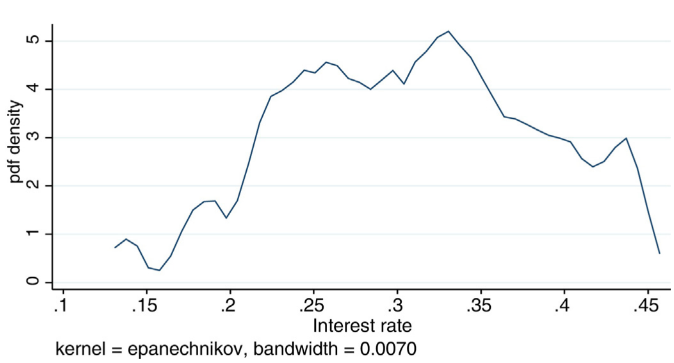

Fig. 2. Banks' competitive interest rates for the year 2006.

5. A historical simulation of financial distress

5.1. Baseline simulations and time-series validation

Fig. 3 compares the model's simulated consumer delinquency rate with the historical data in Chile, particularly in terms of the

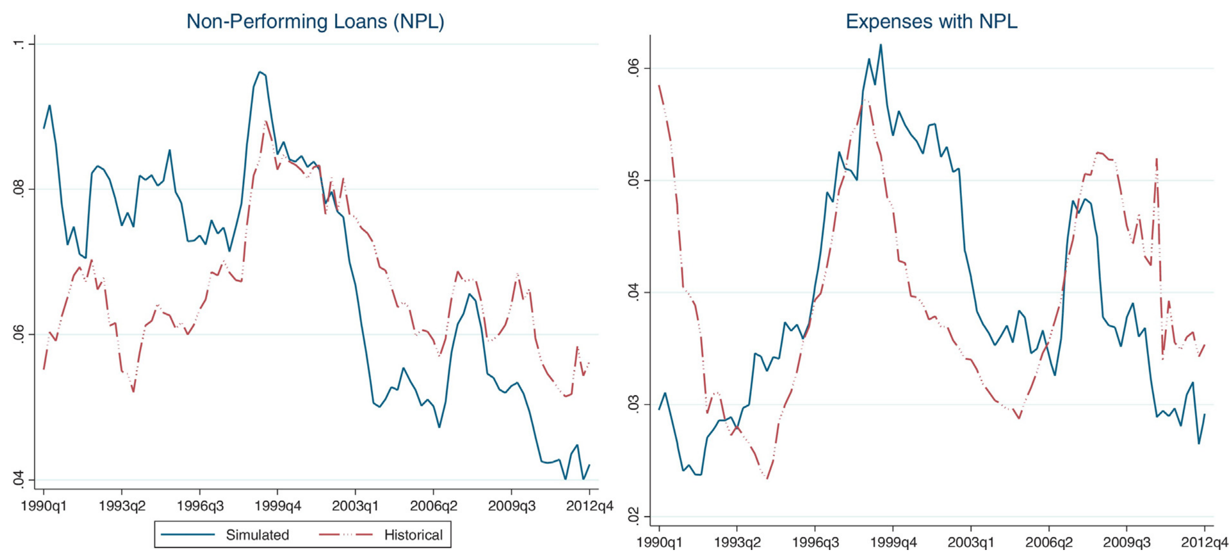

Fig. 3. Simulated NPL and ENPL versus historical data for the Chilean Banking System.

NPL, the Non-Performing-Loan Rate (the ratio of the consumer loans classified as non-performing over total consumer loans), and the ENPL, the Expenses with Non-Performing Loans Rate (the ratio of total expenses with non-performing loans over total loans). Both the simulated and historical series are sums over 8 quarters. Unfortunately, the time series of NPL and ENPL are only available for the Chilean Banking System, therefore one cannot evaluate the model's historical accuracy for non-bank lenders. Even for Chilean Banks there is a break of the time series in 1997[6] and it is unclear how to adjust the statistics before that date.[7] There were also statistical breaks in household income and unemployment surveys in 1994, 1999 and 2009 (Madeira, 2015). The simulated banking consumer debt default replicates broadly the different historical phases, including the high default periods in the early and late 90s, as well as the strong declines in the mid 1990s and mid 2000s, and the moderate increase in 2008 during the recent international crisis.

In the case of non-banking lenders it is unfeasible to contrast the model's simulations with a historical time series. However, the model counterfactual simulations for non-banking lenders and for all lenders in Fig. 4 are qualitative similar to the banks, except that the NPL and ENPL rates are much higher for non-banking lenders. The NPL rate for banks fluctuates between 4% and 10% (Fig. 3), while for non-banking lenders the same rate fluctuates between 8% and 15%, therefore consumer default is much higher for Non-Banks in all periods and the model successfully matches the survey result that delinquency is twice as high for retail lenders as in banks (Table 3).

Table 6 compares the simulated rates for Non-Performing Loans (NPL_t) and Expenses with Non-Performing Loans ($ENPL_t$) versus their real values over the period 1990Q1–2012Q4. The simulated and historical rates of NPL_t and $ENPL_t$ are similar in expected mean, standard-deviation and minimum-maximum values. Also, there is a correlation of 55.5% and 43.6% between the simulated and historical values of NPL_t and $ENPL_t$, respectively. However, the model does even better in the period after 1997 during which there is better data, presenting a correlation of 90.6% and 47.3% between the simulated and historical values of NPL_t and $ENPL_t$, respectively.

The model simulations have uncertainty since all the parameters are estimated from different datasets. Using 50 bootstrap replica samples of all the survey datasets applied to calibrate the model, it is possible to obtain the standard-errors of the model's simulated results for the NPL_t and $ENPL_t$ series. Table 7 shows the standard-errors of the simulated time-series for several distinct combinations of household types. The table shows how the standard-error of the simulated default risk (NPL or ENPL) varies as ones reduces the number of household types. The uncertainty around the estimations is fairly small if one is just considering the aggregate default risk in each time period, since the standard-errors around the mean aggregate default risk are just 1.3% and 0.7% for NPL and ENPL measures of risk, respectively. Also, this uncertainty does not change substantially across different time periods, since even in the most uncertain periods (those which correspond to the percentile 90th of the highest standard-errors) the standard-errors

Table 6
Model's fit of the historical series of Banking delinquency.

Moments of NPL and ENPL	Data (%)	Model (%)
$E[NPL_t]$	6.6	6.8
Standard-deviation $[NPL_t]$	0.9	1.2
min– max$[NPL_t]$	5.1–9.0	4.0–9.6
$E[ENPL_t]$	3.8	3.9
Standard-deviation $[ENPL_t]$	0.9	1.0
min– max$[ENPL_t]$	2.3–5.8	2.4–6.2
$Corr(NPL_t, ENPL_t)$	23.9	43.9
NPL: $Corr(Data, Model)$		55.5
ENPL: $Corr(Data, Model)$		43.6
NPL (after 1997): $Corr(Data, Model)$		90.6
ENPL (after 1997): $Corr(Data, Model)$		47.3

[6] Accounting standards for the Non-Performing-Loans (NPL) changed in Chile during the 1990s (Matus, 2015). Before 1997 non-performing-loans only included the loan payments in a state of arrears, while after that date the entire loan is considered to be non-performing after a few payments in arrears. This break in the Chilean data of the NPL and ENPL series is quite normal at the international level. Some countries use 90, 60 or 30 days in arrears as an NPL definition, and others simply use "doubtful" or "loss" loans (Beck et al., 2015). A few jurisdictions consider that all loans of a debtor are non-performing once one of its loans is under arrears. The Chilean definition of NPL and ENPL for the period before 1997 is still applied in several countries, such as Russia. Even for the European Monetary Union there are only 7 countries with NPL series for household loans that stretch before the year 2000 (Rinaldi and Sanchis-Arellano, 2006). Also, both banks and regulators may change slightly the criteria of Expenses with NPL (ENPL) over time due to changing prospects of risk such as an economic crisis.

[7] Another problem is that after the Asian crisis in the late 90s the Chilean banks bought several troubled non-banking financial institutions that specialized in consumer credit for low income families. Unfortunately, it is not possible to adjust the NPL and EPNL series for this sudden change in the Chilean banking system.

Fig. 4. Simulated NPL and ENPL for non-banking lenders and for all lenders.

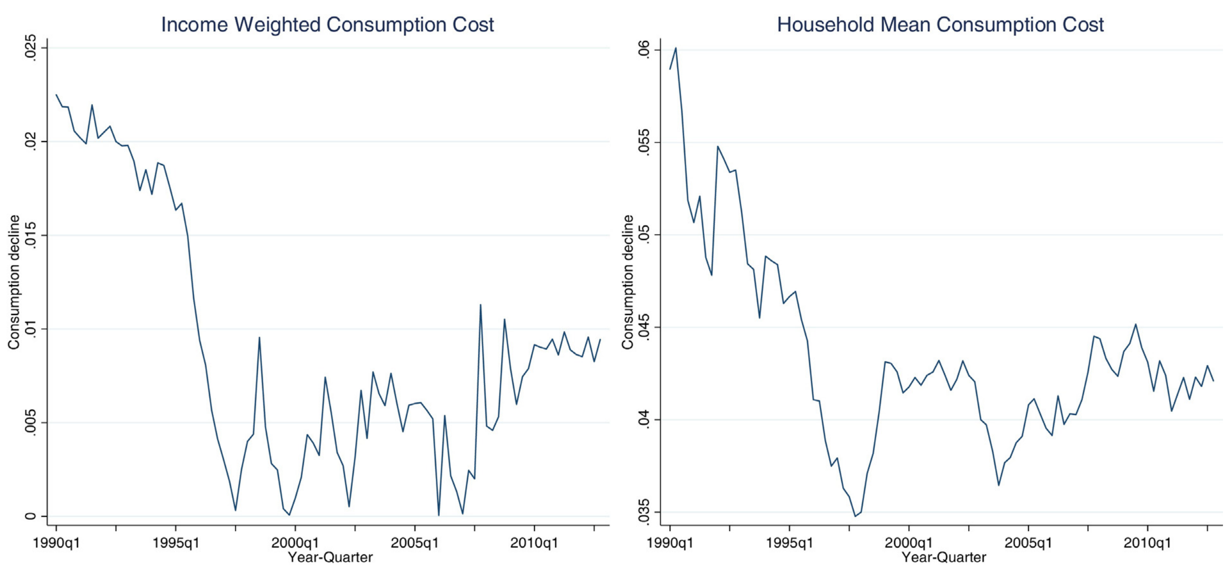

Fig. 5. The simulated impact on household consumption of binding credit constraints.

are only 1.4% and 1.0% for the NPL and ENPL rates, confirming that the model is reliable for simulating aggregate default.

Now in Fig. 5 I show the model's simulated consumption cost enforced by the credit constraints on households, CC_t. The Consumption Cost variable can be measured either with income weights (giving its economic impact in terms of aggregate output) or as a household mean. Income weights and household mean measures can differ substantially, since the income measure (which is more similar to the aggregate national accounts) gives more value to the richer households than to the poor households. In terms of income weights the overall consumption cost due to credit constraints fluctuates between 0.5% and 2% over the period 1990–2012, which is a significant impact on overall economic activity. If consumption cost is measured in terms of a household mean (which counts poor and rich families in the same way), then the time series evolution is relatively similar, although the level fluctuates

Table 7
Bootstrap standard-errors for the simulated non-performing loans (%).

	NPL_{t,x_1}	$ENPL_{t,x_1}$	NPL_{t,x_2}	$ENPL_{t,x_2}$	NPL_{t,x_3}	$ENPL_{t,x_3}$	NPL_{t,x_4}	$ENPL_{t,x_4}$
Mean	4.0	2.7	4.0	3.5	2.5	1.9	1.3	0.7
Percentile 10	0.9	0.6	1.5	0.7	1.0	0.7	1.1	0.5
Percentile 25	1.5	1.1	1.8	1.1	1.4	1.0	1.2	0.5
Percentile 50	2.6	1.8	2.7	1.8	2.1	1.3	1.3	0.6
Percentile 75	4.0	3.9	5.7	3.6	3.1	2.2	1.3	0.7
Percentile 90	11.2	6.6	9.0	7.9	4.5	3.7	1.4	1.0

50 bootstrap replicas. x_1 = {Age of Household Head × Household Income Quintile}, x_2 = {Age × Education of Household Head}, x_3 = {Lender type (Both Bank and Retail Loans, Only Bank Loan, Only Retail Loan) × Household Income Quintile}, x_4 = {Constant}. The vectors x_1, x_2, x_3, x_4 have 15, 9, 15 and 1 groups of distinct family types, respectively. All vectors include 92 different time periods (1990Q1–2012Q4).

Table 8
Log-consumption and simulated consumption cost.

Regressors/dependent variable	$\ln(C_t)^{a}$	$\ln(\frac{C_t}{C_{t+1}})^{a}$	$\ln(C_t)^{a}$	$\ln(\frac{C_t}{C_{t+1}})^{a}$
Log-income growth of current quarter	12.96 (2.75)***	11.85 (4.73)**	11.21 (2.22)***	9.79 (3.19)***
Consumption cost (income weights)	−1.94 (0.63)***	−1.76 (1.06)*		
Consumption cost (household mean)			−3.85 (1.08)***	−2.64 (1.32)**
Constant	0.01 (0.01)	0.01 (0.01)	0.15 (0.05)	0.01 (0.06)
R-square / Nr of observations	0.156 / 91	0.067 / 91	0.282 / 91	0.099 / 91

[a] HP residual. Robust standard-errors in ().
* 10% statistical significance.
** 5% statistical significance.
*** 1% statistical significance.

between 3.5% and 6% of total consumption. The consumption cost of credit constraints is different from the default rates such as NPL and ENPL, creating a trade-off for policy makers. In the early 1990s there was a low level of consumer credit in Chile, therefore the default rate was low. However, at the same time the real interest rate was high in that period and the consumption costs faced by the credit constraints were significant in the early 1990s. Regulators and policy makers face the trade-off that liberalization policies may create easy credit and higher default risk, but restricting credit imposes significant costs in terms of welfare.

Table 8 shows linear regressions of the quarterly time series of the aggregate log-consumption level and the log-consumption growth in Chile, using the simulated consumption cost and log-aggregate income growth as regressors. Both the level and the growth rate of log-consumption are Hodrick–Prescott residuals of the original variables with the standard smoothing parameter of 1600. The regressions find that the simulated Consumption Cost is negatively related to the real consumption over the last 23 years, showing the model's welfare cost of consumption is consistent with the actual data.

5.2. Financial fragility across different income groups

Unemployment and income risk fall disproportionately on the poorer households (Madeira, 2015). This section shows how the default risk (NPL and ENPL rates) in Banks and Non-Banks changes across the income distribution, from the lowest income families (the quintile 1 or poorest 20% of all households) to the highest income (the quintile 5). Over the period 1990–2012 upper income families (quintile 5) suffered quite low financial risk, whether in terms of banking (Fig. 6) or non-banking loans (Fig. 7). According to the model the highest income families have a much lower risk and sensitivity to the business cycle than the families in the quintile 4. This makes sense since Chile is a country of high income inequality, especially between the highest income households and all the others (Madeira, 2015). In comparison the families in the lower 40% of the income distribution (that is, the quintiles 1 and 2) show significant increases in their simulated financial distress during the Asian crisis of 1998–99. This is consistent with the historical fact that several Chilean financial institutions that specialized in low income families were bought by larger banks after suffering large losses during the Asian crisis. Banks also show a higher risk of default for the loans granted to the income quintile 2 (which is the second poorest group), while for Non-Banks the highest risk happens in the loans for the income quintile 1 (the poorest households). This result is due to the credit selection policies of banks, which grant only small loans to the lowest income families.

An interesting result is that the simulated risk of lower income families for Non-Bank lenders fell substantially during the early 2000's. Regulators in Chile have expressed concern about the large expansion of retail banking over the last 10 years (MMFS, 2011). This work shows that a plausible explanation is that non-bank lenders such as retail stores are capturing a segment of families whose credit risk declined and not that loans expanded due to an increased appetite for risk.

5.3. Simulation results if terms for new loans deteriorate

Credit market shocks to loan terms such as maturities, interest rates, and loan access can lead illiquid households to default. I

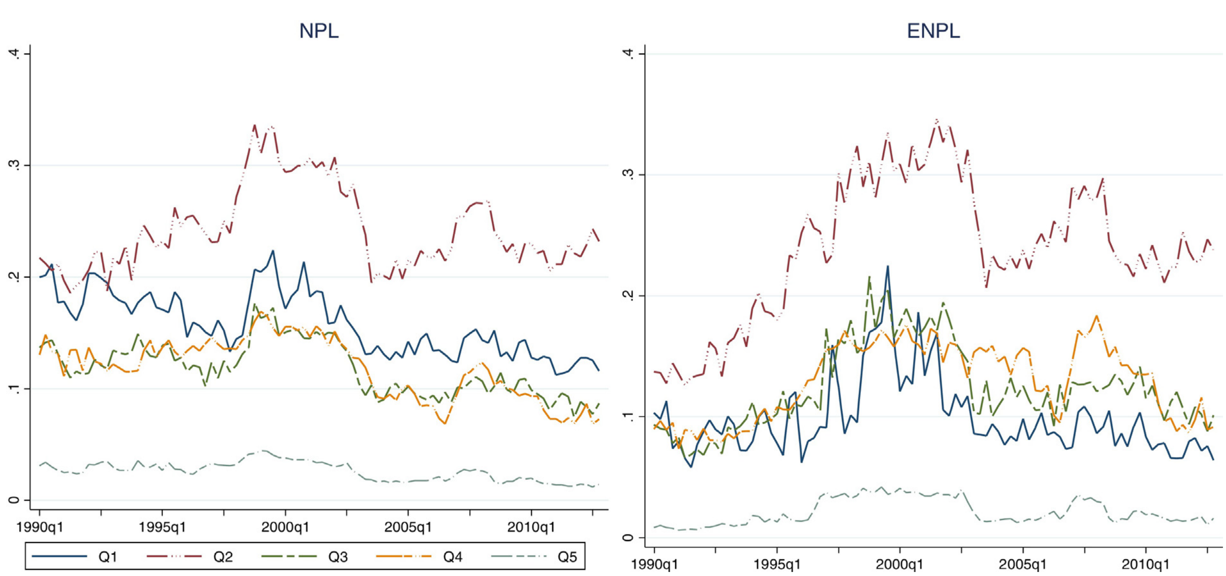

Fig. 6. Simulated NPL and ENPL of the Bank loans for the households in each income quintile.

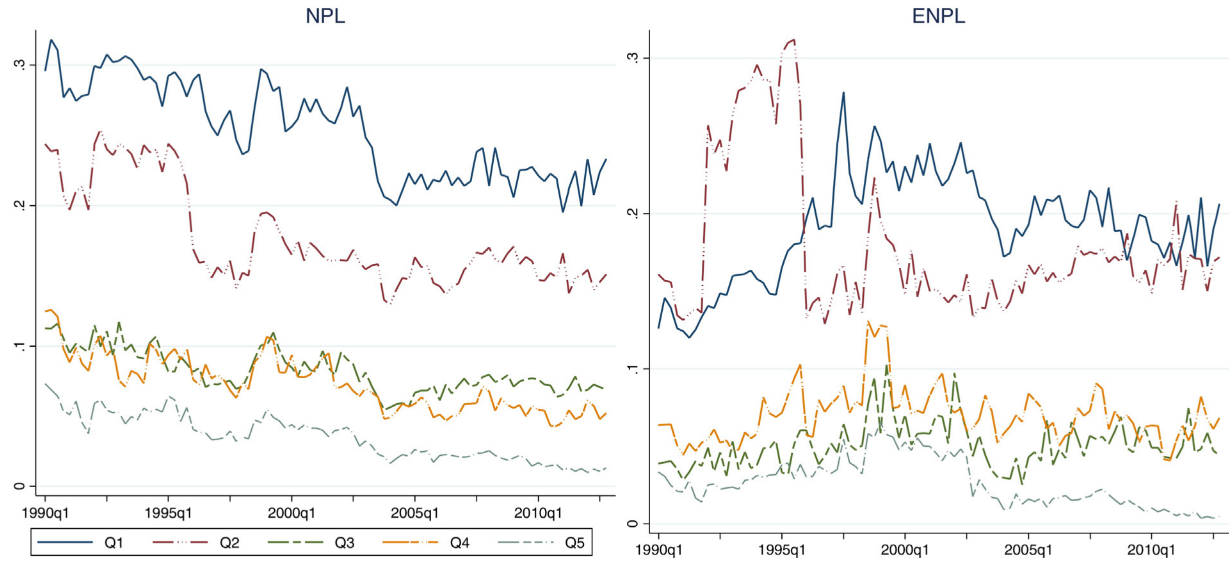

Fig. 7. Simulated NPL and ENPL of the Non-Banking loans in each household income quintile.

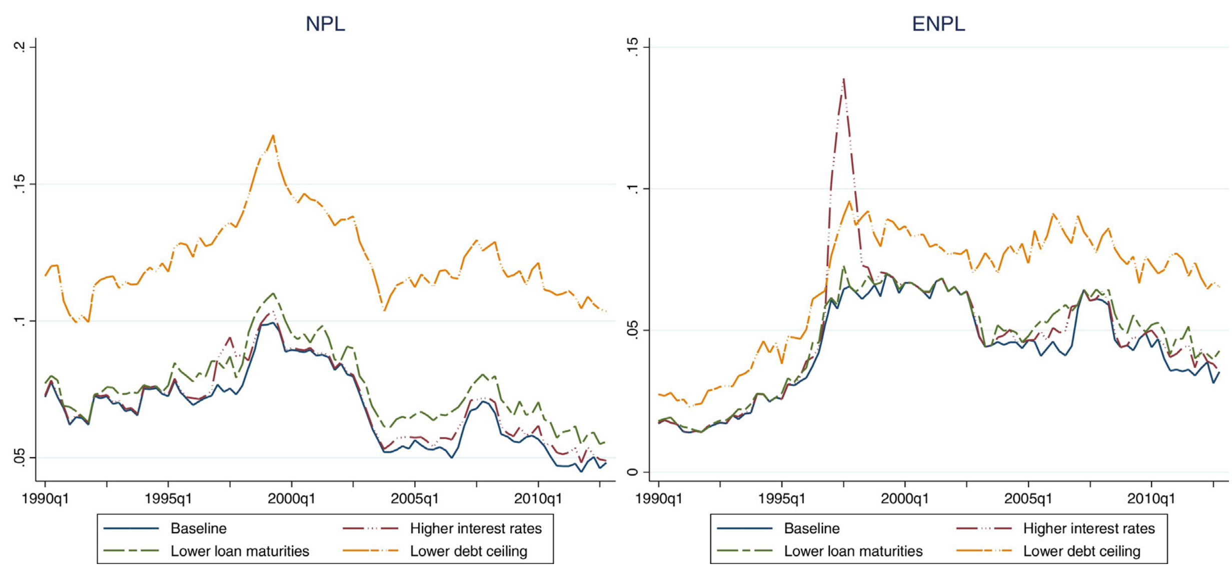

Fig. 8. Simulated default for Bank loans: baseline versus other scenarios.

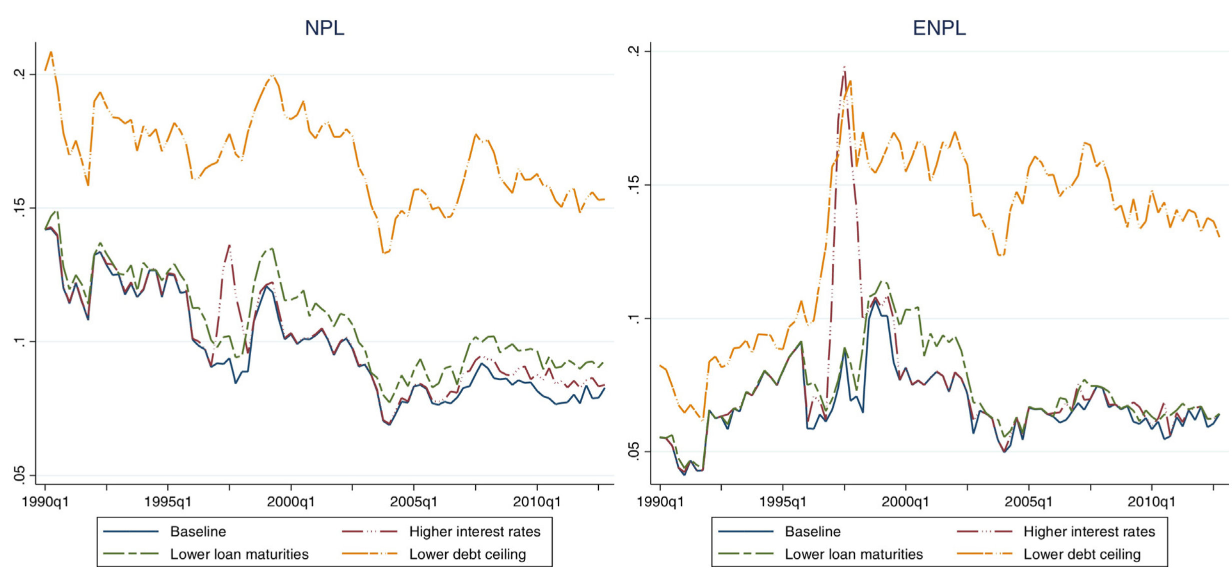

Fig. 9. Simulated default for Non-Banking loans: baseline versus other scenarios.

study this possibility by using the model to simulate Chilean history under 3 different scenarios: (1), maturities for new loans at banks and retail stores fall by 25% (i.e., maturities are 6 quarters for banks and 3 quarters for retail stores); (2) the cost of deposits for banks increases 25% relative to their historical ones, $i_t(new) = 1.25 i_t$; and (3) the debt ceilings for the loan amounts offered by lenders to consumers fall by 25%. The simulated scenarios for Bank loans (Fig. 8) and Non-Bank loans (Fig. 9) show that the NPL rate is more sensitive to a reduction in the debt ceiling granted to new loan amounts, but the ENPL rate is more sensitive to an increase in real interest rates especially for a negative period such as the 1998 Asian crisis. Therefore, shocks to loan amounts create havoc for a large number of loans, but the shock to interest rates is more costly in terms of loan expenses during an ongoing recession.

An interesting result is that while Non-Bank lenders were much more sensitive to the income and unemployment shocks over the last 23 years (Fig. 4), the results reverse in terms of credit market shocks. Banks face a high increase in delinquency after shocks to the credit market, but Non-Bank lenders are not so affected. This result is explained by the focus of Non-Bank Lenders on short maturities of one year or less (MMFS, 2011), implying that they are not as sensitive to reductions in loan maturities, available loan amounts or increases in interest rates.

6. Conclusions

This work studies the determinants of the business cycle risk of consumer debt, using a structural model of household consumption, credit markets and default decisions. Several past studies of household risk in recent years have employed micro data to implement stress tests, but fail to replicate the fact that consumer debt default rates are highly volatile, implying that unemployment and interest rate shocks increase the stock of consumer loans in default by less than 30%. Time series data for countries such as Chile, Finland, Spain, and the USA, however, shows that in recessions the consumer delinquency rate can be 400 percent higher than during booms, which represents variations more than 10 times bigger as the ones implied by several stress test studies.

Model simulations show that household financial distress is non-linearly linked to unemployment and shocks to loan refinancing, such as increased interest rates and lower maturities. Long periods of low default are not therefore a signal of a permanent period of stability. Brief unemployment spells may be endured with no default by households, while longer spells imply worse dynamics for household finances. Furthermore, the welfare consumption cost due to credit constraints increases from 3.5% to 4.3% of average household consumption when the economy suffers a recession.

The model accurately explains the historical evolution of consumer delinquency in Chile, implying it can be a serious tool for evaluating policies, such as capital buffers, usury laws or creating a common credit register for all lenders. Financial institutions know little of the macro risk of consumer debt and its correlation with other assets, affecting good assessments of required buffer capital. My results conclude that current risk models severely underestimate the volatility of consumer debt default, therefore both banks and regulators require richer information and models.

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