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EXPLAINING THE CYCLICAL VOLATILITY OF CONSUMER DEBT RISK*

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Abstract

Previous studies of consumer debt risk estimate low sensitivities to negative economic 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 new loans contracts, defaulting on debt commitments when unable to finance minimum consumption standards. Using survey data I simulate household credit default for Chile over the last 20 years, replicating successfully the highs and lows of consumer delinquency. Households, especially those of low income, are shown to be highly vulnerable to changes in interest rates, credit maturities and liquidity.

Resumen

Estudios previos del riesgo de deuda de consumo estiman una baja sensibilidad de su nivel en relación a choques económicos negativos, lo que contradice los datos históricos. Este trabajo propone un modelo de agentes heterogéneos de las finanzas de los hogares y su riesgo de crédito. Las familias sufren choques de ingreso laboral y seleccionan de un menú de nuevos contratos de préstamo, decidiendo no pagar sus deudas cuando se encuentran incapaces de financiar un padrón mínimo de consumo. Utilizando datos de encuestas yo simulo el riesgo de crédito de los hogares en Chile al largo de los últimos 20 años, replicando con éxito los altos y bajos de la morosidad de la deuda de consumo. Los hogares, especialmente los de bajo ingreso, se muestran vulnerables a cambios de tasas de interés, madurez de los préstamos y liquidez.

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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, Mohanty, and Zampolli, 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. The importance of measuring the sensitivity of consumer credit risk to different aggregate shocks is therefore highly important now as regulators discuss new policies to curb financial risk and macro-prudential tools such as countercyclical capital buffers (Hanson, Kashyap, Stein, 2011). For emerging economies high default rates of consumers may also represent a significant macro risk.

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 amount 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.

I calibrate this household default model with survey data on consumption, debt and income, which is available in most developed countries. Using several sources of survey data from Chile, the model is able to replicate the fluctuations of consumer loans' default rates observed in the

period 1990 to 2009. Chile provides a strong base 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). Furthermore, Chile presents a challenging empirical case, having suffered through periods of high consumer default under different circumstances: the early 1990s, the Asian crisis of 1999-2001, and the recent international credit crisis of 2007-09.

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% to 1%, with worse effects during recessions.

In order to estimate this structural model of household credit risk I take three steps: 1) establishing the distribution of income, expenditure and debt across the Chilean population, 2) the measurement of individual 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 in terms of maturities and interest rates conditional on households' risk background. Each of these 3 components is measured with highly informative and accurate data sources.

To measure the debt distribution among Chilean families I consider 2 distinct datasets, the CASEN and the EFH surveys. These surveys comprise a representative sample of 51,000 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 of these families conditional on households' demographic profiles, permanent income, expected income volatility and an idiosyncratic preference for consumption. This stochastic consumption is implemented by using the Household Expenditure Survey (EPF 2007), which covers a detailed measure of consumption from 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 in a single quarter 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, I consider the credit markets available to agents, providing a basic structure similar to actual loan conditions in Chile. Families of different backgrounds can access different amounts of credit by lenders, with loan amounts depending on a multiple of households' income. Banks charge interest rates that are risk-adjusted for neutral profits according to each family's repayment risk. The EFH and CASEN survey provide a metric of repayment risk given by households' answer to whether the family "failed any loan payment over the last 12 months". Here I assume lenders estimate a parametric default risk model given their information on households' debt, unemployment risk, income and demographic background. Lenders then use their default estimates for each consumer to decide whether to give him credit and which interest rate to charge them. 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, however, they are limited to charging the same interest rate for all clients and to an "accept/reject" decision on loan applicants. This inability to discriminate loan conditions leads retail stores to charge high interest rates.

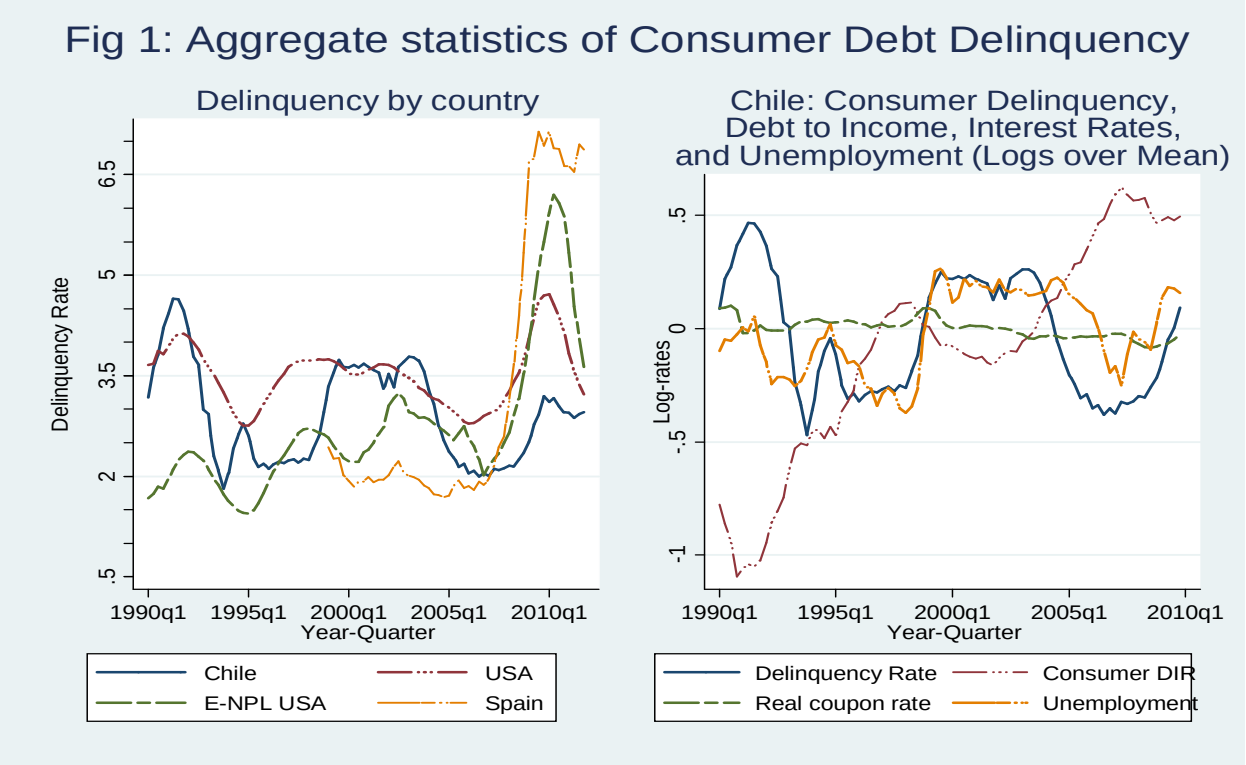
The model's expected dynamics for household income, consumption and default are then simulated for each quarter of the last 20 years, considering the historical evolution of banks' funding costs and the labor market shocks experienced by each type of worker profile. Unemployment and income volatility dynamics are accurately measured over a 20 year period, using the Chilean Income and Employment Survey 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, default and economic shocks of the households (Chatterjee et al., 2007, Athreya et al., 2015, Livshits, MacGee and Tertilt, 2010, 2015). Other studies show that countercyclical income risk in the US can explain the rise in credit spreads and consumer debt default during recessions (Luzzetti and Neumuller, 2015, Nakajima and Rios-Rull, 2014) and that labor market shocks explain part of the surge in default during the Great Recession (Gerardi, Herkenhoff, Ohanian and Willen, 2013, Athreya et al., 2015). However, the

high computational costs of these models limit their analysis to a world without aggregate shocks and a small number of agents' types, which hinders the study of the cyclical volatility of default and the estimation of standard-errors of the estimates. My model limits these computational demands in two ways: 1) households' decisions happen in a partial equilibrium framework and do not feed back into aggregate production or interest rates; and, 2) agents use a simple behavioral rule for consumption and default decisions, avoiding the computational cost of optimizing their entire life-path. Both of these two assumptions have some empirical support. One, Chile is a small open economy, therefore the aggregate interest rate and credit conditions are at least partly determined by international developments unrelated to local savings decisions. Also, empirical evidence shows support for households use of simple behavioral rules for both consumption (Carroll, 1994) and loan decisions (Agarwal, Driscoll, Gabaix and Laibson, 2009, Agarwal and Mazumder, 2013, Einav, Jenkins, and Levin, 2012), rather than complete optimization.

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



Sources: Central Bank of Chile, SBIF, Bank of Spain, Federal Reserve Board.

Consumer debt default has strong fluctuations over the business cycle. The current standard international 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 over total loans for the USA. Figure 1 shows that over the last 20 years consumer delinquency rates fluctuated between 2.69% to 4.85% in the USA and 0.77% to 2.74% in Chile, with strong fluctuations happening in all economic cycles. Measuring relative fluctuations as a peak-to-trough ratio, $\frac{delinquency(high)}{delinquency(low)}$, one concludes that consumer delinquency during recessionary periods increased up to 80% (if using arrears over 30 days) or even 477% (if using banks' expenses) in the USA, 356% in Chile, and much more in Spain. Also, similarly strong

cyclical fluctuations in household debt delinquency were observed in the eurozone countries that have collected these statistics 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, $\frac{i_{v,t}/12}{1-(1+i_{v,t}/12)^{-12}}$, 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 there is no easy relationship between consumer debt delinquency and other aggregate indicators. Unemployment is the variable with highest correlation with Consumer Debt Delinquency, which is suggestive that strong income shocks on a few households explain part of the consumer delinquency swings. Periods of high consumer delinquency are positively correlated with high consumer interest rates, but the variation in the real cost of debt service is too small relative to the big swings in consumer delinquency. The aggregate value of Consumer Debt relative to Household Income shows a positive trend over the whole period of 1990 to 2010 and yet this ratio of indebtedness does not increase during periods of high consumer delinquency. Therefore it is difficult to argue that aggregate shocks to interest rates or high values of household debt can explain consumer debt 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, Kennedy, and André, 2007).

Table 1: Estimated impact of unemployment on the debt at risk of default (Dar), $\ln(\frac{Dar(+shock)}{Dar(initial)})$

Country	**Unemployment**	**Log-change in Dar**	**Source**
Canada	+3%	+14%	Djoudad, 2011
Chile	+(5%, 10%, 15%)	+(10%, 23%, 35%)	Fuenzalida, Ruiz-Tagle, 2009
European Union	+3%	+24.7%	Jappelli, Pagano, Maggio, 2010
Finland	+3%	+10.3%	Herrala and Kauko, 2007
Sweden	+3%	+11.8%	Johansson and Persson, 2006

Default is driven by a small proportion of credit constrained households, leading several central banks to perform stress tests using micro survey data. An overview in Table 1 however shows that these studies estimate that even significant increases in unemployment rates imply log-changes in default rates lower than 25%, which are fluctuations much smaller than the ones observed historically. For instance in Finland consumer debt delinquency fell from 8% in 1994 to 3% in

1998, a log-decline larger than 98% (Jappelli, Pagano, Maggio, 2010). Furthermore, 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%, a log-change of 129% and a much bigger shock than these tests suggest.

A significant problem in these studies is that default is measured by a limited statistic such as whether households' debt service to income ratio is below 40%. This ignores important elements such as the actual debt owed, the heterogeneity of families' income volatility and risk premia, as well as liquid access to new credit. A high debt service could be a signal of borrower confidence, not necessarily a risk. Also, a debt service to income cutoff implicitly assumes consumption can be flexibly reduced to pay debts, since expenditure is reduced proportionally to income even after large shocks. Finally, these studies consider one-period unemployment spells, ignoring realistic income dynamics. In this paper I show that ignoring the richness of loan terms and the dynamic effects of income shocks on credit constraints provides an inaccurate view of consumers' financial troubles.

3 A framework to analyze household debt risk

3.1 Theoretical background

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, Goldberg, and Kyriazidou, 2008). Interest rates and loan amounts are therefore not enough to judge credit conditions.

The interaction of these factors can be represented using a simplified version of the contract pricing model of Einav, Jenkins, and Levin (2012). Assume families have heterogeneous characteristics ζ and in each period t receive a stochastic income y_t, choose their consumption and assume a

loan contract $\phi_t = f(y_t, \zeta)$, with ϕ_t being a vector of relevant terms such as interest rate, loan amount, and maturity. Loan terms affect debtors' repayment probability, therefore lenders offer contracts $\phi \mid y_t, \zeta, \Psi_t$ conditional on debtors' characteristics and a vector of global credit factors, Ψ_t, such as interest rate ceilings or banks' funding costs. Therefore households 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, $u_d(y_t)$, plus their sequential value discounted by β:

$$1)\ Df_t = \arg \max_{Df_t \in \{0,1\}} U_t(y_t, \phi_t) = \max\{u(y_t, \phi) + \beta E_t \left[U_{t+1}(y_{t+1}, \phi_{t+1})\right], u_d(y_t) + \beta E_t \left[\bar{U}(y_{t+1})\right]\}.$$

In this model shocks to income, debt maturity, and the liquidity of future credit access clearly play a role even if previous loan contracts ϕ_t have fixed interest rates and unchanging terms. Suppose a household is able to pay the amortization component of his debt only partially. These liabilities are therefore in a declining path, but the family remains solvent only with access to new credit. This is similar to models of corporate financial frictions where instability explodes if credit is suddenly rationed (Brunnermeier, Eisenbach, and Sannikov, 2012).

3.2 An empirical model of household default and consumption

Expenditure and default decisions depend on how households compare the intertemporal utility afforded by current income and debt commitments versus its punishment costs. However, default costs are hard to specify, since the existence of competitive unsecured credit markets requires that a significant proportion of the borrowers are "honest" agents with stigma costs and not purely strategic agents (Jaffee and Stiglitz, 1990, Gross and Souleles, 2002). Finally, consumer loans and debt default may happen with agents who fail to optimize their decisions completely, therefore optimal decisions from a computationally hard utility function may not add extra insight (Einav, Jenkins, and Levin, 2012). For these reasons 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' income dynamics, budget constraint and credit contracts.

The behavioral rule assumes households value paying back their commitments and try to reduce expenditures voluntarily in order to meet creditor demands, however they choose default when faced with an extreme reduction in consumption. Households therefore default when being at kinks of

their budget constraint and when facing large income shocks. I assume all households start in a state of no-default, $Df_t = 0$, at time t, and with given debt commitments, ϕ_t, and liquid assets A_t. The initial endowments of debt commitments, assets and income are heterogeneous across households, but for simplicity of notation I ommit the household identifier i for now. Now I model the households' dynamic decisions of default and consumption for the future periods $t+s$, for $s = 1, .., M$, with M being a long-term debt maturity. 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.

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. Expenditure therefore reflects income risk and precautionary motives (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 simply consume their current income, $C_{t+s} = Y_{t+s}$ (as in Campbell and Mankiw, 1989):

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

2.2) $\{Df_{t+s}, C_{t+s}\} = \{1, Y_{t+s}\}$ if $B(g(\zeta, C_{t+s-1}, S_{t+s-1})) < 0$, with both 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 rule-of-thumb consumption rule $g(\zeta, C_{t+s-1}, S_{t+s-1})$ assumes expenditure has some persistence over short periods of time. Note that households' expenditure depends substantially on persistent factors such as demographic structure, health and insurance contracts, and the location of work (restricting the choice of schools, supermarkets, transportation, housing, and even leisure).

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, $v = 1, 2, .., V$. Negative savings require using either liquid assets or new debt contracts. The feasible consumption budget function $B(C_t)$ is now defined as:

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

Each lender v offers differentiated credit contracts every period t. Interest rates $i_{v,t} = i(. \mid CF_t, X_{v,t})$ are strategically priced for the cost of funds at time t plus the borrowers' default risk conditional on the information set observed by v, $X_{v,t}$. Lender v has a fixed loan maturity, $m_{v,t}$, and imposes a top debt ceiling allowed to households, $dc_{v,t} = dc_v(P_t, Y_t, \zeta)$, as a function of their demographics, ζ, plus permanent and current income, P_t,Y_t. Market equilibrium is therefore given by households' demand to keep a smooth consumption and by perfectly elastic loans offered by lenders up to a top amount, $D_{v,t+1} = D_{v,t} - Am_{v,t} + ND_{v,t} \leq dc_{v,t+1}$. Besides consumer debt some households also have a mortgage debt, MD_{t+1}, with a required payment, MG_{t+1}. For simplicity mortgages are exogenous and with no default option, since these are well collateralized loans.

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:

4.1) $DS_{t+1} = MG_{t+1} + \sum_{v=1}^{V} DS_{v,t+1}$,
$DS_{v,t+1} = \sum_{j=0}^{T} ND_{a,t-j} \frac{i_{v,t}}{1-(1+i_{v,t})^{-m_{v,t}}} 1(j < m_{v,t-j})$,
$D_{v,t+1} = D_{v,t} - Am_{v,t} + ND_{v,t} \leq dc_{v,t}$, for $v = 1, .., V$,

with T denoting the oldest household debt. If households decide to default I assume for simplicity that they default on all consumer debts, but not on its mortgage:

4.2) $DS_{t+1} = MG_{t+1}$, $D_{t+1} = MD_{t+1}$, $DS_{v,t+1} = 0$, $D_{v,t+1} = 0$, for $v = 1, .., V$,

The model's dynamic stochastic simulations can then be used to estimate each household's expected non-performing loans (NPL_t), its expenses with non-performing loans ($ENPL_t$), and consumption cut due to credit frictions (CC_t), at a specified horizon of M quarters:

5.1) $NPL_t(M) = \Pr(\max(Df_{t+1}, .., Df_{t+M}) = 1 \mid \zeta, Y_t)$,
5.2) $ENPL_t(M) = E\left[(Df_{t+M} \times D_{t+M})/D_t \mid \zeta, Y_t\right])$,

5.3) $CC_t(M) = E\left[-\ln(\frac{C_{t+M}}{C_t}) \mid \zeta, Y_t\right]$.

This cost measure CC_t only includes consumption and ignores other costs of default whether pecuniary or not, therefore it is a lower bound for the true costs of financial frictions.

The actual estimation of the household default model depends on the data sources used to calibrate its components, as summarized in Table 2. One main component is the initial distribution of families with demographic characteristics ζ and their initial endowments of assets, debts, and income in period t. This is calibrated using two household finance surveys, the CASEN and EFH, which provide information on over 51,000 families and their members. 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[1]. Also, I adjust the expansion factors in order to account for demographic changes in Chile over time. Population estimates for each strata (given by the cross-terms of geographical area, age and education dummies of the household head) are obtained from the Chilean Employment Survey (ENE).

A second main component is the stochastic income dynamics faced by households, which is calibrated using permanent and transitory labor income shocks estimated from the Chilean Unemployment Survey (Madeira, 2015).

The third main component of the model is the consumption function, with its initial stochastic expenditure $C_t = c()$ and the minimum consumption standard of each family, $m(\zeta)$. Both of these elements are estimated using the non-durables expenditures of the Chilean Expenditure Survey. The other consumption parameter remaining is the percentage proportion of expenditure that can be cut down each quarter, which I choose as $\lambda = 0.15$. This parameter is not estimated due to a lack of panel data on consumption in Chile. However, panel studies of consumption for the United States estimate that families losing all of the labor income of one member only reduce consumption

[1] The initial debt endowments in period t for each family in the CASEN-EFH are changed to follow mean debt growth per consumer, $D_{i,t} = D_{i,EFH}\frac{MCD_t}{MCD_{t(EFH)}}$, where MCD_t is the Mean Value of Consumption Debt per Debtor. Also, household i's debt service at period t is given $DS_{i,t} = \frac{MCD_t}{MCD_{t(EFH)}}\sum_d DS_{d,i,t}\frac{C_{t,m(d),M(d)}}{C_{t(CASEN/EFH),m(d),M(d)}}$, where $DS_{d,i,t}$ is the debt service of household's debt d with maturity M and $M-m$ payments left to pay. $C_{t,m,M} = \frac{i_{t-m}/12}{1-(1+i_{t-m}/12)^{-M}}$ is the fixed payment function for loans, with i_{t-m} being the average interest rate for consumer loans in period $t-m$. The quarterly series for MCD_t and i_{t-m} are obtained from time series published jointly by the Central Bank of Chile and the Chilean Financial Authority (SBIF). The initial endowments of financial assets for each family are kept constant as a proportion of household income.

by 12.1% (Gruber, 1997) or 14% if they see household annual income fall by more than 33% (Chetty and Szeidl, 2007), suggesting it is hard to cut consumption by more than 10-15%.

The last major modeling component is the credit market and its main players. The two main types of lenders, banks and large retail stores, lend with maturities of 8 and 4 quarters respectively, which represent the mean loan maturities for these lenders in Chile (Marinovic, Matus, Flores, Silva, 2011, from now MMFS, 2011). Lenders price individual interest rates based on the repayment risk of households observed in the CASEN-EFH and a maximum legal interest rate.

Table 2: Calibrated and estimated parameters

Parameters and Exogenous Shocks	**Source**
Population distribution and endowments	CASEN 06 / EFH 07-08-09
(Income, assets, debts $\mid \zeta$)	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, P_t, σ_t, U_t (Madeira, 2015, ENE 1990-2009)
Expenditure choice	$C_t = c(\zeta, P_t, \sigma_t, \varepsilon^c)$: EPF 2007
	$m(\zeta) = Q_1(C_0 \mid \zeta)$, $\lambda = 0.15$
Default decisions	Budget kink: $B(g(\zeta, C_{t+s-1}, S_{t+s-1})) < 0$
Credit Market equilibrium	$D_{v,t+1}$(household) $\leq dc_{v,t+1}$(lender v)
$v = 1, 2$ lenders ($V = 2$)	Banks, Retail
Loan terms: $i_{v,t} = i(. \mid CF_t, X_{v,t})$	CASEN/EFH: $X_{v,t} = \{\zeta, D_t, P_t, Y_t, \Pr(U_t), DS_t\}$
$m_t = \{m_{1,t}, m_{2,t}\}$	$m_t = \{8, 4\}$ (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	$i_{v,t} \leq 1.50 \times E\left[i_{2,t}\right]$
Banks' fundraising real interest rates, i_t	Central Bank of Chile, 1990Q1-2009Q4

4 Calibration

4.1 Population

To measure the Chilean population I consider the CASEN survey in the year 2006, which included 44,500 urban households, and the EFH survey waves of 2007-08-09, which covered almost 4,000 urban households in 2007 at the national level and 1,200 households from the Great Santiago capital area in 2008 and 2009. Both debt default and unemployment represent rare experiences, which require a large sample to provide accuracy. For this reason I use the CASEN-EFH as a single joint sample, which comprises over 51,000 households. These surveys are designed with unequal selection probabilities over different strata, therefore representative population statistics are obtained by weighting each observation with the inverse of its selection probability, denoted by statisticians as the expansion factor, $f_i = \frac{1}{p_i}$. The expansion factors of the joint CASEN-EFH sample are adjusted for the sample size in each year: $\tilde{f}_i(t, A) = f_i \frac{n_{t,A}}{\sum_{j=2006}^{2009} n_{j,A}}$, with $n_{t,A}$ denoting the sample size of geographical areas $A = 1, 2$ (1 being the Santiago Metropolitan Region and 2 other regions) in survey year $t = 2006, .., 2009$. Standard-errors for any continuous weighted statistic (which includes means, quantiles, and any continuous model) are obtained by bootstrap replica estimates, with each replica sample keeping the same number of observations for each strata.

These surveys have a highly detailed measure of income, assets (financial portfolio, vehicles, and real estate), and debts, including mortgage, educational, auto, retail and banking consumer loans. In order to cover exhaustively the household's commitments, the surveys elicit the loan terms (debt service, loan amount, maturity) for each of the 4 main loans in each category of debt. The CASEN only measures asset and debt values in intervals, and has no information on loan maturities. However, the information of debt service and debt amount interval, plus a minimum-maximum interval for interest rates, also restrict loan maturities to a logical interval range by applying the fixed payment formula. For each household in the CASEN I impute random values for asset and debt amounts plus loan maturity for each type of debt, using a truncated log-normal linear regression estimated from the EFH 2007, with covariates x_i being the debt service, education, income, age, and gender of the household head, and with an heterocedastic exponential variance, $\sigma_i = \exp(\gamma x_i)$. The R-square of these regressions is over 70% for debts and around 30% for assets, which suggests

simulation error is rather moderate, especially since less than 30% of the families have liquid assets.

4.2 Workers' stochastic income process

This section is based on the dynamic income process estimated for Chilean workers by Madeira (2015). 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 $L_{k,i,t}$. The probability of unemployment and the volatility of shocks is both time-varying due to the business cycle (t) and heterogeneous for different worker types ($x_{k,i}$), with professional types 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$\}$. Let $\chi_{k,i,t} = \{t, U_{k,i,t}, x_{k,i}\}$ denote the state faced by worker k. $U_{k,i,t}$ ($U_{k,i,t} = 1$ if unemployed, 0 if working). Workers' unemployment transitions at time t follow then a discrete Markov process, with transition probabilities given by worker k's type layoff and job-finding probabilities: $layoff_{k,i,t} = \Pr(U_{k,i,t+1} = 1 \mid t, U_{k,i,t} = 0, x_{k,i})$ and $job_{k,i,t} = \Pr(U_{k,i,t+1} = 0 \mid t, U_{k,i,t} = 1, x_{k,i})$. Workers' income then follows a dynamic process given by:

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

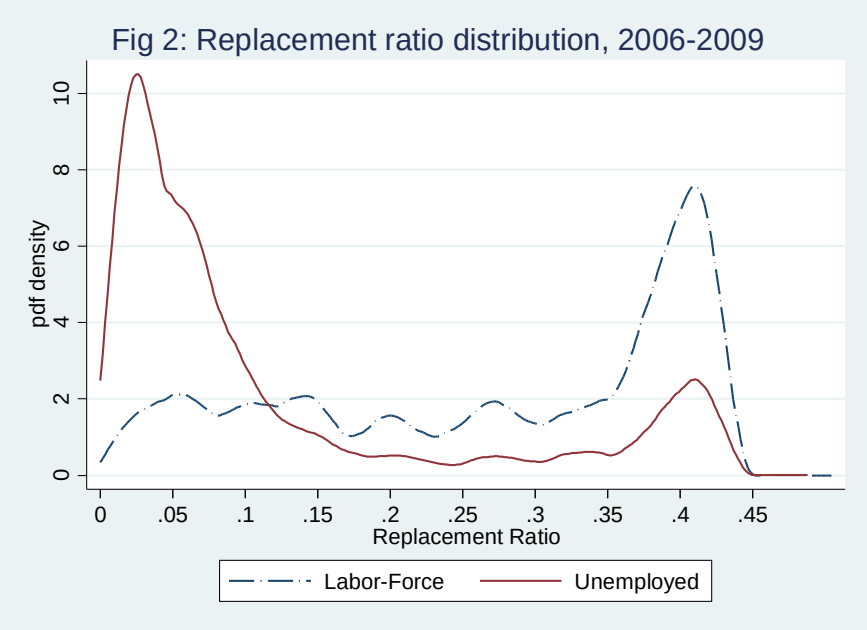
7) $L_{k,i,t+s} = \zeta_{k,i,t+s} RR_{k,i,t+s}^{U_{k,i,t+s}}$,

8) $Y_{k,i,t+s} = P_{k,i,t+s} L_{k,i,t+s}$, for $s = 1, ..., M$.[2]

This income process is similar to the one estimated by Carroll and Samwick (1997), but with the innovation of an added discrete shock to income caused by entry and exit from unemployment. Unemployment transitions are important, since recessions are not merely events with more layoffs,

[2] To complete the random income process simulation one requires initial conditions at time t. I obtain these initial conditions by assuming the initial unemployment status $U_{k,i,t}$ is randomized according to the unconditional unemployment probability, $u_{k,i,t} = \Pr(U_{k,i,t} = 1 \mid t, _{k,i})$. Also, the initial income is assumed to be 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^*, $Y_{k,i,t} = Y_{k,i,t^*} \frac{E(Y_{k,i,t} \mid t, x_{k,i})}{E(Y_{k,i,t^*} \mid t^*, x_{k,i})}$. I then get the initial value of permanent income at time t by $P_{k,i,t} = Y_{k,i,t} L_{k,i,t}^{-1} = Y_{k,i,t} \exp(-\zeta_{k,i,t}) RR_{k,i,t}^{-(U_{k,i,t} - U_{k,i,t^*})}$, using a simulated value for $\zeta_{k,i,t}$.

but also periods with longer unemployment spells and with jobs harder to find (Shimer, 2012). Permanent income, $P_{k,i,t}$, is affected by an heterogeneous drift, $G_{k,i,t} = \dfrac{E(Y_{k,i,t} \mid t, x_{k,i})}{E(Y_{k,i,t-1} \mid t-1, x_{k,i})}$, which represents mean income growth expected for workers with characteristics $x_{k,i}$, 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, $\dfrac{E(Y_{k,i,t} \mid t, U_{k,i,t}=1, x_{k,i})}{E(Y_{k,i,t} \mid t, U_{k,i,t}=0, x_{k,i})}$. Figure 2 shows the $RR_{k,i,t}$ distribution for both labor force and unemployed workers in Chile, showing $RR_{k,i,t}$ ranges from as low of 3% to as high as 40%. Unemployed workers are different from the rest of the labor force, being much more likely to receive low benefits during unemployment. In the USA and Europe unemployment benefits are typically above 60% of workers' income.



After all the households' members incomes are simulated, one obtains the simulated household income as the simple sum of their working members, $Y_{i,t+1} = a_i + \sum Y_{k,i,t+1}$, plus non-labor household income, a_i. Non-labor income tends to be small in most families and is not subject to random shocks, being merely adjusted for nominal income growth. Furthermore, I obtain the permanent household income as $P_{i,t} = a_i + \sum_k P_{k,i,t}(1 - u_{k,i,t}) + P_{k,i,t} RR_{k,i,t}(u_{k,i,t})$. Also, using weights given by the permanent income of each working member one can obtain the household's

mean unemployment risk, $\bar{u}_{i,t} = \sum_k \frac{P_{k,i,t}}{P_{i,t}-a_i} u_{k,i,t}(x_{k,i})$. Similarly, the household weighted income risk without employment transitions is given by $\bar{\sigma}_i = \sum_k \frac{P_{k,i,t}}{P_{i,t}-a_i}(\sigma_\zeta(\chi_{k,i,t}) + \sigma_\zeta(\chi_{k,i,t}))$.

To estimate the unemployment, layoff, and job-finding rates conditional on the workers' characteristics I use the quarterly Chilean Employment Survey, ENE (1990Q1-2009Q4), which covers 35,000 households (corresponding to 45,000 workers) at the national level every quarter. The ENE survey is implemented by the Chilean Institute of National Statistics, therefore participation is compulsory by law and non-response is low. The ENE follows a rotating sample scheme in which selected home addresses are kept for approximately 18 months, allowing me to match the same families and workers over time. Furthermore, during the 4th quarter of each year the ENE has an Income module, the ESI (1990Q4-2009Q4), which provides a similar measure of labor and non-labor income as the CASEN/EFH samples. Madeira (2015) uses this matched ENE/ESI panel dataset to estimate the quarterly unemployment rates, transition probabilities, permanent income growth, and income volatility shocks for 1990Q1-2009Q4, for all the 540 worker types classified by $x_{k,i}$.

4.3 Consumption

The initial simulated expenditure of households at time t is a stochastic function of households' demographics, z_i, an idiosyncratic consumption preference ε_i, plus their permanent income $P_{i,t}$ and labor income volatility $\bar{\sigma}_{i,t}$ (which includes both heterogeneous risk and cyclical effects across t):

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

For $c_{i,t}$ I focus on non-durable expenditures, since previous studies show households keep smooth non-durable expenditures even during unemployment events while durable goods are easy to postpone (Browning and Crossley, 2009, Attanasio and Weber, 2010). Also, durable goods represent a smaller portion of most Chilean households' budgets and have little effect on the results. Since extreme percentiles may be affected by measurement error and under-reporting, simulations are truncated to be above the 20th percentile of consumption conditional on ζ: $p_{20}(c_i \mid \zeta)$. Therefore the 20th percentile of consumption represents the minimum living standards allowed, $m(z_i) = p_{20}(c_i \mid \zeta)$.

This stochastic process is estimated with Robinson's (1988) two-step procedure, using the 10,092 households covered by the Chilean Household Expenditure Survey (EPF) in 2007. This survey provides a high quality measure of durable and non-durable expenditures, with interviewers visiting households multiple times during a period of more than one month and asking for their bills and receipts from expenditures, plus memory reports of non-receipt expenses, made during the period, following the best international measurement procedure (Attanasio and Weber, 2010). Furthermore, participation in the EPF is compulsory by law and therefore non-response rates are low.

Table 3 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.

Table 3: 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 10000 bootstrap replicas, *** 1% statistically significant

4.4 Borrowers' profiles, Credit access and Interest rates

I consider two distinct types of lenders in Chile - banks and retail stores - which provide strategic credit decisions. According to the CASEN-EFH sample 61.5% of the families in Chile have some consumer debt. However, only 22.3% of the Chilean families have banking consumer debt, while 49.4% of all families use consumer credit from large retail stores. Banks tend to cater to higher income clients and also to larger loan amounts. In the EFH 2007 loans in banks' credit cards are about 80% larger than in retail credit cards even after accounting for family income. In Chile banks have access to public information about each borrower's loans in the banking system, but they do

not have knowledge of families' debts with retailers. Therefore banks and retailers' information sets differ significantly and so do the loans and interest rates they offer.

I assume credit markets are competitive and each lender v merely adjusts its loans to their perceived risk for each borrower i at time t, conditional on an observed set of information $X^v_{i,t}$. The cost of providing a loan equals its capital (1) plus the lenders' cost of funds CF_t, which is composed of 7% of loan administration costs plus the interest rate paid on 1-year deposits by Chilean banks. Lenders perceive the probability of a delinquency payment to be $\Pr(Dl_{v,i,t})$, and in case of delinquency they lose a portion LGD of their capital. The revenues of the loan equal the repaid capital plus the interest rate charged, $i_{v,t}(i)$, times the repayment probability $(1-\Pr(Dl_{v,i,t}))$ and the capital recovered in case of a delinquency event $((1-LGD)\Pr(Dl_{v,i,t}))$. By equating loan costs with expected revenues, lender v obtains its competitive interest rate:

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

$$\Leftrightarrow i_{v,t}(i) = \frac{CF_t + (LGD \times \Pr(Dl_{v,i,t}))}{1-(LGD \times \Pr(Dl_{v,i,t}))},$$

with $v = 1$ (for banks) and 2 (for retail stores). The loss-given-default portion of the loan, LGD, is estimated to be around 0.50 at the international level (Botha and van Vuuren, 2009). The risk-adjusted interest rate expression also shows that shocks to lenders' funding cost have asymmetric effect on borrowers with different risk and only safe debtors pay interests close to CF_t.

To obtain lenders' measures of individual borrowers' risk, $\Pr(Dl_{v,i,t})$, I use again the CASEN-EFH sample. The CASEN-EFH differentiates the loan information of each family for banks and retailers in all its components, loan amount, debt service and maturity. Also, the CASEN-EFH has a measure of consumer debt delinquency by asking whether households missed any contract payment over the last 12 months, although with no information on "how late" payments were. The surveys also measure delinquent payments for mortgages in the same way, but mortgage delinquency is rare. The survey measure of delinquency is broader than the official banking standards of a loan in arrears after 90 days. However, consumer delinquency rates in the EFH/CASEN between 2006 to 2009 have values similar to the SBIF banking consumer delinquency rates during the same period, suggesting the surveys can be adequately used to calibrate an adequate model of borrower risk.

Each lender v estimates the borrowers' delinquency risk using a restricted information set, $X^v_{i,t}$:

15) $\Pr(Dl_{v,i,t}) = \Pr(Delinquency_{i,t} = 1 \mid X^v_{i,t}) = \Phi(\theta_v z^v_i + \beta_v x^v_{i,t})$,

with Φ being the standard normal cdf. The information set of the lenders $X^v_{i,t} = \{z^v_i, x^v_{i,t}\}$ includes a vector of fixed demographic characteristics, z^v_i, plus a set of continuous time-varying risk-factors, $x^v_{i,t}$. z^v_i can be understood as a proxy for the financial knowledge of the household or its attitudes towards default. However, changes in the risk vector $x^v_{i,t}$ can induce lenders to modify interest rates over time. In the empirical estimation I choose $z^v_i = \{$ Santiago Metropolitan resident or not, number of household members, gender, marriage status, age and education dummies of the household head $\}$ and $x^v_{i,t} = \{$ household log-income $y_{i,t}$, debtor with lender $1(D^v_{i,t} > 0)$, lenders' consumer debt to permanent income ratio $\frac{D^v_{i,t}}{12 \times P_{i,t}}$, total debt service to income $\frac{DS^v_{i,t}}{Y_{i,t}}$, and the household's unemployment probability $\bar{u}_{i,t}$ $\}$. $\frac{D^v_{i,t}}{12 \times P_{i,t}}$ can be understood as a measure of household solvency, while $\frac{DS^v_{i,t}}{Y_{i,t}}$ measures households' liquidity risk due to high immediate payments.

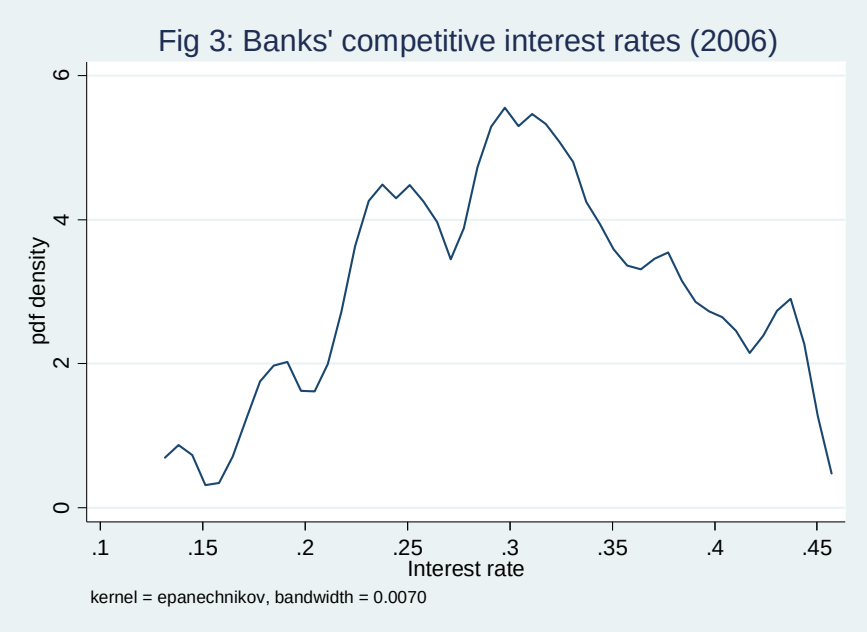
Table 4: Consumer Delinquency Probit model (CASEN-EFH)

Explanatory Variables	Full information	Banks	Retailers
$y_{i,t} = \ln(Y_{i,t})$	-0.289 (0.012***)	-0.314 (0.012***)	-0.259 (0.012***)
$\frac{D^v_{i,t}}{12 \times P_{i,t}}$	0.291 (0.050***)	0.496 (0.056***)	0.143 (0.054***)
$\frac{DS^v_{i,t}}{Y_{i,t}}$	0.712 (0.060***)	0.246 (0.109**)	0.891 (0.055***)
College degree	-0.155 (0.030***)	-0.097 (0.030***)	-0.111 (0.030***)
Unemployment risk, $\bar{u}_{i,t}$	0.898 (0.183***)	0.857 (0.182***)	0.785 (0.183***)
Nr of household members	0.155 (0.005***)	0.152 (0.005***)	0.151 (0.005***)
Constant	3.074 (0.151***)	3.638 (0.2149***)	3.132 (0.235***)
Pseudo R-square	0.096	0.086	0.094
Nr of observations	27374	27374	27374

Standard-errors in () using 1000 bootstrap replicas. *** 1% statistically significant, ** 5% significant. Other conditional variables: Dummies for year, High income town (over 80% of population is above median national income), gender, marriage, education and age of family head.

Table 4 shows the estimated coefficients of this consumer delinquency probit model for both banks, retailers, and a counterfactual lender which would have full information on both banking and retail debt loans of the borrower. Households are more likely to be in financial distress if they have 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 with one significant difference: 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 $\frac{DS^v_{i,t}}{Y_{i,t}}$. Figure 3 plots the simulated population distribution of interest rates for bank debtors in the year 2006. This distribution shows two significant modes of interest rates, one around 20% and the second at 30%, with no rates observed above 45%. This is consistent with the activity of Chilean banks, who offer two main consumer credit products (MMFS, 2011): contractual consumer credit (with interest rates around 28%), and personal credit lines (with interests around 18%). Chile's interest rate ceiling law limits rates to a maximum of 50% above the mean of the banking sector's interest rate, which is again consistent with the model's simulated interest rates.



Banks offer loans with individualized interest rates $i_{1,t}(i)$ and a maturity of 8 quarters. Retail stores discriminate loans just by accepting or rejecting applicants, but offer the same interest rate to all borrowers, $i_{2,t} = E\left[i_{2,t}(i)\right]$ and this induces retail stores to charge high interest rates due to adverse selection. Also, non-financial institutions have less secure funding sources than banks, lending only with a shorter maturity of 4 quarters. Lenders reject loan applications if the family's competitive interest rate does not satisfy the maximum legal interest rate, $i_{v,t}(i) \leq 1.50E\left[i_{1,t}(i)\right]$.

Furthermore, lenders have debt ceilings on the maximum credit amount awarded to borrowers as a multiple of their income (similarly to the credit-constrained representative agent model of

Ludvigson, 1999). Banks observe their clients' wages over long periods, therefore it is reasonable to assume they use information on both households' permanent and current income for their loan ceiling: $b_{1,i,t} = 1(P_{i,t} \geq 70UF)(2P_{i,t} + 1Y_{i,t}) + 1(P_{i,t} \in (7, 70UF))(1P_{i,t} + \frac{1}{3}Y_{i,t})$, with UF being a Chilean real monetary unit value adjusted for the official price index (1-UF corresponds roughly to 45 US Dollars). The larger debt-to-income multiples awarded to higher income families represents the fact that lenders have scale economies for clients' accounts, therefore bigger clients imply lower costs. Retail stores usually gather information on the borrower's profile and income upon opening a consumer client account, putting more trust on their consumption profiles than current income. For this reason, retail stores debt limit is specified as a multiple of permanent income only, $b_{2,i,t} = 1(P_{i,t} \geq 70UF)(2P_{i,t}) + 1(P_{i,t} \in (7, 70UF))(1P_{i,t})$. Also, I account that some families have more access to credit, therefore the actual debt ceiling of the lender is given by the maximum of the income-based borrowing abilities, the family's current debt, and the 75-th quantile of debt of families with similar characteristics z_i: $dc_{h,i,t} = \max(b_{h,i,t}, D_{h,t-1}, Q_{75}(D_{h,t-1} \mid z_i))$ for $h = 1, 2$. The correlation of $b_{h,i,t}$ and $Q_{75}(D_{h,t-1} \mid z_i)$ is 34.6% for banks and 40.7% for retail stores, therefore the model is not too sensitive to choosing a particular measure of borrowing ability or another.

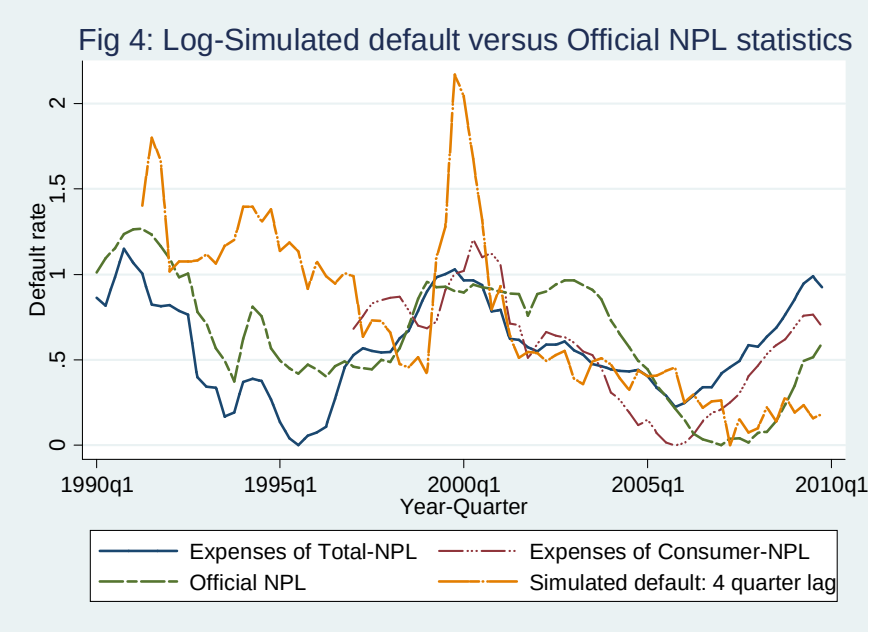
4.5 Asymptotic errors and confidence intervals

This model depends on a large number of statistics and several datasets, including imputed values. Gourinchas and Parker (2002) provide a valid asymptotic matrix for a model with parameters estimated from different datasets, but their derivation ignores imputations, simulation error, and is based on a GMM matrix which is cumbersome for models with a large number of parameters. My model's simulations, however, are parametrized only with continuous statistics, therefore valid asymptotic confidence intervals and standard-errors can be obtained through a bootstrap procedure. Bootstrap replica samples are built with replacement for each one of the CASEN/EFH, ENE, and EPF datasets, with all the household's members sampled in each observation unit. Population strata size is kept the same as in the original data, insuring that population weights are unchanged. Finally, all the model's coefficients and random simulations are re-made on each bootstrap sample. This procedure accounts for all sources of statistical error, including the coefficients' estimation error, imputation of missing data, and the simulation randomness of workers' income dynamics.

5 A Historical Simulation of Financial Distress

5.1 Baseline simulations and time-series validation

Now I present the results of the counterfactual financial distress model simulated for the period 1990-2009 and comment on how well it explains historical events of consumer debt default in Chile. The main official statistics related to consumer default are the delinquency rate, also known as NPL, i.e. Non-Performing-Loan Rate (which measures the ratio of the value of consumer loans classified as non-performing over total consumer loans), and the LLPE rate, the Loan Loss Provision Expense Rate (measuring the ratio of total expenses with non-performing loans over total loans). These measures for consumer loans are available from the Central Bank of Chile. Loss provisions include loans that were renegotiated at a loss for the lender and therefore provide information not entirely covered in the NPL rate. Loan Loss Provisions for Consumer Loans are only available since 1997, therefore I also use the Loan Loss Provision Expense Rate for all loans in the financial system, since both variables are highly correlated. Since the variables have different scales, I graph all variables in a log-scale, $\ln(\frac{x_t}{\min_t(x_t)})$, for an easier visual comparison. The model's simulations replicate broadly with the different phases of historical risk in consumer default in Chilean history (Figure 4), being able to explain the periods of high default in the early and late 90s, as well as the strong decline in consumer loan default which happened in the mid 1990s and mid 2000s. The simulations also show the model is successful in replicating how default can increase 150 or 200 log-points during recessions, therefore it is consistent with consumer debt risk being highly cyclical as portrayed in Figure 1 of this article. The model also coincides with the moderate increase in consumer default which happened in the last years during the recent international credit crisis. A potential problem of the model's simulations is that it seems to show increases in default that are bigger and more short lived than in the actual recessions, while in the real data there is a stronger persistence that is unaccounted for in the fundamentals of the model.



In Table 5 I show a comparison of the simulated rates for Non-Performing Loans (NPL_t) and Expenses with Non-Performing Loans ($ENPL_t$) versus their real historical values over the period 1990Q1-2009Q4. The simulated and historical rates of NPL_t and $ENPL_t$ are similar in terms of expected value, standard-deviation and minimum-maximum values observed over the entire 80 quarters of the time series (1990Q1-2009Q4). Also, there is a correlation of 61.5% and 64.9% between the simulated and historical values of NPL_t and $ENPL_t$, respectively. The model simulations have some uncertainty, since all the parameters need to be 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 6 shows the standard-errors of the simulated time-series for several distinct combinations of household types. One advantage of the model is that one is able to simulate the default risk of several types of households and consider which ones pose a higher risk for the economy and the banking system. 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 first vector includes estimations made for 87 household types for each different time period, but it has a substantial estimation error, since the average bootstrap standard-error is 8.5% and 6.6% for the NPL and ENPL statistics. However, Table 6 shows that uncertainty around the simulations drops

quickly as one reduces the number of different household types. The Standard-errors around the simulations fall by more than a half if one is estimating the default risk of just 9 or 15 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 are only 1.4% and 1.0% for the NPL and ENPL measures of risk. This confirms that the model is just as reliable for simulating aggregate default risk during either recessions or expansions.

Table 5: Model's fit of the historical series of Non-Performing Loans

Moments of NPL and ENPL	**Data (%)**	**Model (%)**
$E[NPL_t]$	5.7	5.0
Standard-deviation $[NPL_t]$	1.2	1.4
$\min - \max\ [NPL_t]$	4.1−8.5	3.1−10.7
$E[ENPL_t]$	3.8	3.3
Standard-deviation $[ENPL_t]$	0.8	0.7
$\min - \max\ [ENPL_t]$	2.5−6.7	2.3−6.5
$Corr(NPL_t, ENPL_t)$	63.1	67.0
$Corr(Data - NPL_t, Model - NPL_t)$		61.5
$Corr(Data - ENPL_t, Model - ENPL_t)$		64.9

Now I study the impact of the model's simulated decline in consumption enforced by the credit constraints on households, CC_t. Table 7 shows the results of a linear regression of quarterly log-consumption growth in Chile, with the simulated consumption decline and log-aggregate income growth over the current quarter and previous year as regressors. The simulated aggregate consumption decline of indebted households is negatively related to observed consumption growth over the last 20 years, which further validates the model.

The predicted reduction in overall consumption due to credit constraints has a significant impact on overall economic activity, with households' inability to smooth consumption representing an aggregate consumption cost of 0.5% to 2% log-points over the period 1990-2009 (Figure 5).

Table 6: Bootstrap Standard-Errors for the simulated Non-Performing Loans (%)

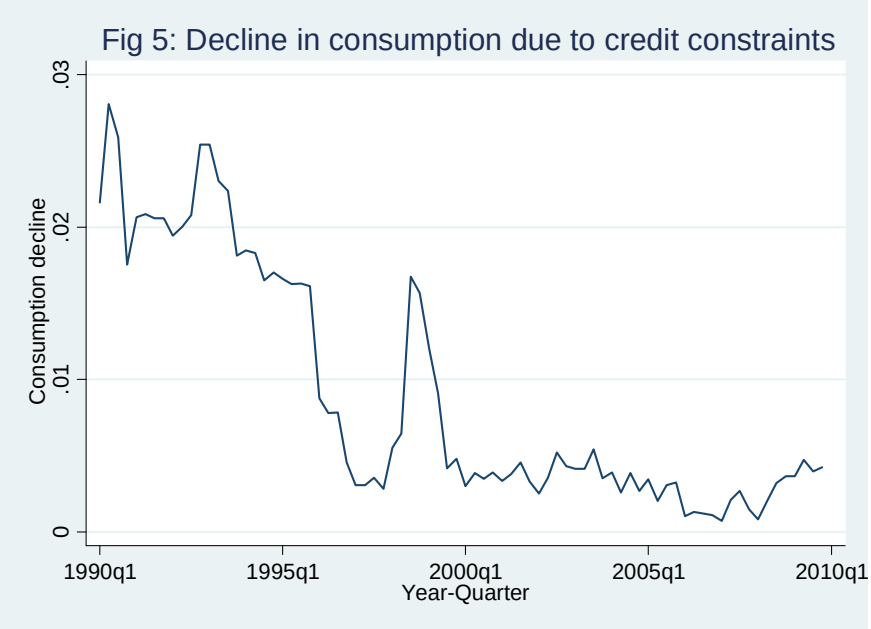
	NPL_{t,x_1}	$ENPL_{t,x_1}$	NPL_{t,x_2}	$ENPL_{t,x_2}$	NPL_{t,x_3}	$ENPL_{t,x_3}$	NPL_{t,x_4}	$ENPL_{t,x_4}$	NPL_{t,x_5}	$ENPL_{t,x_5}$
Mean	8.5	6.6	4.0	2.7	4.0	3.5	2.5	1.9	1.3	0.7
Percentile 10	1.6	1.0	0.9	0.6	1.5	0.7	1.0	0.7	1.1	0.5
Percentile 25	3.1	1.9	1.5	1.1	1.8	1.1	1.4	1.0	1.2	0.5
Percentile 50	6.3	4.1	2.6	1.8	2.7	1.8	2.1	1.3	1.3	0.6
Percentile 75	10.8	7.1	4.0	3.9	5.7	3.6	3.1	2.2	1.3	0.7
Percentile 90	18.1	12.7	11.2	6.6	9.0	7.9	4.5	3.7	1.4	1.0

50 bootstrap replicas. $x_1 = \{$Age x Education of Household Head x Household Income Quintile x Metropolitan Region dummy$\}$, $x_2 = \{$Age of Household Head x Household Income Quintile$\}$, $x_3 = \{$Age x Education of Household Head$\}$, $x_4 = \{$Lender type (Both Bank and Retail Loans, Only Bank Loan, Only Retail Loan) x Household Income Quintile$\}$, $x_5 = \{$Constant$\}$. The vectors x_1, x_2, x_3, x_4, x_5 have 87, 15, 9, 15 and 1 groups of distinct family types, respectively. All vectors include 80 different time periods (1990Q1-2009Q4).

Table 7: Log-Consumption growth and Simulated Consumption Decline

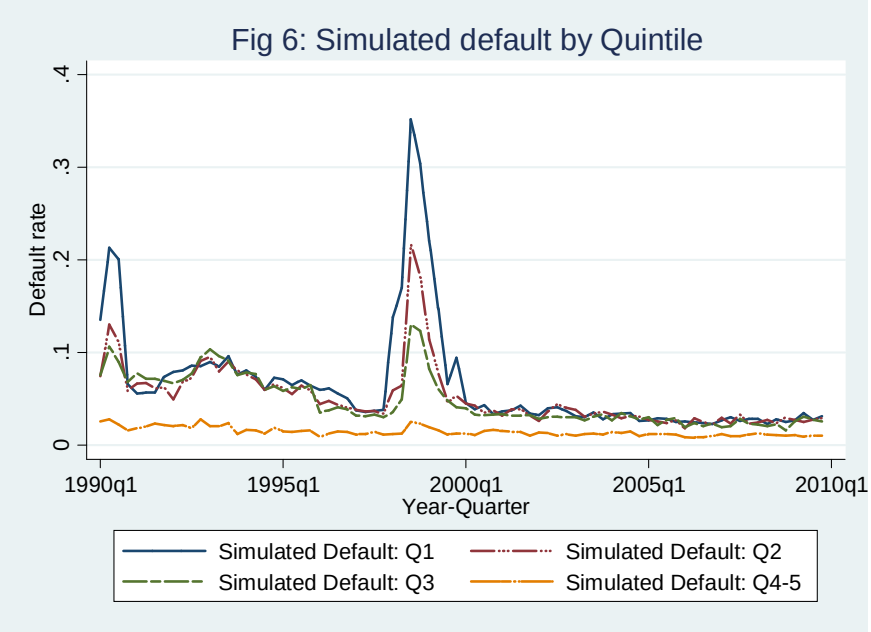
Independent variables	Log-Consumption Growth
Log-Income growth of current quarter	7.023 (3.481)**
Log-Income growth over previous year	-2.120 (1.374)
Simulated Consumption Decline	-9.904 (5.350)*
R-square / Nr of Observations	0.878 / 79

Controls: quarter dummies. Robust Standard-errors in (), ** 5% significant, * 10% significant.



5.2 Financial fragility across demographic groups

Unemployment spells and insecure income tend to fall disproportionately on the poor. Analyzing the simulated insolvency rates across the 51,000 CASEN-EFH households over the period 1990-2009, I find that upper income families (quintiles 4 and 5) suffered small financial risk across both decades. In comparison the families in the lower 60% of the income distribution are found to have suffered significant changes in financial distress, presenting large rates of insolvency in the early 90s and during the Asian crisis of 1998-99. In particular, the model predicts that the lowest income quintile could have jumped from an insolvency rate of 5% in 1997 to almost 30% in 1999, which is a clear illustration of how damaging that period must have been for poorer families.

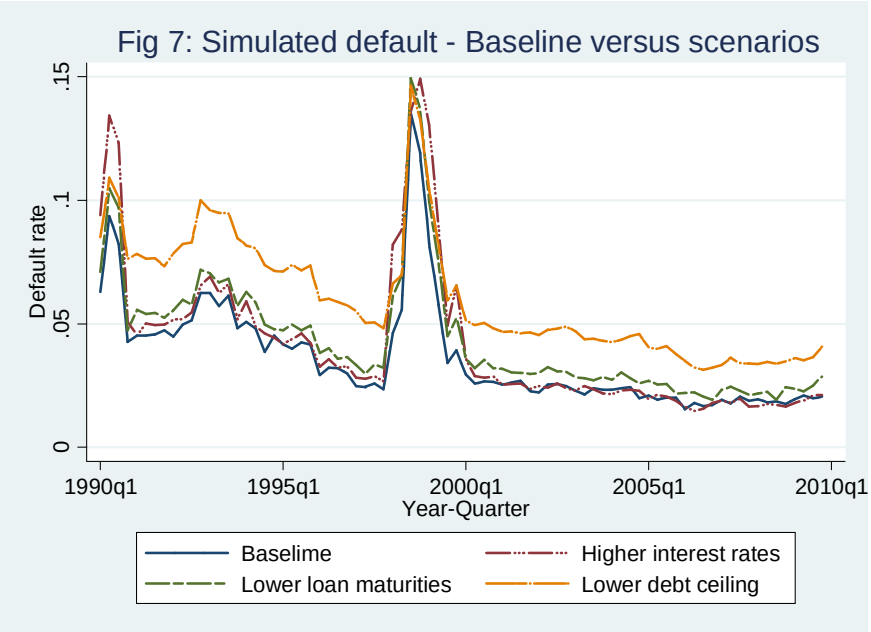


An interesting result is that the model predicts that the financial risk of lower income families in Chile fell substantially during the early 2000's and nowadays the financial insolvency risk of households in the first quintile is actually similar to families in the 3rd quintile of household income, around the median of the income distribution. Several financial analysts in Chile have expressed concern about the large expansion of retail banking across lower income families over the last 10 years (Marinovic, Matus, Flores, Silva, 2011). This work shows that a plausible explanation is that banks and retail stores are capturing a segment of families which are now of similar credit risk as the rest of the population, and not that loans are expanding due to an increased appetite for risk.

5.3 Simulation results if terms for new loans deteriorate

Besides income shocks, changes to loan terms such as maturities, interest rates, and loan access can bring households closer to insolvency, putting illiquid households at a corner of their budget constraints and in a position of default. I study this possibility by using the previous 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%.



All these 3 alternative scenarios have a large impact on the proportion of insolvent families (Figure 7), with insolvency rates during the Asian crisis of 1999 reaching over 10% instead of 9% of the families. A decrease in credit availability over the last 10 years would have increased insolvency rates of households by 2%, showing the relevance of monitoring loan terms.

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 analysis of household risk in recent years have employed micro data to implement stress tests, estimating that consumer debt should be robust to all types of shocks such as substantial increases in unemployment rates and interest rates. However, all of these studies fail to correctly replicate the fact that consumer debt default rates are highly volatile. In particular these studies estimate that even strong recessions imply an increase in the stock of consumer loans in default lower than 30 percent. 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 these stress test studies.

Simulating this structural model of household default under a variety of scenarios, I find that household financial distress is non-linearly linked to unemployment risk and shocks to financing new loans, such as increased interest rates and lower maturities. The fact that consumer debt can experience long periods of low default rates should not therefore be interpreted as signaling a permanent period of stability. Periods with short unemployment spells may be endured with no default by households, while longer unemployment spells create a dynamic of worsening household finances. In particular I estimate that an increase of unemployment rates from 7% to 10.5% - such as the one Chile suffered between late 1998 to 2001 - could easily increase consumer non-performing loans by 3 to 4 times the normal rate. Furthermore, the decline in total expenditure due to household credit constraints increases from 0.5% to 0.7% during downturns.

The model accurately explains the actual historical evolution of consumer delinquency in Chile, implying it can become a serious tool for evaluating economic policies. Particular applications could include studies of capital stress tests, usury laws, or even credit competition policies such as allowing for families' credit history to be publicly available for all lenders. Financial institutions know little of the macro risk of consumer debt and its risk correlation with other asset classes (Botha and van Vuuren, 2009), affecting good assessments of the buffer capital required. My results conclude that current risk models severely underestimate the true volatility of consumer debt default and therefore both banks and their regulators require the use of richer information and better models.

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