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MEASURING THE COVARIANCE RISK OF CONSUMER DEBT PORTFOLIOS*

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Abstract

Consumer loan risk is hard to predict, since households are heterogeneous and suffer significant macro shocks. This work proposes a heterogeneous agents model of household credit risk with shocks to both labor income and credit access. Using the Chilean Household Finance Survey I simulate the default conditions of different households over distinct macro scenarios. I show that banks' loan portfolios have very different covariance risk in relation to macro events, with some banks being prone to high risk during recessions. Also, heterogeneity in covariance risk has a negative impact on loan amounts and the probability of receiving a loan.

Resumen

Es difícil predecir el riesgo de créditos al consumo, dado que los hogares son heterogéneos y además sufren choques macro significativos. Este trabajo propone un modelo de agentes heterogéneos para medir el riesgo de crédito de los hogares, que pueden sufrir choques de ingreso laboral y cambios en el acceso al crédito. Utilizando la Encuesta Financiera de Hogares (EFH) del Banco Central de Chile, yo simulo la morosidad de las familias de acuerdo a distintos escenarios macroeconómicos. Los resultados muestran que los portafolios de préstamos de cada banco tienen diferentes niveles de riesgo de covarianza en relación a los choques macro, y algunos bancos son más propensos a riesgos elevados durante recesiones. Además, la heterogeneidad en el riesgo de covarianza de cada familia tiene un efecto negativo en la probabilidad de recibir crédito y en los montos de deuda a que los hogares tienen acceso.

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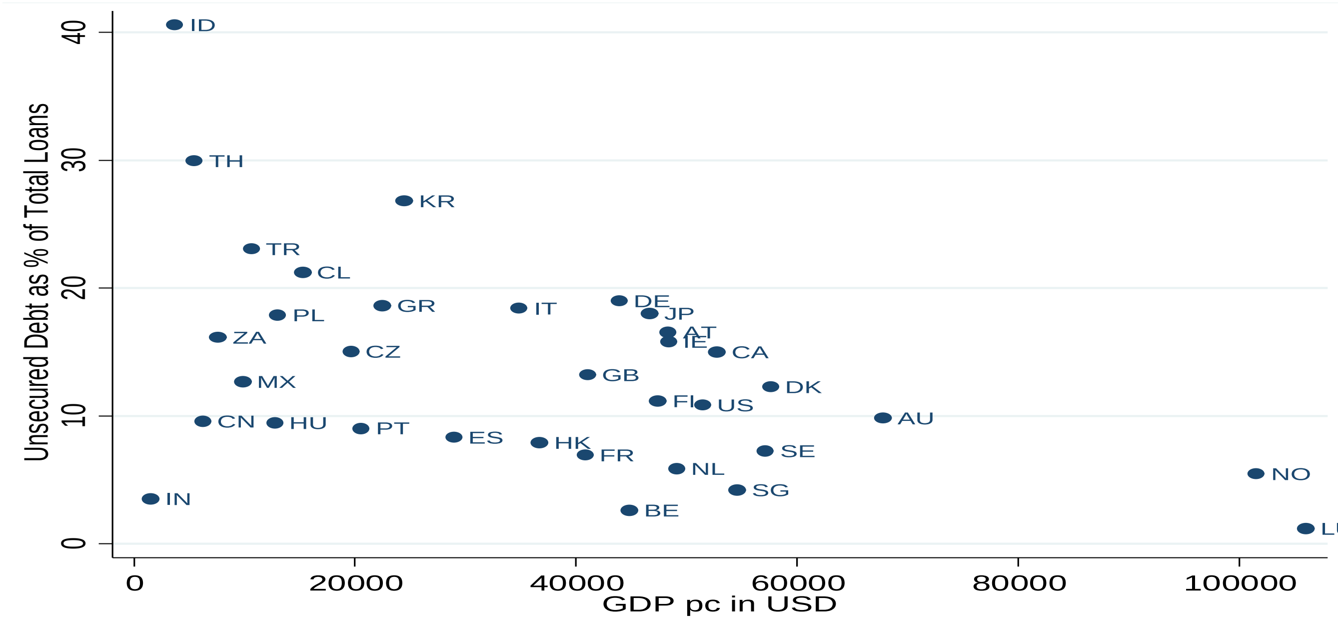
1 Introduction

The asset pricing literature concludes that the best measure of an asset's risk is the undiversifiable risk component, that is, its correlation with the overall market portfolio (Fama and MacBeth, 1973). In a similar way, finance theory predicts that real assets and bonds with credit risk should also be discounted by their covariance risk or market beta (Duffee, 1999, Duffie and Singleton, 2003). Empirical studies have found that default has a large common component with both domestic and international business cycles (Pesaran, Schuermann, Treutler and Weiner, 2006), therefore even if default is a low probability event it tends to cluster with other negative events and its impact on portfolio performance is significant (Zhou, 2001, Das, Duffie, Kapadia and Saita, 2007).

This paper proposes a model approach towards evaluating the default risk of household loans, in particular their systematic risk component. Household debt is an asset of increased relevance in the balance sheets of financial institutions, reaching more than 100% of annual GDP in several developed countries (Cecchetti, Mohanty, and Zampolli, 2011). Banks expenses with non-performing consumer loans from 2006 to 2009 increased more than 3 times in the USA and UK (IMF, 2011), appearing as a high risk asset class and a macro shock unaccounted for in current models. 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 and Stein, 2011). To evaluate the importance of consumer loans in the financial system I show in Figure 1 the percentage value of unsecured household loans (that is, loans not secured by mortgages) in terms of the total credit for the private sector (that is, credit of both households and private non-financial firms) for 34 countries[1]. This plot shows that the importance of consumer loans as a percentage of total loans varies a lot according to different countries, independently of their income level (as measured by GDP per capita). Consumer loans represent around 10% to 25% of all loans for several

[1] To plot the data in Figure 1 I use information for total credit to the private non-financial sector (published by the Bank for International Settlements, hence BIS), total credit to the household sector (from BIS), plus the total amount of home mortgage loans (published by the Housing Finance Information Network, hence HOFINET) and the value of GDP per capita from the World Bank. I then obtain the value of unsecured household loans as the difference between total household loans (BIS data) and home mortgage loans (HOFINET data). Due to the absence of BIS and HOFINET information for Chile, the data for Chile (CL) comes from statistics of the Central Bank of Chile.

Figure 1: Unsecured Household Debt as a percentage of the Total Non-Financial Private Sector Loans (households plus firms) for the year 2012



countries, therefore it is important to evaluate their systematic risk for the financial institutions.

The risk of household loans is harder to measure than for corporate default risk, since households do not have a public history of bond pricing. Risk measures for households such as credit scoring take into account only their cross-sectional risk of default (Musto and Souleles, 2006, Edelberg, 2006), not their correlation with the business cycle or with other aggregate asset returns. Ignoring this covariance risk of household loans is detrimental for financial institutions that engage in household loan operations, since they are susceptible to a large macro default risk that threatens their balance sheets during particularly negative recessions, such as the recent subprime crisis. For this reason I propose a model for simulating the default risk of household consumer loans under several counterfactual scenarios for the business cycle. I build these macro scenarios by replicating the real risk-free interest rate plus the unemployment rate and labor income volatility shocks observed in each quarter over the last 23 years, therefore creating 92 different quarterly scenarios. These counterfactual simulations can then be used for estimating the covariance risk of consumer loans relative to other assets. This is done in two steps. First, I show that the default rate of the total consumer loan portfolio of all Chilean banks has a high covariance risk compared to the

Chilean stock market and to the return on assets of the Chilean banks (note that since consumer loans are only one component in banking assets, then it makes sense to study their systematic risk in relation to the overall bank assets). I also show that the default rate of consumer loans has a high covariance risk relative to an asset pricing kernel based on real consumption fluctuations (Cochrane, 2005), therefore consumer default tends to happen in periods when consumption is low and it is a risky asset. Second, I then calculate the covariance risk of the default rate of the different loan portfolios of each bank in relation to the aggregate loan portfolio of all banks. I show there is systematic heterogeneity across Chilean households in their covariance risk and this implies that some Chilean banks are much more sensitive to the business cycle.

This work is closest to Musto and Souleles (2006), who used the credit scores of a sample of consumers over a period of 37 months to compute their default probabilities and their individual covariance risk or "default-beta" relative to the aggregate default over all consumer loans. Musto and Souleles (2006) then show that higher default-betas are associated with low-income, renters, youth, singles, and residents of states with higher divorce rates and lower coverage of health insurance. Also, consumers with high covariance risk tend to have high default probabilities and lower amounts of credit, even after controlling for their average credit scores and other factors.

As in Musto and Souleles (2006) I use the changes in default risk of each household across different time periods in order to estimate their "default-beta". The main difference is that my methodology uses counterfactual simulations of risk over a range of different aggregate scenarios, while Musto and Souleles (2006) use actual changes in default rates of a fixed sample of households. There are obvious advantages and disadvantages in the methodology of counterfactual. The most obvious disadvantage is that the counterfactual simulations do not necessarily correspond to the actual decisions that households would make and therefore the results are not robust to failures in the model's assumptions. However, an obvious advantage of using a counterfactual model is that there is no limit to the number of different scenarios and time periods where one can study the risk of events. If a researcher computes the "default-betas" in a real panel data sample for a short period, then his results can be affected by a lucky sequence of shocks. A short time period could give the impression that default risk changes little with the aggregate state due to the absence of strong negative states in the observed dataset. In this case the counterfactual results from a model could give a different perspective to both researchers and regulators. The problem of accounting for "lucky sequences" is particularly relevant for studies of households' credit risk, since data from credit bureaus is typically limited to a brief number of years, often for legal reasons such as forgiving older defaults (Musto, 2004). Musto and Souleles' classical study included just 3 years of data.

For simulating the default risk of different households I assume a model with naive agents that follow a behavioral rule for consumption and default. Agents choose consumption based on an idiosyncratic taste for consumption plus their observable demographic profile (say, age, education and number of household members), income and income volatility (which represents a precautionary motive, as in Carroll and Samwick, 1997, since households of higher risk consume less in order to avoid painful shocks in the future). The dynamic choice of consumption is then given by the savings from the previous period, therefore if savings are negative then the household cuts down his log-consumption by λ points in each quarter until it either reaches positive savings or a minimum living consumption level. Agents default on their payments when their budget constraint does not allow them to pay both their consumption level and their debt commitments, in which scenario households limit themselves to consuming their current income. The behavioral rule is constrained by one essential element of the agent's decision, its budget constraint. Households are required to service their consumption needs and accumulated debt obligations, using a budget composed of current income, past savings, and new loan contracts available from banks and non-financial institutions. Agents can get new loan contracts for the amount necessary to fund their consumption and previous debt commitments. New loans are charged the aggregate risk-free interest rate plus a risk-adjusted premium to compensate lenders for their risk of non-repayment. Banks apply heterogeneous interest rates to their loans. However, Chilean non-financial institutions do not adjust interest rates according to debtors' profiles, therefore they get an adverse pool of borrowers and must charge high interest rates. The model accounts for a maximum legal interest rate due to usury laws and agents cannot get new loans once they surpass certain levels of repayment risk.

Chile provides an interesting case for the study of consumer debt default, since it mirrors the consumer credit expansion in the rest of Latin America (IMF, 2006) and it went through different periods of high consumer default: the early 1990s, the Asian crisis of the late 1990s, and the recent international credit crisis of 2007-09. The Chilean Household Finance Survey (EFH) data interviewed a representative sample of 12,000 households during the years 2007 to 2011, eliciting detailed information on their income, labor status, assets, debt commitments and default behavior. This sample of households is then simulated for different scenarios of labor income volatility, unemployment rates and interest rate shocks over the last 23 years. Labor income and unemployment shocks are heterogeneous across different families, with some workers being more vulnerable to the economic cycle. These labor market shocks can be accurately measured from the Chilean Employment Survey (ENE) which covers a large sample of 45,000 workers at a quarterly frequency (Madeira, 2015). I then simulate the actual unemployment rates, income shocks and banks' real costs of capital for 92 different aggregate scenarios which were actually observed in the Chilean labor market over the 23 year period, from the quarter 1990Q1 to 2012Q4. The model's counterfactual simulations accurately reflect the historical evolution of consumer delinquency in Chile, implying the model can be taken as a serious tool for evaluating policy scenarios.

The equity-market literature focuses on the pricing of securities with fixed quantities, therefore the preference for lower covariance is associated with a lower expected return, not higher quantity. Since quantities are endogenous in the credit market, then both quantities and expected returns should adjust in equilibrium. I show that both the probability of getting a consumer credit and the amount of the consumer loan decline with the covariance risk of the household, which is evidence that lenders treat such consumers as having higher risk even after other factors are taken into account. Furthermore, the probability of a household reporting to be credit constrained (that is, a household who wanted a consumer loan, but was rejected) increases with covariance risk.

This paper is related to other recent works which study the risk of consumer debt and how it has changed over time. Livshits, MacGee and Tertilt (2010) show that income shocks cannot account for the rise in bankruptcies in the US over the last 30 years. Studies show that countercyclical income risk in the US explains the rise in credit spreads and consumer debt default during recessions (Luzzetti and Neumuller, 2015, Nakajima and Rios-Rull, 2014) and labor market shocks explain part of the surge in default during the Great Recession (Gerardi, Herkenhoff, Ohanian and Willen, 2013, Athreya, Sanchez, Tam and Young, 2015). Relative to previous literature the consumer debt default model in this work is calibrated with a much larger degree of heterogeneity in wage shocks and unemployment risk, which implies that the results give a wide range of cyclical risk for the portfolios of different financial institutions. One strong assumption in this work is that agents follow behavioral rules for consumption and default instead of rational decision making. However, a large body of empirical research does support the assumption that households follow naive behavioral rules for several decisions regarding consumption and consumer debt (Agarwal, Driscoll, Gabaix and Laibson, 2009, Agarwal and Mazumder, 2013). In order to evaluate the risk of bank portfolios it is essential to have a behavioral model with a large number of heterogeneous agents, since in computationally costly general equilibrium models with only a few agent types (such a Nakajima and Rios-Rull, 2014) all the portfolios of the banks would look similar.

This paper is organized as follows. Section 2 introduces the model's framework of default behavior, then section 3 explains its calibration from different sources of survey data. Section 4 summarizes the Chilean Household Finance Survey and the characteristics of Chilean families. Section 5 shows the covariance risk of consumer debt relative to other financial assets in Chile and its heterogeneity across different Chilean banks. Section 6 then shows how access to loans changes with the covariance risk of borrowers. Finally, section 7 concludes with implications for policy.

2 An empirical model of household default and consumption

Household risk is difficult to assess, since their major asset is future income, which is hard to expropriate as collateral and creates 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). Expenditure and default decisions depend on how agents compare the intertemporal utility afforded by paying back versus the punishment costs of default, but such costs are often vaguely interpreted as "stigma" and not pecuniary fees (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 maximizing a computationally hard utility function may not add extra insight (Einav, Jenkins, and Levin, 2012). For these reasons I propose a simple behavioral model of default and expenditure that approaches the main motivations of households in terms of exogenous demographics, permanent income and consumption habits, while using a rich framework for their budget constraints, income dynamics 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, $Y_{t+s} \sim F(. \mid \zeta, Y_t, \sigma_t)$, 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 consumes their current income, $C_{t+s} = Y_{t+s}$ (as in Campbell and Mankiw, 1989):

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

1.2) $\{Df_{t+s}, C_{t+s}\} = \{1, Y_{t+s}\}$ if $B(g(\zeta, C_{t+s-1}, S_{t+s-1})) < 0$, subject to

1.3) $g(\zeta, C_{t+s-1}, S_{t+s-1}) = 1(S_{t+s-1} \geq 0)C_{t+s-1} + 1(S_{t+s-1} < 0)\max(m(\zeta), C_{t+s-1}\exp(-\lambda))$.

The rule-of-thumb consumption function $g(\zeta, C_{t+s-1}, S_{t+s-1})$ assumes expenditure has some persistence over short periods of time, since households' expenditure depends 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:

2) $B(C_t) = Y_t - C_t - DS_t + (A_t(1+R_t) - A_{t+1}) + \sum_{v=1}^{V} ND_{v,t} = 0$, 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, $Df = 0$, 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:

3.1) $DS_{t+1} = MG_{t+1} + \sum_{v=1}^{V} DS_{v,t+1}$,
$DS_{v,t+1} = \sum_{j=0}^{T} ND_{a,t-j} \frac{i_{v,t}}{1-(1+i_{v,t})^{-m_{v,t}}} 1(j < m_{v,t-j})$,
$D_{v,t+1} = D_{v,t} - Am_{v,t} + ND_{v,t} \leq dc_{v,t}$, 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, expressed as 5.2):

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

The model's dynamic simulations are then used to estimate the households' expected non-performing loans (NPL_t) and expenses with non-performing loans ($ENPL_t$), at an horizon of M quarters:

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

To obtain the simulated NPL and ENPL for the loan portfolio of each bank h, I then sum the default probability of each household i weighted by the value of its loan in the total portfolio:

4.3) $NPL_t(Bank\ h) = \frac{1}{\sum_{i=1}^{N} 1(Bank_{i,t}=h)D_{i,t}} \sum_{i=1}^{N} 1(Bank_{i,t} = h)D_{i,t} \times NPL_t(M \mid \zeta_i, Y_{i,t})$,

4.4) $ENPL_t(Bank\ h) = \frac{1}{\sum_{i=1}^{N} 1(Bank_{i,t}=h)D_{i,t}} \sum_{i=1}^{N} 1(Bank_{i,t} = h)D_{i,t} \times ENPL_t(M \mid \zeta_i, Y_{i,t})$.

The actual estimation of the household default model depends on the data sources used to calibrate its components, as summarized in Table 1. One main component is the initial distribution of heterogeneous families with demographic characteristics ζ and their initial endowments of assets, debts, and income in period t, which is given by the EFH survey. 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 Employment Survey (Madeira, 2014). The third component of the model is the consumption function, with its initial stochastic value $C_t = c(.)$ and the minimum consumption value, $m(\zeta)$, which are estimated using data from the Chilean Expenditure Survey. The parameter λ is not estimated due to a lack of panel data on consumption in Chile. Studies for the United States estimate that families only reduce consumption by 12% or 14% after shocks such as losing all the income of a household member or an annual income fall of 33% or more (Chetty and Szeidl, 2007), therefore I choose $\lambda = 0.15$. The last major modeling component is the credit market. The two main types of lenders, banks and large retail stores, lend with maturities of 8 and 4 quarters respectively, which are their mean loan maturities according to the EFH survey. I assume lenders price interest rates based on households' past repayment risk and a maximum legal interest rate (which in Chile is given by 150% the average banking consumer loan rate). For simplification purposes, the analysis will focus on default at an horizon $M = 8$ quarters which is the most relevant maturity for banks.

Table 1: Data sources for the estimated parameters

Parameters and Exogenous Shocks	Source
Population distribution and endowments	EFH 2007-2011
Heterogeneity: ζ	$\zeta = \{$Region, Sex, Age, Education, Industry,
	Quintile(Y_t), Number of household Members$\}$
Income dynamic shocks (540 types)	Y_t, P_t, σ_t, U_t (Madeira, 2015, ENE 1990-2012)
Expenditure choice	$C_t = c(\zeta, P_t, \sigma_t, \varepsilon^c)$ (EPF 2007)
	$m(\zeta) = Q_1(C_0 \mid \zeta)$, $\lambda = 0.15$
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: $i_{v,t} = i(. \mid CF_t, X_{v,t})$	EFH: $X_{v,t} = \{\zeta, D_t, P_t, Y_t, \Pr(U_t), DS_t\}$
$m_t = \{m_{1,t}, m_{2,t}\}$, $dc_t = \{dc_{1,t}, dc_{2,t}\}$	$m_t = \{8, 4\}$, $\{dc_1(P_t, Y_t, \zeta), dc_2(P_t, \zeta)\}$ (EFH)
Maximum Legal Interest Rate	$i_{v,t} \leq 1.50 \times E\left[i_{2,t}\right]$
Banks' fundraising real interest rates, CF_t	Central Bank of Chile, 1990Q1-2012Q4

3 Calibration

3.1 The Chilean Household Finance Survey (EFH)

To measure the population I use the five EFH survey waves of 2007 to 2011, which covered 12,264 urban households at the national level and with an over representation of richer households. This survey has detailed measures of income, assets (financial portfolio, vehicles and real estate) and debts, including mortgage, educational, auto, retail and banking consumer loans. In order to cover debts exhaustively, the survey elicits the loan terms (debt service, loan amount, maturity) for the 4 main loans in each category of debt. Default represents a rare experience which requires a large sample to provide accuracy and the survey sample does not include a large number of loans for each Chilean bank, therefore I use the EFH as a single pooled sample. This pooled sample then receives aggregate shocks for the real interest rate and for the labor income growth plus the unemployment and job flow rates that happen to different workers in each time period. To reduce simulation error I sample households with replacement to build a sample of 135,000 observations.

3.2 Workers' stochastic income process

Each labor force member k of household i at time t has a simulated labor income $Y_{k,i,t}$, which is affected by permanent $P_{k,i,t}$ and transitory income shocks $L_{k,i,t}$ (as in Carroll and Samwick, 1997), besides discrete income shocks caused by entry and exit from unemployment ($U_{k,i,t} = 1$ if unemployed, 0 if working). Unemployment transitions are important, since recessions are events with both more layoffs and with longer unemployment spells and jobs harder to find (Low, Meghir and Pistaferri, 2010, Shimer, 2012). Shocks are both time-varying due to the business cycle (t) and heterogeneous for different worker types $x_{k,i} = \{$Santiago Metropolitan city or Outside, Industry (primary, secondary, tertiary), Gender, Age (3 year brackets, ≤ 35, $35-54$, ≥ 55), Education (less than secondary, secondary or technical education, college), and Household Income Quintile$\}$. Workers' employment transitions follow a discrete Markov process, with probabilities given by worker k's type separation and job-finding probabilities, $\lambda^{EU}_{k,i,t} = \Pr(U_{k,i,t} = 1 \mid t, U_{k,i,t-1} = 0, x_{k,i})$ and $\lambda^{UE}_{k,i,t} = \Pr(U_{k,i,t} = 0 \mid t, U_{k,i,t-1} = 1, x_{k,i})$. Permanent income, $P_{k,i,t}$, is affected by a non-stochastic drift, $G_{k,i,t} = G(t, x_{k,i})$, which represents mean income growth expected for workers of type $x_{k,i}$, plus a log-normal random shock $\ln(\eta_{k,i,t}) \sim N(0, \sigma_\eta(t, x_{k,i}))$. Transitory income is affected by a continuous log-normal shock, $\ln(\zeta_{k,i,t}) \sim N(0, \sigma_\zeta(t, x_{k,i}))$, plus an extra shock due to changes in unemployment status, $R^{U_{k,i,t}}_{k,i,t}$, with $R_{k,i,t} = R(t, x_{k,i})$ being the replacement ratio of unemployment benefits relative to wages (which is around 25% to 40% in Chile). This unemployment insurance coverage is heterogeneous across agents because it depends on how many years they have worked and it changed over time due to a new legislation in 2001.

Based on the Chilean Employment Survey (ENE), which covers 35,000 households each quarter, Madeira (2014) estimated the vector of labor shocks, $\{G, \lambda^{EU}, \lambda^{UE}, \sigma_\eta, \sigma_\zeta\}$, for each type of worker $x_{k,i}$ and period t from 1990 to 2012. The workers' income dynamics at time t are then given by:

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

5.2) $L_{k,i,t+s} = \zeta_{k,i,t+s} R^{U_{k,i,t+s}}_{k,i,t+s}$, 5.3) $Y_{k,i,t+s} = P_{k,i,t+s}L_{k,i,t+s}$, for $s = 1, ..., M$.[2]

After all the households' members incomes are simulated, one obtains the household income as the sum of their working members, $Y_{i,t+1} = a_i + \sum Y_{k,i,t+1}$, plus a constant non-labor income, a_i. The permanent income of the household can be understood as the sum of non-labor income a_i and the permanent income of its members, $P_{i,t+1} = a_i + \sum P_{k,i,t+1}$.

3.3 Consumption

The simulated expenditure of households at time t is a 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 is the income-weighted average of each member's income volatility):

6) $\ln(c_{i,t}) = g(z_i) + \beta\left[\ln(P_{i,t}), \bar{\sigma}_{i,t}\right] + \varepsilon_i$, 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 (Attanasio and Weber, 2010). Also, 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 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

[2] For the initial period t I randomize unemployment status $U_{k,i,t}$ using the unconditional unemployment probability, $u_{k,i,t} = \Pr(U_{k,i,t} = 1 \mid t_{,k,i})$. The initial permanent income is then obtained from worker k's survey reported income and unemployment status from time t^*: $P_{k,i,t} = Y_{k,i,t^*} R_{k,i,t^*}^{-U_{k,i,t^*}}$.

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 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 10000 bootstrap replicas, *** 1% statistically significant

3.4 Borrowers' profiles, credit access and interest rates

I consider two distinct types of lenders - banks and retail stores - which provide strategic credit decisions. More than 60% of the families in Chile have some consumer debt. However, only 20% of the families have banking consumer debt, while over 35% 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 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 their interest rates.

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 (which is the ratio of non-capital expenses over loans for the Chilean banking system) 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:

$$7)\ (1+CF_t) = E\left[revenues_{v,t}(i) \mid X^v_{i,t}\right] = (1+i_{v,t}(i))\times[(1-\Pr(Dl_{v,i,t})) + (1-LGD)\Pr(Dl_{v,i,t})] \Leftrightarrow$$

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

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.

I assume lenders estimate borrowers' risk, $\Pr(Dl_{v,i,t})$, from a default regression model for whether households missed any contract payment over the last 12 months. Each lender v estimates the borrowers' delinquency risk using a restricted information set, $X^v_{i,t}$: $\Pr(Dl_{v,i,t}) = \Pr(Df_{i,t} = 1 \mid X^v_{i,t}) = \Phi(\theta_v z^v_i + \beta_v \left[x^v_{i,t}\right])$, 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. 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.

Banks offer loans with interest rates $i_{1,t}(i)$ and a maturity of 8 quarters. Retailers offer the same interest rate to all borrowers, $i_{2,t} = E\left[i_{2,t}(i)\right]$, and lend with a maturity of 4 quarters. Lenders reject loans if the family's competitive interest rate is above the maximum legal interest rate, $i_{v,t}(i) \leq 1.50E\left[i_{1,t}(i)\right]$. Furthermore, lenders have ceilings on the maximum amount given to borrowers as a multiple of their permanent income (similar to the credit-constrained representative agent in Ludvigson, 1999): $b_{1,i,t} = 3P_{i,t}$ and $b_{2,i,t} = 2P_{i,t}$. Also, I account that some families have more access to credit, therefore the actual debt ceiling is given by the maximum of the household's income-based borrowing abilities and their current debt: $dc_{v,i,t} = \max(b_{v,i,t}, D_{v,t-1})$ for $v = 1, 2$. In this framework each household is always obtaining credit from the same bank. This assumption is reasonable because the Chilean banks observe the same information regarding the credit history of each applicant and therefore a family that is overindebted with one bank would also be observed as a risky client by all the other banks and would likely be refused for further credit.

Table 3: Population of debtors, loan amounts (thousands of pesos) and delinquency over time (EFH)

Type of Debtor	**Population**		**Loan amount (median)**		**Delinquency rate**	
	2007	**2011**	**2007**	**2011**	**2007**	**2011**
Bank	6.5%	8.2%	968	1,176	8.8%	11.7%
Bank + Retail Store	13.6%	11.8%	1,435	1,826	18.9%	24.6%
Retail Store	31.9%	25.9%	232	177	21.1%	19.5%
Other Consumer Loans	8.4%	12.7%	997	1,185	18.1%	14.4%
No wish for consumer debt	26.6%	28.7%				
No Access to Debt	13.0%	12.7%				

4 Description of the Chilean households and their indebtedness

The Chilean Household Finance Survey (in Spanish, Encuesta Financiera de Hogares, hence on EFH) is a representative survey with detailed information on assets, debts, income and financial behavior, and is broadly comparable to similar surveys in the United States and Europe (Eurosystem, 2009). Table 3 shows the proportion of households with a consumer loan at a Bank, a Retail Store, at both a Bank and Retail Store, or with another kind of consumer loan (such as auto loans or educational debt). I also show the households who report No Wish for Consumer Debt and No Access to Debt (if the family applied for loans, but was refused). Households with "No wish for consumer debt" and "No Access to Debt" represent 27% and 13% of the Chilean population, respectively. Retail Stores represent around 40% of the population, with 12% being users of both Bank and Retail Store Loans. Households with loans at a Bank or a Bank plus Retail Store have larger loan amounts, with the median loan amount having increased between 2007 and 2011. For each debt the survey also asks whether the household has fallen into delinquency or late payments in the last 12 months. The delinquency rate of Bank users increased somewhat in 2011.

The EFH survey has limited data on income volatility and unemployment risks. For this reason I use the income and employment risks of the EFH workers based on the mean statistics for workers with similar characteristics obtained from the ENE dataset (see Madeira, 2014, and the explanation in the previous section). Table 4 reports the households' percentiles 25, 50 and 75 for the unemployment risk ($\bar{u}_{i,t}$), separation rate ($\bar{\lambda}^{EU}_{i,t}$), job finding rate ($\bar{\lambda}^{UE}_{i,t}$), log household income ($\ln(Y_{i,t})$), annual labor income volatility ($\bar{\sigma}_{i,t}$) and its replacement ratio of income during unemployment ($\bar{R}_{i,t}$). These measures are weighted averages of all the members of the household, with weights $\frac{P_{i,k,t}}{P_{i,t-a_i}}$ assigning larger importance to members of higher permanent income. Income volatility is the weighted average of each household's workers' annual standard-deviation of the total permanent and temporary income shocks over 4 quarters, $\bar{\sigma}_{i,t} = \sum_k \frac{P_{i,k,t}}{P_{i,t-a_i}} \sqrt{4\sigma^2_\eta(t, x_{k,i}) + \sigma^2_\zeta(t, x_{k,i})}$.

Chile has a fluid labor market, with substantial job creation ($\bar{\lambda}^{UE}_{i,t}$) and destruction ($\bar{\lambda}^{EU}_{i,t}$). In the list of 14 OECD countries studied by Elsby, Hobijn and Sahin (2013), only the United States had higher inflow and outflow rates from unemployment than Chile. Annual wage volatility ($\bar{\sigma}_{i,t}$) of Chilean workers is around 14% to 17% (Madeira, 2015), which is comparable to values estimated for the United States (Low, Meghir and Pistaferri (2010) estimated a permanent income volatility of 10% plus a temporary income volatility of 9%). These estimates show that Chilean workers face substantial labor earnings risk from year to year even if they are not experiencing unemployment. Estimates of income volatility for other countries are around 30% to 32% for the United States, 27% to 34% for Germany, and 22% for Spain (Krueger, Perri, Pistaferri and Violante, 2010).

Bank customers are the group of highest income, while those with Retail Store loans only or No Access to Debt have the lowest mean income. Unemployment represents a strong income reduction for Chilean households, since the median worker keeps only 23% to 27% of its income during an unemployment spell. Households with No wish for Consumer Debt are the group least susceptible to shocks, since they have the lowest unemployment rate, separation rate and wage volatility, whether we compare the percentiles 25, 50 or 75. In theory agents should use debt to smooth temporary income shocks (see Chatterjee et al., 2007, or Dynan and Kohn, 2007), therefore it makes sense that households with the lowest income risk have the lowest demand for consumer loans.

5 Simulation results and the covariance risk of consumer debt

5.1 Baseline simulations and comparison with historical delinquency rates

To test the accuracy of the model I implement a backward historical simulation for the period 1990-2012 using the aggregate real interest rates i_t and all the labor market shocks, $\{G, \lambda^{EU}, \lambda^{UE}, \sigma_\eta, \sigma_\zeta \mid t, x_{k,i}\}$, for each type of worker from 1990 to 2012. As explained in Section 3, this vector of labor market shocks includes mean income growth (G), the probability of entering unemployment (λ^{EU}), the

Table 4: Percentiles 25, 50 and 75 of labor market risk and household earnings across debtors (EFH)

Debtor Type	$\bar{u}_{i,t}$	$\bar{\lambda}^{EU}_{i,t}$	$\bar{\lambda}^{UE}_{i,t}$	$\ln(Y_{i,t})$	$\bar{\sigma}_{i,t}$	$\bar{R}_{i,t}$
			Percentile 25			
Bank	1.9%	0.8%	22.0%	12.94	12.2%	20.4%
Bank + Retail Store	2.1%	0.9%	25.1%	12.94	11.9%	18.2%
Retail Store	2.6%	1.0%	25.7%	12.56	10.3%	13.2%
Other Consumer Loans	2.3%	0.8%	22.8%	12.75	11.0%	15.9%
No wish for consumer debt	1.8%	0.7%	20.5%	12.57	7.3%	13.1%
No Access to Debt	2.4%	0.8%	21.6%	12.25	7.8%	6.7%
			Percentile 50			
Bank	3.4%	1.3%	33.1%	13.50	17.5%	27.1%
Bank + Retail Store	4.0%	1.6%	35.1%	13.39	17.1%	27.6%
Retail Store	4.5%	1.9%	36.8%	12.98	15.6%	25.1%
Other Consumer Loans	4.0%	1.6%	32.5%	13.32	16.5%	26.4%
No wish for consumer debt	3.3%	1.3%	32.3%	13.08	14.5%	25.4%
No Access to Debt	4.3%	1.6%	33.0%	12.73	15.1%	23.6%
			Percentile 75			
Bank	6.0%	2.7%	43.9%	14.12	22.6%	33.3%
Bank + Retail Store	6.9%	3.1%	45.0%	13.91	22.4%	33.8%
Retail Store	7.5%	3.4%	48.4%	13.43	20.7%	33.7%
Other Consumer Loans	6.5%	3.0%	42.5%	13.77	21.8%	33.1%
No wish for consumer debt	5.8%	2.5%	44.1%	13.61	20.5%	33.2%
No Access to Debt	6.8%	3.1%	44.6%	13.24	22.0%	33.5%

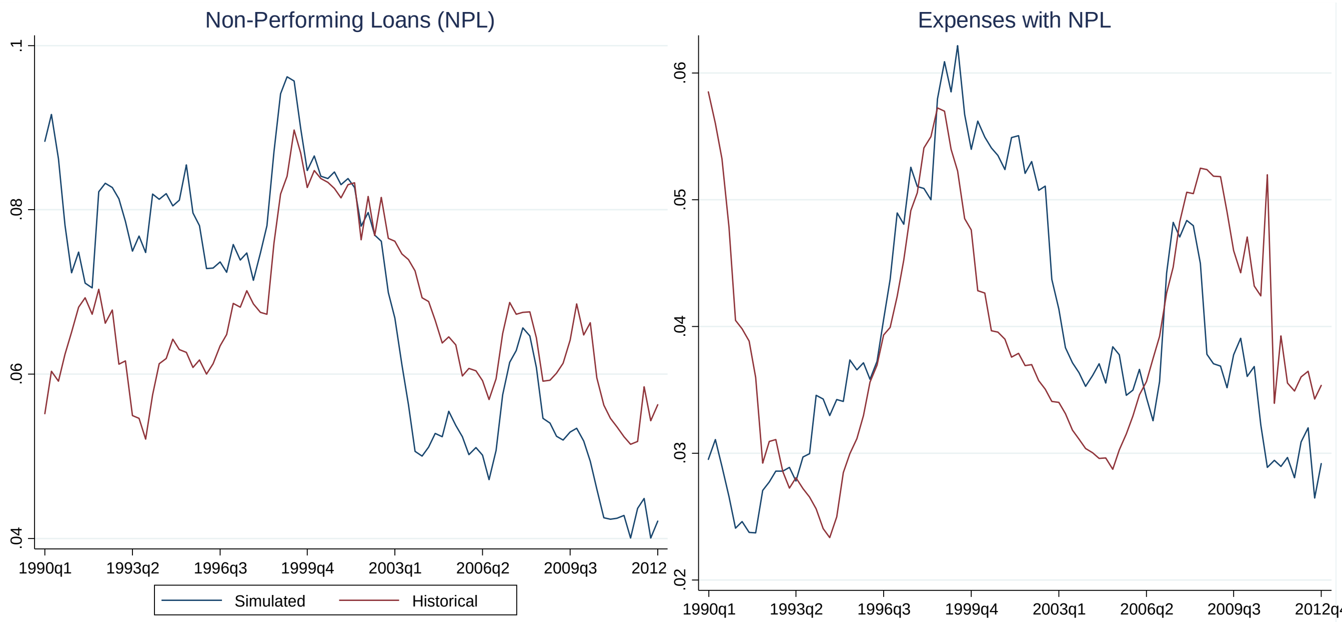
probability of finding a job (λ^{UE}), plus shocks to permanent income volatility (σ_η) and temporary income volatility (σ_ζ). These labor market parameters are estimated from quarterly survey data on labor income and unemployment over the last 23 years (see Madeira, 2015). These are aggregate labor shocks, although the unemployment rate and income growth differ for each one of the 500 types of workers. These shocks then translate into household idiosyncratic shocks, since each worker in the household has an idiosyncratic unemployment transition shock ($U_{k,i,t+s}$), which is Bernoulli-distributed as 1 or 0 with a probability λ^{EU} if the worker is employed and $1-\lambda^{UE}$ if unemployed, plus a continuous idiosyncratic realization for the permanent ($\eta_{k,i,t+s}$) and temporary income realization ($\zeta_{k,i,t+s}$) which are log-normally distributed.

In each period t the initial endowments for each family i are adjusted to reflect the mean income, financial assets, loan amount and debt service values in the past relative to the years of the EFH survey t^*[3]. Also, the expansion factors account for demographic changes in Chile over time: $\tilde{f}_i(t,S) = f_i \frac{n_{t,S}}{n_{t^*,S}}$, with $n_{t,S}$ denoting the number of households in strata S (given by the age and education of the household head) at time t estimated from the Employment Survey (ENE).

The main official statistics from the Central Bank of Chile related to consumer default are the delinquency rate, also known as Non-Performing-Loan Rate or NPL (the ratio of the value of consumer loans classified as non-performing over total consumer loans), and the Expenses with Non-Performing Loans Rate or ENPL (the ratio of total expenses with non-performing loans over total loans). Expenses with losses and provisions includes loans renegotiated at a loss for the lender and therefore provide information not entirely covered in the NPL rate. Figure 2 shows that the backward simulations of NPL and ENPL for the consumer loan portfolio of the Chilean banking system are roughly similar to their actual historical values. Obviously, the model does not explain the past history perfectly, but it does replicate the highs and lows of actual default risk. The historical and simulated NPL rates have a correlation of 56.9%, while the historical and simulated

[3] Initial debt endowments in period t for each EFH family (with information from time t^*) are adjusted for mean debt growth per consumer, $D_{i,t} = D_{i,t^*}\frac{MCD_t}{MCD_{t^*}}$, where MCD_t is the Mean Consumption Debt per Debtor at time t. Household i's debt service at period t is given $DS_{i,t} = \frac{MCD_t}{MCD_{t^*}} \sum_d DS_{d,i,t^*} \frac{C_{t,m(d),M(d)}}{C_{t^*,m(d),M(d)}}$, 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 loan payment, with i_{t-m} being the average interest rate for consumer loans in period $t-m$. Quarterly series for MCD_t and i_{t-m} are from the Central Bank of Chile. Households' initial endowments of financial assets $A_{i,t}$, non-labor income $a_{i,t}$, worker's wages $Y_{i,k,t}$ are all adjusted proportionally to labor income growth, $\frac{E[Y_{i,k,t}|t,x_{k,i}]}{E[Y_{i,k,t^*}|t^*,x_{k,i}]}$.

Figure 2: Historical Non-Performing Loans rate and Expenses with NPL versus the Simulated values (log deviations from the mean)



ENPL rates have a correlation of 39.7%. These correlations appear to be high enough to take the model's counterfactual as a serious signal of risk in the banking system.

It is important to note that the model calibration as explained in Sections 2 and 3 does not target any moments of the NPL and ENPL rates. The model is calibrated to match (see Table 1 for a summary): i) the cross-sectional distribution of household income, loans and assets for the period between 2007 to 2011; ii) the real interest rate observed in each period plus the unemployment rates and income volatility shocks received by different types of workers over each quarter of the period 1990 to 2012. Figure 2 therefore shows that the model can explain well the historical NPL and ENPL rates, although these variables are not targeted in its calibration. Table 5 summarizes the NPL and ENPL moments in both the historical data and the simulated model, which confirms that the model is able to replicate well the moments of these non-targeted variables, with the exception that the NPL simulations have a slightly higher standard-deviation than the data.

Table 5: Model's fit of the historical series of Banking delinquency

Moments of NPL and ENPL	Data (%)	Model (%)
$E\left[NPL_t\right]$	6.7	6.8
Standard-deviation $[NPL_t]$	0.9	1.6
$\min-\max\ [NPL_t]$	5.2−9.0	4.0−9.6
$E\left[ENPL_t\right]$	3.8	3.9
Standard-deviation $[ENPL_t]$	0.9	1.0
$\min-\max\ [ENPL_t]$	2.3−5.9	2.4−6.2
$Corr(NPL_t, ENPL_t)$	22.2	43.8
NPL: $Corr(Data, Model)$		55.5
ENPL: $Corr(Data, Model)$		43.6

5.2 Covariance risk of the consumer loans of the Chilean banking system

Now I take the loan amounts and debt service as they are currently reported in the EFH survey, therefore I no longer do the adjustments to the historical aggregates of past debt. I merely simulate the default risk in the Chilean banking consumer loan portfolio in 2010 and 2011 (the last two years of the survey data) if the past values of the aggregate real interest rates of Chilean bank funds (i_t) and labor market shocks, $\left\{G, \lambda^{EU}, \lambda^{UE}, \sigma_\eta, \sigma_\zeta \mid t, x_{k,i}\right\}$, for each type of worker happened now.

To evaluate the overall risk of consumer loan portfolios I must compute their covariance risk relative to the overall Chilean financial assets. An usual problem of the CAPM is that there is not a single measure of the entire market portfolio of the agents, therefore I apply three different measures of market returns: i) the overall real return on assets of the Chilean banking system (ROA_t), which corresponds to a broad measure of both tradeable (bonds, stocks) and non-tradeable (loans) asset returns; ii) the real returns of the IPSA stock index, which is the most standard stock index in Chile; and iii) the implicit returns deduced from the aggregate quarterly real consumption pricing kernel (Cochrane, 2005), $m_t(\rho) = -\delta(\frac{c_t}{c_{t+1}})^\rho$, with the discount factor $\delta = 0.99$ coefficient of risk aversion ρ being parametrized from 0.5 to 2 which are the most standard values in the macro literature. Real rates are obtained by deducing the CPI inflation at time t from the nominal returns.

In the CAPM literature the expected return of asset j should be $E\left[R_j\right] = r_f + \beta_j(E\left[R_{MP}\right] - r_f)$, with MP being the market portfolio and $\beta_j = \frac{Cov(R_{MP}, R_j)}{Var(R_{MP})}$ (Cochrane, 2005). According

Table 6: Betas of the overall banking consumer loan portfolio relative to banking return on assets (ROA), consumption-factors ($m(\rho)$) and the real return of the Chilean stock market (IPSA)

	ROA	**IPSA**	$m(.5)$	$m(1)$	$m(1.5)$	$m(2)$
Beta NPL_t	-0.526	-1.804	-2.510	-1.216	-0.784	-0.568
Beta $ENPL_t$	-0.503	-1.023	-2.302	-1.129	-0.736	-0.539
Beta $\Delta(1 - NPL_t)$	0.376	1.361	1.826	0.944	0.650	0.504
Beta $\Delta(1 - ENPL_t)$	0.227	0.685	1.675	0.876	0.611	0.479
Beta $IPSA_t$ (real)	0.098	1	1.330	0.674	0.456	0.347

to the consumption asset pricing literature, the expected return of asset j should be $E[R_j] = \frac{1}{E[m(\rho)]}(\frac{Var(m(\rho))}{E[m(\rho)]})\beta_{j,m}$, where $\beta_{j,m} = \frac{Cov(m(\rho),R_j)}{Var(m(\rho))}$. While neither the CAPM or the consumption asset pricing kernel are necessarily complete descriptions of the real world, these betas provide a starting point to evaluate the risk of an asset such as a portfolio of consumption loans.

The payment of a loan portfolio p is given by the probability of repayment, $1 - Df_{p,t}$, therefore the default rates $Df_{p,t}$ are negatively correlated with the return of loans. Consider a consumer who has borrowed 1 unit and promised to repay it at a future date, therefore the market price of the loan on date t is approximated by $1 - Df_{p,t}$. Then $r_{p,t}$ the return on the loan portfolio p at date t is approximated by the change in the probability of repayment or the negative change in the default rate: $r_{p,t} = \Delta(1 - Df_{p,t}) = \Delta(-Df_{p,t}) = -\Delta(Df_{p,t}) = -(Df_{p,t} - Df_{p,t-1})$, with $\Delta(x_t) = x_t - x_{t-1}$ being the time series first difference operator. Now for each loan portfolio p (whether of a single Chilean bank j or of the whole banking system) I ran the following regressions:

8.1) $r_{p,t} = \Delta(1 - Df_{p,t}) = \alpha_p + \beta_p r_{MP,t} + \varepsilon_{i,t}$,

8.2) $Df_{p,t} = \tilde{\alpha}_p + \tilde{\beta}_p r_{MP,t} + v_{i,t}$,

with $r_{MP,t} \in \left\{ROA_t, \ln(\frac{IPSA_t}{IPSA_{t-1}}), m_t(.5), m_t(1), m_t(1.5), m_t(2)\right\}$ and the $Df_{p,t} \in \{NPL_{p,t}, ENPL_{p,t}\}$ being respectively a measure of the market return and the portfolio default rate. Since presumably lenders charged a risk-adjusted premium at the beginning of the loan, then portfolios should only be affected by surprise changes to the default or repayment rates, $r_{p,t} = \Delta(1 - Df_{p,t})$. Therefore $\tilde{\beta}_p$ is just a useful a measure of how cyclical default rates are and not a loan portfolio risk premium. Since default rates are expected to be countercyclical, then $\tilde{\beta}_p$ should be negative.

Table 6 shows the results of the Beta estimates of the overall Chilean banking system's consumer loan portfolio. The negative values of the Beta for the default rates show that both the NPL_t and

$ENPL_t$ are countercyclical, therefore default rates increase in times of negative market returns. In the same way the Beta for the actual loan portfolio returns (or negative change in default rates) is positive relative to all measures of market returns, therefore consumer loan portfolios are an asset with a significant amount of covariance risk. I also compute the betas for the Chilean stock returns relative to ROA_t and $m_t(\rho)$ as a comparison. The results show that the Chilean banking consumer loan portfolio has a higher covariance risk than Chilean stocks for all measures of market returns, with the exception of the Beta of $\Delta(1 - ENPL_t)$ measured by the IPSA return.

5.3 The Loan Portfolios of Chilean banks

Now I repeat the same risk simulation exercise for each single Chilean bank's loan portfolio. The EFH surveys of 2010 and 2011 also elicited the name of the specific institution granting the loan, therefore it is possible to calculate the loan portfolio of each bank in terms of each type of household. I report the statistics of each financial institution by grouping banks into 3 types - Large Banks, Mid-sized Banks and Retail Banks - and applying a randomized number to each bank. The Retail Banks include only 3 institutions: Falabella, Paris and Ripley, which belong to holding institutions that own both a bank and a retail store. The Large Banks category include 4 institutions: Banco de Chile, Banco Estado, BCI and Banco Santander. The Large Banks category correspond to 67.8% of all the banking consumer loans in 2012, with the smallest Large bank having a market share of 9%. The Mid-sized Banks category also includes 4 institutions: BBVA, Corpbanca, Itau and Scotiabank. The largest of the Mid-sized banks only has 4.1% of the total banking consumer loans, which is less than half of the smallest of the Large banks. All together these 11 institutions correspond to more than 99% of the banking consumer credit market in Chile.

Table 7 shows the number of household observations, the number of household debtors for each bank, the mean debt amount and the share of the bank's loan portfolio in each quintile of household income (with Q1 and Q5 representing respectively the lowest and highest income levels). To check the reliability of the EFH data, I compared the number of household debtors and the mean debt value of each bank with the official statistics of the number of consumer loans and average loan per bank from the Chilean Authority of Banks and Financial Institutions (SBIF) in 2012. The comparison yielded a correlation coefficient of 82.6% for the number of household debtors in

Table 7: Number of observations and distribution of loan amounts by household income quintile (EFH)

Bank	Observations	Nr of household debtors	Mean Debt*	Q1	Q2	Q3	Q4	Q5
Large 1	467	31,916	86	4.2%	6.5%	13.3%	15.1%	60.9%
Large 2	298	22,837	68	3.9%	9.2%	18.1%	25.8%	43.0%
Large 3	148	10,215	88	3.1%	1.6%	11.4%	15.4%	68.5%
Large 4	380	29,153	78	3.0%	6.8%	11.0%	21.2%	57.9%
Mid-size 1	71	4,667	72	5.8%	7.4%	6.5%	29.5%	50.8%
Mid-size 2	48	3,226	132	11.4%	4.8%	19.8%	18.1%	45.9%
Mid-size 3	42	2,017	169			0.2%	15.1%	84.6%
Mid-size 4	59	4,238	92	2.1%	2.5%	12.1%	36.5%	46.8%
Retail 1	125	9,892	77	0.7%	15.4%	20.1%	23.3%	40.5%
Retail 2	26	2,051	104	0.2%	1.7%	15.7%	53.5%	29.0%
Retail 3	19	1,977	74	0.6%	15.2%	26.1%	21.8%	36.3%

* Mean value of the banking debt of the entire household is measured in UF. UF is a real monetary unit in Chile adjusted for inflation and has a value around 45 USD.

the EFH and the number of loans for each bank in the official data. Also, there is a correlation coefficient of 52.1% between the mean value of the consumer debt of each bank in the EFH data versus the average loan of the banks in the official data.

Table 8 summarizes the characteristics of the household customers of each Chilean bank, in terms of the monthly consumption expenses, unemployment rates (percentile 75 denotes the groups with highest risk of unemployment within a Banks' customer sample), permanent income, debt to annual permanent income ratio ($\frac{D_{i,t}}{12\times P_{i,t}}$) and debt service to monthly income ratio ($\frac{DS_{i,t}}{Y_{i,t}}$). $\frac{D_{i,t}}{12\times P_{i,t}}$ can be understood as a measure of household solvency, while $\frac{DS_{i,t}}{Y_{i,t}}$ measures households' liquidity risk due to high immediate payments. Mid-size Bank 3 is by far the bank with the highest income clients and also the one with the highest consumption expenses (as given by the mean statistics for similar households in the EPF, see the previous calibration section for details). Large Bank 2 and the Retail Banks have the lowest income customers and the ones with lowest consumption expenses. However, in terms of the debt levels relative to annual income, the more indebted households are clients of Retail Bank 3, plus Mid-size Banks 2 and 4. In fact the percentile 25 of the debt to income ratio in Mid-size Banks 2 and 4, that is their least indebted clients, are as indebted as the median family in other banks, which are the banks with the least indebted clients (in terms

Table 8: Households by Bank. Mean household expenses (thousands of pesos). Percentiles (25, 50, 75) of household permanent income P (thousands of pesos), debt to annual permanent income and debt service to monthly income. Percentile 75 of household unemployment risk u (2012-Q4 rates).

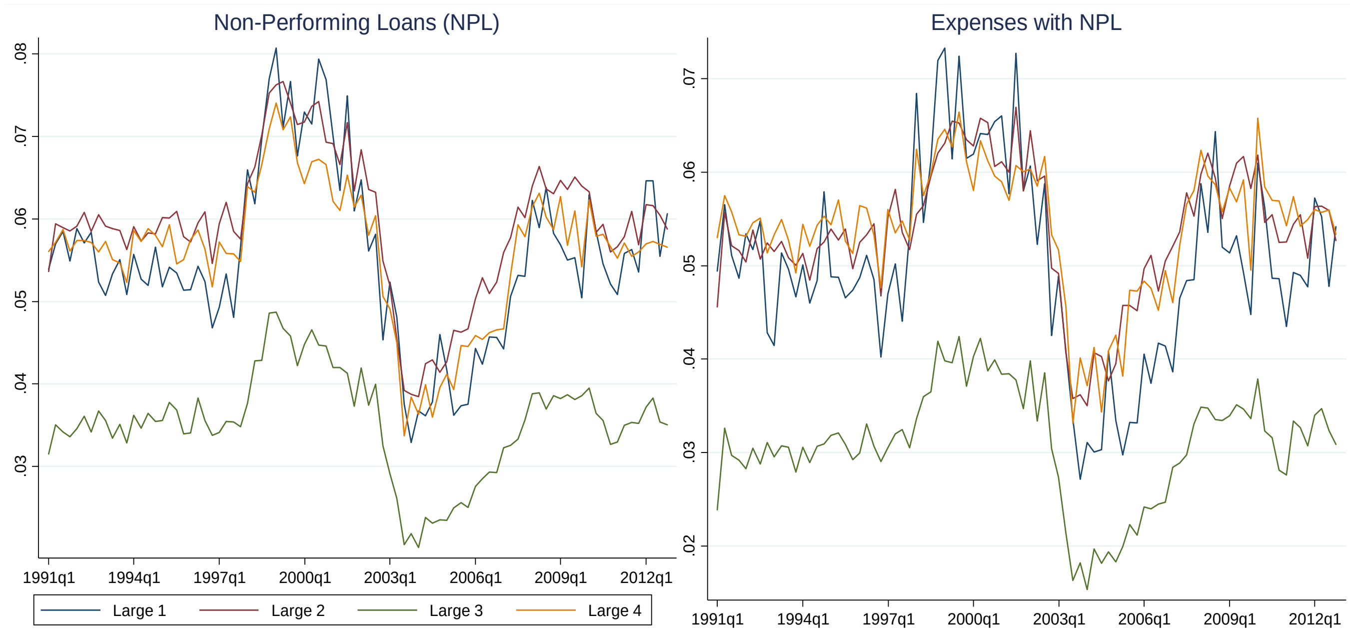
Bank	Expenses	u(p75)	P(p25)	P(p50)	P(p75)	$\frac{D}{12P}$(p25)	$\frac{D}{12P}$(p50)	$\frac{D}{12P}$(p75)	$\frac{DS}{Y}$(p25)	$\frac{DS}{Y}$(p50)	$\frac{DS}{Y}$(p75)
Large 1	1075	0.060	690	1144	2000	0.023	0.070	0.141	0.056	0.111	0.207
Large 2	858	0.066	594	920	1388	0.025	0.071	0.164	0.064	0.122	0.230
Large 3	1020	0.048	766	1098	1967	0.043	0.096	0.164	0.077	0.122	0.213
Large 4	993	0.065	656	1062	1737	0.024	0.072	0.153	0.067	0.115	0.238
Mid-size 1	1046	0.055	580	1225	1731	0.018	0.056	0.124	0.060	0.116	0.194
Mid-size 2	902	0.055	645	1052	1406	0.060	0.100	0.314	0.113	0.230	0.607
Mid-size 3	1570	0.041	1509	2415	3564	0.026	0.057	0.125	0.042	0.079	0.168
Mid-size 4	1004	0.063	832	1144	1908	0.052	0.100	0.187	0.082	0.119	0.221
Retail 1	822	0.083	651	958	1482	0.017	0.057	0.137	0.060	0.111	0.234
Retail 2	938	0.041	722	1100	1371	0.047	0.080	0.159	0.073	0.138	0.167
Retail 3	912	0.043	670	1008	1284	0.083	0.155	0.208	0.090	0.138	0.243

of the percentiles 25, 50 and 75, at least). In terms of the debt service to income ratio, Mid-size Bank 2 has the most indebted clients. However, it is possible that higher debt amounts are given to the households with the safest jobs. The unemployment rate for households (weighted by the permanent income of their members) indicates that Retail Bank 1, Large Banks 2 and 4, plus Mid-size Bank 4 cater to households with the least safe jobs.

5.4 Default simulations of the individual Chilean banks

This section shows the actual simulated NPL and ENPL rates for the Chilean banks under the assumption that the aggregate real interest rate (i_t) and heterogeneous labor market shocks $\{G, \lambda^{EU}, \lambda^{UE}, \sigma_\eta, \sigma_\zeta \mid t,$ observed in the past would happen to their current portfolios as measured by the EFH 2010-2011. Note that this simulation is not about what happened to the past portfolios of each bank, but rather what how the default rate of each bank's current portfolio would change if the the interest rate and labor market shocks of the past 23 years would happen now. Results are shown separately for the four largest banks (Figure 3), the three retail banks (Figure 4) and the mid-sized banks (Figure 5). The Large Banks have very similar risk profiles for all the 92 scenarios in the simulation,

Figure 3: Simulations of Non-performing loans and Expenses with NPL for the four largest banks



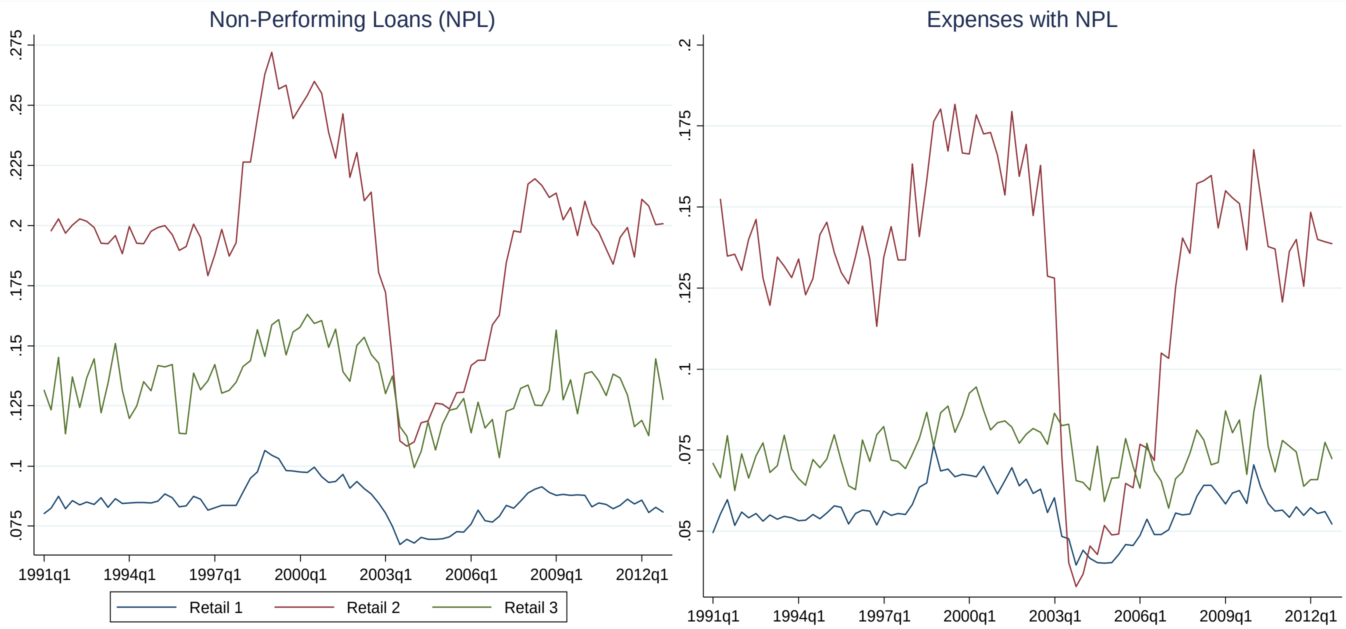
except for Large Bank 3 which is less risky than its competitors. All the large banks would suffer substantially if a similar economic crisis as the one experienced in 1998 would repeat itself again.

In terms of the retail banks I find that all three banks have portfolios with higher default rates than the largest Chilean banks. Retail Bank 1 is the retail bank with the lowest default rates, while Retail 2 shows a high default rate all over the business cycle.

Among the mid-sized Chilean banks, Mid-size Bank 3 is the one with the lowest default rates. It is noticeable that Mid-size Bank 1 has both a high average default rate and one that increases substantially during negative times. Both Mid-size Banks 1 and 2 appear to be highly susceptible to events such as a repeating of the 1998 to 2001 crisis.

Table 9 now repeats the regressions of 8.1) and 8.2), using as a benchmark the Chilean banking system's aggregate default rate ($Df_{p,t}$) and loan portfolio return ($r_{p,t} = \Delta(1 - Df_{p,t})$). Therefore this Beta measures how much more covariance risk has the portfolio of an individual bank relative to the whole banking system. Retail Bank 2, plus Mid-size Banks 1 and 2 have the highest covariance risk and are the ones more susceptible to shocks affecting household default. Retail Bank 3 has a high expected default rate, but its covariance risk is not higher than the other banks.

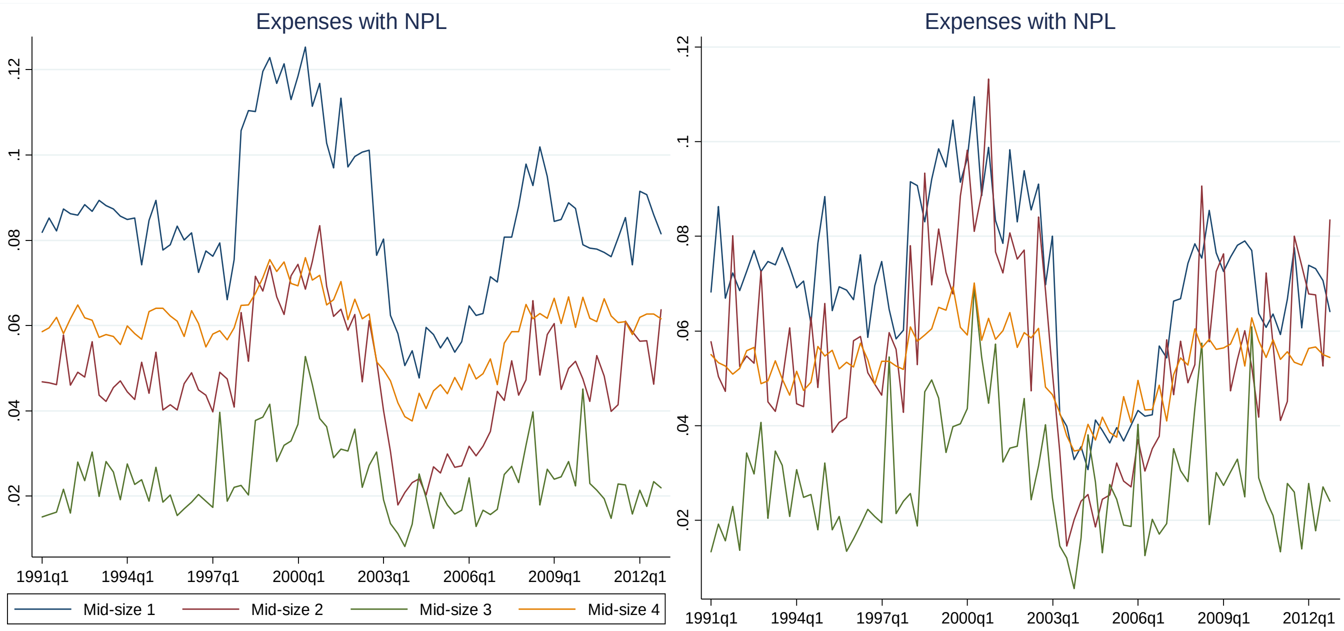
Figure 4: Simulations of Non-performing loans and Expenses with NPL for the three Retail banks



6 Heterogeneity of covariance risk and its impact on loan amounts

Finally, I report how heterogeneous different households are in terms of their simulated risk, in particular how it changes by income and age of the household head. Table 10 shows a clear pattern in terms of the Beta for the portfolio returns (i.e., the change in default rates, $\Delta(-NPL_t)$ and $\Delta(-ENPL_t)$). Within each quintile, Table 10 always shows that the covariance risk decreases with age, being highest for younger households (≤ 35) and lowest for the older ones (≥ 55). The only exception for this rule is the highest income quintile (i.e., the richest households), since for this high income group covariance risk is low for all age brackets. Also, for the oldest households (≥ 55) there is a declining pattern of covariance risk in terms of income, since the beta of $\Delta(-NPL_t)$ and $\Delta(-ENPL_t)$) declines quickly after quintile 1 and is very low for the high income quintiles (4 and 5). In particular, the oldest group (≥ 55) does not show a covariance risk much higher than one for any income quintile, implying that its returns are not more volatile than average. For the youngest households (≤ 35) there is a high beta from quintiles 1 to 3, reaching values as high as 2 (implying an asset with returns twice as volatile as the mean consumption loan). The middle-aged $(35-54)$ also have a high covariance risk for the income quintiles 1 and 2, with some return betas

Figure 5: Simulations of Non-performing loans and Expenses with NPL for the mid-sized banks



higher than 1.5. In terms of their average default probabilities (NPL_t and $ENPL_t$), it is clear that the highest income group (quintile 5) has the lowest rate of default. Also, quintile 1 and 2 have a higher default probability than the middle class and higher income groups (quintiles 3, 4, 5), implying that they have both a high covariance risk and a high default probability.

It is well known that lenders take into account a consumer's expected probability of default in determining the amount of credit they provide. The open question is whether consumers with greater covariance risk obtain less credit, even controlling for their mean default risk and other factors. I study this hypothesis by estimating the impact of 4 different measures of covariance risk of the household: i) the first two measures correspond to the beta between household i's simulated default probability and the default probability of the banking system (NPL_t and $ENPL_t$); ii) the third and fourth measures correspond to the beta between the household i's simulated quarterly innovations to default probability and the overall changes to the default probability of the banking system ($\Delta(-NPL_t)$ and $\Delta(-ENPL_t)$). Table 11 shows the result of linear regressions of the log amount of consumer credit of each household i in the EFH survey and a measure of the covariance beta risk of the household plus its default risk. For each of the four measures of covariance beta risk I report two regressions, one with just the beta and default risk of the household as controls,

Table 9: Betas of each bank's loan portfolio relative to the overall consumer loan portfolio

Bank	B: NPL_t	B: $ENPL_t$	B: $\Delta(-NPL_t)$	B: $\Delta(-ENPL_t)$	$E[NPL_t]$	$E[ENPL_t]$
Large 1	0.824	0.728	1.317	1.058	0.056	0.048
Large 2	0.828	0.727	0.708	0.676	0.061	0.055
Large 3	0.583	0.611	0.430	0.401	0.037	0.032
Large 4	0.773	0.652	0.754	0.736	0.057	0.054
Mid-size 1	1.630	1.649	1.878	1.230	0.085	0.070
Mid-size 2	1.248	1.779	1.137	1.978	0.048	0.055
Mid-size 3	0.411	0.514	0.617	0.731	0.026	0.033
Mid-size 4	0.760	0.705	0.870	0.748	0.060	0.052
Retail 1	0.759	0.730	0.590	0.617	0.087	0.059
Retail 2	2.981	4.218	2.183	3.098	0.261	0.325
Retail 3	0.821	0.328	0.870	0.833	0.138	0.079
All Banks	1	1	1	1	0.063	0.057

Table 10: Betas of each household type's loans relative to the overall consumer loan portfolio

Income Quintile	Age of Head	B: NPL_t	B: $ENPL_t$	B: $\Delta(-NPL_t)$	B: $\Delta(-ENPL_t)$	$E[NPL_t]$	$E[ENPL_t]$
1	≤ 35	1.462	2.228	2.012	1.900	0.144	0.098
1	$35-54$	1.166	0.901	1.581	1.332	0.168	0.125
1	≥ 55	1.139	0.796	1.004	1.060	0.249	0.112
2	≤ 35	1.143	1.361	1.860	2.187	0.114	0.095
2	$35-54$	2.168	1.899	1.704	1.184	0.198	0.179
2	≥ 55	1.092	-0.089	0.696	0.616	0.285	0.220
3	≤ 35	0.735	0.827	1.367	2.014	0.094	0.058
3	$35-54$	0.883	1.146	0.741	0.903	0.083	0.084
3	≥ 55	0.818	1.122	0.561	0.813	0.108	0.074
4	≤ 35	1.070	1.322	1.405	1.181	0.105	0.108
4	$35-54$	1.835	1.938	1.112	1.251	0.093	0.109
4	≥ 55	0.393	0.053	0.273	0.048	0.097	0.074
5	≤ 35	0.332	0.333	0.237	0.125	0.040	0.023
5	$35-54$	0.540	0.856	0.286	0.245	0.035	0.040
5	≥ 55	0.224	0.306	0.160	0.140	0.012	0.010

and a second one which also controls for the log income of the household plus age and education dummies of the household head. All the regressions confirm that the amount of consumer credit of each household declines with the covariance beta of the household. After adding further controls such as income, age and education, the coefficient for the covariance beta falls in absolute value, but it remains statistically significant. For the regressions with controls, the estimated coefficient varies between -0.075 and -0.190. This implies that a household with a covariance beta equal to the average of the banking system (i.e., households with a beta equal to 1) has a credit amount that is 7.5% to 19.0% lower than a similar household with zero covariance risk.

Since the analysis of Table 11 is limited to households with a positive credit amounts, I also report the impact of the household's covariance beta on the probability of having a consumer loan (Table 12). The Probit coefficients show that the probability of having a consumer loan declines with the covariance beta of the borrower. Even after taking into account other controls such as income, education and age, the negative impact of covariance beta on having a consumer loan persists and is statistically significant at the 5% or 1% levels. Therefore consumers with high covariance risk are underrepresented in lenders' portfolios both in terms of loan amount and number of loans.

The results of Table 12 do not differentiate between the households who were refused credit by lenders and those who did not seek credit because they had no need for loans. To separate these alternatives, I use the EFH survey to create a measure of the households who are "Credit Constrained" or have "No Access to Debt" . "No Access to Debt" represents families with credit constraints, including those who applied for credit but were denied and the ones who did not apply for credit because they expected to be refused. Table 13 shows the Probit estimates of the impact of covariance beta risk on the probability of being credit constrained. The coefficients show that covariance risk has a positive and statistically significant impact on the probability of being credit constrained, even after taking into account other controls such as income, age and education. This analysis confirms that indeed households with higher covariance risk are more likely to be rejected by lenders and do not just keep themselves out of the credit market for other reasons.

Table 11: Linear regression (OLS) of the amount of consumer credit (in log) and the default-beta of the households

Variables / Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta NPL_t	-0.476***	-0.101*						
	(0.0412)	(0.0586)						
Beta $\Delta(-NPL_t)$			-0.464***	-0.190***				
			(0.0424)	(0.0663)				
Beta $ENPL_t$					-0.141***	-0.0753*		
					(0.0266)	(0.0389)		
Beta $\Delta(-ENPL_t)$							-0.323***	-0.133**
							(0.0428)	(0.0594)
$E[NPL_{i,t}]$	-19.81***	-7.123***	-15.76***	-6.558***				
	(1.136)	(1.438)	(1.159)	(1.373)				
$E[ENPL_{i,t}]$					-10.54***	-3.201***	-11.13***	-3.852***
					(0.475)	(0.582)	(0.729)	(0.793)
$\ln(P_{i,t})$		0.499***		0.457***		0.532***		0.482***
		(0.0474)		(0.0511)		(0.0300)		(0.0496)
Age 25-34		0.350***		0.344***		0.465***		0.350***
		(0.130)		(0.130)		(0.0940)		(0.131)
Age 35-44		0.177		0.0893		0.386***		0.177
		(0.129)		(0.130)		(0.0914)		(0.128)
Age 45-54		0.236*		0.145		0.414***		0.244*
		(0.129)		(0.129)		(0.0911)		(0.127)
Age >54		0.0938		-0.0415		0.160*		-0.0208
		(0.126)		(0.133)		(0.0961)		(0.135)
Technical education		0.233***		0.229***		0.253***		0.230***
		(0.0814)		(0.0810)		(0.0549)		(0.0817)
College education		0.347***		0.346***		0.336***		0.326***
		(0.0700)		(0.0701)		(0.0465)		(0.0702)
Constant	13.23***	6.267***	13.25***	6.993***	13.13***	5.707***	13.12***	6.592***
	(0.0534)	(0.650)	(0.0580)	(0.725)	(0.0388)	(0.415)	(0.0575)	(0.695)
Observations	7,571	7,571	7,571	7,571	7,571	7,571	7,571	7,571
R-squared	0.090	0.146	0.086	0.147	0.069	0.145	0.082	0.146

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistically significance.

Age and education dummies refer to the age of the household head.

Table 12: Probability of having a consumer credit (Probit) and the default-beta of the households

Variables / Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta NPL_t	-0.0324*	-0.0402**						
	(0.0167)	(0.0172)						
Beta $\Delta(-NPL_t)$			-0.0478***	-0.0551***				
			(0.0176)	(0.0180)				
Beta $ENPL_t$					-0.345***	-0.399***		
					(0.0129)	(0.0143)		
Beta $\Delta(-ENPL_t)$							-0.0419**	-0.0595***
							(0.0192)	(0.0201)
$E[NPL_{i,t}]$	-0.290**	0.0344	-0.283**	0.0280				
	(0.138)	(0.141)	(0.136)	(0.140)				
$E[ENPL_{i,t}]$					-0.960***	-0.957**	-0.0990*	-0.0196
					(0.302)	(0.394)	(0.0519)	(0.0521)
$\ln(P_{i,t})$		0.213***		0.205***		0.0475**		0.205***
		(0.0290)		(0.0288)		(0.0191)		(0.0276)
Age 25-34		0.359***		0.353***		0.165**		0.349***
		(0.101)		(0.100)		(0.0676)		(0.100)
Age 35-44		0.271***		0.253***		0.308***		0.240**
		(0.0961)		(0.0953)		(0.0650)		(0.0968)
Age 45-54		0.251***		0.234**		0.209***		0.225**
		(0.0953)		(0.0945)		(0.0644)		(0.0959)
Age >54		-0.155*		-0.170*		-0.258***		-0.189**
		(0.0929)		(0.0921)		(0.0634)		(0.0931)
Technical education		0.164***		0.183***		-0.0899**		0.175***
		(0.0620)		(0.0622)		(0.0415)		(0.0622)
College education		-0.121**		-0.0974**		-0.219***		-0.110**
		(0.0504)		(0.0496)		(0.0331)		(0.0494)
Constant	0.256***	-2.605***	0.254***	-2.489***	0.126***	-0.784***	0.254***	-2.477***
	(0.0235)	(0.386)	(0.0213)	(0.382)	(0.0246)	(0.275)	(0.0213)	(0.368)
Observations	12,268	12,265	12,268	12,265	12,268	12,265	12,268	12,265
Pseudo R-square	0.0019	0.0358	0.0030	0.0370	0.0009	0.0358	0.0019	0.0367

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistically significance.

Age and education dummies refer to the age of the household head.

Table 13: Probability of being Credit Constrained (Probit) and the default-beta of the households

Variables / Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta NPL_t	0.0692***	0.0477***						
	(0.0159)	(0.0177)						
Beta $\Delta(-NPL_t)$			0.0581***	0.0465***				
			(0.0158)	(0.0170)				
Beta $ENPL_t$					0.0433***	0.0260**		
					(0.0108)	(0.0116)		
Beta $\Delta(-ENPL_t)$							0.0734***	0.0341*
							(0.0175)	(0.0195)
$E[NPL_{i,t}]$	0.720***	0.164	0.778***	0.184				
	(0.139)	(0.139)	(0.137)	(0.138)				
$E[ENPL_{i,t}]$					0.149***	0.0779	0.159***	0.0851
					(0.0538)	(0.0546)	(0.0533)	(0.0544)
$\ln(P_{i,t})$		-0.281***		-0.284***		-0.295***		-0.293***
		(0.0254)		(0.0252)		(0.0240)		(0.0243)
Age 25-34		-0.196**		-0.193**		-0.195**		-0.192**
		(0.0869)		(0.0870)		(0.0869)		(0.0869)
Age 35-44		-0.179**		-0.173**		-0.182**		-0.178**
		(0.0830)		(0.0830)		(0.0838)		(0.0840)
Age 45-54		-0.173**		-0.165**		-0.175**		-0.172**
		(0.0823)		(0.0823)		(0.0831)		(0.0833)
Age >54		-0.0724		-0.0647		-0.0710		-0.0678
		(0.0791)		(0.0792)		(0.0798)		(0.0803)
Technical education		-0.169***		-0.172***		-0.155***		-0.164***
		(0.0588)		(0.0589)		(0.0588)		(0.0588)
College education		-0.223***		-0.222***		-0.204***		-0.210***
		(0.0495)		(0.0494)		(0.0487)		(0.0490)
Constant	-1.249***	2.695***	-1.225***	2.732***	-1.274***	2.883***	-1.265***	2.858***
	(0.0212)	(0.335)	(0.0191)	(0.331)	(0.0200)	(0.317)	(0.0188)	(0.323)
Observations	12,268	12,265	12,268	12,265	12,268	12,265	12,268	12,265
Pseudo R-square	0.0075	0.0531	0.0068	0.0531	0.0033	0.0529	0.0034	0.0526

Robust Standard-errors in (), ***,**,* denote 1%, 5% and 10% statistically significance.

Age and education dummies refer to the age of the household head.

7 Conclusions

This paper takes a portfolio view of consumer credit, using a structural model of households' budget constraints and a behavioral default decision rule. Using this model to evaluate the risk of Chilean households, I find that consumer loan portfolios have a substantial covariance risk and are substantially more risky than stocks by several measures. Banks differ a lot in terms of their counterfactual risk of loan default, which depends on the age and income of their portfolio of clients. Some banks' portfolios appear safe during normal times, but are highly susceptible to negative shocks. The model predicts that most Chilean banks - except for two institutions - would suffer substantially if a similar economic crisis as the one in 1998 to 2001 would happen again. Financial institutions could reduce the default rate and covariance risk of their loan portfolio by choosing customers that suffer less unemployment risk and fewer shocks during economic downturns.

I also show that both the probability of getting a consumer credit and the amount of the consumer loan decline with the covariance risk of the household, which is evidence that lenders treat such consumers as having higher risk even after other factors are taken into account. Furthermore, the probability of a household reporting to be credit constrained (that is, a household who wanted a consumer loan, but was rejected) increases with covariance risk. This result confirms that households with higher sensitivity to the business cycle are indeed more likely to be rejected by lenders' choice and not for reasons related to agents' demand factors for debt.

This article has strong implications for policy makers and financial institutions. It argues that regulators should care about measuring the systematic risk of consumer debt and not simply the default rates over the last few years. The reason is that low default rates can be explained by lucky economic shocks instead of better management or more cautious behavior from financial institutions. Therefore measuring the systematic risk component of the consumer debt portfolios can be a more accurate measurement of the risk each financial institution is undertaking when a strong negative shock happens. Another implication of the methodology exposed in this paper is that covariance risk is a better approach for the valuation of consumer loan portfolios. This can help financial institutions provide better information to markets on the risk-return trade-off of their loans and improve the process of securitization of consumer loans as a tradeable asset.

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