Simulating the covariance risk of consumer debt portfolios

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Abstract

Consumer loan risk is hard to predict, since loans are heterogeneous, have no measurable prices in financial markets and may be significantly correlated with macro events. 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.

JEL Classification: E21; E24; E32; E51; G01; G21.

Keywords: Credit supply; Consumer credit; Default risk; Business cycle fluctuations; Unemployment shocks.

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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 (Sharpe, 1964). Empirical research in equities finds support for the role of covariance measures of asset prices, such as the CAPM betas, as a discount factor for risky cashflows (see 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 common risk component. 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). The recent subprime financial crisis showed a significant macro 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).

The risk of household loans is harder to measure than for corporate default risk, since unlike corporate bonds these loans are not publicly traded and have no measurable price risk. 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. These counterfactual simulations can then be used for estimating the covariance risk of consumer loans relative to other assets. I show there is systematic heterogeneity across Chilean households in their covariance risk. This heterogeneity of covariance risk has strong practical implications, since some Chilean banks are shown to be 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 renters, youth, singles, low-income and residents of states with higher divorce rates 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 counterfactuals. 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" of different consumers in a real panel data sample, then his results are limited to the time period of his dataset and can be seriously affected by a lucky sequence of good shocks.[1] A short time period could give the impression that default risk changes little with the aggregate state, but such a result could be purely driven by 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, since it may show that default risk is less benevolent for certain aggregate states, such as scenarios similar to the Great

[1] Some observers interpret that the Great Moderation period observed in many developed economies or the recent 2000's decade in Latin America are examples of a long sequence of lucky shocks (De Gregorio, 2014).

Depression of 1929 or the Asian crisis of 1998. 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.

I then simulate this model using Chilean survey data. 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 since it suffered 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, 2014). I then simulate the actual unemployment rates and income shocks 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. Furthermore, in each of these 92 scenarios I apply the real risk-interest rates observed in the Chilean financial system, which is a measure of a specific shock to credit markets. 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.

This paper is organized as follows. Section 2 introduces the model's framework of households' 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 how the default risk of consumer loans changes across the portfolios of different Chilean banks. Finally, section 6 concludes with implications for policy and future research.

2 An empirical model of household default and consumption

Household risk is difficult to assess, since their major asset is given by future income which is hard to expropriate as collateral, creating asymmetric information between lenders and borrowers. Lenders react to the adverse selection of borrowers by capping loan size, interest rates and debt maturities (Jaffee and Stiglitz, 1990). 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. This calibration has a substantial degree of heterogeneity and is explained in more detail in the next section. 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, 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 (Gruber, 1997, 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. 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: Calibrated and 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, 2014, 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: $X_{v,t} = \{\zeta, D_t, P_t, Y_t, \Pr(U_t), DS_t\}$
$m_t = \{m_{1,t}, m_{2,t}\}$	$m_t = \{8, 4\}$ (EFH)
$dc_t = \{dc_{1,t}, dc_{2,t}\}$	$\{dc_1(P_t, Y_t, \zeta),\ dc_2(P_t, \zeta)\}$
Maximum Legal Interest Rate	$i_{v,t} \leq 1.50 \times E\left[i_{2,t}\right]$
Banks' fundraising real interest rates, CF_t	Central Bank of Chile, 1990Q1-2012Q4

3 Calibration

3.1 The Chilean Household Finance Survey (EFH)

To measure the Chilean population I consider 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. Default represents a rare experience which requires a large sample to provide accuracy, therefore I use the EFH as a single pooled sample. Since the model implies random simulations, I sample household units with replacement to build a sample of 135,000 observations in order to reduce simulation error. This survey has 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 debts exhaustively, the surveys elicit the loan terms (debt service, loan amount, maturity) for each of the 4 main loans in each category of debt.

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, $\lambda^{EU}_{k,i,t} = \Pr(U_{k,i,t+1} = 1 \mid t, U_{k,i,t} = 0, x_{k,i})$ and $\lambda^{UE}_{k,i,t} = \Pr(U_{k,i,t+1} = 0 \mid t, U_{k,i,t} = 1, x_{k,i})$. 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 employment status, $R^{U_{k,i,t+1}-U_{k,i,t}}_{k,i,t-1}$, 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).

Based on the Chilean Employment Survey (ENE), which covers 35,000 households each quarter, Madeira (2014) estimated the vector of labor shocks, $\{G, \sigma_\eta, \sigma_\zeta, R\}$, 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) $L_{k,i,t+s} = \zeta_{k,i,t+s} R^{U_{k,i,t+s}-U_{k,i,t+s-1}}_{k,i,t+s-1}$,

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.

[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^*: $P_{k,i,t} = Y_{k,i,t^*} R^{-U_{k,i,t^*}}_{k,i,t^*}$.

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, $\sigma_\eta(t, x_{k,i})$):

6) $\ln(c_{i,t}) = g(z_i) + \beta\,[\ln(P_{i,t}), \bar{\sigma}_{i,t}] + \varepsilon_i$, 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 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. Around 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 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 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 $v = 1, 2$.

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

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

Type of Debtor	**Population**		**Loan amount (median)**		**Morosity 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%				

each debt the survey also asks whether the household has fallen into morosity or late payments in the last 12 months. The morosity 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' mean values of the unemployment rate ($\bar{u}_{i,t}$), separation rate ($\bar{\lambda}_{i,t}^{EU}$), job finding rate ($\bar{\lambda}_{i,t}^{UE}$), 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 averages of the values of all the members of the household, with income-weights in order to assign larger importance to members of higher 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, $\bar{\sigma}_{i,t} = \sum_k \frac{P_{i,k,t}}{P_{i,t}} \sqrt{4\sigma_\eta^2(t, x_{k,i}) + \sigma_\zeta^2(t, x_{k,i})}$.

Chile has a fluid labor market, with substantial job creation ($\bar{\lambda}_{i,t}^{UE}$) and destruction ($\bar{\lambda}_{i,t}^{EU}$). 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%, which are roughly comparable to similar values estimated for the United States (Low, Meghir and Pistaferri (2010) estimated a permanent income volatility of 0.10 plus a temporary income volatility of 0.09). 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).

Table 4: Mean values of labor market risk and household earnings across debtors (EFH)

Debtor Type	$\bar{u}_{i,t}$	$\bar{\lambda}^{EU}_{i,t}$	$\bar{\lambda}^{UE}_{i,t}$	$\ln(Y_{i,t})$	$\bar{\sigma}_{i,t}$	$\bar{R}_{i,t}$
Bank	4.6%	2.0%	33.8%	13.56	17.0%	25.9%
Bank + Retail Store	5.2%	2.2%	35.4%	13.44	16.8%	25.5%
Retail Store	5.7%	2.4%	36.6%	13.00	15.7%	23.4%
Other Consumer Loans	5.1%	2.2%	32.6%	13.19	16.3%	24.2%
No wish for consumer debt	4.5%	1.9%	30.6%	13.12	14.5%	23.2%
No Access to Debt	5.4%	2.2%	31.0%	12.73	15.5%	21.4%

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 mean worker keeps only 25% of its income during an unemployment spell. Households with No Consumer Debt are the group least susceptible to shocks, since they have the lowest unemployment rate, separation rate and wage volatility. The permanent income theory of consumption predicts that 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, $\{G, \sigma_\eta, \sigma_\zeta, R \mid t, x_{k,i}\}$, for each type of worker from 1990 to 2012. In each period t I adjust the initial endowments for each family i to reflect the fact that the mean income, financial assets, loan amount and debt service, was lower in the past in relation to the years of the EFH survey t^*[3]. Also, I adjust the expansion

[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

Figure 1: Historical Non-Performing Loans rate and Expenses with NPL versus the Simulated values (log deviations from the mean)

factors in order to 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 Chilean 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. Since the variables have different scales, I graph all variables in a log-scale, $\ln(\frac{x_t}{mean(x_t)})$, for an easier visual comparison.

Figure 1 shows that the backward simulations of NPL and EPNL 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

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, $\frac{E[Y_{i,k,t}|t,x_{k,i}]}{E[Y_{i,k,t^*}|t^*,x_{k,i}]}$.

actual default risk. The historical and simulated NPL rates have a correlation of 56.9%, while the historical and simulated ENPL rates have a correlation of 39.7%. These correlations appear to be high enough to take the model's counterfactuals as a serious signal of risk in the banking system.

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, $\{G, \sigma_\eta, \sigma_\zeta, R \mid t, x_{k,i}\}$, 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 $E[R_j] = r_f + \beta_j(E[R_{MP}] - r_f)$, with MP being the market porfolio and $\beta_j = \frac{Cov(R_{MP},R_j)}{Var(R_{MP})}$ (Cochrane, 2005). According 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

Table 5: 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

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 contracyclical, then $\tilde{\beta}_p$ should be negative.

Table 5 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 contracyclical, therefore default rates increase in times of negative market returns. In the same way the Beta for the actual loan portfolio returns (or enagtive 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.

Table 6: Number of consumer loans and average loan amount (SBIF, 2012). Number of observations and distribution of loan amounts by household income quintile (EFH)

Bank	Nr of loans	Mean Amount (UF*)	EFH Obs	Q1	Q2	Q3	Q4	Q5
Chile	343,750	144	467	4.2%	6.5%	13.3%	15.1%	60.9%
Estado	114,305	133	298	3.9%	9.2%	18.1%	25.8%	43.0%
Scotia	41,474	240	71	5.8%	7.4%	6.5%	29.5%	50.8%
BCI	215,087	152	148	3.1%	1.6%	11.4%	15.4%	68.5%
CorpBanca	45,215	169	48	11.4%	4.8%	19.8%	18.1%	45.9%
Itau	24,991	396	42			0.2%	15.1%	84.6%
Santander	187,273	254	380	3.0%	6.8%	11.0%	21.2%	57.9%
Falabella	127,322	104	125	0.7%	15.4%	20.1%	23.3%	40.5%
Ripley	68,429	72	26	0.2%	1.7%	15.7%	53.5%	29.0%
Paris	49,724	69	19	0.6%	15.2%	26.1%	21.8%	36.3%
BBVA	51,916	337	59	2.1%	2.5%	12.1%	36.5%	46.8%

UF is a real monetary unit in Chile adjusted for inflation and has a value around 45 USD.

5.3 The Loan Portfolios of Chilean banks

Now I repeat the same exercise that I did for the aggregate consumer banking system portfolio 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. Table 6 summarizes the number of consumer loans and average loan amount of each Chilean bank in 2012 as reported by the Chilean Authority of Banks and Financial Institutions (SBIF). I also report the number of observations in the EFH 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). In general, the largest banks in terms of loan contracts (Chile, BCI, Santander, Estado) also have the largest number of observations in the EFH data. Also, banks with the lowest loan amounts in the official SBIF statistics (Estado, and the three retail banks, Falabella, Ripley and Paris) are also the banks that have the lowest shares of richest clients (i.e., those of the household income quintile 5) in their portfolios. Therefore overall the official SBIF statistics validate the reliability of the EFH sample.

Table 7 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

Table 7: 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)
Chile	1075	0.060	690	1144	2000	0.023	0.070	0.141	0.056	0.111	0.207
Estado	858	0.066	594	920	1388	0.025	0.071	0.164	0.064	0.122	0.230
Scotia	1046	0.055	580	1225	1731	0.018	0.056	0.124	0.060	0.116	0.194
BCI	1020	0.048	766	1098	1967	0.043	0.096	0.164	0.077	0.122	0.213
CorpBanca	902	0.055	645	1052	1406	0.060	0.100	0.314	0.113	0.230	0.607
Itau	1570	0.041	1509	2415	3564	0.026	0.057	0.125	0.042	0.079	0.168
Santander	993	0.065	656	1062	1737	0.024	0.072	0.153	0.067	0.115	0.238
Falabella	822	0.083	651	958	1482	0.017	0.057	0.137	0.060	0.111	0.234
Ripley	938	0.041	722	1100	1371	0.047	0.080	0.159	0.073	0.138	0.167
Paris	912	0.043	670	1008	1284	0.083	0.155	0.208	0.090	0.138	0.243
BBVA	1004	0.063	832	1144	1908	0.052	0.100	0.187	0.082	0.119	0.221

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. Itau 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). Estado, Falabella, Ripley and Paris 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 Paris, CorpBanca, BBVA and BCI. In fact the percentile 25 of the debt to income ratio in Corpbanca and BBVA, that is their least indebted clients, are as indebted as the median family in other banks such as Scotia, Itau and Falabella, which are the banks with the least indebted clients (in terms of the percentiles 25, 50 and 75, at least). In terms of the debt service to income ratio, CorpBanca is again the bank with 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 Falabella, Estado, Santander and BBVA are the banks catering to households with the least safe jobs.

Figure 2: Simulations of Non-performing loans and Expenses with NPL for the four largest banks

5.4 Default simulations of the individual Chilean banks

5.4.1 Simulations for the four largest banks

This section shows the actual simulated NPL and ENPL rates for the four largest Chilean banks, under the assumption that the aggregate real interest rate (i_t) and heterogeneous labor market shocks $\{G, \sigma_\eta, \sigma_\zeta, R \mid t, x_{k,i}\}$ observed in the past would happen to their current portfolios as measured by the EFH 2010-2011. Chile, Estado and Santander have very similar risk profiles for all the 92 scenarios in the simulation. BCI appears to be substantially less risky than its big competitors. The model predicts, however, that all banks would suffer substantially if a similar economic crisis as the one experience in 1998 to 2001 would repeat itself again.

5.4.2 Simulations for the three Retail banks

In terms of the retail banks I find that all three banks have portfolios with higher default rates than the largest Chilean banks (Estado, BCI, Chile, Santander). Falabella is the retail bank with the lowest default rates, while Ripley shows a high default rate all over the business cycle.

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

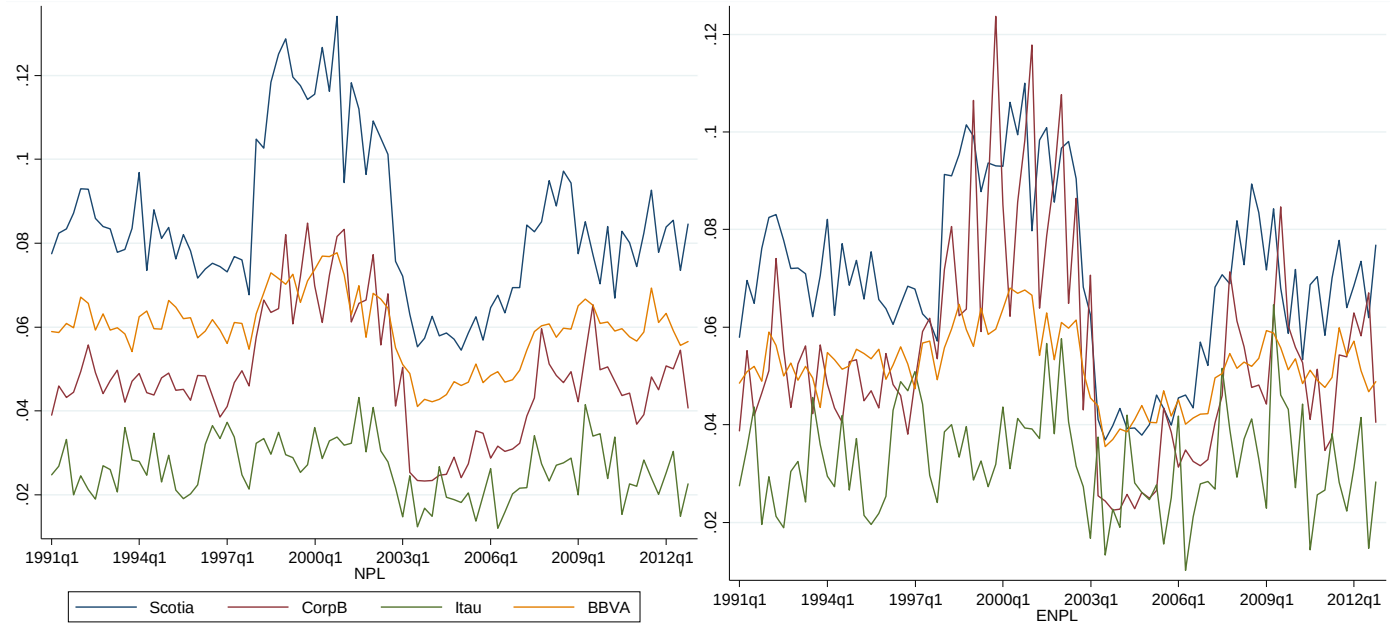
5.4.3 Simulations for the mid-sized banks

Among the mid-sized Chilean banks, Itau is the one with the lowest default rates, followed by CorpBanca and BBVA. It is noticeable that Scotia has both a high average default rate and one that increases substantially during negative times. Both Scotia and CorpBanca appear to be highly susceptible to events such as a repeating of the 1998 to 2001 crisis.

5.4.4 Default-Betas of the banks' loan portfolios

Table 8 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. Ripley, Scotia and CorpBanca have the highest covariance-risk and are the ones more susceptible to shocks affecting household default. Paris has a high expected default rate of their loan portfolio, but their covariance-risk is not higher than the other banks.

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



5.5 Heterogeneity of covariance-risk among different types of households

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 9 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 9 always shows that the covariancer-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

Table 8: 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: $\Delta(-ENPL_t)$	$E[NPL_t]$	$E[ENPL_t]$
Chile	0.824	0.728	1.317	1.058	0.056	0.048
Estado	0.828	0.727	0.708	0.676	0.061	0.055
Scotia	1.630	1.649	1.878	1.230	0.085	0.070
BCI	0.583	0.611	0.430	0.401	0.037	0.032
CorpBanca	1.248	1.779	1.137	1.978	0.048	0.055
Itau	0.411	0.514	0.617	0.731	0.026	0.033
Santander	0.773	0.652	0.754	0.736	0.057	0.054
Falabella	0.759	0.730	0.590	0.617	0.087	0.059
Ripley	2.981	4.218	2.183	3.098	0.261	0.325
Paris	0.821	0.328	0.870	0.833	0.138	0.079
BBVA	0.760	0.705	0.870	0.748	0.060	0.052
All Banks	1	1	1	1	0.063	0.057

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.

6 Conclusions

This paper takes a portfolio view of consumer credit, using a structural model of households' budget constraints and a behavioral default decision rule. I use this model to build the counterfactual risk of the consumer loan portfolios of Chilean banks relative to the economic shocks observed in the last 23 years. 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, with ITAU and BCI being the safest banks both in terms of the average default rate and in terms of their covariance risk over time. Ripley is the riskiest bank, both in terms of its expected default rate and in terms of its covariance risk with the economic cycle. CorpBanca and Scotia have a moderate value of expected default risk, but their covariance risk is high. Therefore these are banks whose portfolios appear safe during normal times, but are

Table 9: Betas of each household type's loans relative to the overall consumer loan portfolio

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

highly susceptible to negative shocks. The model predicts that most Chilean banks - except for Itau and BCI - would suffer substantially if a similar economic crisis as the one in 1998 to 2001 would happen again. The counterfactual simulations show that households with older heads and higher income have a lower covariance-risk, therefore these appear to be market segments that financial institutions could target to reduce their fragility relative to the economic cycle.

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