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Measuring the covariance risk of consumer debt portfolios

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A B S T R A C T

The covariance risk of consumer loans is difficult to measure due to high heterogeneity. Using the Chilean Household Finance Survey I simulate the default conditions of heterogeneous households over distinct macro scenarios. I show that consumer loans have a high covariance beta relative to the stock market and bank assets. Banks' loan portfolios have very different covariance betas, with some banks being prone to high risk during recessions. High income and older households have lower betas and help diversify banks' portfolios. Households' covariance risk increases the probability of being rejected for credit and has a negative impact on loan amounts.

1. Introduction

Finance theory argues that assets' most crucial risk measure is the undiversifiable risk component or covariance with aggregate factors (Duffie and Singleton, 2003). However, common macro risks are difficult to price for corporate debt securities (Das et al., 2007; Pesaran et al., 2006) and even more so for consumer loans due to a lack of tradeable securities on households' payments (Shiller and Schneider, 1998), heterogeneity across households (Madeira, 2018) and moral hazard issues (Lusardi, 2006). Consumer loans represent around 10% to 25% of all loans for several countries (Fig. 1), therefore it is important to evaluate their systematic risk for financial institutions, especially at a time when regulators discuss macro-prudential policies such as countercyclical capital buffers and loss provisions (Rubio and Carrasco-Gallego, 2014). Finally, traditional measures such as consumers' credit scores only account for their cross-sectional risk of default (Edelberg, 2006; Musto and Souleles, 2006), not their sensitivity to the business cycle and other aggregate risks.

This paper uses a calibrated microdata model to estimate the systematic risk component in consumer debt portfolios. The model uses a population of naive households that repay their commitments through their income, assets or access to new loans, following a behavioral rule for default and consumption (Madeira, 2018). The model is then simulated using a sample of 12,000 households from the Chilean Household Finance Survey (hence on, EFH, which is Encuesta Financiera de

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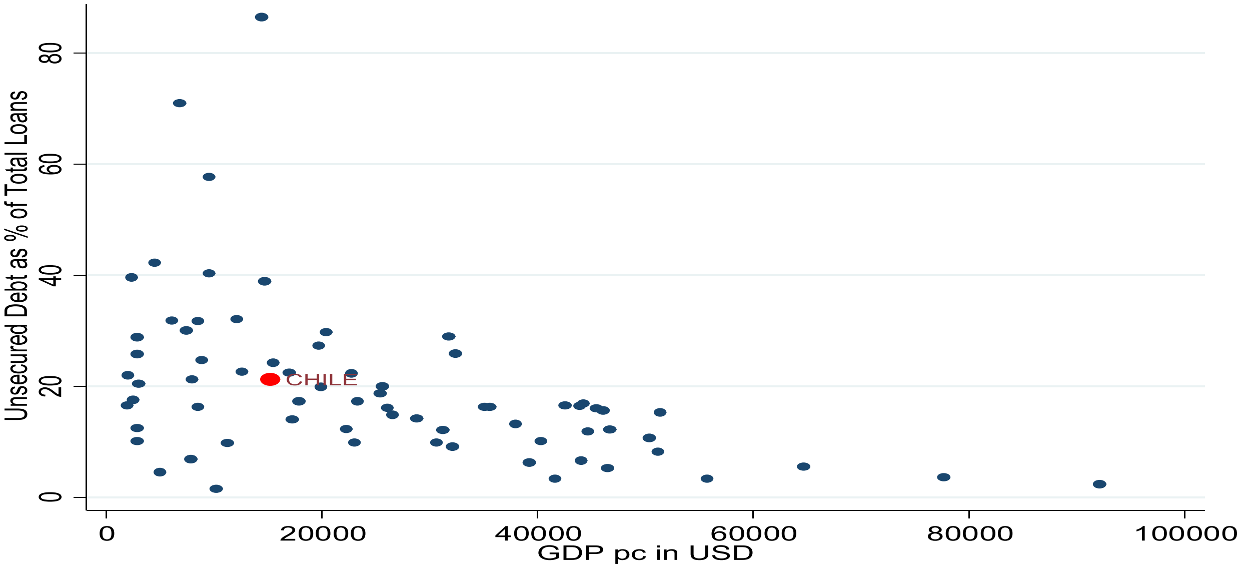

Fig. 1. Unsecured Household Debt as a percentage of the Total Non-Financial Private Sector Loans (households plus firms) in 2012 (71 countries). The y-axis plots $\frac{hc_i - hm_i}{pc_i}$. Sources: credit to the private non-financial sector (pc_i, BIS, IMF), credit to the household sector (hc_i, BIS, IMF), total amount of home mortgage loans (hm_i, HOFINET, IMF), GDP per capita (IMF).

Hogares in Spanish), which experience heterogeneous and time-varying labor income volatility, unemployment rates and interest rate shocks observed during the last 23 years, giving 92 quarterly observations of default for each household type. Covariance default risk will therefore be heterogeneous across households, depending on their finances and the vulnerability of their members' income and employment relative to the economic cycle (Madeira, 2015; Parker, 2014).

The results 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 total assets of the Chilean banks. Estimates of the covariance beta relative to the main stock market index for the overall consumer loan portfolio of the Chilean banks range between 1 and 1.8. Furthermore, 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 already low. 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, showing that some Chilean banks are much more sensitive to the business cycle. The covariance beta of each of the eleven Chilean banks relative to the aggregate loan portfolio ranges from 0.3 to 4.2. After excluding the safest and the riskiest banks, the estimated covariance beta still ranges between 0.5 and 1.8 for the other nine banks. Quantile regressions of the percentiles 25, 50 and 75 of the banks' portfolio performance confirm these results, showing that banks' are equally sensitive to aggregate risk both during bad and good periods. Finally, all the banks' consumer loan portfolios would suffer significantly if Chile experienced a recession similar to the Asian crisis of 1998.[2]

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 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 work is closest to Musto and Souleles (2006), who used the credit scores of a sample of consumers over a period of 3 years to compute their individual covariance risk or "default-beta" relative to the aggregate default over all consumer loans, finding 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. This paper is also related to microeconomic studies of household debt (Ampudia et al., 2016) and to studies showing how the

[2] The Asian crisis was the largest crisis experienced by Chile since the early 1990s. Chile entered a recession in 1998 due to its trade dependence on Asia, with 30.5% of Chilean exports going to Asian countries (IMF, Direction of Trade Statistics). The crisis had a strong effect on the Chilean credit markets, with Chilean banks presenting negative consumer credit growth rates. As the central bank tried to prevent an exchange rate depreciation and its effects on domestic inflation, interest rates in the interbank market reached 60%, which effectively blocked all loan creation for some time since the rate was above the legal ceiling on loan rates (Fuentes and Saravia, 2014).

countercyclical income risk of households explains the rise in consumer debt default during recessions (Gerardi et al., 2018; Luzzetti and Neumuller, 2016; 2019). Finally, this study is related to a growing literature applying heterogeneous agents' models to the analysis of financial instability (Battiston et al., 2016; 2007; Caiani et al., 2016; Catullo et al., 2015; Delli Gatti et al., 2010; Hommes and Iori, 2015; Riccetti et al., 2013).

As in Musto and Souleles (2006) I use the changes in default risk of each household across different time periods to estimate their individual "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 individuals. The most obvious disadvantage of counterfactual simulations is that the results are not robust to imperfections of the model. However, an obvious advantage of using a counterfactual model is that there is no limit to the number of different scenarios and time periods analyzed. In a real panel data sample for a short period, the "default-betas" can be affected by a lucky sequence of shocks, giving the incorrect view that risk is low. The problem of "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 for legal reasons of privacy protection (Musto, 2004), with disclosure of negative information on credit history such as late payments being typically limited by law to three or five years in most countries (IFC, 2012). For Chile, the UK and the USA, the "memory" of credit bureaus is limited to 5, 6 and 7 years, respectively. Also, riskier borrowers are getting larger debts relative to past decades (Edelberg, 2006), therefore historical data may give an overly optimistic view relative to forward looking stress tests. Canals-Cerdá and Kerr (2015) show that credit card risk analysis in the US prior to the 2007 recession systematically underestimated portfolio losses, because the models failed to account for the absence of a strong recession in the pre-2007 data and for the time trend of increasing debt levels relative to the past.

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

2. Simulating counterfactual scenarios of households' loan risk

2.1. A heterogeneous agents model of household consumer loan default

Consumer loan risk is difficult to assess (Parker, 2014), since households' major asset is their 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 view the punishment costs of default, which are often vaguely interpreted as "stigma" and not pecuniary fees (Gross and Souleles, 2002; Jaffee and Stiglitz, 1990). For these reasons I use a simple behavioral model of default and expenditure that assumes households choose default when faced with an extreme reduction in consumption, while using a rich framework for their budget constraint, income dynamics and credit contracts. Madeira (2018) explains this model and its calibration in higher detail, showing that its simulated outcomes accurately replicate 90% and 47% of the fluctuations in the Non-Performing Loans (NPL) and Expenses with Non-Performing Loans (ENPL) quarterly series of the Chilean banking system between 1997 and 2012.

Households (I ommit the household identifier i for now) start at time t with heterogeneous debt commitments ϕ_t and liquid assets A_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 demographics ζ, permanent income P_t, income volatility σ_t, and an idiosyncratic taste component ε^c, which reflects income risk and precautionary motives (Madeira, 2018; Parker, 2014). $B(.)$ denotes the budget constraint function, which determines whether a given expenditure is affordable $B(C_t) \geq 0$ or unaffordable $B(C_t) < 0$, including interest payments on liquid assets R_t and new loans 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. Each lender v offers credit contracts every period t with a fixed loan maturity, $m_{v,t}$, and with risk-priced interest rates $i_{v,t} = i(. \mid CF_t, X_{v,t})$ conditional on its information set $X_{v,t}$ and with an overall consumer debt ceiling $dc(P_t, Y_t)$ as a function of their permanent P_t and current income Y_t.[3] 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

[3] For simplicity households take new loans with the lender v that represented its largest debt in the previous periods. Besides consumer loans with lenders v, $(D_{t+1} = \sum_{v=1}^{V} D_{v,t+1})$, some households also have a mortgage payment, MG_{t+1}, which for simplicity is exogenous and with no default due to collateral. If households decide not to default, $Df_t = 0$, then they accept to satisfy their total debt service: $DS_{t+1} = MG_{t+1} + \sum_{v=1}^{V} DS_{v,t+1}$, with debt amount and service for each lender v given by $DS_{v,t+1} = \sum_{j=0}^{m_v - 1} ND_{v,t-j} \frac{i_{v,t}}{1-(1+i_{v,t})^{-m_v}}$ and $D_{v,t+1} = \sum_{j=0}^{m_v - 1} ND_{v,t-j} \frac{1-(1+i_{v,t})^{j-m_v}}{1-(1+i_{v,t})^{-m_v}}$. If households decide to default I assume for simplicity that they default on all consumer debts, but not on its mortgage: $DS_{t+1}^{df} = MG_{t+1}$, $DS_{v,t+1} = 0$, $D_{v,t+1} = 0$, for $v = 1, .., V$.

decide to default, $Df_{t+s} = 1$, and become excluded from credit for a period of 8 quarters, consuming their current income Y_{t+s} minus some debt service DS^{df}_{t+s} that cannot be reduced by default (such as mortgages):[4]

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) $\{Df_{t+s}, C_{t+s}\} = \{1, Y_{t+s} - DS^{df}_{t+s}\}$ if $B(g(\zeta, C_{t+s-1}, S_{t+s-1})) < 0$, subject to $C_t, A_{t+1}, ND_{v,t} \geq 0$,

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

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

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

2.1) $NPL_t(M \mid \zeta, Y_t) = \Pr(\max(Df_{t+1}, \ldots, Df_{t+M}) = 1 \mid \zeta, Y_t)$,

2.2) $ENPL_t(M \mid \zeta, Y_t) = E[(Df_{t+M} \times D_{t+M})/D_t \mid \zeta, Y_t])$.

The horizon parameter M is calibrated to be $M = 8$ quarters, which is the average maturity of consumer loans in Chile. There is a random sampling treatment of households. A household that has finished repaying its debts is replaced by another household with the same characteristics ζ from the data sample of households. In the same way households in default stay in the sample for 8 quarters without credit[5] and then are randomly replaced by another observation of the same characteristics ζ in the initial sample with probability $p_i(\zeta) = \frac{1}{\sum_j 1(\zeta_i = \zeta)}$. The length of this punishment period does not overly affect the results because in each quarter the percentage of households in default is small relative to the overall stock of debtors. The random sample replacement of households after their consumer loans are repaid or after a default plus a limited punishment period has two motivations: (1) it limits the horizon of each agent and avoids complex lifetime decisions such as marriage/divorce; (2) this gradual random replacement of households with similar ones in the original data insures a long-run steady-state equilibrium, which is given by the initial empirical micro-data. Therefore the model in this article has an inner mechanism in which observations are replaced after a certain period with new observations from the initial sample data and this insures the model is always converging back to a steady-state equilibrium (as suggested in Gentile et al., 2012). Furthermore, Section 3.3 of this article shows that the simulations of this model have a good fit for the historical NPL and ENPL consumer loan series of each bank.

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:

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

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

The model simulation uses three main sources of micro-data and several calibrated parameters which are summarized in Table 1. The main component is the initial distribution of heterogeneous families with demographic characteristics ζ and their initial endowments of assets, debts, and income, which is given by the Chilean Household Finance Survey (EFH). Credit markets are competitive and each lender v adjusts its loans to their perceived risk for each borrower i at time t, conditional on an observed set of information $X^v_{i,t}$ and a loss-given-default LGD of 0.50 and a time-varying cost of banking funds of CF_t.[6] By equating loan costs with expected revenues, lender v obtains its competitive interest rate: $i_{v,t}(i) = \dfrac{CF_t + (LGD \times \Pr(Dl_{v,i,t}))}{1 - (LGD \times \Pr(Dl_{v,i,t}))}$, with $v = 1$ (for banks) and 2 (for retail stores). 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, $X^v_{i,t}$: $\Pr(Dl_{v,i,t}) = \Pr(Dl_{i,t} = 1 \mid X^v_{i,t}) = \Phi(\theta_v z^v_i + \beta_v[x^v_{i,t}])$, with Φ being the standard normal cdf. The information set of the lenders $X^v_{i,t} = \{z^v_i, x^v_{i,t}\}$ includes a vector of fixed demographic characteristics, z^v_i, plus a set of continuous time-varying risk-factors, $x^v_{i,t}$. z^v_i can be understood as a proxy for the financial knowledge of the household or its attitudes towards default. 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 $y_{i,t}$, 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. The risk horizon M is set as 8 quarters, which is the mean maturity of consumer loans in Chile.

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 (ENE) for 540 different worker types

[4] Accounting standards for the Chilean banks recommend that consumer loans and mortgages should expect losses of 100% and 20%, respectively after 6 months in arrears (Matus, 2015), therefore banks prefer to assume default on consumer loans as a loss but mortgage capital can be recovered.

[5] Accounting standards for banks recommend that loans in arrears are written-off the balance sheet after 24 to 36 months (Matus, 2015), therefore lenders lose most repayment expectations after 8 quarters.

[6] The BIS suggests a LGD parameter between 0.55 to 0.67 for revolving consumer credit (credit cards, unsecured credit lines) and between 0.45 to 0.48 for consumer credit contracts (these parameter calibrations were based on a group of 10 non-G10 countries, which included Australia, Bahrain, Chile, India, Indonesia, Peru and Singapore - see Table 23 in BCBS (2006). An IMF team also suggests a parameter of 0.45 for the Loss Given Default of consumer loans in Chile and Peru (Wezel et al., 2012). Most Chilean banks take a fixed parameter of 0.50 based on the BIS results (Matus, 2015; BCBS, 2006), which makes this value reasonable for this model calibration.

Table 1
Calibrated and estimated parameters.

Parameters and exogenous shocks	Source
Population distribution and endowments	EFH 2007–2011
(Income, assets, debts $\|\zeta$)	ζ = {Region, Sex, Age, Education, Industry, Quintile(Y_t), Number of household Members}
Shocks to Initial Debt Endowments	Mean Debt and Interests Growth (SBIF)
Income dynamic shocks (540 types)	Y_t, σ_t (Madeira, 2015, ENE 1990–2012)
Expenditure choice	$C_t = c(\zeta, P_t, \sigma_t, \varepsilon^c)$ (EPF 2007)
	$m(\zeta) = Q_1(C_0\|\zeta)$, $\lambda = 0.15$
Default decisions	Budget kink: $B(g(\zeta, C_{t+s-1}, S_{t+s-1})) < 0$
Credit Market, 2 lenders ($\nu = 1, 2$)	Banks, Retail: $D_{\nu,t+1} \leq dc_{\nu,t+1}$(lender ν)
Loan terms: $i_{\nu,t} = i(.\|CF_t, X_{\nu,t})$	EFH: $X_{\nu,t} = \{\zeta, D_t, P_t, Y_t, \Pr(U_t), DS_t\}$
$m_t = \{m_{1,t}, m_{2,t}\}$	$m_t = \{8, 4\}$ (EFH data, MMFS, 2011)
Debt ceiling: $D_{i,t} \leq dc_t = \max(4P_{i,t} + 1Y_{i,t}, D_{i,t-1}, Q_{75}(D_{i,t-1}\|\zeta))$ (Madeira, 2018)	
Maximum Legal Interest Rate	$i_{\nu,t} \leq 1.50 \times E[i_{2,t}]$
Banks' fundraising real interest rates, i_t	Central Bank of Chile (1990Q1-2012Q4)
Parametric distribution of simulations	
Permanent income shock: $\ln(\eta_{k,i,t}) \sim N(0, \sigma_\eta(x_{k,i}))$	
Temporary income shock: $\ln(\zeta_{k,i,t}) \sim N(0, \sigma_\zeta(x_{k,i}))$	
Unemployment: $U_{k,i,t+1} = 1(u_{k,i,t+1} \leq (1 - U_{k,i,t}) \Pr(U_{k,i,t+1} = 1 \mid t, U_{k,i,t} = 0, x_{k,i})$ $+ U_{k,i,t} \Pr(U_{k,i,t+1} = 1 \mid t, U_{k,i,t} = 1, x_{k,i}))$, with $u_{k,i,t+1} \sim Uniform(0, 1)$	
Consumption taste shock: $\varepsilon_i \sim N(0, \upsilon(z_i))$	
Random replacement of households with another observation from micro data$\|\zeta$:	
for non-defaulters, replacement after consumer loans are paid ($D_{i,t} = 0$)	
for defaulters, replacement M periods after first default ($M = 8$ quarters)	

conditional on their education, age, industry, income quintile and region (Madeira, 2015). Permanent income of each worker k in the first period t_0 is given by a weighted average of the income of its working occupation (Y_k) and its income while unemployed ($Y_k RR_k$) given by a replacement ratio of unemployment benefits (RR_k): $P_{k,t_0} = Y_k(1 - u_{k,t_0}) + Y_k RR_k u_{k,t_0}$. The permanent income of each member k of the household i at time t is then given by $P_{k,i,t+s} = G_{t+s} P_{k,i,t+s-1} \eta_{k,i,t+s}$, with G_{t+s} being an exogenous income drift (such as wage increase for all workers of a given type) and $\eta_{k,i,t+s}$ being an idiosyncratic permanent income shock. The current income is then given by the permanent income plus a log-normal temporary income shock that lasts a single quarter, $\zeta_{k,i,t+s}$, and a discrete income fall when the worker experiences an unemployment spell ($U_{k,i,t+s}$): $Y_{k,i,t+s} = P_{k,i,t+s} \zeta_{k,i,t+s} RR_k^{U_{k,i,t+s}}$. The households' permanent and current income is then obtained as the income sum of their working members, plus a constant non-labor income, a_i: $Y_{i,t+1} = a_i + \sum_k Y_{k,i,t+1}$ and $P_{i,t+1} = a_i + \sum_k P_{k,i,t+1}$. 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 (EPF). 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): $\ln(c_{i,t}) = g(z_i) + \beta\left[\ln(P_{i,t}), \bar{\sigma}_{i,t}\right] + \varepsilon_i$, with $\varepsilon_i \sim N(0, \sigma_i = \upsilon(z_i))$.

2.2. Description of the Chilean households and their indebtedness

The Chilean Household Finance Survey (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. The five EFH survey waves of 2007 to 2011 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.

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 Chilean Employment Survey (see Madeira, 2015). Table 2 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.

Table 2
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%
			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%
			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%

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, $\bar{\sigma}_{i,t} = \sum_k \frac{P_{i,k,t}}{P_{i,t-a_i}} \sqrt{4\sigma^2_\eta(t, x_{k,i}) + \sigma^2_\zeta(t, x_{k,i})}$. Bank customers are the group of highest 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.

Chile has a fluid labor market, with substantial job creation ($\bar{\lambda}^{UE}_{i,t}$) and destruction ($\bar{\lambda}^{EU}_{i,t}$). Only the United States had higher inflow and outflow rates from unemployment than Chile among the OECD countries (Madeira, 2015). Annual wage volatility ($\bar{\sigma}_{i,t}$) of Chilean workers is around 14% to 17%, which is comparable to values estimated for the United States (Madeira, 2015).

3. Simulation results and the covariance risk of consumer debt

3.1. Covariance risk of the consumer loans of the Chilean banking system

To evaluate the overall risk of consumer loan portfolios I compute their covariance risk relative to the overall Chilean financial assets. For this reason I simulated the default risk in the Chilean banking consumer loan portfolio as if the past values of the aggregate real interest rates of Chilean bank funds (i_t) and labor market shocks, $\{G, \lambda^{EU}, \lambda^{UE}, \sigma_\eta, \sigma_\zeta | t, x_{k,i}\}$, for each type of worker happened now. A problem of the capital asset pricing model (CAPM) is that there is not a single measure of the entire market portfolio, 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 $\delta = 0.99$ and the 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 portfolio 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 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:

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

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

with $r_{MP,t} \in \{ROA_t, \ln(\frac{IPSA_t}{IPSA_{t-1}}), m_t(.5), m_t(1), m_t(1.5), m_t(2)\}$ 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 a useful measure of the cyclicality of default rates and of the loan portfolio systematic risk premium. Since default rates are expected to be countercyclical, then $\tilde{\beta}_p$ should be negative.

Table 3
Betas of the simulated 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*
(Std)	(0.311)	(0.627)	(0.382)	(0.365)	(0.349)	(0.332)
R2	0.017*	0.051	0.002	0.001	0.011	0.001
Beta $ENPL_t$	−0.503	−1.023**	−2.302***	−1.129***	−0.736**	−0.539**
(Std)	(0.288)	(0.356)	(0.306)	(0.297)	(0.287)	(0.276)
R2	0.010	0.011	0.010	0.013	0.011	0.012
Beta $\Delta(1-NPL_t)$	0.376***	1.361***	1.826*	0.944**	0.650	0.504*
(Std)	(0.112)	(0.177)	(0.942)	(0.381)	(0.662)	(0.301)
R2	0.151	0.001	0.010	0.010	0.011	0.011
Beta $\Delta(1-ENPL_t)$	0.227***	0.685***	1.675**	0.876**	0.611*	0.479
(Std)	(0.068)	(0.089)	(0.756)	(0.422)	(0.357)	(0.575)
R2	0.010	0.013	0.011	0.012	0.010	0.010
Beta $IPSA_t$ (real)	0.098***	1	1.330	0.674	0.456	0.347
(Std)	(0.035)		(1.130)	(0.572)	(0.386)	(0.293)
R2	0.020		0.015	0.015	0.015	0.015

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

Table 3 shows the results of the Beta estimates of the simulated 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 increases in times of negative market returns. Similarly, the Beta for the loan portfolio returns (or negative change in default rates) is positive relative to all measures of market returns, therefore consumer loans 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. Almost all the estimated Beta coefficients are statistically significant for explaining the consumer loan portfolio simulated returns, although the R-squared values are relatively low, perhaps because a large part of the consumer default is explained by labor market risks of households and not by factors associated with the capital risk of companies. The stock market real return is positively correlated with the banking asset returns and the consumer pricing kernel, although the coefficients of the consumption pricing kernel are not statistically significant, which reflects the literature that the consumption pricing kernel is not as powerful empirically as the theory would expect (Cochrane, 2005).

3.2. The Loan Portfolios of the individual Chilean banks

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 an anonymous random 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. These 11 institutions correspond to more than 99% of the Chilean banking consumer credit market.

Table 4 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 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 5 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, consumer 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 ones with the highest consumption expenses (as given by the mean statistics for similar households in the EPF, see the previous section). Large Bank 2, Mid-size Bank 2 and the Retail Banks have the lowest income customers. In terms of the

Table 4
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	4667	72	5.8%	7.4%	6.5%	29.5%	50.8%
Mid-size 2	48	3226	132	11.4%	4.8%	19.8%	18.1%	45.9%
Mid-size 3	42	2017	169			0.2%	15.1%	84.6%
Mid-size 4	59	4238	92	2.1%	2.5%	12.1%	36.5%	46.8%
Retail 1	125	9892	77	0.7%	15.4%	20.1%	23.3%	40.5%
Retail 2	26	2051	104	0.2%	1.7%	15.7%	53.5%	29.0%
Retail 3	19	1977	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.

Table 5
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

debt amount relative to income, the more indebted households belong to 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 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.

3.3. Validation of the banks' simulated risk versus real historical data

For a stronger model validation, I compare the simulated consumer portfolios risk measures for each Chilean bank with its equivalents in real historical data. Fig. 2 shows the residuals between the simulated variable and the real historical time series for each j bank: $res_{j,t} = y_{j,t}(sim) - y_{j,t}(\text{real})$, with $y_{j,t} = NPL_{j,t}$ or $ENPL_{j,t}$. Both the simulated and historical series are sums over 8 quarters. The real NPL time series of the banks exist since the last quarter of 1996, while the real ENPL series are only available since the start of 2004. Since there was entry of foreign banks and new bank creation since 1996, a few banks only show activity for a shorter time period. Fig. 2 shows that both the residuals for the NPL and ENPL rates of each bank fluctuate around zero, but the deviations are larger for the NPL rate, especially between the years 1998 and 2002. These larger deviations during 1998–2002 make sense because the simulated data are implemented with the current portfolio of customers that each bank has and an expansion in the number of customers in recent years has led to a riskier demographic profile for their loan portfolio (Madeira, 2018; Matus, 2015). However, deviations larger than 3% in absolute value are rare in the NPL panel time series, while for the ENPL almost all deviations are smaller than 2% in absolute value.

A further validation exercise is to show how strong is the cyclical comovement between the simulated and real variables. Table 6 reports the coefficients from OLS regressions of the simulated values of $NPL_{j,t}$ and $ENPL_{j,t}$ on their real counterparts as covariates for each bank: $y_{j,t}(sim) = \alpha_j + \theta_j y_{j,t}(\text{real}) + \varepsilon_{j,t}$. A positive comovement between simulated and real results corresponds to a positive value of θ_j, while a perfect comovement would correspond to a θ_j coefficient equal to 1. For the case of the NPL series, only one bank shows a negative value of θ_j, [7] while all the other banks have positive values of

[7] This bank corresponds to the state-owned institution, which is mandated to support credit growth among poorer families. Therefore this bank can take larger risks with its portfolio during downturns and it can behave different from the other private banks.

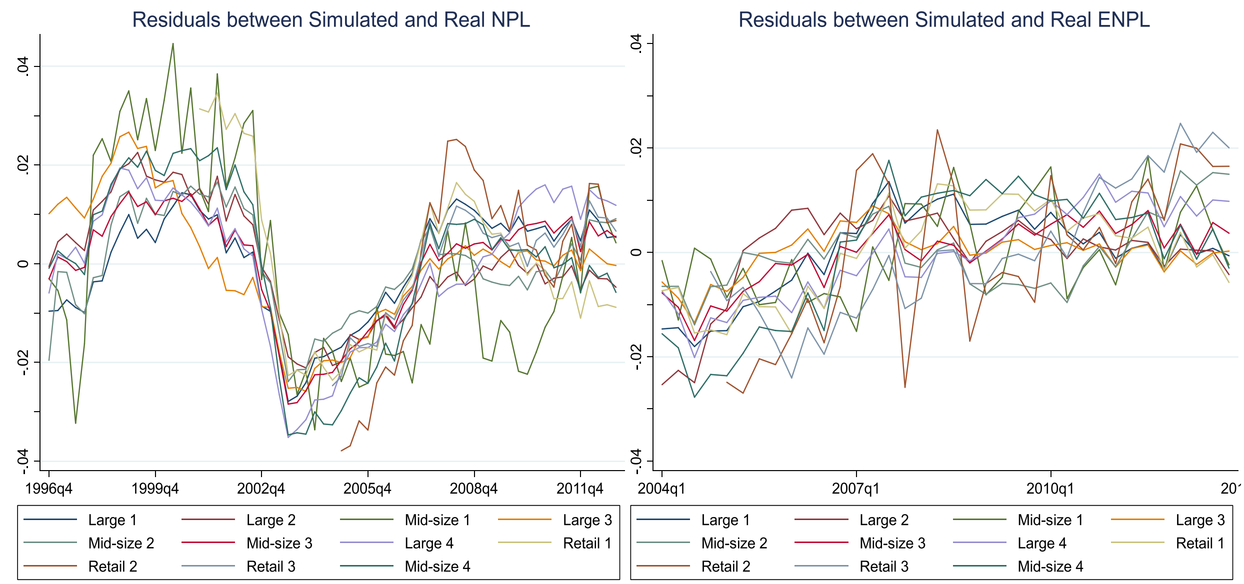

Fig. 2. Residual differences between the simulated risk of each bank and its historical series.

Table 6
OLS regressions of Non-Performing Loans (NPL) or Expenses with NPL (ENPL) by bank (j).

$y_{j,t}(sim) = \alpha_j + \theta_j y_{j,t}(real) + \varepsilon_{j,t}$, with $y_{j,t} = NPL_{j,t}$ or $ENPL_{j,t}$

	$NPL_{j,t}$ (period 1996Q4-2012Q4)				$ENPL_{j,t}$ (period 2004Q1-2012Q4)			
	OLS results		Standard-errors of		OLS results		Standard-errors of	
Bank	$\hat{\theta}_j$ (Std)	R-squared	$y_{j,t}(sim)$	$y_{j,t}(real)$	$\hat{\theta}_j$ (Std)	R-squared	$y_{j,t}(sim)$	$y_{j,t}(real)$
Large 1	0.465*** (0.046)	0.475	0.0151	0.0220	0.874 *** (0.086)	0.745	0.0124	0.0122
Large 2	−0.174** (0.070)	0.080	0.0093	0.0125	0.845*** (0.123)	0.484	0.0070	0.0109
Large 3	0.120** (0.061)	0.031	0.0105	0.0154	0.650*** (0.046)	0.839	0.0088	0.0149
Large 4	0.170*** (0.056)	0.063	0.0145	0.0214	0.457 *** (0.073)	0.404	0.0116	0.0152
Mid-size 1	0.509*** (0.116)	0.236	0.0235	0.0225	0.734*** (0.079)	0.564	0.0154	0.0188
Mid-size 2	0.558*** (0.063)	0.571	0.0149	0.0205	0.443*** (0.086)	0.410	0.0113	0.0245
Mid-size 3	0.764*** (0.112)	0.385	0.0138	0.0113	0.825*** (0.078)	0.748	0.0100	0.0112
Mid-size 4	1.002*** (0.241)	0.193	0.0182	0.0095	1.028*** (0.254)	0.399	0.0153	0.0089
Retail 1	0.187** (0.085)	0.038	0.0164	0.0172	0.945*** (0.109)	0.635	0.0135	0.0114
Retail 2	0.965*** (0.216)	0.423	0.0221	0.0095	0.924*** (0.175)	0.466	0.0243	0.0363
Retail 3	0.815*** (0.143)	0.432	0.0129	0.0109	0.265*** (0.055)	0.386	0.0123	0.0274

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

θ_j and four of them even show coefficients close to 1. In the case of the ENPL series, all the regressions show a positive comovement between simulations and real data ($\theta_j > 0$), with at least six banks having coefficients close to 1. The R^2 values of the linear regressions tend to be higher for the ENPL results, although several R^2 values for the banks' NPL series are also around 40% or higher. Finally, Table 6 reports the standard-deviation of the simulated and real values of the NPL and ENPL series for each bank. These results show that the simulated results have a similar standard-deviation as the real series, with roughly half of the banks having a higher standard-deviation as the actual series and half showing a lower value.

Overall, Tables 3 and 6 confirm that there is a strong comovement between the model's simulations and real outcomes and that the fluctuations of both variables are similar in size. Note also that all the simulations correspond to values simulated out of the sample, since the model is simulated with the Chilean Household Finance Survey sample for the period 2007–2011 and this sample corresponds to a small subset of the portfolio of loans of the banks for these years (Table 4 shows that roughly one in every 1,000 customers are sampled as observations for each bank).

3.4. Default simulations of the individual Chilean banks

I show now the 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 $\{G, \lambda^{EU}, \lambda^{UE}, \sigma_\eta, \sigma_\zeta | t, x_{k,i}\}$ observed in the past 23 years (which corresponds to 92 quarters) would happen to their current EFH portfolios. This simulation is not about what happened to the past portfolios, but rather how the default rate of each bank's current portfolio would change if the past shocks would

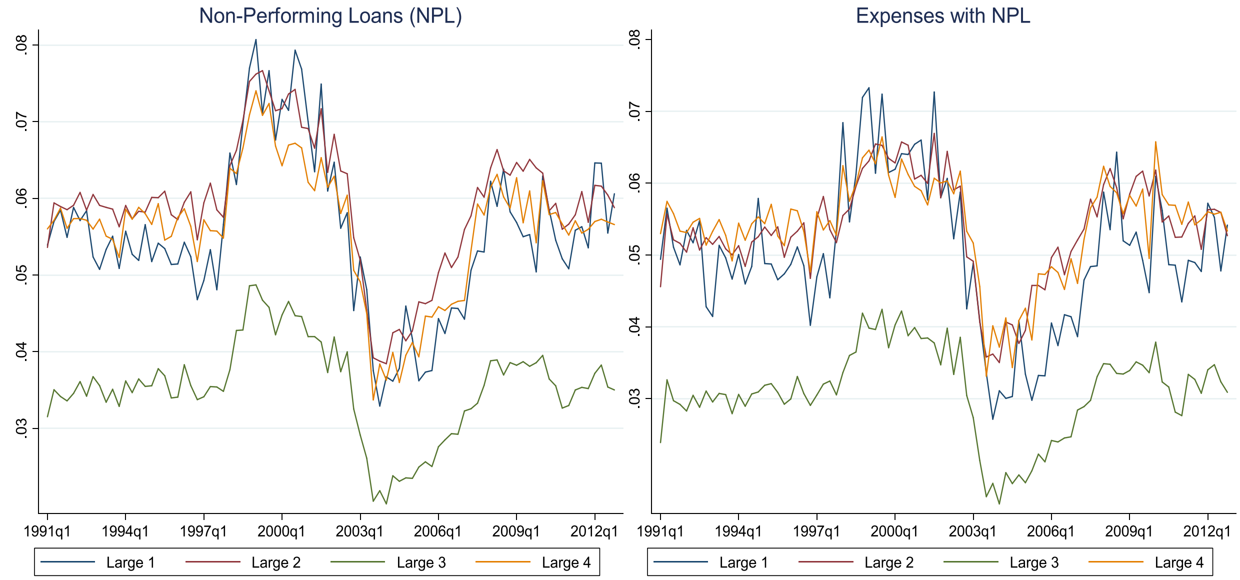

Fig. 3. Simulations of non-performing loans and expenses with NPL for the four largest banks.

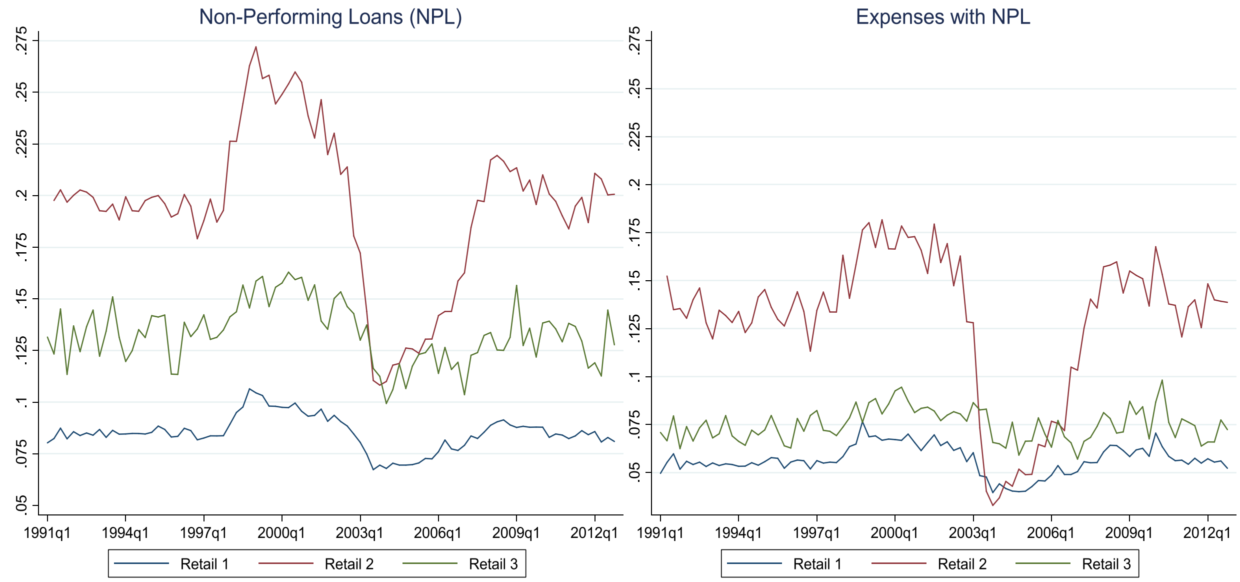

Fig. 4. Simulations of non-performing loans and expenses with NPL for the three Retail banks.

happen now. Results are shown separately for the four largest banks (Fig. 3), the three retail banks (Fig. 4) and the mid-sized banks (Fig. 5). In Fig. 3 the Large Banks have similar risk profiles for all the 92 simulated scenarios, except for Large Bank 3 which is less risky than its competitors. All the large banks would suffer substantially with a shock similar to the Asian crisis of 1998.

In terms of the retail banks (Fig. 4) 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 (Fig. 5), 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 repeat of the 1998 crisis.

Table 7 repeats the regressions of (3.1) and (3.2) 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 the covariance risk of an individual bank's loan portfolio relative to the whole banking system. Retail Bank 2, plus Mid-size Banks 1 and 2 have the highest

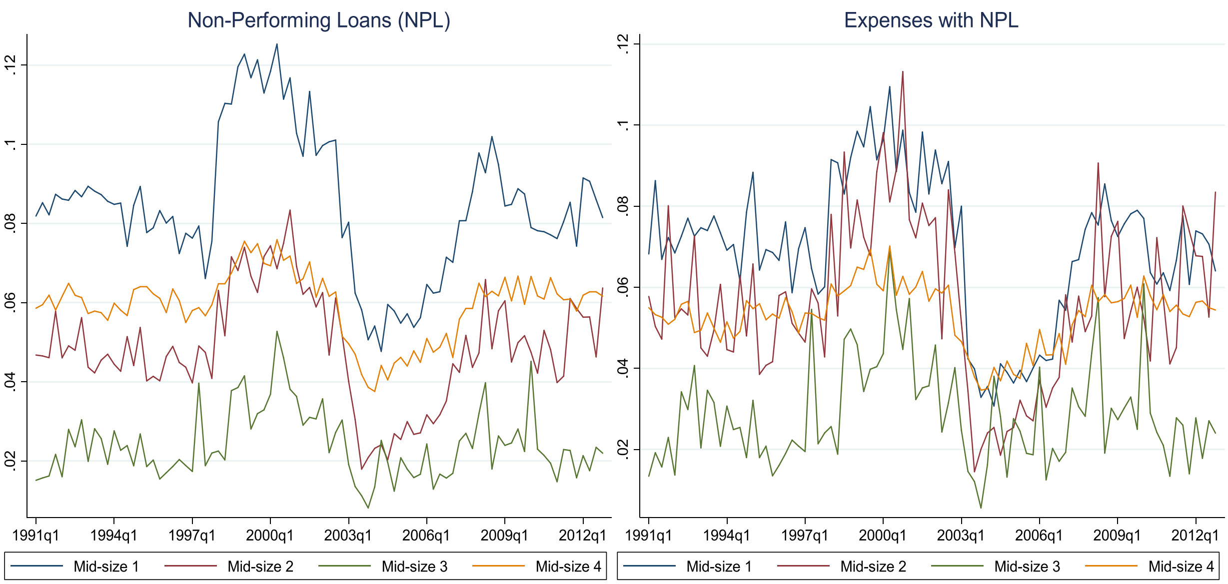

Fig. 5. Simulations of non-performing loans and expenses with NPL for the mid-sized banks.

Table 7
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
(Std / R2)	(0.053 / 0.895)	(0.070 / 0.818)	(0.125 / 0.699)	(0.189 / 0.654)		
Large 2	0.828***	0.727***	0.708***	0.676***	0.061	0.055
(Std / R2)	(0.025 / 0.947)	(0.042 / 0.811	(0.071 / 0.624)	(0.081 / 0.510)		
Large 3	0.583***	0.611***	0.430***	0.401***	0.037	0.032
(Std / R2)	(0.016 / 0.943)	(0.022 / 0.880)	(0.077 / 0.452)	(0.075 / 0.427)		
Large 4	0.773***	0.652***	0.754***	0.736***	0.057	0.054
(Std / R2)	(0.029 /0.947)	(0.045 / 0.858)	(0.109 / 0.620)	(0.123 / 0.534)		
Mid-size 1	1.630***	1.649***	1.878***	1.230***	0.085	0.070
(Std / R2)	(0.106 / 0.864)	(0.138 / 0.729)	(0.362 / 0.409)	(0.345 / 0.372)		
Mid-size 2	1.248***	1.779***	1.137***	1.978***	0.048	0.055
(Std / R2)	(0.061 / 0.825)	(0.132 / 0.623)	(0.277 / 0.229)	(0.419 / 0.091)		
Mid-size 3	0.411***	0.514**	0.617*	0.731*	0.026	0.033
(Std / R2)	(0.114 / 0.587)	(0.213 / 0.448)	(0.368 / 0.289)	(0.435 / 0.267)		
Mid-size 4	0.760***	0.705***	0.870***	0.748***	0.060	0.052
(Std / R2)	(0.028 / 0.883)	(0.037 / 0.814)	(0.114 / 0.431)	(0.126 / 0.385)		
Retail 1	0.759***	0.730***	0.590***	0.617***	0.087	0.059
(Std / R2)	(0.029 / 0.898)	(0.047 / 0.744)	(0.076 / 0.329)	(0.108 / 0.233)		
Retail 2	2.981***	4.218***	2.183	3.098	0.261	0.325
(Std / R2)	(0.864 / 0.838)	(1.494 / 0.543)	(1.947 / 0.182)	(3.729 / 0.167)		
Retail 3	0.821***	0.328***	0.870*	0.833***	0.138	0.079
(Std / R2)	(0.129 / 0.578)	(0.119 / 0.315)	(0.522 / 0.065)	(0.256 / 0.045)		
All Banks	1	1	1	1	0.063	0.057

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

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 similar to the other banks. All the Beta coefficients of the simulated loan portfolios of each bank relative to the entire banking system are statistically significant. Each bank's regression has relatively high R-squared values for the Beta coefficients based on the NPL_t and $ENPL_t$; however, in the case of the regressions based on the first differences $\Delta(-NPL_t)$ and $\Delta(-ENPL_t)$ the estimated R-squared values can be a bit lower.

3.5. Stress tests of banks and quantile regressions of covariance risk

Credit market shocks to loan terms such as maturities, interest rates, and loan access can lead illiquid households to default. For this reason I add to the baseline (which includes heterogeneous shocks to income volatility and unemployment) three extra sources of stress that make new household loans more costly and illiquid: (1) maturities for new loans at banks and retail stores fall by 25% (i.e., maturities fall from 8 to 6 quarters for banks and from 4 to 3 quarters for retail stores); (2)

Table 8
Baseline simulations of banks' risk versus scenarios with additional liquidity shocks.

	Baseline		Fall in maturity by 25%		Real interest increases 5.1%		Debt Ceiling falls 25%	
Bank	$E[NPL_t]$	$E[ENPL_t]$	$E[NPL_t]$	$E[ENPL_t]$	$E[NPL_t]$	$E[ENPL_t]$	$E[NPL_t]$	$E[ENPL_t]$
Large 1	0.056	0.048	0.147	0.101	0.224	0.147	0.312	0.188
Large 2	0.061	0.055	0.139	0.099	0.202	0.144	0.298	0.191
Large 3	0.037	0.032	0.096	0.064	0.157	0.100	0.242	0.144
Large 4	0.057	0.054	0.128	0.086	0.185	0.127	0.273	0.170
Mid-size 1	0.085	0.07	0.179	0.121	0.228	0.139	0.309	0.170
Mid-size 2	0.048	0.055	0.140	0.133	0.199	0.182	0.342	0.278
Mid-size 3	0.026	0.033	0.152	0.114	0.208	0.137	0.279	0.150
Mid-size 4	0.06	0.052	0.142	0.095	0.205	0.122	0.296	0.177
Retail 1	0.087	0.059	0.154	0.096	0.207	0.134	0.308	0.199
Retail 2	0.261	0.325	0.394	0.251	0.488	0.264	0.553	0.279
Retail 3	0.138	0.079	0.169	0.087	0.243	0.131	0.383	0.241

Table 9
Quantile regressions of banks' beta covariance risk.

Bank	Quantile	B: NPL_t	B: $ENPL_t$	B: $\Delta(-NPL_t)$	B: $\Delta(-ENPL_t)$
Large 1	25	0.929*** (0.045)	0.930*** (0.068)	0.974*** (0.176)	0.969*** (0.178)
Large 1	50	0.947*** (0.069)	0.953*** (0.069)	0.970*** (0.104)	0.971*** (0.164)
Large 1	75	0.950*** (0.078)	0.964*** (0.096)	0.962*** (0.170)	0.965*** (0.199)
Large 2	25	1.038*** (0.023)	1.065*** (0.033)	1.059*** (0.078)	1.056*** (0.089)
Large 2	50	1.045*** (0.027)	1.068*** (0.068)	1.058*** (0.101)	1.058*** (0.099)
Large 2	75	1.054*** (0.035)	1.087*** (0.071)	1.050*** (0.086)	1.077*** (0.140)
Large 3	25	0.815*** (0.029)	0.844*** (0.034)	0.793*** (0.117)	0.801*** (0.107)
Large 3	50	0.823*** (0.023)	0.850*** (0.025)	0.780*** (0.108)	0.830*** (0.064)
Large 3	75	0.815*** (0.035)	0.858*** (0.034)	0.800*** (0.076)	0.855*** (0.115)
Large 4	25	0.969*** (0.029)	0.981*** (0.065)	0.983*** (0.154)	0.966*** (0.152)
Large 4	50	0.975*** (0.033)	0.982*** (0.063)	0.976*** (0.119)	0.961*** (0.140)
Large 4	75	0.978*** (0.027)	0.982*** (0.051)	0.965*** (0.119)	0.957*** (0.153)
Mid-size 1	25	1.058*** (0.106)	1.049*** (0.119)	1.072** (0.431)	1.060*** (0.319)
Mid-size 1	50	1.060*** (0.125)	1.045*** (0.112)	1.063*** (0.353)	1.063** (0.449)
Mid-size 1	75	1.056*** (0.129)	1.054*** (0.138)	1.041** (0.408)	1.034** (0.510)
Mid-size 2	25	0.984*** (0.059)	0.997*** (0.104)	1.019** (0.401)	1.058 (0.804)
Mid-size 2	50	1.009*** (0.081)	0.979*** (0.160)	1.004*** (0.371)	1.075** (0.522)
Mid-size 2	75	1.018*** (0.105)	1.014*** (0.190)	0.982** (0.394)	1.029 (0.733)
Mid-size 3	25	0.703*** (0.073)	0.718*** (0.157)	0.700 (0.510)	0.713 (0.472)
Mid-size 3	50	0.698*** (0.109)	0.772*** (0.197)	0.647 (0.443)	0.765 (0.637)
Mid-size 3	75	0.675*** (0.174)	0.766** (0.372)	0.61 (0.451)	0.73 (0.609)
Mid-size 4	25	1.001*** (0.035)	1.011*** (0.042)	1.055*** (0.160)	1.079*** (0.186)
Mid-size 4	50	1.015*** (0.032)	1.028*** (0.046)	1.046*** (0.158)	1.065*** (0.156)
Mid-size 4	75	1.017*** (0.036)	1.04*** (0.070)	1.044*** (0.154)	1.110*** (0.187)
Retail 1	25	0.994*** (0.036)	0.975*** (0.058)	1.048*** (0.142)	0.994*** (0.112)
Retail 1	50	0.996*** (0.026)	0.963*** (0.046)	1.089*** (0.119)	1.022*** (0.132)
Retail 1	75	1.009*** (0.030)	0.971*** (0.072)	1.016*** (0.141)	1.042*** (0.147)
Retail 2	25	1.504 (1.125)	1.548 (1.274)	1.302* (0.75)	1.432 (2.357)
Retail 2	50	1.522 (1.045)	1.602 (1.401)	1.248 (1.019)	1.439 (1.792)
Retail 2	75	1.552 (2.718)	1.590 (1.377)	1.355 (2.45)	1.559 (2.077)
Retail 3	25	0.994*** (0.236)	0.773*** (0.142)	1.048*** (0.279)	0.873** (0.353)
Retail 3	50	0.99*** (0.214)	0.815*** (0.205)	0.990 (0.802)	0.945* (0.489)
Retail 3	75	1.014*** (0.200)	0.879*** (0.223)	1.038 (0.854)	0.973** (0.405)

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

the cost of funds for lenders increases by 510 basis points (i.e., an increase of 5.1% points in the real interest rate of banks' capital costs); and (3) the debt ceilings for the loan amounts offered by lenders to consumers fall by 25%. The results show that all the banks' portfolios would be severely affected by the three stress scenarios, with the fall in loan maturities having a lower impact than the increase in the real interest rate of banks or the reduction in the debt ceiling of the households. The Mid-sized banks' NPL and ENPL rates are more affected by the fall in maturities than the Large and Retail banks, with Large Bank 3 and Retail Bank 3 being the least affected by this scenario. The increase in interest rates has a strong effect on all banks, but it is particularly negative for Mid-sized Bank 2, Retail Bank 2 and Retail Bank 3. Again, just as in Madeira (2018), the fall in the debt ceiling has the strongest effect on the NPL and ENPL rates of all banks, but it is particularly negative for Mid-sized Bank 2 and Retail Bank 2. The reason is that the reduction in the debt ceiling is a strong liquidity shock, because households that are repaying part of the past debts with new loans suddenly become credit constrained and unable to finance their commitments.

Table 9 shows a further robustness check, which are the results of Quantile Regressions for the percentiles 25, 50 and 75 of each bank's portfolio risk (as given by the NPL and ENPL rates) in relation to the aggregate consumer loan portfolio of the banking system. The results are roughly similar to the ones shown in Table 7, with the Mid-sized Banks 1 and 2 and the Retail Bank 2 being the most sensitive banks to aggregate risk as measured by their default-beta coefficients. Again, Retail Bank 2 is by far the riskiest institution in terms of covariance-risk. In a similar way as Table 7, the Large Bank 3 has the lowest covariance risk among the Large banks category, with the difference that now Large Bank 2 is significantly more sensitive to covariance risk relative to Large Banks 1 and 4. The quantile estimates (25, 50, 75) for the beta-covariance risk are all similar within each bank, therefore aggregate risk seems to affect both good periods (as expressed by the low quantile 25 for the NPL and ENPL), median periods and bad periods (the quantile 75 estimates) in a similar way for each bank. In summary the results show that aggregate banking risk affects each bank in a symmetric way during the good and bad periods of the business cycle.

4. Heterogeneity of covariance risk and its impact on loan amounts

Now I report the heterogeneity of the covariance risk across different households, showing 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 fact, even for the lowest income quintiles (1 and 2) the oldest group (≥ 55) shows a covariance risk around or below 1. 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 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, quintiles 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. Almost all the coefficients for each household type (given by age and income) are statistically significant, with the overall R^2 values ranging from 0.19 to 0.54.

It is well known that lenders take into account a consumer's expected probability of default for determining their loans. However, an open question is whether consumers with greater covariance risk obtain less credit, even after controlling for

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
(Std)		(0.0194)	(0.0297)	(0.286)	(0.319)		
1	35 – 54	1.166***	0.901***	1.581**	1.332***	0.168	0.125
(Std)		(0.0216)	(0.0324)	(0.644)	(0.325)		
1	≥ 55	1.139***	0.796***	1.004 **	1.060***	0.249	0.112
(Std)		(0.0200)	(0.0287)	(0.509)	(0.142)		
2	≤ 35	1.143***	1.361***	1.860 ***	2.187***	0.114	0.095
(Std)		(0.0205)	(0.0290)	(0.207)	(0.246)		
2	35 – 54	2.168***	1.899***	1.705*	1.184***	0.198	0.179
(Std)		(0.0198)	(0.0280)	(1.031)	(0.306)		
2	≥ 55	1.092***	0.890***	0.696 ***	0.616***	0.285	0.220
(Std)		(0.0222)	(0.0304)	(0.238)	(0.218)		
3	≤ 35	0.735***	0.827***	1.367 ***	2.014***	0.094	0.058
(Std)		(0.0182)	(0.0283)	(0.094)	(0.129)		
3	35 – 54	0.883***	1.146***	0.741***	0.903***	0.083	0.084
(Std)		(0.0170)	(0.0279)	(0.082)	(0.119)		
3	≥ 55	0.818***	1.122***	0.561 ***	0.813***	0.108	0.074
(Std)		(0.0210)	(0.0294)	(0.163)	(0.281)		
4	≤ 35	1.070***	1.322***	1.405 ***	1.181***	0.105	0.108
(Std)		(0.0170)	(0.0288)	(0.111)	(0.208)		
4	35 – 54	1.835***	1.938***	1.112***	1.251***	0.093	0.109
(Std)		(0.0180)	(0.0314)	(0.088)	(0.276)		
4	≥ 55	0.393***	0.053*	0.273**	0.048	0.097	0.074
(Std)		(0.0182)	(0.0300)	(0.129)	(0.086)		
5	≤ 35	0.332***	0.333***	0.237 ***	0.125**	0.040	0.023
(Std)		(0.0168)	(0.0276)	(0.041)	(0.052)		
5	35 – 54	0.540***	0.856***	0.286***	0.245***	0.035	0.040
(Std)		(0.0168)	(0.0281)	(0.005)	(0.039)		
5	≥ 55	0.224***	0.306***	0.160 ***	0.140	0.012	0.010
(Std)		(0.0168)	(0.0276)	(0.015)	(0.086)		
R-squared		0.547	0.479	0.235	0.194		

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

Table 11
Linear regression (OLS) of the amount of consumer credit (in logarithm).

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.

their mean default risk and other factors. I study this hypothesis by estimating the impact of four 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, 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 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 the 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 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* (0.0167)	−0.0402** (0.0172)						
Beta $\Delta(-NPL_t)$			−0.0478*** (0.0176)	−0.0551*** (0.0180)				
Beta $ENPL_t$					−0.345*** (0.0129)	−0.399*** (0.0143)		
Beta $\Delta(-ENPL_t)$							−0.0419** (0.0192)	−0.0595*** (0.0201)
$E[NPL_{i,t}]$	−0.290** (0.138)	0.0344 (0.141)	−0.283** (0.136)	0.0280 (0.140)				
$E[ENPL_{i,t}]$					−0.960*** (0.302)	−0.957** (0.394)	−0.0990* (0.0519)	−0.0196 (0.0521)
$\ln(P_{i,t})$		0.213*** (0.0290)		0.205*** (0.0288)		0.0475** (0.0191)		0.205*** (0.0276)
Age 25–34		0.359*** (0.101)		0.353*** (0.100)		0.165** (0.0676)		0.349*** (0.100)
Age 35–44		0.271*** (0.0961)		0.253*** (0.0953)		0.308*** (0.0650)		0.240** (0.0968)
Age 45–54		0.251*** (0.0953)		0.234** (0.0945)		0.209*** (0.0644)		0.225** (0.0959)
Age > 54		−0.155* (0.0929)		−0.170* (0.0921)		−0.258*** (0.0634)		−0.189** (0.0931)
Technical education		0.164*** (0.0620)		0.183*** (0.0622)		−0.0899** (0.0415)		0.175*** (0.0622)
College education		−0.121** (0.0504)		−0.0974** (0.0496)		−0.219*** (0.0331)		−0.110** (0.0494)
Constant	0.256*** (0.0235)	−2.605*** (0.386)	0.254*** (0.0213)	−2.489*** (0.382)	0.126*** (0.0246)	−0.784*** (0.275)	0.254*** (0.0213)	−2.477*** (0.368)
Observations	12,268	12,265	12,268	12,265	12,268	12,265	12,268	12,265
Pseudo R-squared	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*** (0.0159)	0.0477*** (0.0177)						
Beta $\Delta(-NPL_t)$			0.0581*** (0.0158)	0.0465*** (0.0170)				
Beta $ENPL_t$					0.0433*** (0.0108)	0.0260** (0.0116)		
Beta $\Delta(-ENPL_t)$							0.0734*** (0.0175)	0.0341* (0.0195)
$E[NPL_{i,t}]$	0.720*** (0.139)	0.164 (0.139)	0.778*** (0.137)	0.184 (0.138)				
$E[ENPL_{i,t}]$					0.149*** (0.0538)	0.0779 (0.0546)	0.159*** (0.0533)	0.0851 (0.0544)
$\ln(P_{i,t})$		−0.281*** (0.0254)		−0.284*** (0.0252)		−0.295*** (0.0240)		−0.293*** (0.0243)
Age 25–34		−0.196** (0.0869)		−0.193** (0.0870)		−0.195** (0.0869)		−0.192** (0.0869)
Age 35–44		−0.179** (0.0830)		−0.173** (0.0830)		−0.182** (0.0838)		−0.178** (0.0840)
Age 45–54		−0.173** (0.0823)		−0.165** (0.0823)		−0.175** (0.0831)		−0.172** (0.0833)
Age > 54		−0.0724 (0.0791)		−0.0647 (0.0792)		−0.0710 (0.0798)		−0.0678 (0.0803)
Technical education		−0.169*** (0.0588)		−0.172*** (0.0589)		−0.155*** (0.0588)		−0.164*** (0.0588)
College education		−0.223*** (0.0495)		−0.222*** (0.0494)		−0.204*** (0.0487)		−0.210*** (0.0490)
Constant	−1.249*** (0.0212)	2.695*** (0.335)	−1.225*** (0.0191)	2.732*** (0.331)	−1.274*** (0.0200)	2.883*** (0.317)	−1.265*** (0.0188)	2.858*** (0.323)
Observations	12,268	12,265	12,268	12,265	12,268	12,265	12,268	12,265
Pseudo R-squared	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.

Table 14
Loan regressions estimated on group means by age-cohorts of the household head.

Variables / Model	(1)	(2)[b]	(3)	(4)[b]	(5)	(6)[b]	(7)	(8)[b]
A: Linear regression (OLS) of the amount of consumer credit (in log) and the default-beta								
Beta NPL_t	−0.935***	−1.175***						
	(0.115)	(0.342)						
Beta $\Delta(-NPL_t)$			−1.204***	−0.745**				
			(0.147)	(0.301)				
Beta $ENPL_t$					−0.236**	−1.151***		
					(0.104)	(0.332)		
Beta $\Delta(-ENPL_t)$							−0.755***	−0.470**
							(0.154)	(0.219)
$E[NPL_{i,t}]$	−23.02***	−16.98**	−2.462	−13.47*				
	(2.839)	(7.102)	(3.366)	(7.053)				
$E[ENPL_{i,t}]$					−10.08***	−10.75***	−2.642	−7.031**
					(1.504)	(3.359)	(2.203)	(3.129)
Observations	262	262	262	262	262	262	262	262
R-squared	0.295	0.445	0.298	0.432	0.194	0.446	0.247	0.430
R-squared weighted[a]	0.388	0.644	0.311	0.649	0.251	0.645	0.248	0.643
B: Probability of having a consumer credit (Probit) and the default-beta of the households								
Beta NPL_t	−0.423***	−1.003***						
	(0.145)	(0.388)						
Beta $\Delta(-NPL_t)$			−0.368**	−0.802**				
			(0.175)	(0.352)				
Beta $ENPL_t$					−0.169***	−0.920**		
					(0.024)	(0.365)		
Beta $\Delta(-ENPL_t)$							−0.179**	−0.573**
							(0.071)	(0.266)
$E[NPL_{i,t}]$	−9.801***	−29.63***	−2.895	−25.50***				
	(3.787)	(9.059)	(4.345)	(8.735)				
$E[ENPL_{i,t}]$					−3.779*	−12.03***	−2.254	−9.910**
					(1.999)	(4.216)	(2.831)	(4.033)
Observations	516	514	516	514	516	514	516	514
Pseudo R-squared	0.025	0.062	0.156	0.288	0.021	0.056	0.071	0.122
Pseudo R^2 weighted[a]	0.029	0.245	0.326	0.570	0.331	0.470	0.047	0.209
C: Probability of being Credit Constrained (Probit) and the default-beta of the households								
Beta NPL_t	0.825***	1.808***						
	(0.164)	(0.426)						
Beta $\Delta(-NPL_t)$			0.752***	1.453***				
			(0.188)	(0.385)				
Beta $ENPL_t$					0.361***	1.689***		
					(0.136)	(0.391)		
Beta $\Delta(-ENPL_t)$							0.367**	1.107***
							(0.182)	(0.299)
$E[NPL_{i,t}]$	18.36***	42.82***	3.301	33.87***				
	(4.441)	(10.20)	(4.814)	(9.691)				
$E[ENPL_{i,t}]$					8.307***	19.50***	4.262	15.44***
					(2.546)	(4.729)	(3.403)	(4.544)
Observations	516	514	516	514	516	514	516	514
Pseudo R-squared	0.070	0.159	0.053	0.192	0.041	0.156	0.039	0.141
Pseudo R^2 weighted[a]	0.099	0.275	0.074	0.349	0.137	0.329	0.056	0.302

a) Weighted by the population of each age cohort. b) Regressions with controls for the log of the Permanent Income, 10-year age groups and education dummies. Robust Standard-errors in ( ). ***, **, * :1%, 5% and 10% statistical significance.

The $\underline{R}$-squared or Pseudo R-squared values of the regressions in Tables 11, 12 and 13 are low. This is to be expected because these regressions are at the level of individual households, unlike the previous sections that analyzed a portfolio of many loans for a certain segment, an entire bank or even the sum of all the banks. If a researcher estimates a model on micro-data such as $y_{i,t} = \beta x_{i,t} + \varepsilon_t + \tilde{\varepsilon}_{i,t}$, with $\tilde{\varepsilon}_{i,t}$ being an individual idiosyncratic term, then the R-squared usually increases substantially as the model is estimated on averages of groups of many observations since the error $\tilde{\varepsilon}_{i,t}$ disappears. The reason is that the data of individuals are influenced by many idiosyncratic factors that affect their loan options (ex: the family decided to get a new loan for a car and was rejected, or their previous bank agency's loan officer moved to another county), while data aggregated by means of groups such as age-cohorts and counties are less affected by such individual specific shocks. This implies that an economic model with a low R-squared on a micro-data of individuals may actually have a reasonable predictive power at a more aggregate level.

To represent the predictive power of the default-beta I re-estimate the regressions of Tables 11, 12 and 13 on means of age-cohorts of the household heads (i.e., observations represent the mean of heads with age 22, 23,...). Table 14 summarizes the results of this age-aggregation exercise. All the coefficients of the default-beta and expected default frequency keep the same sign and interpretation as in the individual data regressions, with the default-beta having a negative impact on loan amounts (Table 14.A) and on the probability of getting a loan (Table 14.B), while having a positive impact on the probability of being excluded from credit (Table 14.C). The statistical significance of the age-cohort regression coefficients remains as high or higher as in the individual regressions. R^2 values are reported for both the case in which all age-cohorts are treated equally and for the case in which the errors are weighted by the population value of each age-cohort. For the loan amount regressions, the R-squared values are in the range of 0.19–0.45 for the non-weighted cohorts and between 0.25–0.65 for the weighted cohorts. For the probability of getting a loan, the R-squares have a range of 0.021–0.29 for the non-weighted cohorts and between 0.029–0.57 for the weighted cohorts. The R^2 values of the probability of being excluded from credit have a range of 0.039–0.19 for the non-weighted cohorts and of 0.056–0.35 for the weighted cohorts.

In summary, this analysis shows that while the default-beta may be a poor predictor of the behavior of a specific household, it has a strong predictive power for measuring loan behavior for an average group of consumers or a portfolio of several loans (as shown in the previous sections).

5. Conclusions

This article advances a strong research agenda on households and economy wide risk linkages (Parker, 2014). It takes a portfolio view of consumer credit, using a structural model of households' budget constraints and a behavioral default decision rule (Madeira, 2018). I find that consumer loan portfolios have a substantial covariance risk and are substantially more risky than stocks. Also, the impact of aggregate risk on banks is roughly symmetric during both the good and negative periods of the business cycle. Banks differ substantially in terms of their covariance risk, which depends on the age and income of their clients. Banks' portfolios are highly susceptible to negative shocks in recessions and would suffer substantially if a similar economic crisis as the Asian crisis would happen again. Banks 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 find that both the probability of getting consumer credit and the loan amount decline with the household's covariance risk, showing that lenders treat such clients as having higher risk even after other factors are taken into account. Furthermore, the probability of households being credit constrained (borrowers who wanted a consumer loan, but were rejected) increases with covariance risk, confirming that the increased credit restrictions come from the lenders side.

This article has strong implications for policy makers and financial institutions (Parker, 2014). 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. An analysis of three stress tests (fall in loan maturities, increase in real interest rates, and a reduction in the access to new loans) show that the Chilean banks' loan portfolios would deteriorate significantly in all scenarios, especially in the case of liquidity shortage.

Finally, investors that are aware of the heterogeneity of beta covariance risk across loan portfolios and household types, can assess their aggregate risk and correlation to other assets. 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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