Incomplete Information in the Mortgage Loan Market

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1. Introduction

There is broad evidence in the literature on the effects informational asymmetries —scenarios in which one agent has more or better information than a counterparty— have on the efficient allocation of resources, in specific these may translate into price distortions and suboptimal equilibrium outcomes (Akerlof, 1970). These asymmetries are present in many settings, including the credit market (Jaffee and Russell, 1976). This document examines the case of the mortgage market in Chile, whose informational structure gives rise to strategic behavior and distortions in credit assessment. The implications of these asymmetries can be extrapolated to other segments —for example, the consumer segment— which are characterized by the same information failures described below.

In the particular case of the credit market, there are elements of both adverse selection and moral hazard, where the lenders do not know the true intention or payment capacity of the debtors and therefore must infer these characteristics based on information available from credit registries and other sources. Debtors, in turn, send signals to the lenders through their payment behavior and information on income and assets. When information is not shared among parties, and when the available information does not allow the identification of debtors in terms of their payment probability, the resulting uncertainty is reflected in credit rationing and increases in the differential between lending and deposit rates (Stiglitz and Weiss, 1981; King, 1986).

2. Information structure

In the case of Chile, the credit information system is dominated by negative information (e.g., arrears), with some positive information (e.g., on-time payments)[2]/ (Turner, 2010; Álvarez et al., 2011). On the one hand, the Superintendency of Banks and Financial Institutions (SBIF) maintains a credit registry containing both positive and negative bank information reported by banks and some savings and loan associations. On the other, the Chamber of Commerce collects information on debt arrears (both bank and nonbank) associated to a given debtor. However, there is no consolidated registry of financial obligations comprising information from all lenders. Rather, the available information is fragmented. Furthermore, there is a lag in the updating of the bank debtor registry, which creates a window of time during which debtors can engage in strategic behavior, in order to present themselves as having less debt than they actually do. Consequently, lenders could have an incomplete perspective of their clients' debt situation when they are assessing their payment capacity. Here, the literature recognizes two main channels through which mortgage default can occur: a lack

[1]/ Financial Stability Area, Financial Policy Division, Central Bank of Chile.
[2]/ Positive event records include on-time past payments and unused revolving credit.

of liquidity and negative equity. Under the liquidity channel, debtors stop paying when they receive an income shock that leaves them with insufficient funds. Debtors with a high level of debt service are more vulnerable to this risk. In the case of negative equity, homeowners default on their mortgage when the loan exceeds the value of the property. This mechanism is not very important in Chile, however, given the local institutional framework. Thus, access to complete information on the totality of a debtor's obligations is crucial for a correct assessment of credit risk (Eiul et a l., 2010; Goodman et a l., 201o; Pagano and Japelli, 1993).

The analysis in this box is confined to the mortgage market in the period from 2012 to 2017. However, the conclusions obtained can be extrapolated to the consumer loan segment, which is characterized by a larger number of both lenders and borrowers than the mortgage segment /3. The analysis centers on two market participants who only partially share information: banks and mutual societies /4. Banks cannot observe mortgage debt contracted with mutuals, whereas mutual do have access to bank debt information-published by the SBIF- for assessing loan applications, although they do not observe loans from other mutuals. Additionally, new bank loans are added to the registry with a lag. Finally, negative credit history information is available for both banks and mutual. Taken together, this creates a scenario in which neither type of institution is working with complete information.

3. Background on the mortgage market

Banks are the main mortgage lenders in Chile, with a total of 1,1 million debtors and a mortgage portfolio equivalent to 29% of GDP in the third quarter of 2018. Mutual societies are nonbank mortgage lenders that are usually associated with life insurance companies; they serve a total of 65.000 debtors and have a portfolio equivalent to 2,4% of GDP. The main financing instrument used by banks is non-endorsable mortgage loans, which offer a lot of loan flexibility and usually finance 90% of the value of the property (FSR, second half of 2018). In contrast, mutuals generally use endorsable mortgage loans, with a loan-to-value (LTV) ratio of around 80%. This gap in the LTV between institutions narrowed after the introduction of new bank mortgage regulations in January 2016, when the median bank LTV was adjusted from 90 to 80% (FSR, second half of 2018). Additionally, in July 2012-when changes were introduced to the Insurance Law-new regulations were applied to mortgage insurances/5 in order to increase competition and reduce the costs of brokerage through public auctions of mortgage loan insurance (FSR, first half of 2012).

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[3]/ According to SBIF data, there were over a million bank; mortgage debtors in July 2018, versus 4,4 million consumer loan debtors (without discounting debtors who have both types of debt). In terms of lenders, banks (13 in July 2018), mutuals (12 in October 2018), and some S&Ls (4 in October 2018) participate in the mortgage loan market. The consumer loan market includes the former lenders plus the family compensation funds, retailers, car lenders, and others.

[4]/ Also called Endorsable Mortgage Management Agencies (Agentes Administradores de Mutuos Hipotecarios no Endosables, AAMHE)

[5]/ Joint SVS Rule N° 330 and SBF Rule N° 3530 f or Banks, N° 147 for Savings and Loan Associations, N° 62 for Subsidaries, on the individual and collective contracting of mortgage insurance.

4. Types of mortgage debtors

The sample can be used to compare three groups of debtors: namely, those who have mortgage debt (i) only from banks, (ii) only from mutuals, and (iii) from both banks and mutuals. The "only mutuals" group has a somewhat lower default rate than the "only banks" group, in the case of both one and two lenders by type. This may reflect the relatively higher savings capacity necessary for choosing a mutual loan, given the lower LTV ratio. The group of debtors that simultaneously has loans from both banks and mutuals provides an opportunity to verify the hypothesis on the existence of distortions described earlier. Specifically, given that lenders do not share complete information, their credit assessment cannot take into account all financial obligations and thus underestimates the debtor's financial burden and default probability. The results support the hypothesis: the default rate in the group that holds mortgages with both banks and mutuals is more than double the rate of those with loans from just one type of institution (figure 1). This finding is in line with other empirical studies, which conclude that a system characterized by more and better information can improve debtors' access to credit and lenders' credit assessment, thereby reducing the adverse selection and moral hazard problems (Brown and Zehnder, 2007)

In terms of sequencing, there is no evidence of a bias in the order of default, that is, there is no indication of preference toward defaulting first on one debt versus the other. However, for the group with loans from both types of lenders, the bank loan is usually granted before the mutual loan, with a median of 40 days between the two events. This period is less than the usual lag of 45 days before the bank mortgage appears in the debt report published by the SBIF, so the mutuals are not able to take these loan originations into account in their credit assessment.

5. Determinants of Mortgage Default

In order to study the determinants of mortgage default, we conduct logit regressions including the behavior of mortgage debtors in mutuals, banks and both. We consider the three types of default rate, depending on persistence of the default:

DR1: Percentage of debtors with arrears of over 90 days up to 180 days.

DR2: Percentage of debtors with arrears of over 90 days up to 1 year.

DR3: Percentage of debtors with arrears of over 90 days up to 3 years.

We can say that DR1 measures the new "flow" of default, debtors that recently have fallen into arrears, and DR3 measures the default with high persistence.

As explanatory variables, we use separately the number of banks and mutuals that a debtor is holding debt within a quarter, the tercile of the total debt to credit card limit, and the credit history. The credit history is a binary variable and its definition varies according to the kind of default under analysis in the logit model. It takes the value one if the debtor was on default at least one period within a year, where the year ends when the time window of the contemporaneous default starts.

Thus, we are not overlapping the credit history and the contemporaneous default. This variable is not considered if the default rate goes from 90 days up to 3 years due to sample length limitations. Additionally, we add the electoral district as a characteristic of the debtor.

$$log\left[\frac{P(DR^{(j)}=1)}{1-P(DR^{(j)}=1)}\right] = \alpha + \beta^{(j)}CH^{(j)} + \gamma B + \delta M + \rho RDC3 \qquad \text{j=1, 2 y 3}$$

Where DR1, DR2 and DR3 are the definitions of default rate specified before. CH1 and CH2 are dummies capturing the credit history according to DR1 and DR2, respectively. RDC3 is the tercile of total debt to credit card limit. M and B are the number of mutuals and banks that the debtor is holding debt with, respectively. The panel time window is from March 2012 to September 2017 with quarterly data.

The magnitude of the impact of each variable is calculated by marginal effects (table 1). The credit card limit tercile is significant and negative for all the definitions of default. Therefore, the higher the income debtor, the lower the probability that the debtor will default on his mortgage debt. The probability increases with the type of default, being higher with long-term default. The number of banks have a significant and positive impact. The effect of the number of mutuals is only significant for one mutual. The credit history is an important variable reflecting the fact that the past behavior of a debtor is important to predict the future behavior. Furthermore, it has a bigger effect when the default goes from 90 days up to 1 year.

6. Final Remarks

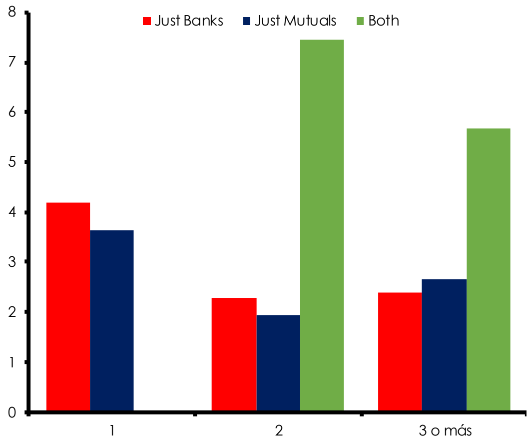
The absence of a consolidated system for reporting loan information hinders the identification and analysis of credit risk, especially in the case of debtors who have loans from more than one type of lender. A system containing both positive and negative information would help lenders predict default probabilities more precisely /[6]. In the particular context of the Chilean mortgage market, the evidence suggests that the existence of information asymmetries has an impact on the behavior of market agents, in particular in terms of default. Debtors who simultaneously hold loans from lenders that do not share debt information have a higher probability of default. This derives from a partial credit assessment, in which the debtor's total financial burden and default probability are underestimated. These findings confirm that the Chilean financial system needs to make progress in terms of closing the information gaps, in order to reduce distortions in both prices and equilibrium outcomes and to minimize the risks for financial stability (FSR, first half 2018, chapter II).

[6]/ Barren y Staten, 2002; Powell et al., 2004; Turner et al., 2007.

Figure 1

Mortgage Default Rate by Type and Number of Institution. Third quarter 2017.

(Percent of debtors in each group)



(*) 90 to 180 day default rate. The "only banks" group includes 95,2% of debtors; only mutuals, 4,4%; and both 0,3%

Fuente: Central Bank of Chile based on SBIF and CMF data.

Table 1

Logit Regression Output: Marginal Effects (*)

	DR1	DR2	DR3
Credit Hist. 1.	0.257***	0.322***	-
Banks (*)			
1	0.013***	0.022***	0.039***
2	0.005**	0.010***	0.014***
3	0.011**	0.016***	0.021***
Mutuals (*)			
1	0.019***	0.027***	0.058***
2	-0.013	-0.026	-0.045*
3	-0.007	-0.010	-0.028
RDC3 (*)			
2	-0.003***	-0.005***	-0.015**
3	-0.008***	-0.013***	-0.031**
N	1068346	1068346	1068346
r2_p	0.2088	0.1927	0.0159
Cluster	Region Quarter	Region Quarter	Region Quarter
Obs (**)	controlled by region and quarter	controlled by region and quarter	controlled by region and quarter

(*) Banks and Mutuals: The variables are discrete in the range 0, 1, 2 and 3, where three can be three or more. Additionally, per number we add a dummy.

Source: Central Bank of Chile.

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Household stress testing using micro survey data: evidence from Chile

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Abstract

This note details the methodology used to estimate the impact of different stress test scenarios on the household debt delinquency in Chile. The model uses the Chilean Household Finance Survey (EFH) micro data to estimate loan delinquency for mortgages, consumer installment loans and credit cards. The delinquency risk of each type of loan is then aggregated to give the debt at risk for the total household debt. Stress test scenarios are considered for small, moderate and large increases of unemployment. More severe stress test scenarios consider a shock to consumer loan renewal, house price declines and a crisis of rental properties, in addition to the large increase in unemployment.

1. Introduction

Household debt is an asset of increased relevance in the balance sheets of financial institutions, reaching more than 100% of the GDP in several countries (Cecchetti, Mohanty, and Zampolli, 2011). Measuring household loan risk is increasingly relevant (Parker, 2014), especially as regulators discuss countercyclical macro-prudential tools, such as capital buffers and loan loss provisions (Rubio and Carrasco, 2016).

Table 1
Stress test scenarios (EFH: 2011, 2014, 2017) (1) (2)

Type of shock	Scenarios				
	A	B	C.0	C.1	C.2
1. Increase in the national unemployment rate (heterogeneous by worker type: gender, age, industry, income quintile, region). Shock affects both the frequency and duration of each worker's type unemployment spells.	1%	2%	4%	4%	4%
2. Job quality: income volatility, increased labor flows to self-employment, smaller companies, jobs with less than the desired hours.	-	Average rates in ENE 2010-17	Worst rates in ENE 2010-17	Worst rates in ENE 2010-17	Worst rates in ENE 2010-17
3. Frictions in renewing consumer loans.	-	-	-	Yes	Yes
4. Increase in 5% of the real interest rate for new consumer loans.	-	-	-	-	Yes

(1) Calibration made from micro-survey data on employment/income (ENE/ESI, 1990-2017) and expenditures (EPF, 2012).
(2) Methodology for unemployment risk, labor flows, income volatility and non-durable expenditures is described in Madeira (2015, 2018).
Source: Central Bank of Chile.

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This article uses micro-survey data to show how the debt portfolio of households in Chile would react under different stress test scenarios. The scenarios include a small increase in the national unemployment rate (1%), a moderate increase in unemployment (2%) and a severe increase in unemployment (4%). The moderate and the sharp increase in unemployment are also, respectively, accompanied by an average and severe deterioration of the job quality for the workers who remain employed and therefore did not experience an unemployment spell. Table 1 summarizes the stress exercises.

Table 2
Stress test scenarios for property owners (EFH, 2014, 2017) (1)(2)(3)

Type of shock	Scenarios: C.0: + 4% unemployment	+ home prices and rental market crisis	+ Credit frictions
1. Increase in unemployment frequency and duration (heterogeneous by worker type: gender, age, industry, income quintile, region).	4%	4%	4%
2. Job quality: income volatility, increased labor flows to self-employment, smaller firms, jobs with hours less than the desired.	Worst rates in ENE/ESI 2010-2017	Worst rates in ENE/ESI 2010-2018	Worst rates in ENE/ESI 2010-2019
3 & 4. Frictions in renewing consumer loans. Increase in 5% of the real interest rate for new consumer loans.	-	-	Yes
5. Nominal drop in property prices similar to the USA (2006-2012): 51%, 40%, 28%, for low, middle and high tier homes, respectively	-	Yes	Yes
6. Rental vacancies increase in 50%. Non-payment by renters that suffer unemployment or a 20% income drop (heterogeneous shocks for low, middle and high tier properties based on the EFH).	-	Yes	Yes

(1) Calibration made from micro-survey data on employment/income (ENE/ESI, 1990-2017) and expenditures (EPF, 2012).
(2) Methodology for unemployment risk, labor flows, income volatility and non-durable expenditures is described in Madeira (2015, 2018).
(3) Calibration for house price drops based on Cohen et al. (2012) and vacancy increase based on US 1993-2000 change (US Census Bureau, 2019).
Source: Central Bank of Chile.

Then I consider even more extreme scenarios that include credit frictions (with difficulties for highly indebted households to access new consumer loans or with households receiving new loans at a 5% higher real interest rate). Finally, I consider three harsher scenarios that deal specifically with the housing market: i) a drop in nominal housing prices that mirrors the American crisis of 2006 (see Table 3); ii) an increase in 50% in the number of vacant properties for renting (similar to the increase in the US between 1993 and 2009, US Census Bureau, 2019) and an increase in non-payment from families of renters affected by unemployment or an income shock higher or above 20%; and iii) a scenario that combines both shocks. The role of shocks to housing prices and also to rent income from second properties has been highlighted in other countries such as the US (Haughwout et al., 2011, Albanesi et al., 2017). These shocks are increasingly relevant for Chile as more households invest in the purchase of second properties that are then rented to others (Sabatini et al., 2014, Banco Central de Chile, 2019). Table 2 summarizes the stress scenarios affecting the property market. The idea of these scenarios is that a drop in housing prices affects all property owners (whether it is the main property of the household or a second property used for renting or investment purposes), while a shock to the vacancy rate and nonpayment of renters affects the finances of those households that receive income from renting other properties.

The calibration of the Debt at Risk in the stress tests is estimated with the Chilean Household Finance Survey (EFH), following a delinquency model that accounts for several risk factors of the household, including demographics (age, education, region and number of members of the household), unemployment risk, income, plus loan liquidity and financial solvency.

The results, which are discussed in detail in the most recent Financial Stability Report (Banco Central de Chile, 2019), show that the Chilean households are robust to small and moderate shocks, but that severe shocks that combine severe unemployment increases and credit frictions have a significant impact on loan default and could affect the banking system's balance sheet. This article is limited to discussing the methodology and calibration of the exercises shown in the Financial Stability Report.

Table 3
Home price change across 19 US metropolitan areas
(percentage, median)

Home price change between 2006-2012	Nominal	Real
All	-35.3	-41.3
Low tier	-51.0	-57.0
Middle tier	-40.2	-46.2
High tier	-27.6	-33.6

Source: Own calculations based on tables in Cohen et al. (2012).

Section 2 describes the micro survey datasets used to estimate the stress test scenarios. Section 3 describes the concept of Debt at Risk and how the delinquency model is estimated. Section 4 describes the implementation of the labor market stress test scenarios. Section 5 describes the implementation of the credit market stress test scenarios and the property market scenarios. Section 6 concludes.

2. Data

This work uses mainly the Chilean Household Finance survey (in Spanish, Encuesta Financiera de Hogares, from hence on, EFH). The EFH is a survey with extensive information on household finances, including their demographics, income, labor status, assets, loans, plus default behavior.

I match each EFH household member to the unemployment risk and job finding rates of workers with similar characteristics in the Chilean Income and Unemployment Survey (in Spanish, Encuesta Nacional de Empleo / Encuesta Suplementaria de Ingresos, from hence on, ENE/ESI, 1990-2017), according to the procedure described in Madeira (2018, 2019). The ENE/ESI survey has information on the employment and income of around 35,000 households in each quarter, therefore it provides accurate information on the unemployment, job separation and job finding rates for several types of workers (Madeira, 2015).

For each EFH household I also build a non-durable expenditure profile using the Chilean Household Expenditure Survey (in Spanish, Encuesta de Presupuestos Familiares, EPF, wave 2012). The EPF survey has highly detailed information on non-durable and durable expenditures for a sample of 10,000 households.

3. Methodology for measuring Debt at Risk (DAR)

$DAR_t(k)$, the debt at risk for each loan category k (with k being mortgages, consumer installment loans, banking credit cards, retail credit cards) is measured as the sum of the delinquency probabilities for the debt of each household weighted by its debt amount in relation to the total value of the loan portfolio:

$$DAR_t(k) = \frac{\sum_{i=1}^{N} Pr\left(Df_{i,t}(k) = 1 \middle| X_{i,t}, \beta_k\right) D_{i,t}(k)}{\sum_{i=1}^{N} D_{i,t}(k)}$$

where Pr(.) comes from a binary event model (ex: probit), $Df_{i,t}(k)$ is a dummy variable denoting 1 if the household i's loan at time t is in delinquency and $D_{i,t}(k)$ is its total debt amount in category k. $X_{i,t}$ denotes the household's risk vector and β_k is the vector of coefficients for the probability model of each debt type.

Finally, DAR_t, the debt at risk for the total household debt is given as the sum of the individual values of the debt at risk for each type of loan k, weighted by the value of each loan type among the total debt:

$$DAR_t = \frac{\sum_k \sum_{i=1}^{N} Pr\left(Df_{i,t}(k) = 1 \middle| X_{i,t}, \beta_k\right) D_{i,t}(k)}{\sum_k \sum_{i=1}^{N} D_{i,t}(k)}$$

Using the EFH Survey I estimate a loan delinquency model for each kind of debt: mortgages, consumer installment loans, banking consumer installment loans, banking credit cards and lines of credit, and retail store credit cards. The loan delinquency model considers the household current income (monthly, in log), the household's unemployment risk (a weighted average of the unemployment probability of each member, see Madeira, 2018), the ratio of consumer debt to the household's annual permanent income (RDI, with permanent income being the sum of the non-labor income and of the labor income of each household member during the employment and unemployment spells over a year, see Madeira, 2018, 2019), the ratio of current debt service to monthly household income (RDSI), the number of household members, plus the region, education, age, gender and civil status of the household head. For the mortgage loan model I also use as a control the ratio of total household debt to assets (RDA) as a measure of solvency.

Table 4

Probit estimates of the delinquency of each debt type (pooled EFH 2010, 2011, 2014, 2017) (1)

Controls	Consumer instalment loans (3 months or more)	Banking consumer loans (3 months or more)	Banking credit card (2)	Retail store credit card (2)	Mortgage (3 months or more)
$RDA_{i,t}$ = Total Debt / Assets	-	-	-	-	0.341**
u(x(i),t): unemployment risk	2.492***	1.254	3.290***	2.566***	-0.356
$\log(Y_{i,t})$: log income	-0.117***	-0.219***	-0.0848**	-0.201***	-0.206***
$RDI_{i,t}$ = Consumer Debt/P	0.291**	0.743***	0.724***	0.228*	0.195
$RDSI_{i,t}$ = Total Debt Service/Y	0.445***	-0.259	0.761***	0.597***	0.265
Nr of Members of the household	0.112***	0.0826***	0.0171	0.122***	0.147***
College education of household head	-0.343***	-0.581***	-0.222**	-0.535***	-0.436***
Number of observations	4,808	2,327	4,796	7,591	2,787
Pseudo R^2	0.07	0.108	0.096	0.122	0.118
R^2: income strata /year regression	0.478	0.715	0.844	0.766	0.807

(1) Other controls: age, region (metropolitan region dummy), gender and technical education dummy of the household head.

(2) For credit cards the definition of delinquency is a payment below the minimum amount charged (this option is used because credit card missed payments can become revolving debt).

Source: Central Bank of Chile based on Household Financial Survey 2014 and 2017 and ENE/ESI 1990-2017.

The estimated delinquency model, shown in Table 4, applies several risk variables used in previous research for loan default in Chile (Madeira, 2014) and the US (Elul et al, 2010). The EFH waves before 2010 are not used because in those years the survey only recorded whether the household was in arrears over the last year for any of its loans, but it did not ask which loan was in arrears and for how many months. I measure the risk of loans at 3 months or more in arrears, because it is the most usual international indicator for loan delinquency (Madeira, 2019) and it is correlated with large loan losses in Chile (Matus, 2015). Delinquency risk increases with households' unemployment risk (except for mortgages), low income, high consumer loan leverage measured by RDI (although not statistically significant for mortgages), high debt service measured by RDSI (although not statistically significant for banking installment loans and mortgages), lower education and larger households. The Pseudo-R squared of the delinquency models is low for the microdata sample (Wooldridge, 2010). However, if one obtains the predictions from each model and then computes the mean prediction for borrower groups in a larger sample such as households with the same income strata (low, middle, high income, given by percentiles 1-50, 51-80, and 81-100), then the mean predictions of the models have a high R-square for the actual mean observations of those groups, which shows the models have power to explain aggregate events.

The variables of the loan delinquency model in Table 4 are then affected by the stress test scenarios, which change some variables directly (such as the unemployment risk, the current monthly income Y and the annual permanent income P) and some financial ratio variables that are affected indirectly due to a change in the denominator (such as RDI and RDSI). Finally, some shocks such as the credit market shock can affect the loan default probability directly (Pr(Df)) and the housing prices affect the ratio of debt to assets (RDA). Table 5 summarizes how the stress tests change each one of the loan delinquency risk factors. The next sections will explain in more detail the labor and non-labor shocks faced by the households in the stress test scenarios.

Table 5
Type of shock and affected variables in the delinquency model

Shock	Direct impact	Indirect Impact through Y and P
Unemployment risk and its duration	u(x,t),Y	RDI, RDSI
Labor quality and wage volatility	Y	RDI, RDSI
Credit market shock	Pr(Df), RDSI	
Housing prices	RDA	
Property vacancy and non-payment	Y	RDI, RDSI

Source: Central Bank of Chile

4. Methodology for the Labor market shocks

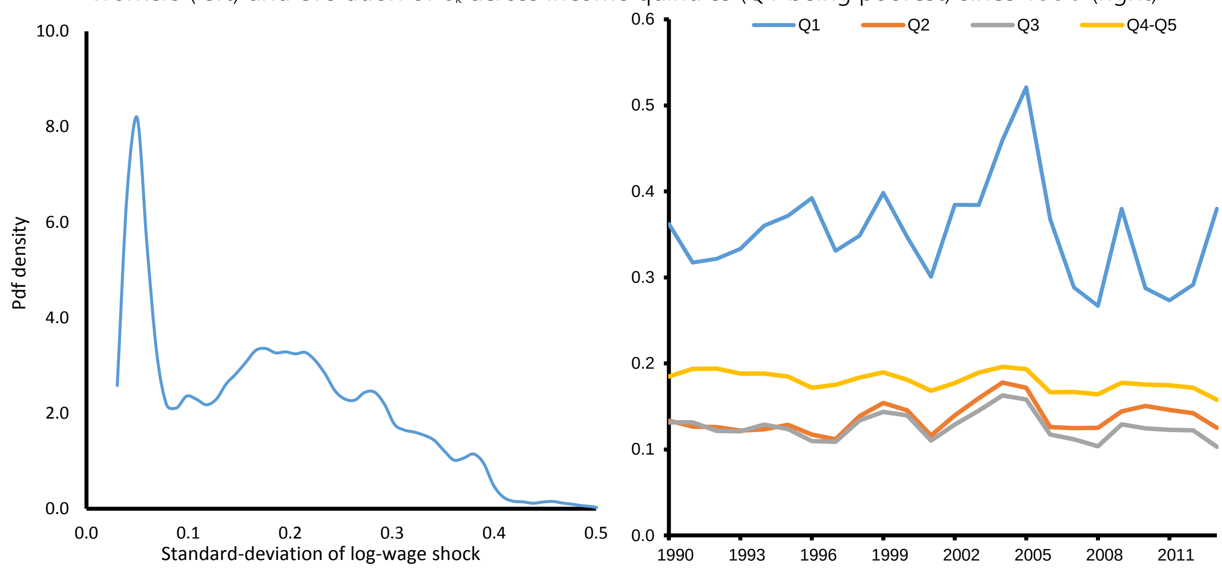
The variables of each household are then changed according to whether they were affected by an idiosyncratic shock. Using the unemployment, job separation and job finding rate for 504 different types of workers (according to gender, age, education, industry, and Metropolitan Region or not) from Madeira (2015), I estimate the sensitivity of each group k relative to aggregate unemployment shocks:

$$y(k,t) = \gamma x(k) + \theta x(k) u(t)$$

where x(k) corresponds to dummies of gender, age, education, industry and Metropolitan Region of the workers of type k. The variable y is a generic notation for a labor variable of each group k at at time t such as unemployment (u), the job separation (λ^{EU}) and the job finding rate (λ^{UE}).

For each scenario of an increase in the unemployment rate, I then obtain the predicted unemployment increase for each group and the predicted job finding rate for each worker affected by unemployment. Using pseudo uniform numbers some EFH workers are assigned to unemployment conditional on the estimated unemployment increase of their type k. Also, for each worker in unemployment I assign 4 pseudo-uniform random numbers in order to obtain the duration of the unemployment spell. If the first pseudo uniform random number is below the worker's job finding rate for the scenario then his unemployment duration is just one quarter, if the number is above then we go to the second number and check whether it is below or not the job finding rate, and if above we check the worker's job-finding luck in the third quarter, and so on until the fourth quarter which determines whether the worker faced an unemployment spell of 1 year or more. According to the duration of the unemployment spell, then the workers lose 40% of their labor income for one quarter of unemployment duration, 50% for two quarters, 57% for three quarters and 62% for four quarters or more (these income loss rates for spells above 2 quarters are somewhat optimistic, see Madeira (2015)). Therefore the scenarios consider both a higher frequency of unemployment and a higher duration, which is common in downturns (Madeira, 2015).

Figure 1
Distribution of the standard-deviation of the log-earnings shock σ_k across the population of employed workers (left) and evolution of σ_k across income quintiles (Q1 being poorest) since 1990 (right)



Source: Madeira (2015) based on the ENE/ESI survey data.

Finally, each worker experiences a log-normal income shock given by $\exp(\epsilon_{i,t}\sigma_k)$, where $\epsilon_{i,t}$ is a pseudo-normal random number and σ_k is the mean earnings' volatility of workers of type k in the ESI that remain employed in consecutive years for the period 1990-2017 (Madeira, 2015). Figure 1 shows the heterogeneity of σ_k across different workers and its evolution across different income quintiles since 1990. The mean volatility σ_k is 18.3%, but it ranges between 3% and 40% depending on the worker's type. Since the labor income volatility σ_k does not have a clear cyclical pattern (it increases both in recessions and expansions), then this parameter is set as constant for each worker type. Workers also get other labor quality shocks. The shocks include a 20% income drop if the worker changes from a formal job with contract to an informal job (no contract) or to self-employment. Workers also have a 15% income drop if they change from a large company (with more than 50 workers) to a small or medium company. Finally, some workers receive a 10% income drop if they are not satisfied with their current employment or if they are looking for more hours of work. These shocks are calibrated based on the average and worst rates of these self-reported employment status in the ENE survey between 2010 and 2017. Due to the small number of years, the calibration of the income drop after such events is based on a general rule of thumb.

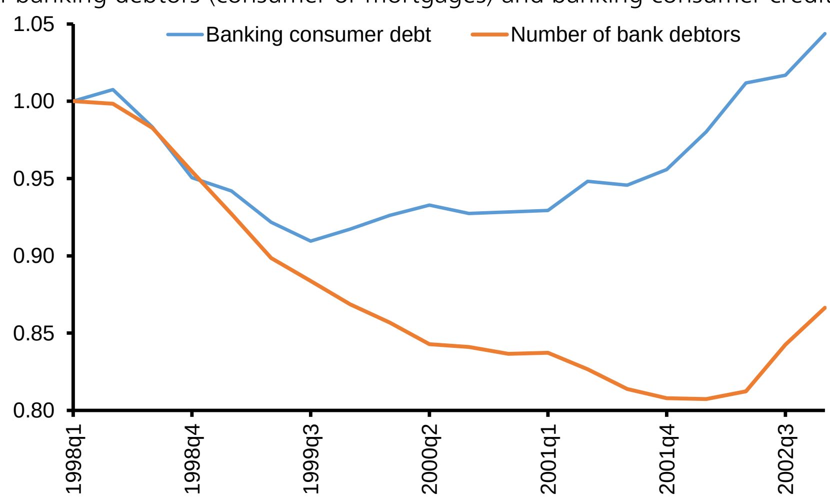
In each stress test, the households' risk vector changes to stress-$X_{i,t}$ (due to shocks to unemployment risk, current income and annual permanent income, which is affected by unemployment duration and by half of the wage volatility: u(x), ln($Y_{i,t}$), $RDI_{i,t}$, $RDSI_{i,t}$), therefore their default probability in the debt at risk (DAR) becomes $Pr\left(Df_{i,t}(k) = 1 \middle| stress - X_{i,t}, \beta_k\right)$. To reduce the simulation error of households suffering shocks by randomness, I expand the EFH sample 50 times with replacement for each test (Madeira, 2018).

5. Methodology for the non-labor shocks: Credit Market and Real Estates shocks

Some consumers can be subject to shocks from credit constraints (Attanasio et al., 2008, Attanasio and Weber, 2010), which happen when households are at a kink of their budget constraint. Suppose households can pay the interest component of their debt commitments and pay part of the amortization component but not the entire amortization payment. In such a case these households remain solvent and are able to keep repaying their debt, but only if they have access to new loans (Madeira, 2018).

Figure 2

Number of banking debtors (consumer or mortgages) and banking consumer credit after 1998



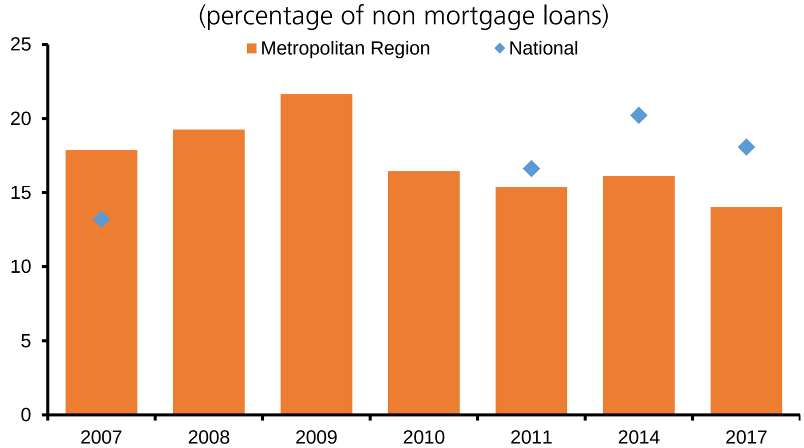
Source: Superintendence of Banks and Financial Institutions.

Some statistics show that in several households in Chile may have had difficulties in accessing new loans or renewing their credit lines in past recessions (Madeira, 2018, Fuentes and Saravia, 2014). After the Asian crisis (Figure 2) there was a contraction of around 10% in the total amount of banking consumer debt and 20% in the number of banking debtors (which includes both mortgage and consumer credit debtors). Also, during the Chilean recession of 2009 there was an increase in the fraction of consumer loans that had a motivation for paying previous debts in the Santiago Metropolitan Region (Figure 3).

For this reason some stress test scenarios include credit market shocks. Households are credit constrained or not (CCi,t=1) if they fulfill two conditions. The first condition is that households have a requirement for more debt, which happens if their monthly debt service ($DS_{i,t}$, obtained from the EFH) plus their estimated consumption needs ($C_{x(i)}^{P50}$) is above their monthly income ($Y_{i,t}$, obtained from the EFH): $1(C_{x(i)}^{P50} + DS_{i,t} > Y_{i,t})$. The consumption needs of each EFH household is obtained from the median non-durable expenditures of households with similar characteristics x in the Chilean Family Expenditure Survey (EPF, 2012). The second condition is that households must be highly indebted already ($1(CD_{i,t} > CD_{x(i)}^{P90})$), therefore lenders may refuse further loans to them. This condition is evaluated by measuring how many households have a consumer debt amount ($CD_{i,t}$, obtained from the EFH) that is above the percentile 90 of debt for other households ($CD_{x(i)}^{P90}$) with similar characteristics x in the EFH survey. To estimate $CD_{x(i)}^{P90}$ and $C_{x(i)}^{P50}$, I use estimates in a linear quantile regression with households of similar characteristics x(i), in terms of permanent household income, number of adults aged 18-65 and children in the household, age and education of the household head, home ownership dummy, Santiago Metropolitan Region dummy.

In Table 6 I report the average amounts for the estimated non-durable expenditures, the sum of non-durable expenditures plus monthly debt service, and the fraction of households that are subject to a need for extra debt ($1(C_{x(i)}^{P50} + DS_{i,t} > Y_{i,t})$), a condition of being already highly indebted ($1(CD_{i,t} > CD_{x(i)}^{P90})$), and the condition of being Credit Constrained ($CC_{i,t}$, both conditions simultaneously).

Figure 3
Self-reported motivation of "paying previous debts" for households
(percentage of non mortgage loans)



Source: EFH, Central Bank of Chile.

The results show that expenditures and the sum of expenditures plus debt service are increasing in income. However, the need for higher debt is decreasing in income level, although there is a higher fraction of upper income households with high values of indebtedness. The results for the credit constraint calibration also make sense. Although only 4.3% of the indebted households are credit constrained, note that the fraction of credit constrained households that are in delinquency for any loan is 12% and the fraction of households with a delayed payment in their bank credit card is 16.4%. This indicates that the credit constraint measure is highly correlated with household liquidity needs and loan payment problems, as expected.

For the stress test scenarios with credit market shocks, I consider that the probability of delinquency of the household is at least 50% if the household was already credit constrained prior to the stress test and 35% if the household only became credit constrained after the stress test: max($15\%1(CC_{i,t}) + 35\%1(CC_{i,t}^{stress-X}), Pr(Df_{i,t}(k) = 1 | stress - X_{i,t}, \beta_k)$). Note that since the stressed values of each household are always worse than the original starting point, then a credit constrained household in the baseline scenario ($CC_{i,t} = 1$) is also constrained for the stress test ($CC_{i,t}^{stress-X} = 1$). This calibration takes into account that some households could access loans prior to becoming credit constrained in the test. The delinquency probability values of 35% and 50% are chosen as high values as a rule of thumb, since households suffering arrears due to liquidity needs remain in default with a high probability after 6 months (Matus, 2015, Madeira, 2018, 2019).

Finally, I consider stress test scenarios that deal specifically with the housing market: i) a drop in nominal housing prices that mirrors the American crisis of 2006 (Cohen et al., 2012); ii) an increase in 50% in the number of vacant properties for renting (similar to the increase in the US between 1993 and 2009, US Census Bureau, 2019) and an increase in non-payment from families of renters affected by unemployment or income falls higher than 20%; and iii) a scenario that combines both shocks. The idea is that a drop in housing prices affects all property owners, while a shock to the vacancy rate and nonpayment of renters affects those households that receive income from renting other properties. Therefore the housing prices shock changes the households' value for the ratio of debt to assets ($RDA_{i,t}$), while the vacancy rate and payment difficulties shocks affects the households' income related variables (log income $Y_{i,t}$, $RDI_{i,t}$, $RDSI_{i,t}$). For simplicity, I consider that the income shock implied by the loss of rental income has the same monetary effect on the current monthly income $Y_{i,t}$ and the annual permanent income $P_{i,t}$.

Table 6

Average values of non-durable expenditures and non-durable expenditures plus debt service (Chilean pesos, monthly) across different types of households. Fraction of households with debt requirements, high indebtedness and credit constrained (percentage of the households in each group).

Household Type	C^{P50}	$CP^{P50} + DS$	$1(CP^{P50} + DS > Y)$	$1(CD > CD^{P90})$	CC
All	352.867	537.982	16,4%	6,4%	2,8%
Income Strata 1: P1-P50 (poorest group)	193.028	269.753	23,0%	5,2%	3,3%
Income Strata 2: P51-P80	394.861	572.315	13,5%	7,3%	2,7%
Income Strata 3: P81-P100	677.848	1.135.566	5,0%	8,0%	1,9%
Debtors	394.340	674.631	19,7%	9,7%	4,3%
Mortgage Debtors	454.489	851.756	12,6%	10,6%	3,3%
Consumer Debtors	394.287	697.874	20,9%	10,5%	4,7%
Bank Credit Card Debtors	421.281	712.425	19,1%	8,3%	3,7%
Retail Credit Card Debtors	373.091	605.688	19,0%	7,7%	3,7%
No delinquency	422.118	758.126	18,8%	12,3%	5,1%
In delinquency (1)	364.956	698.206	29,9%	23,4%	12,0%
Delinquency (3months) for consumer loan	383.658	748.734	33,1%	26,6%	14,4%
Bank credit card delay	430.623	983.436	41,9%	29,3%	16,4%
Retail credit card delay	298.520	573.140	39,7%	12,8%	8,8%

(1) Delinquency includes households with mortgage or consumer installment loans that are 3 months in arrears.
Source: Own estimates based on the pooled EFH survey (2011, 2014, 2017).

In Chile there was never a crisis of real estate prices in nominal terms since 2000. However, since it is possible that Chile may at some point in the future face a crisis similar to other countries, I chose to apply the observed housing market shock from the US crisis of 2006 as an example (see Table 3).

The increase in non-payment due to the unemployment of renters is obtained from the EFH survey itself. Basically, I estimate how many households across three different home tiers (with the low tier being properties with a value or rent in the bottom percentiles 1 to 50 in Chile, the middle tier being properties with a value or rent in the percentiles 51 to 80, and high tier being the top percentiles 81 to 100) had an income shock or a member in unemployment after each stress test. I then assume that this fraction of households with "income difficulties" across different home tiers stopped paying their rents. Furthermore, the stress test scenario assumes that the Chilean national vacancy rate increased from 11% (value from the EFH 2014 and 2017) to 16.5%, with an extra 5.5% of landlords being unable to find renters. Therefore some household owners that were renting other properties stopped receiving income from rents.

6. Conclusions

This article describes the technical implementation for the stress test scenarios described in Chapter IV of the Financial Stability Report. Further information is available from the author upon request. It is worth noting that all the reactions of the households in relation to the stress test scenarios are calibrated. These estimates could be substantially different if the calibration included, for instance, an additional unemployment shock due to a crisis in the construction sector.

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Antecedentes del Mercado de Arriendo Residencial

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1. Introducción

El mercado de arriendo residencial en Chile ha experimentado un importante crecimiento en los últimos quince años. La baja rentabilidad de los activos financieros tradicionales, además de favorables condiciones de financiamiento, han llevado a que inversionistas utilicen los activos inmobiliarios como un activo financiero. De la misma forma, cambios demográficos, como mayor número de hogares unipersonales, cambios en las preferencias de nuevas generaciones, mayor flujo migratorio, entre otros, han impulsado el desarrollo del mercado de arriendo. Sin embargo, a pesar de dicho desarrollo, la información disponible es escasa. Dada la naturaleza descentralizada de las transacciones entre privados, información relevante como precios y holgura de mercado no está disponible de forma sistemática. Así, los agentes deben tomar decisiones basadas en información parcial, lo cual pudiese llevar a estimar con error la rentabilidad por parte de quienes invierten en este tipo de activos. Este documento discute los antecedentes disponibles sobre este mercado y propone nuevas medidas para su seguimiento. Sobre la base de ello, describe el comportamiento de sus cantidades de equilibrio en el último tiempo. De este análisis se desprenden vulnerabilidades y potenciales riesgos de estabilidad financiera.

El porcentaje de hogares chilenos que arrienda su vivienda ha ido en aumento en las últimas dos décadas, según datos de la encuesta CASEN este porcentaje alcanzó 22% en 2017, lo cual contrasta con 17% en 2003. Este aumento se ha dado con la consiguiente disminución en la tasa de propietarios, la cual pasó desde 70 a 60% en el mismo periodo. En la Región Metropolitana (RM) este cambio fue aún mayor, aumentando desde 20 a 28% en igual lapso, siendo gran parte del incremento concentrado en departamentos. Así, en la RM el porcentaje de hogares que habita un departamento arrendado aumentó de 36 a 48% entre los años 2003 y 2017. Como se mencionó previamente, este fenómeno ha ido de la mano con los cambios en factores demográficos, entre ellos, el mayor flujo de inmigrantes (Gráfico 1).

En comparación internacional la tasa de arriendo de Chile se ubica por sobre países en desarrollo, pero en la parte baja de desarrollados (IEF del segundo semestre de 2018), lo que sugiere que existe espacio para que este mercado continúe profundizándose. Por su parte, la EFH 2017 da cuenta que en los últimos años ha aumentado el número de personas que utilizan el crédito hipotecario para adquirir una segunda vivienda con el fin de arrendarla. Estos elementos resaltan la importancia de contar con información respecto del desarrollo de dicho mercado, el cual permita a los agentes tomar decisiones informadas.

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En Chile gran parte de los contratos de arriendo se celebran entre privados de forma descentralizada, lo que dificulta la mantención de estadísticas provenientes de transacciones efectivas, como se realiza por ejemplo en el caso del índice de precios de vivienda para las ventas de inmuebles. Por su parte, considerando la relevancia que han tomado los portales de internet en la búsqueda de propiedades /[2], en este recuadro se utilizan los avisos listados en un portal web /[3] para el período 2011 a 2018, con el fin de construir medidas de precios y de disponibilidad de viviendas en arriendo.

2. Datos y metodología

- Base de datos

La principal base de datos fue proporcionada por Mercado Libre, y corresponde a los avisos de arriendo con sus correspondientes programas (metros cuadrados construidos, metros cuadrados de terreno, número de dormitorios, número de baños y comuna donde se ubica la vivienda) para casas y departamentos con frecuencia trimestral de 2011 hasta 2018. Esta base fue complementada con información de la encuesta CASEN, donde se obtienen las tasas de arriendo a nivel comunal, además de información del Censo y del Catastro de Bienes Raíces (CBR) para obtener el stock de viviendas por comuna.

Como es habitual en el trabajo con bases de datos, se aplicaron algunos filtros para eliminar aquellos datos que pudieran presentar errores de reporte. Debido a que las comunas presentan diferencias en sus distribuciones tanto en tamaño como en precio, los filtros fueron aplicados a nivel comunal. Así, los principales filtros aplicados fueron los siguientes:

- Se eliminan observaciones sin información o con valor cero para precio, dormitorio, baño o construcción.
- Se eliminan observaciones cuyo precio de arriendo en UF se ubica en las colas de la distribución (1% superior e inferior de la muestra).
- Se eliminan observaciones cuyos metros construidos se ubican en las colas de la distribución (1% superior e inferior de la muestra).
- En el caso de las casas, se eliminan observaciones cuyos metros de terreno se ubican en las colas de la distribución (1% superior e inferior de la muestra).
- Se eliminan observaciones cuyo precio de arriendo en UF por metro cuadrado se ubica en las colas de la distribución (1% superior e inferior de la muestra).
- Se eliminan observaciones cuyo número de dormitorios o de baños se ubica en la cola superior de la distribución respectiva (1% superior de la muestra).
- Se eliminan las comunas con menos de 3.000 observaciones para todo el período.

Una vez aplicados los filtros, la base final contiene aproximadamente 230.000 avisos para casas y 754.000 para departamentos.

- Metodología Precios Hedónicos

2/ Zillow Group (2016) indica que un 87% de los compradores usaba internet para buscar propiedades en EE.UU.
3/ Mercado Libre.

Para la determinación de los precios de arriendo se siguió el marco teórico de precios hedónicos (Rosen, 1974), que sugiere que el precio final de un bien (P) está compuesto por la acumulación de valoraciones de sus atributos (C). Así, el logaritmo del precio final se puede expresar de la siguiente forma:

$$ln(P_{it}) = \alpha_0 + \sum_{k=1}^{K} \beta_k C_i^k + \sum_{n=1}^{N} \gamma_n T^n \qquad (1)$$

Donde:

P_{it}: Precio de arriendo de la vivienda i en el periodo t.

C_i^k: Valor de la k-ésima característica para la vivienda i. Las características consideradas pueden incluir: Tamaño de la vivienda, tamaño del terreno (para el caso de casas) y número de baños.

T^n: Dummy temporal que toma el valor 1 si la vivienda es transada en n=t y 0 en otro caso.

La estimación de la ecuación (1) se realiza mediante Mínimos Cuadrados Ordinarios a nivel comunal y por tipo de vivienda. Una vez calculada la valoración de los distintos atributos, se construye un índice de precios considerando el valor de arriendo de una vivienda representativa, esto es, aquella con las características medianas de la muestra a nivel de RM para cada tipo de vivienda. Considerando lo anterior, el índice de precios para la comuna m ($IP_t^m(\overline{C})$) se define como el valor de arriendo estimado de una vivienda con características $\overline{C}$ en el período t respecto del valor de la misma vivienda en el período inicial.

$$IP_t^m(\overline{C}) = \frac{\exp(\alpha_{0,m} + \sum_{k=1}^{K} \beta_{k,m} \overline{C_k} + \gamma_{t,m})}{\exp(\alpha_{0,m} + \sum_{k=1}^{K} \beta_{k,m} \overline{C_k} + \gamma_{1,m})}$$

Una vez que se estima el índice de precios de arriendo para cada comuna, el índice para la RM se obtiene como un promedio ponderado de estás, utilizando como ponderador (ω) una estimación del número de viviendas destinadas al mercado del arriendo de cada comuna. Este ponderador se construye a partir de la información del Catastro de Bienes Raíces (CBR), que permite construir una serie de tiempo del stock de viviendas (ST) para cada comuna. Por otra parte, de la Encuesta CASEN 2015, se estima la tasa de arriendo de cada tipo de vivienda por comuna, la que, por razones de disponibilidad de información, se asume fija en el tiempo. De esta manera, se obtiene una estimación del número de viviendas destinadas al arriendo en cada comuna y periodo.

Así, el stock de viviendas para arriendo (SPA) y el ponderador (ω) se definen como:

$$SPA_t^m = ST_t^m \times Tasa\ de\ arriendo^m$$

Finalmente, debido a que los ponderadores para cada comuna son variables en el tiempo, el índice RM se construye encadenando los índices construidos a partir de los índices comunales. Así:

$$IP_t^{RM} = \prod_{j=1}^{t} I_{(j-1)j}$$

Donde:

$$I_{(t-1)t} = \sum_{m=1}^{M} \frac{IP_t^m}{IP_{t-1}^m} \omega_{t-1}^m$$

- Estimación Tasa de Avisaje

La estimación de la tasa de avisaje se realiza descomponiéndola en sus dos elementos: incidencia y duración (Gabriel y Nothaft, 2001). La incidencia se refiere a la probabilidad que una unidad este vacante, mientras que la duración corresponde al intervalo de tiempo en que la unidad permanece vacante. Debido a la disponibilidad de los datos, estás variables se determinan trimestralmente a nivel comunal. Por su parte, la incidencia se calcula como el número de avisos (A) publicados en una unidad de tiempo sobre el stock destinado a arriendo en el mismo periodo. Así, la incidencia para la comuna m en el período t queda definida como:

$$N_t^m = \frac{A_t^m}{SPA_t^m}$$

Por otra parte, la duración promedio se obtiene como el tiempo total, como proporción del año, que los avisos permanecieron publicados en el trimestre sobre el total de avisos de ese trimestre.

$$D_t^m = \frac{\sum_i Días_i}{A_t^m} * \frac{1}{360}$$

De esta manera la tasa de avisaje (TA) corresponde al producto de la incidencia y la duración promedio.

$$TA_t^m = \frac{A_t^m}{SPA_t^m} * \frac{\sum_i Días_i}{A_t^m} * \frac{1}{360}$$

- Metodología Panel: Relación entre Precio de Arriendo y Tasa de Avisaje

La relación entre tasa de vacancia y precios de arriendo ha sido estudiada previamente en la literatura (Smith, 1974; Rosen y Smith, 1983; Hagen y Hansen, 2010). Esta relación se sustenta en que desviaciones de la tasa de vacancia de su equilibrio, tendría efectos sobre el mecanismo de ajuste de los precios. La descomposición de la tasa de vacancia en sus dos componentes, incidencia y duración, mejora la valoración del efecto de cada uno de estos sobre el cambio en precio. Tanto una menor demanda por unidades como una mayor duración de las unidades vacantes, provocaría un aumento en la tasa de vacancia respecto a su equilibrio, presionando los precios de arriendo a la baja. Cabe destacar, que la medida presentada difiere de la definición de tasa de vacancia, por lo que se aproxima mediante la tasa de avisaje presentada anteriormente.

Para una comuna determinada, la tasa de cambio en los precios de arriendo se expresa como una función de las desviaciones de la tasa de avisaje respecto a su nivel equilibrio o a su tasa natural, donde estas dos últimas variables se encuentran expresadas en logaritmo. Sin embargo, debido a que la tasa de avisaje es el producto de la incidencia y duración, la tasa de cambio en los precios de arriendo se puede expresar como una función de desviaciones respecto de los niveles de equilibrio de cada uno de estas, como sigue:

$$\Delta\, ln(IP_t^m) = \beta\ (\ln(D_n^m) - \ln(D_t^m)) + \kappa\ (\ln(I_n^m) - \ln(I_t^m)) \quad (2)$$

Se asume que los niveles de equilibrio para las distintas variables se mantienen constante en el tiempo para las distintas comunas. De esta manera, la ecuación (2) agregada a nivel comunal queda escrita de la siguiente forma:

$$\Delta\, ln(IP_t^m) = \alpha_0 + \sum_{m=1}^{M-1} \alpha_m * C_m + \beta \ln(D_t^m) + \kappa \ln(I_t^m) \qquad (3)$$

La estimación de la ecuación (3) se realiza mediante un panel para un total de 14 comunas de la RM para departamentos y 13 comunas para casas en el periodo 2011-2018 con frecuencia trimestral, adicionalmente se agregan dummies temporales, con el objetivo de capturar los movimientos agregados del mercado. De forma adicional, se agregan como controles una serie de variables que afectan el mecanismo de ajuste de los precios de arriendo. Entre estas se encuentran variables de financiamiento como la tasa de interés de los BCU5 y relación precio a garantía (LTV), cambios en los precios de vivienda y cambios demográficos como el flujo migratorio. Conceptualmente el valor de una propiedad debiese ser una función, entre otros elementos, del valor presente de los flujos que está podría generar por concepto de arriendo (valor del arriendo) descontados a una tasa que refleje el costo de esta. De esta manera, se espera que tanto el valor de la propiedad como la tasa de interés tengan un efecto positivo sobre los precios de arriendo.

3. Resultados

En primer lugar, si se observa la dinámica de los precios de arriendo, estos mostraron un importante aumento de 28% en el período 2011-2013. Luego se estabilizaron entre los años 2014 y 2016, y retomaron el dinamismo a partir de 2017 (gráfico 2). Lo que respecta a la tasa de avisaje y su descomposición en incidencia y duración, es posible identificar tres períodos. En el primero (2011-2013), el de estabilidad en la tasa de avisaje, se observó una caída en la duración de los avisos al tiempo que aumentaba la incidencia (gráfico 3), lo que ha ido en conjunto con alzas importantes en los precios de arriendo. Por su parte, en el segundo período (2014-2016) se observan aumentos tanto en duración como incidencia, lo que refleja una mayor holgura en este mercado. Esto es coherente con la estabilidad de precios observada en el mismo periodo. En lo reciente, ambas medidas se han reducido, lo que refleja una menor holgura en este mercado, esto ocurre en conjunto con una recuperación del dinamismo en los precios de arriendos en los últimos dos años.

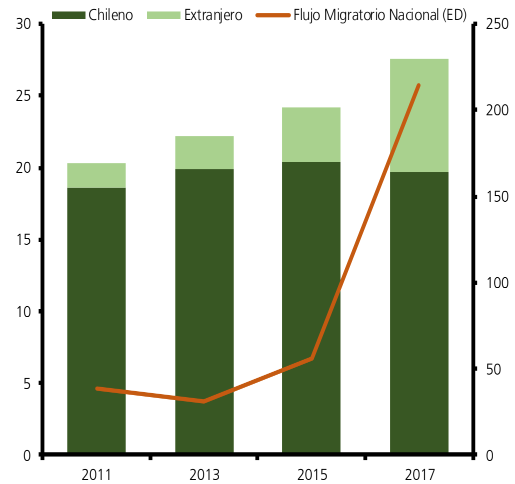
Los resultados confirman los hallazgos de estudios anteriores, indicando la existencia de una relación negativa entre la tasa de avisaje y el crecimiento de los precios de arriendo (Tabla 1). De igual manera, se puede observar que tanto la duración como la incidencia de forma conjunta tienen un efecto negativo y significativo sobre los cambios en precios de arriendo. En particular, un incremento de 4pp en incidencia (unidades disponibles) está asociado con una disminución promedio de 5% anual en precio de arriendo. El efecto en precios es el mismo si la duración aumenta en 4pp. Estos efectos son de significancia estadística y económica considerando que el crecimiento promedio de los precios de arriendo ha sido cercano a 6% anual en la muestra utilizada. De igual manera, cuando se estima el panel para casas y departamentos por separado (Tabla 2 y 3), los efectos de estas variables tienen magnitudes distintas. Un aumento de 4pp en las casas disponibles para arriendo en un trimestre estaría asociado a una reducción de 8% en el precio de arriendo de estas, sin embargo, en departamentos sería de 4% sin ser estadísticamente significativo. Por otra parte, el tiempo que permanecen estas unidades disponibles como proporción del año tendría un mayor efecto en los precios de departamentos, disminuyendo su valor en 7%, pero en casas el impacto en precios sería levemente menor, de un 6%.

Aumentos en la tasa de interés real a cinco años (BCU5) aumentan la demanda y precios de arriendo al elevar el costo relativo de adquirir una vivienda. Al contrario, alzas en la razón deuda a garantía (LTV) presionan a la baja los precios de arriendos. Sin embargo, cuando se considera el efecto del flujo migratorio en los precios de las distintas comunas, el efecto del LTV no es significativo.

4. Conclusiones / Reflexiones Finales

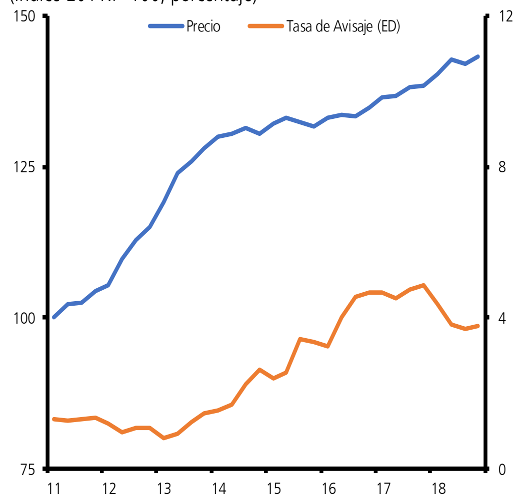
En síntesis, el mercado de arriendo residencial experimentó un crecimiento importante en la última década y, tomando en cuenta el tamaño de dicho mercado en otros países, es posible que continué profundizándose. Desde el punto de vista de estabilidad financiera, hay elementos deseables en la profundización del mercado de arriendos, donde la entrada de agentes con patrimonio suficiente para soportar shocks de ingreso y/o precios puede contribuir a amortiguar el efecto de los mismos. Por otra parte, existen factores que pudiesen amplificar el impacto de shocks como los antes mencionados. En particular, cambios en la holgura de mercado originados en eventos idiosincráticos, además de reducir la rentabilidad de quienes no consiguen arrendar su vivienda, pueden tener un impacto agregado sobre los precios de arriendo reduciendo aún más la rentabilidad de otros agentes. Esta menor rentabilidad podría motivar la salida de inversionistas de este mercado con un potencial impacto sobre los precios de venta de las viviendas. Es más, fuertes aumentos en la holgura del mercado podrían incluso llevar al no-pago de deudores hipotecarios que adquirieron la vivienda con el fin de arrendarla (inversionistas minoristas apalancados). Por lo tanto, el nivel de endeudamiento de dichos inversionistas y su capacidad para enfrentar shocks de ingreso son claves para cuantificar el nivel de vulnerabilidad de este grupo y sus efectos sobre la estabilidad financiera. El ejercicio de tensión del Capítulo IV de este Informe presenta cuantificaciones al respecto.

GRÁFICO 1
Tasa de arriendo en RM y flujo migratorio neto (*)
(porcentaje de los hogares, miles de personas)



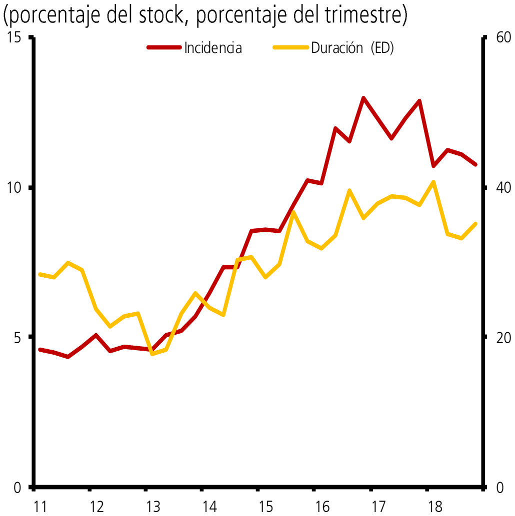
(*) La Nacionalidad es determinada por el jefe de hogar.
Fuente: Banco Central de Chile en base a datos de la encuesta CASEN e INE.

GRÁFICO 2
Índice de precios de arriendo y tasa de avisaje en RM
(Índice 2011:I=100, porcentaje)



Fuente: Banco Central de Chile en base a información de Mercado Libre.

GRÁFICO 3
Incidencia y duración en RM
(porcentaje del stock, porcentaje del trimestre)



Fuente: Banco Central de Chile en base a información de Mercado Libre.

Tabla 1
Resultados Panel: Casas y Departamentos (*)

CASAS Y DEPARTAMENTOS						
	Crecimiento Anual en el Precio					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Tasa de Avisaje)	-0.032***		-0.033***		-0.038***	
Ln(Incidencia)		-0.033***		-0.033***		-0.038***
Ln(Duración)		-0.030*		-0.034***		-0.038***
Tasa BCU5			0.052***	0.053***	0.054***	0.054***
Crecimiento Anual IPV			0.023	0.022	0.064	0.064
LTV promedio			-0.004**	-0.004**	0.003	0.003
Constante	0.047***	0.190***	0.305**	0.455**	-0.292*	-0.118
Observaciones	864	864	810	810	810	810
R2 within	0.61	0.61	0.508	0.508	0.556	0.556
FE	Comunal, Temporal	Comunal, Temporal	Comunal	Comunal	Comunal	Comunal
Otras variables	No	No	No	No	Flujo Migratorio	Flujo Migratorio

(*) *** p<0,01, ** p<0,05, *p<0,1.
Fuente: Banco Central de Chile en base a datos de Mercado Libre.

Tabla 2
Resultados Panel: Casas (*)

CASAS						
	Crecimiento Anual en el Precio					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Tasa de Avisaje)	-0.048***		-0.038***		-0.043***	
Ln(Incidencia)		-0.062***		-0.055***		-0.058***
Ln(Duración)		-0.031*		-0.026*		-0.033**
Tasa BCU5			0.058***	0.052***	0.060***	0.054***
Crecimiento Anual IPV			-0.082	-0.086	-0.056	-0.063
LTV promedio			-0.005	-0.006**	0	-0.001
Constante	0.062***	0.253***	0.361	0.643**	-0.093	0.204
Observaciones	416	416	390	390	390	390
R2 within	0.607	0.611	0.524	0.532	0.56	0.565
FE	Comunal, Temporal	Comunal, Temporal	Comunal	Comunal	Comunal	Comunal
Otras variables	No	No	No	No	Flujo Migratorio	Flujo Migratorio

(*) *** p<0.01, ** p<0.05, *p<0.1.
Fuente: Banco Central de Chile en base a datos de Mercado Libre.

Tabla 3
Resultados Panel: Departamentos (*)

DEPARTAMENTOS						
	Crecimiento Anual en el Precio					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Tasa de Avisaje)	-0.024*		-0.034***		-0.037**	
Ln(Incidencia)		-0.028		-0.025		-0.028
Ln(Duración)		-0.018		-0.041***		-0.042**
Tasa BCU5			0.046***	0.051***	0.049***	0.054***
Crecimiento Anual IPV			0.096	0.084	0.163	0.155
LTV promedio			-0.004	-0.003	0.005	0.006
Constante	0.030*	0.130*	0.283	0.376	-0.478*	-0.373
Observaciones	448	448	420	420	420	420
R2 within	0.679	0.68	0.506	0.508	0.562	0.563
FE	Comunal, Temporal	Comunal, Temporal	Comunal	Comunal	Comunal	Comunal
Otras variables	No	No	No	No	Flujo Migratorio	Flujo Migratorio

(*) *** p<0.01, ** p<0.05, *p<0.1.
Fuente: Banco Central de Chile en base a datos de Mercado Libre.

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Minuta: Descripción modelo inversionistas minoristas

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1. Introducción

Esta minuta describe brevemente el modelo base utilizado en Calani, Moreno y Ramírez (2019) para analizar el rol de los inversionistas minoristas (IM) en el mercado inmobiliario residencial en Chile. La versión utilizada en este informe utiliza modelo de equilibrio parcial de agentes heterogéneos en tiempo continuo. Siguiendo a Flötotto, Kirker y Ströbel (2016), se permite que los agentes sean heterogéneos en sus ingresos lo que incide en diferentes dinámicas de consumo de bienes finales, y servicios de vivienda así como de acumulación de activos financieros y residenciales. Resolvemos este modelo utilizando técnicas de diferencias finitas expuestas en Achdou y col. (2017). Este modelo es parte de una iniciativa que busca avanzar hacia un modelo de equilibrio general que considere la determinación de precios de viviendas y arriendos, sin abstraerse del sector de la construcción y los hogares que demandan bienes residenciales como activos de inversión.

Este modelo se enmarca en una agenda más general de modelación atingente a temas de estabilidad financiera. A nuestro saber, no existen disponibles modelos que pongan énfasis en la posibilidad de tener espacios para ofrecer en arriendo además del lugar de habitación propio, que como se ha detallado en distintos IEFs previos, es un fenómeno que se ha observado en Chile en los últimos años[1]

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1. En la gran mayoría de los trabajos donde se modela el mercado hipotecario, las viviendas ofrecidas en arriendo son propiedad de instituciones financieras.

La conclusión preliminar –aunque robusta a una gran familiar de parametrizaciones– es que, ante perturbaciones en el ingreso, los inversionistas minoristas, tal como se define en el presente IEF, pueden ajustar su cartera de viviendas más fácilmente que aquellos que solo son propietarios de su residencia, lo que se ajusta a evidencia internacional sobre el tema, tales como Albanesi, Giorgi y Nosal (2017) y Haughwout y col. (2011) en Estados Unidos, y evidencia preliminar para el caso chileno.

2. Descripción del modelo

2.1. Dinámica del ingreso

El ingreso sigue un proceso Poisson estocástico exógeno, donde la probabilidad de cambiar de estado, está dado por λ_k, donde el estado toma valores $k = 1, 2$.

2.2. Preferencias de los hogares

La función de utilidad tiene un coeficiente de aversión al riesgo constante, representado por σ y una participación constante del gasto en servicios residenciales en los ingresos dada por θ. Adicionalmente, el parámetro α representa la menor valoración de los servicios residenciales entregados por las estructuras usadas por parte de los arrendatarios, por lo que equivale a 1 si el residente es propietario y menos de 1, si es arrendatario.

$$u(c, \upsilon) = \frac{\left[c^{1-\theta}(\alpha\upsilon)^{\theta}\right]^{1-\sigma} - 1}{1 - \sigma}$$

2.3. Problema de los hogares

Los hogares comienzan, en un período dado, con activos financieros netos b y existencias de estructuras residenciales h. Note que puede vender estas estructuras parcialmente o arrendar la parte que no está cubriendo su demanda por servicios residenciales $h - \upsilon$, aunque solamente si $h > \upsilon$:

$$
\begin{aligned}
(\rho+\pi)V^i(b,h) = \max_{c,\upsilon,x}\ & u(c,\upsilon) + V^i_b(b,h)\dot{b} + V^i_h(b,h)\dot{h} + \lambda\left[V^j(b,h) - V^i(b,h)\right] \\
& \dot{b} = y - c - px - \Gamma(x,h) + p^r(h-\upsilon) + rb && \text{(acumulación de activos)} \\
& \dot{h} = -\delta h + x && \text{(acumulación de estructuras)} \\
& \upsilon \leq h \text{ si } h > 0 && \text{(imposibilidad de ser arrendatario y propietario)} \\
& x \geq -h \\
& c,\upsilon > 0
\end{aligned}
$$

donde $\Gamma(x,h)$ representa los costos de ajuste de las existencias de estructuras residenciales, lo que está dado por la siguiente ecuación:

$$\Gamma(x,h) = \chi_0\,|x| + \frac{1}{2}\chi_1\left(\frac{x}{h}\right)^2 h$$

En caso que $h = 0$, se asume, sin pérdida de generalidad, que $\Gamma(x,0) = \chi_0\,|x|$. Las condiciones de primer orden están dadas por las siguientes ecuaciones:

$$
\begin{aligned}
c &= \frac{(1-\theta)}{\theta}p^r\upsilon && \text{margen consumo/arriendo} \\
x &= \left(\frac{V_h}{V_b} - p + \chi_0\right)^{-}\frac{h}{\chi_1} + \left(\frac{V_h}{V_b} - p - \chi_0\right)^{+}\frac{h}{\chi_1} && \text{decisión de inversión}
\end{aligned}
$$

3. Conclusiones

Como se puede observar, en el modelo hay una clara diferenciación entre la demanda por servicios de vivienda υ y las estructuras h. Esto es relevante por el siguiente motivo. Ante la necesidad de liquidar las viviendas, el inversionista inmobiliario liquida las propiedades que no son su residencia, y por lo tanto, no afecta su utilidad en el presente (puede liquidar para mantener su consumo de bienes y de servicios de vivienda); en cambio, aquel propietario que solo posee su residencia, verá afectada directamente su utilidad, ya sea a través de un consumo menor de servicios residenciales o de bienes. Esto implica que, ante una perturbación negativa que reduzca el precio de las viviendas, el inversionista inmobiliario tiene mayores incentivos a liquidar que aquel agente que solo tiene una propiedad y reside en ella.

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