Measuring Mortgage Availability & Take-Up An Application to Macro-Prudential Policy

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Abstract

We provide a measure of credit availability and credit take-up at the borrower level applying the stochastic frontier analysis to the Irish mortgage market. Results illustrate the credit expansion and the proportionate increase in take-up over the years preceding the financial crisis while they document the fall in credit availability and the diverse trends in credit take-up for first-time and second-time buyers over the following period. For the years following the introduction of macro-prudential loan-to-value and loan-to-income restrictions, results show a marked increase in credit take-up, especially among first-time buyers in Dublin.

JEL Classification: G21, E51, E58
Keywords: Mortgages, credit availability, macro-prudential policy, house prices.

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1 Introduction

The house prices' collapse in 2007-2008 marked the onset of the global financial crisis and the end of a prolonged period of growth during which the perception of borrowers' risk was mitigated by the upward pressure on house prices.

In the context of the boom years, the expected equity gains offset the cost associated with any default: banks increased the credit available to borrowers and eased the access to credit; short-run housing equity gains provided borrowers with substantial down-payments, allowed home-movers to exercise greater leverage of income and enhanced the expectation of even further future house prices.

The post-crisis policy response to the pro-cyclical and ever-growing debt-capacity of home-owners that led to the crash, consisted of a set of macro-prudential policies acting as automatic stabilisers to limit the borrowers leverage of income and down-payments. As post-crisis property markets recover, understanding the impact of these policies on credit availability is of critical importance.

This paper aims therefore to document the pro-cyclicality of access to credit and the effectiveness of the post-crisis macro-prudential policy borrowing constraint by measuring credit availability and credit take-up in the Irish mortgage market over the years 2003 - 2017.[1] Ireland provides an interesting test case, with a boom and bust housing cycle, followed by the introduction of macro-prudential policy.

To estimate the unobserved credit availability at the borrower level, we draw on the well-developed frontier analysis from the industrial organisation field of economics. Traditional

[1] We refrain from using the terms supply and demand to define availability and take-up. For instance, we do not observe the demand for credit that is rejected by banks, we only observe the fraction of demand that is granted access to credit.

stochastic production frontier models estimate a firm-specific output frontier for a given set of inputs and an inefficiency value to capture the distance between a given firm and its most efficient peers. In our set-up, the production frontier corresponds to the maximum attainable amount of credit (i.e. the credit available); the distance between the actual draw-down amount and the maximum attainable credit is what we call credit take-up (i.e. the individual utilisation of credit) and it varies according to borrowers' need or willingness to borrow. Credit constrained borrowers will, for instance, fully leverage (greater) down-payments or income while less constrained borrowers should instead rationally choose to reduce their loan to value ratios or loan-to-income for the same property value.

This paper is structured as follows: Section 2 places this paper in the literature. Section 3 provides an overview on the Irish housing and mortgage developments and the post crisis macro-prudential policies. Section 4 presents and describes the data in use. Section 5 outlines the empirical strategy and provides empirical results. Finally, section 6 concludes our work.

2 Literature

A relatively recent literature has emerged attempting to measure the effectiveness of macro-prudential measures in limiting the build-up of systemic risk through the use of a host of different methodological approaches.[2]

Kuttner and Shim (2016), Cerutti et al. (2015), Lim et al. (2011), DellAriccia et al. (2012), Claessens et al. (2013) and Jasova and Gersl (2012) are relevant contributions to the study of macro-prudential instruments at cross-country level. These papers generally assess the

[2]The methodologies chosen range from the DSGE modelling often used to evaluate the combined effects of the macro-prudential and monetary policy tool-kits, to event-studies, difference-in-difference approaches and IV strategies.

effectiveness of the instruments at reducing systemic risk and establish links between macro-prudential policy, house prices, household credit and credit booms.

The macro-prudential policy tool-kit involves a diverse set of measures; countries have adopted different combinations of measures, they have implemented them at different points in time,[3] they have diversified or standardised cut-offs across borrowers[4] and they clearly also implement a diverse range of fiscal policies that can have an impact on the effectiveness of macro-prudential policies (Se (2013), Galati and Moessner (2018)). Some relevant examples of country-specific analyses can be found in Aiyar et al. (2014) & Peydró et al. (2017) (UK), Kelly et al. (2018) (IRL) , Van Bekkum et al. (2018) (NL),Jiménez et al. (2017) (Spain), Dassatti Camors et al. (2019) (Uruguay),Igan and Kang (2011) and Craig and Hua (2011) (Hong Kong),Geršl and Jašová (2014) (Poland), Neagu et al. (2015) (Romania), Frait et al. (2011) (Czech Republic), Banai et al. (2011) (Hungary), Celeska et al. (2011) (Macedonia), Kenc et al. (2011) (Turkey), Sutt et al. (2011) (Estonia)[5] whereas studies grouping countries with similar socio-economic profiles are, for instance, Tovar Mora et al. (2012) (Latin America) and Vandenbussche et al. (2015) (Central, Eastern, and Southeastern European countries).

Peydró et al. (2017) study the impact of a regulation in the UK which put a cap on the share of mortgages with high loan-to-income (LTI) ratios in the portfolio of UK banking

[3]For instance, Romania and Hungary have been using macro-prudential policy for a decade now, having introduced it during the boom phase of the last financial cycle.

[4]Neagu et al. (2015) suggest that the caps for LTV and DSTI should be tailored and differentiated based on loan characteristics such as the loan currency denomination (domestic or foreign), the purpose of the loan (mortgage or consumer loan), the level of debtors' disposable income or the borrower's age. For some countries, income and age characteristics significantly discriminate credit market conditions or sensitivity of house prices to credit available. Therefore, macro-prudential policy tools can weigh more heavily on some types of borrowers (Albacete et al., 2018). Taking this into account, some macro-prudential authorities are adapting tools to the different types of borrowers, e.g. a lower LTV requirement for first-time buyers in Ireland. From a normative point of view, the debate on whether macro-prudential policy should be designed to have standard cut-offs across borrowers or not is open.

[5]For instance, Aiyar et al. (2014), Tovar Mora et al. (2012), Jiménez et al. (2012), Igan and Kang (2011) provide evidence of the effectiveness of capital requirements on the reduction of credit growth and the smoothening of the credit cycle.

groups.[6] The paper documents an expansion of lending in an intermediate LTI bracket right below the 4.5 LTI limit, an increase in the proportion of high-LTI loans issued to higher income groups and a reduction of the proportion of high-LTI loans issued to lower income groups.

In a recent assessment of the effect of the introduction of an LTV cap in the Netherlands, Van Bekkum et al. (2018) illustrates that the policy succeeded in inducing first-time borrowers to use less mortgage debt to finance new home purchases. The reduction in mortgage debt is accompanied by slower transitions from the rental into the housing market, especially among households lacking sufficient income or the financial assets to finance the transaction.

Kelly et al. (2018) stress the importance of MPP in cooling the rapidly-growing Irish housing market and suggest that the levels at which LTV, LTI and DSTI limits are set are crucially important in determining the impact on prices.[7] They also highlight the importance of the timing of the introduction of an MPP regime: a regime switch at the top of the cycle produces in fact a much larger impact than a switch at a different time.

In an attempt to measure borrowing constraints and credit availability, previous work has adopted measures like the volume of originations, the median credit score of new borrowers, or approval rates. Using a non-parametric frontier estimation approach, Anenberg et al. (2017) illustrates that mortgage credit availability expanded during the first half of the 2000s and contracted significantly during the financial crisis. Increases in credit availability during the boom were fairly similar across borrower types regardless of their income, credit score, or

[6]Since the fourth quarter of 2014, qualifying banking groups can no longer issue more than 15% of their mortgages with LTI $\geq$ 4.5. This constraint, otherwise known as the LTI flow-limit, was binding for a significant cross-section of the mortgage market.

[7]The introduction of an LTV-LTI combination of 70 and 2.8 leads to a house price fall two and a half times as large as a combination of 95 and 4.5.

down-payment. In contrast, the decline in credit availability during the financial crisis was sharp for borrowers with low credit scores, and somewhat sharp for borrowers with lower incomes. Kelly et al. (2018) introduce a novel measure of credit availability at the loan level by modelling credit supply along three channels: the Loan to Value ratio (LTV), the Loan to Income ratio (LTI) and the Debt Service Ratio (DSR). Using prevailing market conditions on the level of originating LTV, LTI and DSR available in a given quarter, they construct three possible loan amounts for each borrower, commensurate with their income, deposit and age; the credit available to a borrower is considered to be the smallest of these three loans. This methodology is adopted by Albacete et al. (2017), who study the effect of different macro prudential restrictions on house prices and credit available. Our work applies a methodology which is similar in spirit to the one used in Anenberg et al. (2017);[8] in our work, the maximum mortgage size that banks are willing to extend to a borrower is estimated conditional on the borrower's observable characteristics through a frontier function model. Following Anenberg et al. (2017) we aim to use the movements in the frontier to illustrate the evolution of credit in the mortgage market over the period 2003 to 2017.

3 The Irish Mortgage Market

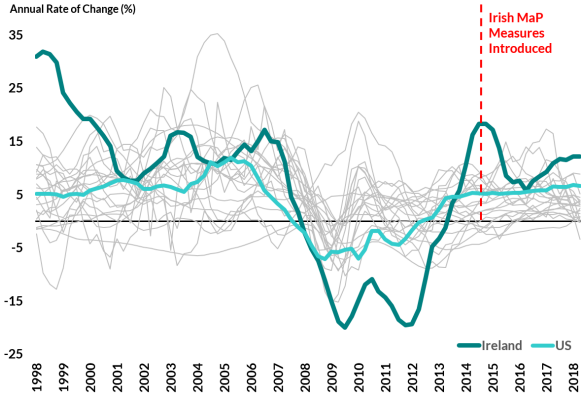
The Irish mortgage market provides an interesting case study in which to investigate income and down-payment leverage. Figure 1a shows it was among the most extreme internationally in terms of growth, collapse and recovery. In the early 2000s, margins narrowed and lending standards loosened due to competition from new entrants to the market. This circumstance was coupled with wage growth due to tight labour market conditions, culminating in strong

[8]Differently from Anenberg et al. (2017) we use a parametric version of the frontier methodology.

upward price pressure for housing. Prices often grew more than twice they did in the US prior to the crisis. Ireland then suffered a banking and sovereign debt crisis following the global financial difficulties in 2008: real economy shocks were severe with considerable declines in disposable incomes and stark increases in unemployment. The housing market fell for 20 consecutive quarters halving in value. Since 2013, a demand-led recovery has seen house prices recover to 20 percent below their peak.

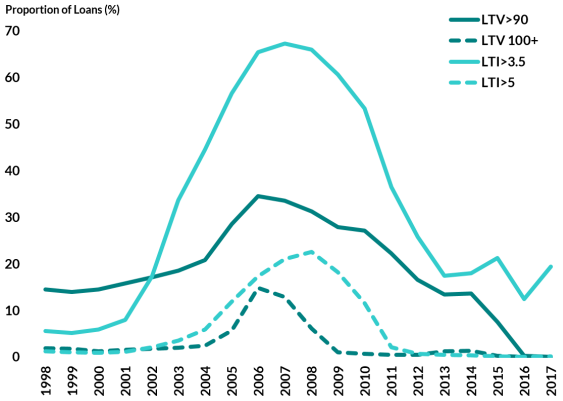
Figure 1: Evolution of Irish House Prices and Credit Conditions

(a) House Prices



Source: Dallas Fed International Hosue Price Database. Annual rate of change for nominal house prices. Grey lines represent rate of chnage for individual counries in database. MaP refers to macro prudential meansure in the form of loan to income and loan to value restrictions (See Table 1)

(b) Credit Conditions



Source: Loan level data and Central Bank of Ireland calculations. Proportion of loans refers to number at origination.

While incomes grew in the early 2000s, they did not keep pace with house price developments. Financing of house purchase required greater leverage of income and down-payments, through higher loan-to-income (LTI) and loan-to-value (LTV) ratios. Figure 1b shows the evolution of these ratios. By the 2006 peak, almost 30 percent of loan balances had LTVs greater than 90 percent, with more than 10 percent requiring no or negative down-payment. In terms of income leverage, LTI ratios show a gradual upward trend to a 2006 peak, where 20 percent of loans had an LTI greater than 5. As the economy slowed in 2008, the house market

collapsed in terms of both transactions and values. Credit conditions tightened considerably, removal of no down payment mortgages and loan to income multiples dropped with less than 20 per of loan balances issued above 3.5.

Table 1: Overview of 2015 Irish Macroprudential Mortgage Market Regulations

	Loan-to-Value		Loan-to-Income	
	Limit	Allowance	Limit	Allowance
First Time Home-buyer	90%*	15%	3.5	20%
Second & Subsequent Buyers	80%			
Investors	70%	10%	N/A	

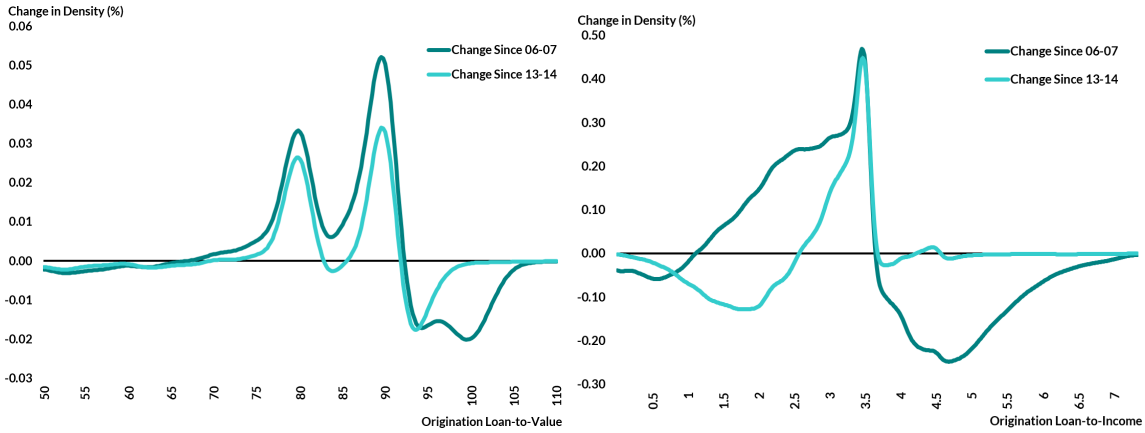
Notes: Exemptions are granted for negative equity mortgages, switchers with no increase in balance and modifications of distressed mortgages. Loan-to-value of 90% up to house value of 220,000. Above 220,000, there is a maximum 80% loan-to-value for the portion above 220,000.

As general economic conditions improved after 2012, housing demand increased and prices began to rise. In 2015, the Central Bank of Ireland introduced macro-prudential measures to limit LTI and LTV ratios for new mortgage lending. These measures aimed at enhancing the resilience of both borrowers and the banking sector. Table 1 provides an overview of the measures. At their core, they limit LTV to 80 (90 for first-time homebuyers) per cent and LTI to 3.5. Similar to other jurisdictions, a portion of the lending is not subject to the limits.[9] This allows the limits to become automatic stabilisers through the cycle, with scope to adjust the allowances in response to cyclical risks.

House prices have continued to rise, averaging 10 per cent annually since the introduction of the measures and rules are potentially more binding as incomes have not grown at the same

[9]For example, in 2014 the UK introduced the measure to limit 15 percent of mortgage lending above a LTI of 4.5.

Figure 2: Comparison of LTV and LTI Distributions



(a) Loan-to-Value (b) Loan-to-Income

rate. Figure 2 compares LTV and LTI ratios in the macro-prudential era to the immediately preceding period and the pre crisis peak of house prices. Overall, the proportion of high leverage loans has reduced since the policy introduction, coupled with an increase at the limits. The recent differential in income and house price growth is evident with a sizeable shift to the right and mass at the limit in the LTI distribution. While this is evidence of the bindingness of the rules, it is a lower bound as individuals could be below the LTI limit because they are bound on another channel such as down-payment or age (term).

4 Data

Our dataset covers the time period between 2003 and 2017. We use two data sources to construct the file used in our baseline estimation: the first one is the Central Bank of Ireland's Loan Level Data (LLD), explained in detail by Kennedy and McIndoe-Calder (2012) and used subsequently in a number of mortgage default analyses for its richness on loan origination information, e.g loan-to-income, loan-to-value, loan interest rate/type, maturity, collateral

information, borrower characteristics (Kelly, 2011; Lydon and McCarthy, 2013; McCarthy, 2014; Kelly et al., 2014);[10] the second data source is instead a loan-level data source gathering the information on new-lending submitted from financial institutions in a return called the "SI 47 Monitoring Template", required of those financial institutions that advance at least €50 million of new mortgage lending in a six month period (January to June or July to December). Data from the LLD dataset cover the time period 2003 - 2014 whereas the information derived from the Monitoring Templates data covers the years between 2015 and 2017, the years after the introduction of the Macro-prudential regulations.

Our work focuses on PDH housing transactions relative to new property purchases and excludes buy-to-let investments. We exclude financial institutions that do not consistently report information across the period and we trim incomes above 250,000 and 16,000 euros.

4.1 Descriptive Statistics

Table 2 divides the group into three time periods and describes the average loan and borrower characteristics over time. The sample size varies over the boom (2003 to 2008), bust (2009 to 2013) and recovery (2014 to 2018): this variation reflects the looseness of lending standards during the boom phase, the tightening of lending standards as well as the selection into borrowing during the crisis and the normalisation of the lending situation at the time of the recovery. The average balance and deposit peak before 2009 whereas income is stable across the first two periods and only increases over the last one.[11] Average interest rates are higher

[10] LLD files contain information on all loans issued by Irish banks participating in the 2011 Financial Measures Programme (FMP). In the case of the Irish residential mortgage market, these lenders account for roughly two thirds of the total market, making the dataset a particularly rich source of data.

[11] The sample of loans originated after 2014 includes mortgages complying with the macroprudential measures introduced in 2015 and mortgages issued with an allowance after the introduction of the

over the second and third period, probably due to the presence of tracker mortgages in the boom period;[12] finally, Table 2 illustrates that the majority of borrowers are FTBs over the second and the third period.

Table 2: Summary Stats 2013 - 2017

	Mean and Std. Deviation (in parentheses)		
Main Variables	2003-2008	2009-2013	2014-2018
Balance	206812.4	189763.3	222171.5
	(96572.24)	(90093.95)	(129860.2)
Deposit	113899.4	87934.91	80542.97
	(118689.8)	(100680.1)	(84681.29)
Rate	3.20	3.67	3.41
	(1.83)	(.93)	(.62)
Income	62615.34	62873.73	80940.98
	(29087.03)	(31427.6)	(40471.61)
Borrower Age	34.95	34.63	36.52
	(8.03)	(7.63)	(6.83)
FTB share	.46	.65	.62
	(.49)	(.47)	(.48)
Total	160,087	40,686	85,835

Table 3 compares instead the characteristics of the loans granted between 2015 and 2018 dividing them into mortgages issued in compliance with the regulations (first column) and loans with an allowance on either LTI or LTV (second column). The group with allowances has the highest average balance, i.e. $304,643.8$ €, lower average deposit, i.e. $71,030.11$ €, and higher income, $86,731.31$ €. The two groups are predominantly composed of FTBs (64% and 59%) with a higher concentration of FTBs among the non-allowance group; average age is lower in the allowance group (35), probably indicating that allowances are granted to those borrowers whose current income is expected to grow steeply in the future.

measures.

[12] In this case, tracker mortgages are home loans where the interest rate charged on the loan tracks the interest rate set by the European Central Bank.

Table 3: Mean Differences Between Allowance/No Allowance

	(Mean)NoAllowance	(Mean)Allowance
MainVariables		
overall balance	207,854.1	304,643.8
	(121,812.8)	(144,487.6)
deposit	82,343.03	71,030.11
	(86,633.87)	(64,347.66)
interest rate	3.28	3.33
	(.41)	(.40)
income	80,178.19	86,731.31
	(40,361.28)	(41,873.56)
FTB	64%	59%
borrower age	36.91	34.87
	(7.07)	(5.33)
N. Obs.	64,353	13,974

Notes: Exemptions are granted for negative equity mortgages, switchers with no increase in balance and modifications of distressed mortgages. Loan-to-value of 90% up to house value of 220,000. Above 220,000, there is a maximum 80% loan-to-value for the portion above 220,000.

5 Empirical Model and Results

5.1 Empirical Model

5.1.1 Model Description

We study mortgage availability and credit teake-up through the use of a frontier production function (or production frontier); the choice of the frontier methodology in this specific context follows the work of Anenberg et al. (2017) that first adopted a non-parametric frontier estimation approach to the measurement of the maximum attainable borrowed amount given a set of inputs, e.g. borrowers' socio-demographic characteristics or financial characteristics.

Generally speaking, this methodology extends the more traditional regression model and it is based on the theoretical premise that a production function represents the maximum

output attainable given a set of inputs. Through the estimation of the "frontier" we calculate the theoretical constraint (or extreme) that all observations lie within, whereas through the measurement of technical "inefficiency" we illustrate the extent to which observed agents fail to achieve the maximum attainable (i.e. the theoretical ideal). In this framework, the measurement of inefficiency is exactly what we are mostly interested in, as it measures the difference between the amount of credit available (frontier) and the amount of credit that borrowers seek to take-up.

A general frontier model can be expressed as:

$$y_i = \alpha + x_i^{'}\beta + \epsilon_i, i = 1, ..., N \tag{1}$$

$$\epsilon_i = \nu_i - u_i \tag{2}$$

$$\nu_i \sim \mathcal{N}(0, \sigma_\nu^2) \tag{3}$$

$$u_i \sim \mathcal{F} \tag{4}$$

[13]

Y_i represents the logarithm of the output (or cost) of the i_{th} productive unit, x_i is a vector of inputs and β is a vector of parameters. The composed error term ϵ_i is the sum[14] of a normally distributed disturbance representing measurement and specification error, ν_i, and

[13] A more general model specification would be:

$$y_i = f(X_i, \beta)TE_i$$

where

$$0 < TE(y_i, X_i) \leq 1$$

The empirical counterpart considers the logs of the terms in the equation above.

[14] Or the difference in cost functions.

a one-sided disturbance representing inefficiency, u_i. In order to make the model estimable, u_i and ν_i are assumed to be independent of each other and independent and identically distributed across observations (Belotti et al., 2012).

Estimates of the model parameters $\hat{\theta}$ are obtained by maximising a log likelihood function $\ell(\theta)$, with $\theta = (\alpha, \beta', \sigma_\nu^2, \sigma_u^2)'$, whereas point estimates of the inefficiency can be obtained through the mean (or the mode) of the conditional distribution $\mathcal{F}\left(u_i|\hat{\epsilon_i}\right)$, where $\hat{\epsilon}_i = y_i - \hat{\alpha} - x_i'\hat{\beta}$.

The error term ϵ_i is defined as $\epsilon_i = \nu_i - u_i$. The first componenet, ν_i, is intended to capture the effects of statistical noise, whereas the second one $u \geq 0$ is intended to capture the effects of technical inefficiency. These two terms are estimated simoultaneously to the parameters of the stochastic frontier, Kumbhakar et al. (1991) provides a full description of this procedure. Different specifications of the u_i and ν_i terms give rise to different models; we assume the idiosyncratic term component, ν_i, to be independently distributed over the observations and we assume u_i to be independently distributed with truncation point at 0, i.e. $\nu_i \sim \mathcal{N}(0, \sigma_\nu^2)$ and $\mathcal{F} \sim \mathcal{N}^+(\mu, \sigma_u^2)$. After formally testing for the presence of inefficiency, we specify the mean of the technical inefficiency as a function of exogenous variables. This specification allows us to explain part of the variation in technical efficiency in terms of loan-specific factors (Kumbhakar et al., 1991).

5.2 Static analysis

Table 5.2 presents the results of two pooled cross-sectional models providing a static picture of the mechanisms determining maximum credit availability and take-up. Availability and take-up are defined as a function of income, deposit, age, interest rate, FTB status and bank

	(1) Balance (in log)	(2) Balance (in log)
Balance		
Deposit	0.0449***	0.04***
	(.001)	(.0007)
Income	0.504***	0.74***
	(.0014)	(.0016)
Age		-0.436***
		(.003)
Interest rate		-0.055***
		(.001)
FTB		-0.016***
		(.0015)
constant	3.35***	3.96***
	(.005)	(.011)
mu		
Deposit	0.543***	1.42***
	(.005)	(.054)
Income	-.764***	-0.049***
	(.0098)	(.025)
Age		-2.83***
		(.122)
Interest rate		0.267***
		(.024)
FTB		-1 .041***
		(.047)
ilgtgamma	2.53***	4.109***
	(.014)	(.0375)
lnsigma2	-0.431***	0.611***
	(.012)	(.039)
Bank FE	Yes	Yes
N	314,373	286,608

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

identifier.

Results in the top part of Table 5.2 illustrate that both income and down-payment increase the maximum attainable amount of credit: namely, in the first specification, a one percent increase in down-payment increases availability by 0.04%, whereas a one percent increase in income increases availability by 0.5%; in the second specification, a one percent increase in down-payment or income increases drawn balance by 0.04% and 0.75% respectively. The second frontier model also illustrates that a one percent increase in interest rates decreases the availability of credit by (minus) 0.05% and a one percent increase in age decreases the availability of credit by (minus) 0.436%.

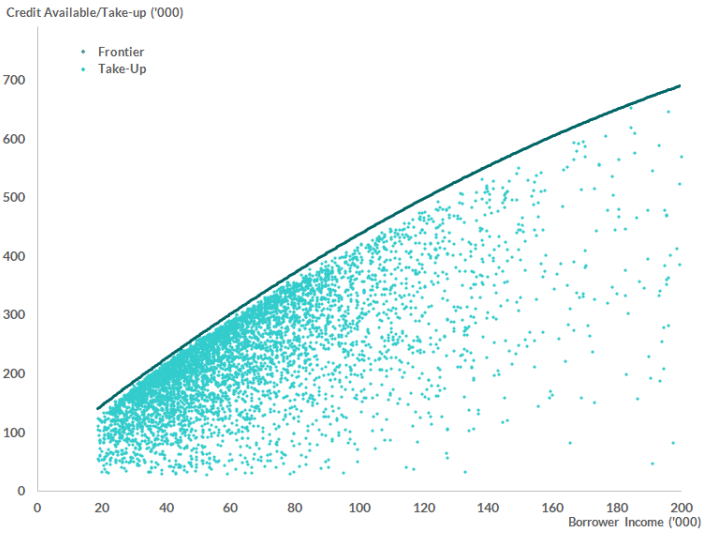
Using the test introduced by Coelli (1995) based on the analysis of the skewness of the residuals, we reject the null hypothesis of no inefficiency component, i.e. our take-up component. Our specifications include therefore the composite error term described in the section dedicated to the model description.[15]

We question whether inefficiency (or take-up) is identically distributed across borrowers or whether there might be heterogeneity across them: for this reason, we define the mean of the inefficiency term as a linear function of income, down-payment, age, rate, bank identifier and FTB status.

For instance, a higher down-payment increases borrowers' maximum attainable output but is also associated with a lower take-up of credit or a higher inefficiency. FTB status decreases instead the level of inefficiency, i.e. it correlates with a higher take-up of credit;

[15]We report a number of statistics to describe the composite error term and namely, (1) the mean, μ, of the truncated-normal distribution of the inefficiency term u_i; (2) the sum of the variance of the two error components, i.e. $\sigma_S^2 = \sigma_\nu^2 + \sigma_u^2$.[16]; and (3) the ratio of the variance of the inefficiency component to the variance of the sum of the inefficiency component and the idiosyncratic component (ilgtgamma[17]), i.e. $\gamma = \sigma_u^2/\sigma_S^2$.

Figure 3: Credit Available and Take-up



Dots in the chart represent the predicted withdrawn balance (loan size) given by the product of the average estimated frontier per income bucket times the individual take-up.

while there is lower credit availability for FTB borrowers, their status brings them closer to the frontier.[18]

We complement the evidence derived from the pooled cross-sectional models with a chart plotting the estimated withdrawn balance, i.e. loan size, across income categories.[19] Figure 3 illustrates that across the entire sample a lower income is associated to a higher take-up of the credit available.

5.2.1 Boom, Bust and Macroprudential Policy

In our second set of models, we explore the changes in credit availability and in credit take-up over time by exploiting the repeated cross-sectional nature of our dataset and interacting income, deposit and the first-time buyer flag with time dummies. These specifications illus-

[18] In the second model specification, a 1% increase in down-payment increases borrowers' inefficiency by 1.42%; the mean of the inefficiency term is instead twice lower for FTBs.

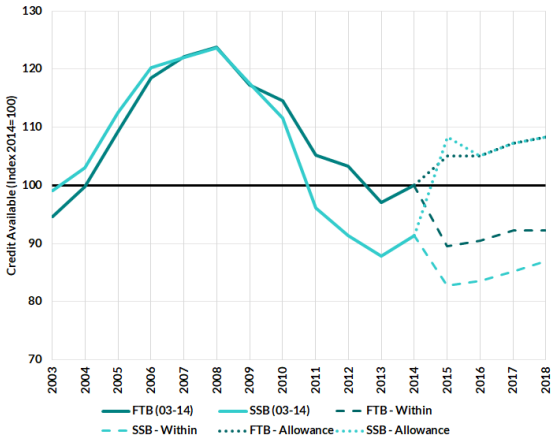
[19] The loan size calculation is based on the average maximum attainable balance (frontier) per income bucket and individual take-up. Moreover, for readability, we plot a random sample of the full sample.

trate the changing effect of a given level of income, deposit and of the first-time buyer status on credit availability as well as their role as borrowing constraints through boom bust and recovery as well as before and after the introduction of macroprudential policy.

The theoretical constraint, i.e. the maximum attainable amount of credit, is a function of income, deposit, FTB status, borrower age, interest rate, bank identifier respectively.[20] The inefficiency term, or rather, the take-up, is modelled instead as a function of income, deposit, age, rate, FTB flag and a time indicator.

In order to interact income and deposit with time, we construct a time indicator for the years between 2003 and 2018. To account for the introduction of macro-prudential regulation in the mortgage market in 2015, our time indicator identifies loans that are granted an allowance with respect to the regulation over the years 2015, 2016, 2017 and 2018.[21]

(a) Average credit available over time



(b) Average take-up over time

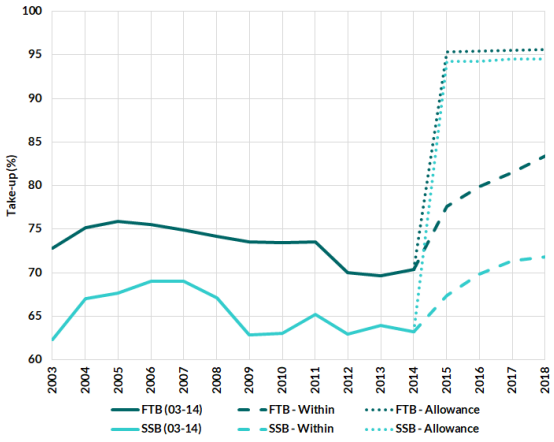


Figure 4a and Figure 4b illustrate the maximum credit available, the amount a bank is willing to supply, and the share of credit available which is drawn down (the take-up) by the

[20] All these characteristics are measured at the origination of the loan.

[21] Income is interacted with a time indicator that accounts for the introduction of an LTI measure whereas deposit is interacted with a time indicator that accounts for the introduction of an LTV rule.

"typical" FTB or SSB over time, i.e. by a borrower with an income of 75.000, a downpayment of 30.000 euros and the remainder variables at 2018 means.[22] During the years preceding the introduction of macroprudential policy, the chart splits credit available between and FTBs and SSBs whereas for the time period following the introduction of the measures, the chart describes the yearly maximum credit available and take-up for borrower groups with and without an allowance.

Figure 4a illustrates that the maximum attainable credit increases overall between 2003 and 2008, a period of general credit expansion and relatively easy access to credit; representative first-time and second-time borrowers had in fact approximately 25% higher credit available in 2008 with respect to the baseline year, i.e. 2014. The years between 2008 and 2010 are characterised by a slow-down in lending capacity which is more pronounced for SSBs and most likely due to house prices falls (see Figure 1a), while the years following the introduction of macro-prudential regulations are characterised by different trajectories for borrowers with an without an allowance. The introduction of the measures reduces the availability of credit for loans issued without an allowance: credit availability for borrowers without allowances to the regulation has decreased by 10-15% whereas credit availability has increased for borrowers with an allowance by approximately 8%.

Figure 4b illustrates that take-up is fairly stable across the years before the introduction

[22]The choice of this "typical borrower" is driven by two sets of thoughts: firstly, due to the nature of the model (i.e. the interaction of variables with time and the comparison between FTBs and SSBs), the maximum credit available reported in the chart has different trajectories for different levels of the inputs and we want to pick levels of the inputs that are representative of the overall input distribution. Secondly, we are interested in comparing FTBs and SSBs over time, isolating banks' behaviour in response to a given income and deposit and not representing compositional changes: choosing a representative borrower per group, i.e. different input levels for FTBs and for SSBs, would make the comparison across borrower types difficult; choosing different representative characteristics over time would also make the comparison quite hard due to the different selection into the housing market over time.

of macroprudential policy and that FTBs' take-up is between 5% and 10% higher than the credit available for SSBs. Given the marked expansion of credit available illustrated in Figure 4a, a fairly stable or slightly increased take-up (calculated as a percentage of credit available) corresponds to increasingly higher balances over the years preceding the introduction of the macroprudential rules. When credit availability falls during the financial crisis, take-up declines for FTBs more than for SSBs: house price falls (see Figure 1a) reduce in fact the ability of SSBs to reinvest their equity while they leave the position of FTBs unaltered, if not improved; while SSBs equity falls together with house prices, FTBs savings for a deposit do not lose their value and FTBs purchasing power increases consequently. For this reason, while the take-up for FTBs slows down, take-up (as a percentage of credit available) remains stable for SSBs.

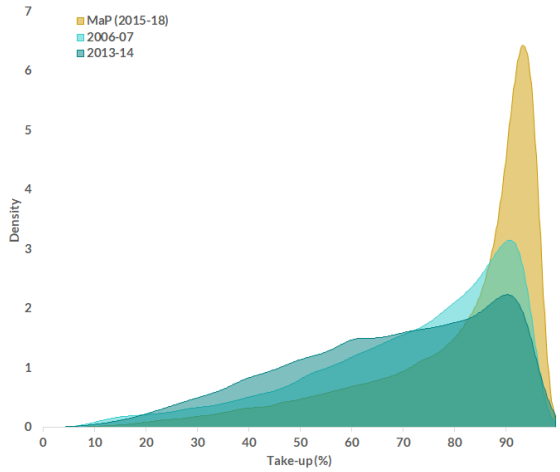
The years after the introduction of macroprudential policy are instead characterised by, on the one hand, lower credit availability and increasing take-up for borrowers within the limit imposed by the Central Bank, on the other hand, by an increase in the credit availability and a level of take-up which is almost corresponding to the totality of the credit available for borrowers with an allowance across the three years 2015 to 2018.

Figure 5a presents the shifts in credit take-up over time for the years 2006-2007, 2013-2014, i.e. immediately prior to the introduction of the measures, and 2015-2018, i.e. after the introduction of the measures. The graph illustrates that the distribution of take-up is markedly left-skewed after the introduction of the measures, with a large share of borrowers taking-up more than 80% of the available credit, and it complements the evidence presented in Figure 4b regarding the trends in mean take-up over time.

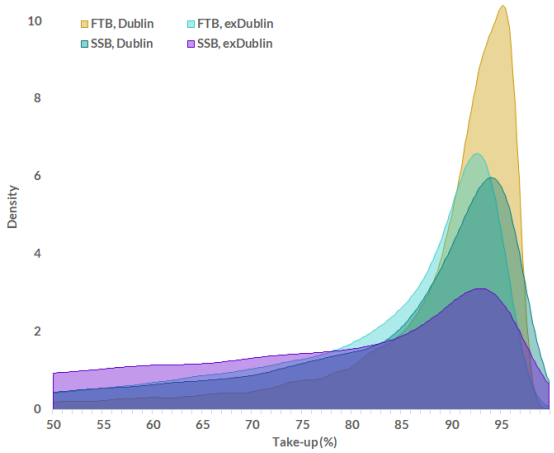
Focussing instead on 2018, Figure 5b illustrates the cross-sectional variation in take-up

Figure 5: Take-Up distribution

(a) Take-up over time



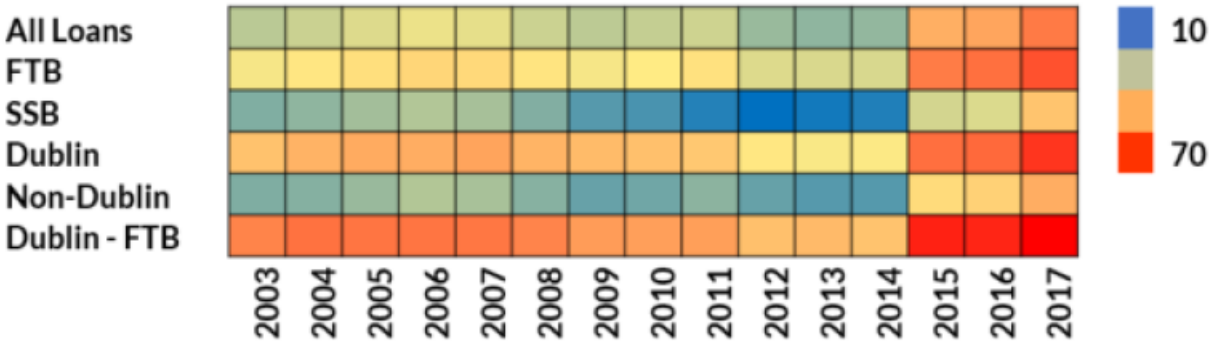
(b) Take-up across borrower types



and breaks down the contribution of borrowers' groups to the take-up distribution presented in the previous chart. The take-up of credit for FTBs based in Dublin is the highest, or rather, FTBs based in Dublin draw down the largest share of available credit. FTBs outside of Dublin have instead the second-highest take-up rates, followed by SSBs based in Dublin and SSBs outside of Dublin. The Dublin versus non-Dublin difference in take-up is likely to be due to the stronger differential in house price and income growth in the area of Dublin.

Finally, in Figure 6 we utilise a heat-map to describe he type of cross-sectional variation in take-up over time. Each cell illustrates the share of loans with a take-up higher than 90%. The cross-sectional variation in take-up in 2017 is not different from the cross-sectional variation over the years: FTBs based in Dublin have always had a higher share of "high take-up mortgages"; FTBs and Dublin-based borrowers have always had higher shares of loans with high take-up if compared to SSBs or borrowers based outside of Dublin. The heat-map shows that, over the last three years, take-up has increased across all groups, crystallising and

Figure 6: Tail measure is the share of loans with take-up higher than 90%.



enhancing the pre-existing variation.

6 Conclusion

We apply a frontier production function to study the evolution of credit supply and credit take-up over the financial cycle and after the introduction of macro-prudential policy in the Irish mortgage market.

This methodology was first used to study the supply and demand for credit in Anenberg et al. (2017) and aims at isolating the maximum available credit and its average take-up in the mortgage market. Our approach focuses on the cohort of draw-downs, not on the unfulfilled demand (lack of supply); the focus here is on borrower credit constraints not the volume of mortgage credit.

The results of our static models illustrate that both higher incomes and down-payments increase the maximum attainable amount of credit; a higher interest rate, borrowers' age and the FTB status are instead associated with a lower attainable amount of credit available. The models also show that a higher down-payment and interest rates are predictors of lower take-

up rates; for instance, a higher down-payment increases the size of the maximum attainable loan but reduces the share of maximum attainable amount of credit drawn down on average. Similarly, while there is lower credit availability for FTB borrowers, FTBs drawn down a quantity that is remarkably closer to the maximum with respect to the quantity that non-FTBs would opt for.

We provide evidence of the evolution of credit supply and take-up over the financial cycle starting from 2003 and up to 2018 and document the general expansion in credit availability in the years prior to the crisis and the reduction in the availability of credit during the crisis; the level of available credit for both FTBs and SSB complying with the regulations remains below pre-crisis level after 2014 whereas the availability of credit for borrowers with an allowance has instead gone back to pre-crisis levels. Credit take-up remains instead stable across FTBs and SSBs until 2014 and significantly increases in the years after 2014 across borrower types and across allowance groups. A further break-down of the sample (which does not differentiate across allowance groups) illustrates that FTBs based in Dublin are the group whose take-up rates are the highest over the years following the introduction of the rules.

The analysis provides an accurate description of the trends credit availability and take-up throughout the period under consideration and also points to a remarkable change in the environment starting from the introduction of macroprudential policy. The constraint imposed by the rules is binding, particularly for first-time borrowers in Dublin whose take-up rates have remained above 90% for the vast majority of borrowers (more than 70%) over the last four years.

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