The Anatomy of the Transmission of Macroprudential Policies*

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Abstract

We show that banks play an important role in the transmission of macroprudential policies aimed at limiting household leverage. Combining granular house price data and loan-level residential mortgage and firm credit data, we examine the introduction of loan-to-income and loan-to-value limits on the issuance of residential mortgages – a policy adopted by 41 countries between 2000 and 2013. Our empirical context is the introduction of these limits in February 2015 on residential mortgages in Ireland, a country that experienced a severe real estate boom-bust cycle from 2000 to 2010. In response to this policy, banks reallocate credit from low- to high-income borrowers and from counties where borrowers are close to the limits to counties where borrowers are more distant from the limits. Banks more exposed to the policy reduce their mortgage issuance to borrowers in the bottom quintile of the income distribution by 10% and increase their issuance to borrowers in the top quintile by 15%, controlling for local economic conditions and credit demand. High-income borrowers obtain larger loans and increase their leverage. This bank mortgage credit reallocation is effective in slowing down house price growth in "hot" housing markets from well above 20% year over year to around 4% year over year. Banks try to maintain a stable risk exposure by increasing their risk-taking in asset classes not targeted by the regulation, such as credit to firms and holdings of securities, and reallocating mortgage credit to borrowers more likely to default during real estate busts.

JEL: G21, E21, E44, E58, R21
Key words: Macroprudential Regulation, Household Leverage, Residential Mortgage Credit, House Prices

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1 Introduction

Policymakers have recently proposed, designed, and implemented macroprudential policies to limit household leverage and, consequently, slow down the feedback loop between credit and house prices and preserve financial stability. The rationale for these interventions, adopted by 41 countries between 2000 and 2013, is based on the observation that build-ups of household leverage have historically led to lower output growth and higher unemployment (Mian et al., 2017).

In this paper, we analyze the most widely used type of macroprudential regulations, namely, policies that limit household leverage in the residential mortgage market. In particular, we study the introduction in 2015 of loan-to-value (LTV) and loan-to-income (LTI) limits for residential mortgages issued by Irish banks.[1] Ireland is a prime laboratory because it recently experienced a dramatic boom-bust cycle: The household debt-to-GDP ratio almost doubled (from 55% to 101%) from 2002 to 2007, followed by a collapse in GDP growth (-10%) and a jump in the unemployment rate (+8%) over the next three years. In this context, we collect data on loan-level residential mortgages, county-level house prices, loan-level bank credit to firms, and bank security-level holdings.

We show that banks play an important role in the transmission. We document that, whereas the lending limits affect 43% of the residential mortgage market, mortgage issuance keeps growing after the policy introduction as the market "moves" to conform with the newly imposed limits. Our analysis of this reallocation provides three main findings: (i) In response to the policy, banks reallocate credit from low- to high-income borrowers and from counties where borrowers are close to the lending limits to counties where borrowers are more distant from the lending limits; (ii) this

[1] Cerutti et al. (2015) collected data from 2000 to 2013 on 119 countries, 107 of which have implemented at least one type of macroprudential regulation. Limits on LTV and LTI are the most widely used tool, adopted by 34 and 27 countries, respectively.

bank mortgage credit reallocation is effective in slowing down house price growth in "hot" housing markets; and (iii) banks try to maintain a stable risk exposure by increasing their risk-taking in asset classes not targeted by the regulation, such as credit to firms and holdings of securities, and reallocating mortgage credit to borrowers more likely to default during real estate busts.

Our analysis proceeds in four steps. First, we show that the lending limits affect a large part of the market, because 43% of the mortgage issuance in the year before the policy would have been affected if the rules had been in place during this period. However, originations seem almost unaffected by the policy, because the increase in "conforming" issuance offsets the collapse in the issuance of those mortgages that exceed the newly imposed limits. But not everyone is affected in the same way. In the cross section of counties, urban counties that experienced a high house price appreciation before the policy are closer to lending limits ("low-distance" counties) than rural counties with modest pre-policy house price appreciation ("high-distance" counties). In the cross-section of borrowers, high-income borrowers are more distant from the limits than low-income borrowers. We show that residential mortgage issuance moves from low- to high-income borrowers and from low- to high-distance counties after the policy. In particular, high-income borrowers obtain larger loans and increase their leverage.

Second, we show that bank portfolio choice drives this credit reallocation. We exploit bank-level heterogeneity by calculating the share of bank mortgage issuance that would have been affected if the rules had been in place in the year before the policy. After confirming that more-exposed banks drive the aggregate reallocation, we find that more-exposed banks reduce their mortgage issuance to borrowers in the bottom quintile of the income distribution by 10% and increase their issuance to borrowers in the top quintile by 15%, controlling for local economic conditions and credit demand using fixed effects. More-exposed banks reduce mortgage rates more than less-exposed banks, inducing high-income borrowers to take out larger loans and increase their leverage.

Third, we show that the evolution of house prices is consistent with the observed credit reallocation. House price growth, around 14% YoY and rapidly increasing at the time of the policy announcement, decreased and stabilized below 10% post-regulation. This evolution is driven by low-distance counties where house price growth, well above 20% YoY and rapidly increasing at the time of announcement, collapsed to reach around 4% post-regulation. The evolution of house prices is also consistent with the credit reallocation across the income distribution, because the differential evolution of house price growth across counties is more pronounced for larger properties, usually purchased by high-income borrowers.

Fourth, we show that banks try to maintain stable risk exposure by analyzing banks' holdings of securities, credit to firms, and residential mortgage credit, thus capturing approximately 80% of banks' assets. We find that more-exposed banks increase their holdings of high-yield securities (buy more and sell less) more than less-exposed banks, relative to the pre-period. Our estimates include stringent security-time and bank-time fixed effects to control for time-varying confounding factors at the bank and security level. Similarly, we find that more-exposed banks increase their corporate lending (higher volumes and lower rates), targeting mostly risky borrowers. Finally, in the residential mortgage space, we find that banks reallocate their credit to borrowers more likely to default in bad times. Given that we do not observe mortgage defaults (the policy is very recent), we use machine learning techniques to estimate loan-level default probabilities exploiting characteristics at origination of loans that defaulted during the 2007-10 bust. We find this conditional probability increased right after the policy. Of course, our results on house prices strongly suggest the recurrence of a similar bust became presumably less likely.

The rationale for macroprudential policies is based on the observation that agents over-borrow in good times, not internalizing all the costs of their financing choice (Lorenzoni, 2008; Bianchi, 2011; Bianchi and Mendoza, 2010, forthcoming; Farhi and Werning, 2016; Bianchi et al., 2012; Jeanne and

Korinek, 2017). In the U.S., the increase in mortgage credit contributed to the rapid appreciation of house prices (Favara and Imbs, 2015; Mian and Sufi, 2009; Adelino et al., 2014). Their collapse, channeled through the balance sheets of households (Mian et al., 2013; Mian and Sufi, 2014; Hall, 2011; Eggertsson and Krugman, 2012; Midrigan and Philippon, 2016) and intermediaries (Gertler and Kiyotaki, 2011; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Chodorow-Reich, 2014; Moreira and Savov, 2017), contributed, in turn, to the Great Recession.

In the growing field of macroprudential regulation, we contribute to the rising literature on policies aimed at limiting household leverage by (i) showing that banks play an important role in the transmission and (ii) jointly analyzing, for the first time, mortgage credit, house prices, and bank risk exposure.[2] A few other papers analyze some aspects of LTV/LTI limits and find results consistent with ours.[3] In the U.S., DeFusco et al. (2017) show how the Dodd-Frank "Ability-to-Repay" rule (similar to a LTI limit) successfully reduced borrower leverage, but with limited effect on default rates in a crisis scenario. Although not analyzing the role of banks, Tzur-Ilan (2017) and Igan and Kang (2011) show that borrowers move away from hot real estate markets, slowing down house price growth in Israel and Korea, respectively.[4]

[2]See Aikman et al. (2018), Freixas et al. (2015), Claessens et al. (2013), Claessens (2015), and Gambacorta and Murcia (2017) for excellent overviews of macroprudential policies. Our paper is also related to the literature, theoretical (Landvoigt and Begenau, 2017; Elenev et al., 2017; Begenau, 2016; Kashyap et al., 2014; Malherbe and Bahaj, 2018) and empirical (Aiyar et al., 2014; Jimenez et al., forthcoming; Gropp et al., 2016; Benetton et al., 2017; De Marco and Wieladek, 2015; Dassatti Camors et al., 2015; Ayyagari et al., 2017), on macroprudential policies (mostly capital requirements) aimed at limiting bank risk taking.

[3]In our same empirical setting, Kinghan et al. (2017) show that, following the introduction of the limits, LTV fell for first time buyers and second and subsequent buyers. Compared with their paper, we focus on the reallocation of mortgage credit across the income and geographical distributions, as well as house prices and bank risk exposure.

[4]Auer and Ongena (2016) and Basten and Koch (2015) show that countercyclical capital buffers on Swiss residential lending led to higher growth in commercial lending and shifted mortgages from less to more resilient banks, respectively. Using Singaporean data, Agarwal et al. (2018) show that policies that impose limits on only LTV cause an increase in high-LTI mortgage issuance. These papers do not analyze house prices or banks' overall risk exposure.

2 Setting and Data

In Section 2.1, we provide some background on the Irish residential mortgage market. In Section 2.2, we describe the policy introduced in February 2015. In Section 2.3, we describe our data set.

2.1 Residential Mortgage Credit in Ireland

In the years leading up to 2000, Ireland experienced a period of steady economic growth often interpreted as a healthy convergence of the "Celtic Tiger" with the rest of the European Union. However, the surge in output from 2003 to 2007 was of a different type, fueled by a construction boom financed through bank credit extended to home owners and property developers (Honohan, 2010). In Figure 1, we show the issuance of residential mortgages (dashed line) from 2000 to 2016 and observe a stark increase in new mortgages from 2002 to 2007. Issuance then collapsed and started increasing again in 2013. House prices (solid line) followed a remarkably similar pattern.

During the bust of 2007-10, prices declined sharply and construction activities collapsed. The fall in quarterly Gross National Product (GNP) is estimated to be about 17%.[5] In addition to the sharp decrease in real estate prices, an increase in unemployment from 4.6% in 2007 to 13.3% in 2010 left many households unable to service their debt burden. This increase in non-performing mortgage credit led to losses for banks that consequently experienced severe funding dry-ups. In September 2008, public funds had to be used to recapitalize almost all large domestic credit-taking institutions, which needed further government assistance in March 2011 (Lane, 2011; Acharya et al., 2014).

[5] Irish economic performance is better measured in relation to GNP rather than GDP, because the latter is inflated by profits of international companies, which are transferred to Ireland because of low corporation tax.

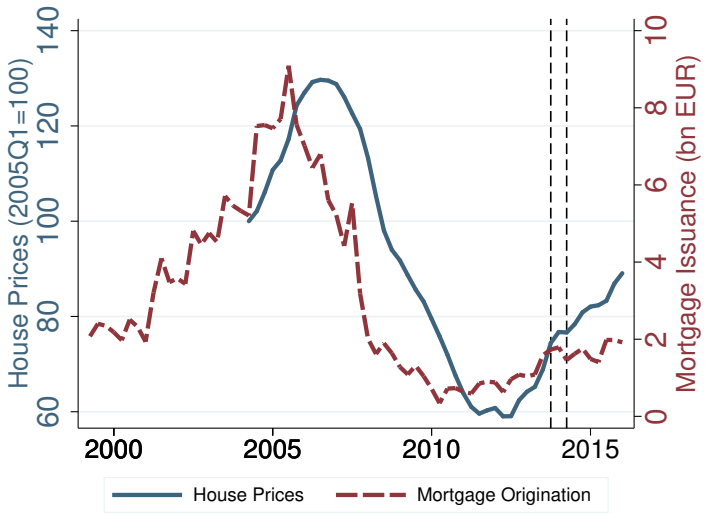

Figure 1: Ireland Real Estate Boom-Bust Cycle. This figure shows the evolution of real estate prices from 2005Q1 to 2016Q4 (left axis, index is 100 in 2005Q1) and residential mortgage issuance from 2000Q1 to 2016Q4 (right axis, billion euros). The two vertical dashed line indicate the announcement and the implementation of the lending limits, respectively. Sources: Department of Housing, Planning and Local Government and Central Statistics Office.

2.2 The February 2015 Mortgage Lending Limits

To avoid a recurrence of this boom-bust cycle in the property market, the Central Bank of Ireland introduced new macroprudential rules aimed at increasing the resilience of households and banks to financial shocks and dampening the pro-cyclical dynamics between property lending and house prices.[6] In the words of Patrick Honahan in January 2015, at that time Governor of the Central Bank of Ireland, "What we are trying to prevent is another psychological loop between credit and prices and credit. If we avoid that, we can keep banks safe, we can keep borrowers safe."

The lending limits were first discussed in October 2014 (our "announcement" date) and introduced on February 9, 2015 (our "implementation" date).[7] In Table 1, we provide an overview of

[6] Almost all mortgages in Ireland are held on banks' balance sheets. There is no active securitization market in Ireland. More specifically, securitization is solely used to create collateral eligible to be pledged at the European Central Bank. Risk transfer off banks' balance sheets is not common.

[7] The lending limits were first proposed in a paper (Consultation Paper 87) published to stimulate discussion by the central bank on October 7, 2014 and available on the Central Bank of Ireland website (link). Mortgages issued after February 9, 2015 could exceed the lending limits if approved before February 9, 2015.

Regulation	Target Group	Limits	Allowances for each bank
LTV limits	For primary dwelling homes:	**First-Time Buyers**: Sliding LTV limits from 90%* **Subsequent Buyers**: 80%	15% of all new lending limits
	For Buy-to-Let:	70% LTV limit	10% of new lending above the buy-to-let limit is allowed
LTI limits	For primary dwelling homes:	3.5 times income	20% of new lending above the limit is allowed
Exemptions	**From LTV limit** Borrowers in negative equity	**From LTI limit** Borrowers for investment properties	**From both limits** * Switcher mortgages * Restructuring of mortgages in arrears

*A limit of 90% LTV applies on the first €220,000 of the value of a residential property and a limit of 80% LTV applies on any value of the property thereafter.

Table 1: Lending Limits. This table provides a summary of the lending limits. Source: Central Bank of Ireland.

the limits on loan-to-value (LTV) and loan-to-income (LTI) ratios on new originations of residential mortgages. The LTI limit is 3.5. The LTV limit depends on the type of borrowers. Lending for primary-dwelling housing (PDH) is limited to 80% LTV. For first-time buyers (FTB), a more generous LTV limit of 90% is imposed for houses up to €220,000.[8] For any amount exceeding €220,000, the excess amount over €220,000 faces an LTV limit of 80%. The measures impose a stricter threshold for buy-to-let (BTL) properties, requiring banks to apply an LTV limit of 70%.[9]

2.3 Data

In this section, we describe the data set construction and the empirical work. The core of our final data set is the result of combining loan-level information on residential mortgages and credit to firms, bank security-level holdings, and county-level house prices. The loan-level data and security

[8] First-time buyers are four percentage points or 30 per cent relatively less likely to default than subsequent-time buyers in Ireland (Kelly et al., 2015).

[9] In addition to loans that are exempted from the rule, banks can issue loans exceeding the limits to a small share of borrowers, as shown in the last column of the table. In November 2016, the rules were relaxed, extending the LTV limit for FTBs to 90%. The analysis of this subsequent period goes beyond the scope of this paper.

register are proprietary data sets obtained from the Central Bank of Ireland.

First, we observe loan-level data on the issuance of residential mortgages to households at a daily frequency from January 2013 to June 2016.[10] We observe all outstanding residential mortgages by the most significant institutions that have to submit loan-level data to the Central Bank of Ireland.[11] This sample consists of the five largest banks and covers more than 90% of the domestic mortgage market. The data set also contains household-month demographic (age, marital status), income, and residential mortgage credit characteristics (first-time or subsequent-time buyer, buy-to-let).

Second, we observe loan-level data on bank credit to firms at a semi-annual frequency from June 2013 to June 2016. At the bank-firm-period level, we observe credit granted and drawn and the rate charged by bank b to firm f at time t. We match this information with firm characteristics such as county of incorporation, industry, and asset class (very small/SME/large). We observe the borrower rating assigned to each loan from internal rating models of each lender.[12] The data have one main limitation. In contrast to most credit registries, our borrower identifier is consistent within a bank over time, but not across banks.

Third, we observe bank security-level holdings at a quarterly frequency from January 2011 to June 2016. At the security-bank-quarter level, we observe each security s identified by an International Securities Identification Number (ISIN) held by bank b at time t. We match this information with security characteristics (rating and yield) from Datastream.

[10] These data are a combination of two sources: We use the *loan-level data* until 2015 and the *Monitoring Template Data* after 2015. The latter has to be submitted to the Central Bank of Ireland for regulatory purposes as prescribed by the macroprudential regulations introduced on February 9, 2015. More information is in the Appendix.

[11] Irish banks that received a public bailout are required to report loan-level data. The rest of the significant mortgage issuers in Ireland submit loan-level data following the encouragement from regulators and in accordance with data submissions required by the ECB-SSM Comprehensive Assessment in 2013.

[12] The Central Bank of Ireland internal mapping scales are used to classify each internal rating into a consistent categorization between 1 and 6. It ranges from 1 (highest-quality borrower) to 5 (very risky borrower) for non-defaulted loans and equals 6 for defaulted loans.

Fourth, at the bank-month level, we observe monthly balance sheet items from the European Central Bank Individual Balance Sheet Statistics (IBSI).

Fifth, at the county-period level, we observe quarterly house prices from the Irish property website Daft.ie. This data set is publicly available and regularly updated with quarterly reports published on the website.

3 Some Facts

In this section, we present three aggregate facts. In Section 3.1, we show the pace of originations of residential mortgages seems almost unaffected by the lending limits even if these limits affect more than one third of the market. In Section 3.2, we show that counties and borrowers are differentially exposed to the lending limits, with urban counties and low-income borrowers being more affected than rural counties and high-income borrowers. In Section 3.3, we show that after the policy, mortgage credit is reallocated from low- to high-income borrowers and from counties where borrowers are closer to the limits to counties where borrowers are further away from the limits.

3.1 Evolution of Residential Mortgage Issuance

The lending limits announced in October 2014 and implemented in February 2015 prevented banks from originating high-LTV and high-LTI residential mortgages. These rules affected a large fraction of the mortgage market, because 43% of the volume of residential mortgage issuance (35% of mortgages issued) from October 2013 to September 2014 would have been affected if the policy had been in place during that period. Out of the total €1.6 billion mortgages in our sample in that period, non-conforming (i.e., not complying with the new rules) mortgages accounted for €0.7 billion. The LTV limits affected the largest fraction of the market. LTV-non-conforming mortgages

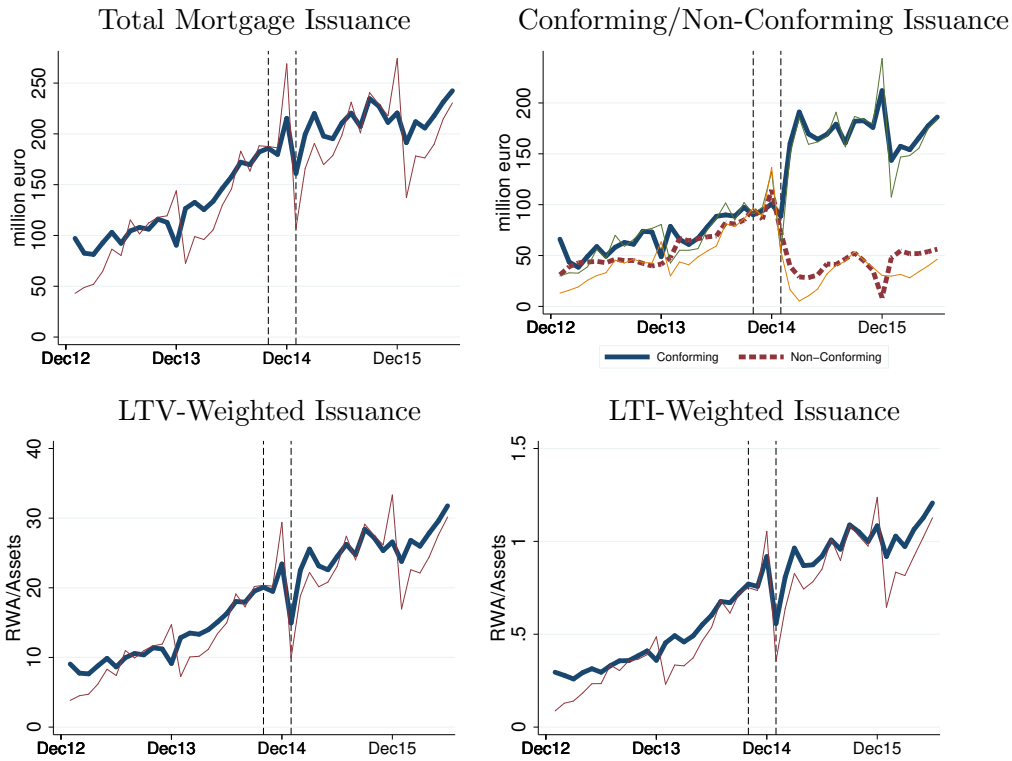

Figure 2: Aggregate Residential Mortgage Issuance. This figure shows the evolution of residential mortgage issuance of our sample banks from January 2013 to June 2016. The top-left panel shows total mortgage issuance (million euro). The top-right panel shows issuance of conforming (solid line) and non-conforming (dashed line) mortgages. The bottom-left panel shows LTV-weighted monthly mortgage issuance divided by total assets (percentage). The bottom-right panel shows LTI-weighted monthly mortgage issuance divided by total assets (units). Thick lines are seasonally adjusted and thin lines are not seasonally adjusted. The vertical dashed lines indicate the announcement and the implementation of the lending limits. Source: Central Bank of Ireland.

accounted for €0.5 billion and LTI-non-conforming mortgages accounted for €0.3 billion. Moreover, approximately half of the LTI-non-conforming mortgages were also LTV-non-conforming.

Whereas the lending limits affected more than one third of the typical residential mortgage issuance, the pace of originations and the build-up of mortgage credit risk exposure seem almost unaffected by the policy. In the top-left panel of Figure 2, we show the evolution of mortgage issuance from January 2013 to June 2016. We find that mortgage credit growth – high since the beginning of 2014 – did not stop after the implementation of the lending limits. This aggregate evidence suggests an increase in the issuance of *conforming* mortgages might have compensated the mechanical reduction of the issuance of *non-conforming* mortgages, as banks followed the new rules. In the top-right panel, we show the evolution of originations of conforming (solid line) and non-

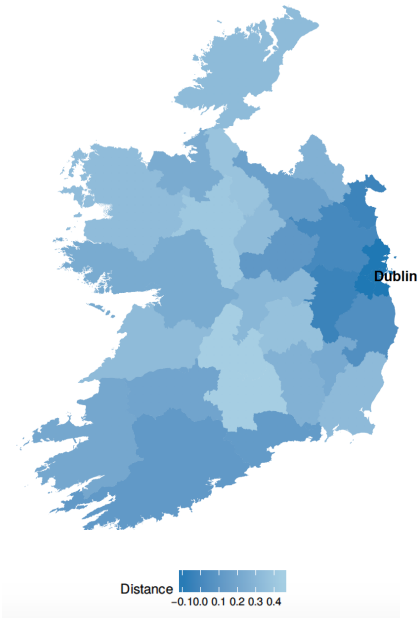

Figure 3: Counties and Lending Limits. This figure shows county-level distance from the lending limits. Darker colors indicate counties that are less distant. Source: Central Bank of Ireland.

conforming (dashed line) mortgages and confirm the two time-series diverge starting in February 2015.[13] In the bottom panels, we show that mortgage originations keep increasing even when weighted by LTV and LTI, suggesting the lending limits do not affect the build-up of residential mortgage risk exposure of our sample banks is unaffected by the lending limits.[14]

3.2 Exposure to the Lending Limits

We now show that counties and borrowers are differentially exposed to the lending limits. First, we define a county-level variable *Distance*, which measures the average distance of borrowers in county c from the lending limits in the year prior to the policy announcement.[15] In Figure 3, we

[13]The issuance of non-conforming mortgages is still strictly positive after the policy implementation as the new rules allow banks to exceed the limits for a limited fraction of their issuance.

[14]While the figure suggests that the volume and riskiness of mortgage issuance was increasing around the policy introduction, borrower leverage and originations were low compared with historical levels.

[15]We proceed in three steps. First, for each mortgage, we measure the distance from the respective LTV and LTI limits. Second, given the very different scale of LTV and LTI, we rescale both distances to have a mean of zero and

	Unit	*Income Quintiles*				
		Q1	Q2	Q3	Q4	Q5
Borrower Characteristics						
Income	€	32,635	47,659	64,899	91,756	168,129
Married	%	16.5	36.2	49.0	66.8	65.1
Age	Years	34.2	35.3	36.2	37.7	40.0
First-Time Buyer	%	82.7	78.1	65.1	41.7	27.0
Buy-to-Let	%	1.7	2.3	3.2	4.3	8.4
No. Borrowers	Units	1,559	2,023	2,378	1,977	2,664
Loan Characteristics						
Size	€	95,030	127,008	168,902	215,070	235,801
LTV	%	77.2	77.2	78.3	76.7	71.8
LTI	Units	3.2	3.0	3.0	2.7	2.3
House Value	€	133,518	177,142	230,458	298,620	385,940
Term	Months	326	328	326	314	286
Fixed Rate	%	44.9	41.8	40.3	34.9	24.4
Rate	%	4.15	4.26	4.25	4.26	4.27
Distance from LTI Limit	Units	0.54	0.75	0.73	1.00	1.28
Distance from LTV Limit	Units	6.73	5.92	3.64	4.22	10.00
Standardized Distance from Lending Limits	Units	-0.13	-0.10	-0.09	-0.02	0.45

Table 2: Summary Statistics by Household Income. This table shows household and loan characteristics by household income quintile during the 12-month period before the policy implementation from February 2014 to January 2015. Income quintiles are adjusted monthly for wage inflation. Source: Central Bank of Ireland.

show the county-level distance from the lending limits. Darker colors indicate counties that are closer to the the lending limits. Perhaps not surprisingly, urban counties – and the Dublin area in particular – are closer to the lending limits. These are the counties that experienced a larger house price increase before the policy and where households were therefore more likely to borrow close to the to-be-imposed limits. Substantial heterogeneity exists in the distance from the lending limits across counties: The average distance is 0.21, the median distance is 0.23, and the standard deviation is 0.15.[16]

Second, in Table 2, we divide households who obtain a mortgage in the year prior to the policy

a standard deviation of one. Third, we average these two distances at the county level. See the Online Appendix for details.

[16]In Figure A.1 in the Appendix, we show that counties closer to the limits are more densely populated and experienced a sharper house price appreciation before the policy than more distant counties. In the Online Appendix, we show the county-level distance from the LTV and LTI limits, separately.

in five quintiles based on their income.[17] The income distribution is negatively skewed, because the average income of the top quintile is almost double the average income of the fourth income quintile. High-income borrowers also have lower LTV and lower LTI and tend to be older and less likely to be single or first-time buyers than lower-income borrowers.

Borrowers across the income distribution are differentially exposed to the LTI and LTV limits. Somewhat mechanically, the distance from the LTI limit increases monotonically with income. Low-income borrowers are the closest and high-income borrowers are the furthest from the limit. This monotonicity does not apply to the distance from the LTV limit: Borrowers in the bottom quintile of the income distribution are on average further away from the LTV limit than borrowers in the second to fourth quintiles, whereas borrowers in the top quintile are the furthest from the limit.[18] In sum, the LTV and LTI limits do not seem to be most binding for the same type of household. To measure how tight the regulation is for households based on their income, we create a standardized measure of the distance from both the LTV and LTI limit. This measure shows that borrowers in the top income quintile are by far the most distant from the lending limits compared with other borrowers.

3.3 Reallocation of Residential Mortgage Credit

We now document a mortgage credit reallocation from counties where borrowers are closer to the lending limits ("low-distance" counties) to counties where borrowers are further away from the lending limits ("high-distance" counties) and from low-income to high-income borrowers.

[17] Income quintiles are based on the January 2014 income distribution and adjusted monthly for Irish wage inflation using OECD data.

[18] On the one hand, high-income borrowers tend to face stricter LTV limits because they are often second- or subsequent-time buyers. On the other hand, low-income borrowers tend to face laxer LTV limits because they are often first-time buyers.

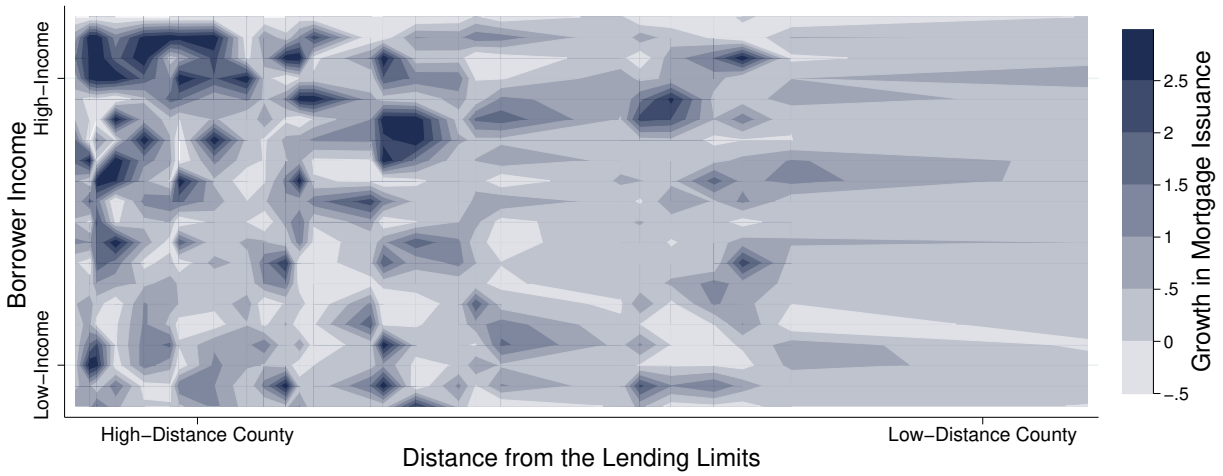

Figure 4: Reallocation of Mortgage Credit. This figure shows the reallocation of mortgage credit across counties and the across the income distribution of borrowers. The x-axis shows counties ranked according to their distance from the lending limits. The y-axis shows borrowers ranked according to their position in the income distribution (20 ventiles). Each point in the map indicates the change of mortgage issuance in the post-period (February 2015 to January 2016) compared with the pre-period (February 2014 to January 2015). Darker colors indicate higher growth of mortgage issuance, as indicated by the legend on the right.

We show this reallocation, non-parametrically, in Figure 4. On the x-axis, the 26 counties are ordered based on their distance from the lending limits: high-distance counties on the left and low-distance counties on the right. On the y-axis, borrowers are grouped and ordered in 20 ventiles based on their position in the income distribution: low-income borrowers on the bottom and high-income borrowers on the top. In sum, a point in the heatmap is an income group-county group pair. For each pair, we compute the change in mortgage origination from the pre-policy period (February 2013 to January 2014) to the post-policy period (February 2014 to January 2015). Darker colors indicate higher growth.

We observe darker colors on the left, toward the top, and especially in the top-left corner. In sum, this figure documents that the growth in mortgage issuance after the policy implementation has been driven by high-distance counties and high-income borrowers.[19]

[19] In the Online Appendix, we show a version of this heatmap where the post-period is from February 2014 to January 2015 and the pre-period is from February 2013 to January 2014. In this "placebo" period, we do not observe a reallocation to high-income borrowers and high-distance counties.

4 Bank Credit Reallocation

In this section, we show the reallocation of mortgage credit from low-distance to high-distance counties and from low-income to high-income borrowers is driven by bank portfolio choice.

4.1 Mortgage Credit Reallocation

The bank credit reallocation channel is based on the idea that banks react to the policy by reallocating their mortgage issuance to keep their risk exposure unchanged. This transmission mechanism has a clear cross-sectional implication: Banks with a larger fraction of non-conforming issuance in the pre-regulation period should reallocate their mortgage credit more aggressively than banks with less non-conforming issuance.

Following this intuition, we measure banks' differential exposure to the policy based on the relative importance of non-conforming issuance relative to a bank's total mortgage issuance during the year before the policy announcement. In particular, for each bank b, we define the following variable:

$$Exposure_b = \frac{\sum_{t=Oct13}^{Sep14} \text{Non-Conforming Mortgage Issuance}_{bt}}{\sum_{t=Oct13}^{Sep14} \text{Total Mortgage Issuance}_{bt}} \tag{1}$$

where the numerator is the sum of total non-conforming mortgage issuance between October 2013 and September 2014 by bank b, and the denominator is the sum, over the same period, of total mortgage issuance by bank b. Constructing this measure solely for the period before the announcement allows us to capture a bank's typical mortgage issuance without any temporary effects caused by the announcement of the lending limits.

We validate our measure in Figure 5, where we show the evolution of conforming mortgages issued by high-exposure banks (exposure above median, blue line) and low-exposure banks (ex-

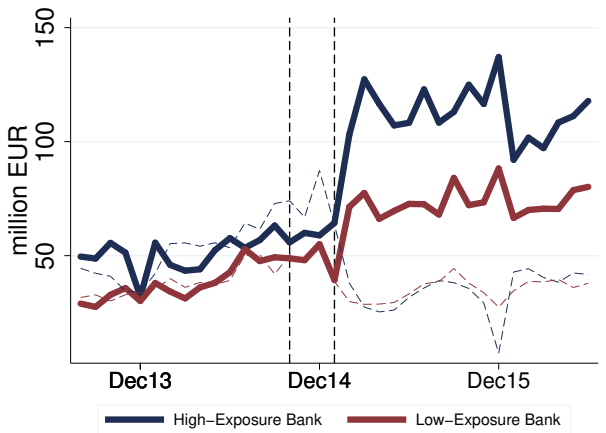

Figure 5: Residential Mortgage Issuance, High- vs. Low-Exposure Banks. The figure shows the issuance of conforming (solid thick lines) and non-conforming (dashed thin lines) mortgages for high-exposure (above median exposure) and low-exposure (below median exposure) banks from January 2013 to June 2016. The vertical lines indicate the announcement date and the implementation date of the lending limits. All time series are seasonally adjusted. Source: Central Bank of Ireland.

posure below median, red line). The thin dashed lines show non-conforming mortgage issuance, collapsing for both groups of banks after the policy implementation. This figure documents that high-exposure banks experience a greater drop in non-conforming mortgage issuance and a greater increase in conforming mortgage issuance than low-exposure banks.

Having shown non-parametric evidence of cross-sectional variation in bank credit reallocation, we now estimate the following difference-in-differences specification:

$$Y_{bcht} = \alpha + \beta Post_t \times Exposure_b + \gamma X_{b,t-1} + \nu_b + \eta_{ct} + \theta_{ht} + \epsilon_{bcht} \tag{2}$$

where our unit of observation is bank b, county c, household income bucket h, and month t. We divide households into 20 income buckets to ensure households are similar enough to properly capture mortgage demand. The sample period includes 24 months and runs from February 2014 to January 2016. The key independent variable is the interaction term between a $Post_t$ dummy equal to 1 from February 2015 to January 2016 and the bank-level $Exposure_b$ variable defined in (1). We saturate the specification with county-time fixed effects to capture time-varying geographical heterogeneity (e.g., county-specific demand for credit), bank fixed effects to capture bank time-invariant hetero-

geneity (e.g., specialization in mortgage issuance), income bucket-time fixed effects, and lagged bank time-varying controls (logarithm of total assets, equity capital ratio, and loans/total assets).

We run our specification in subsamples based on borrower income quintiles. We show the estimation results in Table 3 where each column corresponds to an income quintile. In Panel A and Panel B, the independent variables are total loan volume and mortgage size, respectively. We find that more-exposed banks increase the total loan volume issued to high-income (Q5) borrowers, whereas they reduce the total loan volume to low-income (Q1) borrowers more than less-exposed banks. Moreover, the top income quintile households also obtain larger loans than other quintiles after the policy. More precisely, a one standard deviation higher $Exposure_b$ leads to a 10% decrease in total new mortgage issuance to low-income (Q1) borrowers and to a 15% increase in total new mortgage issuance to high-income (Q5) borrowers. These results are consistent with more-affected banks reallocating credit to richer households that are further away from the lending limits and thus have potentially more room to increase their LTV and LTI, while still conforming with the newly imposed limits.

In Panel C, we consider the (loan volume-weighted) LTV as a dependent variable. We find that banks more exposed to the policy reduced their LTV compared with less-exposed banks in income quintiles Q1 and Q2, consistent with the lending limits affecting exposed banks more and with lower income households being more constrained. For households in the bottom income quintile, a one standard deviation higher $Exposure_b$ implies a reduction in the LTV of 6.6 percentage points. However, in the top income quintile (column (5)), more-affected banks *increased* their LTV compared with less-exposed banks. Borrowing from banks with a one standard deviation higher $Exposure_b$ leads to a 4.9 percentage points higher LTV in the top income quintile. Hence, by issuing larger loans to high-income households, banks can (partially) make up for the lost business caused by the introduction of the lending limits.

	Income Quintiles				
	Q1	Q2	Q3	Q4	Q5
Panel A: Total Loan Volume					
Post×Exposure	-1.311**	-0.570	-0.307	-0.773	2.085**
	(0.553)	(0.552)	(0.642)	(0.615)	(0.928)
Observations	2,404	2,786	2,947	2,512	1,929
R-squared	0.496	0.505	0.582	0.590	0.655
Panel B: Loan Size					
Post×Exposure	-0.546	-0.773***	-1.050**	-1.856***	4.591***
	(0.386)	(0.273)	(0.469)	(0.476)	(1.250)
Observations	2,404	2,786	2,947	2,512	1,929
R-squared	0.446	0.359	0.360	0.369	0.476
Panel C: LTV					
Post×Exposure	-91.148***	-30.657**	-0.421	-6.747	67.309**
	(14.915)	(14.100)	(16.285)	(12.749)	(26.549)
Observations	2,363	2,755	2,896	2,466	1,866
R-squared	0.389	0.264	0.242	0.265	0.372
Panel D: LTI					
Post×Exposure	-4.855	3.548	5.461	2.357	4.453***
	(6.830)	(4.521)	(4.001)	(4.193)	(1.579)
Observations	1,396	1,775	1,929	1,743	1,267
R-squared	0.426	0.419	0.484	0.492	0.538
Time Varying Bank Controls	✓	✓	✓	✓	✓
Bucket-Time FE	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
County-Time FE	✓	✓	✓	✓	✓

Table 3: Bank Credit Reallocation, Residential Mortgages, Heterogeneity Across Households. This table shows regressions at the bank-county-income bucket level separately for each quintile of the income distribution. Income quintiles are adjusted monthly for wage inflation. The dependent the logarithm of total mortgage volume to an income bucket (Panel A), the logarithm of the average loan size to an income bucket (Panel B), the value-weighted LTV (Panel C), and the value-weighted LTI (Panel D). *Exposure* is defined in (1), and *Post* is a dummy equal to 1 from February 2015 to January 2016. Time-varying bank-level controls include the logarithm of total assets, equity capital ratio, and the ratio of loans to total assets. All control variables are lagged by one period. Standard errors are double clustered at the bank-county and month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

In Panel D, the independent variable is the (loan volume-weighted) LTI. Similar to the finding for the LTV, we document a significant increase in the LTI for high-income households borrowing from more-exposed banks. More precisely, a one standard deviation higher $Exposure_b$ implies an increase in the loan-to-income ratio of high-income borrowers by 0.3 percentage points.[20]

4.2 Mortgage Rates

Having shown evidence consistent with bank portfolio choice driving mortgage credit reallocation, we now analyze mortgage rates to understand why high-income borrowers and borrowers located in high-distance counties take out larger loans and increase their leverage after the policy introduction.

We first examine the time-series evolution of mortgage rates for each quintile of the borrower income distribution. In Panel A of Table 4, we document that, although mortgage rates are falling for all borrowers during our sample period, high-income borrowers experience the largest reduction.[21] Borrowers in the top income quintile (Q5) experience a reduction of 46 whereas borrowers in the bottom income quintile (Q1) experience a reduction of 29 basis points.

Having shown that high-income borrowers experience the largest reduction in mortgage rates around the introduction of the lending limits, we resort again to the cross-section of banks to capture the bank portfolio choice channel. In particular, we re-estimate specification (2), using the mortgage rate as a dependent variable.

We show estimation results in Panel B of Table 4, where columns correspond to income quintiles. We find that (i) households in the top quintile of the income distribution were charged significantly

[20] In Figure A.3 in the Appendix, we show non-parametric evidence consistent with exposed banks driving high-income borrowers' LTV and LTI increase in the post-regulation period.

[21] Irish banks do not offer mortgage rates based on the income of borrowers. Banks typically offer an interest rate-LTV schedule, allowing borrowers to self-select into the product they prefer.

Panel A	Pre	Post	Difference
Q1	4.12	3.84	-0.29
Q2	4.24	3.85	-0.39
Q3	4.21	3.81	-0.40
Q4	4.21	3.80	-0.40
Q5	4.24	3.78	-0.46

	Income Quintiles				
Panel B	Q1	Q2	Q3	Q4	Q5
Post×Exposure	0.628	0.668	-0.224	-0.205	-1.427**
	(0.607)	(0.501)	(0.573)	(0.842)	(0.641)
Observations	2,366	2,666	2,717	2,220	1,682
R-squared	0.482	0.538	0.491	0.472	0.516
Bucket-Time FE	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
County-Time FE	✓	✓	✓	✓	✓

Table 4: Mortgage Interest Rates. Panel A shows (value-weighted) mean interest rates paid by households in different quintiles of the income distribution from February 2014 to January 2015 and from February 2015 to January 2016. Panel B shows estimation results from specifications (2) separately for each income quintile. Each column refers to an income quintile. The unit of observation is month-income bucket-bank. The dependent variable is the mortgage rate. *Exposure* is defined in (1), and *Post* is a dummy equal to 1 from February 2015 to January 2016. Standard errors clustered at the bank-time level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

lower rates if they borrowed from banks more affected by the lending limits, consistent with more-exposed banks offering favorable interest rates to high-income households who take larger loans.[22] Conversely, low-income households borrowing from more-affected banks faced relatively higher interest rates after the introduction of the lending limits. The results in this section are therefore consistent with more-exposed banks offering lower interest rates to attract high-income households to take out larger loans, thus trying to make up for the lost business due to the introduction of the lending limits.

One obvious question is why were high-income borrowers, and especially those located in high-distance counties, not borrowing as much *before* the lending limits? Two explanations are possible.

[22]Banks have several ways to influence the rates charged to clients, including offering more fixed- or non-fixed-rate mortgages.

First, banks suffered large losses exactly from high-income borrowers during the 2008-10 bust and therefore might have been reluctant to increase credit to this types of borrower when the housing market started to pick up again.[23] Second, banks might have a risk-shifting incentive to tilt their mortgage issuance toward low-distance counties such as the Dublin area, because the payoffs of mortgages in these counties are more correlated with banks' legacy assets (Malherbe and Bahaj, 2018; Landier et al., 2015).

4.3 Geographical Reallocation

In this subsection, we investigate whether the geographical reallocation of mortgage credit is consistent with the bank credit reallocation channel, i.e., whether more-exposed banks drive the change in credit reallocation across counties. To this end, we rerun the model in (2) separately for high- and low-distance counties.

Results are presented in Table 5. In column (1) of Panel A, we show that households in the bottom quintile of the income distribution receive significantly less credit if they are located in a low-distance county and are borrowing from more-exposed banks. More precisely, a one standard deviation higher $Exposure_b$ leads to a 13% reduction in new mortgage issuance in low-distance counties. Conversely, high-income households see a significant increase in the loan volume coming from more-exposed banks, especially if they are located in high-distance counties (column (5)). Here, a one standard deviation higher $Exposure_b$ leads to a 19% increase in new mortgage issuance. Moreover, these high-income households again take out larger loans from more-exposed banks, especially in high-distance counties (Panel B).

[23] In Figure A.4 in the Appendix, we show that our sample banks experienced the largest losses from high-income high-LTV borrowers during the 2007-10 bust.

	Income Quintiles				
	Q1	Q2	Q3	Q4	Q5
Panel A: Total Volume					*Low Distance Counties*
Post×Exposure	-1.763*	-1.231	-0.101	-0.306	1.327*
	(0.954)	(0.991)	(0.529)	(0.811)	(0.661)
Observations	664	850	981	933	795
R-squared	0.531	0.564	0.660	0.623	0.715
					High Distance Counties
Post×Exposure	-0.840	-0.204	-0.372	-0.439	2.664*
	(0.575)	(0.646)	(0.823)	(0.689)	(1.519)
Observations	1,739	1,936	1,965	1,579	1,134
R-squared	0.432	0.372	0.397	0.421	0.425
Panel B: Loan Size					*Low Distance Counties*
Post X Exposure	-1.118*	-1.036**	-0.486*	-1.729***	2.642*
	(0.611)	(0.426)	(0.267)	(0.488)	(1.289)
Observations	664	850	981	933	795
R-squared	0.410	0.290	0.365	0.343	0.385
					High Distance Counties
Post×Exposure	-0.237	-0.691	-1.296*	-1.860**	6.706***
	(0.460)	(0.489)	(0.659)	(0.679)	(1.410)
Observations	1,739	1,936	1,965	1,579	1,134
R-squared	0.446	0.330	0.303	0.360	0.493
Panel C: LTV					*Low Distance Counties*
Post X Exposure	-95.156***	-34.655	12.483	-12.752	26.131
	(32.174)	(28.343)	(14.928)	(23.987)	(21.635)
Observations	655	849	976	924	785
R-squared	0.453	0.312	0.241	0.239	0.311
					High Distance Counties
Post×Exposure	-83.793***	-30.936	-7.822	3.152	99.522***
	(17.870)	(19.919)	(23.212)	(11.624)	(34.871)
Observations	1,707	1,906	1,919	1,542	1,080
R-squared	0.412	0.287	0.277	0.295	0.434
Panel D: LTI					*Low Distance Counties*
Post×Exposure	-1.167	3.838	4.893	2.669	2.345
	(10.739)	(5.222)	(4.555)	(4.352)	(2.099)
Observations	398	587	706	689	590
R-squared	0.451	0.394	0.461	0.421	0.541
					High Distance Counties
Post×Exposure	-6.045	-1.345	6.755	0.899	8.516**
	(6.901)	(7.612)	(6.265)	(6.182)	(3.436)
Observations	993	1,188	1,223	1,054	676
R-squared	0.426	0.383	0.417	0.468	0.519
Time Varying Bank Controls	✓	✓	✓	✓	✓
Bucket-Time FE	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
County-Time FE	✓	✓	✓	✓	✓

Table 5: Bank Credit Reallocation, Residential Mortgages, Geographical Reallocation. This table presents the results from specification (2), separately for mortgages issued in high- and low-distance counties. The sample period includes 24 months and runs monthly from February 2014 to January 2016. The unit of observation is county-month-bank-income bucket. Income quintiles are adjusted monthly for wage inflation. The dependent variables are logarithm of total mortgage volume to an income bucket (Panel A), the logarithm of the median loan size to an income bucket (Panel B), the value-weighted LTV (Panel C), and the value-weighted LTI (Panel D). *Exposure* is defined in (1), and *Post* is a dummy equal to 1 from February 2015 to January 2016. Time-varying bank-level controls include the logarithm of total assets, equity capital ratio, and the ratio of loans to total assets. All control variables are lagged by one period. Standard errors are double clustered at the bank-county and month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

We also find that low-income households face a significant reduction in their LTV both in high- and low-distance counties (Panel C). However, the magnitude of the reduction is larger for low-income households in low-distance counties (a one standard deviation higher $Exposure_b$ leads to a 6.9 percentage points lower LTV in low-distance counties versus 6.0 percentage points in high-distance counties). Focusing on the top income quintile, we find that high-income households in high-distance counties receive mortgages with a significantly higher LTV after the introduction of the lending limits (for a one standard deviation higher $Exposure_b$, LTV increases by 7.2 percentage points). Similarly, the LTI of these households increases by 0.6 percentage points.

More affected banks thus seem to reallocate mortgage credit from low-income households in low-distance counties to high-income households in high-distance counties, which have the largest distance from the lending limits. This group of borrowers represents the segment of the market with the greatest opportunities for conforming credit expansion after the introduction of the regulations. More precisely, whereas high-income households in low-distance counties have an average distance of 0.3 from the lending limits, high-income households in high-distance counties have an average distance of 0.7 from the lending limits.

5 House Prices

In this section, we show the time-series evolution of house prices is consistent with the mortgage credit reallocation documented in the previous sections.

First, we show non-parametric evidence consistent with the credit reallocation across counties. In the left panel of Figure 6, we show yearly growth in house prices from January 2011 to June 2017. We observe that house price growth stopped increasing at the time of the policy announcement

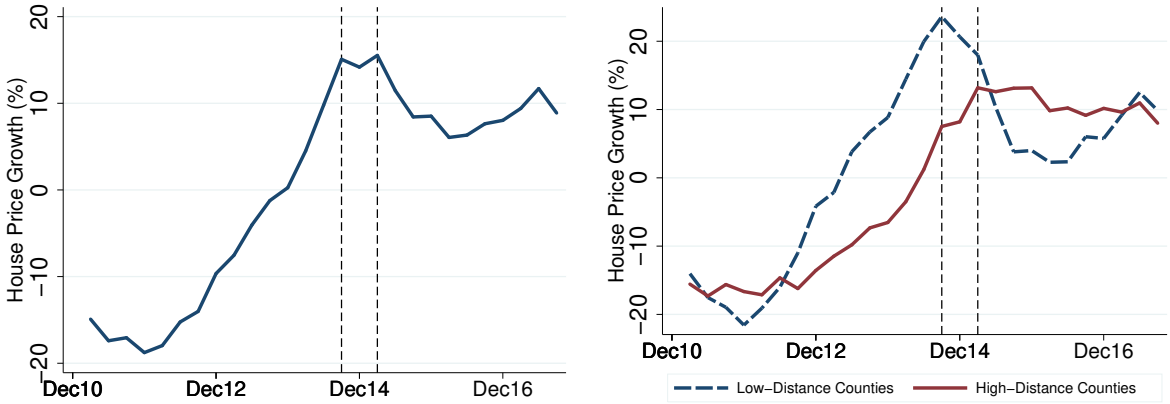

Figure 6: House Price Changes. The left panel of this figure shows the evolution of yearly house price growth. The right panel shows the evolution of yearly house price growth for high-distance and low-distance counties separately. The vertical dashed lines indicate the announcement and the implementation date of the lending limits. The sample period runs from January 2011 to June 2017. Source: Central Bank of Ireland, Daft.ie.

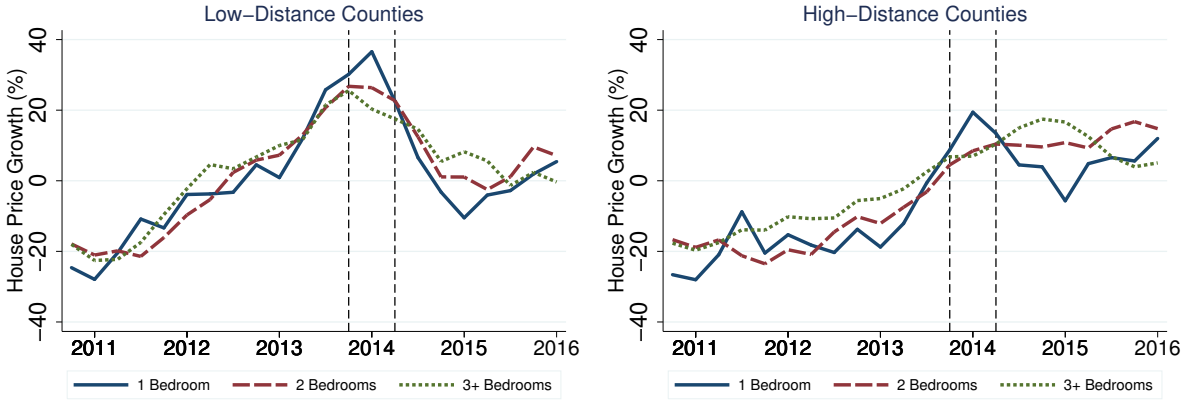

Figure 7: House Price Changes and Property Type. This figures shows the evolution of yearly house price growth for 1-bedroom properties (solid line), 2-bedroom properties (dashed line), and 3-bedroom or larger properties (dotted line). The left (right) panel shows data for low-distance (high-distance) counties. The vertical dashed lines indicate the announcement and the implementation date of the lending limits. The sample period runs from January 2011 to June 2017. Source: Central Bank of Ireland, Daft.ie.

and then stabilized around 10% after the policy implementation.[24] In the right panel, we plot house price growth separately for high-distance (solid line) and low-distance (dashed line) counties. We find that low-distance counties experienced a stark contraction of house price growth after

[24]House prices reacted at the time of the policy announcement, anticipating the credit reallocation at the time of the policy implementation. In Figure A.2 in the Appendix, we show, using survey data, that households expected a decline in house prices after the announcement, exactly because of the imminent implementation of the lending limits.

the policy implementation, whereas house price growth remained stable at the pre-policy level in high-distance counties.

Second, we show non-parametric evidence consistent with the credit reallocation across the income distribution. In Figure 7, we the show yearly growth in house prices from January 2011 to June 2017 separately for one-bedroom, two-bedroom, and three-or-more-bedroom apartments in low-distance counties (left panel) and high-distance counties (right panel). To the extent that property size is correlated with the income of the buyers, this figure is consistent with the mortgage credit reallocation documented in the previous section: The slow-down in house price growth in low-distance counties is driven by small apartments, and the relative stability of house price growth in high-distance counties is driven by large apartments.[25]

We complement these graphs with parametric evidence. In particular, we estimate the following specifications at the county (c) level and at the county-property type (c, p) level:

$$\Delta HP_c^{14Q3-16Q4} = \alpha + \beta Distance_c + \epsilon_c \tag{3}$$

$$\Delta HP_{cp}^{14Q3-16Q4} = \alpha + \beta_1 Distance_c \times Size_p + \beta_2 Distance_c + \beta_3 Size_p + \epsilon_{cp} \tag{4}$$

where the dependent variable is the change in house prices from 2014Q3 to 2016Q4, *Distance* is the county-level distance from the lending limits, and *Size* is an integer equal to the number of bedrooms.[26] We interact *Distance* with the measure of property size to check whether the effect

[25] Table 2 shows that borrower income is strongly correlated with the price of the property purchased. In the Online Appendix, we attempt to map the number of bedrooms to the income of buyers by regressing the price of the residential property collateralizing the residential mortgage (from the credit registry data) on property size-county-level house price data. We find these loadings are consistent with high-income (low-income) borrowers predominantly buying large (small) properties. Of course, this mapping is not perfect, because, for example, high-income borrowers might buy a one-bedroom property to rent it out.

[26] The geographical breakdown of the house price data is more granular than the mortgage-level data. In particular, we observe data for each of the 22 Dublin postal districts. Given that we cannot compute the distance from the lending limits at this more granular level, we are forced to assume the distance is constant within a county. We then

LHS: ΔHP	(1)	(2)	(3)	(4)	(5)
Distance × Size		0.007**	0.007**	0.007**	0.007**
		(0.003)	(0.003)	(0.003)	(0.003)
Distance	0.296***	0.276***		0.276***	
	(0.072)	(0.076)		(0.077)	
Size		0.012***	0.012***		
		(0.000)	(0.000)		
Country FE			✓		✓
Size FE				✓	✓
Observations	54	270	270	270	270
R-squared	0.360	0.281	0.736	0.468	0.924

Table 6: House Prices and Lending Limits. This table shows estimation results from specification (4) in column (1) and estimation results from specification (4) in columns (2)-(5). The dependent variable is the change in house prices between 2014Q3 and 2016Q4. *Distance* is the county-level distance from the lending limits. *Size* is the number of bedrooms (1 to 5). Standard errors clustered at the county-level in parentheses. Source: Central Bank of Ireland, Daft.ie.

of the lending limits changes depending on the type of property.

We show the estimation results in Table 6. The county-level estimation (3), in column (1), confirms the positive correlation between changes in house price growth after the policy and county-level distance from the lending limits. In columns (2)-(5), we show the county-property size-level estimation. We confirm that house price growth increased more in high-distance counties than in low-distance counties, and this different evolution is more pronounced for larger properties. These results are consistent with the documented reallocation of mortgage credit across counties and – to the extent that property size is correlated with the income of the buyers – across the distribution of incomes of borrowers.

cluster our standard errors at the county-level to take into account that standard errors might be correlated within counties.

6 Bank Risk Exposure

In the previous section, we showed that, thanks to their effect on house prices, the lending limits likely reduced the probability of a bust like the 2007-10 one. In this section, we analyze the risk exposure of banks should the economy fall again in that – now less probable – state of the world. We combine security-level holdings, loan-level credit to firms, and loan-level residential mortgages, capturing approximately 80% of banks' assets. We find that banks increased their risk exposure in asset classes not targeted by the policy (holdings of securities and credit to firms) and reallocated their residential mortgage credit to borrowers more likely to default during busts.[27] In Section 6.1 and Section 6.2, we analyze banks' holdings of securities and credit to firms, respectively. In Section 6.3, we analyze residential mortgages.

6.1 Security Holdings

We use security-level holdings data and examine whether banks changed their risk exposure in this asset class. In particular, we use the yield of a security to measure its exposure to events like the 2007-10 bust. Following Davis and Haltiwanger (1992), we define the "net buys" of security s by bank b from time $t-1$ to time t as follows:

$$NetBuys_{s,b,t} = \frac{Holdings_{s,b,t} - Holdings_{s,b,t-1}}{0.5(Holdings_{s,b,t} + Holdings_{s,b,t-1})} \in [-2, 2] \tag{5}$$

where *Holdings* is the euro value of holdings of security s by bank b at time t. Compared with simple percentage changes, this measure also captures final sales and initial purchases. Its value is

[27] We do not observe substantial reallocation across asset classes. In the Online Appendix, we show the evolution of the aggregate balance sheet of our sample banks.

	Net Buys				Buys	Sells
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure×Yield×Post	0.021**	0.019**	0.057***	0.067***	0.290***	-0.251**
	(0.008)	(0.009)	(0.016)	(0.022)	(0.098)	(0.102)
Time FE	✓					
Security FE	✓	✓				
Bank-Time FE		✓		✓	✓	✓
Security-Time FE			✓	✓	✓	✓
Observations	7,707	7,707	7,707	7,707	7,707	7,707
R-squared	0.247	0.281	0.943	0.949	0.919	0.915

Table 7: Bank Portfolio Reallocation, Holdings of Securities. This table shows the estimation results from specification (6). The unit of observation is security-bank-quarter. The sample runs at a quarterly frequency from 2013Q1 to 2016Q2. The dependent variable is defined in (5). *Exposure* is defined in (1), *Post* is a dummy equal to 1 from 2015Q2 onwards, and $Yield$ is the yield of the security. Double-interaction terms and uninteracted terms (when not absorbed by fixed effects) are not shown for brevity. Standard errors clustered at the security-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

always between -2, corresponding to final sales, and 2, corresponding to initial purchases.

We exploit again the cross-sectional heterogeneity in bank exposure to the lending limits. In particular, we estimate the following specification:

$$NetBuys_{sbt} = \alpha + \beta Exposure_b \times Post_t \times Yield_{st} + \gamma_{bt} + \eta_{st} + \epsilon_{sbt} \tag{6}$$

where the unit of observation is security s, bank b, quarter t.[28] Our independent variable of interest is a triple interaction term between bank exposure to the lending limits defined in (1), a *Post* dummy equal to 1 in the post period, and the yield of the security. We saturate our specification with several fixed effects. In our most conservative estimation, we include bank-time fixed effects to capture any time-varying bank heterogeneity and security-time fixed effects to capture eventual changes in price and amounts outstanding of specific securities.

We show estimation results in Table 7. We progressively saturate the regression with more stringent fixed effects. Column (4) includes all the pairs of two-way fixed effects. The coefficient of

[28] We observe security-level holdings at a quarterly frequency.

interest, stable across specifications, indicates that more-exposed banks increase their holdings of risky securities compared with less-exposed banks after the policy implementation than before it. Moreover, in columns (5) and (6), we explicitly distinguish between the buying and selling behavior of banks. *Buys* are defined as the logarithm of the amount of security s bought by bank b at time t, and zero otherwise. Similarly, *Sells* are defined as the logarithm of the amount of security s sold by bank b at time t, and zero otherwise. We find that more-exposed banks buy more and sell less high-yield securities than less-exposed banks.

6.2 Credit to Firms

We now use the corporate loan-level data and analyze whether banks changed their credit supply to firms. To this end, we adapt specification (2) and estimate the following specification:

$$Y_{bclqt} = \alpha + \beta Post_t \times Exposure_b + \gamma X_{bt-1} + \delta_{bc} + \eta_{clqt} + \epsilon_{bclqt} \tag{7}$$

We measure the credit provided by bank b to firms in county c, industry l, of quality q in semester t, i.e., we group firms into clusters based on their county, industry, and quality at time t and investigate the lending behavior of banks to a cluster of firms (Acharya et al., 2018).[29] Forming clusters based on county and industry is motivated by the fact that firms in a particular industry in a particular county share many characteristics and are thus likely affected in a similar way by macroeconomic developments that might influence credit demand.

Note that because we do not have a unique firm identifier across loans, we are unable to analyze credit extended to the *same* firm by different banks (Khwaja and Mian, 2008). To determine the

[29] We observe loan-level credit to firms at a biannual frequency.

quality of a firm that receives a loan, we use the ratings obtained by the Central Bank of Ireland.[30] More precisely, the Central Bank of Ireland employs a rating scale from 1 (best) to 5 (worst). We use these rating categories to divide firms into three quality buckets: high quality (rating 1-2), medium quality (rating 3-4), and low quality/high risk (rating 5).

The dependent variable is either the change in log (stock of) credit granted ($\Delta VOLUME$) or the change in the interest rate charged ($\Delta RATE$). Similar to the previous section, we are interested in the coefficient of the interaction term between the *Post* dummy and the bank exposure to the intervention. We include industry-county-quality-time fixed effects to control for credit demand of firms and other variables that are shared by firms of similar quality operating in the same county and industry. We also include bank-county fixed effects to capture time-invariant bank-county heterogeneity (e.g., time-constant heterogeneity in the geographical preference of banks).

We show estimation results in Table 8. In Panels A and B, the dependent variable is the change in volume of credit and change in interest rate charged, respectively. Column (1) considers the full sample of firms. The estimates document that more-exposed banks increase their lending volume to firms and decrease the price of corporate loans more than less-exposed banks. In a next step, we split our sample firms into risky (rating 5) and non-risky (rating 1-4) firms and re-run our specification (7) separately for these two groups of borrowers. The estimation results in columns (2) and (3) show that, although a credit expansion in the corporate sector occurs for both risky and non-risky firms, the effect is economically and statistically more pronounced for risky firms relative to the pre-period. A one standard deviation higher *Exposure* leads to a 10 percentage points higher credit supply to firms and a 20 percentage points higher credit supply to risky firms.

[30] These ratings come from the banks' internal models but are homogenized by the Central Bank of Ireland to ensure the rating classes correspond to similar probabilities of default.

Panel A	Sample			
LHS: $\Delta VOLUME$	Total	Risky	NonRisky	Total
Exposure × Post	1.382***	2.761***	0.740*	0.697
	(0.401)	(0.659)	(0.435)	(0.449)
Exposure × Post × Risky				2.253***
				(0.547)
Exposure × Risky				-0.182
				(0.307)
Time-Varying Bank Controls	✓	✓	✓	✓
Industry-County-Quality-Time FE	✓	✓	✓	✓
Bank-County FE	✓	✓	✓	✓
Observations	10,092	3,227	6,865	10,092
R-squared	0.525	0.569	0.493	0.527

Panel B	Sample			
LHS: $\Delta RATE$	Total	Risky	NonRisky	Total
Exposure × Post	-0.719***	-1.677***	-0.234	-0.187
	(0.195)	(0.557)	(0.268)	(0.262)
Exposure × Post × Risky				-1.753**
				(0.674)
Exposure × Risky				0.058
				(0.367)
Time-Varying Bank Controls	✓	✓	✓	✓
Industry-County-Quality-Time FE	✓	✓	✓	✓
Bank-County FE	✓	✓	✓	✓
Observations	10,007	3,183	6,823	10,007
R-squared	0.478	0.508	0.463	0.479

Table 8: Bank Portfolio Reallocation, Credit to Firms. This table shows the estimation results of specification (7). The unit of observation is bank-industry-county-quality-time. The sample runs at a bi-annual frequency from 2013H1 to 2016H1. *Exposure* is defined in (1) and *Post* is a dummy equal to 1 from 2015H1 to 2016H1. A risky loan has a rating equal to 5. The dependent variables are the change in log (stock of) credit granted in Panel A and the (value weighted) change in the interest rate charged in Panel B. Standard errors clustered at the bank-county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

These results are confirmed in the last column of Panel A, where we employ a triple interaction of our bank exposure variable with a *Post* dummy and a dummy for whether the borrowing firms are risky. The coefficient shows the increase in loan volume is mostly driven by an increase toward risky firms relative to the pre-period. Similarly, in Panel B, we find the decrease in the cost of bank loans is mostly benefiting risky firms.

6.3 Residential Mortgage Lending

The analysis of the risk exposure of residential mortgage credit is particularly delicate because we do not observe mortgage-level ratings or have data on ex-post defaults (the lending limits were introduced very recently). Hence, we use machine learning techniques to predict mortgage-level default probabilities using loan characteristics at origination.[31] Our goal is to exploit patterns of loan and/or borrower characteristics that predict defaults (Mullainathan and Spiess, 2017) using the cross-section of all outstanding mortgages in December 2013.[32] Given that the majority of mortgage defaults in Ireland occurred during the 2007-10 real estate bust, our predicted default probabilities should be interpreted as conditional on a similar bust in the housing market.[33] More specifically, we follow Liberman et al. (2018) and estimate these conditional default probabilities with a random forest model. This supervised algorithm consists of various regression trees where each tree uses a random selection of standard loan and borrower characteristics at origination. The algorithm chooses a combination of explanatory variables (branches) to maximize in-sample prediction power. At the end of each tree, the values of variables are used to determine whether or not a loan is predicted to default. The final prediction of the model is obtained by calculating the average of all trees in the forest.[34]

In Figure 8, we plot the evolution of the (value-weighted) conditional default probability of newly issued mortgages by our sample banks. The top-left panel shows the bank credit reallocation in the mortgage book seems to have led to an increase in the average default probability of newly

[31] The intuition underlying this approach is that we let past data tell us which predictors are significant for mortgage default. We do not manually pick variables as we would for standard OLS or logit hazard models.

[32] December 2013 is the earliest date on which we have a well populated data set on all outstanding mortgages.

[33] Because houses are hard to repossess in Ireland, a portion of defaults in the crisis was likely strategic. McCann (2017) shows that 40% of borrowers who are in long-term arrears have never engaged with their lender for a renegotiation, suggesting some of them might have been strategic defaulters.

[34] In the Online Appendix, we provide a detailed description of this machine learning exercise.

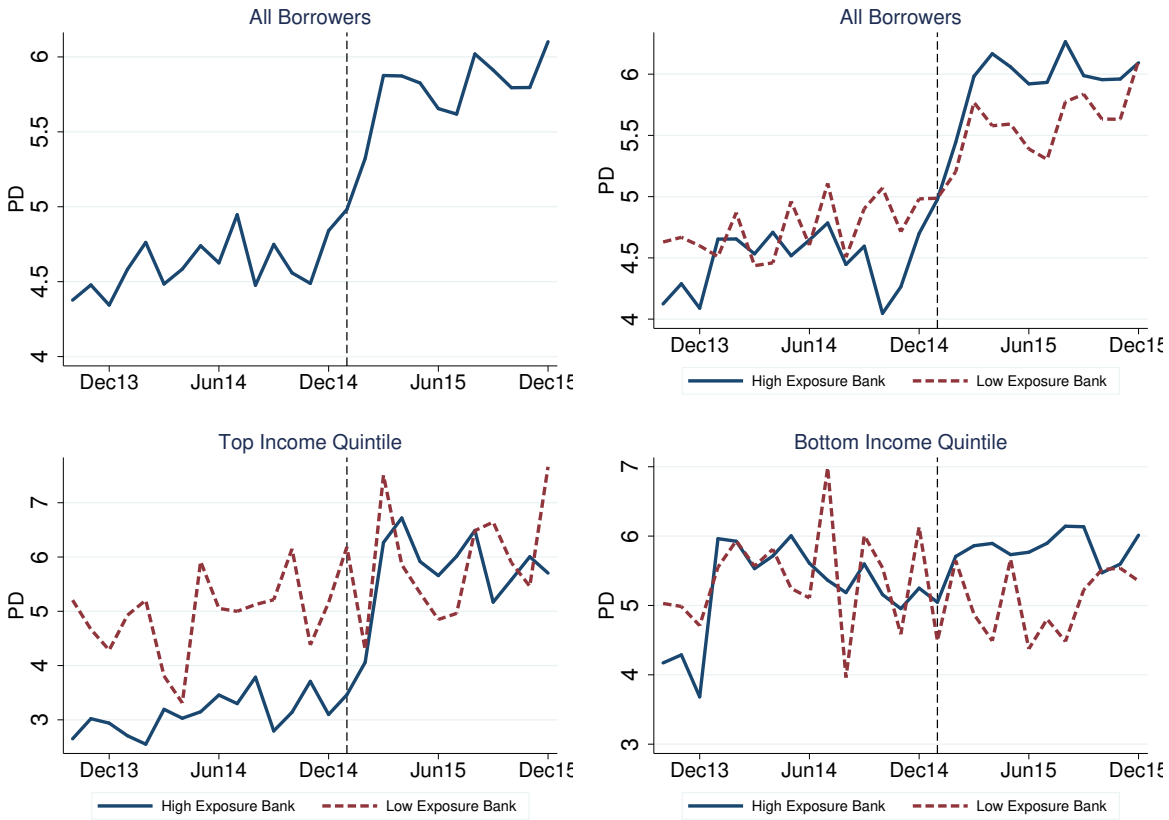

Figure 8: Mortgage Probability of Default. This figure shows the evolution of mortgage probability of default from October 2013 to February 2016. Panel A shows the default probability of newly issued mortgages by all Irish banks. Panel B shows the default probability of newly issued mortgages separately for high- and low-exposure banks. Panel C (D) shows the default probability of newly issued mortgages in the top (bottom) income quintile separately for high- and low-exposure banks. The vertical dashed lines indicate the implementation of the lending limits. Source: Central Bank of Ireland.

issued mortgages.[35] The top-right panel confirms this increase is driven by more-affected banks, whereas the two bottom panels show this increase is concentrated in the high-income household segment of the mortgage market.

We confirm this graphical evidence by re-running specification (2) using default probabilities as the dependent variable. The results, presented in Table 9, show that more-exposed banks issue mortgages with a higher default probability to high-income households than do less-exposed banks.

[35]These relatively high default probabilities should again be interpreted conditional on a severe real estate bust. In particular, during the 2007-10 bust, unemployment rose from 4% to 13% and house prices collapsed by more than 50%, in a context where household debt was among the highest in world.

	Income Quintiles				
	Q1	Q2	Q3	Q4	Q5
PANEL A. Sample Counties: Full Sample					
Post×Exposure	0.041	-0.031**	-0.027	0.073***	0.253***
	(0.030)	(0.013)	(0.021)	(0.025)	(0.056)
Observations	2,366	2,666	2,717	2,220	1,682
R-squared	0.501	0.527	0.475	0.438	0.472
PANEL B. Sample Counties: Low Distance					
Post×Exposure	0.012	-0.040*	0.026	0.099***	0.113**
	(0.041)	(0.019)	(0.032)	(0.029)	(0.044)
Observations	648	785	850	778	651
R-squared	0.527	0.626	0.509	0.408	0.505
PANEL C. Sample Counties: High Distance					
Post×Exposure	0.063*	-0.031	-0.056*	0.051	0.386***
	(0.034)	(0.018)	(0.031)	(0.039)	(0.070)
Observations	1,717	1,881	1,866	1,442	1,031
R-squared	0.511	0.514	0.488	0.469	0.535
Time Varying Bank Controls	✓	✓	✓	✓	✓
Bucket-Time FE	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
County-Time FE	✓	✓	✓	✓	✓

Table 9: Bank Credit Reallocation, Residential Mortgages, Default Probability. This table presents the results from specification (2) using the value-weighted default probability as the dependent variable. The sample period includes 24 months and runs monthly from February 2014 to January 2016. The unit of observation is county-month-bank-income bucket. Income quintiles are adjusted monthly for wage inflation. *Exposure* is defined in (1), and *Post* is a dummy equal to 1 from February 2015 to January 2016. Time-varying bank-level controls include the logarithm of total assets, equity capital ratio, and the ratio of loans to total assets. All control variables are lagged by one period. Standard errors double clustered at the bank-county and month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

Consistent with the results in the previous sections, this effect is strongest in counties that are further away from the lending limits. More precisely, a one standard deviation higher *Exposure* in counties that are more distant from the lending limits leads to a 2.7 percentage points higher default probability for mortgages issued to high-income households.

The higher default probability in a bust for high-income households is consistent with data from past real estate busts. In the U.S., Adelino et al. (2016) document that middle class and

high-income borrowers were responsible for a high share of mortgage dollars in delinquency during the bust. In Ireland, in Figure A.4 in the Appendix, we show our sample banks experienced the largest losses from high-income high-LTV borrowers.[36] Consistent with DeFusco et al. (2017), these results suggest that limits to household leverage have a limited effect in reducing mortgage default rates in bad times.

Of course, these findings have to be considered in the context of the changes in the evolution of house prices documented in Section 5. On the one hand, the lending limits induced banks to issue mortgages more likely to default in case of a bust like the 2007-10 one. On the other hand, given the decrease in house price growth rates, especially in low-distance counties, the lending limits made the recurrence of a bust like the 2007-10 one less likely. In sum, we cannot conclude the risk of banks' mortgage book actually increased, because two opposing effects need to be considered.

7 Conclusion

We inform the academic literature and policy debate by providing a comprehensive micro-level analysis of the transmission of macroprudential policies aimed at limiting household leverage in the residential mortgage market. Combining loan-level data on residential mortgages and bank credit to firms, county-level house prices, and security-level data on bank holdings of securities, we examine the February 2015 introduction of LTV and LTI limits in Ireland.

We find that banks played a key role in the transmission. Following the policy introduction, banks reallocated their mortgage issuance from low-income to high-income households and from low-distance to high-distance counties. Our effects are consistent with the evolution of house price

[36] Kelly et al. (2015) show that Irish first-time buyers, which are primarily low-income households, are four percentage points less likely to default than second and subsequent home buyers, which tend to be higher-income households.

growth, which stopped increasing at the time of the policy announcement, driven by a collapse in low-distance counties. Consistent with the goal of keeping their risk exposure unchanged, banks increased their risk exposure in credit to firms and holdings of securities, the two largest asset classes not targeted by the regulation.

References

Acharya, V., I. Drechsler, and P. Schnabl (2014): "A pyrrhic victory? Bank bailouts and sovereign credit risk," *The Journal of Finance*, 69, 2689–2739.

Acharya, V. V., T. Eisert, C. Eufinger, and C. W. Hirsch (2018): "Real effects of the sovereign debt crisis in Europe: Evidence from syndicated loans," *Review of Financial Studies*, forthcoming.

Adelino, M., A. Schoar, and F. Severino (2014): "Credit Supply and House Prices: Evidence from Mortgage Market Segmentation," *Working Paper*.

——— (2016): "Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class," *Review of Financial Studies*, 29, 1635–1670.

Agarwal, S., C. Badarinza, and W. Qian (2018): "The Effectiveness of Housing Collateral Tightening Policy," *Working Paper*.

Aikman, D., J. Bridges, A. K. Kashyap, and C. Siegert (2018): "Would Macroprudential Regulation Have Prevented the Last Crisis?" *Working Paper*.

Aiyar, S., C. Calomiris, and T. Wieladek (2014): "Does Macro-Pru Leak? Evidence from a UK Policy Experiment," *Journal of Money, Credit and Banking*, 46, 181–214.

Auer, R. and S. Ongena (2016): "The Countercyclical Capital Buffer and the Composition of Bank Lending," *Working Paper*.

Ayyagari, M., T. Beck, and M. S. Martinez Peria (2017): "Credit growth and macroprudential policies: preliminary evidence on the firm level," *Working Paper*.

Basten, C. C. and C. Koch (2015): "Higher bank capital requirements and mortgage pricing: evidence from the Countercyclical Capital Buffer (CCB)," .

Begenau, J. (2016): "Capital Requirements, Risk Choice, and Liquidity Provision in a Business Cycle Model," *Working Paper*.

Benetton, M., P. Eckley, N. Garbarino, L. Kirwin, and G. Latsi (2017): "Capital Requirements and Mortgage Pricing: Evidence from Basel II," *Working Paper*.

Bianchi, J. (2011): "Overborrowing and Systemic Externalities in the Business Cycle," *American Economic Review*, 101, 3400–3426.

Bianchi, J., E. Boz, and E. G. Mendoza (2012): "Macroprudential Policy in a Fisherian Policy Model of Financial Innovation," *Working Paper*.

Bianchi, J. and E. G. Mendoza (2010): "Overborrowing, Financial Crises and Macro-prudential Policy," *Working Paper*.

——— (forthcoming): "Optimal Time-Consistent Macroprudential Policy," *Journal of Political Economy*.

Brunnermeier, M. and Y. Sannikov (2014): "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 104, 379421.

Cerutti, E. M., S. Claessens, and L. Laeven (2015): "The Use and Effectiveness of Macroprudential Policies; New Evidence," IMF Working Papers 15/61, International Monetary Fund.

Chodorow-Reich, G. (2014): "The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 200809 Financial Crisis," *Quarterly Journal of Economics*, 129, 1–59.

Claessens, S. (2015): "An Overview of Macroprudential Policy Tools," *Annual Review of Financial Economics*, 7, 397–422.

Claessens, S., S. R. Ghosh, and R. Mihet (2013): "Macro-prudential policies to mitigate financial system vulnerabilities," *Journal of International Money and Finance*, 39, 153–185.

Dassatti Camors, C., J.-L. Peydro, and F. R. Tous (2015): "Macroprudential and Monetary Policy: Loan-level Evidence from Reserve Requirements," *Working Paper*.

Davis, S. and J. C. Haltiwanger (1992): "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *Quarterly Journal of Economics*, 107, 819–864.

De Marco, F. and T. Wieladek (2015): "The Real Effects of Capital Requirements and Monetary Policy: Evidence from the United Kingdom," *Working Paper*.

DeFusco, A., S. Johnson, and J. Mondragon (2017): "Regulating Household Leverage," *Working Paper*.

Eggertsson, G. and P. Krugman (2012): "Debt, Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach," *Quarterly Journal of Economics*, 127, 14691513.

Elenev, V., T. Landvoigt, and S. van Nieuwerburgh (2017): "A Macroeconomic Model with Financially Constrained Producers and Intermediaries," *Working Paper*.

Farhi, E. and I. Werning (2016): "A Theory of Macroprudential Policies in Presence of Nominal Rigidities," *Econometrica*, 84, 1645–1704.

Favara, G. and J. Imbs (2015): "Credit Supply and the Price of Housing," *American Economic Review*, 105, 958–992.

Freixas, X., L. Laeven, , and J. L. Peydro (2015): "Systemic Risk, Crises and Macroprudential Policy," *MIT Press*.

Gambacorta, L. and A. Murcia (2017): "The Impact of Macroprudential Policies and Their Interaction with Monetary Policy: an Empirical Analysis Using Credit Registry Data," *Working Paper*.

Gertler, M. and N. Kiyotaki (2011): "Financial Intermediation and Credit Policy in Business Cycle Analysis," *Handbook of Monetary Economics*.

Gropp, R., T. C. Mosk, S. Ongena, and C. Wix (2016): "Bank Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment," *Working Paper*.

Hall, R. (2011): "The Long Slump," *American Economic Review*, 101, 431469.

He, Z. and A. Krishnamurthy (2013): "Intermediary Asset Pricing," *American Economic Review*, 103, 732770.

Honohan, P. (2010): "The Irish Banking Crisis: Regulatory and Financial Stability Policy 2003-2008," Report of the commission of investigation into the banking sector in ireland, Central Bank of Ireland.

Igan, D. and H. Kang (2011): "Do loan-to-value and debt-to-income limits work? Evidence from Korea," .

Jeanne, O. and A. Korinek (2017): "Macroprudential Regulation Versus Mopping Up After the Crash," *Working Paper*.

Jimenez, G., J.-L. Peydro, S. Ongena, and J. Saurina (forthcoming): "Macroprudential Policy, Countercyclical Bank Capital Buffers and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments," *Journal of Political Economy*.

Kashyap, A. K., D. Tsomocos, and A. Vardoulakis (2014): "How Does Macroprudential Regulation Change Bank Credit Supply?" *Working Paper*.

Kelly, R., T. O'Malley, and C. O'Toole (2015): "Designing Macro-prudential Policy in Mortgage Lending: Do First Time Buyers Default Less?" *Working Paper*.

Khwaja, A. and A. Mian (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 98, 1413–1442.

Kinghan, C., Y. McCarthy, and C. O'Toole (2017): "Macroprudential Policy and Borrower Behaviour: How Do Limits on Loan-to-Value and Loan-to-Income Ratios Impact Borrower Leverage and House Purchasing Decisions?" *Working Paper*.

Landier, A., D. A. Sraer, and D. Thesmar (2015): "The Risk-Shifting Hypothesis: Evidence from Subprime Originations," *Working Paper*.

Landvoigt, T. and J. Begenau (2017): "Financial Regulation in a Quantitative Model of the Modern Banking System," *Working Paper*.

Lane, P. R. (2011): "The Irish Crisis," Cepr discussion papers.

Liberman, A., C. Neilson, L. Opazo, and S. Zimmerman (2018): "The Equilibrium Effects of Asymmetric Information: Evidence from Consumer Credit Markets," Tech. rep.

Lorenzoni, G. (2008): "Inefficient Credit Booms," *Review of Economic Studies*, 75, 809–833.

Malherbe, F. and S. Bahaj (2018): "The Forced Safety Effect: How Higher Capital Requirements Can Increase Bank Lending," *Working Paper*.

McCann, F. (2017): "Borrower-Lender Engagement During the Irish Mortgage Arrears Crisis," *Economic Letters*, Central Bank of Ireland.

Mian, A., K. Rao, and A. Sufi (2013): "Household Balance Sheets, Consumption, and the Economic Slump," *Quarterly Journal of Economics*, 128, 1–40.

Mian, A. and A. Sufi (2009): "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis," *Quarterly Journal of Economics*, 124, 1449–1496.

——— (2014): "What Explains the 2007-2009 Drop in Employment?" *Econometrica*, 82, 21972223.

Mian, A., A. Sufi, and E. Verner (2017): "Household debt and business cycles worldwide," *The Quarterly Journal of Economics*, 132, 1755–1817.

Midrigan, V. and T. Philippon (2016): "Household Leverage and the Recession," *Working Paper*.

Moreira, A. and A. Savov (2017): "The Macroeconomics of Shadow Banking," *Journal of Finance*, 72, 2381–2432.

Mullainathan, S. and J. Spiess (2017): "Machine Learning: An Applied Econometric Approach," *Journal of Economic Perspectives*, 31, 87–106.

Tzur-Ilan, N. (2017): "The Effect of Credit Constraints on Housing Choices: The Case of LTV Limit," *Working Paper*.

Appendix A Additional Figures

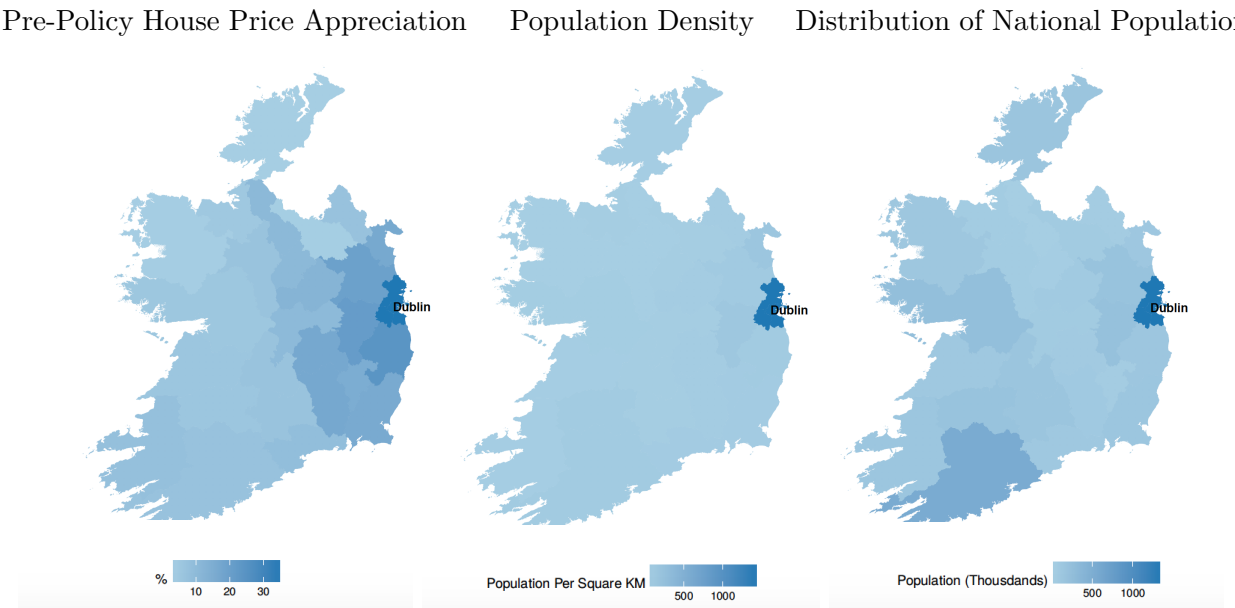

Figure A.1: Demographics and House Price Appreciation Across Counties. The left panel of this figure shows county-level population. Darker colors indicate more densely populated counties. The right panel shows county-level increase in house prices from their lowest point after the bust to September 2014. Darker colors indicate sharper a larger increase in house prices. Source: Central Bank of Ireland, Daft.ie

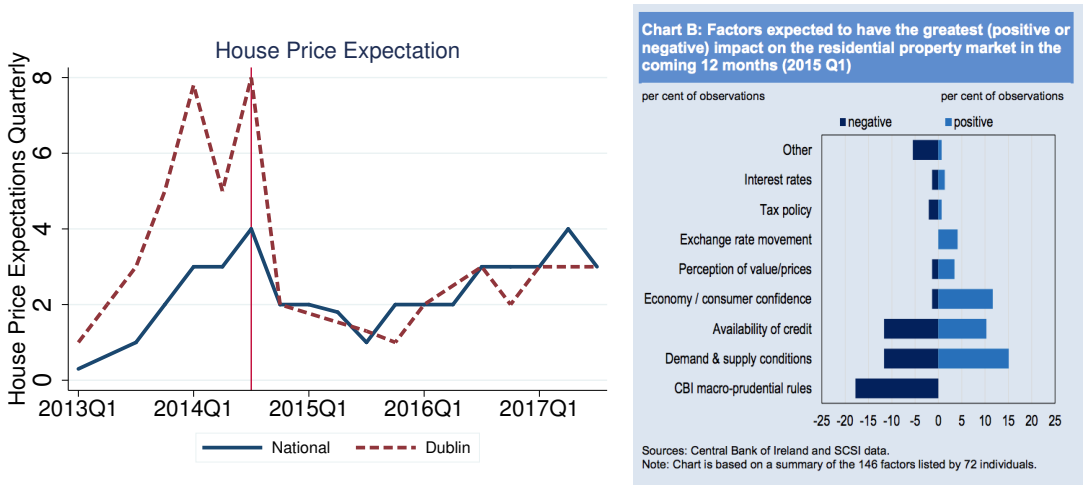

Figure A.2: House Price Expectations. This figure shows survey evidence suggesting that the announcement of the lending limits caused households to revise their expectations about house prices downward, especially in low-distance counties. The left panel shows the evolution of house price expectations in Dublin (dashed line) and at the national level (solid line) at a quarterly frequency. The right panel shows a breakdown of factors affecting expectations in 2015Q1. Source: Central Bank of Ireland.

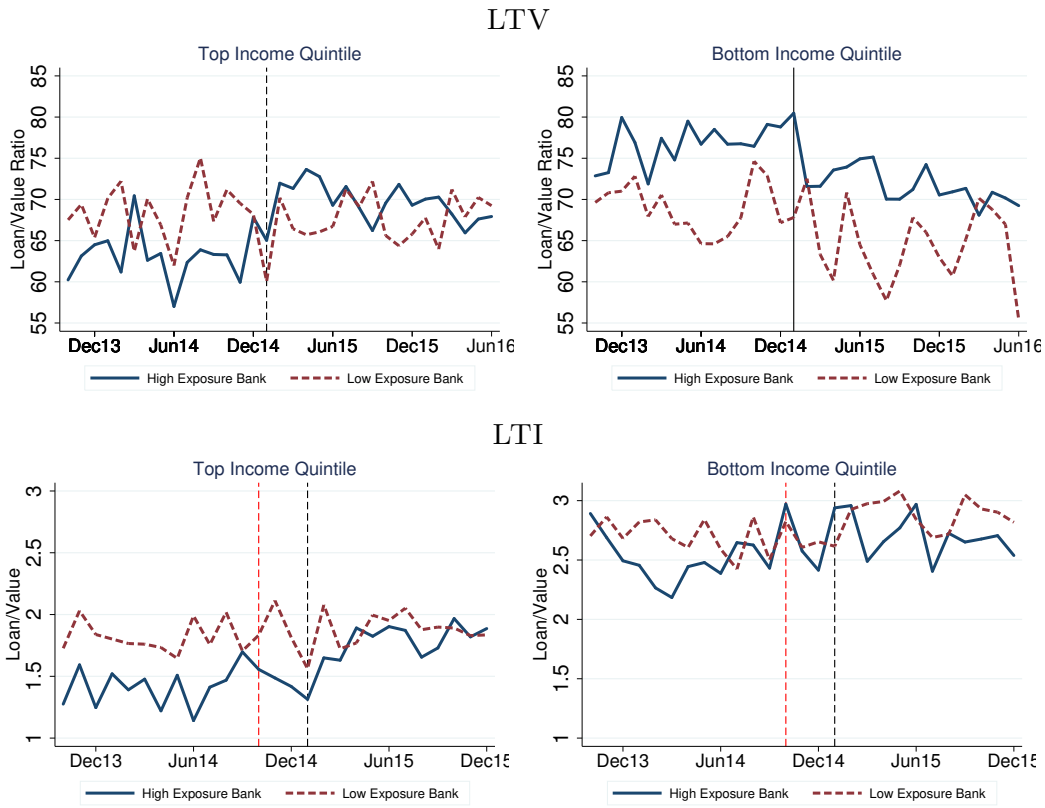

Figure A.3: LTV and LTI, High and Low Exposure Banks, Top Income Quintile Vs. Bottom Income Quintile. This figure shows the evolution of LTV (top panel) and LTI (bottom panel) of mortgage issuance by high-exposure (solid line) and low-exposure (dashed line) banks from October 2013 to June 2016. Blue lines corresponds to high exposure banks (exposure above median). Red lines corresponds to low exposure banks (exposure below median). Income quintiles are obtained from the January 2014 income distribution and adjusted monthly for Irish wage inflation. Source: Central Bank of Ireland.

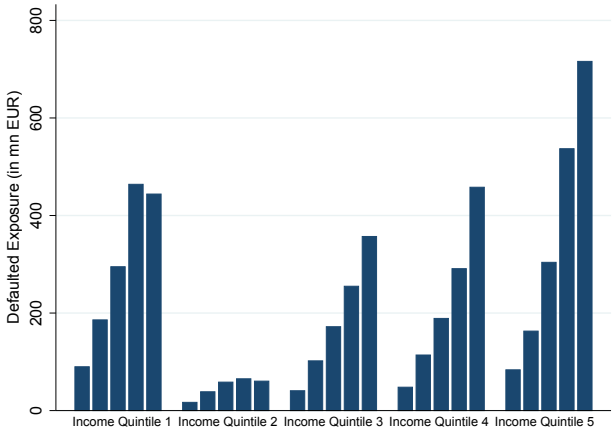

Figure A.4: Defaulted Exposure accumulated during the run-up to the Financial Crisis. This figure shows the defaulted exposure of Irish banks from 2000-2012. The bars represent the loss of the individual LTV Quintiles which are shown in an ascending order from left to right within each income quintile. It is calculated by multiplying the default intensity for a bucket with the total original exposure of the bank in that bucket. We create 25 buckets based on income and LTV quintiles where the former is scaled according wage growth figures. Source: Central Bank of Ireland.

Online Appendix[1]

OA.1 Data Sources

- Data on Lending including loan and borrower characteristics
  - Data on mortgages in Ireland and abroad:
    - up to Jan 2015: Loan Level Data from the Central Bank of Ireland (Financial Stability Division)
    - Jan 2015 - June 2016: Monitoring Templates from the Central Bank of Ireland (Financial Stability Division)
  - Data on commercial lending in Ireland and abroad: Central Bank of Ireland (Financial Stability Division)
- Quarterly Security Holdings: Central Bank of Ireland (Statistics Division)
- Monthly Balance Sheets: Individual Balance Sheet Items (IBSI) survey from the ECB
- County-level house prices from daft.ie (`https://www.daft.ie/report`).
- Regional house prices from Central Statistics Office (CSO) of Ireland

The loan specific characteristics include

- Date of loan origination
- Amount outstanding (current and at origination)
- Interest rate and interest type (current and at origination)
- Data on collateral (location, type, purpose, and value; all at origination)

The borrower specific characteristics (all measured at origination of the loan) include

- Type of Borrower (FTB, SSB, BTL)
- Age, marital status, occupation

[1]Date: November 2018. Not for publication. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Reserve Bank of India, the Central Bank of Ireland, or anyone associated with these institutions. All results have been reviewed to ensure that no confidential information is disclosed. All errors are our own.

- Total household income. For one of our banks, this is missing from 2010-2014 but is available before and after this period. As we expect heterogeneity in the risk taking of the different banks in our sample, we cannot just assume that income will be the same for similar borrowers across banks. Therefore, we use the period where we do obtain all the data to construct a scalar that measures how income of costumers of this specific bank behaves differently from all other borrowers. For the period we do not have income data for this specific bank, we then take the average income of a similar borrower in terms of loan- and borrower characteristics and multiply it with the scalar.

OA.2 Calculation of County-level Distance

To calculate the average distance from the lending limits in a county we proceed in several steps:

1. For each mortgage in our sample during the 12 months before the announcement of the macroprudential regulation (October 2013 - September 2014) we calculate the distance of the mortgage from both the LTV and the LTI limit that applies to this mortgage.

2. If the mortgage was exceeding the limit (i.e., would have violated the the lending limits, had they already been in place), we set the distance equal to zero.

3. This leads to an average distance in our sample of 14.69 for the LTV limit and 0.94 for the LTI limit. In order to compute the average distance across both limits for each mortgage, we have to rescale the distances.

4. We rescale both the distance from the LTV and the distance from the LTI limit to have a mean of zero and a standard deviation of one. The average distance (across both limits) of a particular mortgage is then calculated as the average of the rescaled LTV distance and the rescaled LTI distance for any given mortgage.

5. In a last step we calculate the mean of the mortgage-level average distance at the county level (measured from October 2013 - September 2014) to arrive at our measure of how distant a county is from the lending limits in the pre-regulation period ($Distance_c$).

OA.3 Machine Learning Technique

We follow Mullainathan and Spiess (2017) and use a machine learning approach for the evaluation of the risk, i.e. the probability of default, of new loans issued after the start of the macroprudential regulation. The intuition is that we let past data tell us which predictors are significant for mortgage default instead of manually picking variables to include in standard stress testing, like it is the case for standard OLS or logit hazard models. Thus, we hope to be able to uncover generalizable patterns which can be used for default predictions on the on current loan book of banks.

More specifically, we estimate the determinants of default with a random forest model. This supervised algorithm can be used for classification, in our case to determine whether is performing or not. As our data provides the standard loan and borrower characteristics, the random forest will then consist of various regression trees where each one will use a random selection of the available variables (see Figure OA.1).

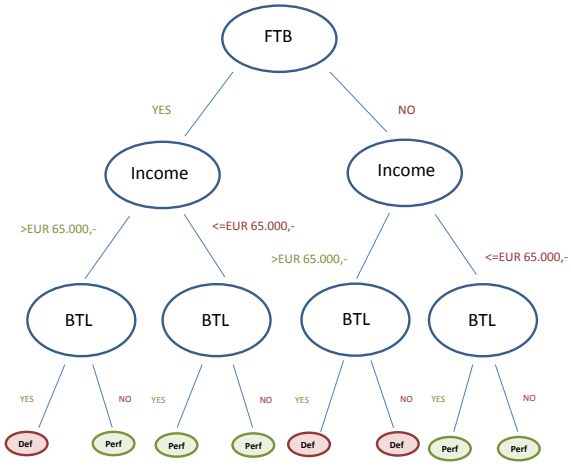

Figure OA.1: Example for a Tree.

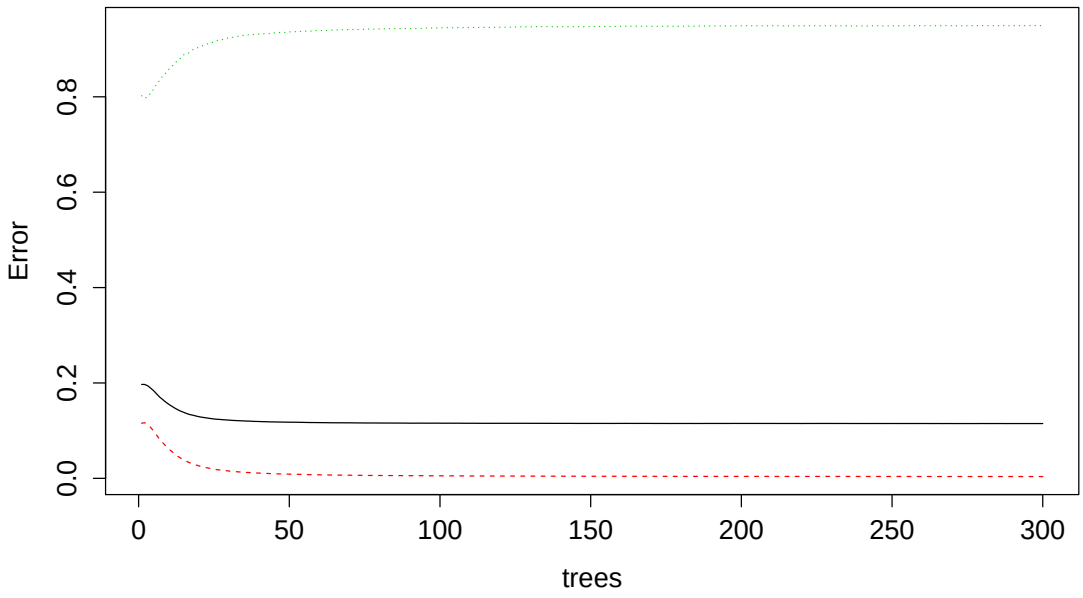

Figure OA.2: Optimal Number of Trees. This graphs whose the average error for the different amounts of trees planted in the forest.

More specifically, our analysis itself involved 3 steps

1. **Fine-Tuning of the model** where we supervise the algorithm in order to get the highest accuracy possible for the prediction of default
2. **Estimating the model** using the resulting optimal model on data covering past loans where we have data on default
3. **Predicting default** of new loans issued after the start of the macroprudential regulation including a short analysis of the determinants of default in this model

(1) Fine Tuning of the Model

One of the reasons why random forest is often referred to as the most popular algorithm for econometricians is that the supervisor only has to decide on two characteristics of the process: (i) the number of trees and (ii) the number of variables (nodes) in each tree. We use straight forward measures in order to establish the optimal choice for these two determinants. In order to find the optimal number of trees, we run our model with a large number of trees (500) and check graphically where the error does not decrease significantly anymore. As can be seen in Figure 1, our model almost stops to improve at around 100 trees. As there is a trade-off of the number of trees and the computational power needed to estimate our model, we choose to use 100 trees for our model.

As a second step, we use a fine tuning mechanism embedded in the R-package *RandomForest* in order to determine the optimal number of variables. Figure OA.3 shows that the Out-Of-Bag Error is the smallest when we use 3 variables for each tree. This graph is the result when we fine-tune

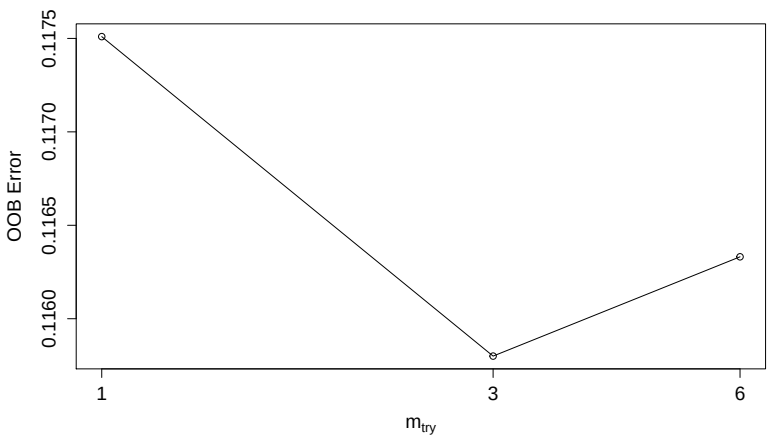

Figure OA.3: Optimal Number of nodes for each Regression Tree. This graph shows the average OOB (Our of Bag) Error for the different amounts of variables randomly selected for each Regression Tree.

our forest with 100 trees according to our findings in Figure OA.2, but is robust to the same fine tuning mechanism for bigger forests (300 or 500 trees).

(2) Estimating the Model

For the second step, we use data on loans defaulted in the past to estimate the model. Our data consists of a snapshot of all outstanding loans in June 2012 and its characteristics. As this is the earliest snapshot available, we capture the maximum amount of loans where we have information on whether default happened or did not happen. Therefore, we capture a significant part of mortgage issuance from 1995 onwards. [2]

We feed the algorithm with the following

- **Loan Characteristics**: Loan-to-Value Ratio, Value of Collateral, Loan Amount, Loan-to-Income Ratio, Interest Rate, Interest Rate Type, Year of Issuance;
  and
- **Borrower Characteristics**: Household Gross Income, Age, County, Marital Status, First-Time-Buyer, Buy-To-Let;

(3) Predicting Default

Finally, we use the estimated trees to predict default for newly issued loans based on their characteristics. In both datasets we standardize all variables with a (strong) time trend[3]. This is necessary

[2] We also have information whether a loan issued after macropru is performing or not. However, we use the earlier data as default is a protracted process which is unlikely to be determined until the end of our data sample (June 2016) if loans are issued after January 2015. We argue that by using data that includes a significant part of mortgage issuance from 1995, we can be more confident about the precision of our NPL variable.

[3] Household Gross Income, House Price, Loan Amount

in order to get precise coefficients which will only be possible if the value of a variable is comparable over the two data sets.

In contrast to a simple OLS or a logit hazard model, it is not usual to interpret coefficients and their signs as every tree represents different versions of regressions and interaction terms. What we can show, however, is the importance of variables, i.e. which characteristics are determining default and which attributes are only weakly correlated with default. Figure OA.4 shows how much the accuracy[4] of the model would decrease if the variable were excluded from the estimation. We can see that (standardized) income has the strongest prediction power for default, followed by LTV.

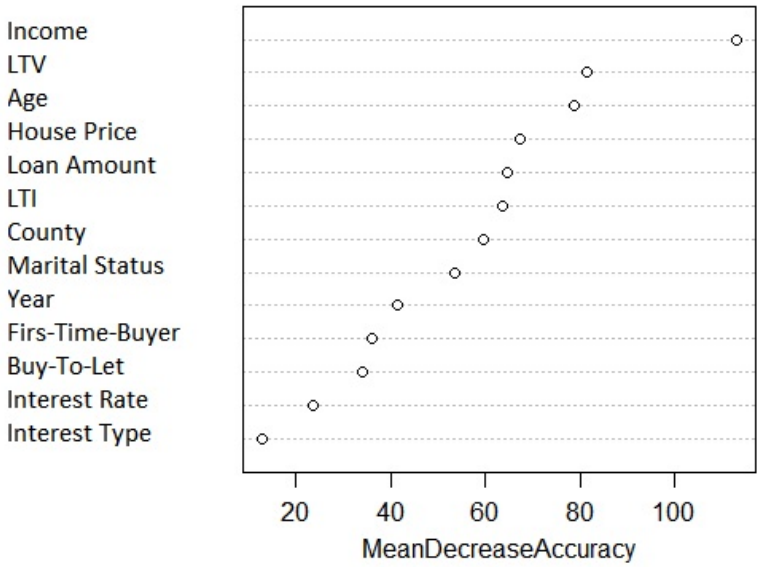

Figure OA.4: Importance of Variables. This graph shows the loss of Accuracy if variables would not be included in the Model.

[4]This refers to a decrease in accuracy over all out-of-bag cross validated predictions, when a given variable is permuted after training, but before prediction.

OA.4 Additional Figures

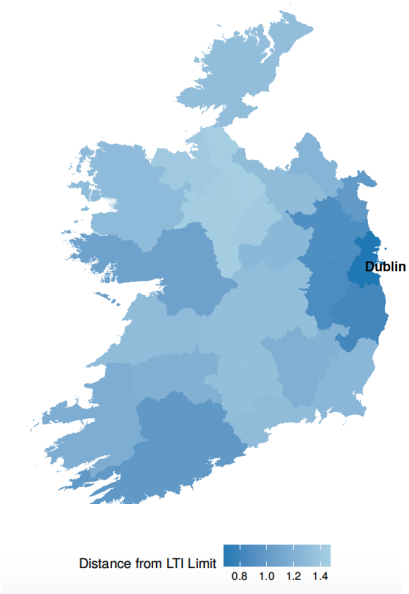

Figure OA.5: Counties and LTI Lending Limits. This figure shows county-level distance from the LTI lending limits. Darker colors indicate counties that are less distant. Source: Central Bank of Ireland.

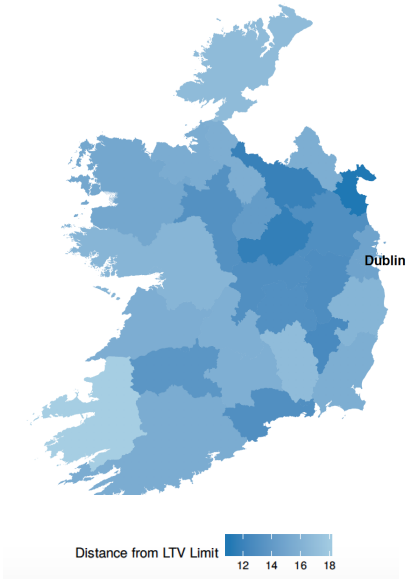

Figure OA.6: Counties and LTV Lending Limits. This figure shows county-level distance from the LTV lending limits. Darker colors indicate counties that are less distant. Source: Central Bank of Ireland.

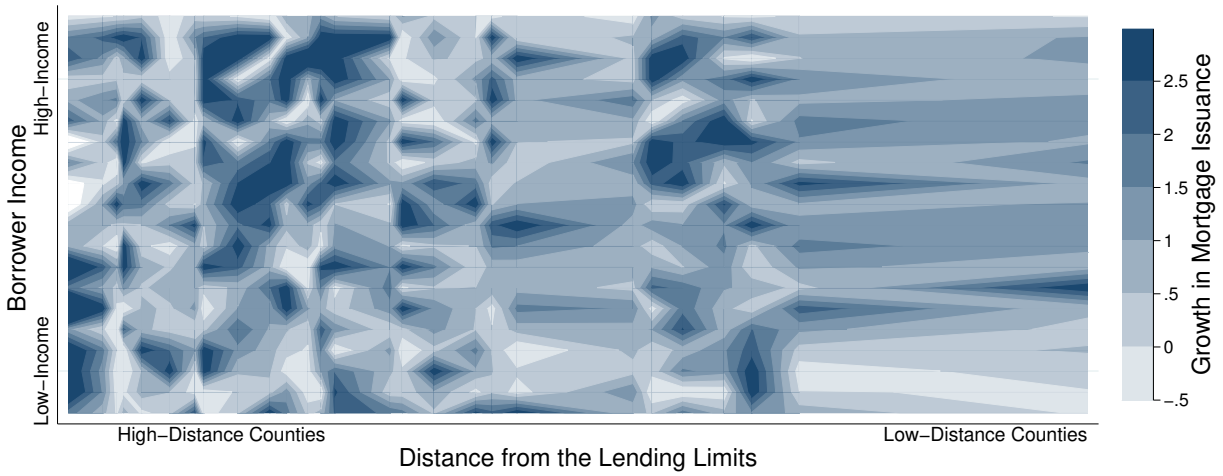

Figure OA.7: Reallocation of Mortgage Credit, Placebo. This figure shows the growth of mortgage credit across counties and the across the income distribution of borrowers before the policy implementation. The x-axis shows counties ranked according to their distance from the lending limits. The y-axis shows borrowers ranked according to their position in the income distribution (20 ventiles). Each point in the map indicates the change of mortgage issuance in the post-period (February 2014 to January 2015) compared with the pre-period (February 2013 to January 2014). Darker colors indicate higher growth of mortgage issuance, as indicated by the legend on the right.

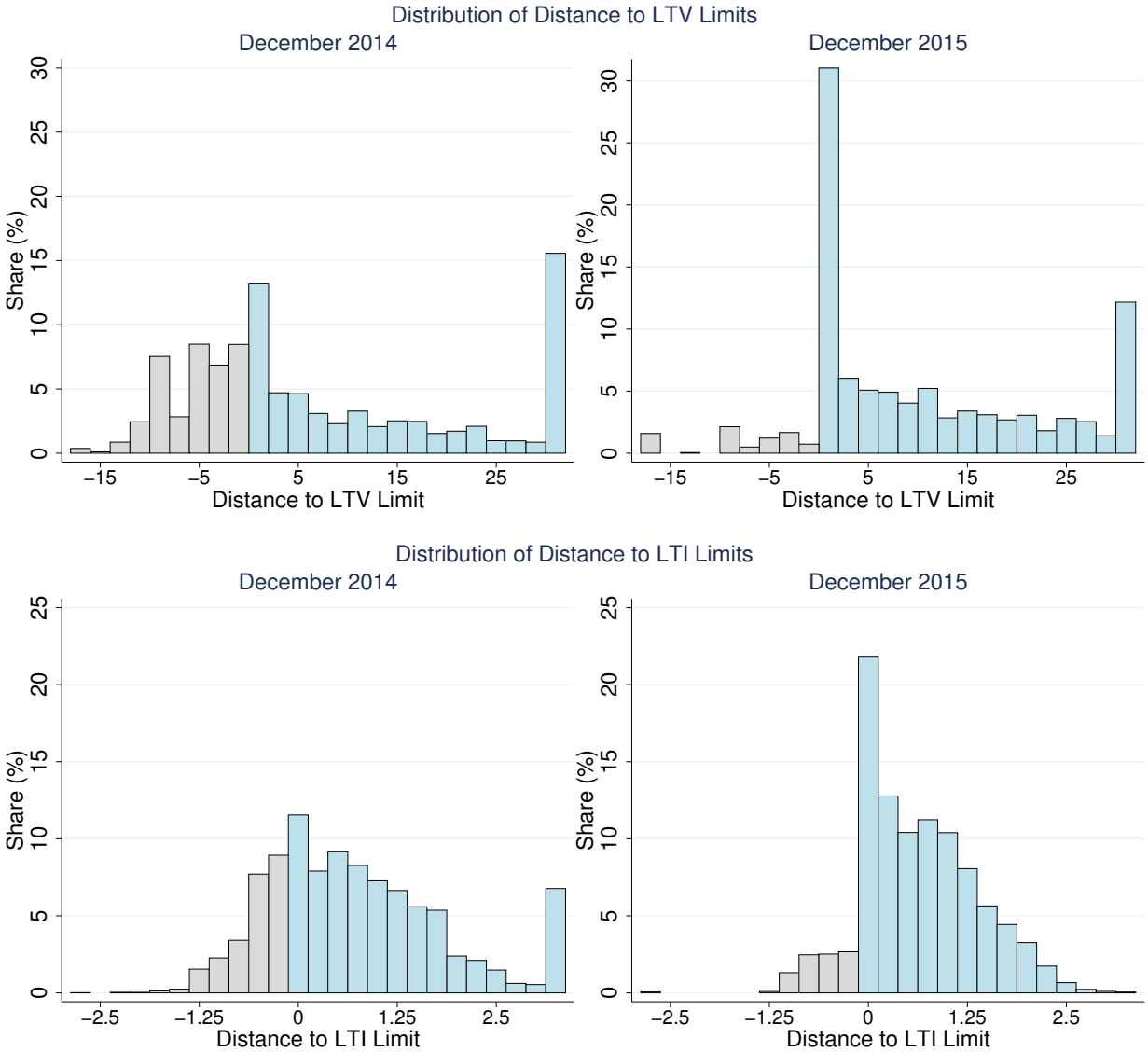

Figure OA.8: Distribution of Distance to Lending Limits. This figure shows the distribution of the distance to the lending limits. The top panel shows the distribution of the distance to the LTV limits. The bottom panel shows the distribution of the distance to the LTI limit. The left figures are the share of total mortgage issuance volume. The right panels are the share of total number of mortgages issued. Grey bars indicate non-conforming mortgages. Blue bars indicate conforming mortgages. Source: Central Bank of Ireland.

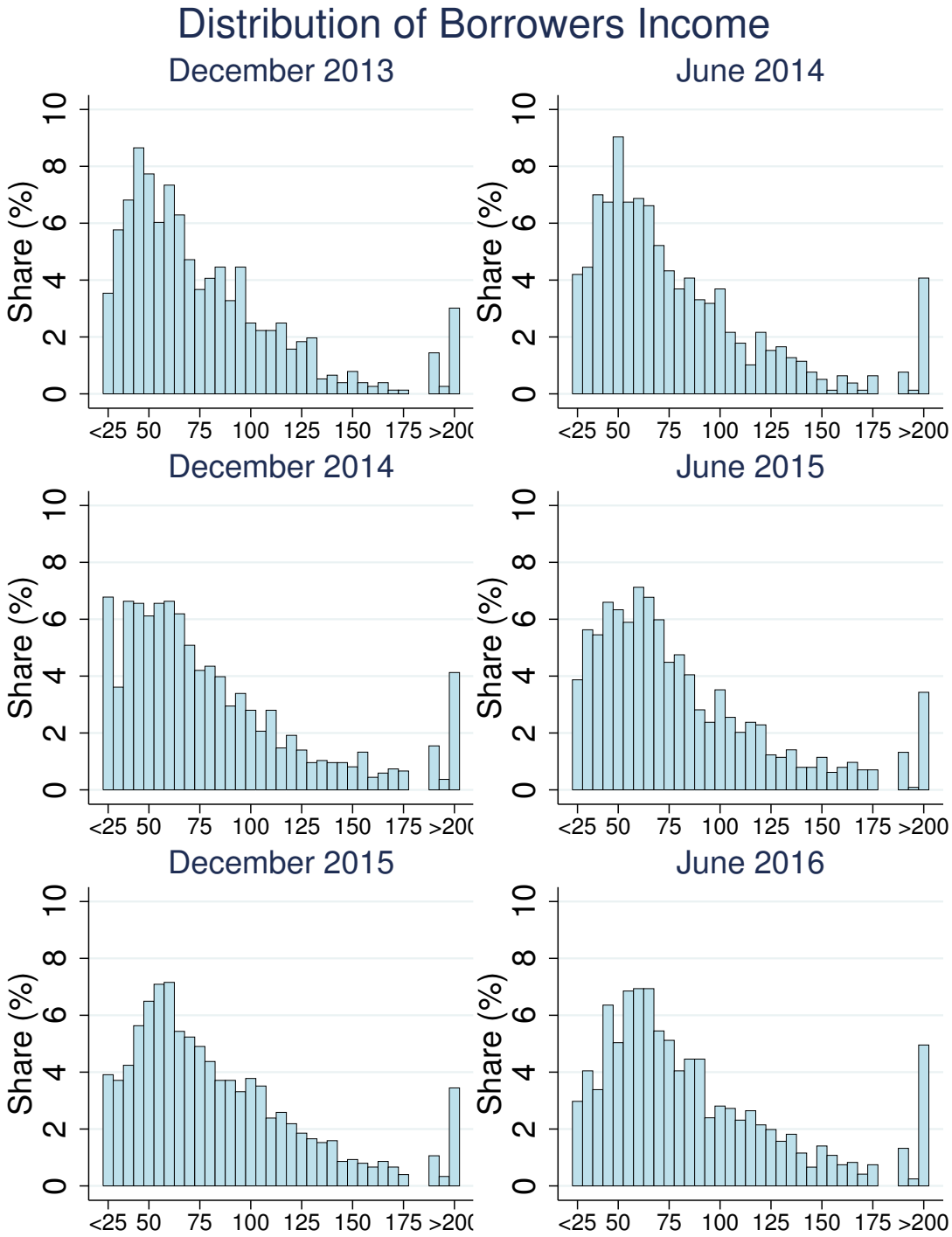

Figure OA.9: Evolution of Distribution of Borrowers' Income. This map shows the evolution of the distribution of borrowers' income at a semi-annual frequency from December 2013 to June 2016. We group households who receive a mortgage at time t in buckets of €5,000 from €25,000 to €200,000 on the x-axis. The y-axis shows the share of total issuance at time t in each bucket. *Source: Central Bank of Ireland.*

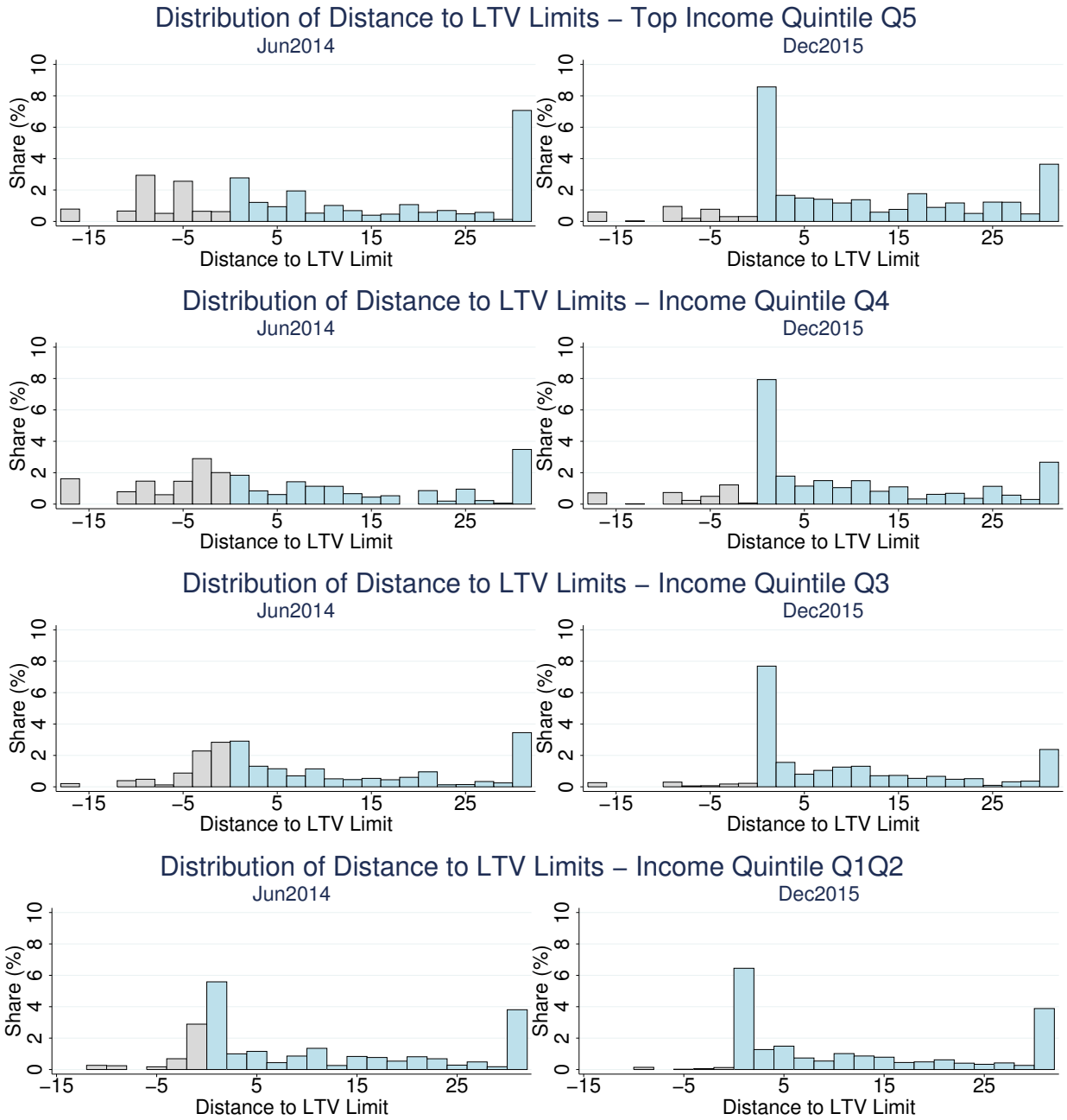

Figure OA.10: Distribution of Distance to LTV Lending Limits, by Borrower Income. This figure shows the distribution of the distance to the LTV lending limits. Each row corresponds to an income quintile, except the last row that combines the two bottom quintiles. Income quintiles are adjusted monthly for wage inflation. The distributions on the left (right) panel are measured in June 2014 (December 2015). Grey bars indicate non-conforming mortgages. Blue bars indicate conforming mortgages. Source: Central Bank of Ireland.

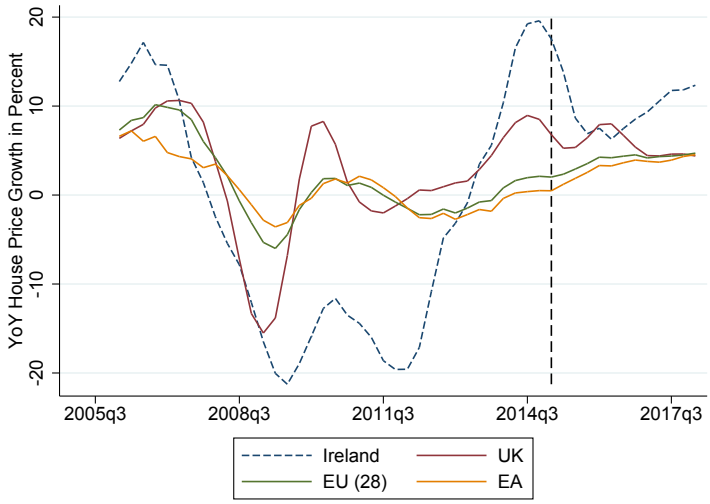

Figure OA.11: House Price Growth Outside Ireland. This figure shows house price growth (YoY) for Ireland, the U.K., the Euro Area, and the European Union (28). The vertical dashed line indicates the introduction of the lending limits. Source: Eurostat.

OA.5 Additional Tables

	Income Quintiles				
	Q1	Q2	Q3	Q4	Q5
LHS: House Price					
$HP1BR$	0.632	0.779**	1.131**	0.0431	-0.796
	(0.399)	(0.394)	(0.439)	(0.657)	(1.030)
$HP2BR$	-1.315***	-1.568***	-2.492***	-2.280***	-2.441*
	(0.391)	(0.379)	(0.449)	(0.736)	(1.266)
$HP3BR^{+}$	0.593***	0.717***	1.070***	1.496***	2.314***
	(0.156)	(0.154)	(0.184)	(0.299)	(0.519)
Observations	1,862	2,356	2,752	2,339	3,323
R-squared	0.155	0.206	0.183	0.178	0.189

Table OA.1: House Prices, Number of Bedrooms, Borrower Income. This table shows the estimation results for the following specification: $CollateralPrice_{lct} = \alpha + \beta_1 1BRHP_{ct} + \beta_2 2BRHP_{ct} + \beta_3 3BR^{+}HP_{ct} + \epsilon_{lct}$. The unit of observation is loan l, county c, and quarter t. The dependent variable is the price of the residential property used as collateral (from the credit registry data). The independent variables are the house prices (from the county-level house price data) for one-bedroom properties, two-bedroom properties, and three-or-more-bedroom properties. The specification is estimated separately in each quintile of the borrower distribution. Source: Central Bank of Ireland, Daft.ie.

Balance Sheet Item	**Unit**	**Jun14**	**Dec14**	**Jun15**	**Dec15**	**Jun16**
Total Assets	billion €	344	336	325	298	281
Liquid Assets	billion €	118	118	114	108	103
Dom. Govt Bonds	billion €	18	19	16	17	15
Loans	billion €	190	184	176	168	160
Households	billion €	79	81	78	77	73
NFC (< 1Y)	billion €	19	17	14	10	9
NFC (≥ 1Y)	billion €	40	38	34	32	32
MFI	billion €	38	36	39	38	37
ICPF	billion €	14	11	11	10	10

Table OA.2: Aggregate Balance Sheet. This table shows the aggregate balance sheet of our sample banks from June 2014 to June 2016. Source: Central Bank of Ireland.