The Anatomy of the Transmission of Macroprudential Policies[*]

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Abstract

We analyze the transmission of macroprudential policies aimed at limiting household leverage and preserving financial stability. Combining supervisory loan-level and house price data, we examine the effect of loan-to-income and loan-to-value limits on residential mortgages in Ireland on mortgage credit, house prices, and financial stability. We find that banks reallocate their mortgage credit toward high-income borrowers and areas with low house price appreciation. This reallocation slows down house prices in "hot" areas, but allows banks to maintain a stable risk exposure as they increase mortgage credit to historically risky borrowers, corporate credit to risky firms, and holdings of high-yield securities.

JEL: G21, E21, E44, E58, R21

Key words: Macroprudential Regulation, Residential Mortgage Credit, House Prices, Financial Stability

1 Introduction

Following the recent financial crises, policy-makers around the world have been proposing, designing, and implementing macroprudential policies aimed at limiting household leverage and preserving financial stability. The rationale for these interventions is based on the observations that (i) build-ups of household leverage have historically led to lower output growth and higher unemployment (Mian et al., 2017) and (ii) banks, benefiting from several types of guarantees, do not internalize all the costs associated with their risk taking. Perhaps not surprisingly, recent policies have primarily targeted residential mortgage credit, the asset class at the core of these concerns.

We provide a comprehensive analysis of borrower-based macroprudential policies that impose restrictions on household leverage in the residential mortgage market. In particular, we study the introduction of loan-to-value (LTV) and loan-to-income (LTI) limits for residential mortgages issued by Irish banks starting in February 2015.[1] Ireland is a prime laboratory in which to investigate the effectiveness of these macroprudential measures, as it experienced a strong credit-fueled boom bust cycle during the recent financial crisis. In the run-up to the financial crisis from 2002 to 2007, the household debt to GDP ratio almost doubled in Ireland (from 55% to 101%), followed by strongly negative GDP growth (-10%) over the following three years.

In a first step, we show that the lending limits imposed by the Central Bank of Ireland affected a large share of the mortgage market, as more than one third of the typical issuance of Irish banks in the year prior to the policy announcement would have violated the rules. Nevertheless, mortgage issuance kept growing after the introduction of the limits, and neither the LTV nor the LTI of the mortgage portfolio of Irish banks changed significantly, suggesting that the mortgage market

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[1]These borrower-based limits are the most widely used macroprudential policy tool worldwide (see Figure B.1).

"moved" to conform with the new rules.

We find that, after the introduction of the lending limits, mortgage credit is reallocated from low-income to high-income borrowers and from counties where borrowers are closer to the lending limits to counties where borrowers are further away from the lending limits. Consistent with this geographical reallocation, we find that house prices and price-rent ratios in counties that receive more credit grow relatively more. This is especially true for larger properties (three or more bedrooms) which are likely to be bought by high-income households, that benefited most from the credit expansion. Conversely, we see a significant decrease in house price growth rates for counties where borrowers were closer to the lending limits.

Having shown how aggregate credit is reallocated across counties and across the income distribution, we provide evidence on the channels underlying this credit reallocation. The lending limits directly affected the portfolio choice of borrowers and lenders. On the one hand, households (borrowers) that were demanding high LTV/LTI mortgages became non-conforming and could therefore not obtain the mortgage they wanted anymore. They faced two possible outcomes. First, they could increase their downpayment or buy a cheaper property to lower their LTV/LTI, therefore becoming conforming. Second, if changes to property choice or the posting of larger downpayments was not possible, they were forced to postpone their purchase and momentarily opt out the mortgage market. On the other hand, lenders (banks) had to reduce their non-conforming mortgage issuance which constituted more than one third of their typical issuance in 2014. The lending limits inevitably caused banks to re-optimize their portfolio choice triggering a reallocation of credit to households and firms, and holdings of other assets.

We find that this reallocation affected borrowers based on their income. First, we show that low-income households borrowed less from more exposed banks. Second, more exposed banks reallocated credit to high income households, especially in counties that were further away from

3

the lending limits. These households had the largest distance to the lending limits and thus the highest borrowing capacity. This credit expansion led to an increase in the LTV and LTI of high income households after the introduction of the lending limits, allowing more exposed banks to make up for the significant share of non-conforming mortgages that could no longer be issued. In aggregate, we show that high income borrowers have lower LTI/LTV compared with low income borrowers before the policy implementation and that the gap between the two groups narrows after the policy implementation.

Having shown that high income households increased their LTV after the implementation date borrowing especially from exposed banks, we show that these banks lowered their rates to high income households that, in turn, obtained larger loans. This finding is driven by exposed banks, consistent with these banks incentivizing high income borrowers to obtain larger loans.

In a final step, we provide evidence on the evolution of banks' risk exposure in mortgage lending and other asset classes. Given that the lending limits were implemented in February 2015, we do not observe defaults on mortgages issued after the policy. We then use machine learning techniques to estimate loan-level default probabilities using data on the originating characteristics of loans that had defaulted by December 2013. We find that the average value-weighted default probability of newly issued mortgages increased after the introduction of the lending limits.

Besides the riskiness of banks' mortgage lending, we also analyze how banks adjust their risk-taking behavior in corporate lending and holdings of securities, the two other largest asset classes on their balance sheet. We document that more exposed banks increase their corporate lending more than less affected banks relative to the pre-policy period. This increase is mostly targeted towards riskier borrowers and occurs both in the quantity (higher loan volumes) and price (lower spreads) dimension. Banks increase their risk taking also in their holdings of securities. We find that more exposed banks increase their holdings of risky (based on yield) securities compared with

4

less affected banks, relative to the pre-policy period. More precisely, more affected banks both buy more and sell less securities with higher yields than less affected banks.

The rationale for macroprudential policies is based on the observation that agents over-borrow and lever up in good times, not internalizing all the costs of their financing choice (Lorenzoni (2008), Bianchi (2011), Clerc et al. (2015), Bianchi and Mendoza (2010), Bianchi and Mendoza (forthcoming), Farhi and Werning (2016), Bianchi et al. (2012), Jeanne and Korinek (2017), Korinek and Simsek (2016), Malherbe (2017)). In the context of the U.S., the rapid increase in mortgage credit – and the rise in securitization – has been shown in some papers to be a causal factor for the appreciation of house prices (Favara and Imbs (2015), Mian and Sufi (2009), Adelino et al. (2016)). The subsequent collapse in house prices 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 (forthcoming)) was a contributory factor in the onset of the Great Recession.

While there are various types of macroprudential policies (see Freixas et al. (2015) and Claessens (2015)), existing studies have mainly focused on capital requirements. The literature on capital requirements, both theoretical (Landvoigt and Begenau (2017), Elenev et al. (2017), Begenau (2016), Kashyap et al. (2014), Malherbe and Bahaj (2017)) and empirical (Aiyar et al. (2014), Jimenez et al. (forthcoming), Gropp et al. (2016), De Marco and Wieladek (2015), Dassatti Camors et al. (2015), Ayyagari et al. (2017)), focuses on the effect of these requirements on bank credit to firms. In this paper, we analyze borrower-based limits and their impact on bank credit to firms and households and house prices. Residential mortgage credit and macroprudential policies are also

analyzed by Auer and Ongena (2016), Basten and Koch (2015), and Benetton et al. (2017).[2] Igan and Kang (2011) find that the introduction of loan-to-value and debt-to-income ratios in Korea led to a decline in house price appreciation and transaction activity. Kinghan et al. (2017) analyze the effect of the lending limits imposed by the Central Bank of Ireland and find that LTVs fell for both first time homebuyers and second and subsequent homebuyers. Compared with this paper, we focus on the reallocation of mortgage issuance across the income and geographical distributions, aggregating the data set at the county-time-income-bank level.

2   Setting and Data

In Section 2.1, we provide some background on the residential mortgage market in Ireland and its link to financial stability. In Section 2.2, we describe the lending limits 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 in the run-up to the financial and sovereign debt crisis. After mortgage issuance collapsed during the crisis, another increase in new issuances began

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[2]See also DeFusco et al. (2017), De Nicolo et al. (2014), Gambacorta and Murcia (2017), Han et al. (2017), Epure et al. (2017).
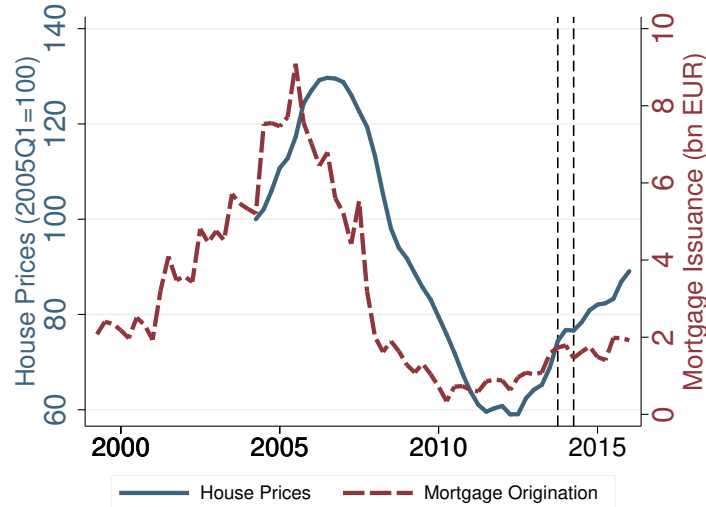
Figure 1: Ireland Real Estate Boom-Bust Cycle. This figure shows the evolution of real estate prices from 2005Q1 to 2016Q4 (left axis, index equal to 100 in 2005Q1) and residential mortgage issuance from 2000Q1 to 2016Q4 (right axis, billion euros). The two vertical dashed line indicate the announcement and the implementation of the lending limits, respectively. Sources: Department of Housing, Planning and Local Government and Central Statistics Office.

in 2013. House prices (solid line) on the secondary y-axis followed a remarkably similar pattern.

At the bust of 2007-08, prices declined sharply and construction activities collapsed. The fall in quarterly Gross National Product (GNP) is estimated to be about 17%.[3] 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 which 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)).

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

2.2 The February 2015 Mortgage Lending Limits

In order 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 banks and households to financial shocks and dampening the pro-cyclical dynamics between property lending and house prices. 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 proposed in October 2014 and announced (and effective immediately) on February 9, 2015.[4] In Table 1, we provide an overview of the limits on loan-to-value (LTV) and loan-to-income (LTI) ratios on new originations of residential mortgages. The regulation takes into account that not all borrower groups are equally risky. Lending for primary dwelling housing (PDH) is limited to 80% LTV and to an LTI of 3.5. For First-Time-Buyers (FTB), a more generous LTV limit of 90% is imposed for houses up to €220,000.[5] 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% for this type of loans.[6]

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[4]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.

[5]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)).

[6]In addition to loans that are generally exempted from the rule (last line of Table 1), banks are granted allowances for each group of borrowers. Banks can issue loans exceeding the limits to a small number of borrowers as show in column (4). In the Online Appendix, we show the distribution of the lending limits across the distributions of LTV and LTI. 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.

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.

2.3 Data

In this section, we describe the data set construction and the empirical framework. 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 and rental prices. The loan-level data and security register are proprietary data sets obtained from the Central Bank of Ireland.

First, we observe loan-level data on the issuance of new residential mortgages to households at a daily frequency for our period of interest from January 2013 to June 2016.[7] We observe all outstanding residential mortgages by the most significant institutions that have to submit loan-level data to the Central Bank of Ireland.[8] This sample covers more than 90% of the domestic mortgage market. The data set also contains household-month demographic (age, marital status), income,

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[7]This data is 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 by the Central Bank of Ireland on the February 9, 2015. More information can be found in the Appendix.

[8]Irish banks which 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.

and residential mortgage credit (first-time or subsequent time buyer, buy-to-let) characteristics.

Second, we observe loan-level data on bank credit to firms at originations 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.[9] There is one main limitation to the data. 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.

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 and rent-price ratios from the Irish property website Daft.ie. This data set is publicly available and regularly updated with quarterly reports published on the website.

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[9]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.

3 Some Facts

In this section, we present the aggregate evidence that motivates our analysis. We show that (i) the lending limits affect more than one third of the residential mortgage market, (ii) banks' build-up of residential mortgage risk exposure keeps increasing after the policy implementation, and (iii) 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.

Importance of Lending Limits 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 as 35% of residential mortgages issued from October 2013 to September 2014 would have been affected if the policy was 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 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.

Adjustment of the Residential Mortgage Market While 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 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, delimited by the second vertical dashed line. This aggregate evidence suggests that 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

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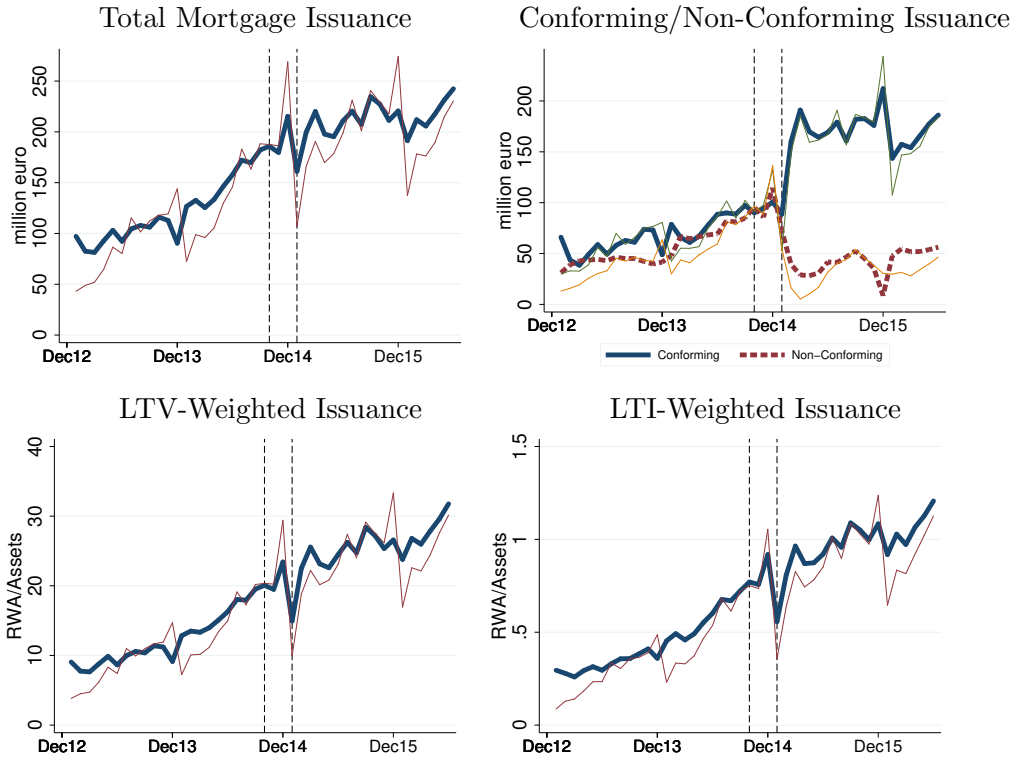
Figure 2: Aggregate Residential Mortgage Issuance. This figure shows the evolution of residential mortgage issuance of our sample banks from January 2013 to June 2016. The top-left panel shows total mortgage issuance (million euro). The top-right panel shows issuance of conforming (solid line) and non-conforming (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.

top-right panel, we show the evolution of originations of conforming (solid line) and non-conforming (dashed line) mortgages and confirm that the two time-series diverge starting in February 2015.[10] In the bottom-left and bottom-right panels, we show that mortgage originations keep increasing even when weighted by LTV and LTI, respectively, suggesting that the build-up of residential mortgage risk exposure of our sample banks seems unaffected by the lending limits.[11]

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[10]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.

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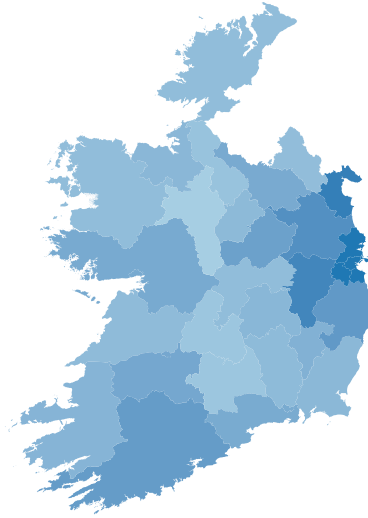
Figure 3: Counties and Lending Limits. This figure shows county-level distance from the lending limits. Darker colors indicate counties that are less distant. Source: Central Bank of Ireland.

Lending Limits Across Counties and Borrowers We now show how 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.[12] In Figure 3, we 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. There is substantial heterogeneity 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.[13]

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[12]We proceed in thee 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 a standard deviation of one. Third, we take the average of these two distances at the county level. In the Online Appendix, we describe how we obtained the county-level distance in greater detail.

[13]In Figure B.2 in the Appendix, we show that counties closer to the lending limits are more densely populated and experienced a sharper house price appreciation before the policy compared with more distant counties. In the Online Appendix, we show two maps of Ireland that show the county-level distance from the LTV and LTI limits,

	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
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 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.

Second, in Table 2, we divide households that obtain a mortgage in the year prior to the policy in five quintiles based on their income.[14] The income distribution is negatively skewed as the average income of the top quintile is almost double the average income of the fourth income quintile. High-income borrowers have also lower LTV and lower LTI and tend to be older and less likely to be single or first-time-buyers compared with lower income borrowers. Moreover, not surprisingly, high-income borrowers are more distant from the lending limits compared with low income households.[15]

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respectively.

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

[15]Note that, even if they have lower LTV, high income households are subject to stricter limits because they are often non-first time buyers.

# 4 Aggregate Changes in Mortgage Lending and House Prices

In the previous section, we have shown that the distance from the lending limits is strongly correlated with the income and geographical location of borrowers. In this section, we document (i) a reallocation of mortgage credit across counties and across the income distribution and (ii) consistent time-series evolutions of house prices and borrower leverage. In Section 4.1, we analyze the reallocation of mortgage credit. In Section 4.2, we analyze the evolution of house prices and rent to price ratios. In Section 4.3, we analyze the evolution of borrower leverage.

4.1 Mortgage Lending

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.

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 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. For each income group-county group, we compute the change in mortgage origination from the pre-policy period (February 2014 to January 2015) to the post-policy period (February 2015 to January 2016). Darker colors indicate higher growth.

The dark mass in the top-left corner of the figure documents that the growth in mortgage issuance after the policy implementation has been driven by high-distance counties and high-income

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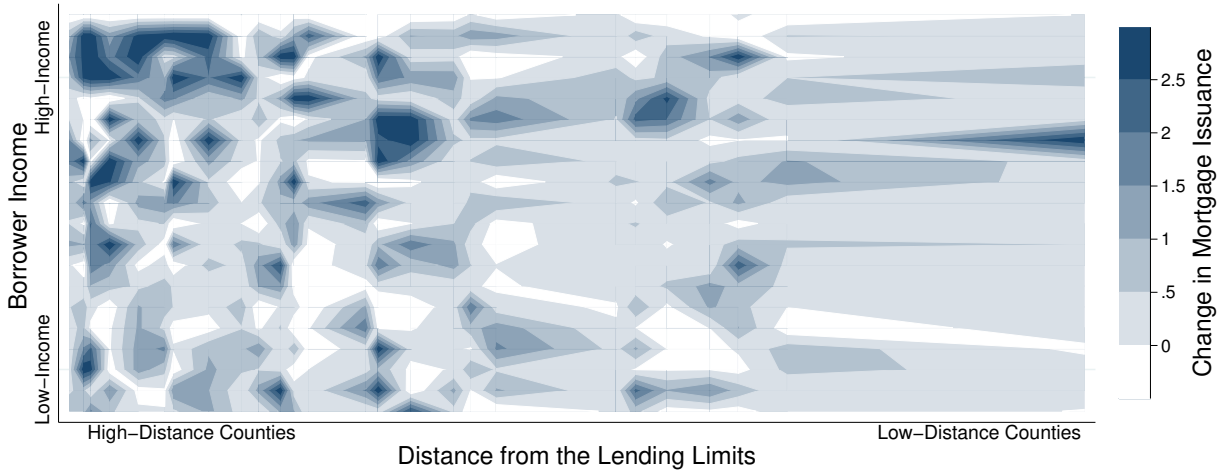
Figure 4: Reallocation of Mortgage Credit. This figure shows the reallocation of mortgage credit across counties and the across the income distribution of borrowers. The x-axis shows counties ranked according to their distance from the lending limits. The y-axis shows borrowers ranked according to their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

borrowers.[16]

4.2 House Prices

We now show that the time-series evolution of house prices is consistent with the mortgage credit reallocation documented in the previous subsection.

In the left panel of Figure 5, we plot yearly changes in house prices from January 2011 to June 2017. We observe that house price growth stopped increasing at the time of the policy announcement and then stabilized around 10% after the policy implementation. 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 the policy implementation, while house price growth remained stable at the pre-policy level

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[16]In Table C.1 in the Appendix, we analyze this reallocation of credit in a differences-in-differences setting.
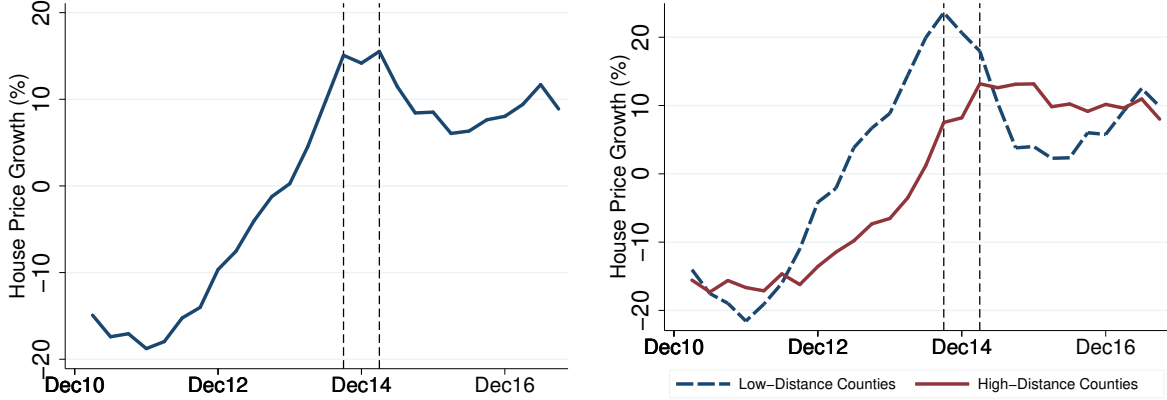
Figure 5: House Price Changes. The left panel of this figure shows the evolution of yearly house price growth. The right panel shows the evolution of yearly house price growth for high-distance and low-distance counties separately. The vertical dashed lines indicate the announcement and the implementation date of the lending limits. The sample period runs from January 2011 to June 2017. Source: Central Bank of Ireland, Daft.ie.

in high-distance counties.[17]

We complement these graphs with parametric evidence. In our house price data, we observe house prices and price-rent ratios by size of the property (number of bedrooms). Formally, we estimate the following specifications at the county-time (c, t) level at the county-property type-time (c, p, t) level:

$$\Delta Y_c^{14Q3-16Q4} = \alpha + \beta Distance_c + \epsilon_c \tag{1}$$

$$\Delta Y_{cp}^{14Q3-16Q4} = \alpha + \beta_1 Distance_c \times Size_p + \beta_2 Distance_c + \beta_3 Size_p + \epsilon_{cp} \tag{2}$$

where the dependent variable is the change in house prices (and rent-price ratio) from 2014Q3 to 2016Q4, $Distance$ is the county-level distance from the lending limits, and $Size$ is a dummy equal to one if the property has one bedroom property or two bedrooms or, finally, three or more

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[17]House prices reacted at the time of the policy announcement anticipating the credit reallocation at the time of the policy implementation. In Figure B.3 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.

	ΔHouse Price				ΔPrice-Rent Ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance	0.324***	0.253***	0.249***	0.275***	0.427***	0.376***	0.363***	0.389***
	(0.080)	(0.064)	(0.071)	(0.072)	(0.055)	(0.047)	(0.048)	(0.050)
Distance × 1BR	-0.147***				-0.115***			
	(0.026)				(0.017)			
Distance × 2BR		0.068***				0.038**		
		(0.024)				(0.016)		
Distance × 3BR+			0.078***				0.077***	
			(0.011)				(0.009)	
1BR	-0.114***				-0.088***			
	(0.006)				(0.004)			
2BR		0.080***				0.042***		
		(0.006)				(0.004)		
3BR+			0.034***				0.046***	
			(0.001)				(0.001)	
Observations	162	162	162	54	162	162	162	54
R-squared	0.485	0.339	0.244	0.319	0.712	0.560	0.575	0.666

Table 3: House Prices and Lending Limits. This table shows estimation results from specification (2) in columns (4) and (8) and estimation results from specification (2) in columns (1)-(3) and (5)-(7). The dependent variable is the change in house prices in columns (1)-(4) and the change in price-rent ratio in columns (5)-(8). These changes are computed between 2014Q3 and 2016Q4. *Distance* is the county-level distance from the lending limits. $1BR$, $2BR$, $3BR+$ are dummy variables equal to one if the property has one, two, three or more bedrooms, respectively. Standard errors clustered at the county-level in parentheses. Source: Central Bank of Ireland, Daft.ie.

bedrooms.[18] We interact *Distance* with the measure of property size to check whether the effect of the lending limits changes depending on the type of property.

We show the estimation results in Table 3. In the first four columns, the dependent variable is the change in house price. In the last four columns, the dependent variable is the change in price-rent ratio. In columns (4) and (8), we show estimation results at the county-time level. In columns (1)-(3) and (5)-(7), we show estimation results at the county-property type-time level. We find that (i) house price growth and price-rent ratio increased in high-distance counties compared with low-distance counties and (ii) this different evolution is driven by larger properties. These results are consistent with the documented reallocation of mortgage credit across counties and – to

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[18]The geographical breakdown of the house price data is more granular compared with 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 that the distance is constant within a county. We then cluster our standard errors at the county-level to take into account that standard errors might be correlated within counties. Figure B.4 in the Appendix shows the graphical representation of this estimation.

the extent that property size is correlated with the income of the buyers – across the distribution of incomes of borrowers.[19]

4.3 Borrower Leverage

Several channels are consistent with the reallocation of mortgage credit from low-distance counties to high-distance counties and from low-income borrowers to high-income borrowers.

On the borrower side, the lending limits likely prevented some borrowers, especially those low-income households located in low-distance counties, to obtain their high LTV/LTI mortgage as it became non-conforming under the new rules. To still obtain their mortgage, these households could have increased their downpayment or purchased a cheaper property to lower their LTV and/or LTI and therefore qualify under the new rules.[20] Alternatively, they could have postponed the transaction to save more to afford the higher downpayment in the future.

On the lender side, the lending limits prevented banks from originating more than one third of their typical mortgages issuance. In response, banks could have changed their issuance to make up for the lost business by actively trying to originate more high-LTV (and high-LTI) mortgages while still conforming with the lending limits.

On the one hand, the observed reallocation is consistent with both lenders and borrowers responding to the limits. Households could have "switched" from a non-conforming to a conforming mortgage and banks could have actively increased their issuance of conforming mortgages to make-up for the lost non-conforming mortgage business. On the other hand, the responses of households

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[19]While Table 2 shows that borrower income is strongly correlated with the price of the property purchased, the mapping between number of bedrooms and income of buyers is far from perfect as, for example, high-income borrowers might buy a one-bedroom property to rent it out.

[20]Given that income cannot be easily manipulated and does not change in the short-term, we can show that the house value and the downpayment drive LTI and LTV by writing these ratios as $LTV = 1 - DownPayment/House$ and $LTI = (House - DownPayment)/Income$.
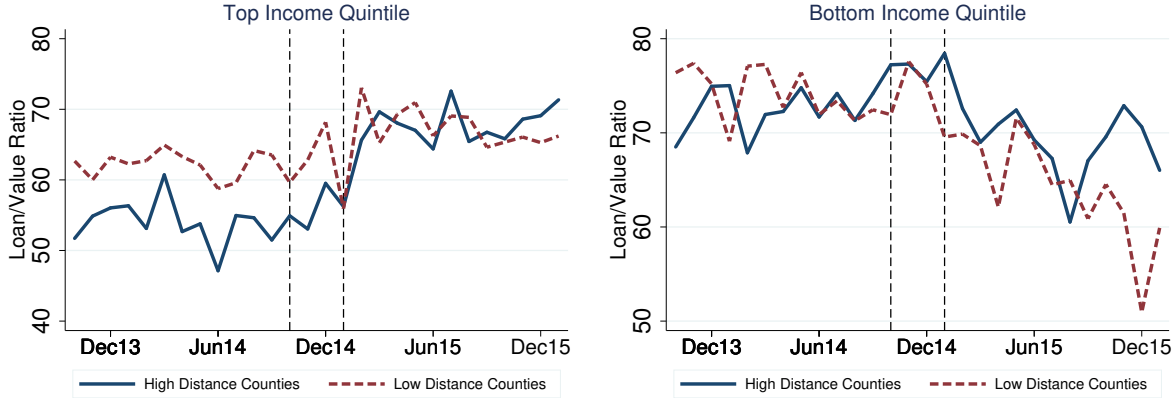
Figure 6: Borrower Leverage, High and Low Income Households. This figure shows the time-series evolution of LTV for high-distance counties (solid line) and low distance counties (dashed line) for the top borrower income quintile (left panel) and bottom income quintile (right panel). Income quintiles are adjusted monthly for wage inflation. The vertical dashed lines indicate the announcement and the implementation date of the lending limits. The sample period runs from October 2013 to January 2016. Source: Central Bank of Ireland.

and banks have different implications for the evolution of LTV and LTI.

According to the borrower's response, LTV and LTI should *decrease* after the policy as households looking to obtain a non-conforming mortgage actively lower their LTV and LTI to qualify under the new rules. According to the banks' response, LTV and LTI should *increase* after the policy for those households that are more distant from the lending limits. Recall that the increase in the issuance of total mortgages occurred primarily towards high income households in counties with a higher distance to the lending limits. This is suggestive that the effect is at least partly driven by a change in bank mortgage issuance.

In Figure 6, we show the time series evolution of LTV by high income (left panel, top quintile of the income distribution) and low income households (right panel, bottom quintile of the income distribution) from October 2013 to June 2016. Solid lines indicate originations in high-distance counties. Dashed lines indicate originations in low-distance counties. Consistent with the geographical reallocation documented above, we observe that (i) high-income borrowers increase their LTV driven by high-distance counties and (ii) low-income borrowers reduce their LTV.

20

5 Bank Credit Reallocation

In this section, we show that banks more affected by the lending limits reallocate their mortgage more compared with less affected banks.

## 5.1 Mortgage Credit Reallocation

The bank credit reallocation channel is based on the idea that banks react to the policy by reallocating their portfolio 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 compared with 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:

$$Exposure_b = \frac{\sum_{t=Oct13}^{Sep14} \text{Non-Conforming Mortgage Issuance}_{bt}}{\sum_{t=Oct13}^{Sep14} \text{Total Mortgage Issuance}_{bt}} \tag{3}$$

where the numerator is the sum of total non-conforming mortgages issued between October 2013 and September 2014 by bank b and the denominator is the sum, over the same period, of the entire mortgage issuance by bank b. Constructing this measure solely for the period before the announcement of the macroprudential policies allows us to capture a bank's typical mortgage issuance without any temporary effects caused by the announcement of the lending limits that were not yet binding.

In Figure 7, we show the evolution of conforming mortgages issued by high exposure banks
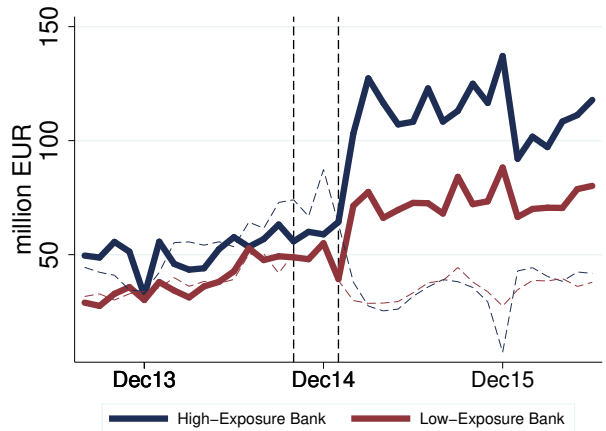
Figure 7: Residential Mortgage Credit Issuance, High- Vs. Low-Exposure Banks. The figure shows the issuance of conforming (solid thick lines) and non-conforming (dashed thin lines) mortgages for high-exposure (above median exposure) and low-exposure (below median exposure) banks from January 2013 to June 2016. The vertical line indicates the introduction of the lending limits. All time series are seasonally adjusted. Source: Central Bank of Ireland.

(exposure above median, blue line) and low exposure banks (exposure below the median, red line). The thin dashed lines show non-conforming mortgages, 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 compared with low exposure banks, relative to the pre-intervention period.

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

$$Y_{bcht} = \alpha + \beta Post_t \times Exposure_b + \gamma X_{b,t-1} + \nu_b + \eta_{ct} + \theta_{ht} + \epsilon_{bcht} \tag{4}$$

where our unit of observation is bank b, county c, household income bucket h, and month t. We divide households into twenty income buckets to ensure that 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 one from February 2015 to January 2016 and the bank-level $Exposure_b$ variable defined in Equation (3). 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 heterogeneity (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 estimation results in Table 4 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) households, whereas they reduce the total loan volume to low income (Q1) households more strongly than less exposed banks. Moreover, the top income quintile households also obtain larger loans compared with 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) households, and to a 15% increase in total new mortgage issuance to high income (Q5) households. These results are consistent with more affected banks reallocating credit to richer households which are further away from the lending limits and thus have potentially more room to increase their LTV and LTI, which is now constrained by the lending limits.

In Panel C we consider the loan volume weighted LTV as 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 6.6pp. However, in the top income quintile (column (5)), more affected banks *increased* their LTV compared with less

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	✓	✓	✓	✓	✓
Income Sample	Q1	Q2	Q3	Q4	Q5

Table 4: 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 (3), *Post* is a dummy equal to one 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.

exposed banks.[21] Borrowing from banks with a one standard deviation higher $Exposure_b$, leads to a 4.9pp 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.

In Panel D, the independent variable is 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 0.3pp

5.2   Effect on Mortgage Rates

In the last section, we show that exposed banks (i) drive the increase of LTV of high income households and the decrease of LTV of low income households and (ii) increased and decreased their mortgage credit to high income and low income households, respectively, compared with less exposed banks after the policy implementation. In this section, we analyze mortgage rates to investigate how banks adjusted their pricing in response to the macroprudential policy.

We first compare the average interest rate in the pre and post period for each quintile of the income distribution. In Panel A of Table 5, we document that, while interest rates on mortgages decreased in general for all borrowers, the extent to which interest rates decreased differs across the income quintiles. Initially paying comparatively high interest rates, high income households saw their interest rates decrease the most (by 0.46pp) and ended up paying the lowest interest rates across the entire income distribution.

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[21]In Figure B.5 in the Appendix, we show non-parametric evidence consistent with exposed banks driving high income households LTV increase in the post-regulation period.

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				
LHS=Rate	Q1	Q2	Q3	Q4	Q5
Post×Exposure	0.805*	0.127	0.002	-0.592	-1.829***
	(0.482)	(0.376)	(0.467)	(0.536)	(0.525)
Observations	383	383	383	383	371
R-squared	0.620	0.727	0.782	0.622	0.581
Bank FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓

Table 5: 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 (5) 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 (3) and *Post* is a dummy equal to one from February 2015 to January 2016. Standard errors clustered at the bank-time level level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Central Bank of Ireland.

This descriptive evidence suggests that one potential reason why high income households started to borrow more is that they were facing more attractive interest rates on their mortgages. Conversely, low income households saw the smallest reduction in their interest rate. To provide more formal evidence on this mechanism, we estimate the following equation:

$$Y_{hbt} = \alpha + \beta Post_t \times Exposure_b + \eta_b + \mu_t + \epsilon_{hbt} \tag{5}$$

where the unit of observation is month t, income bucket h, bank b and the dependent variable is the mortgage rate. The sample period runs monthly from February 2014 to January 2016 with 12-month pre- and post-periods. We saturate the specification with bank and time fixed effects, therefore absorbing the uninteracted terms.

We show estimation results in Panel B of Table 5 where columns correspond to income quintiles. We find that (i) households in the top quintile of the income distribution were charged significantly

lower interest rates if they borrowed from banks more affected by the regulation, consistent with more affected banks offering more 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 macroprudential policies.

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 and thus (partially) make up for the lost business due to the introduction of the macroprudential policy.

5.3   Geographical Reallocation

In a next step we investigate whether the geographical reallocation of total mortgage credit is indeed driven by the bank credit reallocation channel, i.e., whether more exposed banks are driving the change in credit reallocation across counties. To test this, we rerun the model in equation 4 separately for high and low distance counties.

Results are presented in Table 6. 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 county with a lower distance from the lending limits 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 (see 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

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

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	✓	✓	✓	✓	✓
Income Sample	Q1	Q2	Q3	Q4	Q5

Table 6: Bank Credit Reallocation, Residential Mortgages, Geographical Reallocation. This table presents the results from specification (4), 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 (3), *Post* is a dummy equal to one 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.

larger loans from more exposed banks, especially in high distance counties (Panel B).

Considering borrower leverage, we 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 6.9pp lower LTV in low distance counties compared to 6.0pp high distance counties), suggesting that low income households in low distance counties borrow less after the introduction of the lending limits. Focusing on the top income quintile in column (5), 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 7.2pp). Similarly, as shown in Panel D, the LTI of these households increases by 0.6pp.

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 to the lending limits. This group of borrowers represent the segment of the market with the greatest opportunities for conforming credit expansion after the introduction of the regulations. More precisely, while high income households in low distance counties have an average distance of 0.3 to the lending limits, high income households in high distance counties are have an average distance of 0.73 to the lending limits.

6   Bank Risk Exposure

In this section, we analyze the effect of the lending limits on bank risk exposure, both in mortgage lending as well as in other asset classes that were not affected by the regulation. We show that, after the policy implementation, banks increased their mortgage issuance to households that tend to default during busts and increased their risk taking in their lending to firms and holdings of

29

securities.

6.1 Riskiness of Mortgage Lending

To assess the evolution of risk of mortgage lending, we use loan characteristics at originations. Given that the lending limits were introduced in early 2015, we do not have data on defaults for newly issued mortgages after the introduction of the lending limits. We thus use machine learning techniques to estimate the default probability for each newly issued mortgage. The intuition underlying this approach 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. As suggested in Mullainathan and Spiess (2017), we attempt to uncover generalizable patterns of loan and/or borrower characteristics that are significant for default predictions. With the results of this model, we then estimate the probability of default for all new loan issuances in our pre- and post-period so that we can analyze the evolution of the risk of the newly issued loans around the introduction of the macroprudential regulation.

We follow Liberman et al. (2017) and estimate the determinants of default with a random forest model in the cross section of all outstanding mortgages at December 2013. This supervised algorithm can be used for classification, in our case to determine whether a loan 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. Iteratively, branches are created with the explanatory variables while maximizing in-sample prediction power. At the end of each tree, the values of variables are used to determine whether a loan is predicted to default or not whereby the final outcome of the model will be obtained
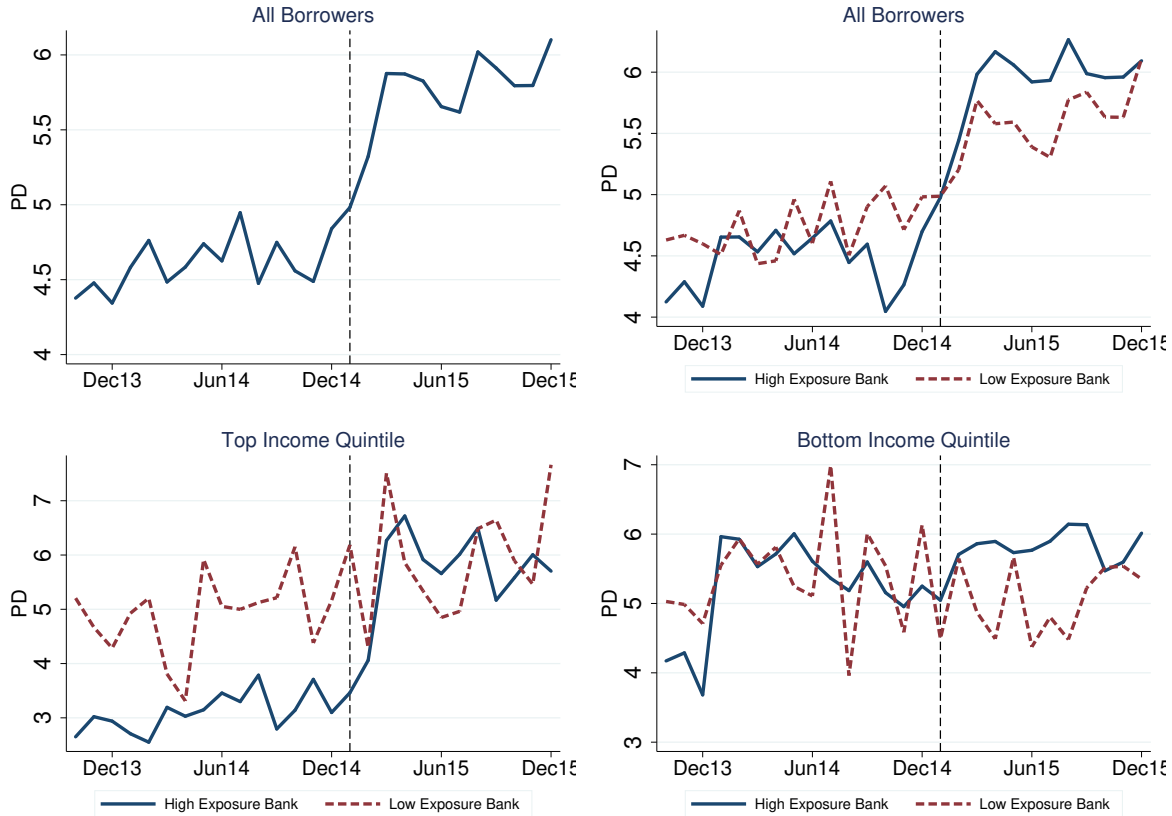
Figure 8: Mortgage Probability of Default. This figure shows the evolution of mortgage probability of default from October 2013 to February 2016. Panel A shows the default probability of newly issued mortgages by all Irish banks. Panel B shows the default probability of newly issued mortgages separately 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.

by calculating the average of all trees in the forest.[23]

In Figure 8, we plot the evolution of the value-weighted default probability of newly issued mortgages by our sample banks. The top left panel shows that the bank credit reallocation in the mortgage book seems to have led to an increase in the average default probability of newly issued mortgages. The top right panel confirms that this increase is driven by more affected banks, whereas the two bottom panels show that this increase is concentrated in the high income household segment of the mortgage market. We confirm this graphical evidence by re-running specification (4)

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[23]A more detailed description of this machine learning exercise can be found in the Online Appendix.

Panel A: Value Weighted PD					Entire 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: Value Weighted PD					Low Distance Counties
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: Value Weighted PD					High Distance Counties
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	✓	✓	✓	✓	✓
Income Sample	Q1	Q2	Q3	Q4	Q5

Table 7: Bank Credit Reallocation, Residential Mortgages, Default Probability. This table presents the results from specification (4) using the value-weighted default probability as 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 (3), *Post* is a dummy equal to one 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.

and considering the value-weighted default probability as dependent variable. Results are presented in Table 7. The results show that more exposed banks indeed issue mortgages with a higher default probability to high-income households. Consistent with the change in lending volumes and the significant increase in LTV, 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 2.7pp higher default probability for mortgages issued to high income households.

The higher default probability for high income households is consistent with the findings of

Kelly et al. (2015). They show that 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 richer households. Hence, by reallocating more credit to richer households, the riskiness of newly issued mortgages seems to increase.[24] Given that the majority of mortgage defaults in Ireland occurred during the 2007-2009 financial crisis when house prices collapsed in Ireland, our results should be interpreted as follows: Conditional on another boom bust cycle in the housing market, the mortgage book of banks would have a higher default probability after the introduction of the lending limits compared with the year immediately before their introduction.

This of course has to be considered in the context of the changes in the evolution of house prices documented in Section 4.2. Given the decrease of house price growth rates especially in low-distance counties, the introduction of the lending limits made the recurrence of a strong boom bust cycle in the Irish housing market less likely. Thus, we cannot draw overall conclusions as to whether the risk of banks' mortgage book actually increased since two opposing effects need to be considered. On the one hand, in case of the recurrence of a strong boom-bust cycle, the model-fitted default probability of new loans is higher in the year after the policy than the year before. On the other hand, given the slow-down in house price growth, the probability of a recurrence of a strong boom-bust cycle has decreased, leaving the net effect unclear.

Having documented that banks reallocate their residential mortgage portfolio in response to the macroprudential regulation, we now ask whether the new rules induced them to adjust their risk taking in other asset classes not affected by the lending limits. We thus focus on the two other largest asset classes held by banks: corporate loans and security holdings.

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[24]In Figure B.6, we show that our sample banks had the largest losses from borrowing to high LTV borrowers in the top income quintile during the recent financial crisis of 2007-09.

6.2 Credit to Firms

In a next step we start investigating whether the lending limits induce banks to change their behavior in non-regulated parts of their business (corporate lending and security holdings). We start by investigating whether banks change their credit supply to *firms* following the implementation of the mortgage lending limits. Given that the macroprudential regulation is aimed at limiting risk taking in the real estate market, banks might take more risk in other types of private credit that are not targeted by the regulatory intervention.

To this end, we exploit the corporate loan-level data set collected by the Central Bank of Ireland. We adapt specification (4) and estimate the following specification:

$$Y_{bclqt} = \alpha + \beta Post_t \times Exposure_b + \gamma X_{bt-1} + \delta_{bc} + \eta_{clqt} + \epsilon_{bclqt} \qquad (6)$$

We measure the credit provided by bank b to firms in county c, industry l, of quality q in period 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 (see Acharya et al. (2018)). 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 since 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 quality of a firm that receives a loan, we use the ratings obtained by the Central Bank of Ireland.[25]

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

This ensures that the rating categories are homogeneous across banks and our results are not driven by different probabilities of default. 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 volume of credit ($\Delta VOLUME$) 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 macroeconomic effects that are shared by firms of similar quality operating in the same county and industry. Moreover, 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 Panel A and B, the dependent variable is the change in total volume of credit and change in interest rate charged, respectively. Column (1) considers the full sample of firms. The estimates document that banks more affected by the regulation increase their lending volume to corporate clients and decrease the price of corporate loans. This is consistent with a credit expansion in the corporate loan market in response to the new lending restrictions in the mortgage market.

In a next step we split our sample firms into risky (rating 5) and non-risky (rating 1-4) firms and rerun our specification (6) separately for risky and non-risky borrowers. The estimation results in Columns (2) and (3) show that, while a credit expansion in the corporate sector occurs for both risky, and non-risky borrowers, the effect is economically and statistically more pronounced towards risky borrowers relative to the pre-period.

This is confirmed in Column (4) of Panel A, where we employ a triple interaction of our bank

| | Panel A: $\Delta VOLUME$ | | | |
	Total	Risky	NonRisky	Total
Exposure $\times$ Post	1.382***	2.761***	0.740*	0.697
	(0.401)	(0.659)	(0.435)	(0.449)
Exposure $\times$ Post $\times$ Risky				2.253***
				(0.547)
Exposure $\times$ Risky				-0.182
				(0.307)
Observations	10,092	3,227	6,865	10,092
R-squared	0.525	0.569	0.493	0.527

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

Table 8: **Bank Portfolio Reallocation, Credit to Firms.** This table shows the estimation results of specification (6). The unit of observation is bank-industry-county-quality-time. The sample runs at a semi-annual frequency from 2013H1 to 2016H1. *Exposure* is defined in (3) and *Post* is a dummy equal to one from 2015H1 to 2016H1. A loan is classified as risky if the rating given by the Central Bank is either a 5 or worse. Standard errors clustered at the bank-county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

exposure variable with a *Post* dummy and a dummy for whether the borrowing firms are risky. The coefficient shows that the increase in loan volume is mostly driven by an increase towards risky borrowers relative to the pre-period. Similarly, we find that the decrease in the cost of bank loans is mostly benefiting risky borrowers (see Panel B of Table 8).

6.3 Security Holdings

Having shown that banks more exposed to the mortgage lending limits increase their supply of conforming mortgages and loans to risky firms compared with less affected banks, we now turn to

analyzing how banks adjust their holdings of securities in response to the macroprudential policy.

In particular, we take advantage of security-level holdings data[26] and examine whether banks changed their risk exposure in the security portfolio around the introduction of the mortgage lending limits. We measure the risk of securities using their yield. Following Davis and Haltiwanger (1992), we define the "net buys" of security s by bank i from time $t-1$ to time t as follows:

$$NetBuys_{s,b,t} = \frac{Holdings_{s,b,t} - Holdings_{s,b,t-1}}{0.5(Holdings_{s,b,t} + Holdings_{s,b,t-1})} \in [-2,2] \tag{7}$$

where *Holdings* is the euro value of holdings of security s by bank b at time t. Compared to simple percentage changes, this measure allows us to capture final sales and initial purchases. The value of *NetBuys* is always between -2, corresponding to final sales, and 2, corresponding to initial purchases.

Similar to the analysis of credit reallocation to households and firms, we exploit the cross-sectional heterogeneity in bank exposure to the lending limits. In particular, we estimate the following specification:

$$NetBuys_{sbt} = \alpha + \beta Exposure_b \times Post_t \times Yield_s + \gamma_{bt} + \eta_{st} + \epsilon_{sbt} \tag{8}$$

where the unit of observation is security-bank-quarter (s, b, t). Our dependent variable is defined in (7), and our independent variable of interest is a triple interaction term between bank exposure to the macroprudential policy as defined in (3), a *Post* dummy equal to one in the post period, and

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[26]We obtain data on all security holdings that have an International Securities Identification Number (ISIN). The sum of these holdings is mostly within 10% of the values in the banks' balance sheets which is reassuring regarding the coverage of the data.

	Net Buys	Net Buys	Net Buys	Net Buys	Buys	Sells
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)
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
Time FE	✓					
Security FE	✓	✓				
Bank-Time FE		✓		✓	✓	✓
Security-Time FE			✓	✓	✓	✓

Table 9: Bank Portfolio Reallocation, Holdings of Securities. This table shows the estimation results from specification (8). 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 (7). *Exposure* is defined in (3) and *Post* is a dummy equal to one from 2015Q2 onwards. Standard errors clustered at the security-level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Source: Central Bank of Ireland.

a measure of the risk of the security.[27]

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 9. We progressively saturate the regression with more stringent fixed effects. Column (4) includes all the pairs of two-way fixed effects. The coefficient of interest, stable across specifications, indicates more exposed banks increase their holdings of risky securities compared to less exposed banks in the post regulation period. 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 (see Abbassi et al. (2016)). We find that banks more exposed to the regulation both buy more and sell less high yield securities, relative to banks less affected by the regulation.

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[27]We measure the risk of the security using the yield of the respective securities. Information on yields are obtained from Thomson Reuters Datastream.

7 Conclusion

We provide a comprehensive micro-level analysis of the transmission of macroprudential policies aimed at limiting bank risk-taking in the residential mortgage market. Combining loan-level data on residential mortgages with bank credit to firms, and security-level data on bank holdings of securities, we examine the February 2015 introduction of LTV and LTI limits on the issuance of residential mortgages in Ireland.

We analyze how the policy affected banks and households. Following the introduction of the lending limits, banks increased their risk-taking in both credit to firms and holdings of securities, the two largest asset classes not targeted by the regulation. Following the policy, low income households borrowed less while higher income households borrowed more. Interestingly, low leverage high income households increased their leverage post regulation. This was potentially driven by more exposed banks reducing the rate charged to high income household who levered up and obtained larger loans.

Our effects are consistent with the time-series evolution of house prices. In particular, we find that the increase in mortgage credit to high income households is mostly driven by high-distance counties. On the other hand, the contraction in mortgage credit to low income household is driven by the low-distance counties, like the Dublin area. House price appreciation continues to grow in the entire country, with the exception of low-distance counties where borrowers tend to be highly levered and therefore more affected by the policy.

Our findings inform the academic literature and policy debate. They also open several new avenues for future research. For example more research is needed to compare lender-based (e.g., capital requirements) and borrower-based policies (e.g., LTV/LTI limits). Our analysis also highlight sizable spillovers to asset classes not targeted by the regulation. Of course, other spillovers are also possible, like cross-border spillovers as policies might target only one jurisdiction or spillovers

to the unregulated financial sector. Finally, the transmission of macroprudential regulation might be affected by other contemporaneous policies including monetary policy.

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Appendix A   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
- 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.
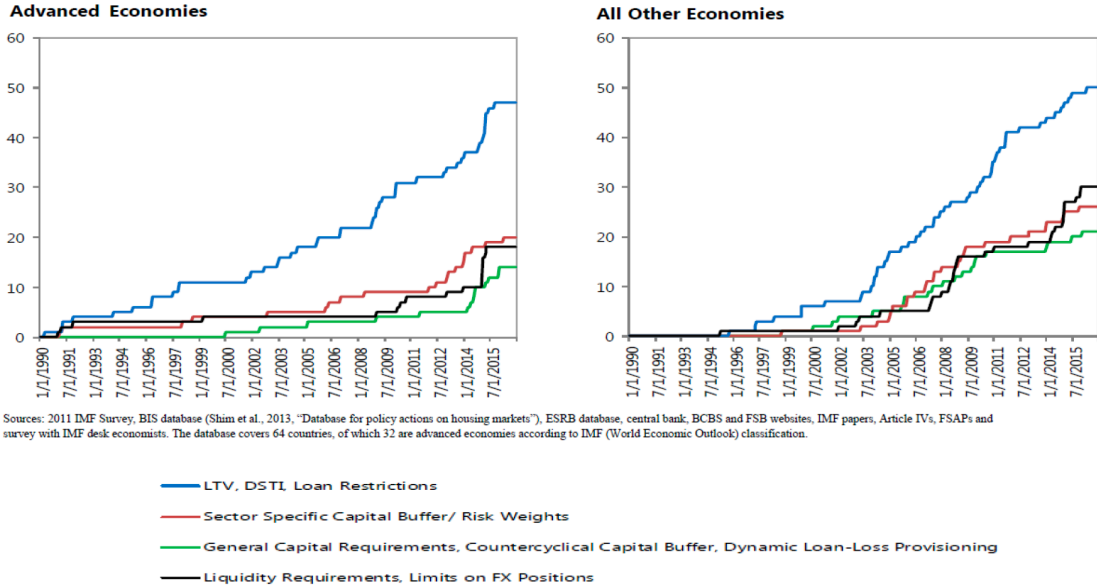
Appendix B   Additional Figures

Advanced Economies

All Other Economies

Sources: 2011 IMF Survey, BIS database (Shim et al., 2013, "Database for policy actions on housing markets"), ESRB database, central bank, BCBS and FSB websites, IMF papers, Article IVs, FSAPs and survey with IMF desk economists. The database covers 64 countries, of which 32 are advanced economies according to IMF (World Economic Outlook) classification.

— LTV, DSTI, Loan Restrictions
— Sector Specific Capital Buffer/ Risk Weights
— General Capital Requirements, Countercyclical Capital Buffer, Dynamic Loan-Loss Provisioning
— Liquidity Requirements, Limits on FX Positions

Figure B.1:   Usage of macroprudential policies around the world.

Pre-Policy House Price Appreciation   Population Density   Distribution of National Population
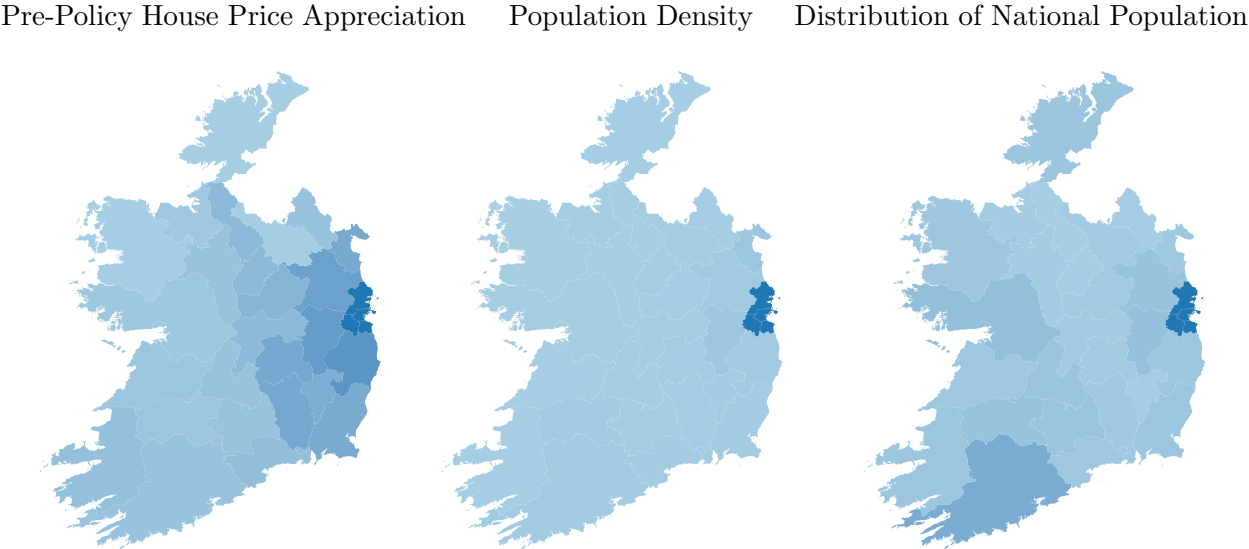
Figure B.2: Demographics and House Price Appreciation Across Counties. The left panel of this figure shows county-level population. Darker colors indicate more densely populated counties. The right panel shows county-level increase in house prices from their lowest point after the bust to September 2014. Darker colors indicate sharper a larger increase in house prices. Source: Central Bank of Ireland, Daft.ie
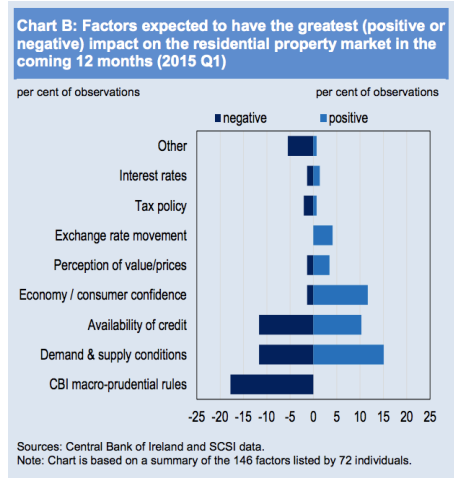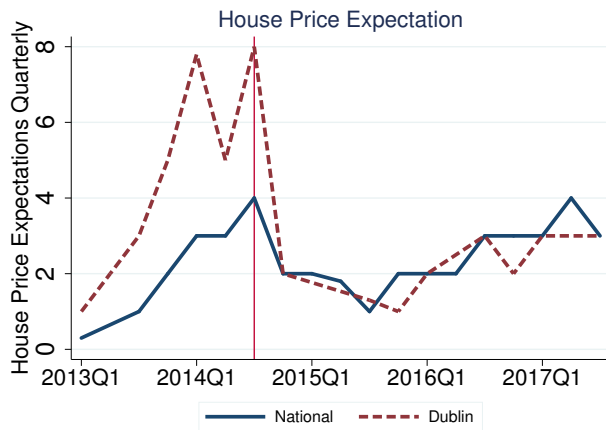
Figure B.3: House Price Expectations. This figure shows survey evidence suggesting that the announcement of the lending limits caused households to revise their expectations about house prices downward, especially in low-distance counties. The left panel shows the evolution of house price expectations 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.
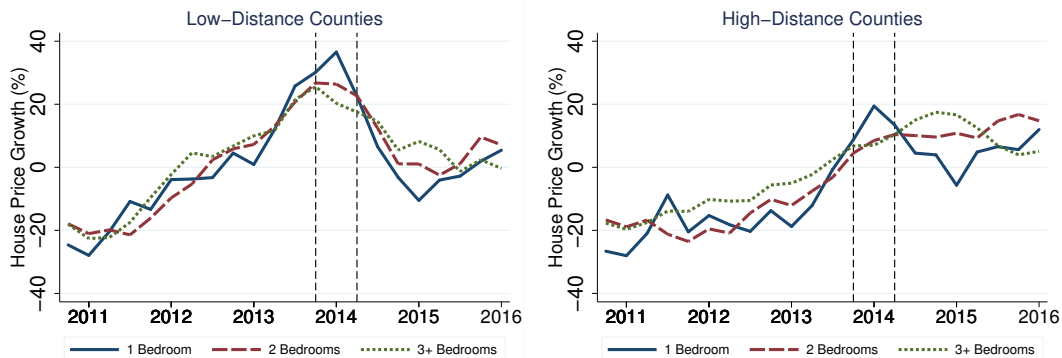

Figure B.4: House Price Changes and Property Type. This figures shows the evolution of yearly house price growth for 1-bedroom properties (solid line), 2-bedroom properties (dashed line), and 3-bedroom or larger properties (dotted line), underlying specification (2). The left (right) panel shows data 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.

47
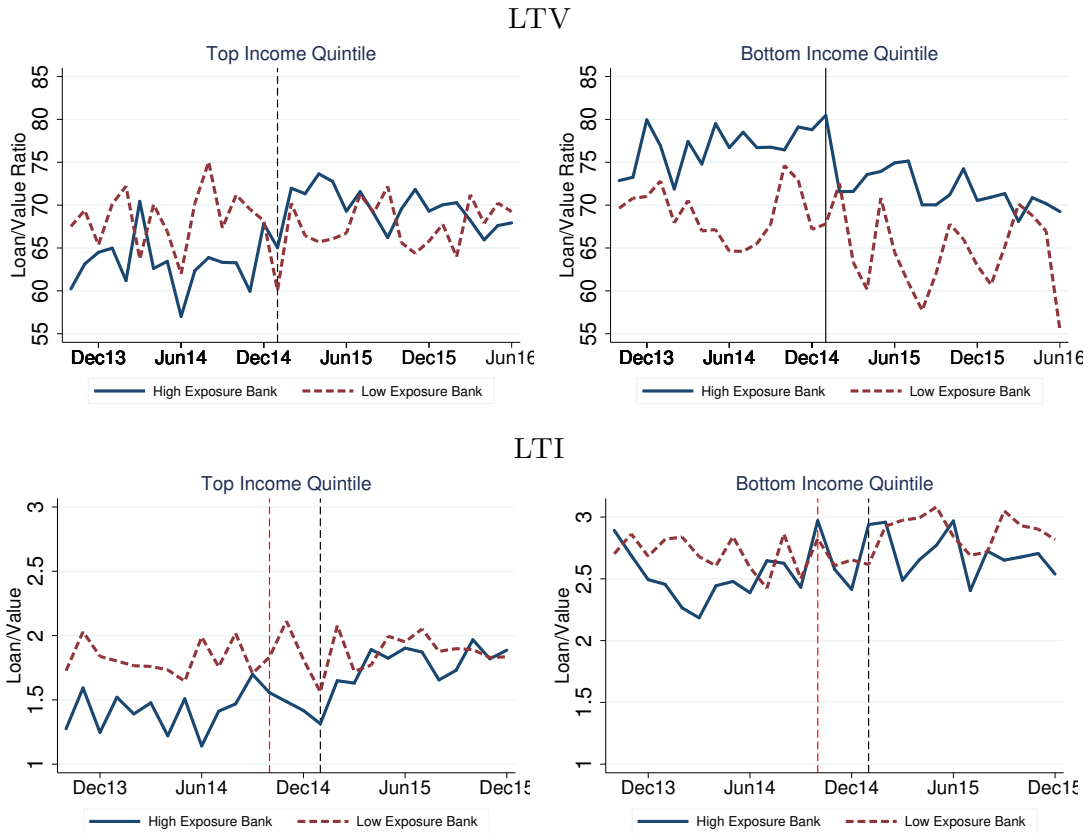
Figure B.5: LTV and LTI, High and Low Exposure Banks, Top Income Quintile Vs. Bottom Income Quintile. This figure shows the evolution of LTV (top panel) and LTI (bottom panel) of mortgage issuance by high-exposure (solid line) and low-exposure (dashed line) banks from October 2013 to June 2016. Blue 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.
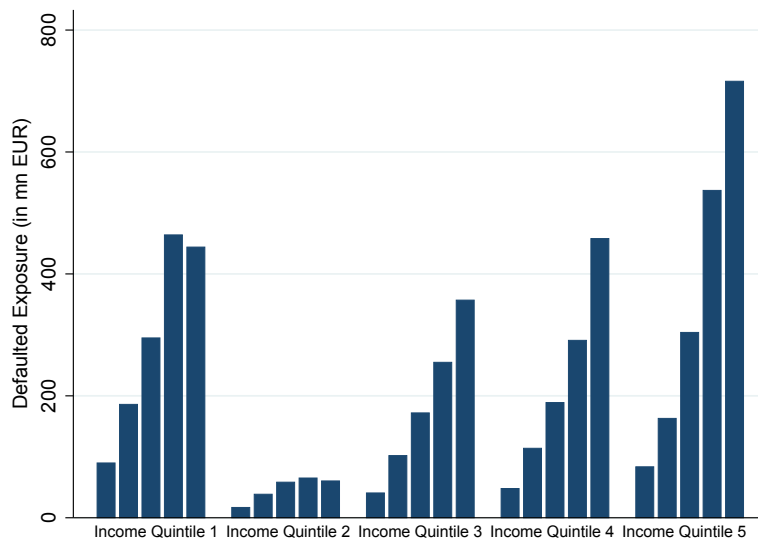
Figure B.6: Defaulted Exposure accumulated during the run-up to the Financial Crisis. This figure shows the defaulted exposure of Irish banks from 2000-2012. The bars represent the loss of the individual LTV Quintiles which are shown in an ascending order from left to right within each income quintile. 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.

Appendix C   Additional Tables

	(1)	(2)	(3)	(4)
Distance×Income×Post	0.709***	0.631***	0.652***	0.630***
	(0.141)	(0.155)	(0.165)	(0.106)
Distance×Post	-0.388**	-0.328**		
	(0.142)	(0.148)		
Observations	2,846	2,846	2,846	2,846
R-squared	0.707	0.742	0.792	0.801
Time FE	✓	✓		
County FE	✓	✓		
Income Bucket FE		✓	✓	
County-Time FE			✓	✓
Income Bucket-Time FE				✓

Table C.1: Mortgage Credit Reallocation. This table shows estimation results from specification (**??**). Column (1) covers the full sample and columns (2)-(6) show estimates separately for each of the quintiles of the borrower income distribution. Income quintiles are adjusted monthly for wage inflation. The dependent variable is the logarithm of total mortgage volume, *Distance* is the average county-level distance from the lending limits in the 12-month period prior to their introduction, *Post* is a dummy equal to one from February 2015 to January 2016. County-level controls include average income, average house values, and average age of the population. All control variables are lagged by one period. Standard errors double clustered at the county and month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

Online Appendix[1]

OA.1   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 ($Distance_c$).

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[1]Date: May 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 Board of Governors of the Federal Reserve System, 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.

OA.2 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).
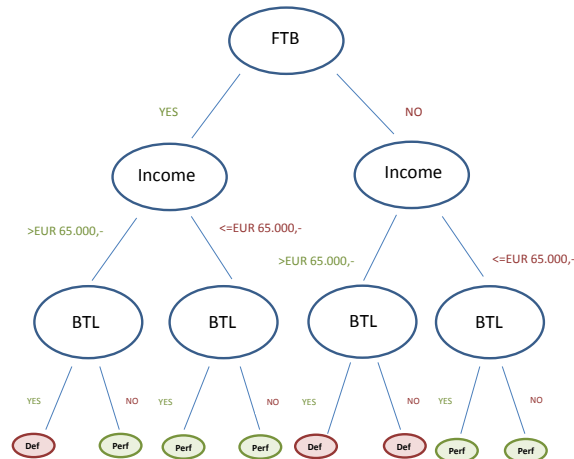
Figure OA.1: Example for a Tree.
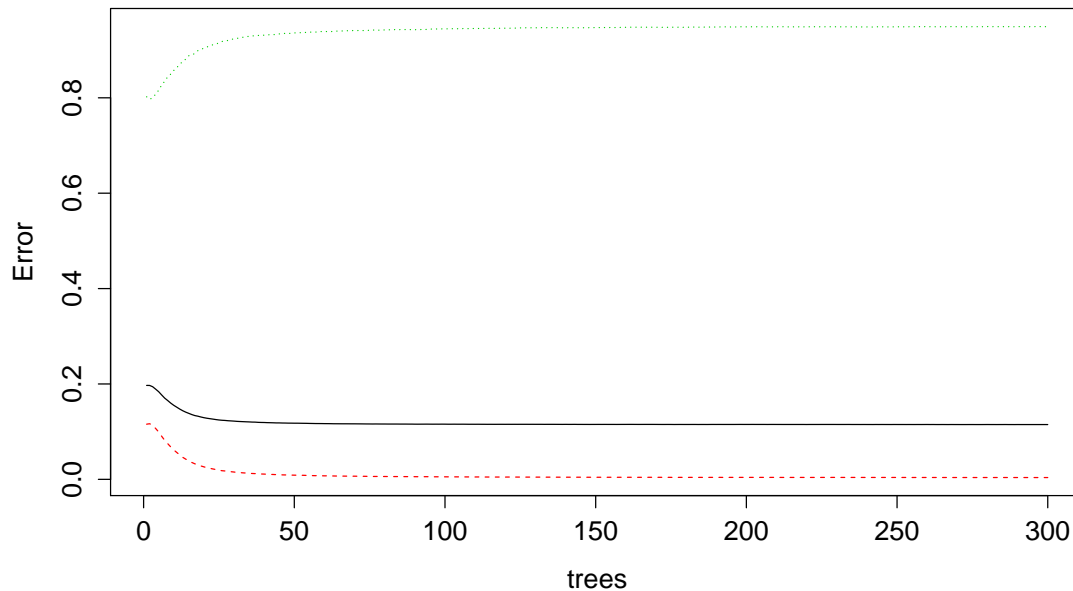
Figure OA.2: Optimal Number of Trees. This graphs whose the average error for the different amounts of trees planted in the forest.

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

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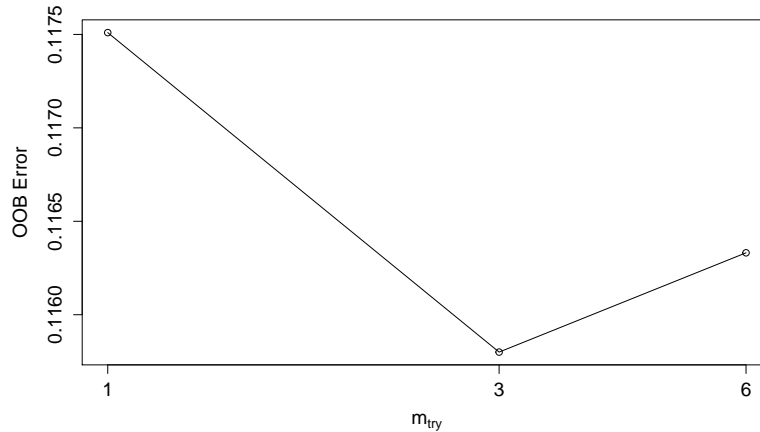
Figure OA.3: Optimal Number of nodes for each Regression Tree. This graph shows the average OOB (Our of Bag) Error for the different amounts of variables randomly selected for each Regression Tree.

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

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[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.

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[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.3   Additional Figures
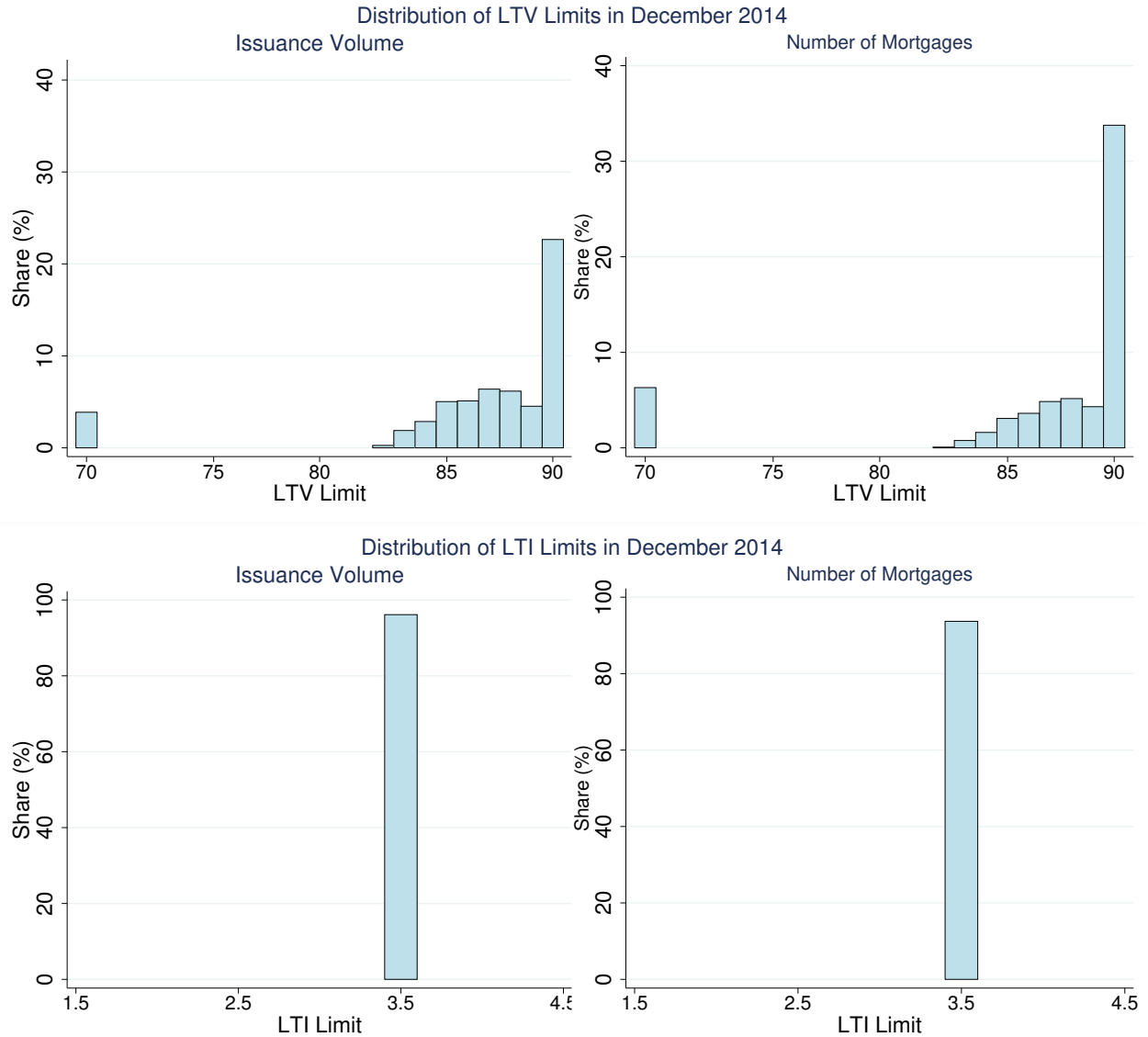
Figure OA.5: Distribution of Lending Limits. This figure shows the distribution of the lending limits in December 2014. The top panel shows the distribution of LTV limits. The bottom panel shows the distribution of LTI limits. The left figures are the share of total mortgage issuance volume. The right panels are the share of total number of mortgages issued. In the bottom panel, the shares do not sum to one as buy-to-let mortgages are exempt from the LTI limit. Source: Central Bank of Ireland.
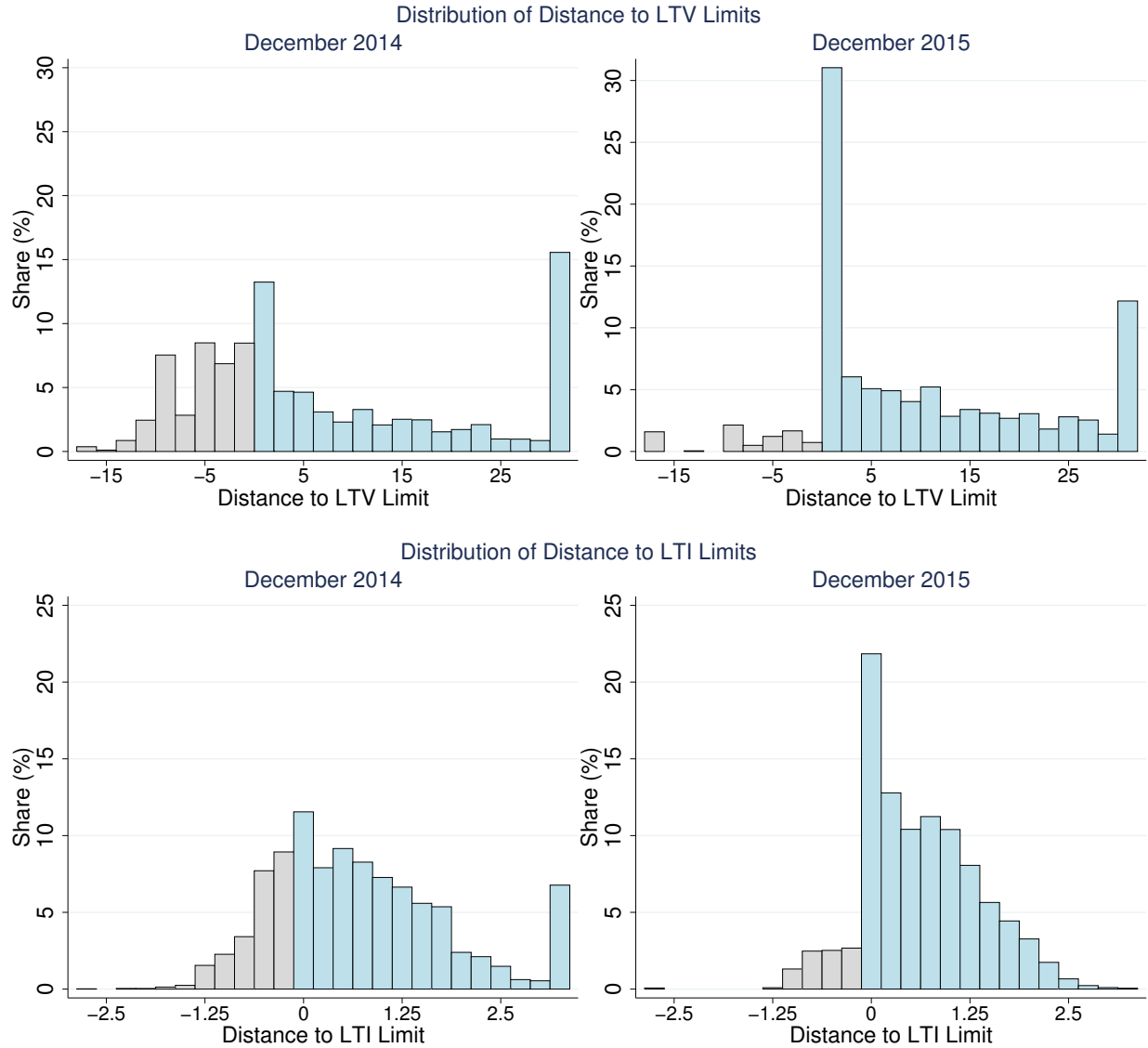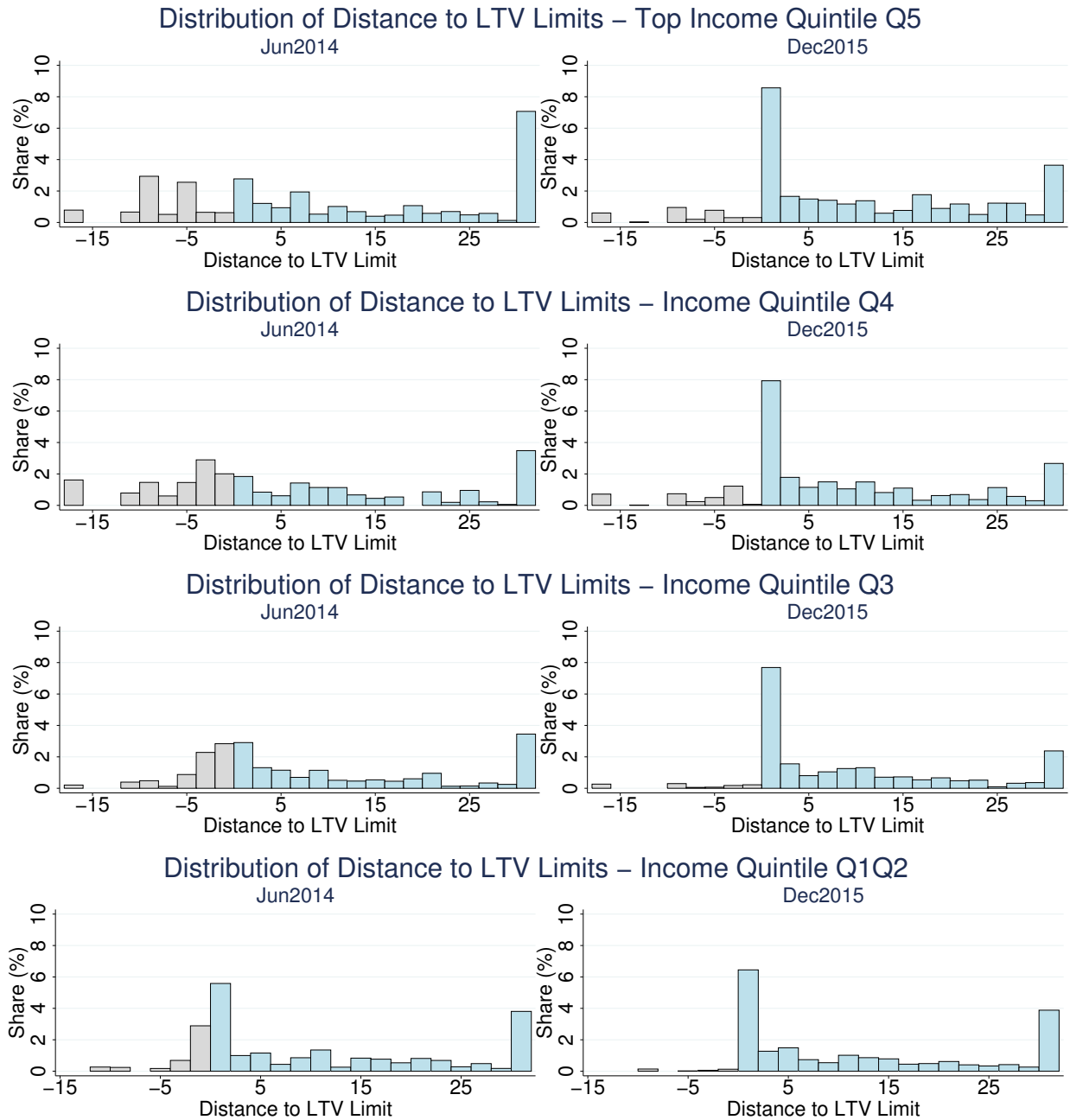
Figure OA.6: Distribution of Distance to Lending Limits. This figure shows the distribution of the distance to the lending limits. The top panel shows the distribution of the distance to the LTV limits. The bottom panel shows the distribution of the distance to the LTI limit. The left figures are the 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.

Distribution of Borrowers Income
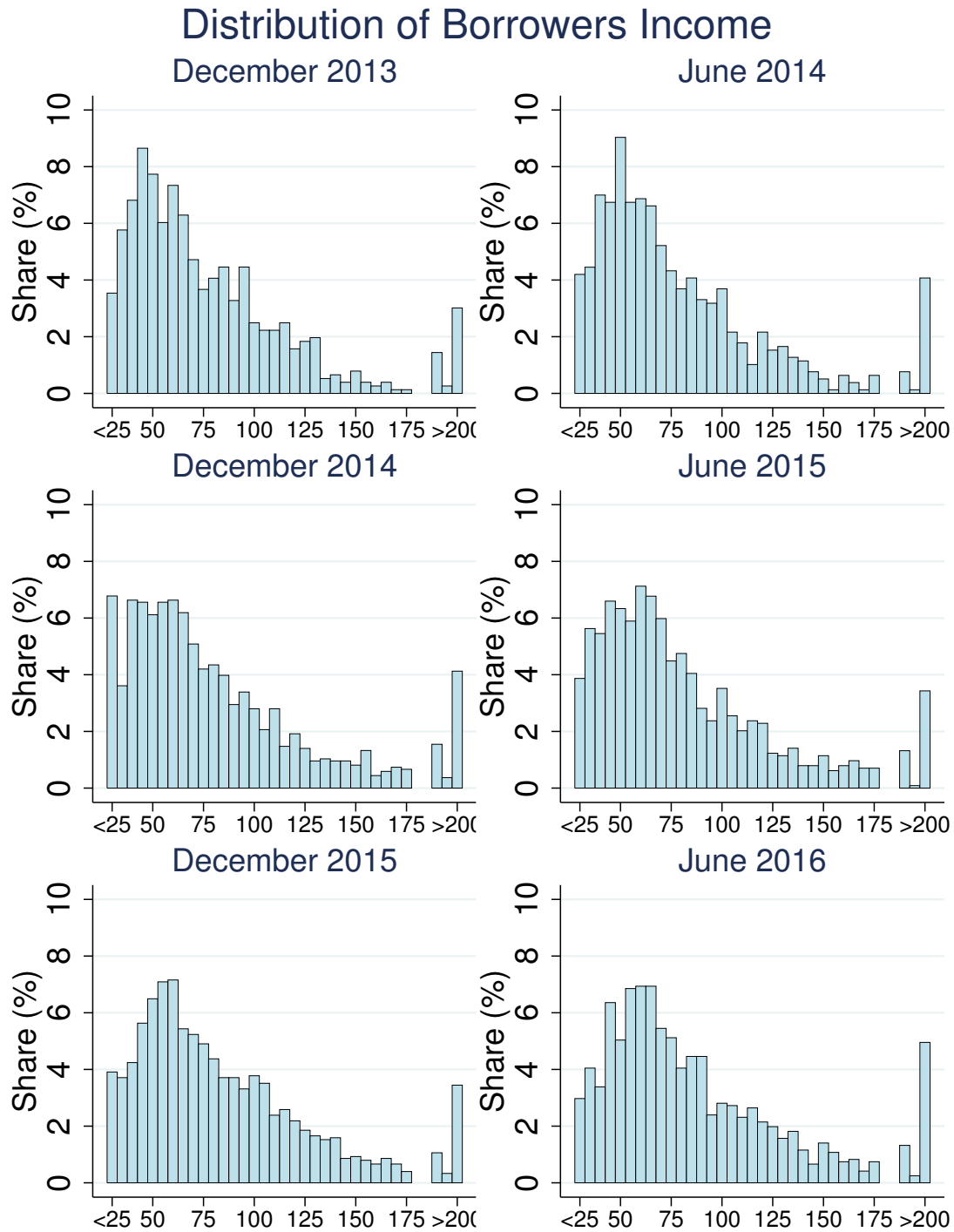
Figure OA.7: **Evolution of Distribution of Borrowers' Income.** This map shows the evolution of the distribution of borrowers' income at a semi-annual frequency from December 2013 to June 2016. We group households that receive a mortgage at time t in buckets of €5,000 from €25,000 to €200,000 on the x-axis. The y-axis shows the share of total issuance at time t in each bucket. *Source: Central Bank of Ireland.*

Figure OA.8: 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.