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The Anatomy of the Transmission of Macroprudential Policies

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Abstract

We analyze how regulatory constraints on household leverage—in the form of loan-to-income and loan-to-value limits—affect residential mortgage credit and house prices as well as other asset classes not directly targeted by the limits. Supervisory loan level data suggest that mortgage credit is reallocated from low-to high-income borrowers and from urban to rural counties. This reallocation weakens the feedback loop between credit and house prices and slows down house price growth in "hot" housing markets. Consistent with constrained lenders adjusting their portfolio choice, more-affected banks drive this reallocation and substitute their risk-taking into holdings of securities and corporate credit.

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1 Introduction

Policymakers have recently proposed and implemented macroprudential policies aimed at limiting household leverage to slow down the feedback loop between credit and house prices. The academic literature—by showing that build-ups of household leverage have historically led to busts, lower output growth, and higher unemployment (Mian et al., 2017)—has highlighted the importance of these policies, adopted by more than 60 countries since 1990.

In this paper, we provide a comprehensive analysis of the most widely used type of macroprudential regulations, namely, policies that limit household leverage in the residential mortgage market. Combining county level house price data, loan level data on residential mortgages and credit to firms, as well as bank security level holdings, we study the introduction in 2015 of loan-to-value (LTV) and loan-to-income (LTI) limits for residential mortgages issued by Irish banks.[1] The policy was introduced in the aftermath of a dramatic boom-bust cycle that led to a financial crisis that, in turn, forced the government to adopt a costly bailout (Acharya et al., 2014).[2] The lending limits affect 43% of the typical mortgage origination and are immediately effective after the announcement. The goal, in the words of at the time central bank governor Patrick Honahan, was to *"prevent another psychological loop between credit and prices and credit"* and *"keep banks and borrowers safe."*

We document that whereas the lending limits affect a large share of the residential mortgage market, mortgage issuance keeps growing after the policy introduction as the market "moves" to conform with the new limits. Our analysis of this reallocation provides three main findings: (i) Mortgage credit is reallocated from low- to high-income borrowers and

[1] Alam et al. (2019) collected data from 1990 to 2016 on macroprudential policies in 134 countries. LTV and LTI limits have been adopted by 60 and 42 countries, respectively. LTV limits are the most widely used tool in advanced economies. See Cerutti et al. (2017) for another cross-country database.

[2] The household debt/GDP ratio increased from 55% to 101% from 2002 to 2007, followed by -10% GDP growth and a +8% unemployment rate change over the next three years.

from counties where borrowers are close to the lending limits (typically urban areas) to counties where borrowers are more distant from the lending limits (typically rural areas); (ii) this reallocation is effective in slowing down house price growth, and in turn, the feedback loop between mortgage credit and house prices, in "hot" housing markets; and (iii) this reallocation is consistent with a *bank portfolio choice* channel as banks more affected by the limits drive the mortgage credit reallocation and increase their risk-taking in their holdings of securities and credit to firms, two asset classes not targeted by the policy.

Next, we describe these results in detail. First, we show that 43% of the mortgage issuance in the year before the policy would have been affected if the rules had been in place during this period. Nevertheless, the increase in "conforming" issuance offsets the collapse in the issuance of those mortgages that exceed the newly imposed limits, leaving aggregate issuance barely affected. However, not every mortgage is affected in the same way. In the cross-section of counties, "hot" housing markets (typically urban counties) are closer to the limits than "cool" housing markets (typically rural counties). In the cross-section of borrowers, high-income borrowers are more distant from the limits than low-income borrowers. We show that, after the policy introduction, residential mortgage issuance moves from hot to cool housing markets and from low- to high-income borrowers. Following the methodology in Mian et al. (2019), we compare estimated coefficients with and without county-time fixed effects, which absorb the general equilibrium forces at the county level. This comparison suggests that the policy weakened the sizable general equilibrium *"loop between credit and prices and credit"* at work before the policy introduction.

Second, we show that the evolution of house prices is consistent with the observed geographic credit reallocation. House price growth, around 14% year-on-year (YoY) and rapidly increasing at the time of the policy announcement, stabilized below 10% post-regulation. This evolution is driven by hot housing markets where house price growth, well above 20% YoY and rapidly increasing at the time of announcement, collapsed to around 4% post-regulation. As a result, the lending limits substantially reduced the geographical heterogeneity in house price growth. House prices are also consistent with the reallocation across the income distribution as the differential evolution of house price growth across counties is more pronounced for larger properties, more likely to be purchased by high-income borrowers.

Third, we show that our findings are consistent with a *bank portfolio choice* channel. Consider an environment where banks solve their portfolio problem subject to a binding balance sheet constraint (e.g., funding or regulatory capital constraint) and introduce the additional mortgage lending limit constraint.[3] According to this channel, following the introduction of the lending limits, banks reallocate their portfolio and issue mortgages that would have not otherwise been funded. We test this channel exploiting bank level heterogeneity. We calculate the share of bank issuance that would have been affected if the limits had been in place the year before the policy. After confirming that more-exposed banks drive the aggregate reallocation, we find that more-exposed banks reduce their issuance to borrowers in the bottom quintile of the income distribution by 10% and increase their issuance to borrowers in the top quintile by 15%, controlling for local economic conditions and credit demand.

We further confirm the role of banks by documenting (i) bank risk taking in asset classes not targeted by the lending limits and (ii) the evolution of banks' risk exposure. First, we analyze banks' holdings of securities and credit to firms, capturing, together with residential mortgages, approximately 80% of banks' assets. We find that more-exposed banks increase their holdings of high-yield securities more than less-exposed banks, relative to the pre-policy period, controlling for stringent security-time and bank-time fixed effects. Similarly, we find that more-exposed banks increase their corporate lending (higher volumes and lower rates), targeting mostly risky borrowers. Second, we show that Irish banks' equity returns, usually

[3] In our setting, residential mortgages are almost entirely issued by banks that hold them on balance sheet. Irish banks are also likely constrained at this time as they hold a large stock of non-performing loans and are adjusting their balance sheets to comply with new capital and liquidity regulations.

positively correlated with real estate returns, become insensitive to real estate and positively correlated with non-financial firms' equity returns after the introduction of the lending limits.

The rationale for macroprudential policies is based on the observation that agents over-borrow in good times, not internalizing all the costs of their financing choice (Lorenzoni, 2008; Bianchi, 2011; Bianchi and Mendoza, 2010, 2018). In the U.S., the increase in mortgage credit contributed to the rapid appreciation of house prices (Favara and Imbs, 2015; Mian and Sufi, 2009, 2019; Adelino et al., 2015; Di Maggio and Kermani, 2017). Their collapse, channeled through the balance sheets of households (Mian et al., 2013; Mian and Sufi, 2014; Hall, 2011; Eggertsson and Krugman, 2012; Jones et al., 2018) and intermediaries (Gertler and Kiyotaki, 2011; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Chodorow-Reich, 2014), contributed, in turn, to the Great Recession.

We contribute to the literature on macroprudential regulation aimed at limiting household leverage, by (i) jointly analyzing mortgage credit, house prices, and—using the methodology of Mian et al. (2019)—their feedback loop, and (ii) showing that lenders play an important role in the transmission.[4] A few other papers analyzing LTV/LTI limits find results consistent with ours.[5] DeFusco et al. (2020) show how the Dodd-Frank "Ability-to-Repay" rule (similar to a LTI limit) successfully reduced borrower leverage, and Van Bekkum et al. (2019) show LTV limits caused Dutch borrowers to increase their downpayments. Although they do not

[4]See Aikman et al. (2019), Freixas et al. (2015), Claessens et al. (2013), Claessens (2015), and Gambacorta and Murcia (forthcoming) for excellent overviews of macroprudential policies. Our paper is also related to the literature, empirical (Aiyar et al., 2014; Jimenez et al., 2017; Gropp et al., 2019; Benetton, 2019; Benetton et al., 2017; De Marco and Wieladek, 2015; Ayyagari et al., 2019) and theoretical (Landvoigt and Begenau, 2017; Elenev et al., 2018; Begenau, forthcoming; Kashyap et al., 2019; Malherbe and Bahaj, forthcoming), on macroprudential policies (mostly capital requirements) aimed at limiting bank risk-taking. We use the methodology in Sarto (2018) and Mian et al. (2019) to decompose the general equilibrium effect of the policy in a partial equilibrium component and a general equilibrium multiplier.

[5]Analyzing the policy of this paper, Kinghan et al. (2017) show LTV fell for first-time and subsequent-time buyers. Compared with their paper, we focus on house prices and document a reallocation of mortgage credit across the income and geographical distributions.

analyze the role of banks, Tzur-Ilan (2019) and Igan and Kang (2011) show borrowers move away from hot housing markets, slowing down house prices in Israel and Korea, respectively.[6]

The rest of the paper is structured as follows. Section 2 describes the data and the setting. Section 3 documents the mortgage credit reallocation. Section 4 analyzes house prices. Section 5 presents the bank portfolio choice channel. Section 6 discusses financial stability. Section 7 concludes.

2 Setting and Data

Section 2.1 provides some background on the Irish residential mortgage market. Section 2.2 and Section 2.3 describe the macroprudential policy and our data.

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 (Honohan, 2010). In Figure 1, we show the issuance of residential mortgages (dashed line) from 2000 to 2016 and observe a stark increase from 2002 to 2007. Issuance then collapsed and started increasing again in 2013. House prices (solid line) followed a remarkably similar pattern.[7]

[6] Auer and Ongena (2019) and Basten (forthcoming) show that capital buffers on Swiss residential lending led to higher growth in commercial lending and shifted mortgages from less to more resilient banks, respectively. Using Singaporean data, Agarwal et al. (2018) show that policies that impose limits on LTV cause an increase in high-LTI issuance. These papers do not analyze house prices or banks' risk exposure.

[7] In the online appendix, we show that the boom-bust cycle in the housing market has been more pronounced in Ireland compared with the U.K., the euro area, and the U.S. around the same period. After the bust, mortgage originations and house prices rebounded, mostly driven by "pent up" demand of households

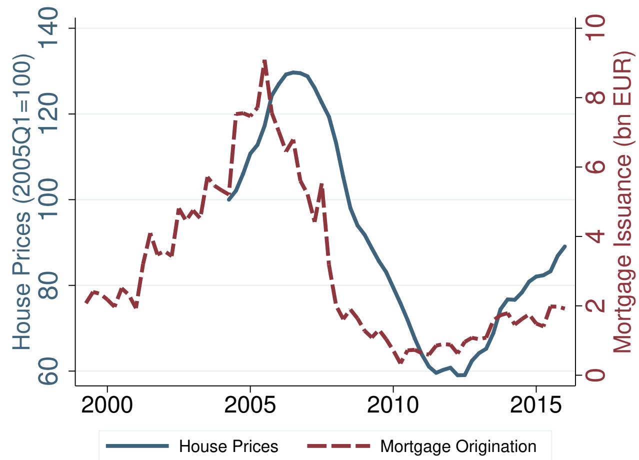

Figure 1: Ireland Real Estate Boom-Bust. This figure shows real estate prices from 2005Q1 to 2016Q4 (left axis) and residential mortgage issuance from 2000Q1 to 2016Q4 (right axis). Sources: Department of Housing, Planning and Local Government and Central Statistics Office.

During the bust of 2007-10, prices declined sharply and construction activities collapsed. The fall in quarterly Gross National Product (GNP) is estimated to be about 17%.[8] In addition to the sharp decrease in real estate prices, the increase in unemployment from 4.6% in 2007 to 13.3% in 2010 left many households unable to service their debt. This increase in non-performing mortgage credit led to losses for banks that consequently experienced funding dry-ups.[9] In September 2008, public funds had to be used to recapitalize almost all large domestic credit-taking institutions, which needed further government assistance in

whose incomes were not affected by the crisis but avoided buying during the bust (the share of renters that became first-time buyers had fallen to 2% in 2012 and then rose steadily up towards 7-8%). This increased demand interacted with a weakened supply elasticity.

[8]The Irish economic performance is better measured with GNP because GDP is inflated by profits of international companies transferred to Ireland because of low corporate tax.

[9]Almost all mortgages in Ireland are held on banks' balance sheets. No active securitization market exists. Securitization is solely used to create collateral eligible to be pledged at the ECB and in certain recent cases to transfer nonperforming exposures off banks' balance sheets. Risk transfer off banks' balance sheets is not common. Refinancing mortgages are not part of our sample. They account for less than 15% of total mortgage issuance during our sample period.

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 new lending can be above limits
	For buy-to-let:	70% LTV limit	10% of new lending can be above limits 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 to the first €220,000 of the value of a residential property and a limit of 80% LTV applies to any value of the property thereafter.			

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

March 2011 (Lane, 2011; Acharya et al., 2014).

2.2 The February 2015 Mortgage Lending Limits

To avoid a recurrence of this boom-bust cycle, the central bank introduced new macroprudential rules. In the words of Patrick Honahan, 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 idea of introducing lending limits was first discussed in October 2014 and announced and immediately implemented on February 9, 2015 (implementation date).[10] In Table 1, we provide an overview of the limits on LTV and LTI ratios on new originations of residential

[10]The lending limits were first mentioned in a paper (Consultation Paper 87) published on October 7, 2014 to stimulate discussion and available on the Central Bank of Ireland website (link). The limits were announced and implemented on February 9, 2015, with no limits being in place prior to this date. Mortgages issued after February 9, 2015 could exceed the lending limits if approved before February 9, 2015.

mortgages. The LTI limit is 3.5. The LTV limit depends on the type of borrowers.[11] Lending for primary-dwelling housing (PDH) is limited to 80% LTV. For first-time buyers (FTBs), a more generous LTV limit of 90% is imposed for houses up to €220,000. For any amount exceeding €220,000, the excess amount over €220,000 faces a 80% LTV limit. The measures impose a stricter threshold of 70% for buy-to-let (BTL) properties.[12]

2.3 Data

The core of our final data set is the result of combining loan level information on residential mortgages and credit to firms, bank security level holdings, and county level house prices. The loan level data and security register are proprietary data sets obtained from the Central Bank of Ireland.

First, we observe loan level data on the issuance of residential mortgages at a daily frequency from January 2013 to June 2016. We observe all outstanding residential mortgages by the most significant institutions that have to submit loan level data to the Central Bank of Ireland.[13] This sample covers more than 90% of the domestic market and consists of the five largest banks. The data set also contains information on borrower income and demographics (e.g., age, marital status) and mortgage type (e.g., first-time buyer, buy-to-let).

[11] Given that banks have to use an independent valuation, house prices are unlikely to be manipulated. Incomes are more prone to manipulation by loan officers and borrowers but this manipulation would work against us, making it more difficult to find a reallocation across counties and across the income distribution.

[12] First-time buyers are four percentage points or 30% less likely to default than subsequent-time buyers in Ireland (Kelly et al., 2014). In addition to loans that are exempted from the rule, banks can issue loans exceeding the limits to a small share of borrowers (see last column of the table). In November 2016, the rules were relaxed, extending the LTV limit for FTBs to 90%. The analysis of this subsequent period goes beyond the scope of this paper.

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

Second, we observe loan level data on bank credit to firms at a semi-annual frequency from June 2013 to June 2016. At the bank-firm-period level, we observe credit granted and drawn and the rate charged by banks. We match this information with firm characteristics such as the county of incorporation, industry, and size (very small/SME/large). We observe the borrower rating assigned to each loan from internal rating models of each lender. The Central Bank of Ireland internal mapping scales are used to classify each internal rating into a consistent categorization between 1 and 6. It ranges from 1 (highest-quality borrower) to 5 (very risky borrower) for non-defaulted loans and equals 6 for defaulted loans. The data have one main limitation. In contrast to most credit registries, our borrower identifier is consistent within a bank over time but not across banks.

Third, we observe bank security level holdings at a quarterly frequency from January 2011 to June 2016. At the security-bank-quarter level, we observe each security s identified by an International Securities Identification Number (ISIN) held by bank b at time t. We match this information with security characteristics (e.g., 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 from the Irish property website Daft.ie. This data set is publicly available and regularly updated with quarterly reports published on the website. The statistics are based on properties advertised on the website for a given period. The average monthly sample size for sale properties is 5,000. Indices are quality adjusted, holding the mix of characteristics constant.

3 Mortgage Credit Reallocation

In this section, we document four facts. In Section 3.1, we show that the lending limits affect more than one third of the market but the originations of residential mortgages seem almost unaffected by these limits. In Section 3.2, we show that borrowers are differentially exposed to the limits, with low-income borrowers and borrowers located in "hot" (mostly urban) housing markets being more affected than high-income borrowers and borrowers located in "cool" (mostly rural) housing markets. In Section 3.3, we show that after the policy mortgage credit is reallocated from low- to high-income borrowers and from hot to cool housing markets. In Section 3.4, we show that the policy was effective in weakening the feedback loop between mortgage credit and house prices.

3.1 Evolution of Residential Mortgage Issuance

The lending limits affected a large fraction of the mortgage market as 43% of the volume of residential mortgage issuance (35% of mortgages issued) from October 2013 to September 2014 would have been affected if the policy had been in place during that period. Out of the total €1.6 billion in 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.[14]

Whereas the lending limits affected more than one third of residential mortgage issuance, mortgage originations seem almost unaffected by the policy. In the left panel of Figure 2, we show the evolution of aggregate mortgage issuance from January 2013 to June 2016. We find that mortgage credit growth—high since the beginning of 2014—did not collapse after the implementation of the lending limits. This aggregate evidence suggests an increase in

[14] 2,797 LTV non-conforming mortgages and 1,467 LTI non-conforming mortgages were issued from October 2013 and September 2014. Only 665 mortgages worth €134 million were LTI non-conforming and LTV conforming during the same period. The limits are more binding for second and subsequent time buyers and buy-to-let buyers compared with first-time buyers.

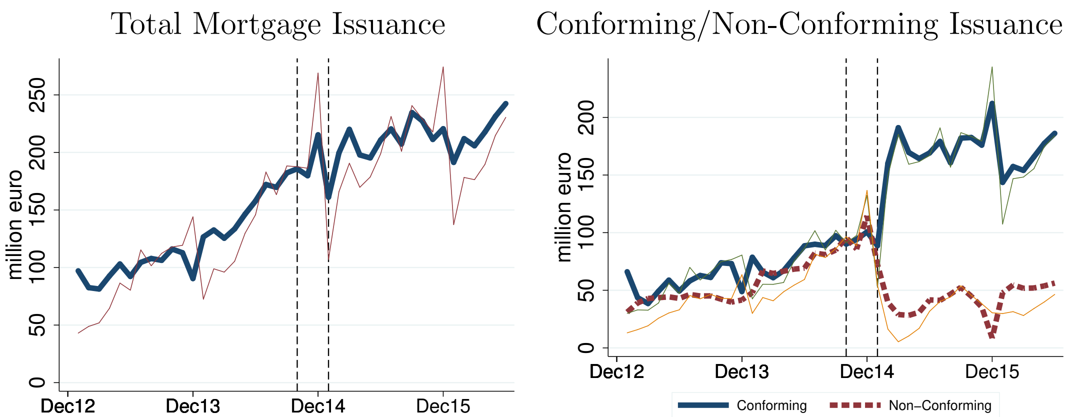

Figure 2: Aggregate Residential Mortgage Issuance. This figure shows the aggregate residential mortgage issuance of our sample banks from January 2013 to June 2016. The left panel shows total issuance. The right panel shows issuance of conforming (solid line) and non-conforming (dashed line) mortgages. Thick lines are seasonally adjusted and thin lines are not seasonally adjusted. The vertical dashed lines indicate the first rumors and the implementation of the lending limits. Source: Central Bank of Ireland.

the issuance of *conforming* mortgages might have compensated the mechanical reduction of the issuance of *non-conforming* mortgages, as banks followed the new rules.[15] In the right panel, we show the evolution of originations of conforming (solid line) and non-conforming (dashed line) mortgages and confirm the two time-series diverge starting in February 2015.

3.2 Exposure to the Lending Limits

We now show that borrowers are differentially exposed to the lending limits: (i) low-income borrowers are more exposed than high-income borrowers and (ii) borrowers located in hot housing markets, mostly urban counties, are more exposed than borrowers located in cool housing markets, mostly rural counties.

In Table 2, we show how borrowers across counties and across the income distribution

[15]The non-conforming issuance is strictly positive after the policy implementation because the new rules allow banks to exceed the limits for a limited fraction of their issuance. In the online appendix, we show mortgage originations keep increasing even when weighted by LTV and LTI.

Hot Housing Markets (Urban Counties)

	Unit	*Income Quintiles* Bottom	Q2	Q3	Q4	Top
Borrower Characteristics						
Income	€	33,353	47,715	64,875	92,168	172,009
Married	%	16.6	34.3	44.7	64.2	68.4
Age	Years	34.2	35.6	35.7	37.4	40.0
First-Time Buyer	%	83.3	75.9	68.6	44.7	24.7
Buy-to-Let	%	1.1	2.6	2.3	3.8	7.3
Loan Characteristics						
Size	€	108,821	141,815	191,243	237,807	280,653
LTV	%	77.2	76.7	79.0	76.9	72.1
LTI	Units	3.5	3.3	3.2	2.9	2.4
House Value	€	154,230	202,438	260,519	331,049	453,416
Term	Months	336.0	331.0	336.4	322.1	292.2
Fixed Rate	%	44.2	43.1	43.2	35.9	26.6
Rate	%	4.1	4.2	4.2	4.2	4.2
Distance from LTI Limit	Units	3.5	3.3	3.2	2.9	2.4
Distance from LTV Limit	Units	77.2	76.7	79.0	76.9	72.1

Cool Housing Markets (Rural Counties)

	Unit	*Income Quintiles* Bottom	Q2	Q3	Q4	Top
Borrower Characteristics						
Income	€	32,021	47,599	64,931	90,994	156,749
Married	%	16.5	38.2	54.9	71.5	58.3
Age	Years	34.2	34.9	37.0	38.4	40.1
First-Time Buyer	%	82.2	80.4	60.3	36.0	31.7
Buy-to-Let	%	2.3	2.0	4.5	5.2	10.6
Loan Characteristics						
Size	€	83,256	111,588	138,590	173,037	145,027
LTV	%	77.3	77.8	76.9	75.9	70.6
LTI	Units	2.9	2.7	2.5	2.3	1.8
House Value	€	115,835	150,799	189,671	238,668	249,379
Term	Months	317.1	324.4	312.5	297.9	274.5
Fixed Rate	%	45.6	40.5	36.6	33.1	20.4
Rate	%	4.2	4.3	4.3	4.3	4.3
Distance from LTI Limit	Units	2.9	2.7	2.5	2.3	1.8
Distance from LTV Limit	Units	77.3	77.8	76.9	75.9	70.6

Table 2: Summary Statistics. This table shows household and loan characteristics by household income quintile during the 12-month period before the first rumors about the policy (October 2013 to September 2014). Income quintiles are adjusted monthly for wage inflation. The top (bottom) panel shows the summary statistics for the subsample of counties with high (low) house price appreciation in the pre-policy period. Source: Central Bank of Ireland.

differ along observable characteristics. We divide households who obtain a mortgage in the year prior to the policy in five quintiles based on their income (Q1 is the bottom quintile, Q5 is the top quintile) and in borrowers located in hot housing markets (counties that experienced a rapid house price appreciation before the policy, top panel) and cool housing markets (counties that experienced a more moderate house price appreciation before the policy, bottom panel). Across the income distribution, high-income borrowers tend to (i) have lower LTV and LTI, (ii) be older and more married, and (iii) be less first-time buyers than lower-income borrowers. The table also shows that the income distribution is positively skewed as the average income of the top quintile is almost double the average income of the fourth income quintile. Somewhat mechanically, the distance from the LTI limit increases monotonically with income. This monotonicity does not apply to the distance from the LTV limit as high-income borrowers tend to face stricter limits because they are often buy-to-let or second- or subsequent-time buyers. Across the distribution of counties, borrowers located in hot housing markets borrow more, have higher LTI and LTV, and purchase more expensive properties compared with borrowers located in cool housing markets.

To measure the distance of borrowers from the lending limits, we calculate what would have been the distance from the limits for each borrower in the year before the policy, assuming that the limits were in place during that period.[16] We calculate the mean of this borrower level distance at the income bucket-county level, where we group borrowers in 20 buckets (ventiles) based on the national income distribution. The thresholds of the income buckets are adjusted monthly for wage inflation using OECD data. In sum, we obtain a *Distance* variable that captures the exposure to the lending limits across the 26 counties

[16]We proceed in three steps. First, we calculate the distance of each mortgage from its LTV and LTI limit during the 12 months before the first rumors about the limits. If the mortgage exceeds one limit, we set its distance equal to zero. Second, given the difference scale of LTI and LTV, we rescale these two distances to have a mean of zero and a standard deviation of one. Third, we calculate the minimum of these two limits.

and across the income distribution.

In Figure 3, we show that the borrowers that are more exposed to the lending limits tend to have a low income and tend to be located in hot housing markets, namely counties, predominantly urban, that experienced a rapid house price appreciation before the policy. On the x-axis, counties are size weighted (larger counties take up a larger interval on the axis) and ordered based on their house price appreciation before the policy: cool housing markets on the left and hot housing markets on the right. On the y-axis, borrowers are grouped and ordered in 20 buckets based on their position in the income distribution: low-income borrowers on the bottom and high-income borrowers on the top. A point in this heatmap is an income bucket-county pair and darker colors indicate a lower distance from the limits. Perhaps not surprisingly, we observe darker colors toward the bottom and the right of the graph, suggesting that low-income borrowers and borrowers located in hot housing markets are closer (more exposed) to the lending limits. This heterogeneity across counties is intuitive. Borrowers located in counties that experienced a rapid house price appreciation before the policy are more likely to borrow close to the to-be-imposed limits.[17]

3.3 Reallocation of Residential Mortgage Credit

We now document a mortgage credit reallocation from hot to cool housing markets and from low-income to high-income borrowers around the policy implementation.

Figure 4 is another heatmap where, for each income bucket-county pair, we show the change in mortgage origination from the pre-policy period (February 2013 to January 2014)

[17]In the online appendix, we show, in two additional versions of Figure 3, the distance from the LTI and LTV limits, separately. In Figure A.1 in the appendix, we show that the most exposed counties are located around the Dublin area. In the online appendix, we show that more exposed counties are more densely populated and have more residents compared with less exposed counties.

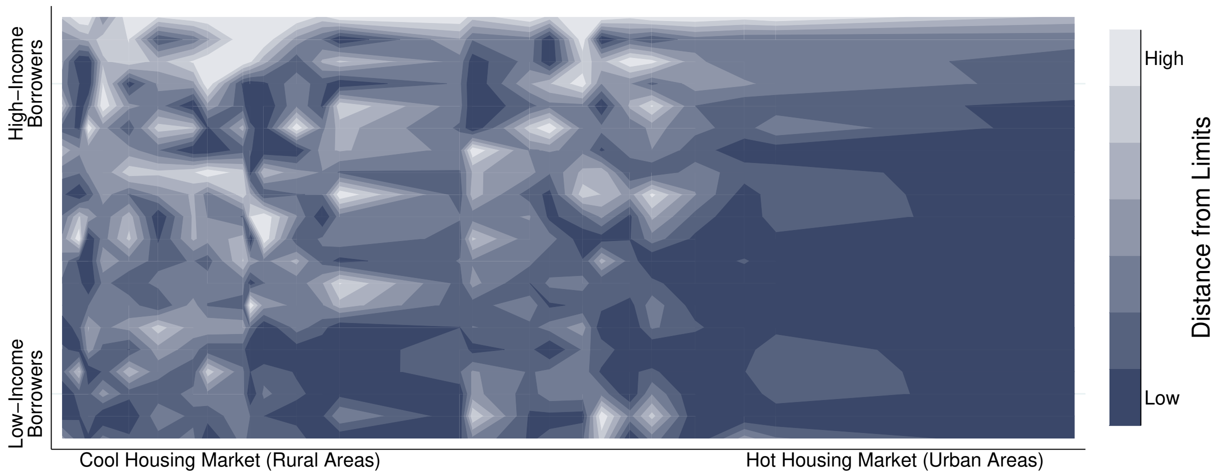

Figure 3: Distance from the Lending Limits Across Counties and Incomes. This figure shows the exposure to the lending limits across counties and across the income distribution of borrowers. The x-axis shows counties ranked according to the house price appreciation pre-policy (from 2012Q4 to 2014Q3). The space taken by each county on the x-axis is proportional to its size (population). The y-axis shows borrowers ranked according to their position in the income distribution (20 ventiles). Each point in the map indicates the distance from the lending limits. Darker colors indicate a higher distance.

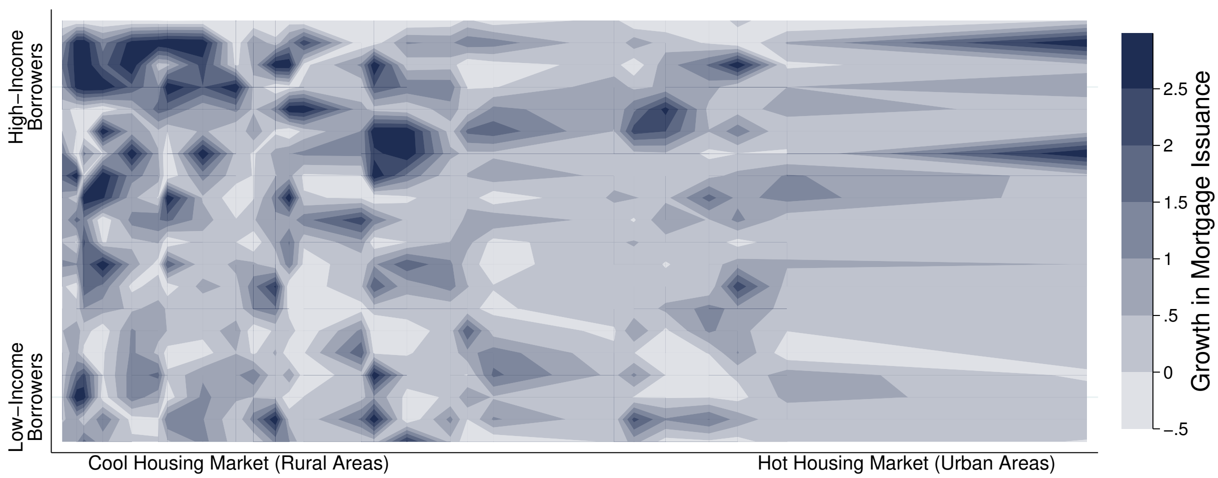

Figure 4: Reallocation of Mortgage Credit. This figure shows the reallocation of mortgage credit across counties and across the income distribution of borrowers. The x-axis shows counties ranked according to the house price appreciation pre-policy (from 2012Q4 to 2014Q3). The space taken by each county on the x-axis is proportional to its size (population). The y-axis shows borrowers ranked according to their position in the income distribution (20 ventiles). Each point in the map indicates the change of mortgage issuance in the post-period (February 2015 to January 2016) compared with the pre-period (February 2014 to January 2015). Darker colors indicate higher growth of issuance.

to the post-policy period (February 2014 to January 2015). Darker colors indicate high credit growth. We observe darker colors on the left, toward the top, and especially in the top-left corner. In sum, this figure documents that the growth in issuance after the policy implementation has been driven by cool housing markets and high-income borrowers.[18]

In Figure 5, we confirm that this reallocation takes place around the implementation of the lending limits. The solid line corresponds to those borrowers that are closer to the lending limits (lowest tercile of the distance distribution). The dashed red line indicates borrowers that are more distant from the lending limits (highest tercile of the distance distribution). As suggested by Table 2, low-distance borrowers tend to be low-income borrowers and located in urban counties while high-distance borrowers tend to have a higher income and are predominantly located in rural counties. In the top panel, we observe that originations and loan size are very similar for the two groups of borrowers before the policy introduction. After the policy implementation, the evolution of originations and loan size flattens for low-distance borrowers while keeps increasing for high-distance borrowers. In the bottom panel, we show that LTI and LTV, both higher for low-distance borrowers in the pre-policy period, tend to converge after the policy implementation.

We confirm this reallocation estimating the following specification:

$$Y_{cht} = \alpha + \beta Post_t \times Distance_{ch} + X_{cht} + \gamma_{ct} + \eta_{ch} + \mu_{ht} + \epsilon_{cht} \tag{1}$$

where c is a county, t is a month, and h is a borrower income bucket, where we divide borrowers into 20 income buckets. The sample includes 24 months and runs from February 2014 to January 2016. The key independent variable is the interaction term between a

[18]While there is anecdotal evidence of borrowers moving from Dublin to its commuting towns, the counties with the largest change in mortgage credit are too far from large cities for its residents to commute.

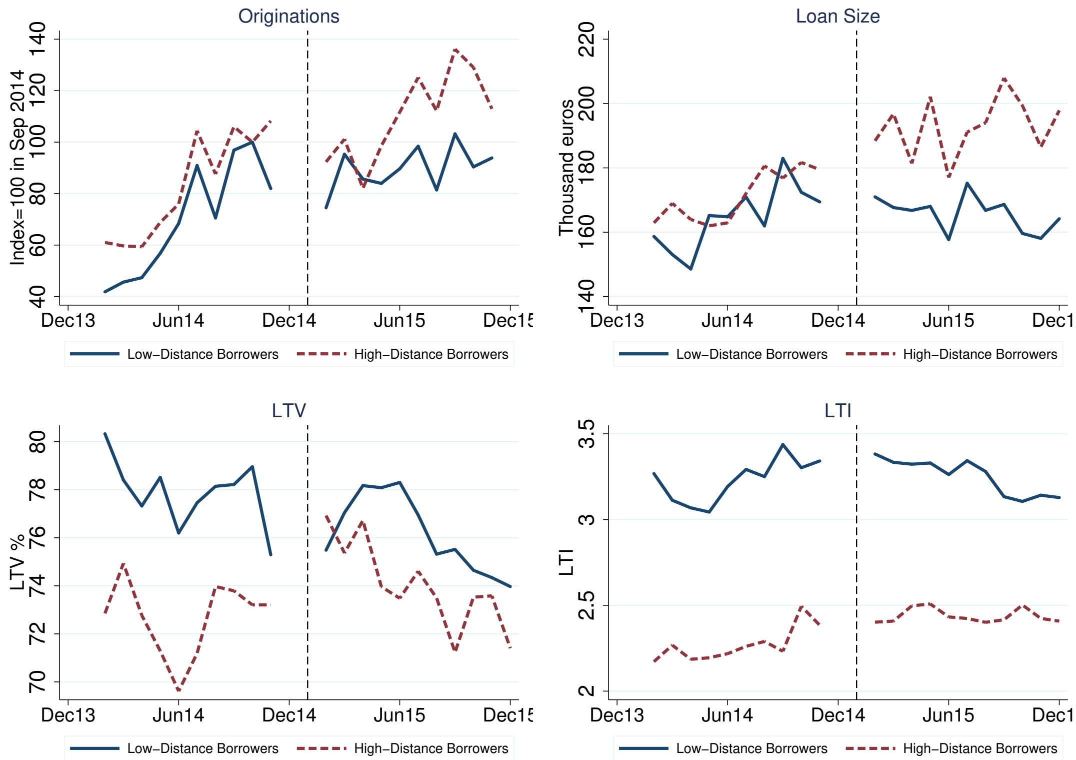

Figure 5: Mortgage Credit Reallocation, Non-Parametric Evidence. These figures show mortgage originations, loan size, loan to value, and loan to income from February 2014 to January 2016. The dashed (solid) lines indicate high-distance (low-distance) borrowers, namely the highest (lowest) tercile of the distance variable. Source: Central Bank of Ireland.

Post dummy equal to 1 from February 2015 to January 2016 (12-month period after the policy implementation) and the (pre-policy) distance from the lending limits for each income bucket-county pair, as defined in the previous subsection. We include as controls, in the vector X, the share of originations to first-time buyers and to buy-to-let investors. Finally, we saturate the specification with stringent fixed effects: county-time fixed effects capture county time-varying heterogeneity (e.g., county-specific demand for credit), income bucket-time fixed effects capture income bucket time-varying heterogeneity (e.g., income bucket-specific demand for credit), and county-income bucket fixed effects to capture time-invariant borrower and geographic characteristics.

We show the estimation results in Table 3. In the first three columns, the dependent

	Volume	Loan Size	No. Loans	LTV	LTI
Distance × Post	0.233***	0.241***	0.038	9.118***	0.320***
	(0.054)	(0.036)	(0.177)	(1.452)	(0.050)
County-Time FE	✓	✓	✓	✓	✓
Bucket-Time FE	✓	✓	✓	✓	✓
County-Bucket FE	✓	✓	✓	✓	✓
Observations	7,203	7,203	7,206	7,112	7,051
R-squared	0.754	0.603	0.892	0.366	0.590

Table 3: Reallocation of Mortgage Credit, Parametric Evidence. This table shows estimation results from specification (1). The dependent variable is the logarithm of total mortgage volume, the logarithm of the average loan size, the number of loans issued, the value-weighted LTV, and the value-weighted LTI. *Distance* is the distance from the lending limits at the county-income bucket level described in Section 3.2. All regressions include the share of originations to first-time buyers and to buy-to-let investors at the county-time-income bucket level, county-time fixed effects, income bucket-time fixed effects, and income bucket-county fixed effects. Standard errors clustered at the county-income bucket level in parentheses. Source: Central Bank of Ireland.

variables are the logarithm of mortgage issuance, the average loan size, and the number of mortgages issued. We find that a one standard deviation increase in the distance from the limits is associated with a 6.2% higher issuance and a 13.6% higher loan relative to the pre-period. We do not find a statistical significant effect on the number of mortgages. We also find, in columns (4) and (5), that a one standard deviation increase in the distance from the limits is associated with a 4.13 percentage points higher LTV and a 0.14 percentage points higher LTI relative to the pre-period. In sum, these estimation results confirm the reallocation of mortgage credit from low- to high-income borrowers and from low- to high-distance counties documented in the heatmap.[19]

[19] In Table A.1 and Table A.2, we show two alternative estimations of specification (1) where the distance variable is at the income bucket and county level, respectively. In unreported tests, we confirm (i) that the origination volume of conforming credit is positively correlated with the distance variable and (ii) that the documented reallocation is at work for both first-time buyers and subsequent time buyers.

3.4 General Equilibrium Multipliers

In Table 3, we show that a higher distance from the limits is associated with an increase in mortgage issuance after the policy introduction, capturing the partial equilibrium effect of the policy on mortgage issuance. We now estimate the general equilibrium effect and relate it to our partial equilibrium estimates.

We employ the methodology of Sarto (2018) and Mian et al. (2019). The intuition behind this approach is as follows. The estimated coefficient in (1) captures the partial equilibrium effect of the policy. The county-time fixed effects absorb the general equilibrium effect at the county level. For example, lower mortgage credit to hot housing markets might reduce house prices, reducing the households' borrowing capacity. The resulting lower local demand for mortgage credit might further reduce local house prices. The partial equilibrium effect of the policy might be amplified by this feedback loop. By collapsing our specification at the county-month level, the coefficients capture the general equilibrium effect of the policy. By comparing these estimates with the estimates in (1), we decompose the general equilibrium effect in its partial equilibrium component and a "general equilibrium multiplier."

More specifically, we estimate the following specifications:

$$Volume_{cht} = \alpha + \beta_1^{PE} Distance_{ch} + \beta_2^{PE} Post_t \times Distance_{ch} + X_{cht} + \gamma_{ct} + \eta_{ht} + \epsilon_{cht} \quad (2)$$

$$Volume_{ct} = \alpha + \beta_1^{GE} Distance_{c} + \beta_2^{GE} Post_t \times Distance_{c} + X_{ct} + \gamma_{t} + \epsilon_{ct} \quad (3)$$

The unit of observation in the familiar first specification is county-month-income bucket. The unit of observation in the second specification is county-month. The superscripts PE and GE refer to partial and general equilibrium, respectively. The county-time fixed effects in the first specification capture the general equilibrium forces at work at the county level. Hence, by comparing the estimated coefficients in the two specifications, we can decompose the general equilibrium effect in (i) its partial equilibrium component and (ii) its general

Panel A

Unit of obs: income bucket-county-time

LHS: Credit	Full Sample	Hot Housing Markets	Cool Housing Markets
Distance × Post	0.247***	0.206	0.301***
	(0.072)	(0.123)	(0.075)
Distance	-0.230***	-0.231**	-0.226***
	(0.064)	(0.110)	(0.055)
County-Time FE	✓	✓	✓
Bucket-Time FE	✓	✓	✓
Observations	7,203	4,237	2,966
R-squared	0.701	0.755	0.433

Panel B

Unit of obs: county-time

LHS: Credit	Full Sample	Hot Housing Markets	Cool Housing Markets
Distance × Post	0.323	0.581*	0.581*
	(0.193)	(0.295)	(0.301)
Distance	-4.182***	-4.709***	-1.368
	(1.127)	(1.338)	(1.793)
Time FE	✓	✓	✓
Observations	622	311	311
R-squared	0.392	0.399	0.198

Table 4: Partial and General Equilibrium Effects. This table presents the estimation results from (2) in Panel A and (3) in Panel B. The dependent variable is the logarithm of total mortgage volume. *Distance* is the distance from the limits (mean at the relevant unit of observation). The share of originations to first-time buyers and to buy-to-let investors (mean at the relevant unit of observation) are included as controls. The standard errors are clustered at the county-income bucket and county level, respectively. Source: Central Bank of Ireland.

equilibrium multiplier. More specifically, by comparing $\widehat{\beta_1^{GE}}$ and $\widehat{\beta_1^{PE}}$, we obtain the general equilibrium multiplier before the policy was introduced. Similarly, by comparing $\widehat{\beta_2^{GE}}$ and $\widehat{\beta_2^{PE}}$, we obtain the general equilibrium multiplier after the policy introduction.

Table 4 shows the estimated coefficients. During the pre-policy period, the general equilibrium effect is very large (-4.18), driven by hot housing markets. The general equilibrium effect can be decomposed in its partial equilibrium component of 6% (-0.23/-4.18) and its general equilibrium multiplier of 94%. Mian et al. (2019) find a 80% general equilibrium multiplier during the 2002-05 boom in the US. Our larger multiplier is consistent with the Irish setting, prone to extreme boom-bust episodes like the 2002-10 one. The estimated coefficients in the post-period show a weakened general equilibrium effect (0.32) and identical general equilibrium effects in hot and cool housing markets.

Taken together, these results suggest that the policy was effective in weakening the feedback loop *"between credit and house prices and credit"*, using governor Honahan's own words. This interpretation of the amplification mechanism at work in the pre-policy period is consistent with the theory literature. As in Kiyotaki and Moore (1997), higher mortgage credit leads to higher housing demand and higher house prices. Higher house prices in turn relax the collateral constraint of borrowers, allowing them to obtain a larger mortgage. Consistent with this channel, in the next section we document that house price growth collapsed after the policy introduction, driven by hot housing markets.

4 House Prices

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

First, we show non-parametric evidence. In the left panel of Figure 6, we show yearly growth in house prices from January 2011 to June 2017. House price growth stopped increasing at the time of the first rumors about the policy and then stabilized around 10% after the implementation. In the online appendix, we show that survey data suggests that households anticipated, at the time of the first rumors, a decline in house prices exactly because of the soon-to-be announced limits. In the right panel, we plot house price growth for high-distance or cool counties (solid line) and low-distance or hot (dashed line) counties. Low-distance counties experienced a stark contraction of house price growth after the policy implementation, whereas house price growth remained stable at the pre-policy level in high-

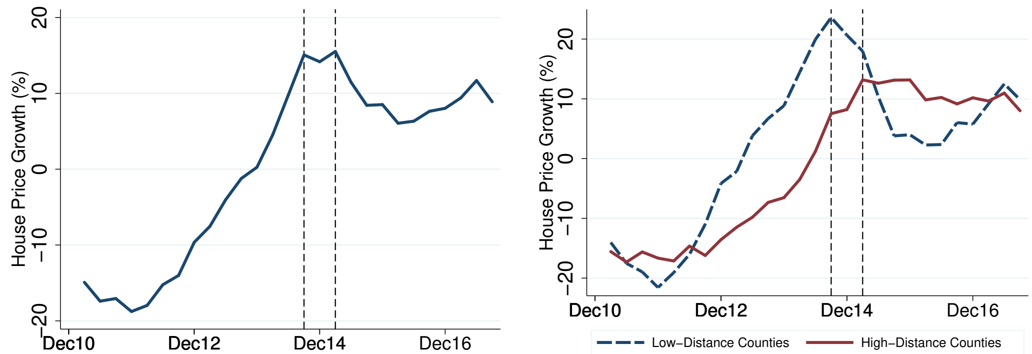

Figure 6: House Price Changes. The top panel of this figure shows the evolution of yearly house price growth. The bottom panel shows the evolution of yearly house price growth for high-distance and low-distance counties separately (groups split by median value). The vertical dashed lines indicate the first rumors about the limits and their implementation date. The sample period runs from January 2011 to June 2017. Source: Central Bank of Ireland, Daft.ie.

distance counties.[20] In the online appendix, we show the slowdown in house price growth in low-distance counties is driven by small properties, and the relative stability of house price growth in high-distance counties is driven by large properties. This evidence is consistent with the documented credit reallocation across counties and, to the extent that property size is correlated with the income of the buyers, with the reallocation across the distribution of borrowers' income.[21]

Second, we show parametric evidence consistent with the mortgage credit reallocation across counties and across the income distribution. In particular, we estimate the following

[20]The housing supply is more elastic in high-distance than low-distance counties, potentially explaining why house price growth did not increase in high-distance counties after the policy. Granted planning permissions did not change in low-distance counties (66% in 2012Q4-2014Q4; 69% in 2014Q4-2016Q4) but substantially increased in high-distance counties (-2% in 2012Q4-2014Q4; 81% in 2014Q4-2016Q4).

[21]See Figure IA.9. Table 2 shows borrower income is strongly correlated with the price of the property purchased. In the online appendix, we attempt to map the number of bedrooms to the income of buyers by regressing the price of the residential property collateralizing the residential mortgage (credit registry data) on property size-county level house price data. We find these loadings are consistent with high-income (low-income) borrowers predominantly buying large (small) properties. Of course, this mapping is not perfect, because, for example, high-income borrowers might buy a one-bedroom property to rent it out.

LHS: ΔHP	(1)	(2)	(3)	(4)	(5)
Distance $\times$ Size		0.006**	0.006**	0.006**	0.006**
		(0.002)	(0.002)	(0.002)	(0.002)
Distance	0.272***	0.255***		0.255**	
	(0.058)	(0.062)		(0.062)	
Size		0.014***	0.014***		
		(0.001)	(0.001)		
Country FE			✓		✓
Size FE				✓	✓
Observations	54	270	270	270	270
R-squared	0.398	0.307	0.736	0.495	0.924

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

specifications at the county (c) level and at the county-property type (c, p) level:

$$\Delta HP_c = \alpha + \beta Distance_c + \epsilon_c \tag{4}$$

$$\Delta HP_{cp} = \alpha + \beta_1 Distance_c \times Size_p + \beta_2 Distance_c + \beta_3 Size_p + \epsilon_{cp} \tag{5}$$

where the dependent variable is the change in house prices from 2014Q3 to 2016Q4, *Distance* is the county level (pre-policy) distance from the lending limits, and *Size* is an integer equal to the number of bedrooms.[22] 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 5. The county level estimation in column (1) confirms

[22]The geographical breakdown of the house price data is more granular than the mortgage level data as we observe house price 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 assume 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.

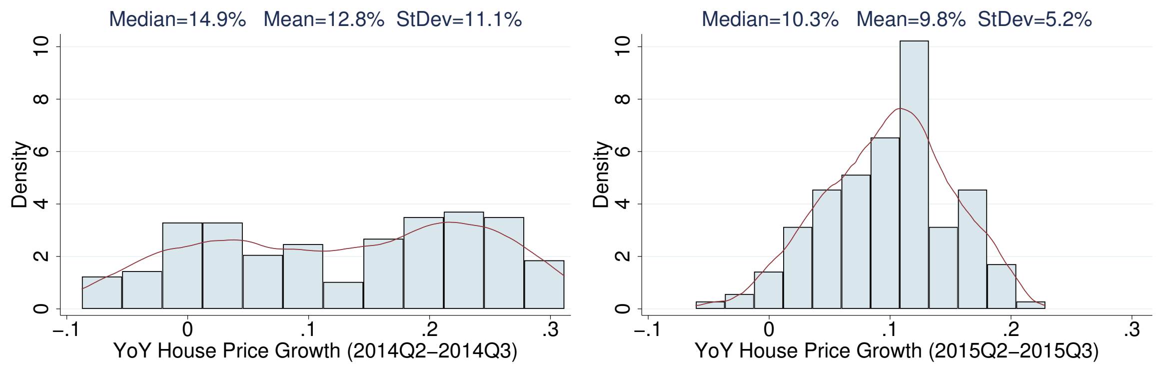

Figure 7: Distribution of House Price Growth. This figure shows the change in the distribution of house price growth. The left and right graphs show the density of YoY house price growth before (2014Q2-2014Q3) and after (2015Q2-2015Q3) the policy, respectively. Source: Daft.ie.

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

Third, we show that, following the introduction of the lending limits, the geographical distribution of house price growth became less fat-tailed. The left and right panels of Figure 7 show the distribution of house price growth across counties before and after the policy, respectively. The distribution in the post-period is substantially less fat-tailed (standard deviation from 0.11 to 0.05), suggesting that the lending limits also reduced the geographical heterogeneity in house price growth. In the online appendix, we show that the tails were not shrinking before the policy. Taken together our general equilibrium estimates in Section 3.4, these results suggest that the policy was effective in cooling down the housing market and in making housing market more homogeneous across counties and less prone to feedback loops.

5 Bank Credit Reallocation

In this section, we show the reallocation of mortgage credit from hot to cool housing markets and from low- to high-income borrowers is consistent with a "bank portfolio choice" channel.

According to this channel, the lending limits cause banks to reallocate their portfolio to fund projects that would have not otherwise been funded.[23] Consider an environment where banks solve their portfolio problem subject to a binding balance sheet constraint (e.g., funding or regulatory capital constraint). Introduce in this setting, where banks cannot fund all positive NPV projects, a new constraint that prevents banks from investing in a specific asset (e.g., high-leverage mortgages). If this new constraint is also binding, banks reallocate their portfolio to fund some positive NPV projects that were not funded before the introduction of the new constraint.[24] The bank portfolio choice channel critically relies on the financial sector being constrained. Note that, in our setting, Irish banks are adjusting to new capital and liquidity regulatory requirements and hold a large stock of non-performing loans. Moreover, mortgages are almost entirely issued by banks that hold them on balance sheet and there is no public support for the residential mortgage market.[25] With the notable exception of the US, many countries around the world only have a small securitization market and do not provide a public support for the mortgage market.

In Section 5.1, we show that the mortgage credit reallocation is driven by banks more exposed to the policy. In Section 5.2, we show that banks, especially those highly exposed

[23]In the online appendix, we provide a formal characterization of banks' portfolio problem.

[24]See Goel et al. (forthcoming) for a model of how banks allocate capital across their business units when facing multiple constraints, including various regulatory ones. More generally, our results are consistent with a model where bank capital is "scarce" and the marginal equity issuance costs are very steep. See Harris et al. (2019) for a theoretical framework.

[25]Non-performing loans are about one-quarter of the value of outstanding bank loans at the time of the policy implementation. Irish banks returned to profitability in 2014 for the first time since 2008. See Central Bank of Ireland (2014) for more details.

to the policy, increase their risk exposure in asset classes not targeted by the limits, namely holdings of securities and credit to firms.

5.1 Mortgage Credit Reallocation

The bank portfolio choice channel has a clear cross-sectional prediction: Banks with a larger fraction of non-conforming issuance in the pre-policy period drive the mortgage credit reallocation compared with banks with less non-conforming issuance. Following this intuition, we measure banks' differential exposure to the policy based on the importance of non-conforming issuance relative to a bank's total mortgage issuance during the year before the first rumors about the policy. In particular, for each bank b, we define

$$Exposure_b = \frac{\sum_{t=Oct13}^{Sep14} \text{Non-Conforming Mortgage Issuance}_{bt}}{\sum_{t=Oct13}^{Sep14} \text{Total Mortgage Issuance}_{bt}} \tag{6}$$

where the numerator is the sum of total non-conforming mortgage issuance between October 2013 and September 2014 and the denominator is the sum, over the same period, of total mortgage issuance. Of course, banks' exposure is not randomly assigned. In Table 6, we show banks' summary statistics for high-exposoure and low-exposure banks.

We validate our measure in Figure 8, where we show the evolution of conforming mortgages issued by high-exposure banks (exposure above median, blue line) and low-exposure banks (exposure below median, red line). The thin dashed lines show non-conforming mortgage issuance, collapsing for both groups of banks after the policy implementation. This figure documents that high-exposure banks experience a greater drop in non-conforming issuance and a greater increase in conforming issuance than low-exposure banks.

Having shown non-parametric evidence of cross-sectional variation in bank credit reallocation, we estimate a triple difference-in-differences specification, obtained by adding the

	Unit	Dec13	Dec14	Dec15
Exposed Banks				
Total Assets	million euro	126,798	116,752	109,122
Leverage	Units	19.1	19.2	18.1
Domestic Govt Bonds	% Assets	6.3	6.2	6.4
Liquid Assets	% Assets	33.4	32.9	32.5
Loans	% Assets	55.5	58.2	59.5
Non-Exposed Banks				
Total Assets	million euro	40,792	34,644	28,194
Leverage	Units	26.6	29.6	30.0
Domestic Govt Bonds	% Assets	3.2	3.5	4.3
Liquid Assets	% Assets	36.4	44.1	48.0
Loans	% Assets	47.2	46.2	48.5

Table 6: Banks' Summary Statistics. This table shows banks' average balance sheet characteristics at an annual frequency from December 2013 to December 2015 separately for high-exposure and low-exposure banks. Source: Central Bank of Ireland.

bank exposure defined in (6) to specification (1):

$$\begin{aligned} Y_{bcht} = \alpha + \gamma_{ct} + \eta_{ch} + \mu_{bt} + X_{cht} + \beta_1 Post_t \times Distance_{ch} \times Exposure_b \\ + \beta_2 Distance_{ch} \times Exposure_b \\ + \beta_3 Post_t \times Distance_{ch} + \epsilon_{bcht} \end{aligned} \tag{7}$$

where the unit of observation is bank b, county c, household income bucket h, and month t. Again, we divide borrowers into 20 income buckets and our sample period runs from February 2014 to January 2016. In addition to the county-time and county-income bucket fixed effects used in (1), we add bank-time fixed effects to ensure our results are not driven by the non-random nature of bank exposure to the policy (e.g., larger banks being more exposed to the limits and changing their lending decision after the policy).

We present the estimation results in Table 7. The independent variables are issuance volume, loan size, LTV, LTI, and rate, in columns (1) to (5), respectively. The positive coefficient β_1 shows the credit reallocation documented in Section 3 is primarily driven by

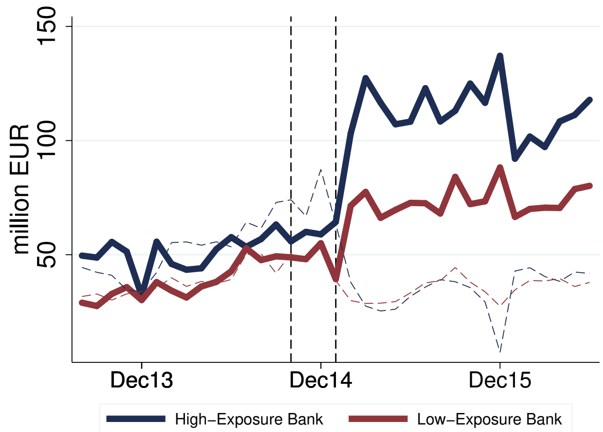

Figure 8: Issuance and Bank Exposure. The figure shows the issuance of conforming (solid thick lines) and non-conforming (dashed thin lines) mortgages for high-exposure (above median exposure) and low-exposure (below median exposure) banks from January 2013 to June 2016. The vertical lines indicate the first rumors and the implementation date of the limits. All time series are seasonally adjusted. Source: Central Bank of Ireland.

banks more exposed to the limits. The sum of the first two coefficients ($\beta_1 + \beta_2$) being very close to zero in columns (2)-(4) shows that banks maintained a similar loan size, LTV, and LTI after the policy compared with the pre-policy period, suggesting that banks, while conforming with the new limits, issued mortgages with similar characteristics to the mortgages they issued before the policy. However, the negative sum of the first two coefficients in column (1) suggests banks were forced to partially reduce their mortgage issuance and were, therefore, unable to completely "undo" the new limits. Finally, although rates are falling for all borrowers during our sample period, the last column shows that more exposed banks reduced mortgage rates more than less-exposed banks.[26]

Table 3 and Table 7 suggest banks, especially those highly exposed to the policy, tried to undo the limits by lending to borrowers more distant from the lending limits, namely, high-

[26]Irish banks do not offer mortgage rates based on the income of borrowers. Banks typically offer an interest rate-LTV schedule, allowing borrowers to self-select into products. Banks have several ways to influence the rates charged to clients, including offering more fixed- or non-fixed-rate mortgages.

		Volume	Size	LTV	LTI	Rate
Distance × Exposure × Post	(β_1)	1.638**	4.633***	108.309***	0.931	-1.203***
		(0.729)	(0.667)	(18.522)	(0.946)	(0.402)
Distance × Exposure	(β_2)	-3.877***	-5.375***	-126.769***	-0.971	1.284***
		(0.912)	(0.509)	(14.369)	(0.845)	(0.305)
Distance × Post	(β_3)	-0.558*	-1.719***	-36.681***	-0.206	0.544***
		(0.304)	(0.271)	(7.818)	(0.386)	(0.174)
County-Time FE		✓	✓	✓	✓	✓
County-Bucket FE		✓	✓	✓	✓	✓
Bank-Time		✓	✓	✓	✓	✓
Observations		12,960	12,960	12,757	12,708	12,577
R-squared		0.605	0.482	0.226	0.451	0.543

Table 7: Bank Mortgage Credit Reallocation. This table presents the results from specification (7). The sample period runs monthly from February 2014 to January 2016. The unit of observation is county-month-bank-income bucket. The dependent variables are the logarithm of mortgage volume, the logarithm of the median loan size, the value-weighted LTV, the value-weighted LTI, and the value-weighted rate. *Exposure* is defined in (6), and *Post* is a dummy equal to 1 from February 2015 to January 2016. All regressions include the share of originations to first-time buyers and to buy-to-let investors at the county-time-income bucket level. Standard errors double clustered at the bank-county level in parentheses. Source: Central Bank of Ireland.

income borrowers and borrowers located in high-distance counties. To further confirm this interpretation, we estimate, in various subsamples of borrowers, the following specification:

$$Y_{bcht} = \alpha + \beta Post_t \times Exposure_b + \gamma X_{b,t-1} + \nu_b + \eta_{ct} + \theta_{ht} + \epsilon_{bcht} \tag{8}$$

where our unit of observation is bank b, county c, household income bucket h, and month t. The partition of borrowers in income buckets, the sample period, the definitions of $Post_t$ and the $Exposure_b$ variables are unchanged. In addition to county-time, bank, and income bucket-time fixed effects, we include lagged bank time-varying controls (logarithm of total assets, equity capital ratio, and loans/total assets).

We run our specification in subsamples based on borrower income quintiles. We show the estimation results in Table 8 where each column corresponds to an income quintile. In Panel A and Panel B, the dependent variables are total loan volume and mortgage size, respectively. We find that more-exposed banks increase their loan issuance to high-income (Q5) borrowers

	Income Quintiles				
	Bottom	Q2	Q3	Q4	Top
Panel A: 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
Bank Controls	✓	✓	✓	✓	✓
Bucket-Time FE	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓
County-Time FE	✓	✓	✓	✓	✓

Table 8: Bank Mortgage Credit Reallocation, Heterogeneity across Households. This table shows regressions at the bank-county-income bucket level separately for each income quintile. Income quintiles are adjusted monthly for wage inflation. The dependent variables are the logarithm of volume of mortgage issuance (Panel A), the logarithm of the average loan size (Panel B), the value-weighted LTV (Panel C), and the value-weighted LTI (Panel D). *Exposure* is defined in (6), and *Post* is a dummy equal to 1 from February 2015 to January 2016. Time-varying bank level controls include the logarithm of total assets, equity-capital ratio, and the loans/assets ratio. Control variables are lagged by one period. Standard errors double clustered at the bank-county and month level in parentheses. Source: Central Bank of Ireland.

and reduce it to low-income (Q1) borrowers compared with less-exposed banks. The top-income quintile borrowers also obtain larger loans than other quintiles after the policy. More precisely, a one standard deviation higher $Exposure_b$ leads to a 10% decrease in issuance to low-income (Q1) borrowers and to a 15% increase in issuance to high-income (Q5) borrowers. These results are consistent with more-affected banks reallocating credit to richer households that are further away from the limits and thus likely have more room to increase their LTV and LTI, while still conforming with the limits.

In Panel C, we consider the (volume-weighted) LTV as a dependent variable. We find that more-exposed banks reduced their LTV compared with less-exposed banks in income quintiles Q1 and Q2, consistent with the limits affecting these banks more and with low-income households being more constrained. For households in the bottom income quintile, a one standard deviation higher $Exposure_b$ implies a 6.6 percentage points lower LTV. However, in the top-income quintile, more-affected banks *increased* their LTV compared with less-exposed banks. Borrowing from banks with a one standard deviation higher $Exposure_b$ leads to a 4.9 percentage points higher LTV in the top-income quintile. Hence, by issuing larger loans to high-income households, banks can partially make up for the lost business caused by the policy introduction. In Panel D, the independent variable is the (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 a 0.3 percentage points increase in the loan-to-income ratio of high-income borrowers.[27]

[27]In the online appendix, we show non-parametric evidence consistent with exposed banks driving high-income borrowers' LTV and LTI increase in the post-regulation period.

5.2 Other Asset Classes

In the previous sections, we have shown that, after the policy introduction, banks issued mortgages with similar characteristics to the mortgages they previously issued, but partially reduced their total mortgage issuance. In this section, we show that banks, consistent with the bank portfolio choice channel, increased their risk-taking in their holdings of securities and credit to firms, two types of assets not targeted by the policy. These results are also consistent with the observation that banks were seeking hot housing markets in their pre-policy mortgage lending.

5.2.1 Security Holdings

We use security level holdings data and examine whether banks changed their risk exposure in this asset class. Following Davis and Haltiwanger (1992), we define the "net buys" of security s by bank b from $t-1$ to t as follows:

$$NetBuys_{s,b,t} = \frac{Holdings_{s,b,t} - Holdings_{s,b,t-1}}{0.5(Holdings_{s,b,t} + Holdings_{s,b,t-1})} \in [-2, 2] \tag{9}$$

where *Holdings* is the euro value of holdings. Compared with percentage changes, this measure also captures final sales, corresponding to a value of -2, and initial purchases, corresponding to a value of 2.

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

$$NetBuys_{sbt} = \alpha + \beta Exposure_b \times Post_t \times Yield_{st} + \gamma_{bt} + \eta_{st} + \epsilon_{sbt} \tag{10}$$

where the unit of observation is security s, bank b, and quarter t (we observe security level holdings at a quarterly frequency). The independent variable of interest is the triple interaction term between bank exposure defined in (6), a *Post* dummy equal to 1 in the

	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)
Time FE	✓					
Security FE	✓	✓				
Bank-Time FE		✓		✓	✓	✓
Security-Time FE			✓	✓	✓	✓
Observations	7,707	7,707	7,707	7,707	7,707	7,707
R-squared	0.247	0.281	0.943	0.949	0.919	0.915

Table 9: Bank Portfolio Reallocation, Holdings of Securities. This table shows the estimation results from specification (10). 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 (9). *Exposure* is defined in (6), *Post* is a dummy equal to 1 from 2015Q2 onwards, and *Yield* is the yield of the security. Double-interaction terms and uninteracted terms (when not absorbed by fixed effects) are not shown for brevity. Standard errors clustered at the security level in parentheses. Source: Central Bank of Ireland.

post period, and the yield of the security. In our most conservative estimation, we include bank-time and security-time fixed effects to capture time-varying bank heterogeneity and time-varying security heterogeneity, respectively.

We show estimation results in Table 9, where 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 with less-exposed banks after the policy implementation. In columns (5) and (6), we 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 securities sold. We find that more-exposed banks buy more and sell less high-yield securities than less-exposed banks.

5.2.2 Credit to Firms

We now use the corporate loan level data and ask whether banks changed their credit supply to firms. To this end, we adapt specification (8) and estimate the following specification:

$$Y_{bclqt} = \alpha + \beta Post_t \times Exposure_b + \gamma X_{bt-1} + \delta_{bc} + \eta_{clqt} + \epsilon_{bclqt} \quad (11)$$

We measure the credit provided by bank b to firms in county c, industry l, of quality q in semester t (we observe credit to firms at a biannual frequency). We group firms into clusters based on their county, industry, and quality at time t and investigate the lending behavior of banks to a cluster of firms (Acharya et al., 2018). We form clusters based on county and industry because firms in a particular industry in a particular county share many characteristics and are thus likely affected in a similar way by macroeconomic developments that might influence credit demand. Note that because we do not have a unique firm identifier across loans, we are unable to analyze credit extended to the *same* firm by different banks (Khwaja and Mian, 2008). To determine the quality of a firm that receives a loan, we use the ratings obtained by the Central Bank of Ireland that employs a rating scale from 1 (best) to 5 (worst). These ratings come from the banks' internal models but are homogenized by the Central Bank of Ireland to ensure the rating classes correspond to similar probabilities of default. We divide firms into three quality buckets: high quality (rating 1-2), medium quality (rating 3-4), and low quality/high risk (rating 5).

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

Panel A

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

Panel B

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

Table 10: Bank Portfolio Reallocation, Credit to Firms. This table shows the estimation results of specification (11). The unit of observation is bank-industry-county-quality-time. The sample runs at a bi-annual frequency from 2013H1 to 2016H1. *Exposure* is defined in (6) and *Post* is a dummy equal to 1 from 2015H1 to 2016H1. A risky loan has a rating equal to 5. The dependent variables are the change in log (stock of) credit granted in Panel A and the (value weighted) change in the interest rate charged in Panel B. Standard errors clustered at the bank-county level in parentheses. Source: Central Bank of Ireland.

geographical preference of banks).

We show estimation results in Table 10. In Panels A and B, the dependent variable is the change in volume of credit and change in interest rate charged, respectively. Column (1) considers the full sample. The estimates document that more-exposed banks increase their lending volume to firms and decrease the price of corporate loans more than less-exposed banks. In a next step, we split our sample firms into risky (rating 5) and non-risky (rating 1-4) firms and re-run our specification (11) separately for these two groups of borrowers. The estimation results in columns (2) and (3) show that although a credit expansion in the corporate sector occurs for both risky and non-risky firms, the effect is economically and statistically more pronounced for risky firms relative to the pre-period. A one standard deviation higher *Exposure* leads to a 10 percentage points higher credit supply to firms and a 20 percentage points higher credit supply to risky firms. These results are confirmed in the last column of Panel A, where we employ a triple interaction of our bank exposure variable with a *Post* dummy and a dummy for whether the borrowing firms are risky. The coefficient shows the increase in loan volume is mostly driven by an increase toward risky firms. Similarly, in Panel B, we find the decrease in the cost of bank loans is mostly benefiting risky firms.

6 Financial Stability

In the previous section, we have shown that the credit reallocation caused by the lending limits is consistent with a bank portfolio choice channel. In this section, we analyze the effect of the limits on banks' overall risk exposure to real estate, non-financial firms, and government bonds.

To this end, we analyze the correlation of bank equity returns with the equity returns of portfolios that capture the performance of real estate firms, non-financial non-real estate firms, and government bonds around the implementation of the lending limits. We obtain

	R^{Banks}	R^{Banks}	R^{Banks}	*Placebo* R^{Banks}	*Placebo* R^{Banks}
Real Estate × Post	-1.125***	-1.092**	-1.039***	0.233	-0.480
	(0.403)	(0.416)	(0.352)	(0.421)	(0.624)
Real Estate	1.298***	1.401***	1.265***	0.301	1.168**
	(0.266)	(0.264)	(0.236)	(0.391)	(0.567)
Firms × Post	1.343***	1.400**	0.852*	-0.049	-0.525
	(0.499)	(0.543)	(0.433)	(0.547)	(0.722)
Firms	-0.679**	-0.630*	-0.244	0.374	0.624
	(0.317)	(0.339)	(0.270)	(0.521)	(0.651)
Govt × Post	-0.056	0.003	-0.074	-0.033	0.132
	(0.117)	(0.159)	(0.077)	(0.053)	(0.123)
Govt	-0.013	-0.055	0.027	-0.008	0.047
	(0.100)	(0.110)	(0.064)	(0.046)	(0.111)
Post	0.005	0.006	0.003	0.033	-0.000
	(0.005)	(0.003)	(0.003)	(0.004)	(0.006)
Sample Period	±3mo	±2mo	±4mo	±3mo	±3mo
Treatment Date	9Feb15	9Feb15	9Feb15	9Jun15	9Jun14
Observations	130	87	173	131	131
R-squared	0.214	0.319	0.199	0.256	0.151

Table 11: Financial Stability. This table presents the results from specification (12). In column (1), the sample period runs daily from November 9, 2014 to May 9, 2015 and the *Post* dummy is equal to 1 from February 9, 2015 onward. In columns (2) and (3), the sample period runs for 2 and 4 months around February 9, 2015, respectively. In column (4) and (5), the sample period runs from 3 months around June 9, 2015 and June 9, 2014, respectively. Source: Reuters Datastream.

equity returns of all stocks currently listed on Euronext Dublin from Reuters Datastream and manually classify stocks in three groups: bank stocks, real estate stocks, and non-financial non-real estate stocks. We also obtain 10-year Irish government bond yields from Reuters Datastream. We estimate the following specification:

$$R_t^{banks} = \alpha + Post_t + \sum_{i \in \mathcal{I}} \left(\beta^i R_t^i \times Post_t + R_t^i\right) + \epsilon_t \tag{12}$$

$$\text{where} \quad \mathcal{I} = \{\text{Real Estate, Firms, Govt}\}$$

where the dependent variable is the mean return of bank stocks and the independent variables are (i) the mean return of real estate stocks (to capture mortgage credit), (ii) the mean return of non-financial non-real estate stocks (to capture the non-financial private sector), and (iii) the change in the 10-year Irish government bond yields (to capture holdings of securities). In our baseline estimation, the sample period runs daily from November 9, 2014 to May 9, 2015 (three months around the implementation date) and the *Post* variable is equal to one starting from February 9, 2015.

We show the estimation results in Table 11. The interaction coefficients suggest that banks become less exposed to real estate and more exposed to the non-financial non-real estate private sector following the introduction of the limits—consistent with the reallocation documented in the previous section. In columns (2) and (3), we change the estimation period to two months and four months around the implementation date, respectively. Our results are robust. To further confirm our findings, we run a placebo test in the last two columns, where the *Post* dummy is equal to one in the three months after June 9, 2015 and June 9, 2014, respectively. The coefficients of interest are not significant, suggesting that our effects are not present in times other than the treatment period.[28]

7 Conclusion

We provide a comprehensive micro-level analysis of the transmission of macroprudential policies aimed at limiting household leverage in the residential mortgage market and, in turn, reducing the feedback loop between credit and house prices. Combining loan level data on residential mortgages, county level house prices, and detailed data on banks' other

[28] In an unreported test, we run another placebo regression with the equity return of financial institutions not subject to the limits (e.g., insurance companies and asset management firms) as a dependent variable. The coefficients of interest are not significant, confirming that our effects are limited to those institutions subject to the policy.

assets, we examine the February 2015 introduction of LTV and LTI limits in Ireland.

The policy caused a substantial reallocation of mortgage credit. We document a reallocation of mortgage credit from low- to high-income households and from hot, mostly urban, housing markets to cool housing markets. This reallocation is effective in slowing down house price growth, and in turn, the feedback loop between mortgage credit and house prices, in hot housing markets. Consistent with constrained lenders adjusting their portfolio choice, more-affected banks drive this reallocation and also increase their risk exposure in credit to firms and holdings of securities, two assets not targeted by the limits.

Our analysis of macroprudential regulation opens up a promising area for future research. In particular, our results on bank asset allocation naturally call for the development of equilibrium models to measure how macroprudential regulation affects welfare and the likelihood of busts. Having documented how limits to household leverage affect bank portfolio choice and house prices in a partial equilibrium framework, we provide a set of correlations and suggested transmission mechanisms that these equilibrium models should take into account.

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Appendix

A.1 Additional Figures

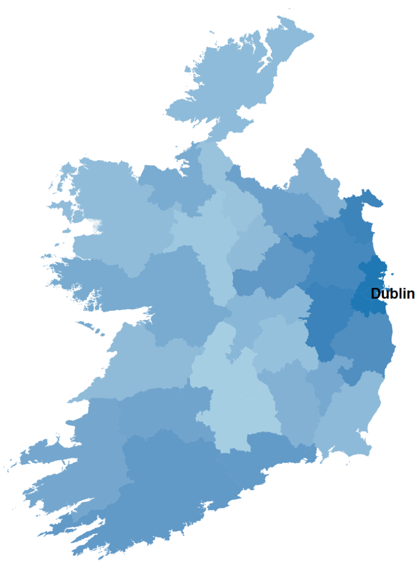

Figure A.1: Counties and Lending Limits. This figure shows county level distance from the limits. Darker colors indicate less distant counties. Source: Central Bank of Ireland.

A.2 Additional Tables

	Volume	Loan Size	LTV	LTI
Distance × Post	0.147***	0.744***	15.659***	0.154***
	(0.054)	(0.202)	(2.125)	(0.058)
County-Time FE	✓	✓	✓	✓
Bucket-Time FE	✓	✓	✓	✓
County-Bucket FE	✓	✓	✓	✓
Observations	7,253	7,253	7,160	7,101
R-squared	0.679	0.498	0.245	0.514

Table A.1: Reallocation of Mortgage Credit, Parametric Evidence, Distance at the Income Bucket Level. This table shows estimation results from specification (1). The dependent variable is the logarithm of total mortgage volume, the logarithm of the average loan size, the value-weighted LTV, and the value-weighted LTI. *Distance* is the distance from the lending limits at the income bucket level. All regressions include the share of originations to first-time buyers and to buy-to-let investors at the county-time-income bucket level, county-time fixed effects, income bucket-time fixed effects, and income bucket-county fixed effects. Standard errors clustered at the county-income bucket level in parentheses. Source: Central Bank of Ireland.

	Volume	Loan Size	LTV	LTI
Distance × Post	0.226**	0.254***	12.788***	0.339***
	(0.102)	(0.055)	(1.661)	(0.109)
County-Time FE	✓	✓	✓	✓
Bucket-Time FE	✓	✓	✓	✓
County-Bucket FE	✓	✓	✓	✓
Observations	7,253	7,253	7,160	7,101
R-squared	0.649	0.497	0.223	0.496

Table A.2: Reallocation of Mortgage Credit, Parametric Evidence, Distance at the County Level. This table shows estimation results from specification (1). The dependent variable is the logarithm of total mortgage volume, the logarithm of the average loan size, the value-weighted LTV, and the value-weighted LTI. *Distance* is the distance from the lending limits at the county level. All regressions include the share of originations to first-time buyers and to buy-to-let investors at the county-time-income bucket level, county-time fixed effects, income bucket-time fixed effects, and income bucket-county fixed effects. Standard errors clustered at the county-income bucket level in parentheses. Source: Central Bank of Ireland.

Internet Appendix[1]

IA.1 Data Sources

The data on bank lending, including loan and borrower characteristics, is obtained from the Central Bank of Ireland. In particular, the data on mortgages is obtained from the Loan Level Data from the Central Bank of Ireland (Financial Stability Division) up to January 2015 and from the Monitoring Templates from the Central Bank of Ireland (Financial Stability Division) from January 2015 to June 2016. The data on commercial lending is obtained from the Central Bank of Ireland (Financial Stability Division). Bank quarterly security holdings are from the Central Bank of Ireland (Statistics Division). Monthly bank balance sheet variables are from the Individual Balance Sheet Items ECB survey. The county level house prices are from `www.daft.ie/report`. The regional house prices are from Central Statistics Office of Ireland.

The loan level characteristics are (i) date of origination, (ii) amount outstanding (current and at origination) (iii) interest rate and interest type (current and at origination), and (iv) data on collateral (location, type, purpose, and value; all at origination). The borrower level characteristics (measured at origination of the loan) include (i) the type of borrower (FTB, SSB, BTL), (ii) age, marital status, occupation, and (iii) total household income.[1]

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[1]Date: April 2020. 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 Central Bank of Ireland. All results have been reviewed to ensure that no confidential information is disclosed. All errors are our own.

[1]For one of our banks, this income is missing from 2010 to 2014. As we expect heterogeneity in the bank-borrower match across banks, we do not assume that income will be the same for similar borrowers across banks. In particular, we use the period where we have the income 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.

IA.2 Additional Figures

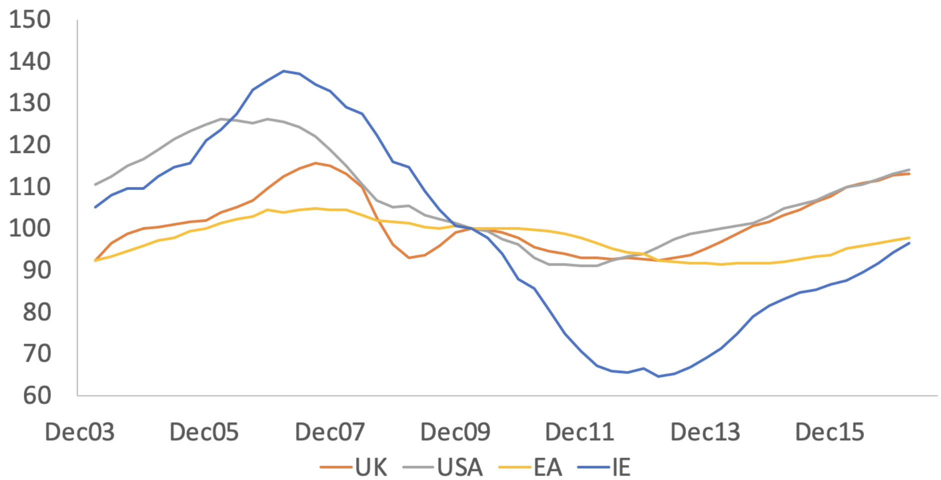

Figure IA.1: House Prices Outside Ireland. This figure shows real house prices (index 100 in 2010Q1) for Ireland, the U.K., the Euro Area, and the U.S. Source: OECD.

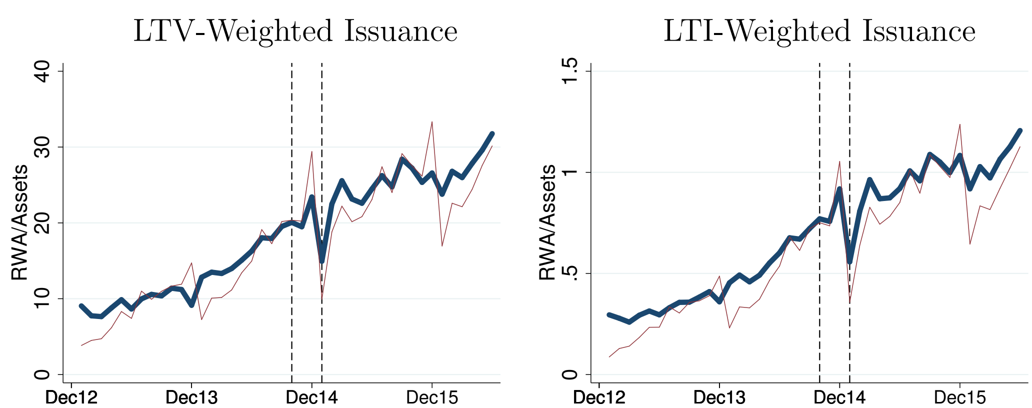

Figure IA.2: Aggregate Residential Mortgage Issuance. This figure shows the evolution of residential mortgage issuance of our sample banks weighted by LTV and LTI from January 2013 to June 2016. The left panel shows LTV-weighted monthly mortgage issuance divided by total assets (percentage). The right 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 first rumors about the limits and their implementation. Source: Central Bank of Ireland.

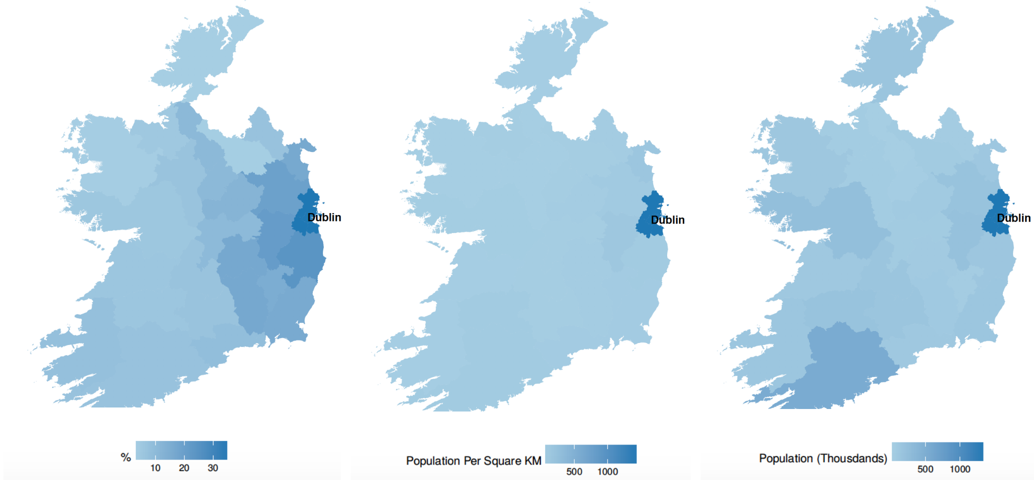

Figure IA.3: Demographics and House Price Appreciation Across Counties. The left panel of this figure shows county level increase in house prices from their lowest point after the bust to September 2014. Darker colors indicate a larger increase in house prices. The center panel shows county level density. Darker colors indicate more densely populated counties. The right panel shows county level population (thousands). Darker colors indicate more populated areas. Source: Central Bank of Ireland, Daft.ie

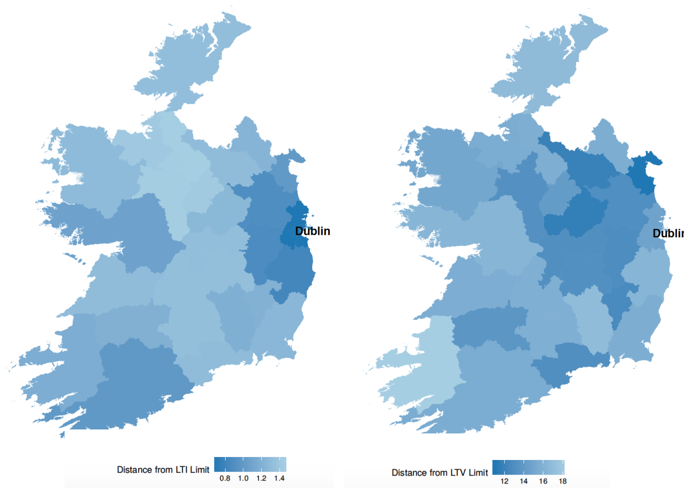

Figure IA.4: Counties and LTI Lending Limits, Counties and LTV Lending Limits. The figure on the left shows county level distance from the LTI lending limits. This figure on the right shows county level distance from the LTV lending limits. Darker colors indicate counties that are less distant. Source: Central Bank of Ireland.

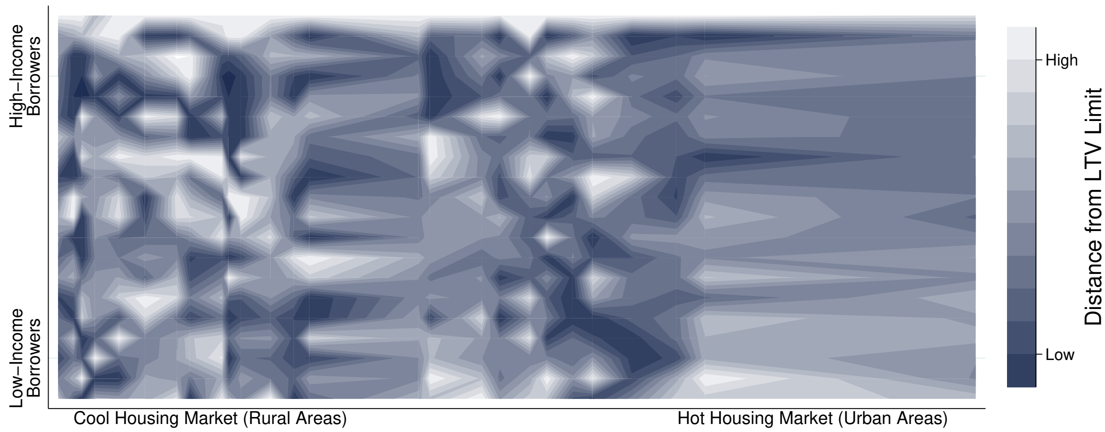

Figure IA.5: Exposure to the LTV Lending Limits Across Counties and Incomes. This figure shows the exposure to the LTV lending limit across counties and across the income distribution of borrowers. The x-axis shows counties ranked according to the house price appreciation pre-policy (from 2012Q4 to 2014Q3). The interval for each county on the x-axis is proportional to its population. The y-axis shows borrowers ranked according to their position in the income distribution (20 ventiles). Each point in the map indicates the distance from the LTV lending limits. Darker colors indicate a higher distance.

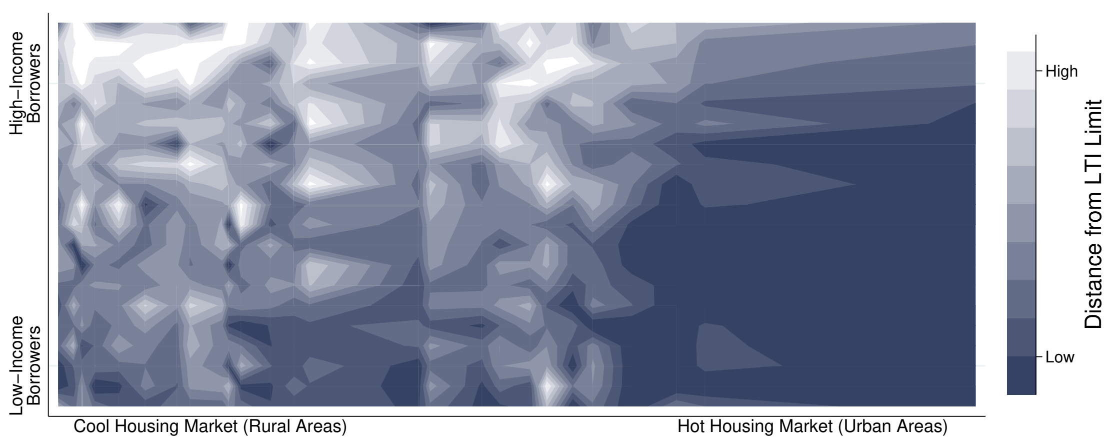

Figure IA.6: Exposure to the LTI Lending Limits Across Counties and Incomes. This figure shows the exposure to the LTI lending limit across counties and across the income distribution of borrowers. The x-axis shows counties ranked according to the house price appreciation pre-policy (from 2012Q4 to 2014Q3). The interval for each county on the x-axis is proportional to its population. The y-axis shows borrowers ranked according to their position in the income distribution (20 ventiles). Each point in the map indicates the distance from the LTI lending limits. Darker colors indicate a higher distance.

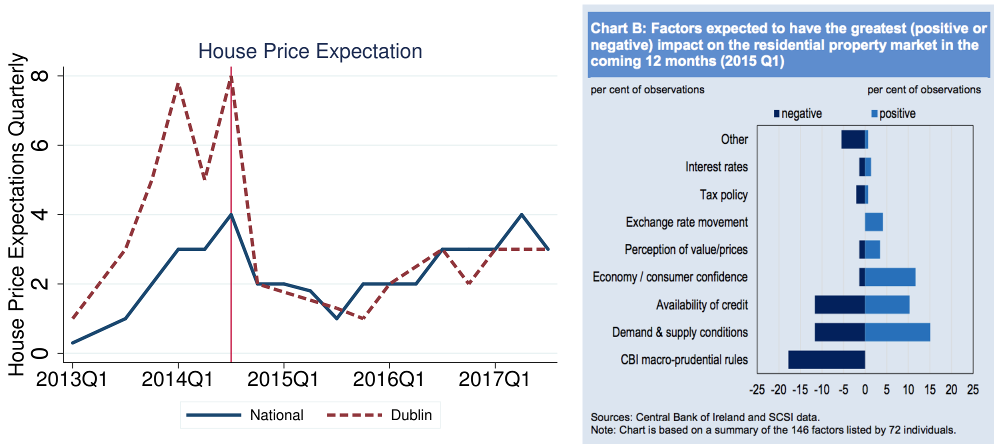

Figure IA.7: House Price Expectations. This figure shows survey evidence suggesting that the first rumors about the limits caused households to revise their expectations about house prices downward, especially in low-distance counties. The left panel shows the evolution of house price expectations in 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.

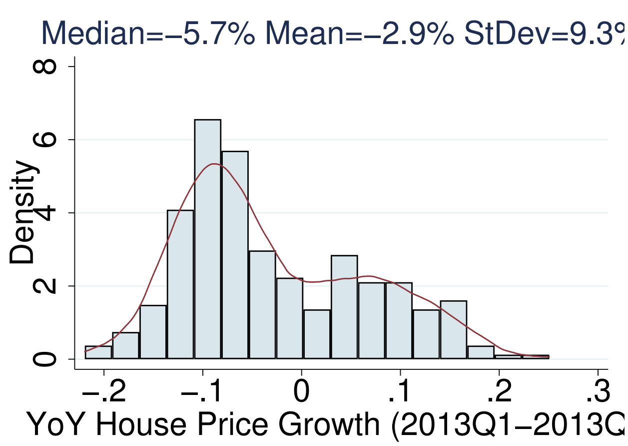

Figure IA.8: Pre-Policy Distribution of House Price Growth. This figure shows the distribution of house price growth (YoY) from 2013Q1 to 2013Q4. Source: Daft.ie.

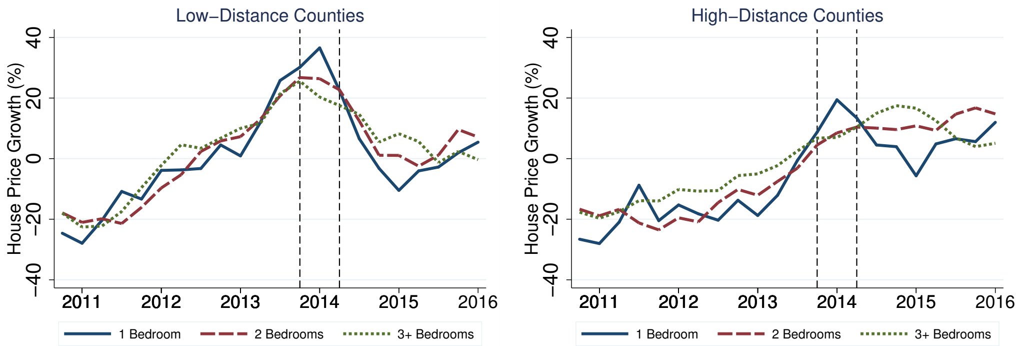

Figure IA.9: House Prices and Property Type. These figures shows house price growth for 1-bedroom (solid line), 2-bedroom (dashed line), and 3-bedroom or larger properties (dotted line). The top (bottom) panel shows data for low-distance (high-distance) counties. The vertical dashed lines indicate the first rumors and the implementation date of the lending limits. Source: Central Bank of Ireland, Daft.ie.

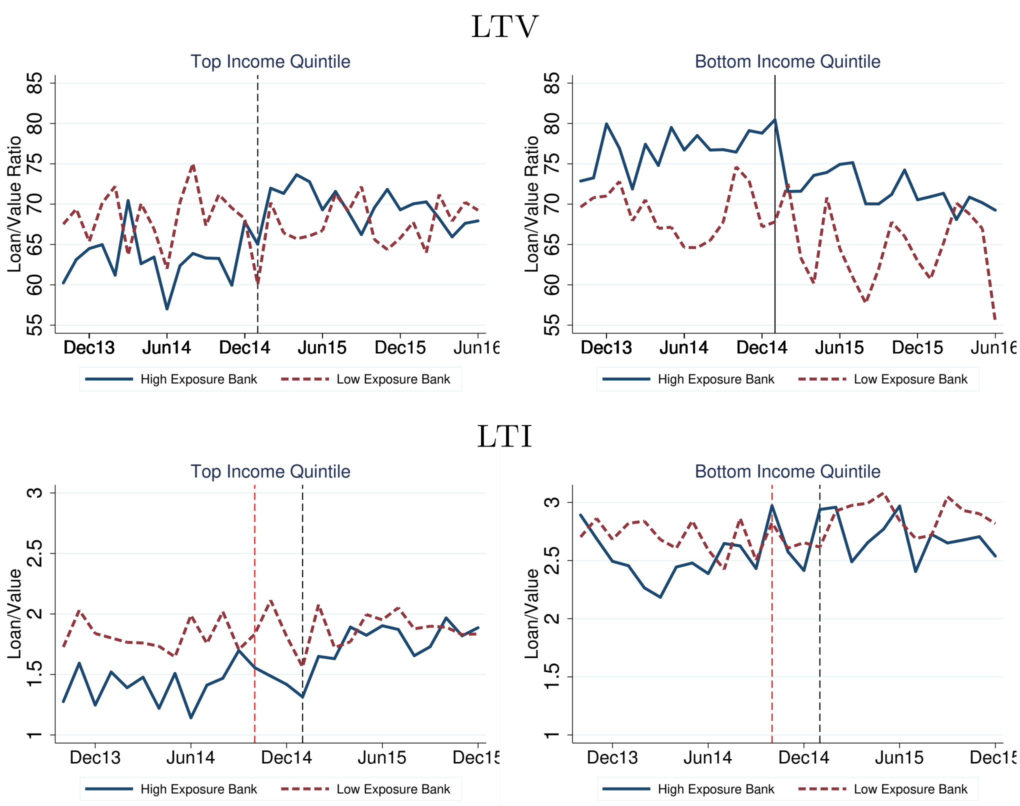

Figure IA.10: LTV and LTI, High and Low Exposure Banks, Top Vs. Bottom Income Quintile. This figure shows the evolution of LTV (top panel) and LTI (bottom panel) of mortgage issuance by high-exposure (solid line) and low-exposure (dashed line) banks. Blue (red) lines corresponds to banks with exposure above (below) the median. Income quintiles are obtained from the January 2014 income distribution and adjusted monthly for Irish wage inflation. Source: Central Bank of Ireland.

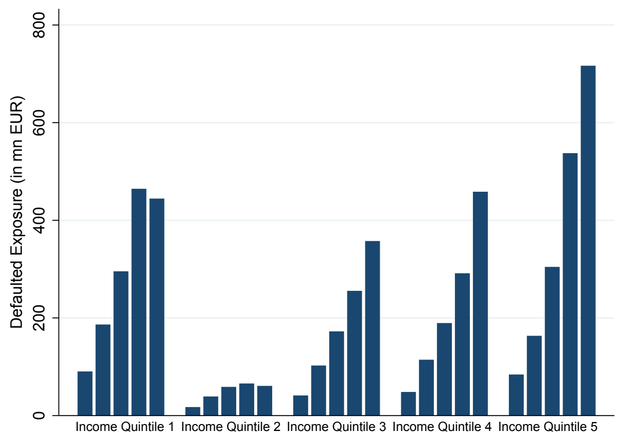

Figure IA.11: Defaulted Exposure accumulated during the run-up to the Financial Crisis. This figure shows the defaulted exposure of Irish banks from 2000 to 2012. The bars represent the loss of the individual LTV Quintiles which are shown in an ascending order from left to right within each income quintile. 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.

IA.3 Additional Tables

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

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

IA.4 Bank Portfolio Choice and Lending Limits

In this section, we develop a simple model of bank portfolio choice to show how the lending limits affects bank portfolio choice. In our environment, a representative bank solves:

$$
\begin{aligned}
& max_{x_i} \sum_{i=1}^{3} \Big(x_i \mathbb{E}(R_i) - \frac{\alpha_i}{2} x_i^2 \Big) \\
s.t. \quad & x_i \leq K_i \qquad\qquad i = \{1,2,3\} \\
& \sum_{i=1}^{3} \kappa_i x_i \leq K_4
\end{aligned}
$$

The bank chooses how much to invest in three assets x_i, where $i = \{1,2,3\}$, subject to four constraints. The first three constraints are lending limits that constrain each asset to be less than a specific threshold. The last constraint is a balance sheet constraint where the weighted sum (weights κ_i) of each asset is forced to be less than a threshold.

In this environment, we compare the bank portfolio choice with and without lending limits. In the economy with no lending limits, only the last constraint binds. In an economy with lending limits, the constraint on asset 1 also binds, namely $x_1 = K_1$.

Portfolio Choice with No Lending Limit Suppose only the last constraint binds. The bank then chooses:

$$
\begin{aligned}
x_1^* &= \frac{\mathbb{E}(R_1)(\alpha_2\kappa_3^2 + \alpha_3\kappa_2^2) - \alpha_3\kappa_1\kappa_2\mathbb{E}(R_2) - \alpha_2\kappa_1\kappa_3\mathbb{E}(R_3) + K_4\alpha_2\alpha_3\kappa_1}{\alpha_2\alpha_3\kappa_1^2 + \alpha_1\alpha_3\kappa_2^2 + \alpha_1\alpha_2\kappa_3^2} \\
x_2^* &= \frac{\mathbb{E}(R_2)(\alpha_1\kappa_3^2 + \alpha_3\kappa_1^2) - \alpha_3\kappa_1\kappa_2\mathbb{E}(R_1) - \alpha_1\kappa_2\kappa_3\mathbb{E}(R_3) + K_4\alpha_1\alpha_3\kappa_2}{\alpha_2\alpha_3\kappa_1^2 + \alpha_1\alpha_3\kappa_2^2 + \alpha_1\alpha_2\kappa_3^2} \\
x_3^* &= \frac{\mathbb{E}(R_3)(\alpha_1\kappa_2^2 + \alpha_2\kappa_1^2) - \alpha_1\kappa_2\kappa_3\mathbb{E}(R_2) - \alpha_2\kappa_1\kappa_3\mathbb{E}(R_1) + K_4\alpha_1\alpha_2\kappa_3}{\alpha_2\alpha_3\kappa_1^2 + \alpha_1\alpha_3\kappa_2^2 + \alpha_1\alpha_2\kappa_3^2}
\end{aligned}
$$

Portfolio Choice with a Lending Limit Suppose now that $\widetilde{K}_1 < K_1$ such that the last constraint and the first constraint, namely $x_1 = \widetilde{K}_1$, bind. The bank then chooses:

$$x_1^{**} = \widetilde{K}_1$$
$$x_2^{**} = \frac{\alpha_3\kappa_2(K_4 - \kappa_1\widetilde{K}_1) - \kappa_2\kappa_3\mathbb{E}(R_3) + \kappa_3^2\mathbb{E}(R_2)}{\alpha_3\kappa_2^2 + \alpha_2\kappa_3^2}$$
$$x_3^{**} = \frac{\alpha_2\kappa_3(K_4 - \kappa_1\widetilde{K}_1) - \kappa_2\kappa_3\mathbb{E}(R_2) + \kappa_2^2\mathbb{E}(R_3)}{\alpha_3\kappa_2^2 + \alpha_2\kappa_3^2}$$

Comparison We now want to compare the two portfolio choices. In particular, we ask under what conditions the bank chooses to increase more its investment in x_3 than its investment in x_2 in the presence of the lending limit on x_1 compared with the portfolio choice with no lending limit. More formally, we ask under what conditions $x_3^{**} - x_3^* > x_2^{**} - x_2^*$. By comparing the solutions above, we obtain that $x_3^{**} - x_3^* > x_2^{**} - x_2^*$ if and only if

$$\frac{\alpha_2}{\alpha_3} > \frac{\kappa_2}{\kappa_3}$$

To develop some intuition, note that we can write the first order conditions with respect to x_2 and x_3 in the problem with and without a lending limit as follows:

$$\mathbb{E}(R_2) - \alpha_2 x_2^* = \kappa_2\lambda_4 \qquad \mathbb{E}(R_3) - \alpha_3 x_3^* = \kappa_3\lambda_4$$
$$\mathbb{E}(R_2) - \alpha_2 x_2^{**} = \kappa_2\lambda_4' \qquad \mathbb{E}(R_3) - \alpha_3 x_3^{**} = \kappa_3\lambda_4'$$

where λ_4 and λ_4' are the Lagrange multipliers for the last constraint in the case without and with the lending limit, respectively. By combining these conditions, we obtain $\frac{\alpha_2}{\kappa_2}(x_2^* - x_2^{**}) = \frac{\alpha_3}{\kappa_3}(x_3^* - x_3^{**})$. In general, (i) a smaller risk aversion α_i causes asset i to be more desirable and (ii) a larger contribution κ_i to the balance sheet constraint causes that asset i to be more constrained in the optimal portfolio choice. When we move to the portfolio choice with a lending limit, we analyze how x_2 and x_3 change following a de facto relaxation of the balance sheet constraint. The asset that gains the most has a low α (less risk) and a high κ (more constrained before the relaxation of the balance sheet constraint).