The Anatomy of the Transmission of Macroprudential Policies: Evidence from Ireland^{*}

Viral V. Acharya Reserve Bank of India Katharina Bergant Central Bank of Ireland Matteo Crosignani Federal Reserve Board

Tim Eisert Erasmus University Rotterdam Fergal McCann Central Bank of Ireland

September 2017

Abstract

We provide a comprehensive analysis of the transmission of macroprudential policies aimed at limiting bank risk-taking in residential real estate. Combining supervisory loan- and security-level data, we examine the effect of loan-to-income and loan-to-value limits on residential mortgages issued by Irish banks after February 2015 on household access to credit and bank risk-taking. We find that, in response to the macroprudential policy, banks increase their risk-taking in both corporate credit and holdings of securities and reduce the rate charged to high income households who lever up buying expensive properties.

JEL: G21, E21, E44, E58, R21

Key words: Macroprudential Regulation, Bank Credit Supply, Residential Mortgages

^{*}The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System, the Reserve Bank of India, the Central Bank of Ireland, or anyone associated with these institutions. All results have been reviewed to ensure that no confidential information is disclosed. All errors are our own.

1 Introduction

Following the recent financial crises, policy-makers throughout the world have been proposing, designing, and implementing several types of macroprudential policies aimed at making the financial sector less vulnerable to crises (Claessens (2015)). The goal of these rules is usually to counter an excessive build-up of risk on banks' balance sheet to maintain financial stability. However, the literature on the transmission of macroprudential regulation is very limited. Our goal is to fill this gap.

In this paper, we analyze the transmission of borrower-based macroprudential regulations that impose restrictions on bank credit supply. The goals of these policies is typically to limit overly rapid private credit growth and possibly counter ongoing credit fueled asset price appreciations. In particular, we study the introduction of loan-to-value (LTV) and loan-toincome (LTI) limits for residential mortgages issued by Irish banks starting in February 2015. We find that, in response to the introduction of the lending limits, banks (i) reallocated their mortgage portfolio reducing the rate charged to high income households who lever up buying expensive properties, (ii) increased their credit supply to risky firms, and (iii) increased their holdings of risky securities.

The LTI and LTV limits introduced by the Central Bank of Ireland are quantitatively important as they affect approximately half of the typical mortgage issuance of banks subject to the regulation. However, the evolution of both issuance volume and LTV and LTI of newly issued mortgages seemed unaffected by the policy, pointing at a likely reallocation of credit. Following the implementation of the lending limits, banks in fact increase their issuance of conforming (i.e., within the lending limits) mortgages to compensate for the fall of nonconforming (i.e., exceeding the limits) mortgages.

Two transmission channels can explain the increased issuance of non-conforming mortgages. The first one is the "borrower adapting" channel. As a result of the policy introduction, a large fraction of households could not obtain the mortgage they wanted anymore. According to this channel, these borrowers could have fine tuned their mortgage application to lower their LTV and/or lower their LTI and to qualify under the new rules and effectively "become conforming" by buying a cheaper house and/or increasing their downpayment. The second one is the "bank credit reallocation" channel. The introduction of the lending limits affected approximately half of the typical residential mortgage issuance, mainly driven by the LTV limits. According to this channel, banks could have changed their residential mortgage issuance to achieve the same risk exposure under the new constraints.

The two channels have different implications for the time-series evolution of LTV and LTI for high income households. According to the borrower adapting channel, borrower LTV and LTI should *decrease* after the policy introduction as households looking to obtain a nonconforming mortgage actively lower these ratios to qualify under the new rules. According to the bank credit reallocation channel, borrower LTV and LTI should *increase*, especially for high income household that are far away from the lending limits, as banks try to make-up for the lost risk exposure. The aggregate evidence supports the credit reallocation channel as high income borrowers (i) have much lower LTI/LTV compared with low income borrowers before the policy implementation and therefore have more room to increase these ratios and (ii) high income borrowers *increase* their LTI/LTV compared with low income borrowers after the policy, narrowing the gap between the two groups.

We find that the policy had an heterogeneous effect across income buckets. Low-income and high-income households after the regulation reduced and increased their LTV on newly issued mortgages, respectively. In particular, the LTV of the top quintile of the income distribution *increased* by 4.4 points and the LTV of the bottom quintile *decreased* by 4.3 units compared with other quintiles, relative to the pre-policy period. We find similar but weaker effects for the LTI, consistent with the LTV limit being quantitatively more important compared to the LTV limit for banks.

Having shown that high income households increase their LTV and LTI after the implementation date borrowing especially from exposed banks, we show that banks induced high income households to borrow more lowering their mortgage rates. We find that high income households were charged 12.5 basis points less than other households after the policy implementation. This finding is driven by exposed banks, consistent with these banks inducing high income borrowers to obtain larger loans and buy more expensive properties levering up to take advantage of the attractive mortgage rates.

We then turn to analyze whether more affected banks change their portfolio choice in the other two largest asset classes: lending to firms and holdings of securities. Since banks lost part of their risky mortgage business, it is entirely possible that they might take on more risk in corporate lending that is not targeted by the regulation. Indeed, we document, that more affected banks increase their corporate lending more strongly than less affected banks. This increase is mostly targeted towards riskier borrowers and occurs both in the quantity (higher loan volumes) and price (lower spreads) dimension.

Banks increase their risk taking also in their holdings of securities. We find that banks more exposed to the macroprudential intervention increase their holdings of risky (based on yield) securities compared with less affected banks, after the policy implementation. More precisely, more affected banks both buy more and sell less securities with higher yields. Thanks to our security-level data set, in our most conservative estimation we control for security time varying characteristics (e.g., amount outstanding) and bank time-varying characteristics (e.g., leverage) using security-time and bank-time fixed effects.

Our paper adds to the literature on the impact of macroprudential regulation on bank lending behavior and financial stability. First, we contribute to the literature on capital regulation. In the theoretical literature, Begenau (2016) develops a quantitative dynamic general equilibrium model to analyze the effect of capital requirements on bank lending, Kashyap et al. (2014) present a full general equilibrium analysis and show the effects of capital regulation on risk taking, and Elenev et al. (2017) provide a calibrated macro-economic model to evaluate macro-prudential policy imposing restrictions on firm and bank leverage. In the empirical literature, Jimenez et al. (forthcoming) investigate the impact of pro-cyclical bank capital regulation on loan supply to firms, Aiyar et al. (2014) show that in response to tighter capital requirements, regulated banks reduce lending, while unregulated banks might even increase it, Gropp et al. (2016) study the transmission of higher capital requirements to the real economy and find that banks decrease credit supply instead of raising more equity to meet the new targets, and Auer and Ongena (2016) find that extra capital requirement on residential mortgages led to higher growth in commercial lending.

Our paper also contributes to the broader literature on macruprudential tools available to regulators. Cerutti et al. (2015) study macroprudential measures in 119 countries and show that LTV and LTI limits are effective. Kinghan et al. (2017) analyze the effect of the lending limits imposed by the Central Bank of Ireland and find that LTVs fell for both first time homebuyers and second and subsequent homebuyers. Compared with this paper, our empirical strategy relies on aggregating the data set at the county-time-income-bank level and our focus is on financial stability and bank credit reallocation. Igan and Kang (2011) find that the introduction of loan-to-value and debt-to-income ratios in Korea led to a decline in house price appreciation and transaction activity. A second group of papers uses cross-country evidence to analyze the impact of macroprudential policies on bank activity. Claessens et al. (2013) analyze the effect macroprudential policies on credit growth and foreign currency lending limits and Ayyagari et al. (2017) find evidence that macroprudential policies are associated with lower credit growth, especially for small firms with limited nonbank financing.

Finally, we also complement the large literature on bank lending and the composition of credit. Residential mortgage credit is analyzed in Michelangeli and Sette (2016) that show that weakly capitalized banks offer the lowest interest rate to relatively safer borrowers once they made an offer. By combining loan and security level registers, our paper relates to the literature that combines mortgage credit, corporate credit, and holdings of securities (Carpinelli and Crosignani (2017), Peydro et al. (2017), Chakraborty et al. (2016)).

2 Setting and Data

In this section, we provide some background on the residential mortgage market in Ireland and its link to financial stability, describe our data set and the lending limits introduced in February 2015, and provide summary statistics.

2.1 Residential Mortgage Lending in Ireland

In the years leading up to 2000, Ireland experienced a 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 excessive bank credit extended to home owners and property developers Honohan (2010). In the left panel of Figure 1, we show the issuance of residential mortgages from January 2000 to June 2016 and we observe a stark increase in new mortgages in the run-up to the financial and sovereign debt crisis. After mortgage issuance collapsed during the crisis, another stark increase in new issuances began in 2013. In the right panel, we show that house prices followed a remarkably similar pattern.

At the bust of 2007-08, prices declined sharply and construction activities collapsed. Peakto-trough fall in quarterly Gross National Product (GNP) is estimated to be about 17%.¹ In addition to the sharp decrease of real estate prices, an increase of unemployment from 4.6% in 2007 to 13.3% in 2010 left many households unable to service their debt burden Honohan (2010). This led to losses for banks which consequently experienced severe funding dry-ups. In September 2008, public funds had to be used in order to recapitalize almost all significant

¹Irish economic performance is usually measured in relation to GNP rather than GDP as the latter is artificially higher due to profits of international companies which are transferred to Ireland because of low corporation tax Honohan and Walsh (2002)).

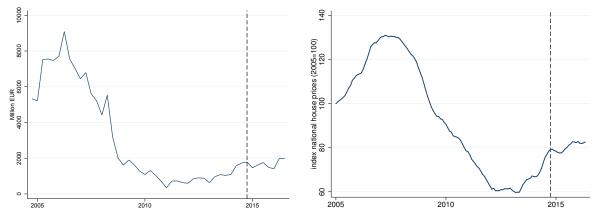


Figure 1: Ireland Real Estate Boom-Bust Cycle. The left panel shows the time-series evolution of aggregate residential mortgage issuance (million euro) from January 2000 to June 2016. The right panel shows the time-series evolution of the national real estate price index starting in the base year 2005 until June 2016. In both panels the vertical dashed line indicates the lending limit regulation announcement date. Sources: Central Bank of Ireland and Central Statistics Office.

credit taking institutions in Ireland (Lane (2011), Acharya et al. (2014)). More specifically, the gross amount of liabilities guaranteed reached \in 365 billion, almost 2.5 times GNP.

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

The lending limits were announced on February 9, 2015 and became effective immediately.² In Table 1, we provide an overview of the limitations on loan-to-value (LTV) and

²The lending limits were first proposed in a paper (Consultation Paper 87) published to stimulate discussion by the central bank on October 7, 2014 and available on the Central Bank of Ireland website (link). Mortgages issued after February 9, 2015 could exceed the lending limits if approved before February 9, 2015.

Regulation	Target Group	Limits	Allowances for each bank
LTV limits	For primary dwelling homes:	FTBs : Sliding LTV limits from 90%* SSBs : 80%	15% of all new lending limits
	For BTL:	70% LTV limit	10% of new lending above the BTL limit is allowed
LTI limits	For primary dwelling homes:	3.5 times income	20% of new lending above the limit is allowed
Exemptions	From LTV limit Borrowers in negative equity	From LTI limit Borrowers for investment properties	From both limits * Switcher mortgages * Restructuring of mortgages in arrears
*A limit of 90%	LTV applies on the first \in	220.000 of the value of a	residential property and a limit

of 80 % LTV applies on any value of the property thereafter.

.

Table 1: Lending Limits. This table provides a summary of the lending limits introduced in February2015. Source: Central Bank of Ireland.

loan-to-income (LTI) ratios on new originations of residential mortgages. The regulation takes into account that not all borrower groups are equally risky so that different limits are imposed. Lending for primary dwelling housing (PDH) is limited to 80% LTV and to an LTI of 3.5. For First-Time-Buyers (FTB), a more generous LTV limit of 90% is imposed for houses up to €220,000. For any amount exceeding €220,000, the excess amount over €220,000 faces an LTV limit of 80%. The measures impose a lower threshold for buy-to-let (BTL) properties, requiring banks to apply an LTV limit of 70% for this type of loans.³

 $^{^{3}}$ In addition to loans that are generally exempted from the rule (last line of Table 1), banks are granted allowances for each group of borrowers so that they can issue loans exceeding those limits to a small number of borrowers (column 4 in Table 1). In Figure B.1 in the Appendix, we show the distribution of the lending limits across the distributions of LTVs and LTIs.

2.2 Data and Summary Statistics

In this section, we describe the data set construction and the empirical framework. The core of our final data set is the result of combining loan-level information on residential mortgages and credit to firms, and bank security-level holdings. The loan-level data and security register are proprietary data sets obtained from the Central Bank of Ireland. In our final data set, the unit of observation is at the (b, h, f, s, t) level, where $b \in \mathcal{B}$ is a bank, $h \in \mathcal{H}$ is a household, $f \in \mathcal{F}$ is a firm, $s \in \mathcal{S}$ is a security, and $t \in \mathcal{T}$ is a period.

First, we observe loan-level data on the issuance of new residential mortgages to households at a daily frequency for our period of interest, Jan 2013 to June 2016.⁴ We aggregate this to (b, h, t) bank-household-month level to observe all outstanding residential mortgages by the most significant institutions that have to submit loan-level data to the Central Bank of Ireland.⁵ This covers more than 90% of the domestic mortgage market. The dataset also contains (h, t) household-month demographic (age, marital status), income, and residential mortgage credit (first-time or subsequent time buyer, buy-to-let) characteristics.

Second, we observe loan-level data on bank credit to firms at a semi-annual frequency from June 2013 to June 2016. At the (b, f, t) bank-firm-period level, we observe credit granted and drawn and the rate charged by bank b to firm f at time t. We match this information with firm characteristics such as county of incorporation, industry, and size. We observe the borrower rating assigned to each loan from internal rating models of each lender. Central Bank of Ireland internal mapping scales are used to classify each internal rating into

⁴This data is a combination of two sources: until 2015, we use the *loan-level data* whereas the *Monitoring Template Data* is used thereafter. The latter has to be submitted to the Central bank of Ireland for regulatory purposes as prescribed by the macroprudential Regulations introduced by the Central Bank of Ireland on the 9th February 2015. More information can be found in the appendix.

⁵Irish banks which received a public bailout are required to report loan-level data. The rest of the significant mortgage issuers in Ireland submit loan-level data following the encouragement from regulators and in accordance with data submissions required by the ECB-SSM Comprehensive Assessment in 2013.

	Jun14	Dec14	Jun15	Dec15	Jun16
Mortgage-Level (Characte	eristics (c	redit to he	ouseholds)	
LTI	2.53	2.78	2.65	2.56	2.65
LTV	73.22	75.55	76.28	73.06	73.45
Loan Size	179.51	188.97	181.50	183.73	196.37
Collateral Value	266.85	273.91	269.61	287.64	298.02
Maturity	323.13	323.07	329.77	313.98	317.88
Interest Rate	4.35	4.07	3.82	3.68	3.59
Household-Level	Charact	eristics			
Income	76.33	81.07	80.46	92.49	85.65
Age	36.38	36.08	35.97	36.83	37.39
Married	47.75	48.03	49.32	56.85	53.31
Employed	87.93	88.13	88.33	88.91	88.98
First Time Buyers	59.56	58.22	60.51	54.01	54.34
Buy-to-Let	2.82	5.90	5.54	7.27	5.42
Loan-Level Chara	acteristi	cs (credit	to firms)		
Rating	3.34	3.27	3.17	3.07	3.06
Loan Amount	$65,\!639$	$67,\!647$	$65,\!146$	$64,\!027$	$62,\!015$
Interest Rate	6.70	6.66	6.65	6.66	6.64
Secured	30.49	29.88	29.32	29.03	28.69

Table 2: Summary Statistics. This table shows summary statistics (cross-sectional means) on mortgages issued at each date. Panel A shows mortgage-level characteristics. Panel B shows characteristics of house-holds receiving a mortgage. Panel C shows loan-level characteristics of loans issued to firms. All variables are cross-sectional means. Source: Central Bank of Ireland.

a consistent categorization between 1 and 6. It ranges from 1 (highest quality borrower) to 6 (riskiest borrower). There is one main limitation to the data. In contrast to most credit registries, we our borrower identifier is consistent within a bank through time, but not across banks.

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

Finally, at the (b, t) bank-period level, we observe monthly balance sheet items from the ECBs Individual Balance Sheet Statistics (IBSI), such as total assets, equity capital ratio.

In Table 2, we present summary statistics. Panel A shows information on mortgages

granted by our sample banks. Both the average loan size and average value of the property bought by households increased over time. Interestingly, we do not observe a clear decrease in either the average LTV or the average LTI, which are both bound by the regulation. Panel B presents summary statistics about the borrowing households. On average, the income of households that received a mortgage increased significantly over time. Moreover, the fraction of first time buyers decreased sharply starting in mid-2015. Panel C shows information on the corporate loans granted by our sample banks. The numbers show that the average quality of corporate borrowers improved slightly over time. Moreover, the average loan amount decreased slightly throughout our sample period. Conversely, we do not see changes in the average interest rate charged or the fraction of secured loans.

3 Effect on Residential Mortgage Credit

In this section, we illustrate the effects of the mortgage lending limits on the residential mortgage market. In Section 3.1, we present aggregate evidence on the evolution of mortgage credit. In Section 3.2, we discuss the transmission channel and the evolution of issuance across the household income distribution. In Section 3.3, we show that banks reallocated their mortgage portfolio increasing their exposure to high income households in response to the policy. In Section 3.4, we show that banks lowered the mortgage rates charged to high income households to induce them to borrow more and lever up.

3.1 Aggregate Evidence

The lending limits implemented in February 2015 prevented banks from originating high-LTV and high-LTI residential mortgages. These rules affected a large fraction of the mortgage market as 49% of residential mortgages issued from January 2014 to January 2015 would have been affected if the policy was in place during that period. Out of the total \in 1.9 billion

mortgages issued by our sample banks in the year before the policy implementation, nonconforming (i.e., not complying with the new rules) mortgages accounted for ≤ 0.93 billion. The LTV limits affected the largest fraction of the market. LTV-non-conforming mortgages accounted for ≤ 0.75 billion and LTI-non-conforming mortgages accounted for ≤ 0.38 billion. Moreover, 52% of LTI-non-conforming mortgages were also LTV-non-conforming.⁶

Somewhat surprisingly, while the lending limits affected almost half of the typical residential mortgage issuance, the pace of originations and the build-up of mortgage credit risk exposure seem unaffected by the policy. In Panel A of Figure 2, we show the evolution of mortgage issuance from December 2012 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, delimited by the vertical dashed line. This aggregate evidence suggests that an increase in the issuance of *conforming* mortgages might have compensated the mechanical reduction of the issuance of *non-conforming* mortgages, as banks followed the new rules. In Panel B, we show the evolution of originations of conforming and non-conforming mortgages and confirm that the two time-series diverge starting in February 2015.⁷ Panel C and Panel D show LTV- and LTI-weighted originations of residential mortgages. Again, we observe that the risk exposure of our sample banks seems unaffected by the lending limits.

We now ask which borrowers were ex ante more exposed to the lending limits. In Table 3, we divide households that obtain a mortgage in the year prior to the policy in five quintiles based on their income. The income distribution is negatively skewed as the average income of the top quintile ($\leq 169,098$) is almost double the average income of the fourth income

⁶There were 3,678 LTV non-conforming mortgages and 1,684 LTI non-conforming mortgages issued from January 2014 to January 2015. The LTI limits alone affected only 882 mortgages worth \in 184 million during the same period. In Figure B.2 in the Appendix, we summarize the relative importance of the two limits.

⁷Note that the issuance of non-conforming mortgages is still strictly positive after the policy implementation as the new rules allow banks to exceed the limits for a limited fraction of their total monthly issuance.

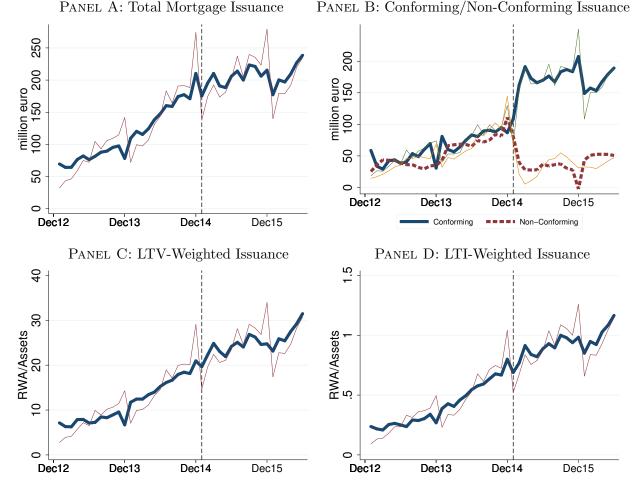


Figure 2: Aggregate Residential Mortgage Issuance. This figure shows the evolution of aggregate residential mortgage issuance of our sample banks from January 2013 to June 2016. Panel A shows total mortgage issuance (million euro). Panel B shows issuance of conforming (solid line) and non-conforming (dashed line) mortgages. Panel C and Panel D show LTV-weighted (measured in percentage) and LTI-weighted (measured in units) monthly mortgage issuance divided by total assets, respectively. In all panels, thick lines are seasonally adjusted and thin lines are not seasonally adjusted. The vertical dashed lines indicate the implementation of the lending limits. Source: Central Bank of Ireland.

		Bottom				Top
Income Quintiles	Unit	$\mathbf{Q1}$	$\mathbf{Q2}$	$\mathbf{Q3}$	$\mathbf{Q4}$	$\mathbf{Q5}$
Borrower Characteristics						
Income	€	32,172	47,582	64,559	$91,\!599$	169,098
Single	%	81.0	61.0	48.2	29.8	24.7
Age	Years	34.3	35.1	36.1	37.5	39.8
First-Time Buyer	%	82.1	78.6	64.6	41.1	23.6
Buy-to-Let	%	1.9	2.3	3.2	4.1	8.8
Non-Conforming	%	52.20	44.50	49.98	52.26	46.10
Non-Conforming LTV	%	28.83	23.58	39.01	44.77	44.04
Non-Conforming LTI	%	38.79	31.51	29.02	20.64	4.53
Loan Characteristics						
Size	€	$95,\!243$	$126,\!355$	$165,\!847$	$211,\!109$	260,774
LTV	%	74.72%	74.79%	74.87%	73.82%	70.47%
LTI	Ratio	2.85	2.69	2.61	2.39	1.96
House Value	€	$141,\!473$	179,069	$235,\!442$	$312,\!460$	444,861
Term	Months	326	330	327	317	292
Rate	%	4.13%	4.25%	4.22%	4.20%	4.11%
Distance From Lending Limit	s (Slack)					
LTV Slack	%	6.66	5.46	3.50	3.63	5.38
LTI Slack	Ratio	0.53	0.73	0.72	0.97	1.26
Normalized LTI & LTV Slack		0.76	0.87	0.89	0.92	1.01

Table 3: Summary Statistics by Household Income. This table shows borrower and loan characteristics by income quintile during the 12-month period before the policy implementation from February 2014 to February 2015. LTV (LTI) slack is defined as the median distance (in pp) of households in an income bucket from the applicable LTV (LTI) threshold in the regulation. The combined measure normalizes both the LTV and LTI slack to have a standard normal distribution and then considers the limit (LTV or LTI) with less slack as the more binding one. Source: Central Bank of Ireland.

quintile ($\in 92,599$). High income households have also lower LTV and lower LTI and tend to be older and less likely to be single or first-time-buyers compared with lower income households. Moreover, while approximately half of the households in each income buckets are non-conforming, high-income borrowers are also more distant from lending limits (have more "slack") compared with low income households.⁸

⁸Even if they have lower LTV/LTI, high income households are subject to stricter limits because they are often non-first time buyers. LTV/LTI limits affect more high and low income households, respectively.

3.2 Transmission Channel

We have shown that, in aggregate, the increased issuance of conforming mortgages compensated for the collapse of non-conforming mortgages after the policy implementation. With this evidence in mind, we now discuss how the lending limits might have affected the mortgage market. Two non-mutually exclusive channels might be at work.

The first one is the "borrower adapting" channel. As a result of the policy, a large fraction of households could not obtain the (high LTV/LTI) mortgage they wanted anymore. According to this channel, these borrowers could have fine tuned their mortgage application to lower their LTV and/or lower their LTI to qualify under the new rules.⁹

The second one is the "bank credit reallocation" channel. As discussed above, banks were hit by the regulation as the lending limits prevented them from originating almost half of their typical mortgages issuance, mainly driven by the LTV limits. According to this channel, banks could have changed their issuance to make up for the lost high-LTV and high-LTI business by actively trying to originate more of these types of mortgages within the lending limits.

On the one hand, both channels are consistent with the increased issuance of nonconforming mortgages. Households fine-tuning their loan request could have "switched" from a non-conforming to a conforming mortgage (borrower adapting channel) and banks could have actively increased their issuance of conforming mortgages to make-up for the lost nonconforming mortgage business (bank credit reallocation channel). On the other hand, the

$$LTV = 1 - \frac{DownPayment}{House}$$
 and $LTI = \frac{House - DownPayment}{Income}$

⁹Given that income cannot be easily manipulated and does not change in the short-term, we can show that the house value and the downpayment drive LTI and LTV by writing these ratios as:

two channels have different implications for the evolution of LTV and LTI. According to the borrower adapting channel, borrower LTV and LTI should *decrease* after the policy as households looking to obtain a non-conforming mortgage actively lower their LTV and LTI to qualify under the new rules. According to the bank credit reallocation channel, borrower LTV and LTI should *increase* after the policy for those households that are more distant from the lending limits as banks try to make-up for their lost risk exposure.

We now present two figures that provide aggregate evidence of the credit reallocation channel being at work. In Figure 3, we show the distribution of mortgage issuance in December 2014 (left) and December 2015 (right) across LTV ratios.¹⁰ We group mortgages issued in December based on their distance to the LTV limit. The blue bars indicate conforming mortgages (positive distance) and the gray bars indicate non-conforming mortgages (negative distance). The first three rows correspond to the first three income quintiles and the last row corresponds to the two bottom income quintiles. We observe that high income households (top row) are very distant from the lending limits in December 2014 and move very close to the limits in December 2015. While borrowers in other income quintiles also obtain mortgages that are just on the right of the lending limits in December 2015, the shape of their distribution does not change as much.

In Figure 4, we show the time series evolution of LTI and LTV by high income (top quintile of the income distribution) and low income households (bottom quintile of the income distribution) from October 2013 to June 2016. We observe that high income borrowers (i) have lower LTI/LTV compared with low income borrowers before the policy implementation (consistent with them having more slack to increase these ratios) and (ii) *increase* their

¹⁰We choose to compare December 2014 to December 2015 to account for the seasonality in mortgage issuance (December is the most active month in the mortgage market). In Figure B.3 in the Appendix, we show the distribution of LTV and LTI in December 2014 and December 2015.

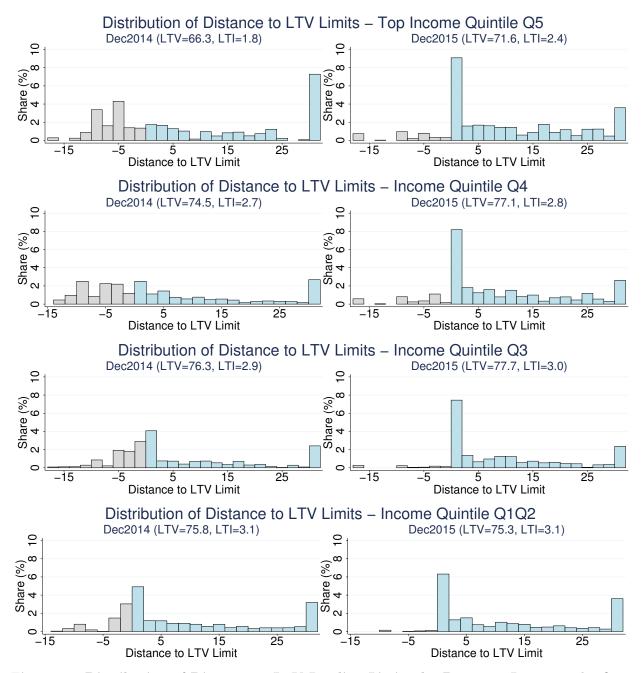


Figure 3: Distribution of Distance to LTV Lending Limits, by Borrower Income. This figure shows the distribution of the distance to the LTV lending limits. Each panel correspond to an income quintile. Income quintiles are adjusted every month for wage inflation. The bottom panel shows the distribution of the distance to the LTV limit. The left figures are the share of total mortgage issuance volume. The right panels are the share of total number of mortgages issued. Grey bars indicate non-conforming mortgages. Blue bars indicate conforming mortgages. Source: Central Bank of Ireland.

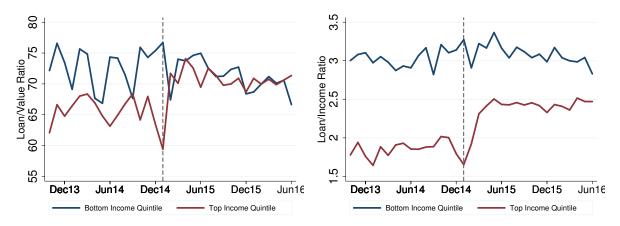


Figure 4: LTV and LTI, High and Low Income Households. This figure shows the time-series evolution of value weighted LTV (left) and LTI (right) of mortgages issued to low income (bottom income quintile, blue line) and high income (top income quintile, red line) households from October 2013 to June 2016. Income quintiles are adjusted every month for wage inflation. Source: Central Bank of Ireland.

LTI/LTV compared with low income borrowers after the policy implementation, narrowing the gap between the two groups.

We complement the non-parametric evidence above by estimating the following standard difference-in-differences specification:

$$MortgageRatio_{hct} = \alpha + \beta Post_t \times Q_h^{Income} + \mu_h + \eta_{ct} + \epsilon_{hct}$$
(1)

where we aggregate our loan-level data set in income buckets based on twenty percentiles obtained from the January 2014 income distribution.¹¹ Hence, our unit of observation is household income bucket h, county c, and month t. The sample period includes 24 months and runs from February 2014 to January 2016. The dependent variables are value weighted LTV and LTI. The independent variables are a vector of dummy variables Q equal to 1 for

¹¹We adjust our buckets at a monthly frequency for Irish wage inflation using data from the Organization for Economic Co-operation and Development (OECD). In Figure B.4, we show the evolution of the distribution of borrowers' income during our sample period.

a specific income quintile (Q1 for the first quintile, Q2 for the second quintile, etc.) and a *Post* time dummy equal to one during the 12-month period after the policy implementation, from February 2015 to January 2016.¹² Finally, we saturate the specification with county-time fixed effects to capture time-varying heterogeneity across counties (e.g., county-specific mortgage demand) and income bucket fixed effects to capture time-invariant heterogeneity across borrower income groups (e.g., income group-specific borrowing habit).

In Table 4, we show the estimation results. The dependent variables are LTV and LTI in the top and bottom panel, respectively. In columns (1)-(5), we include only one interaction term, therefore comparing one specific income quintile with the rest of the income distribution. In column (6), we include all interaction terms (omitting Q1 as our base category) to compare the last four quintiles with a common quintile. We find that the policy had an heterogeneous effect across the income distribution. Low-income (high-income) households reduced (increased) their LTV on newly issued mortgages after the regulation. In particular, the LTV of the top quintile of the income distribution *increased* by 4.4 points and the LTV of the bottom quintile *decreased* by 4.3 units compared with other quintiles, relative to the pre-period, respectively. Estimates in column (6) confirm the heterogeneous — and monotonic — effect of the policy. The effect on LTI is asymmetric as only borrowers in the top income quintile increase their LTI (by 19.1%) compared with other quintiles, relative to the pre-period. In sum, these results support the bank credit reallocation channel as high income households *increase* their LTV and LTI after the policy implementation. Moreover, the stronger results for the LTV are consistent with the LTV limit being more important for banks in terms of the volume of credit, compared to the LTI limit.

¹²During the post period, banks could have issued mortgages exceeding the lending limits if these mortgages were approved before February 9, 2015. The incidence of these mortgages goes progressively down during the post period.

Panel A			L	ΓV		
$Post \times Q1$	-4.340^{***} (0.935)					
Post \times Q2	~ /	-2.703^{***} (0.888)				1.344 (1.174)
Post \times Q3		()	0.739 (0.757)			4.035^{***} (0.883)
Post \times Q4			(0.101)	3.101^{***} (0.730)		(0.839)
Post \times Q5				(0.100)	$\begin{array}{c} 4.372^{***} \\ (1.339) \end{array}$	(0.005) 7.189*** (1.751)
County-Time FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Bucket FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Observations	7,289	7,289	7,289	7,289	7,289	7,289
R-squared	0.156	0.155	0.154	0.155	0.156	0.159
PANEL B			L	ΓI		
$Post \times Q1$	-0.084 (0.053)					
Post \times Q2	~ /	-0.008 (0.042)				0.061 (0.065)
Post \times Q3		()	-0.058 (0.041)			0.022 (0.055)
Post \times Q4			(0.011)	0.003 (0.041)		(0.000) (0.070) (0.061)
Post \times Q5				(0.011)	0.191^{***} (0.051)	(0.001) 0.229^{***} (0.067)
County-Time FE	\checkmark		\checkmark	√	(0.001)	(0.001)
Bucket FE	• √	↓	• •	↓	↓	↓
Observations	7,289	7,289	7,289	7,289	7,289	7,289
	0.472	0.472	• ,= = = =	0.472	0.473	.,==0

Table 4: Bank Credit Reallocation, Residential Mortgages. This table presents the results from specification (1). The sample period includes 24 months and runs monthly from February 2014 to January 2016. The unit of observation is county-month-income bucket. Income buckets are based on twenty percentiles obtained from the January 2014 income distribution and adjusted monthly for wage inflation using OECD data. The dependent variable is value weighted LTV in Panel A and value weighted LTI in Panel B. The variables Q1 to Q5 are dummy variables equal to one based on household income quintiles. All columns include county-time fixed effects and income bucket fixed effects. *Post* is a dummy equal to one from February 2015 to January 2016 (12-month period). Standard errors double clustered at the bucket-county and month level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

3.3 Bank Credit Reallocation

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

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

$$Exposure_{b} = \frac{\sum_{t=Feb14}^{Jan15} \text{Non-Conforming Mortgage Issuance}_{bt}}{\sum_{t=Feb14}^{Jan15} \text{Total Mortgage Issuance}_{bt}}$$
(2)

where the numerator is the sum of total non-conforming mortgages issued between February 2014 and January 2015 by bank b and the denominator is the sum, over the same period, of the entire mortgage issuance by bank b.

In Figure 5, we show the evolution of conforming mortgages issued by high exposure banks (exposure above median, blue line) and low exposure banks (exposure below the median, red line). The thin dashed lines show non-conforming mortgages, collapsing for both groups of banks after the policy implementation. During the year before February 2015, non-conforming mortgages represented 52.5% and 40.1% of total mortgage issuance for high exposure and low exposure banks, respectively.¹³ This figure documents that high exposure banks experience a greater drop in non-conforming mortgage issuance and a greater

 $^{^{13}}$ LTV-non-conforming mortgage issuance represented 43.5% and 28.6% of total issuance for high exposure and low exposure banks, respectively. LTI-non-conforming mortgage issuance represented 21.4% and 17.8% of total issuance for high exposure and low exposure banks, respectively.

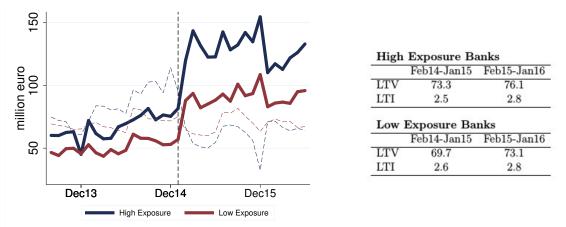


Figure 5: Residential Mortgage Credit Issuance, High- Vs. Low-Exposure Banks. The figure shows the issuance of conforming (solid thick lines) and non-conforming (dashed thin lines) mortgages for high-exposure (above median exposure) and low-exposure (below median exposure) banks from January 2013 to June 2016. The vertical line indicates the introduction of the lending limits. All time series are seasonally adjusted. The table on the right shows the average (value weighted) LTV and LTI of high- and low-exposure banks in the 12-month period before and after the introduction of the lending limits. Source: Central Bank of Ireland.

increase in conforming mortgage issuance compared with low exposure banks, relative to the pre-intervention period. The table on the right shows that both groups of banks were able to avoid reducing their LTI and LTV risk exposure after the introduction of the lending limits. In sum, the evidence suggests that more exposed banks increased their issuance of conforming mortgages to compensate their drop in non-conforming mortgages in February 2015.

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

$$Y_{bcht} = \alpha + \beta Post_t \times Exposure_b + \gamma X_{b,t-1} + \nu_b + \eta_{ct} + \epsilon_{bcht}$$
(3)

where our unit of observation is bank b, county c, household income bucket h, and month t. The sample period includes again 24 months and runs from February 2014 to January 2016. The key independent variable is the interaction term between a *Post* dummy equal to one from February 2015 to January 2016 and the bank-level *Exposure* variable defined in (2). We saturate the specification with county-time fixed effects to capture time-varying geographical heterogeneity (e.g., county-specific demand for credit), bank fixed effects to capture bank time-invariant heterogeneity (e.g., specialization in mortgage issuance), and lagged bank time-varying controls (logarithm of total assets, equity capital ratio, and loans/total assets).

Consistent with the previous subsection, we run our specification in subsamples based on borrower income quintiles. We show estimation results in Table 5 where each column corresponds to an income quintile. In Panel A and Panel B, the independent variables are LTV and LTI, respectively. We find that banks more exposed to the policy reduced their LTV and LTI compared with less exposed banks in income quintiles Q1 to Q4, consistent with the lending limits affecting exposed banks more. However, in the top income quintile (column (5)), more affected banks *increased* both their LTV and LTI compared with less exposed banks.¹⁴

In Panel C and Panel D, the independent variables are mortgage size and house value respectively. We find that the top income quintile buys more expensive properties and obtain larger loans compared with other quintiles after the policy. In Panel E, the independent variables is total mortgage issuance. We find a reduction in the bottom income quintile by more exposed banks compared with less exposed banks. Taken together, these results suggest that banks actively change the composition of their credit *in response* to the missing business caused by the regulation.¹⁵ Our results suggest that high income households borrow more aggressively and purchase more expensive properties to increase their LTI and LTI after the policy introduction.

¹⁴In Figure B.5 in the Appendix, we show non-parametric evidence consistent with exposed banks driving high income households LTV and LTI increase in the post-regulation period.

¹⁵In Table C.2 in the Appendix we show estimates from the triple interaction specification.

	anel A: LT	V
--	------------	---

Panel A: LI V					
Post X Exposure	-83.379***	-37.498***	-34.329***	-25.315^{**}	31.582**
	(10.964)	(9.474)	(11.267)	(10.207)	(12.659)
Observations	2,359	2,765	2,941	2,612	1,957
R-squared	0.349	0.241	0.266	0.238	0.318
Panel B: LTI					
Post X Exposure	-1.767**	-0.789***	-1.596^{***}	-2.372***	2.736***
	(0.821)	(0.232)	(0.406)	(0.373)	(0.709)
Observations	2,359	2,765	2,941	2,612	1,957
R-squared	0.357	0.364	0.431	0.449	0.577
Panel C: Loan Size					
Post X Exposure	-0.511*	-0.392***	-0.637**	-1.245***	1.437**
	(0.291)	(0.135)	(0.276)	(0.277)	(0.565)
Observations	2,359	2,765	2,941	2,612	1,957
R-squared	0.428	0.348	0.364	0.357	0.412
Panel D: House Value					
Post X Exposure	0.379	-0.224	-0.534***	-1.540***	1.892***
	(0.294)	(0.139)	(0.181)	(0.226)	(0.575)
Observations	2,313	2,729	2,886	2,563	1,891
R-squared	0.439	0.416	0.434	0.437	0.491
Panel E: Issuance					
Post X Exposure	-0.777**	-0.373	-0.425	-0.605	0.567
-	(0.382)	(0.228)	(0.425)	(0.454)	(0.532)
Observations	2,359	2,765	2,941	2,612	1,957
R-squared	0.490	0.497	0.583	0.589	0.652
Time-Varying Bank Controls	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Bank FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
County-Time FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Income Sample	Q1	Q2	Q3	Q4	Q5

Table 5: Bank Credit Reallocation, Residential Mortgages, Heterogeneity Across Households. This table shows regressions at the bank-county-income bucket level separately for each quintile of the income distribution. The dependent variables are the value-weighted LTV (Panel A), and the value-weighted LTI (Panel B), the logarithm of the average loan size to an income bucket (Panel C), the average house value (Panel D), and the logarithm of total mortgage volume (Panel E). *Exposure* is defined in (2), *Post* is a dummy equal to one from February 2015 to February 2016. Time-varying bank level controls include the logarithm of total assets, equity capital ratio, and the ratio of loans to total assets. All control variables are lagged by one period. Standard errors are double clustered at the bank-county and month level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Source: Central Bank of Ireland.

3.4 Effect on Mortgage Rates

In the last two sections we have shown (i) that high income households increase their LTV and LTI compared with low income households after the implementation of the lending limits and (ii) that this borrowing is mainly driven by banks more exposed to the regulation. In this section, we analyze mortgage rates and show that banks adjusted their pricing to induce high income borrowers to lever up.

Given that their LTV and LTI increase after the policy implementation, high income borrowers should, holding everything else equal, pay *higher* rates in the post-period. To control for this differential evolution of LTV and LTI across households, we define a dummy variable *High LTV/LTI* equal to one if a mortgage is above median in the LTV distribution and above the median in the LTI distribution, or non-conforming. We then estimate the following specification in each borrower income quintile:

$$Y_{rct} = \alpha + \beta Post_t \times HighLTV/LTI_r + \eta_{ct} + \mu_r + \epsilon_{rct}$$
(4)

where the unit of observation is county c, month t, and LTV/LTI bucket r (two buckets, high and low LTV/LTI) and the dependent variable is the mortgage rate. Again, the period runs from February 2014 to January 2016 with 12-month pre- and post-periods. We saturate the specification with county-time and LTV/LTI bucket fixed effects, therefore absorbing the uninteracted terms. We show estimation results in the top panel of Table 6 where every column corresponds to an income quintile. We find that (i) households in the top quintile of the income distribution were charged 12.5 basis points less and (ii) households in the first three quintile were charged between 11.5 and 14.8 basis points more than other households,

Panel A	Rate	Rate	Rate	Rate	Rate
Post \times High LTV/LTI	0.148***	0.115**	0.131***	0.010	-0.125*
	(0.045)	(0.046)	(0.035)	(0.058)	(0.064)
LTV/LTI Bucket FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
County-Time FE	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Observations	1,545	1,810	1,785	1,456	1,349
R-squared	0.458	0.548	0.561	0.483	0.460
Sample	Q1	Q2	Q3	Q4	Q5
Panel B	Rate	Rate	Rate	Rate	Rate
$\frac{\text{Panel B}}{\text{Exposure} \times \text{Post} \times \text{High LTV/LTI}}$	Rate 0.051	Rate 0.235	Rate 0.153	Rate 0.709	Rate -0.990***
	0.051	0.235	0.153	0.709	-0.990***
Exposure \times Post \times High LTV/LTI	0.051	0.235	0.153	0.709	-0.990***
$\begin{tabular}{lllllllllllllllllllllllllllllllllll$	0.051	0.235	0.153	0.709 (0.479)	-0.990***
$\begin{array}{c} \mbox{Exposure} \times \mbox{Post} \times \mbox{High LTV/LTI} \\ \mbox{Bank-Time FE} \\ \mbox{County-Time FE} \end{array}$	0.051	0.235	0.153	0.709 (0.479)	-0.990***
Exposure × Post × High LTV/LTI Bank-Time FE County-Time FE LTV/LTI Bucket-Time FE	$\begin{array}{c} 0.051 \\ (0.332) \\ \checkmark \\ \checkmark \\ \checkmark \\ \checkmark \end{array}$	$\begin{array}{c} 0.235\\ (0.290) \\ \checkmark \\ \checkmark \\ \checkmark \end{array}$	$\begin{array}{c} 0.153 \\ (0.241) \\ \checkmark \\ \checkmark \\ \checkmark \\ \checkmark \end{array}$	$\begin{array}{c} 0.709\\ (0.479) \end{array}$	-0.990^{***} (0.313) \checkmark \checkmark \checkmark

Table 6: Bank Credit Reallocation, Residential Mortgage Rates. This table shows estimation results from specifications (4) and (5) separately for each income quintile. Each column refers to an income quintile. The unit of observation is month-LTV/LTI bucket-county in Panel A and month-LTV/LTI bucket-county-bank in Panel B. The dependent variable is the mortgage rate. The dummy variable High LTV/LTI is equal to one if a mortgage is above median in the LTV/LTI. *Exposure* is defined in (2), *Post* is a dummy equal to one from February 2015 to February 2016. Standard errors double clustered at the county-LTV/LTI bucket and month (Panel A) and bank-county-LTI/LTI bucket and month (Panel B) level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Source: Central Bank of Ireland.

respectively.¹⁶

We then ask whether these findings are driven by banks ex-ante more exposed to the lending limits. To this end, we augment the specification above to exploit bank differential exposure to the regulation, mirroring specification (3). In particular, we estimate the

¹⁶Banks have several ways to influence the rates charged to clients, including offering more fixed or non-fixed rate mortgages.

following specification:

$$Y_{rbct} = \alpha + \beta Exposure_b \times Post_t \times HighLTV/LTI_r + \eta_{ct} + \mu_{bt} + \xi_{br} + \tau_{rt} + \epsilon_{rbct}$$
(5)

where the unit of observation is county c, month t, LTV/LTI bucket r, and bank b and the sample period is unchanged. We saturate the specification with stringent fixed effects that capture all uninteracted terms including bank-time fixed effects, county-time fixed effects, and LTV/LTI bucket-time fixed effects. In the bottom panel of Table 6, we show estimation results. We find that the lower rates charged to high income borrowers have been driven by exposed banks, consistent with these banks inducing high income borrowers to obtain larger loans and buy more expensive properties levering up to take advantage of the attractive mortgage rates.¹⁷

4 Effect on Other Asset Classes

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

4.1 Credit to Firms

We start by investigating whether banks change their credit supply to *firms* following the implementation of the mortgage lending limits. Given that the macroprudential regulation

¹⁷In Figure B.6 in the Appendix, we present non-parametric evidence consistent with these estimates.

is aimed at limiting risk taking in the real estate market, banks might take more risk in other types of private credit that are not targeted by the regulatory intervention.

To this end, we exploit the corporate loan-level data set collected by the Central Bank of Ireland. We adapt specification (3) and estimate the following specification:

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

We measure the credit provided by bank b to firms in county c, industry l, of quality q in period t, i.e., we group firms into clusters based on their county, industry, and quality at time t and investigate the lending behavior of banks to a cluster of firms (see Acharya et al. (2016)). Forming clusters based on county and industry is motivated by the fact that firms in a particular industry in a particular county share many characteristics and are thus likely affected in a similar way by macroeconomic developments that might influence credit demand. Forming clusters based on ratings follows the theoretical literature that shows that credit quality is an important driver for a firm's loan demand (e.g., Diamond (1991)).

Note that since we do not have a unique firm identifier across loans, we are unable to analyze credit extended to the same firm by different banks (Khwaja and Mian (2008)). To determine the quality of a firm that receives a loan, we use the ratings obtained by the Central Bank of Ireland.¹⁸ This ensures that the rating categories are homogeneous across banks and our results are not driven by different probabilities of default. More precisely, the Central Bank of Ireland employs a rating scale from 1 (best) to 6 (worst). We use these rating categories to divide firms into three quality buckets: high quality (rating 1-2), medium quality (rating 3-4), and low quality/high risk (rating 5-6).

¹⁸These ratings come from the banks' internal models but are homogenized by the Central Bank of Ireland by ensuring that the rating classes correspond to similar probabilities of default.

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

We show estimation results in Table 7. In Panel A and B the dependent variable is change in total volume of credit and change in interest rate charged, respectively. Column (1) considers the full sample of firms. The estimates document that banks more affected by the regulation increase their lending volume to corporate clients and decrease the price of corporate loans. This is consistent with a credit expansion in the corporate loan market in response to the new lending restrictions in the mortgage market.

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

This is confirmed in Column (4) 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 that the increase in loan volume is mostly driven by an increase towards risky borrowers. Similarly, we find that the decrease in the cost of bank loans is mostly benefiting risky borrowers (see Panel B of Table 7).

	Pane	l A: ΔVOL	UME	
	Total	Risky	NonRisky	Total
Exposure*Post	0.847***	2.027***	0.299^{*}	0.258
	(0.19)	(0.50)	(0.17)	(0.18)
Exposure*Post*Risky				1.993^{***}
				(0.42)
Exposure*Risky				-0.065
				(0.23)
Observations	10113	3157	6955	10113
R-squared	0.487	0.480	0.504	0.490
	Pa	nel B: ΔRA	TE	
	Total	Risky	NonRisky	Total
Exposure*Post	-0.660***	-1.625***	-0.191	-0.150
	(0.17)	(0.42)	(0.22)	(0.21)
Exposure*Post*Risky				-1.722***
				(0.48)
Exposure*Risky				0.122

				(0.30)
Observations	10113	3157	6955	10113
R-squared	0.474	0.510	0.458	0.475
Time-Varying Bank Controls	\checkmark	\checkmark	\checkmark	\checkmark
Industry-County-Quality-Time FE	\checkmark	\checkmark	\checkmark	\checkmark
Bank-County FE	\checkmark	\checkmark	\checkmark	\checkmark

Table 7: Bank Portfolio Reallocation, Credit to Firms. This table shows the estimation results of specification (6). The unit of observation is bank-industry-county-quality-time. The sample runs at a semi-annual frequency from 2013H1 to 2016H1. *Exposure* is defined in (2) and *Post* is a dummy equal to one from 2015H1 to 2016H1. A loan is classified as risky if the rating given by the Central Bank is either a 5 or worse. Standard errors clustered at the bank-county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Source: Central Bank of Ireland.

4.2 Security Holdings

Having shown that banks more exposed to the mortgage lending limits increase their supply of conforming mortgages and loans to risky firms compared with less affected banks, we now turn to analyze how banks adjust their holdings of securities in response to the macroprudential policy. In particular, we take advantage of security-level holdings data¹⁹ and examine whether banks changed their risk exposure in the security portfolio around the introduction of the mortgage lending limits. We measure the risk of securities using their yield. Following Davis and Haltiwanger (1992), we define the "net buys" of security s by bank i from time t - 1 to time t as follows:

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

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

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

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

$$\tag{8}$$

where the unit of observation is security-bank-quarter (s, b, t). Our dependent variable is defined in (7), and our independent variable of interest is a triple interaction term between bank exposure to the macroprudential policy as defined in (2), a *Post* dummy equal to one in the post period, and a measure of the risk of the security.²⁰

¹⁹We obtain data on all security holdings that have an International Securities Identification Number (ISIN). The sum of these holdings is mostly within 10% of the values in the banks' balance sheets which is reassuring regarding the coverage of the data.

 $^{^{20}}$ We measure the risk of the security using the yield of the respective securities. Information on yields are obtained from Thomson Reuters Datastream.

	Net Buys	Net Buys	Net Buys	Net Buys	Buys	Sells
Exposure×Post×Yield	0.0162**	0.0128^{*}	0.0436***	0.0509***	0.2251^{***}	-0.1757**
	(2.45)	(1.74)	(3.51)	(3.00)	(3.10)	(-2.16)
Time FE	\checkmark					
Security FE	\checkmark	\checkmark				
Bank-Time FE		\checkmark		\checkmark	\checkmark	\checkmark
Security-Time FE			\checkmark	\checkmark	\checkmark	\checkmark
Observations	8,034	8,034	8,034	8,034	8,034	8,034
R-squared	0.235	0.271	0.943	0.950	0.918	0.914

Table 8: Bank Portfolio Reallocation, Holdings of Securities. This table shows the estimation results from specification (8). The unit of observation is security-bank-quarter. The sample runs at a quarterly frequency from 2013Q1 to 2016Q2. The dependent variable is defined in (7). *Exposure* is defined in (2) and *Post* is a dummy equal to one from 2015Q2 onwards. Standard errors clustered at the security-level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Source: Central Bank of Ireland.

We saturate our specification with several fixed effects. In our most conservative estimation, we include bank-time fixed effects to capture any time-varying bank heterogeneity and, security-time fixed effects to capture eventual changes in price and amounts outstanding of specific securities.

We show estimation results in Table 8. We progressively saturate the regression with more and more stringent fixed effects. Column (4) includes all the pairs of two-way fixed effects. The coefficient of interest, stable across specifications, indicates more exposed banks increase their holdings of risky securities compared to less exposed banks in the post regulation period. Moreover, in Columns (5) and (6), we explicitly distinguish between the buying and selling behavior of banks. Buys are defined as the logarithm of the amount of security s bought by bank b at time t, and zero otherwise. Similarly, Sells are defined as the logarithm of the amount of security s sold by bank b at time t, and zero otherwise (see Abbassi et al. (2016)). We find that banks more exposed to the regulation both buy more and sell less high yield securities, relative to banks less affected by the regulation.

5 Conclusion

To be added...

References

- ABBASSI, P., R. IYER, J.-L. PEYDRÓ, AND F. R. TOUS (2016): "Securities trading by banks and credit supply: Micro-evidence from the crisis," *Journal of Financial Economics*, 121, 569–594.
- ACHARYA, V., I. DRECHSLER, AND P. SCHNABL (2014): "A pyrrhic victory? Bank bailouts and sovereign credit risk," *The Journal of Finance*, 69, 2689–2739.
- ACHARYA, V. V., T. EISERT, C. EUFINGER, AND C. W. HIRSCH (2016): "Real effects of the sovereign debt crisis in Europe: Evidence from syndicated loans," *CEPR Working Paper*.
- AIYAR, S., C. CALOMIRIS, AND T. WIELADEK (2014): "Does Macro-Pru Leak? Evidence from a UK Policy Experiment," *Journal of Money, Credit and Banking*, 46, 181–214.
- AUER, R. AND S. ONGENA (2016): "The Countercyclical Capital Buffer and the Composition of Bank Lending," *Working Paper*.
- AYYAGARI, M., T. BECK, AND M. S. MARTINEZ PERIA (2017): "Credit growth and macroprudential policies: preliminary evidence on the firm level," *Working Paper*.
- BEGENAU, J. (2016): "Capital Requirements, Risk Choice, and Liquidity Provision in a Business Cycle Model," *Working Paper*.
- CARPINELLI, L. AND M. CROSIGNANI (2017): "The Effect of Central Bank Liquidity Injections on Bank Credit Supply," *Working Paper*.
- CERUTTI, E. M., S. CLAESSENS, AND L. LAEVEN (2015): "The Use and Effectiveness of Macroprudential Policies; New Evidence," IMF Working Papers 15/61, International Monetary Fund.
- CHAKRABORTY, I., I. GOLDSTEIN, AND A. MACKINLAY (2016): "Housing Price Booms and Crowding-Out Effects in Bank Lending," *Working Paper*.
- CLAESSENS, S. (2015): "An Overview of Macroprudential Policy Tools," Annual Review of Financial Economics, 7, 397–422.

- CLAESSENS, S., S. R. GHOSH, AND R. MIHET (2013): "Macro-prudential policies to mitigate financial system vulnerabilities," *Journal of International Money and Finance*, 39, 153–185.
- DAVIS, S. AND J. C. HALTIWANGER (1992): "Gross Job Creation, Gross Job Destruction, and Employment Reallocation," *Quarterly Journal of Economics*, 107, 819–864.
- DIAMOND, D. W. (1991): "Monitoring and reputation: The choice between bank loans and directly placed debt," *Journal of Political Economy*, 99, 689–721.
- ELENEV, V., T. LANDVOIGT, AND S. VAN NIEUWERBURGH (2017): "A Macroeconomic Model with Financially Constrained Producers and Intermediaries," *Working Paper*.
- GROPP, R., T. C. MOSK, S. ONGENA, AND C. WIX (2016): "Bank Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment," *Working Paper*.
- HONOHAN, P. (2010): "The Irish Banking Crisis: Regulatory and Financial Stability Policy 2003-2008," Report of the commission of investigation into the banking sector in ireland, Central Bank of Ireland.
- HONOHAN, P. AND B. WALSH (2002): "Catching Up with the Leaders: The Irish Hare," *Brookings Papers on Economic Activity*, 33, 1–78.
- IGAN, D. AND H. KANG (2011): "Do loan-to-value and debt-to-income limits work? Evidence from Korea," .
- JIMENEZ, G., J.-L. PEYDRO, S. ONGENA, AND J. SAURINA (forthcoming): "Macroprudential Policy, Countercyclical Bank Capital Buffers and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments," *Journal of Political Economy*.
- KASHYAP, A. K., D. TSOMOCOS, AND A. VARDOULAKIS (2014): "How Does Macroprudential Regulation Change Bank Credit Supply?" *Working Paper*.
- KHWAJA, A. AND A. MIAN (2008): "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, 98, 1413–1442.
- KINGHAN, C., Y. MCCARTHY, AND C. O'TOOLE (2017): "Macroprudential Policy and Borrower Behaviour: How Do Limits on Loan-to-Value and Loan-to-Income Ratios Impact Borrower Leverage and House Purchasing Decisions?" *Working Paper*.
- LANE, P. R. (2011): "The Irish Crisis," Cepr discussion papers.
- MICHELANGELI, V. AND E. SETTE (2016): "How Does Bank Capital Affect the Supply of Mortgages? Evidence from a Randomized Experiment," *Working Paper*.

PEYDRO, J. L., A. POLO, AND S. ENRICO (2017): "Monetary Policy at Work: Security and Credit Application Registers Evidence," *Working Paper*.

Appendix A Data Sources

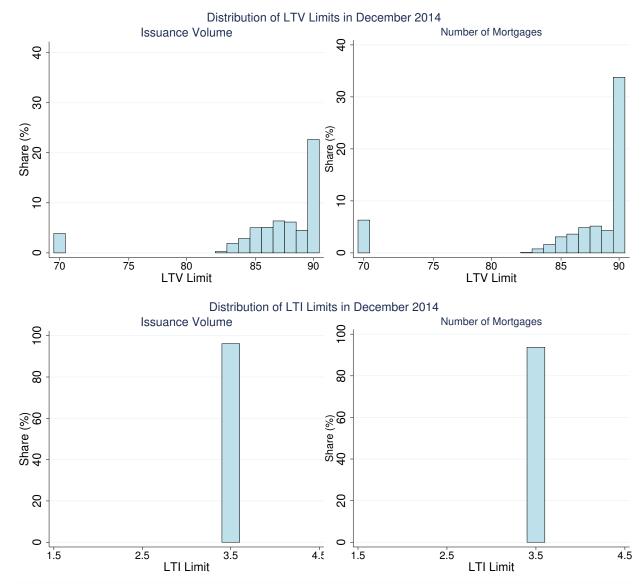
- Data on Lending including loan and borrower characteristics
 - Data on mortgages in Ireland and abroad:
 - * up to Jan 2015: Loan Level Data from the Central Bank of Ireland (Financial Stability Division)
 - * Jan 2015 June 2016: Monitoring Templates from the Central Bank of Ireland (Financial Stability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

The loan specific characteristics include

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

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

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



Appendix B Additional Figures

Figure B.1: Distribution of Lending Limits. This figure shows the distribution of the lending limits in December 2014. The top panel shows the distribution of LTV limits. The bottom panel shows the distribution of LTI limits. The left figures are the share of total mortgage issuance volume. The right panels are the share of total number of mortgages issued. In the bottom panel, the shares do not sum to one as buy-to-let mortgages are exempt from the LTI limit. Source: Central Bank of Ireland.

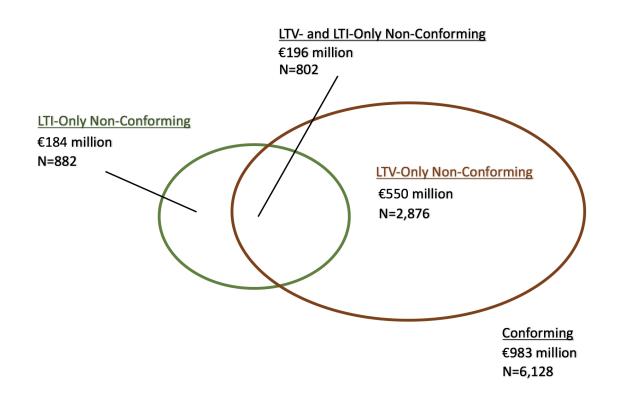


Figure B.2: Lending Limits and Pre-Policy Mortgage Issuance. This scheme provides a stylized view of how many residential mortgages are affected by the lending limits. Volumes (euro million) and number of loans refer to the 12-month period before the policy implementation. *Source: Central Bank of Ireland.*

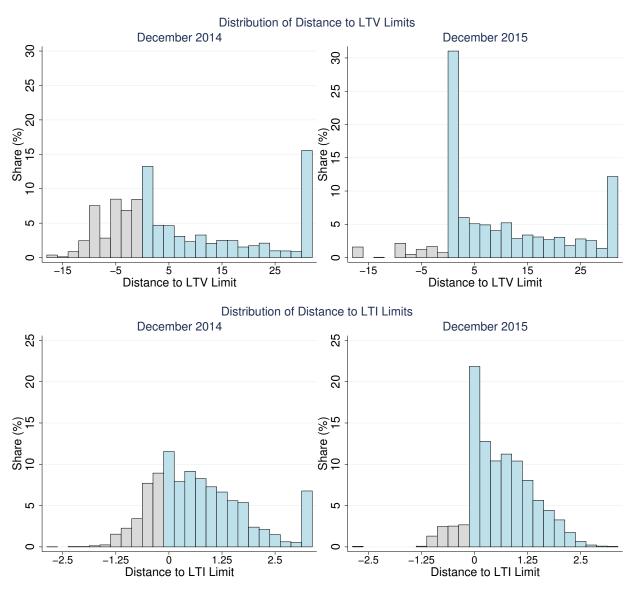


Figure B.3: Distribution of Distance to Lending Limits. This figure shows the distribution of the distance to the lending limits. The top panel shows the distribution of the distance to the LTV limits. The bottom panel shows the distribution of the distance to the LTI limit. The left figures are the share of total mortgage issuance volume. The right panels are the share of total number of mortgages issued. Grey bars indicate non-conforming mortgages. Blue bars indicate conforming mortgages. Source: Central Bank of Ireland.

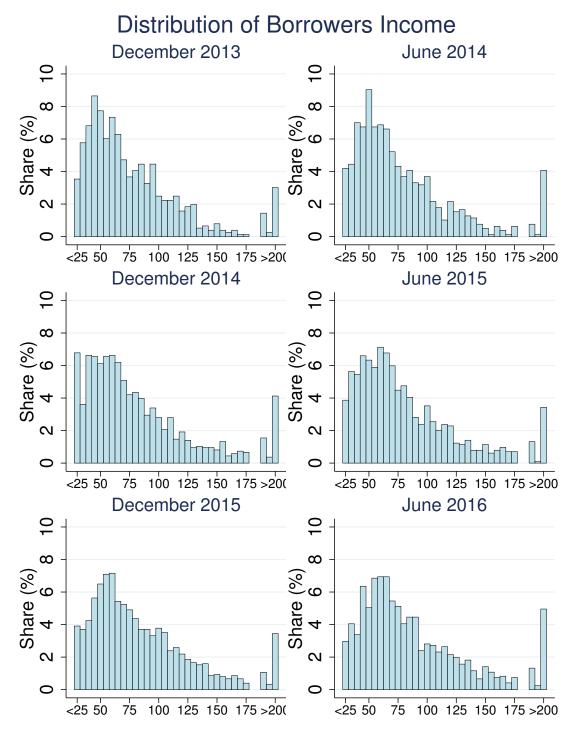


Figure B.4: Evolution of Distribution of Borrowers' Income. This map shows the evolution of the distribution of borrowers' income at a semi-annual frequency from December 2013 to June 2016. We group households that receive a mortgage at time t in buckets of $\leq 5,000$ from $\leq 25,000$ to $\leq 200,000$ on the x-axis. The y-axis shows the share of total issuance at time t in each bucket. Source: Central Bank of Ireland.

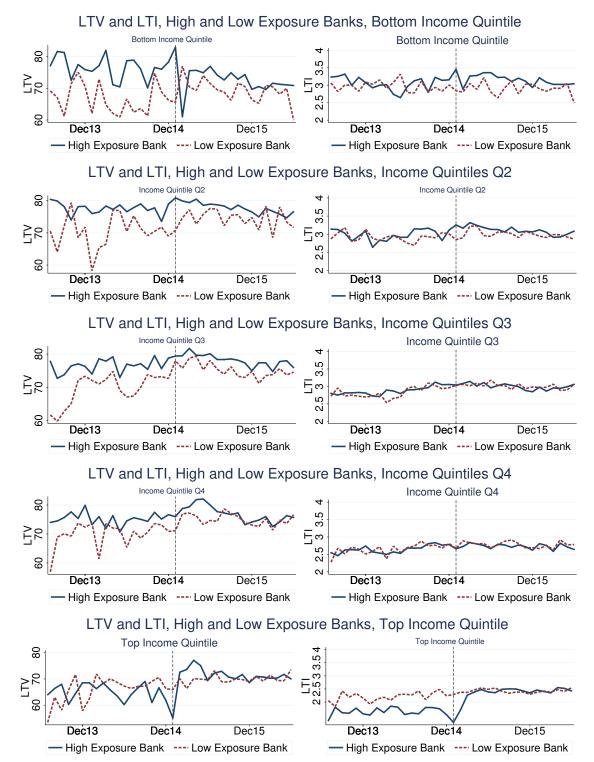


Figure B.5: LTV and LTI, High and Low Exposure Banks, Across the Income Distribution. This figure shows the evolution of LTV (left) and LTI (right) of mortgage issuance by high-exposure (solid line) and low-exposure (dashed line) banks from July 2013 to June 2016. Each row corresponds to a subsample based on income quintiles, obtained from the January 2014 income distribution and adjusted monthly for Irish wage inflation. Source: Central Bank of Ireland.

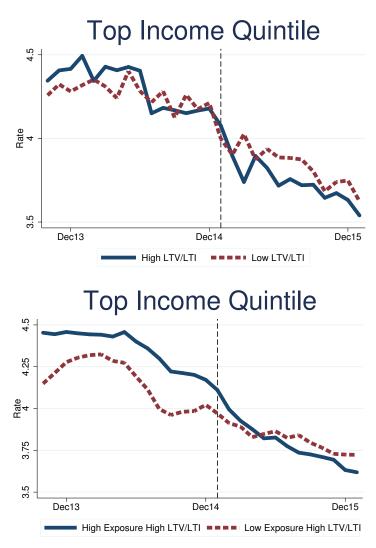


Figure B.6: Mortgage Rates, Top Income Quintile Borrowers. This figure shows the evolution of rates for the top income quintile of borrowers. The top panel shows the evolution of mortgage rates for High LTV/LTI and Low LTV/LTI mortgages. The bottom panel shows the evolution of mortgage rates for High LTV/LTI mortgages by high exposure and low exposure banks. A bank has a high exposure (low exposure) if its exposure calculated using (2) is above (below) median. A mortgage is High LTV/LTI if its either non-conforming, above median of the LTV distribution, or above median of the LTI distribution. Source: Central Bank of Ireland.

Appendix C Additional Tables

Statistics	\mathbf{Unit}	Dec12	Dec13	Dec14	Dec15
Exposed Banks					
Total Assets	million euro	$138,\!376$	126,798	116,752	109,122
Leverage	Units	16.7	19.1	19.2	18.1
Domestic Govt Bonds	% Assets	4.3	6.3	6.2	6.4
Liquid Assets	% Assets	31.7	33.4	32.9	32.5
Loans	% Assets	54.4	55.5	58.2	59.5
Non-Exposed Banks					
Total Assets	million euro	44,825	40,792	$34,\!644$	$28,\!194$
Leverage	Units	37.4	26.6	29.6	30.0
Domestic Govt Bonds	% Assets	0.7	3.2	3.5	4.3
Liquid Assets	% Assets	27.7	36.4	44.1	48.0
Loans	% Assets	62.9	47.2	46.2	48.5

Table C.1: Summary Statistics, Exposed and Non-Exposed Banks. This table shows summary statistics (cross-sectional means) for the subsample of high exposure and low exposure banks. A bank has high (low) exposure if its exposure calculated using (2) is above (below) median. Source: Central Bank of Ireland.

on loan-to-value and loan-to-income ratios impact borrower leverage and house purchasing decisions?

	T.m/	Total Volume)	me)	, u	I'm Avo Loan Size	20		-			-	
Post X Q2 X Exposure		0.840^{*}	0.817*	0.477*	0.473*	0.442	67.106^{***}	64.181***	66.866***	1.233^{*}	1.176^{*}	1.121
	(0.413)	(0.412)	(0.414)	(0.271)	(0.273)	(0.275)	(13.935)	(13.858)	(14.293)	(0.654)	(0.660)	(0.656)
Post X Q3 X Exposure	0.383	0.358	0.308	0.037	0.010	-0.008	55.547^{***}	51.399^{***}	50.527***	0.101	-0.019	-0.001
	(0.548)	(0.556)	(0.564)	(0.286)	(0.295)	(0.300)	(13.089)	(13.232)	(13.110)	(0.643)	(0.652)	(0.655)
Post X Q4 X Exposure	0.448	0.405	0.372	-0.455	-0.508	-0.546^{*}	70.411^{***}	63.138^{***}	64.121^{***}	-0.552	-0.729	-0.728
	(0.418)	(0.429)	(0.450)	(0.295)	(0.304)	(0.309)	(14.690)	(14.512)	(15.080)	(0.556)	(0.574)	(0.588)
Post X Q5 X Exposure	1.344^{**}	1.347^{**}	1.137^{*}	2.055^{***}	2.047^{***}	1.662^{***}	127.467^{***}	121.969^{***}	113.561^{***}	3.940^{***}	3.870^{***}	3.391^{***}
	(0.574)	(0.588)	(0.609)	(0.556)	(0.560)	(0.510)	(16.039)	(15.742)	(14.955)	(1.133)	(1.131)	(1.024)
Q2 X Exposure	0.020	0.061	0.081	-0.014	0.012	0.033	-61.083^{***}	-58.547^{***}	-59.973^{***}	-1.126^{**}	-1.052^{**}	-0.981*
	(0.413)	(0.414)	(0.417)	(0.154)	(0.159)	(0.161)	(11.572)	(11.535)	(11.946)	(0.489)	(0.498)	(0.481)
Q3 X Exposure	0.612	0.643	0.669	0.247	0.273	0.283	-67.846***	-64.470^{***}	-64.527***	-0.426	-0.341	-0.331
	(0.486)	(0.489)	(0.497)	(0.225)	(0.232)	(0.237)	(9.892)	(9.898)	(9.690)	(0.556)	(0.563)	(0.559)
Q4 X Exposure	0.291	0.305	0.304	0.850^{***}	0.883^{***}	0.871^{***}	-72.738***	-68.834***	-70.507***	0.048	0.161	0.156
	(0.362)	(0.371)	(0.390)	(0.185)	(0.192)	(0.200)	(14.228)	(13.910)	(14.248)	(0.434)	(0.442)	(0.434)
Q5 X Exposure	-1.940^{**}	-1.960**	-1.817**	-2.728***	-2.737***	-2.342***	-133.915^{***}	-130.896^{***}	-124.585^{***}	-4.892***	-4.867***	-4.307***
	(0.753)	(0.766)	(0.788)	(0.563)	(0.566)	(0.535)	(14.175)	(13.938)	(13.636)	(0.980)	(0.974)	(0.910)
Post X Exposure	-0.587			-0.619^{**}			-77.556***			-1.755**		
	(0.452)			(0.226)			(9.124)			(0.630)		
Post X Q2	-0.426**	-0.412^{**}		-0.237*	-0.236^{*}		-29.862^{***}	-28.341^{***}		-0.513	-0.488	
	(0.192)	(0.191)		(0.123)	(0.124)		(7.028)	(7.013)		(0.304)	(0.307)	
Post X Q3	-0.187	-0.179		-0.047	-0.036		-21.940^{***}	-19.692^{***}		0.012	0.070	
	(0.261)	(0.265)		(0.137)	(0.142)		(6.536)	(6.628)		(0.315)	(0.320)	
Post X Q4	-0.269	-0.252		0.121	0.146		-28.034^{***}	-24.207^{***}		0.302	0.389	
	(0.204)	(0.212)		(0.138)	(0.143)		(7.076)	(600.2)		(0.273)	(0.283)	
Post X Q_5	-0.675**	-0.685**		-0.975^{***}	-0.972***		-53.237^{***}	-50.424^{***}		-1.648^{***}	-1.615^{***}	
	(0.266)	(0.272)		(0.247)	(0.248)		(7.883)	(7.710)		(0.515)	(0.515)	
Time-Varying Bank Controls	>			>			>			>		
County-Time FE	>	>	>	>	>	>	>	>	>	>	>	>
Bank FE	>			>			>			>		
Bucket FE	>	>		>	>		>	>		>	>	
Bank-Time FE		>	>		>	>		>	>		>	>
Bucket-Time FE			>			>			>			>
Observations	13, 135	13, 135	13, 135	13, 135	13, 135	13, 135	13, 135	13, 135	13, 135	13, 135	13, 135	13, 135
R-squared	0.564	0.568	0.584	0.442	0.447	0.471	0.137	0.148	0.180	0.409	0.416	0.439
Table C.2: Bank Credit Reallocation, Residential Mortgages. This table shows the estimation results of a triple difference-	sdit Rea	allocati	ion, Re	sidentia	Mortg	ages. Tł	nis table sh	nows the es	timation re	esults of a	a triple d	ifference-

equal to one from February 2015 to January 2016, and a borrower income quintile dummy equal to one for one specific borrower income quintile. The dependent variable is logarithm of total volume in columns (1)-(3), logarithm of average loan size in columns (4)-(6), value weighted LTV in columns (7)-(9), and value weighted LTI in columns (10)-(12). Standard errors clustered at the bank-county-cluster and time in parentheses. Source: Central Bank of Ireland. 3 (() 2 Ė.