Specialising in risky mortgages: unintended consequences of Basel II

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ABSTRACT

Since Basel II was introduced in 2008, two approaches to calculating bank capital requirements have co-existed: banks' internal models, and a less risk-sensitive standardised approach. Using a unique dataset for the UK mortgage market, 2005-2015, and novel identification, we provide the first empirical evidence that this leads smaller lenders to specialise in higher risk lending, leading to systemic concentration of risk. Adopting internal model leads to reduced interest rates for lower-risk loans, and a corresponding portfolio shift. A 1pp reduction in risk weights causes a 1.3bp reduction in interest rates. Our results are relevant to live policy debates.

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One of the dilemmas for bank regulation is how to link capital requirements to risk. The first Basel agreement (1988) used simple risk metrics, known as risk weights, set by regulators. To link capital more closely to banks own risk estimates, the Basel II agreement (2004) allowed banks to use their internal risk models to set risk weights. More recently, concerns about pro-cyclicality and variability in risk weights derived from internal models have led to proposals, such as the leverage ratio, that would reduce the link between internal models and capital. Internal models are costly to set up and manage, and while most of the largest banks have adopted them, smaller banks tend to rely on the simple metrics set by regulators. As a result, different approaches to measure risk, and set risk weights, can co-exist in the same market. These differences can affect how lenders compete against each other, and which risks they take, as they specialise in the assets for which regulation gives them a comparative advantage (Repullo and Suarez (2004)).

In this paper we test the effect on specialisation of differences in risk weight methodology. To do so, we build on recent advances in the empirical literature that uses loan-level data and exploits borrower risk heterogeneity to test the impact of risk-based bank regulation (Behn, Haselmann, and Wachtel (2015)). We rely on granular data for the UK mortgage market and develop a novel empirical strategy to identify the effect of differences in risk weights on pricing. We find evidence that the introduction of internal models has led to increased specialisation and concentration of risk in the UK mortgage market. We also estimate a pass-through rate of changes in risk-based capital requirements to prices. We find that over the period 2009-2015 a 1 percentage point change in risk weights led to a 1.3 basis point change in mortgage rates.

To conduct our analysis, we construct a unique dataset that combines prices, borrower characteristics and risk weights for about 13 million mortgages originated in the UK between 2005 and 2015. Risk is captured in capital requirements through risk weights, and we have detailed information on risk weights by loan-to-value (LTV) and lender. LTVs are a main indicator of credit risk in the UK mortgage market, and mortgages are typically priced by LTV band. The Product Sales Database (PSD) covers all owner-occupied residential mortgages issued in the UK since the second quarter of 2005. It includes information on rates at origination, and on a number of loan and borrower characteristics. The PSD has already been used in studies of the UK mortgage market (Best, Cloyne, Ilzetzki, and Kleven (2015),Uluc and Wieladek (2015)). We match PSD data with a unique dataset of historical risk weights by LTV band for owner-occupied residential mortgages during 2005-2015.

We develop two identification strategies, that exploit some regulatory changes following the introduction of Basel II. Up to end 2007, under Basel I, risk weights were 50% on all mortgages issued by banks and building societies [1]. Since January 2008, following the introduction of the Basel II framework, banks and building societies can calculate risk weights using one of two approaches. Under the standardised approach (SA), the risk weights for different types of loans are given by

[1] With the exception of four firms that moved to foundation IRB during 2007. In the advanced IRB, the firm estimates probabilities of default, loss-given-default, exposure-at-default, and the maturity of the loan. In the foundation IRB approach the firm estimates only the probabilities of default.

the regulator [2]. Under the internal-ratings based (IRB) approach, firms can use their own internal models to calculate risk weights. To adopt IRB models, firms need to satisfy the PRA that they have sufficient data, modelling experience and governance controls to estimate their credit risk accurately. All the largest firms have adopted IRB models, but the majority of lenders has not and uses the standardised approach. As a result, IRB firms issued 83% of the mortgages [in the year to Q2 2015], while SA firms issued 12% of the mortgages (the remaining 5% were by other lenders).

Our identification strategy exploits the variation in risk weights following the introduction of the internal models. We perform two main tests of specialisation. The first test focuses on the change in regulatory regime for risk weights brought by Basel II, and its impact on average risk weights for two groups of lenders: those that have adopted IRB models and those that haven't and use the standardised approach. The second test exploits the information on historical risk weights in our database, which captures differences in risk weights across lenders and LTV bands in the period 2009-2015.

Risk weights based on IRB models tend to be lower than those based on the standardised approach, and the gap is larger for lower-LTV (and thus typically less risky) mortgages. In 2015, the gap between the average risk weight using IRB, compared to the standardised approach, was about 30 percentage points for LTV below 50% and less than 15 percentage points for LTV above 80%. We expect banks and building societies that adopt IRB models to specialise in low-LTV mortgages, where their advantage against other lenders is larger in terms of risk weights. We test whether the introduction of Basel II has led to specialisation, using a triple difference approach. We take the price difference between IRB adopters and other lenders (first difference), and compare the changes after 2008 (second difference) for low- vs high LTV mortgages (third difference). In particular, we expect that lenders that adopt IRB models: i) reduce their relative price (compared to other lenders) for low-LTV more than for high-LTV mortgages; ii) increase the share of high-LTV mortgages in their portfolio (compared to other lenders).

We find that lenders that adopted IRB models after 2008: i) reduced relative prices for low-LTV mortgages of by about 31 basis points; ii) increased the relative portfolio share of low-LTV mortgages increased by an additional 12 percentage points. These are differential effects, after the remove the dynamics for high-LTV mortgages. We interpret these results as evidence that lenders that adopt IRB models specialise in low-LTV mortgage to exploit their advantage in terms of risk weights.

Our first test only compares average risk weights and prices at an aggregate level for two groups of firms, those that adopted IRB and the others. But if differences in how regulatory risk weights are calculated lead to specialisation, we should observe correlation between risk weights and mortgage prices also at disaggregated loan level. Our second test uses historical information, which has never been used before, on risk weights by LTV band for lenders that have adopted IRB models.To control for other factors we include pairwise-interacted fixed effects for lender-LTV, time-LTV and

[2]For residential mortgages, the risk-weight is 35% on all balances for LTV 80% and 75% on balances above 80% LTV. LTV = loan-to-value ratio, and gives the amount of the loan as a proportion of the total value of the home.

lender-time. We also include a number of borrower and loan characteristics from PSD.

We estimate that, over 2009-15, a 1 percentage point change in risk weights led to a 1.3 basis point change in mortgage rates. For a typical 30 percentage point gap at LTV ratios below 50%, this corresponds to a price advantage of about 40 basis points.

Our paper contributes to three main strands of literature. First, our analysis complements the growing literature trying to assess the appropriateness of new macro-prudential regulations, by looking at the impact of risk-based capital requirements (Admati and Hellwig (2014); Acharya, Engle, and Pierret (2014)). Our work is mostly related to two recent studies that study empirically the effect of IRB models on the cyclicality of lending (Behn et al. (2015)) and its quantity and composition (Behn, Haselmann, and Vig (2014)). Both these papers develop an identification strategy focusing on within firm variation across banks, a la Khwaja and Mian (2008), and exploite the staggered introduction of IRB over time by German banks. They focus on lending to SMEs and show that banks that use internal models react more strongly to credit shocks. They also provide evidence that the impact on lending is larger for higher risk borrowers, which can be seen as consistent with the specialisation hypothesis. Compared to them, our contribution differs in terms of the policy [theoretical] question that we explore, and the identification strategy. We develop a new identification strategy, which takes advantage of the variation coming from the new regulation on different lenders and products and does not rely on multiple borrowing relations to control for demand. Moreover, we exploit both the variation at the time of the regulatory change and ongoing variation during the new regime from actual changes in risk-weights. In this way we avoid confounding effects coming from the global financial crisis and increase the external validity of our results.

Second, our work is related to the vast literature on how banks pass on to their customers costs arising from monetary and (macro) prudential policies. These estimates are based on aggregated data at industry (eg banking), sector (eg mortgages) or firm-level (Gambacorta (2008), Brooke, Bush, Edwards, Ellis, Francis, Harimohan, Neiss, and Siegert (2015), Michelangeli and Sette (2016), Cohen and Scatigna (2015)) and typically have to assume that the products are homogenous at the relevant level. However, credit risk is borrower-specific, and variation in lending volumes or prices at aggregated level can mask changes in the distribution of risk (and average risk) (Kashyap and Stein (2000); Jiménez, Ongena, Peydró, and Saurina (2014); Behn et al. (2015)). We allow for heterogeneity in risk exploting loan-level information and we build on these recent studies using micro-data, by focusing on the impact of regulation on banks price setting behaviour (Neumark and Sharpe (1992); De Graeve, De Jonghe, and Vander Vennet (2007)). We estimate a pass-through coefficient of the effect of risk weights on prices, which play a central role for the allocation of credit and has despite that received less attention(Gambacorta and Mistrulli, 2014).

In our paper we also test, to our knowledge for the first time, the specialisation mechanism first identified by Repullo and Suarez (2004) [34]. Specialisation can be seen as a structural effect of the introduction of internal models (as opposed to the pro-cyclical aspects of models tested by BHW). Specialisation arises simply from the co-existence of two different approaches to measuring risk, and setting risk-based capital requirements, for the same asset/risk. We do not provide evidence on the effectiveness of either approach, in terms of capturing risk and affecting firm behaviour. There is already an extended literature, eg. under-reporting of risk when models are used (Behn et al. (2014), Mariathasan and Merrouche (2014), BCBS) and risk arbitrage when regulators set standard risk weights (Acharya, Schnabl, and Suarez (2013), Acharya and Steffen (2015)). To test specialisation we develop a new identification strategy that is suitable for mortgage lending. The literature that uses loan-level information to control for risk heterogeneity relies on multiple banking relationships for the same borrower and hence focus on SME/corporate lending (as in (Jiménez et al., 2014; Behn et al., 2015)). This approach cannot be extended to the mortgage market, where households only borrow from one lender at a time. As explained above, our identification strategies rely on a triple difference and on disaggregated risk weight data at LTV band-lender level.

The rest of the paper is organized as follows. Section I describes the setting and the data; section II explains the identification strategy and section III presents our results and robustness checks. Section IV concludes.

I. Setting and data

A. Background

Under the 'Pillar 1' aspect of the Basel Accords (as implemented in the EU under the Capital Requirement Regulations) banks have to meet capital adequacy requirements, which are expressed as a percentage of risk-weighted assets (RWAs).[5] Banks are required to hold capital resources of at least 8% of RWAs. Risk-weighted assets are obtained by multiplying the value of each asset on the bank's balance sheet by a ratio (i.e. a risk weight) that reflects the relative riskiness of the asset. High risk assets are assigned high risk weights; this can reflect credit risk, market risk, or operational risk. Typically, credit risk - the risk of losses arising from a borrower or counterparty failing to meet its obligations to pay as they fall due – represents by far the largest component in firms' RWA bases.

The approach to measuring credit risk has evolved over time. In 1988, the Basel I Accord established minimum levels of capital for internationally active banks, incorporating off-balance-sheet exposures and a risk-weighting system which aimed (in part) not to deter banks from holding low risk assets. However, since risk weights varied only by asset class – for example, all residential

[3]See also Rime (2005), Fees and Hege 2007, Ruthenberg and Landskroner (2008),Gropp, Hakenes, and Schnabel (2011).

[4]Basten and Koch (2015) do not find any effect of risk weights on pricing following an increase in regulatory capital (application of countercyclical capital buffers)but they don't use data from IRB firms so they can't test specialisation (and limited variation in risk weights). Swiss data (online mortgage applications)[Sette].

[5]Comprising a minimum of 6% Tier 1 capital (made up of a minimum of 4.5% Common Equity Tier 1 capital and 1.5% Additional Tier 1 capital) and 2% Tier 2 capital.

mortgages had a risk weight of 50%[6] – the Basel Committee on Banking Supervision came to the conclusion that degrees of credit risk exposure were not sufficiently calibrated as to adequately differentiate between borrowers' differing default risks. This in turn raised concerns about regulatory arbitrage through securitisation, or a shift in banks' portfolio concentrations to lower quality assets.[7]

Accordingly, in 2004 Basel II agreed a new capital adequacy framework aimed at increasing risk sensitivity by allowing banks to use internal risk-based (IRB) models to calculate capital requirements; these models being subject to explicit supervisory approval to ensure their integrity. Those firms lacking the (financial and data-related) resources needed to obtain approval for IRB models must instead adopt a standardised approach (SA) where risk weights are set in a homogenous manner across banks. Risk weights under the SA are set based on external credit assessments. For claims secured by residential property, the risk weight was reduced from a flat 50% to a range roughly between 35% and 45% based on the LTV ratio of the loan.[8]

Under Basel II, national supervisors are required to assess those risks either not adequately covered (or not covered at all) under Pillar 1, as well as seeking to ensure that firms can continue to meet their minimum capital requirements throughout a stress event. Under this supervisory review of capital adequacy (labelled 'Pillar 2'), national supervisors must impose additional minimum requirements to capture any uncovered risks, as well as setting capital buffers which may be drawn down by distressed banks.

In the aftermath of the Great Financial Crisis, Basel III[9] not only increased Pillar 1 minimum requirements as outlined above,[10] but also introduced a capital conservation buffer above the regulatory minimum requirement calibrated at 2.5% of RWAs. [11] Moreover, a non-risk-based leverage ratio (LR) of at least 3% of Tier 1 capital was introduced, in order to serve as a backstop to the risk-based capital adequacy framework. The calibration of the LR entails that this becomes the binding constraint where the average risk weight across the bank is below approximately 35%.[12].

While the main prudential concern regarding the use of IRB models is that they yield excessive variability in the capital requirements for credit risk,[13] the key issue from a competition angle is

[6] Basel Committee on Banking Regulation and Supervisory Practices, Outcome of the consultative process on proposals for international convergence of capital measurement and capital standards para. 1988, 6(iv), available at `http://www.bis.org/publ/bcbs04b.pdf`.

[7] Basel Committee on Banking Supervision, A New Capital Adequacy Framework, 1999, paras 4-8, available at `http://www.bis.org/publ/bcbs50.pdf`.

[8] Basel Committee on Banking Supervision, International Convergence of Capital Measurement and Capital Standards, 2004, para. 72, available at `http://www.bis.org/publ/bcbs107.pdf`.

[9] See Bank for International Settlements, Group of Governors and Heads of Supervision announces higher global minimum capital standards, September 2010, available at `http://www.bis.org/publ/p100912.htm`.

[10] The quality standards setting out what types of capital instruments are acceptable were also increased.

[11] A countercyclical buffer within a range of 0% - 2.5% of common equity or other fully loss absorbing capital was also introduced. The purpose of the countercyclical buffer is to achieve the broader macroprudential goal of protecting the banking sector from periods of excess aggregate credit growth.

[12] On top of all this, it was also agreed that large banks deemed to be systemically important would have to hold loss absorbing capacity beyond these new standards.

[13] See Basel Committee on Banking Supervision, Reducing variation in credit risk-weighted assets - constraints on the use of internal model approaches, 2016, available at `http://www.bis.org/bcbs/publ/d362.pdf`.

that firms under IRB can undercut prices set by rivals under SA thanks to materially lower risk weights for asset classes with similar risk profiles. This has proven to be particularly the case for residential mortgages, especially at low LTV ratios, as concluded by the UK Competition and Markets Authority in April 2016 as part of its market inquiry into retail banking [14].

B. *Data and summary statistics*

For our analysis we combine a number of different data sources. Our dataset is built around the Financial Conduct Authority's Product Sales Database (PSD). This dataset contains the entire population of owner-occupied mortgage sales in the UK. Beginning in 2005, regulated lenders have had to submit data on all mortgage originations, including detailed information on loan, borrower and property characteristics.

In our analysis we exploit loan-level information about the interest rate, the LTV ratio, the repayment structure and term, and the lender issuing the mortgage. In this way we capture the main characteristics that define a product in the UK mortgage market. The LTV ratio broadly captures the risk associated with the mortgage, but we augment this by including a range of borrower controls to better account for risk factors that may affect pricing. We include borrower age, loan-to-income (LTI), whether or not a borrower has an impaired credit history, whether the income of the borrowers has been verified, and whether the application is based on individual or joint income. We also add information on the location of the property using postal codes.

We complement the PSD data with a unique set of survey data covering detailed information on lenders' risk-weights. For firms using IRB models, we use information provided by firms in January 2016 to the Competition and Markets Authority (CMA) and the Prudential Regulatory Authority (PRA) on historical risk weights. The risk weight data are provided on an annual basis for the period 2008-2015, and stratified by LTV band. For firms using the standardised approach, and for all firms under Basel I (pre-2008), we calculate the risk weights based on the regulatory regime. During Basel I the risk-weight was at 50% on all mortgages. During Basel II, SA lenders have a 35% risk-weight for mortgages below 80% LTV; 75% RW for the proportion above 80% LTV.

The IRB risk weight data from the collection referred to above reflect each bank's entire book of mortgages in the relevant period. These are the risk weights that firms used to calculate capital requirements at that point in time. Implicitly, we are assuming that firms use risk weights on their current book to forecast the risk weights that will apply in the future on the mortgages that they are currently originating. This is like to be a reasonable approximation; it is also a practical one, as it would have been difficult to obtain estimates of risk weights at origination.

Table I summarises the key variables we use in our analysis. We report summary statistics both for the full sample as well as the two subsamples that we use in our analyses. Our use of

[14] See Competition and Markets Authority, Addendum to provisional findings - The capital requirements regulatory regime, 2016, paras 76-79, available at `https://assets.publishing.service.gov.uk/media/5710dc73ed915d117a00006d/addendum-to-provisional-findings-with-appendices.pdf`.

the subsamples reflects missing data on key variables, including interest rates and risk weights.[15] Column (1) contains statistics for the full sample which we use to compute portfolio shares. This sample contains PSD data from banks and building societies only, which represent approximately 90% of the UK market.[16] In Column (2) we report the statistics of the sample we use to estimate the triple-difference model, which takes the interest rate as the dependent variable. The loss of observations is due to missing interest rate data. From a comparison of column (1) and (2) we see that characteristics of the main variables do not appear to be materially different, thus lowering selection bias concerns. Finally column (3) shows the smallest dataset that we use to estimate the risk weights pass-thorugh model. The further reduction in observations stems from incomplete data from the survey on lenders' risk weights, which is largely due to mergers and aquisitions which occured during the sample period. Despite this, we have more than six million observations, and again the main statistics are close to those of the full sample.

Panel A of Table I reports loan-level variables. The 'average' mortgage in the sample has an interest rate of 4.3% on a loan of roughly £140k with an LTV of 62% and a maturity of 21 years. Fixed-rate mortgages account for approximately 70% of loans in the sample, although they are not fixed for long – the duration of the initial period is usually short in the UK mortgage market. The fraction of interest-only mortgages is about 22%. The average risk weight on mortgages is about 28%. This low risk weight is driven by the large share (88%) of mortgages issued by IRB firms.

In Panel B we display the key borrower characteristics we use in our analysis. The average borrower is 39 years old, has an income of slighty more than £50k and is taking out a mortgage on a property worth £240k. The average loan-to-income (LTI) ratio is close to 2.8. Our data is almost exclusively made up of prime mortgages: the fraction of subprime borrowers (those with impaired credit histories) is only 1%. The income is verified in 67% of the transactions, and 51% are joint mortgages, i.e. with two incomes. The fraction of first-time-buyers (FTB) is about 20%, while remortgagers account for approximately 44% of loans. In our sample we have around 90 banks and building societies, of which about 17 use IRB models for at least part of the sample period.

II. Identification strategy

The unconditional correlation between prices and risk-weights is around 0.6, and graphical analysis shows strikingly similar patterns of variation in prices and risk-weights. But many factors other than risk-weights, which are potentially correlated with risk-weights, could also affect prices.

This section explains the two complementary identification strategies that we use to identify the *causal* effect of risk-weights on mortgage prices. The triple-difference (DDD) specification in section II.A exploits the (plausibly exogenous) change in risk-weights arising from a quasi-natural

[15]During part of our sample period, reporting loan-level interest rates in the Product Sales Database was option. A few firms chose not to due so, and we drop these observations for the relevant period when performing analysis on prices. In addition, some smaller IRB firms were not included in the historical risk weight survey, so these firms are not included in the sample for the risk weight pass-through model.

[16]Besides banks and building societies, the other major segment of the UK mortgage market are specialist lenders, who we hope to include in future analysis.

experiment – the introduction of IRB and SA in 2008. The risk-weights pass-through model in II.B is essentially a generalisation of the triple-difference specification. Risk-weight variation appears directly in this model, rather than implied in the regime change. The model can therefore exploit more aspects of risk-weight variation, including between IRB firms, and within the post-crisis period. This makes it possible to estimate our effect for the post-crisis period in isolation. Also, this model's more granular fixed-effects control for more potential sources of confounding. However, we only have data necessary to estimate this richer specification for a subset of firms and years.

A. Triple-difference model

Our first identification strategy exploits the introduction of IRB models in 2008 as a result of Basel II. This generated risk-weight variation in three dimensions as illustrated in 1: time (before/after the introduction of IRB/SA), lender (firms on IRB vs SA), and LTV band. The introduction of IRB/SA leads to a common decrease in lenders' risk weights (upper panel). This decrease is larger for lenders adopting IRB than for lenders using SA, so a gap emerges between IRB and SA lenders (middle panel). And the gap is larger for lower LTV mortgages (lower panel).

[Place Figure 1 about here]

We develop an empirical model that allows us to isolate the effect of risk-weights on prices, by exploiting jointly the variation coming from the regime change between IRB and SA lenders, and between low and high LTV mortgages. We estimate the following specification for lenders' pricing:

$$\begin{aligned} Interest_{ibst} = &\beta_1 BaselII_t + \beta_2 IRB_b + \beta_3 LowLTV_s + \beta_{12} BaselII_t \times IRB_b + \beta_{13} BaselII_t \times LowLTV_s + \\ &\beta_{23} IRB_b \times LowLTV_s + \beta_{123} BaselII_t \times IRB_b \times LowLTV_s + \alpha Controls_{ibst} + \epsilon_{ibst} \end{aligned} \tag{1}$$

The dependent variable is the initial interest rate charged by lender b to borrower i for LTV-band s in period t. The LTV-bands are defined to match the granularity of the available data. Our coefficient of interest is (β_{123}) on the triple interaction term. We interpret this as the differential effect on price of using IRB rather than SA. We expect any such effect to be driven the corresponding difference in risk weights, though this specification does not feature risk weights directly. Following the implementation of Basel II, the decrease in risk weights among lenders adopting IRB models is larger (cf. among lenders using SA), and more so at lower LTV. With lower risk weights, the share of funding that must take the form of capital is lower, so a lender can achieve the same return on equity (RoE) with a smaller margin. To the extent that this advantage is pass through to lower prices by reducing margins, rather than to higher profits by maintaining margins, we expect a positive value for (β_{123}).

Our empirical model deals with confounding factors, which would otherwise bias our results, in several ways. First, the dummy for the period after the regime change ($BaselII_t$) controls for effects on price that were common to all mortgages originated from 2008 onwards, such as macro-financial effects [17] and generalised re-pricing of risk. Second, we include dummies for IRB lenders (IRB_b)[18] and for low LTV mortgages ($LowLTV_s$), to control for all time-invariant structural differences between IRB and SA lenders (e.g. size) and between high and low LTV mortgages (e.g. relative riskiness).

The introduction of IRB models and other concurrent events, like the 2008 financial crisis, can have differential impacts on lenders and LTVs. On the one hand, the crisis may have affected lenders on the SA more than lenders adopting IRB, so that the differences in the interest rate are attributable to the differential impact of the crisis on the two types of lenders, rather than the changes in risk-weights. For example differences in the exposure to the crisis between IRB and SA lenders may have affected their funding costs and then have passed on to prices, regardless of the variation in risk-weights. On the other hand, the crisis is likely to have a stronger impact on high LTV mortgages, which are more exposed to drops in house prices and increases in unemployment. As a results, differential changes in interest rates for high and low LTV mortgages may reflect variation in default risk, that are possibly unrelated to the risk-weights differential that we want to identify.

To address these concerns, we fully interact our specification adding dummies given by the interaction of $BaselII_t$ with IRB_b and $LowLTV_s$. In this way we control for all time varying differences, due to risk weights or other factors between lenders and LTV. To fully interact our model we also include a dummy from the interaction of IRB_b and $LowLTV_s$. The latter controls for structural differences between the two types of lenders in the different LTV segments. In this way we allow IRB lenders to set different interest rate relative to SA lenders in each LTV segment and we use only the over time variation in this difference within each lender-LTV band for idenfication.

We identify the effect of risk weights from the joint variation over time and across lender and LTV bands. Even if our dummies captures several dimensions that affects interest rates, we cannot exclude that there can be time-varying factors affecting differently lenders' pricing strategies across LTV bands. It is possible that IRB and SA firms may attract different borrowers that are more or less risky than average. If lenders price this risk into their mortgage rates, it could pose a problem for our estimation strategy.

On the one hand, lenders adopting IRB models in 2008 may have also changed their strategy, independently of the risk weights, to focus more on low LTV mortgages. As a result we observe after 2008 a decrease in rates by IRB lenders for low LTV mortgages larger than for rates on high LTV mortgages and than for rates by SA lenders in the same segment. If this is the case, the "repositioning" effect for IRB firms on low LTV mortgages will bias β_{123} upward, so that we are overestimating the effect of risk weights [19]. On the other hand, lenders adopting IRB models may have attracted relative riskier borrowers in the low LTV segment after 2008 or have recouped

[17]The Bank of England significantly reduced the policy rate after the Lehman collapse in September 2008

[18]IRB_b is a dummy equal to one if the lender adopted the IRB at some point in time during our sample period (not necessarily when IRB was first introduced).

[19]Note that a "repositioning" effect for SA lenders toward low LTV mortgages may bias our estimates downward.

losses on high LTV mortgages by keeping higher margins on low LTV. Both these channels, could have lowered IRB lenders incentive to decrease prices for low LTV mortgages, despite the lower risk weights. As a result, our model with given a downward biased estimate of β_{123} and we will underestimate the impact of risk weights.

Although we cannot fully control for all time-varying factors at the lender-LTV level, we think that selection bias as a results of differential trends in risk between IRB and SA firms on high vs low LTV is unlikely to bias our results. If SA firms saw a larger post-crisis increase in defaults among their low-LTV lending than among their high-LTV lending, and subsequently raised interest rates in the low-LTV segment relative to IRB firms, this would cause us to overestimate the main coefficient. We consider this scenario relatively unlikely, as most firms took losses primarily in their high-LTV portfolios. Moreover, we include a set of loan-level and borrower-level controls to capture observable differences between lenders and LTV that can affect the interest rate ($Controls_{ibst}$). First, we add loan-to-income (LTI) ratio and a dummy for joint income applications to proxy for expected credit loss (ECL) [20]. Second, we add dummy variables for the type of borrower (First-time-buyer, home-movers and remortgagers) and for subprime borrowers to control for both ECL and for differences in competition intensity between segments. Third, we add dummy variables for the loan rate type (e.g. variable, fixed) and repayment type (e.g. capital and interest, interest only), to control for similar pricing segment effects.

Another concern for our identification strategy is related to the endogeneity of the IRB adoption. If there were no substantial barriers to adopting IRB, all firms that could derive lower risk weights from adopting to IRB would have already done so. In this case, our estimated effect would overestimate the effect of adopting IRB on the firms that have not adopted, and thus on the population at larger. Firms with riskier portfolios (within the same LTV band) would obtain a smaller benefit from switching to IRB because the gap between SA and IRB risk weights would be smaller. However, there is evidence that the costs of adopting IRB models are substantial. These costs are related to model development and maintenance, data collection, investment in infrastructure, governance and compliance (CMA (2015)). As a result, the main factor in adopting IRB is not the riskiness of the portfolio, but the cost of the risk management infrastructure necessary to meet regulatory requirements for the use of IRB models. This limits concerns about self-selection based on risk.

To study further if the difference in risk weights affected lenders' behaviour we look at lenders' portfolio shares. We estimate the following triple difference specification:

$$\begin{aligned} Share_{bst} =& \beta_1 BaselII_t + \beta_2 IRB_b + \beta_3 LowLTV_s + \beta_{12} BaselII_t \times IRB_b + \beta_{13} BaselII_t \times LowLTV_s + \\ & \beta_{23} IRB_b \times LowLTV_s + \beta_{123} BaselII_t \times IRB_b \times LowLTV_s + \epsilon_{bst} \end{aligned} \tag{2}$$

Where $Share_{bst}$ is the shares of mortgages for each lender in each LTV bands in each quarter.

[20] We do not expect LTI to have a material direct effect on price, since lenders typically use LTI to decide the maximum size of the mortgage rather than its price

As in model 1 our coefficient of interest is the one on the triple interaction (β_{123}), that we now use to measures the effect of risk-weights on portfolio shares. It indicates if banks adopting IRB models increase their portfolio shares by more on low LTV mortgages, as a results of their comparative cost advantage in the that segment.

To summarize, our first identification strategy is based on a triple-difference model around the introduction of the new capital regime with Basel II. We isolate the effect of risk weights exploiting the variation arising from the adoption of IRB models and its differential across LTVs. Even if we control for the main variables affecting pricing, we cannot rule out alternative explanations due to unobservable time-varying differences across lenders and LTVs that are contemporaneous to the shock we analyze. Moreover, our model only exploit the variation between IRB and SA, and between pre and post the common adoption of the new regime. In section II.B we develop further our identification strategy to deal with these issues.

B. *Risk weights pass-through model*

In this section we develop a second identification strategy, in which we exploit the actual variation in risk-weights across banks and LTV segments after the introduction of IRB models. Figure 2 shows the variation in risk-weights for lenders in our sample in the year 2015. The figure confirms the overall gap in risk-weights between IRB and SA lenders, that emerged already in figure since the adoption of IRB models 1, and the larger gap at lower LTVs. Figure 2 show an additional dimension of variation in risk weights, that we exploit in this section, which is given by differences in risk weights *within* IRB lenders.

[Place Figure 2 about here]

We exploit this additional sources of variation in risk-weights and we develop a "pass-through" model of regulatory risk weights into mortgage rates [21]. We estimate the following model:

$$Interest_{ibst} = \gamma_{bt} + \gamma_{bs} + \gamma_{st} + \beta RW_{bst} + \alpha Controls_{ibst} + \varepsilon_{ibst} \tag{3}$$

Where the dependent variable is the same as in model 1. Our coefficient of interest is β, that measures the pass-through of risk weights into mortgage rates. To isolate the effect of risk-weights we include interacted fixed effects for bank-time (γ_{bt}); bank-LTV band (γ_{bs}) and time-LTV band (γ_{st}). In this way we control for all time varying unobservables across lender and LTV band and for time-invariant differences at the bank-LTV band level. In this way we rule out alternatives drivers of interest rate differentials, along the lines of the triple difference model (equation 1), but with more granular dummies.

This model has three major advantages with respect to the our first identification approach. First, we can measure the intensity of treatment due to the adoption of IRB models, without being

[21] A full pass-through model requires the knowledge of the marginal cost of issuing a mortgage. To do that, we need information not only about the cost of capital and the capital requirment, but also about the funding mix of the lenders.

constraint to a binary treatment indicator. In this way we can inform policy about what happen if there is a percentage increase in risk weights (intensive margin) and not only a switch from SA to IRB (extensive margin). Moreover, in model 1 we compare IRB and SA lenders, but we could not disentangle difference withing each group due to differences in risk-weights. In model 3 we can also exploit differences in risk-weights within the IRB group. Given that a significant share of new mortgages is issued by IRB firms, a within IRB comparison will reveal potentially important patterns in this group, that we cannot identify with the IRB dummy alone. Second, lender-specific risk weights will be especially useful for identification, allowing us to disentangle their effect on pricing from size and other firm characteristics. Since risk weights vary both across lenders and LTV band and over time, we can control for unobservable time-varying lenders and ltv segments effects with dummies, without losing the key variation for identification. In our specification 3 we add time-lender and time-LTV segment fixed effects to absorb all the lender and LTV segment variation over time, that can bias our estimation of the risk weight pass-through. Third, model 3 does not rely on a single event (the introduction of IRB models), which coincide with the global financial crisis and the subsequent policy responses. Our second identification strategy exploits the full variation in risk weights after the crisis, thus providing a better estimate of the "equilibrium" pass-through.

Even after controlling for unobservable time-varying lenders and ltv segments effects with dummies, our coefficient β may be biased if (i) lenders price in credit risk which is unobservable to us, and (ii) this unobserved credit risk is correlated with risk weights. We think this problem should be minimal for three reasons. First, we include the same set of loan-level controls as in the triple-difference model. Second, for the SA banks in our sample, risk weights are given exogenously, and only depend on LTV ratios. Any bias would have to arise due to the larger IRB banks attracting substantially different customer risk profiles. Third, for identification model 3 primarily relies on the substantial risk weight variation that exists among low-LTV loans. For secured lending below a 75% LTV ratio, the expected loss even at a high probability of default is minimal, given that the lender can recoup their investment in the vast majority of cases. With this in mind, we wouldn't expect a material amount of credit-risk-based pricing in low-LTV loans, so any bias to our estimates should be minor.

In our second model we exploit differences in risk weights not only *between* IRB and SA lender, but also *within* the set of IRB lenders. In the latter case the cost of developing models does not play a substantial role. However, as noted by BCBS, there is substantial variability in risk weights derived from IRB models. By adding loan-level controls for credit risk we are able to isolate the effect of different models to evaluate risk of similar assets.

We view the identification strategy presented in this section as complementary with the triple-differences strategy outlined in section II.A. The former allows us to control more in detail for unobservables and to exploit the within IRB variation to identify the intensive margin. The latter shows a possible way to identify the impact of capital requirements on prices, even in the absence of detailed individual data on risk weights, that may not always be available, and captures the extensive margin following a regime change.

III. Results

In this section we show our main results. We first describe the results of the triple-difference model in section III.A. We then presents the results from the pass-through in section III.B. In section III.C we describe the results from several robustness checks.

A. The effect of IRB models on pricing and specialization

In this section we show two sets of results. First, we find that banks adopting the IRB approach change their mortgage pricing differently from lenders that continued to use the SA. Second, we test if this change in pricing was accompanied by a change in specialization.

We start by proving a graphical illustration of the dynamics of interest rates in figure 3. Interest rate increase immediately after the introduction of IRB models and then drop significantly following the decrease in the policy rate in the end of 2008. The overall decrease in interest rates is characterized by two patterns. First, the average interest rate on low LTV mortgages decrease by more than the one for high LTV mortgages [22]. Second, the decrease on high LTV mortgages is comparable between SA and IRB lenders, while in low LTV mortgages IRB lenders decrease rates by more than SA lenders. Even if we cannot yet claim any causal relation from risk weights to prices, the patterns of interest rates in figure 3 closely resemble the dynamics of risk-weights in figure 1. We present the estimates from model 1 in table II.

Several results emerge from an overall comparison on interest rates in table 1. First, the average interest rate for IRB lenders is *always* below the one by SA lenders.This result can be due to an absolute cost advantage for IRB lenders, which are mostly larger banks with large economies of scale, and this is reflected in pricing of both high and low LTV mortgages. Second, the average interest rate on low LTV mortgages is *always* below the one for high LTV mortgages. This result is attributable to the fact that high LTV mortgages are riskier than low LTV ones and the higher rates is therefore reflecting the higher risk. Third, during Basel I the differences between high and low LTV are smaller than during Basel II and this holds for both type of lenders.

[**Place Table II about here**]

We now explain how we isolate the effect of risk weights on interest rate with the triple difference model. First, in panel A of table II we show the average interest rate for the "treatment" category: low LTV mortgages. Each cell contains the mean interest rates for the IRB and SA lenders in the two period we analyze. Interest rates falls moving from Basel I to Basel I for both IRB and SA lenders. This common effect is driven by the decrease in the policy rate following the global

[22] We define low LTV mortgages as the one with an LTV ≤ 75. This is the most popular threshold in the UK mortgage market used by lenders when they advertise their products. In the estimation we perform robustness tests with different thresholds.

financial crisis. The fall in interest rate for low LTV mortgages in larger for IRB lenders than for SA lenders, 161 and 134 basis points respectively. As a result, we find a 27 basis point relative fall in the interest rates of low LTV mortgages for lenders adopting IRB models and the effect is statistically significant. This result is the difference in difference estimate of the impact of IRB models. As we describe in the identification strategy there can be lenders specific shock contemporaneous to the introduction of IRB models, thus biasing our estimates when we look only at the first-difference.

In Panel B of table II we show the differences in the average rates for the "control" category: high LTV mortgages. BoInterest rates falls moving from Basel I to Basel II for both IRB and SA lenders also in high LTV mortgages. In this case, the fall in interest rates is larger for SA lenders than for IRB lenders by 6 basis point. The effect is however not statistically significant.

Taking the difference between the differences in low and high LTV mortgages we are able to isolate the effect of risk-weights on interest rates. The third level interaction captures all the variation in interest rate specific to IRB lenders (relative to SA lenders) in low LTV mortgages (relative to high LTV) in the years after the introduction of Basel II (relative to Basel I). The coefficient in tableII indicates a statistically significant decrease by 31 basis point in the relative interest rate of low LTV issued by IRB firms, compared to the change in relative interest rate of high LTV.

Next, we estimate model 1 to test for an effect of risk weights on lenders' specialization. To achive this, we compute for each lender in our sample the shares of mortgages for each quarter in each LTV bands. Table III presents our results for model 2 when we use portfolio shares as the dependent variable. In panel A we show the average portfolio share for low LTV mortgages. Each cell contains the mean portfolio share for the IRB and SA lenders in the two period we analyze. The change from Basel I to Basel II IRB lenders increase their average share in low LTV mortgages by about 1%, while SA lenders decrease their exposure to low LTV mortgages by almost 4%. As a result, we find a 5% relative increase for lenders adopting IRB models in their portfolio shares on low LTV mortgages and the effect is statistically significant. This result is the difference in difference estimate of the impact of IRB models on lenders' portfolio shares.

[Place Table III about here]

In Panel B of table II we show the differences in the average portfolio share for the "control" category: high LTV mortgages. IRB lenders decreased their portfolio shares in high LTV mortgages during Basel II relative to Basel I by about 1%. During the same period SA lenders increase their portfolio share in the high LTV category by about 6%. As a result of these trends, IRB firms decrease on average their relative portfolio share in the high LTV sector. We find a significant difference in difference estimate equal to -7%.

Taking the difference between the differences in low and high LTV mortgages we are able to isolate the effect of risk weights on portfolio shares. The third level interaction captures all the variation in portfolio shares specific to IRB lenders (relative to SA lenders) in low LTV mortgages (relative to high LTV) in the years after the introduction of Basel II (relative to Basel I). The coefficient in tableIII shows a statistically significant increase by 12% in the relative portfolio share for low LTV issued by IRB firms, compared to the change in relative portfolio share of high LTV.

B. Risk-weights pass-through

In this section we show the results of model 3, which exploits the granular variation in actual risk-weights and control better for unobservables. Table IV presents the main results. All our specifications include interacted time, lender and LTV segment fixed effets. In this way we control for all time varying factors affecting pricing and we rely only on the differential variation in risk weights across lenders and LTV segments over time. In column (1) we report the coefficients of the benchmark specification. We find a significant pass-through coefficient of 0.013. This implies that a 1 percentage point increase in the risk weights traslate into a 1.3 basis point increase in the interest rate. For mortages below 50% LTV, the average difference in risk weights between IRB and SA lenders is about 30 percentage points. Given our estimate of the pass-through coefficients, such a difference will translate into a price gap of about 40 basis points.

[**Place Table IV about here**]

In column (2) of table IV we add the individual controls that we used for the triple difference model. The coefficient on the risk weight remain statistically significant and the magnitude is almost unaffected. This results is reassuring, confirm that the differential variation in risk weights that we exploit for identification is not correlated with other measures capturing risk at the loan-level.

In column (3) we reduce the analysis to IRB lenders only. The coefficient on risk weights remains significant, even if at the 5% level. This decrease in significance is not surprising, given that we are now only exploiting the within IRB variation in risk weights for identification and not the gap in risk weights between IRB and SA lenders, which was the main source of identification in model 1.We find a pass-through coefficient of 0.010. This implies that a ten percentage points different between the "best" IRB and the "worst" IRB can translate into a price difference of about 10 basis points.

Finally in the last column of table IV we estimate the model only on the subset of lenders, which are in the sample for the whole period. The coefficient is still significant and the magnitude is slighlty reduced.

C. Robustness

We perform several robustness checks, to test the sensitivity of our benchamark results to different assumptions on LTV thresholds and cuts of the data.

Panel A of table V in the appendix show the robustness checks for the triple-difference model (equation 1 using loan-level interest rates as the dependent variable. We report only the estimated of the triple differences, which is our main coefficient of interest. First we consider alternative threholds for high and low LTV mortgages. The results remain significant and the coefficient on the triple difference confirms that IRB lenders decrease average relative interest rates more on low LTV. The changes in the magnitude go in the direction we expect. A lower threshold makes the effect even stronger, since the gap in risk weights between IRB and SA is larger (see figure 2). A higher threshold goes in the opposite direction, but the results are still significant and the magnitude large. The coefficient in column (3) of tableV indicates a statistically significant decrease by 24 basis point in the relative interest rate of LTV below 80% issued by IRB firms, compared to the change in relative interest rate of LTV above 80%.

In columns (4) and (5) of table V we estimate the benchmark version of model 1 in two subperiods of our sample. We compare the years 2005-2006 with 2009-2010 and 2011-2012, thus excluding the year just before and after the change in regime. The coefficient on the triple interaction remain statistically significant and the magnitude increase for the years 2009-2010 and is almost unaffected for the years 2011-2012. These results confirm that we are capturing a long-term equilibrium effects of risk-weights on prices and not only a transitory change due to the switch from Basel I to Basel II.

Third, we add several controls to capture better risk. We add a full set of loan-level controls and borrowers controls to capture the riskiness of the loan. The magnitude of the coefficient is reduced, as we expected since our controls are trying to capture alternative channels that can be correlated with our treatment. The coefficient on the triple interaction remain significant and the magnitude is reduced by about 25%. Last, we estimate the triple difference model on a balanced panel version of our data, where we only include lenders that are present in each quarter of our sample period. By focusing on these set of lenders we can rule out effects driven by entry, exit or merges and acquisitions. The coefficient remain statistically significant and the magnitude is almost unaffected.

In panel B of table V we show the robustness checks for the triple-difference model using portfolio shares as a dependent variable (equation 2). We perform the same robustness as in panel A for interest rates and the results are very similar. The triple-difference coefficient remains statistically significant and the magnitude varies in the range between 10% and 15%.

IV. Conclusions

Several years after their introduction, bank regulators have become more sceptical about the advantages of internal models. Concerned about the wide variation in risk weights obtained using internal models, regulators have recently introduced measures that limit their role in setting regulatory capital. At the international level, one key change has been the adoption of a leverage ratio. Some countries, such as Sweden, have imposed floors on risk weights.

Competition authorities have highlighted the potential impact on competition of internal models, and the potential advantage that they give to larger banks (to the extent that these banks are more likely to be on IRB). Our evidence for the UK residential mortgage market suggests that differences between banks in the way that capital requirements are calculated do affect how banks compete.

There are two main implications for bank regulation. Smaller banks, typically on SA, specialise more in higher-risk mortgages and may be more exposed to credit risk shocks. This may affect their safety and soundness. As highlighted by Rime (2005), banks that do not adopt IRB models, and are arguably less sophisticated in their risk management, increase their specialisation in higher-risk loans. On the other hand, larger, more systemic banks tend to be among those that adopt the IRB approach, and thus end up less exposed to credit risk shocks. Policies that seek to limit the variability of risk weights under internal models could push large banks to take on more risks. Other policies that have a differential effect across banks might have an impact on competition and distribution of risk in the system.

We are planning to develop our research in several directions: i) include a theoretical model that clarifies the link between capital, competition and prices, along the line of Schliephake (2016); ii) calculate loan-level capital requirements by interacting loan level risk weights with firm level capital ratio (both regulatory capital requirements and capital resources); iii) evaluate the impact of other regulatory policies that may have effected regulatory capital for UK lenders, for example include specialist lenders (which are regulated in a different way); iv) conduct a number of robustness checks, including further controls for credit risk (e.g. probabilities of default, regional fixed effects).

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Appendix A. Figures

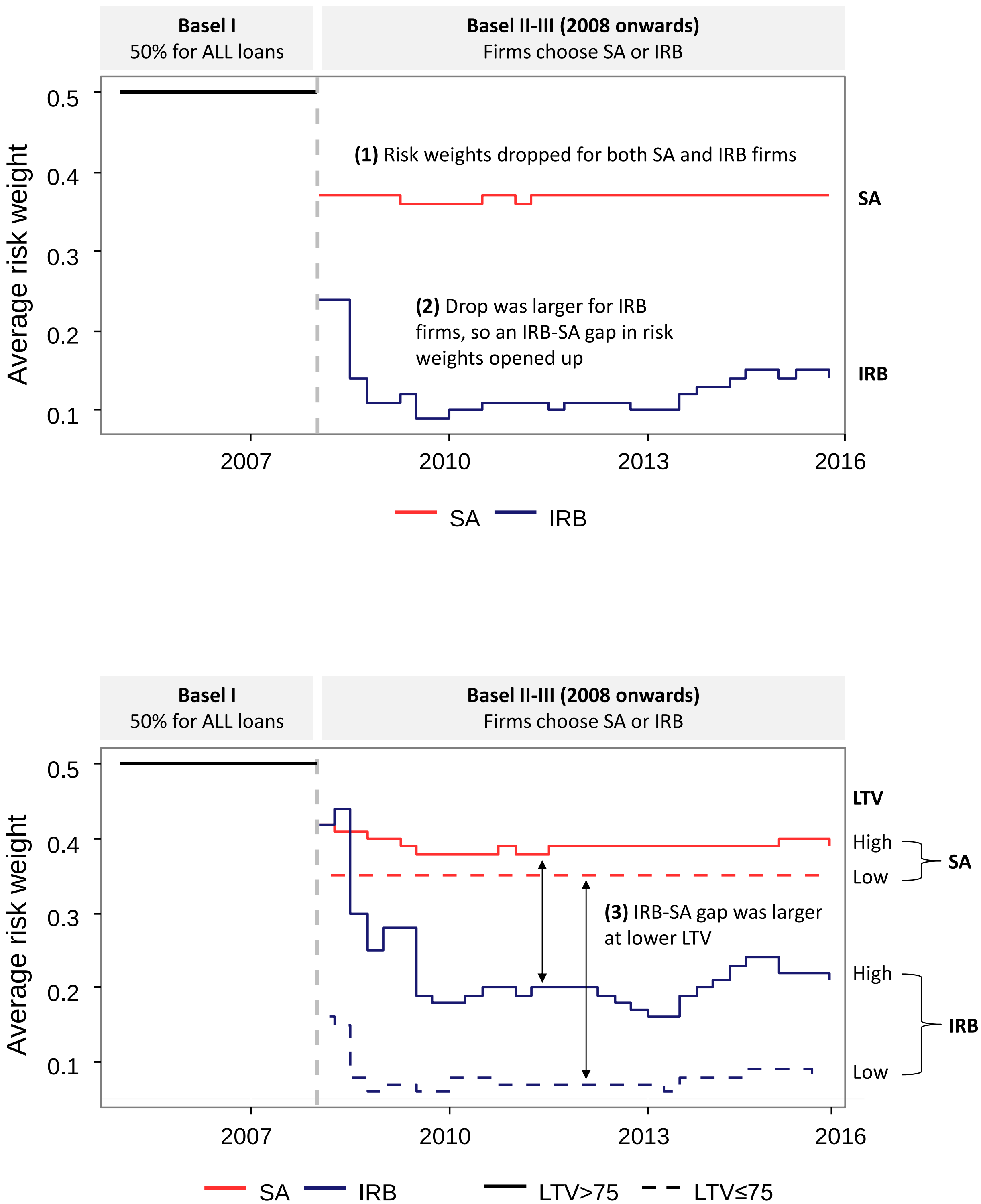

Figure 1. Triple difference: risk-weights.
The figure shows the dynamics of risk-weights in the period 2005-2015

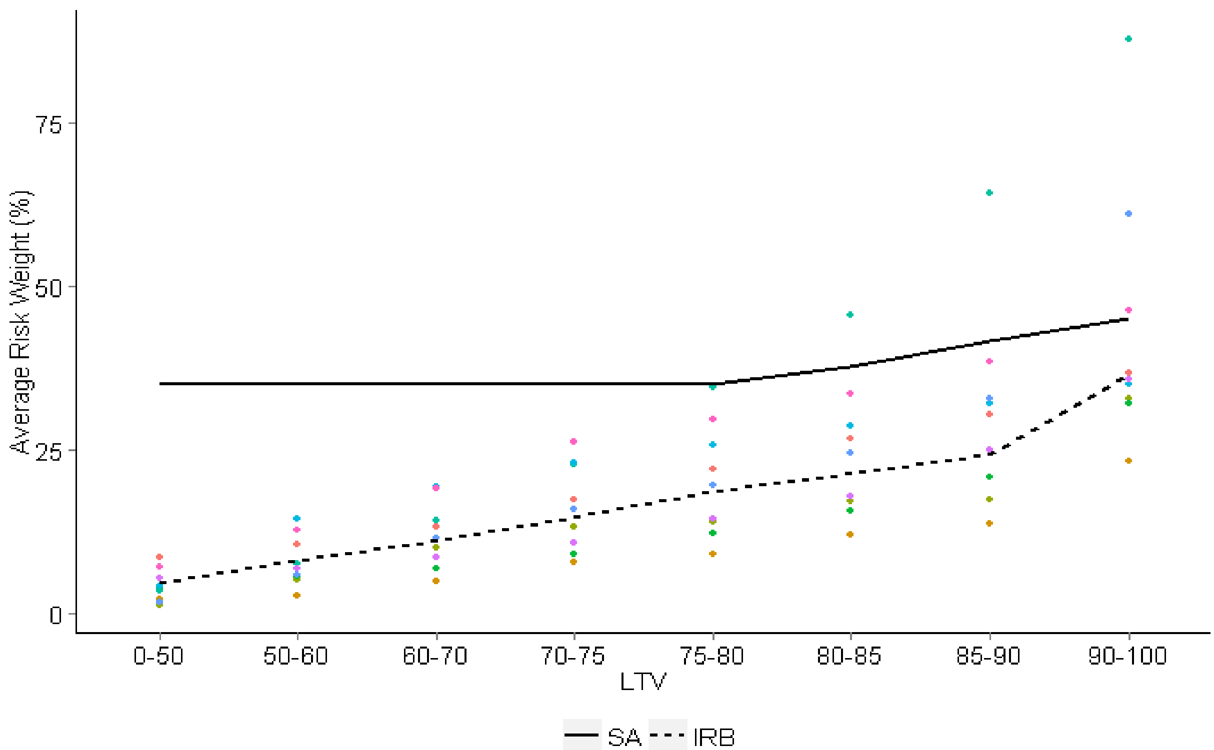

Figure 2. Risk-weights distribution.
The figure shows the gap in risk-wights.

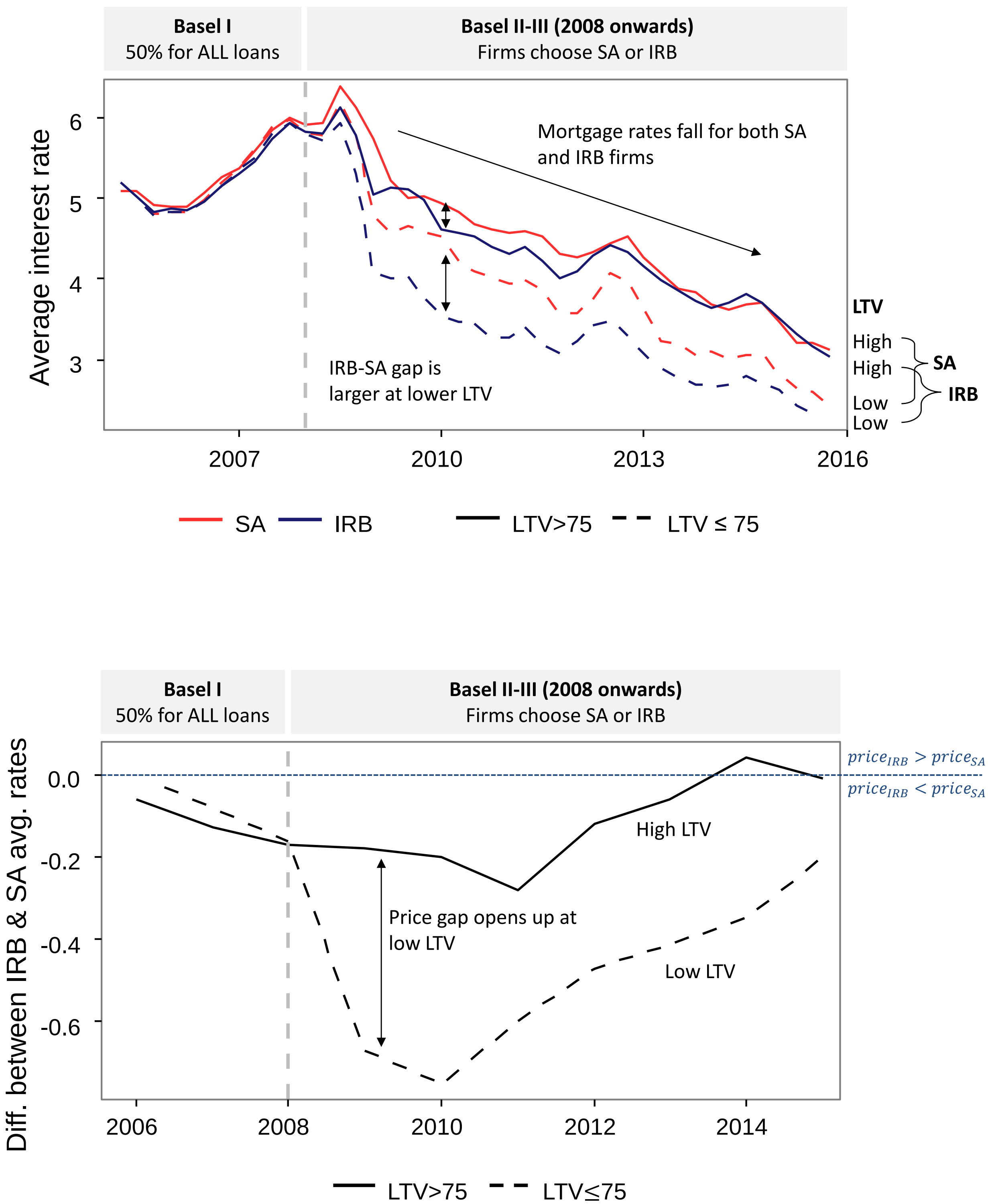

Figure 3. Triple difference: mortgage rates.
The figure shows the dynamics of mortgage rates in the period 2005-2015

Appendix B. Tables

Table I Summary statistics.
The table shows the summary statistics for the different samples that we use in our empirical analysis. We report the mean and the standard deviation (in parenthesis). Column (1) shows our full sample. Column (2) restricts the sample to mortgages where we have the information on interest rates. Finally, column (3) show the sample where we have information on risk-weights.

	(1) Full sample	(2) DDD model	(3) RW model
Panel A: mortgage characteristics			
Interest rate	4.3	4.3	4.21
	(1.34)	(1.34)	(1.32)
LTV	62.87	61.65	61.82
	(22.51)	(22.63)	(22.62)
Loan value	138,607.87	140,943.71	141,554.97
	(97767.12)	(99911.54)	(100006.6)
Maturity	21.64	21.29	21.4
	(7.99)	(7.31)	(7.33)
Risk weight	0.28	0.27	0.28
	(0.2)	(0.19)	(0.19)
Fraction fixed	0.69	0.69	0.7
Fraction interest only	0.24	0.22	0.22
Share of IRB loans	0.91	0.87	0.86
Panel B: borrower characteristics			
Property value	235,296.79	243,999.07	244,402.5
	(172,906.73)	(179,135.77)	(179,372.44)
Age	38.87	39.31	39.28
	(10.04)	(10.08)	(10.1)
Income	52,621.96	53,741.75	53,696.27
	(39,694.92)	(40,351.18)	(40,201.33)
LTI	2.82	2.8	2.82
	(1.05)	(1.05)	(1.06)
Fraction impaired	0.01	0.01	0.01
Fraction joint	0.51	0.52	0.51
Fraction income verified	0.64	0.68	0.69
Fraction FTB	0.21	0.2	0.2
Fraction remortgagors	0.44	0.45	0.44
Panel C: lender characteristics			
No. of lenders	94	85	83
No. of lender-quarters	3084	2542	2409
No. of IRB lenders	19	17	15
Observations	10,605,118	7,323,194	6,698,226

Table II Triple difference model: Interest rates.
The table shows the results from specification 1. The low LTV is defined as LTV below or equal to 75%. The Basel I period includes all mortgages between 2005Q2 and 2007 Q4, while the Basel II period is between 2008 Q1 until 2014 Q4. P-values are given in parentheses; sample sizes in .000 are given in square brackets.

	Basel I		Basel II	Δ Basel II - Basel I
Panel A: Low LTV				
IRB	5.21		3.6	-1.61
	[1403.32]		[2916.81]	(0)
SA	5.2		3.96	-1.25
	[264.38]		[298.32]	(0)
Δ IRB- SA	0.01		-0.36	
	(0)		(0)	
DD		-0.37		
		(0.02)		
Panel B: High LTV				
IRB	5.23		4.23	-1
	[642.12]		[1445.41]	(0)
SA	5.29		4.34	-0.95
	[228.62]		[124.21]	(0)
Δ IRB- SA	-0.06		-0.12	
	(0)		(0)	
DD		-0.05		
		(0.72)		
DDD		**-0.31**		
		(0)		

Table III Triple difference model: Portfolio shares.
The table shows the results from specification 2. The low LTV is defined as LTV below or equal to 75%. The Basel I period includes all mortgages between 2005Q2 and 2007 Q4, while the Basel II period is between 2008 Q1 until 2014 Q4. P-values are given in parentheses; sample sizes are given in square brackets.

	Basel I		Basel II	Δ Basel II - Basel I
Panel A: Low LTV				
IRB	0.14		0.15	0.01
	[700]		[1880]	(0)
SA	0.21		0.17	-0.04
	[2630]		[6130]	(0)
Δ IRB-SA	-0.07		-0.01	
	(0)		(0)	
DD		0.05		
		(0)		
Panel B: High LTV				
IRB	0.11		0.1	-0.01
	[700]		[1830]	0
SA	0.09		0.15	0.06
	[4590]		[2010]	0
Δ IRB-SA	0.02		-0.05	
	(0)		(0)	
DD		-0.07		
		(0)		
DDD		**0.12**		
		(0)		

Table IV Risk-weights model: Benchmark.
The table shows the results from specification 3. All standard errors are clustered at the lender-time level.

	Benchmark	Individual controls	IRB only (Intensive margin)	Balanced panel
RW	0.013***	0.012***	0.010**	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Fixed effects:				
lender-time	Yes	Yes	Yes	Yes
lender-LTV band	Yes	Yes	Yes	Yes
LTV band-time	Yes	Yes	Yes	Yes
Observations	3853825	3840712	3411105	1250889
R2	0.511	0.624	0.609	0.688

Table V Triple difference model: Robustness checks.
The table shows the results of from specification 1. The low LTV is defined as LTV below or equal to 75%. The Basel I period includes all mortgages between 2005Q2 and 2007 Q4, while the Basel II period is between 2008 Q1 until 2014 Q4. All standard errors are clustered at the lender-time level.

	Benchmark	LTV threshold		Subperiods		Individual controls	Balanced panel
		70	80	0506-0910	0506-1112		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: interest rate							
DDD	-0.314***	-0.451***	-0.246***	-0.614***	-0.395***	-0.237***	-0.318***
	(0.090)	(0.090)	(0.093)	(0.131)	(0.129)	(0.086)	(0.098)
Observations	7323194	7323194	7323194	2540092	2626818	7296600	5964040
R2 (adjusted)	0.270	0.259	0.285	0.315	0.532	0.337	0.275
Panel B: portfolio shares							
DDD	0.122***	0.113***	0.107***	0.146***	0.152***		0.139***
	(0.008)	(0.008)	(0.008)	(0.013)	(0.011)		(0.009)
Observations	20454	20454	20454	7345	7445		14037
R2 (adjusted)	0.068	0.089	0.056	0.109	0.099		0.078