# The Effectiveness of LTV Limits In Reducing Systemic Risk in Ireland

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## ECO352 Financial Crisis

#### **Abstract**

After the Great Financial Crisis, Ireland's housing price started to pick up again in 2014 with a year-to-year increase of 15%. To prevent another potential crisis of such magnitude, the Central Bank of Ireland introduced macroprudential measures to limit the mortgage lending with high loan-to-value (LTV) as of February 2015. In this paper, two linear estimation models are used to assess the effectiveness of the LTV caps on mortgage credit tightening and on stabilizing housing prices. The empirical results indicate that the LTV measures are ineffective in mortgage credit tightening and that the policy has no significant effects on housing prices.

#### 1 Introduction

From 2003 to 2008, Ireland experienced an unsustainable credit-driven real estate bubble, which involved in construction and housing well beyond population needs. During the Global Financial Crisis of 2008, due to the relaxation of underwriting standards in the 2000s, Ireland was one of the hardest hit countries. Although the cheap credit on the international market played a certain role, the bubble was mainly caused by the excessive lending of Irish banks. To stimulate housing demand and to help borrowers overcome financing constraints, the Irish banks even came up with "financial innovations" such as 100 percent LTV mortgages (Honohan et al., 2010). From the regulatory point of view, the bank-led property bubble and the subsequent collapse were a result of the major failures of the Irish central bank in terms of bank lending regulation and maintenance of financial stability.

After the financial crisis in 2008, Ireland's financial sector went through a painful restructuring with a €440 billion public bail out. With the enactment of the Central Bank Reform Act of 2010, the Central Bank of Ireland (CBI) also underwent a significant organisational change in terms of structure and process (Honohan et al., 2010). To prevent future crisis, in February 2015, the CBI introduced macroprudential measures to limit the amount of new mortgage lending which can take place at high loan-to-value (LTV) (Cassidy and Hallissey, 2016).

The main aim of this paper is to empirically assess the effectiveness of the LTV caps on tightening the mortgage credit lending and reducing the systemic risk in Ireland's banking system. Our hypothesis assumes that the LTV caps to be effective. To test the hypothesis, we exploited the CBI's implementation of LTV regulation in February 2015. The new mortgage regulation imposed a maximum LTV ratio of 80 percent on non-first-time buyers. For first-time buyers, a higher cap of 90 percent applies for the first €220,000 of the house value and 80 percentage for the rest. A stricter cap of 70 percent LTV was imposed for buyers who are purchasing the property to rent out (Cassidy and Hallissey, 2016).

This paper is structured as follows. Section 2 describes the CBI's intentions in adopting the LTV policies under a post-crisis economic recovery context. Section 3 introduces the descriptive

statistics of the variables used in empirical analysis. Section 4 and 5 review the latest publications assessing the validity and potential drawbacks of the LTV policies. Section 6 presents an empirical analysis through a pair of linear econometric models which demonstrate insignificant effects of LTV measures in tightening mortgage credit lending and in stabilizing housing prices.

#### 2 Background

Initially driven by the export led real economic expansion during the "Celtic Tigers" boom, Ireland's housing market grew rapidly from the early 1990s to early 2000. By about 2003, as the economy approached full employment, and technological constraints began to bite, the potential for continued per capita growth at the previous rates no longer existed (Honohan et al., 2010). Lack of real economic growth, accompanied with the government's procyclical fiscal policy stance and budgetary measures aimed at boosting the construction sector, an unsustainable housing bubble started to emerge. From 1997 to 2007, Ireland's real house price increased nearly fourfold. However, the skyrocketing housing price was fueled by the increasing reliance of Irish banks on wholesale external borrowing from the international financial markets. Over time, the whole Irish banking system became increasingly vulnerable and exposed to a downturn in the international market. Ultimately, the bankruptcy of Lehman Brothers became the last straw that triggered the downfall of the Irish banking system, which in turn, led to the bubble burst of Ireland's housing market (Honohan et al., 2010).

Post financial crisis, CBI's macroprudential policies were introduced with the main objectives to make banks and households more resilient to financial shocks, and to curb pro-cyclicality of the mortgage market (Cassidy and Hallissey, 2016). Come in effect in February 2015, the macroprudential measures were put in place at a time of yet another rapid housing price increase (15% year-on-year nationally and 25% in Dublin year over year), where the rise in price can be mainly attributed to supply shortages (Central Bank of Ireland, 2014).

Compare to direct controlling and targeting housing prices, the CBI believes that the ceilings

on loan-to-value (LTV) is a more precautionary method to ensure that easy credit driven bubble or imprudent lending standard would not destabilize housing market recovery (Cassidy and Hallissey, 2016). In other words, CBI intends to implement a policy that can effectively prevent excessive borrowing and lending while doesn't put too much downward pressure on the real housing demand. A key feature of the Irish LTV measures is the differentiated treatment towards first-time buyers, non-first-time buyers, and buy-to-rent-out. The CBI believes that by offering differentiated LTV caps rather than an uniform one, the policy can better protect the borrowers who are actually in need while prevent excessive borrowing from the speculators. The reasoning behind the differentiated treatment is backed by the Irish Central Bank's empirical research which finds first-time buyers are more sensitive to banks' lending conditions and are also less likely to default compare to other groups. Such a phenomena can be largely explained by the fact that first-time buyers rely mainly on personal savings, and they are also more worried about their credit ratings compare to the other groups (Kelly et al., 2015).

#### 3 Descriptive Statistics

For the empirical study of this paper, we used mortgage pool data from the Central Bank of Ireland and Irish housing market data from the Central Statistics Office Ireland. Most of the data obtained was reported on a monthly basis but had to be collapsed to a quarterly basis so that timeseries comparison to quarterly macro-data was possible. The complete dataset begins from 2010 so that there are only 44 observations up to 2021 <sup>1</sup>. The relatively few observations used for the empirical model (see Section 6) causes concerns for lacking statistical power, but it was inevitable since the construction of Irish mortgage-pool databases only began after the Great Financial Crisis.

The dataset was divided into two periods: before and after the implementation of the LTV caps in February 2015. A dummy variable was used to represent the imposition of the LTV measures where 0 means before and 1 means after. Figure A1 shows the descriptive statistics of aggregate

<sup>&</sup>lt;sup>1</sup> After adjustments for non-data points and data removed to calculate growth rates, we are left with 38 observations.

mortgage lending, housing market indicators, and macro-economic benchmarks.

With reference to Krznar and Morsin (2014), we accounted for mortgage variables such as mortgage credit and mortgage lending rate; housing market variables such as house price index, completed new house, and existing home sales; macro-variables such as unemployment rate, nominal GDP, and average wage. Change in LTV ratio over time is also captured by Indexed LTV. Figure A1 in the appendix illustrates the summary statistics of all the variables.

Assessing the time series graphs of the variables, there is a positive correlation between the housing price and the nominal GDP. In the five years after 2008, the growth rate of housing price index fell to a below -10% territory, which corresponds to the GDP slowdown in the same period. It was not until the end of 2013 when the GDP started to pick up that the housing price also began to recover. Both the nominal GDP and the housing market enjoyed a strong rebound in 2014. However, the 2014 housing market rally was quickly stabilized with the introduction of the LTV regulations in February 2015 suggesting a negative correlation between the housing price and implementation of LTV caps. The nominal GDP growth rate also encountered a minor correction in 2015 implying a negative correlation between the nominal GDP growth and the implementation of LTVs. Chart D4 in the appendix illustrates these trends.

The implementation of the LTV measures also demonstrated strong negative correlations with some other variables in the sample time-series: Existing Home Sales growth slow-down right after the LTV caps was imposed (See Appendix D2); Mortgage Credit declined right before the implementation of the LTVs (Appendix D1); Household Debt and Consumer Credit experienced accelerated decline after the LTV measures was put in place (Appendix D3). Interestingly, the strong negative correlation between the implementation of LTVs and the Mortgage Credit Level could provide evidence supporting our hypothesis which assumes that LTV measures is effective in tightening credit lending. However, even perfect correlation does not entail causation, which leads us to a more rigorous empirical analysis in Section 6.

#### 4 Literature Review

Purchasing a home is an extremely capital intensive process that most households cannot undertake on their own. To fill this gap, prospective home buyers reach out to lending institutions such as commercial banks and make long term lending agreements known as mortgages that outline a strict repayment timeline. While this relationship enables households to have more reasonable capital requirements to purchase a home, it also inextricably links demand for housing, availability of credit, and the property price (Benes et al., 2011). For example, when economic prospects are good, households tend to have higher demand for housing, and banks are more willing to provide credit which causes a positive feedback mechanism that drives housing prices up, improving future expectations. Conversely, demand for housing and willingness to supply credit are both going to be lower in the face of an economic downturn which deflates housing price and exacerbates the sluggishness in the economy. Because of the extreme procyclicality of this relationship, it is often referred to as the deadly embrace, a fitting name considering the role of housing in everyday life (Benes et al., 2011). Loan to value ratios are a macro prudential policy designed to reduce some of the risks associated with the deadly embrace and work by limiting the amount a household can borrow against a house (Igan and Kang, 2011). The rest of this section will focus on how and why loan to value ratios may or may not work.

#### How Loan to Value Ratios (LTV) Work in Reducing Systematic Risk

LTV's are intended to reduce the likelihood and extent that a frothy housing market has decoupled from the real economy by putting more strict capital restrictions on home purchases (Ono et al., 2013). An LTV of 80% means that a home buyer would need to procure 20% of the home's value to enter the mortgage agreement. This is less lenient than an LTV of say 90% which would require the prospective home buyer pay 10% of the home value upfront.

#### Why LTV Caps Work

The deadly embrace is a problem that arises from households' willingness to pay and lending institutions' willingness to lend moving in the same direction in response to a change in housing prices (Benes et al., 2011). Consider a housing market in its equilibrium and then consider an LTV ratio arbitrarily set at 80% is implemented. As Ono et al. (2013) explains, in the face of a housing market boom a household will experience a higher demand for property and a bank would be encouraged to provide a loan considering the high potential profits but the household subject to an LTV ratio will not be able to buy a home even though market prospects are good if they are not able to pay the 20% down payment. This means that even though there is still upward pressure on housing prices, there is still increased demand from households, and increased willingness to lend from banks, further upswings in the market are attenuated to some extent by the heftier capital requirements and the resulting reduction of mortgage availability (Benes et al., 2011). This process reduces systematic risk by ensuring there is at least some collateral a bank can collect in the event of default, softening the blow in the event of a crash (Morgan et al., 2019). The extent to which LTV are effective in curbing extreme exuberance (reducing procyclicality) in the housing market is discussed in section 4.4.

#### How Loan to Value Ratios (LTV) Do Not Work in Reducing Systematic Risk

LTV's ratios do not always have the same kind of attenuating effects described above in the event of a housing market crash. In fact an LTV ratio may exacerbate the slump by making it increasingly difficult for prospective home owners to get capital (Igan and Kang, 2011). Point out that this is especially punishing for young, first time buyers that don't have access to a lot of capital. Additionally, as explained in the next section, LTV ratios can increase procyclicality both in booms and busts (Ono et al., 2013).

#### Why LTV's Don't Work

In the face of a housing market bust a household's demand for property is likely to be quite low and lending institutions will be reluctant to provide loans (Ono et al., 2013). Those that are provided will likely have a higher interest rate, further discouraging household investment in housing (Benes et al., 2011). If there was an LTV ratio implemented during a housing market bust, households would be forced to provide a large pool of capital which they might need for unforeseen future disaster, provided that the economy is not doing well the household is even more unlikely to invest in housing. As a result, LTV can actually deepen housing market slumps (Ono et al., 2013).

LTV ratios increase procyclicality through the way it interacts with marginal lending rates. As mentioned earlier, when the housing market is in a boom an LTV ratio may discourage some interested buyers from entering the market due to capital requirements. But the extent to which this effect attenuates further increases in price depends on how aggressively prices are rising (Benes et al., 2011). This is because when the housing market is doing exceptionally well, commercial banks will reduce the interest rates on loans to reflect the fact that housing is a more desirable investment for the bank. As a result, if households feel very strongly that they want to purchase a home during a housing boom, they can borrow money for the down payment at lower rates. The introduction of an LTV makes it so that a household will borrow more money from the bank to meet the households down payment requirement, exacerbating procyclicality instead of ameliorating it (Ono et al., 2013). Using the same logic as Benes et al. (2011) and Ono et al. (2013) in their papers, we can conceptualize what might happen during a housing market bust. Households will not have a high demand for housing during these times, in addition, banks will be raising interest rates on loans related to housing, making it further unappealing to buy a home. Therefore, introducing an LTV ratio would only force the household to borrow more at a higher rate than normal if they wanted to buy a home.

## 5 Policy Risk

Macroprudential policies are the most versatile set of tools the central bank has at its disposal, however, these policies can still result in unintended consequences (Forster and Sun, 2020). While the implementation of LTV ratios is designed to reduce the risk of serious disruption to the provision of financial services by giving banks more of a cushion in busts, LTV ratios also change consumer behaviour through altering household credit constraints (Benes et al. 2011). An LTV ratio can be understood as a reduction in available funds relative to pre-policy conditions and therefore causes an income effect among affected households (Forster and Sun, 2020). The perceived reduction in income will cause some households to consider substitutes for housing that are cheaper or in less favorable locations. If an overly aggressive LTV policy is introduced, there is a serious risk of long term deflation of real house prices, especially among high-value properties situated in centralized metropolitan areas (Benes et al., 2011). In the paper "Unintended Consequences of Credit Constraints on Housing: The Case of LTV Limits", Nitzan Tzur-Ilan conducts an empirical analysis using data from the bank of Israel and concludes the implementation of an LTV resulted in an approximate decline of 68,000 Israeli shekel in real house prices. In addition Tzur-Ilan finds many households subject to a new LTV ratio chose homes which scored significantly lower on the bank of Israel socioeconomic index.

Unfortunately these effects are also not felt equally among all households. In the paper "Loan-to-value policy and housing finance: effects on constrained borrowers" Araujo et al. (2011). The authors investigate the extent to which LTV ratios made a difference in spending decisions for both low-income and medium-income households in Brazil. Their findings suggest that middle income households spending decisions related to housing were largely unaffected by the change. These households continued to purchase homes that they were planning to purchase before the policy and no significant changes were seen in the number of loans in arrear. On the other hand, low income individuals consistently chose houses worth roughly 30% cheaper than what they had planned but these new mortgages were 5% less likely to be in arrear a year in future.

These findings highlight an inconvenient truth for LTV policies. LTV ratios are designed to

reduce the risk of serious disruption to the provision of financial services by decreasing the likelihood of mass defaults on mortgages but the households most likely to default are also low-income. Therefore, it is most effective to target low-income households. Yet by targeting low income households, the policy also shifts many of the unintended consequences onto these individuals, exacerbating wealth inequality. If policy makers are not careful, they can create a self-enforcing cycle of low-income households being forced into less desirable neighborhoods and declining home values in those neighborhoods due to an influx of low income households.

#### 6 Empirical Model

#### **Baseline Specifications**

This paper extends on the models introduced in Krznar and Morsink (2014) by using the Irish housing market data to analyze the effectiveness of the 2015 LTV limits in Ireland. An overview of the specifications of two baseline models: 1) The first model observes the impact of the measures  $(D_t)$  and housing prices  $(HPI_{t-1})$  on mortgage credit lending  $(Y_t)$  while controlling for average weekly wage growth, the mortgage lending rate growth, and unemployment (Controls are captured in  $C1_{t-1}$ ); 2) The second model observes the impacts of the measures  $(D_t)$  and mortgage credit on housing prices  $(HPI_t)$ , controlling for completed houses, existing home sales, indexed LTV  $^2$ , and nominal GDP (Captured in  $C2_{t-1}$ ). Since the LTVs were imposed in Feburary 2015,  $D_t$  equals 1 for any period t after the first quarter of 2015 (period 21) and zero for all else. Both models use a linear multiple regression model and observes variables using their year-over-year growth as a percentage, and applies a lag on the controls and deflated for inflation $^3$ . We also note that we use different controls in the second model, which addresses potential simultaneity biases.

<sup>&</sup>lt;sup>2</sup>Indexed LTV = Current Loan Outstanding divided by the indexed property valuation

<sup>&</sup>lt;sup>3</sup>All controls are lagged to account for mortgage/housing price sluggishness in response to changes in other determinants.

#### Model 1:

$$fY_t = \alpha + \gamma D_t + \beta H P I_{t-1} + \eta C 1_{t-1} + \varepsilon_t \tag{1}$$

#### Model 2:

$$HPI_{t} = \lambda + \gamma D_{t} + \delta Y_{t-1} + \zeta C 2_{t-1} + \mu_{t}$$
(2)

Compared to prior studies on LTV, our estimates may suffer from a relatively small sample size. The total number of observations (quarters) used in our analysis was 38 between 2010 and 2020, as opposed to the larger sample sizes used in Krznar and Morsink (2014) and other referenced literature such as Kuttner and Shim (2013) and Cassidy and Hallissey (2016). This may be the reason for a low statistical power in our findings in model 1. However, it should be noted that we did find significant results in all but few of the feature variables in our estimation of the second model. The distribution of residuals and the  $R^2$  in model 2 further suggests the adequacy of our sample size. We also note that the standard errors in model 1 are relatively low and the estimates do provide a direction of effects that help in supporting our hypotheses.

Like most of the empirical studies, our empirical models potentially suffer from a high level of endogeneity. With regards to model 1, reverse causality may be an issue between the house pricing index and mortgage credit growth. As loose lending standards of banks may drive up housing prices and aggregate demand for housing while rising house prices may stimulate higher necessity and demand for more mortgage credit. However, reverse causality should not be a concern for our analysis, since prior to the policy implementation, house prices rallied even though mortgage credit was tightened (See Appendix D1). <sup>4</sup>.

Lastly, we can refer to table 6 as the results of estimation using White (1980) standard errors. Ultimately, we find that there is an insignificant difference betweem tje White (1980) standard errors and OLS aside from higher standard errors. This suggests that OLS standard errors may be more efficient in estimating our models. As part of further exploration, we introduce indexed LTV

<sup>&</sup>lt;sup>4</sup>We checked for robustness by introducing dummy variables to control for unexplained or irregular shocks in our data set. Our estimates did not materially change. In particular, these dummies controlled for the shock in lending and house prices that took place between the 9th and 13th period.

ratios as a variable which explores the impact of house price valuation as a ratio of total mortgage lending. The indexed LTV ratios was used primarily as a tool for removing bi-modality in our distribution of our residuals in model 2 (See Appendix C6). Although the variable normalizes our residuals, it should be noted that there is a trade off which results in lower  $R^2$ . Also, by including the indexed LTV ratios, our estimates may suffer from a high level of endogeneity and collinearity due to the variables relation with mortgage credit lending (See Appendix C6, second histogram). Using the 2015 measures variable also provides an unexpected positive coefficient, which is consistent with how it may be endogeneous with mortgage credit, as found in Krznar and Morsink (2014). For all the reasons above, we focus on specification 3 of model 2 in Table 5 as it not only replicates the model in Krznar and Morsink (2014) but also offers a sufficiently high  $R^2$ , while allowing us to mitigate issues of endogeneity and collinearity associated with the 2015 measures and Indexed LTV variables.

#### **Results**

Each of our independent and dependent variables took the level of year-over-year growth rates, which were also deflated by the CPI growth rate. Our results obtained were based on ordinary least squares estimation of our models <sup>5</sup>. Results obtained from OLS standard errors method are materially indifferent from White standard errors method, suggesting the OLS method is more efficient.

Table 4 in Appendix B shows our results from estimating model 1. Out of all 4 of our model 1 specifications, our adjusted  $R^2$  is considerably low at 0.252 without the use of polynomial independent variables. We observed the residuals against its fitted values of model 1 and noticed a quadratic shape, which suggests implementation of squared independent variables (See Appendix C.3). By adding squared regressors, it seemed to improve the fit of model 1 where the adjusted  $R^2$  increased to 0.465. By including the squared regressors, the estimates of model 1 also appeared to

<sup>&</sup>lt;sup>5</sup>We use White (1980) standard errors to account for Heteroscedastic Auto Correlated standard errors due to residual plots representing heteroscedastic behaviour. The result assumes that weights are efficiently applied to our estimates which would result in more consistent estimates than OLS.

be in line with our hypotheses. For this reason, our discussion will focus on the results seen in the fourth specification of model 1.

Table 5 in Appendix B shows our results of model 2. Krznar and Morsink (2014) found that there may be endogeneity between the LTV measures dummies and mortgage credit lending in terms of their impacts on the housing price index. We also found such endogeneity in our results that by including 2015 measures in model 2. Against our hypothesis, a positive coefficient of the LTV measure was observed indicating a positive effect of LTV measures on housing price. However, as we can observe in Appendix D.1, the housing price index effectively decreases after the policy date demonstrating a contradiction  $^6$ . By adopting specification 3 of model 2, it will identically replicate the model explored in Krznar and Morsink (2014) and produces a sufficiently high adjusted  $R^2$  of 0.578. Although the other specifications offer higher  $R^2$ , there is sufficient literature and examination to suggest that endogeneity may exist in introducing the indexed LTV ratio or the 2015 measure variable. As a result of the factors above, we will focus on the results of specification 3 in Table 5 as the main specification for model 2.

With disregard to statistical significance and other potential co-founding factors affecting specification or bias, we identify several notable findings:

• LTV measures insignificantly increased credit tightening: Our hypothesis postulates that macroprudential measures limiting LTV are effective in tightening mortgage credit lending, thereby reducing total exposure to credit risk. Our predictions are in line with the findings in Krznar and Morsink (2014) and Kuttner and Shim (2013), where both papers found a significant negative relationship between mortgage credit and LTV caps. Our results suggest that these policies reduced average mortgage YoY credit growth on average across the next five years by 0.029%, supporting our hypothesis. However, the point estimate is insignificant with a standard error of 0.33. The magnitude of the effect is significantly smaller than those found in Krznar and Morsink (2014). Overall, statistical insignificance and low coefficient may suggest that the policy is ineffective in tightening credit within the mortgage lending

<sup>&</sup>lt;sup>6</sup>Controlling for the shock occurring around 2012 did not materially change results which suggests robustness in our results.

markets in Ireland. We note in Appendix D, credit lending growth appears to stagnate from 2012-Q4 to 2013-Q4 which may have deflated our results <sup>7</sup>.

• Mortgage lending has a significant impact on housing prices with an insignificant portion of its effects coming from the 2015 measures: Our results support findings in Krznar and Morsink (2014) and Kuttner and Shim (2013) showing significant impacts from mortgage lending on house prices. The findings suggest that the LTV measures affect housing prices through total the mortgage credit lending variable. By substituting model 1 into model 2 through a systems of equation, we can see that the impact of the LTV measures on housing prices exists and remains negative. However, insignificance in our model 1 coefficient for the 2015 measure weakens the result. It is prudent to note that Ireland experienced significant growth in housing prices from 2010 to the implementation date of the policy at which point house prices began to decline (See Appendix D.1)<sup>8</sup>. In observation, we can hypothesize that the policy was highly effective in reducing housing prices through its negative effect on mortgage credit. However, we do not observe such a result from our empirical estimation.

Overall, we find that the LTV measures had weak effect in tightening mortgage lending and in reducing house price growth after controlling for factors such as aggregate demand and supply of home sales and GDP. Although insignificant, a surprising finding from model 1 estimation was the positive relationship between mortgage interest rates and mortgage credit. The positive relationship may be explained by banks reacting to a positive outlook in the economy and thereby driving higher expectations of inflation rates, which in turn pushed for an increase in their spreads on mortgage lending. It should be noted that there is potential for a significant confounding variables problems or endogeneity problems pertaining to the existing home sales variable. Factors affecting home sale liquidity aside from pure aggregate demand for homes may drive a bias into our estimates. In addition, the LTV measures may indirectly affect housing prices through its impact on the housing

<sup>&</sup>lt;sup>7</sup>We have tested for robustness on this by introducing dummy variables to control for unexpected shocks seen in our data however, it has not materially changed any of our estimates which suggests its robustness.

<sup>&</sup>lt;sup>8</sup>We tested using dummies to control for large unexplained shocks in the data and found robust results with no changes to our regression estimates.

market liquidity. Our results are likely to deliver greater robustness in consideration of a larger sample size. However, the results appear in line with the results of recent literature and suggests its adequacy.

#### 7 Conclusion

Ireland's housing bubble burst in 2007 still rings a warning bell for over-leveraging. Post financial crisis, as the housing price recovery started to pick up the pace, it became critically important for the Central Bank of Ireland (CBI) to learn from the past failure and to step in early this time. To do so, CBI adopted a macroprudential policy of differentiated LTV caps on different groups of home buyers/borrowers. However, as a relatively new policy that only works great on paper so far, the effectiveness of the LTV measures in reducing pro-cyclicality remains in question. Especially considering the potential exacerbating effect of the policy on housing price decline during a bust. There is also a concern of a policy loophole where home buyers can bypass the LTV caps by borrowing from banks to pay the down payment. From some recent studies, LTV policies have been proven to be useful in reducing systematic risks in countries like Israel and Brazil. However, the implementation of LTV limits in Israel and Brazil also come with certain drawbacks such as depressed real house value and exacerbated wealth gap.

This paper assessed the effects of Ireland's 2015 LTV measures on mortgage credit tightening and housing price reduction through a pair of linear multiple regression models. Potential suffering from the small sample size, only very weak effects were observed on mortgage credit tightening and housing price reduction. Although the causality of the results remains questionable, they do point to the direction of our hypothesis. A significant results may be obtained from a larger sample size in the future studies. As research continues on LTV, in particular on its effect on the economy and its interaction effect with other macroprudential polices such as LTI and DSR, future LTV measures are bound to be sophisticated and robust policy tool for the central banks.

#### References

- D. Araujo, J. Barroso, and R. Gonzalez. Loan-to-value policy and housing finance: effects on constrained borrowers (BIS Working Paper No 673). Bank for International Settlements. Working paper, Bank for International Settlements, June 2011.
- J. Benes, J. Mongardini, and D. Laxton. Mitigating the Deadly Embrace in Financial Cycles: Countercyclical Buffers and Loan-to-Value Limits. Working paper, International Monetary Fund, June 2011.
- M. Cassidy and N. Hallissey. The introduction of macroprudential measures for the irish mortgage market. *The Economic and Social Review*, 47:271–297, 2016.

Central Bank of Ireland. Macro-financial review 2014:ii, 2014.

- R. Forster and X. Sun. Taming the housing crisis: An ltv macroprudential policy. *SSRN*, page 49, 11 2020.
- P. Honohan, D. Donovan, P. Gorecki, and R. Mottiar. The irish banking crisis: Regulatory and financial stability policy. *University Library of Munich, Germany, MPRA Paper*, 01 2010.
- D. Igan and H. Kang. Do Loan-to-Value and Debt-to-Income Limits Work? Evidence from Korea (IMF WP/11/297). Working paper, International Monetary Fund, June 2011.
- R. Kelly, T. O'Malley, and C. O'Toole. Designing Macro-prudential Policy in Mortgage Lending: Do First Time Buyers Default Less? Research technical papers, Central Bank of Ireland, June 2015.
- I. Krznar and J. Morsink. With great power comes great responsibility: Macroprudential tools at work in canada. *IMF Working Papers*, 83, 2014.
- K. N. Kuttner and I. Shim. Can non-interest rate policies stabilise housing markets? evidence from a panel of 57 economies. *IMF Working Papers*, 2013.
- P. Morgan, J. Regis, and N. Salike. Ltv policy as a macroprudential tool and its effects on residential mortgage loans. *Journal of Financial Intermediation*, pages 89–103, 10 2019.
- A. Ono, H. Uchida, G. Udell, and I. Uesugi. Lending pro-cyclicality and macro-prudential policy: Evidence from japanese ltv ratios. *RIETI*, pages 1–69, 2013.

# A Variables

# **A.1 Summary Statistics**

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Observed Quarters	42	21.500	12.268	1	11.2	31.8	42
2015 Measure	42	0.524	0.505	0	0	1	1
Mortgage Credit YoY (%)	42	-0.036	0.065	-0.193	-0.057	-0.005	0.070
House Price Index YoY (%)	42	0.016	0.117	-0.196	-0.094	0.102	0.195
Avg Weekly Wage YoY (%)	42	0.011	0.020	-0.029	-0.004	0.023	0.060
Mortgage Lending Rate	42	0.030	0.002	0.026	0.029	0.032	0.035
Mortgage Lending Rate YoY (%)	42	0.007	0.094	-0.183	-0.049	0.058	0.197
Unemployment Rate YoY (%)	42	-0.082	0.106	-0.250	-0.160	0.005	0.190
Mortgage Lending Rate YoY (%, Lag)	42	-0.035	0.065	-0.193	-0.057	-0.005	0.070
Nominal GDP YoY (%)	42	0.078	0.099	-0.040	0.017	0.100	0.381
Completed Houses YoY (%)	38	0.025	0.157	-0.117	-0.050	0.037	0.507
Existing Home Sales YoY (%)	38	0.118	0.218	-0.339	-0.017	0.201	0.648
Indexed LTV YoY (%)	38	0.012	0.155	-0.100	-0.086	0.067	0.468

#### A.2 Covariance Matrix - Model 1

Table 2: Correlation Matrix - Model 1 Variables

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Mortgage Credit YoY (%)	1	0.545	0.259	-0.158	-0.491	0.715
(2) Housing Price Index YoY (%)	0.545	1	0.411	-0.328	-0.862	0.520
(3) Avg Weekly Wage YoY (%)	0.259	0.411	1	-0.043	-0.443	0.348
(4) Mortgage Lending Rate YoY (%)	-0.158	-0.328	-0.043	1	0.225	-0.378
(5) Unemployment Rate YoY (%)	-0.491	-0.862	-0.443	0.225	1	-0.515
(6) Mortgage Credit YoY (%, Lag)	0.715	0.520	0.348	-0.378	-0.515	1

## A.3 Covariance Matrix - Model 2

Table 3: Correlation Matrix - Model 2 Variables

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Housing Price Index YoY (%)	1	0.510	-0.647	0.281	0.480	-0.554
(2) Mortgages Credit YoY (%)	0.510	1	-0.506	-0.101	0.086	-0.387
(3) Completed Houses YoY (%)	-0.647	-0.506	1	-0.194	-0.304	0.955
(4) Existing Home Sales YoY (%)	0.281	-0.101	-0.194	1	0.117	-0.329
(5) Nominal GDP YoY (%)	0.480	0.086	-0.304	0.117	1	-0.313
(6) Indexed LTV YoY (%)	-0.554	-0.387	0.955	-0.329	-0.313	1

# **B** Regression Results

## B.1 Model 1

Table 4: Model 1 Results

		Dependen	$Dependent\ variable:$	
		Mortgage Cr	Mortgage Credit YoY (%)	
	(1)	(2)	(3)	(4)
2015 Measures	0.022 (0.032)	-0.011 (0.032)	-0.002 (0.029)	-0.029 (0.033)
House Pricing Index YoY (%, Lag)	0.387** (0.159)	0.456*** (0.144)	0.412*** (0.146)	0.299*
Avg Weekly Wage YoY (%, Lag)	-0.113 (0.769)	-0.186 (0.758)	-1.369 (0.980)	-0.690 (1.209)
Mortgage Lending Rate YoY (%, Lag)	0.157 (0.112)	0.151 (0.100)	0.109 (0.102)	0.007
Unemployment Rate YoY (%, Lag)	0.091 (0.196)	0.248 (0.196)	0.061 (0.195)	-0.309 (0.279)
Avg Weekly Wage YoY (%, Lag, Squared)			30.759 (23.238)	27.931 (27.606)
Housing Price Index YoY (%, Lag, Squared)		$-2.625^{***}$ (0.794)	-2.348*** (0.777)	-2.334*** (0.842)
Unemployment Rate YoY (%, Lag, Squared)		0.839 (1.024)		
Indexed LTV YoY (%, Lag)				0.149
Constant	-0.048*** (0.017)	0.003 (0.023)	-0.006 $(0.025)$	-0.037 (0.033)
Observations	41	41	41	38
K <sup>z</sup> Adiisted R <sup>2</sup>	0.345	0.509	0.524	0.581
Residual Std. Error F Statistic	0.057  (df = 35) $3.689^{***} \text{ (df} = 5; 35)$	0.051  (df = 33) 4.881*** (df = 7; 33)	0.050  (df = 33) 5.189*** (df = 7; 33)	0.050  (df = 29) $5.027^{***} \text{ (df} = 8; 29)$
			*p<0.1	p<0.1; **p<0.05; ***p<0.01

#### B.2 Model 2

Table 5: Model 2 Results

		Dependent variable:	
	Н	ousing Price Index YoY (	%)
	(1)	(2)	(3)
Mortgage Credit YoY (%, Lag)	0.513***	0.446**	0.703***
	(0.163)	(0.165)	(0.201)
Completed Houses YoY (%, Lag)	-0.036	-0.456	$-0.178^{*}$
	(0.078)	(0.279)	(0.091)
Existing Home Sales YoY (%, Lag)	0.283***	0.291***	0.062
	(0.066)	(0.065)	(0.058)
Nominal GDP YoY (%, Lag)	0.338***	0.367***	0.513***
	(0.109)	(0.108)	(0.130)
2015 Measure	0.145***	0.127***	
	(0.031)	(0.033)	
Indexed LTV YoY (%, Lag)		0.420	
		(0.268)	
Constant	-0.096***	-0.086***	0.004
	(0.026)	(0.027)	(0.019)
Observations	38	38	38
$R^2$	0.774	0.791	0.623
Adjusted R <sup>2</sup>	0.739	0.750	0.578
Residual Std. Error	0.059 (df = 32)	0.057 (df = 31)	0.075 (df = 33)
F Statistic	$21.972^{***}$ (df = 5; 32)	$19.549^{***} (df = 6; 31)$	$13.656^{***}$ (df = 4; 33)

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

# **B.3** Robust Errors Estimates (White SE)

Table 6: Results

			Dependent variable:	variable:		
	Mortgage Credit YoY (%)	it YoY (%)		Housing Price Index YoY (%)	dex YoY (%)	
	(1)	(2)	(3)	(4)	(5)	(9)
Mortgage Credit YoY (%, Lag)					0.513*** (0.152)	0.446*** (0.157)
Completed Houses YoY (%, Lag)					-0.036 (0.067)	-0.456** (0.204)
Existing Home Sales YoY (%, Lag)					0.283***	0.291***
Nominal GDP YoY (%, Lag)					0.338***	0.367***
2015 Measures	0.022 (0.034)	-0.011 $(0.029)$	-0.002 (0.029)	-0.029 (0.027)	0.145***	0.127***
Housing Price Index YoY (%, Lag)	0.387**	0.456*** (0.120)	0.412*** (0.123)	0.299***		
Avg Weekly Wage YoY (%, Lag)	-0.113 (0.662)	-0.186 $(0.588)$	-1.369* (0.720)	-0.690 (1.003)		
Mortgage Lending Rate YoY (%, Lag)	0.157 (0.094)	0.151 (0.103)	0.109 (0.106)	0.007		
Unemployment Rate YoY (%, Lag)	0.091 (0.174)	0.248 (0.163)	0.061 (0.151)	$-0.309^{**}$ (0.134)		
Avg Weekly Wage YoY (%, Lag, Squared)			30.759* (17.149)	27.931 (19.518)		
Housing Price Index YoY (%, Lag, Squared)		-2.625*** (0.935)	$-2.348^{**}$ (0.924)	$-2.334^{**}$ (0.971)		
Unemployment Rate YoY (%, Lag, Squared)		0.839 (0.826)				
Indexed LTV YoY (%, Lag)				0.149***		0.420** (0.199)
Constant	-0.048*** (0.013)	0.003 (0.029)	-0.006 $(0.027)$	-0.037 (0.033)	-0.096*** (0.026)	-0.086*** (0.024)
Note:					*p<0.1; **p<0.05; ***p<0.01	05; *** p<0.01

# **C** Figures

## C.1 Dependent versus Independent Variable Correlations: Model 1



Figure 1: Correlation of Variables with Dependent Variable (Model 1)

## C.2 Dependent versus Independent Variable Correlations: Model 2

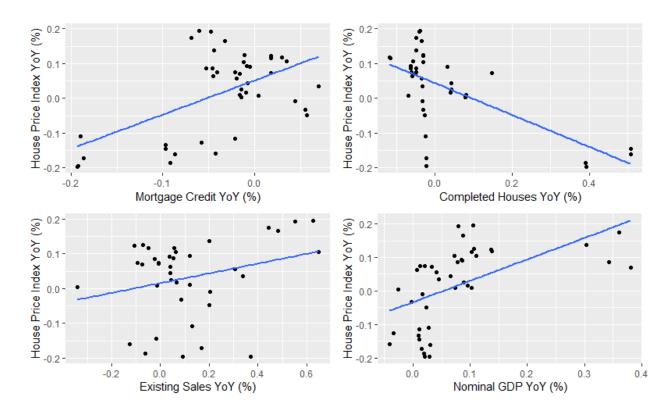


Figure 2: Correlation of Variables with Dependent Variable (Model 2)

## C.3 Residual Diagnostic Tests: Model 1

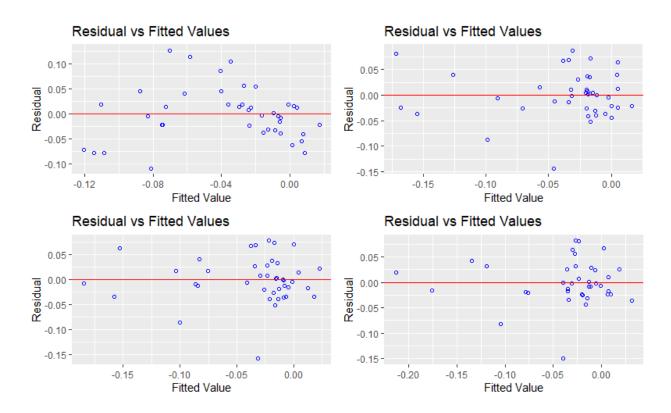


Figure 3: Residuals vs Fitted Values Plot for Model 1

# C.4 Residual Diagnostic Tests: Model 2

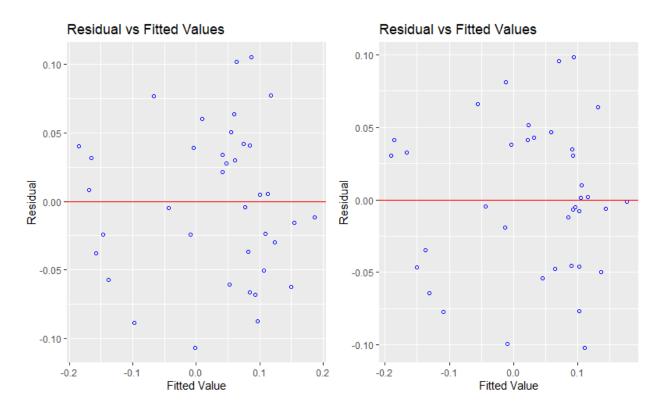


Figure 4: Residuals vs Fitted Values Plot for Model 2

# C.5 Residual Diagnostic Tests: Model 1 Residuals Distribution

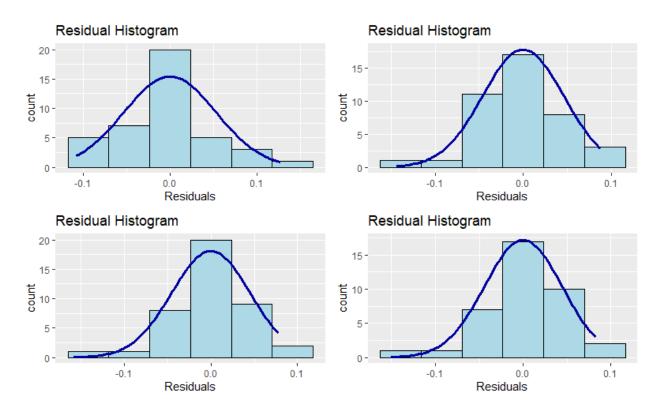


Figure 5: Residuals Distribution For Model 1

# C.6 Residual Diagnostic Tests: Model 2 Residuals Distribution

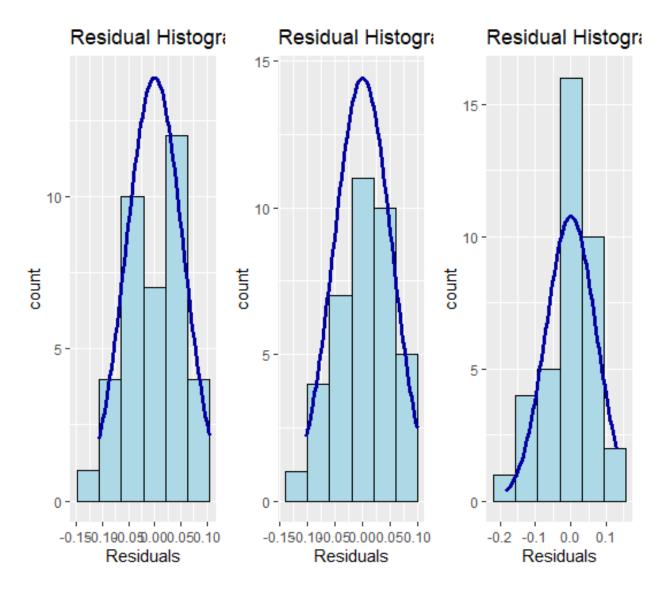
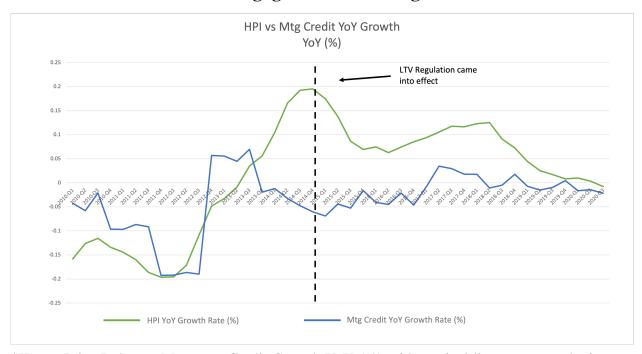


Figure 6: Residuals Distribution For Model 2

## **D** Charts

# **D.1** House Price Index vs Mortgage Credit Lending Growth



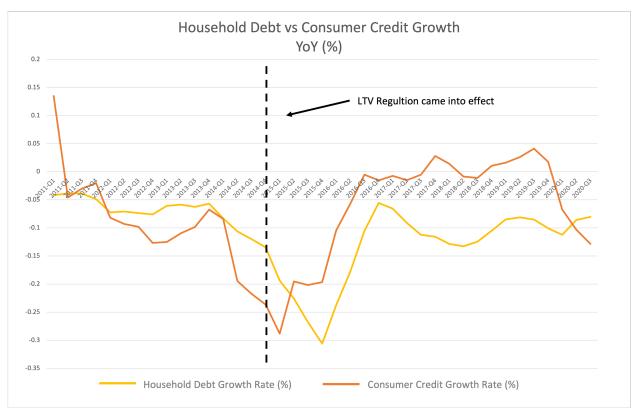
<sup>\*</sup>House Price Index vs Mortgage Credit Growth YoY (%) with vertical line represent the implementation of the 2015 LTV measure.

## D.2 Completed New House vs Existing Home Sales Growth YoY (%)



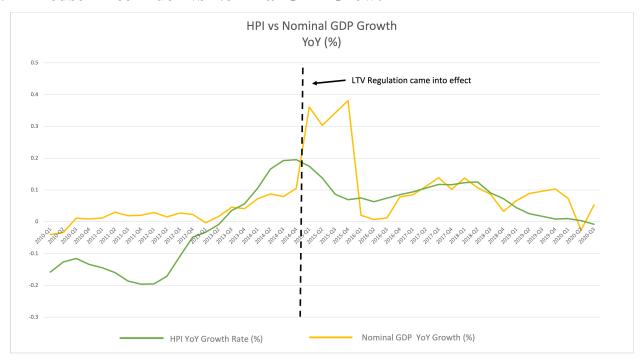
<sup>\*</sup>Completed New House vs Existing Home Sales Growth YoY (%) comparison with vertical line represent the implementation of the 2015 LTV measure.

## **D.3** Household Debt vs Consumer Credit Growth YoY (%)



<sup>\*</sup>Household Debt vs Consumer Credit Growth YoY (%) comparison with vertical line represent the implementation of the 2015 LTV measure.

## **D.4** House Price Index vs Nominal GDP Growth



<sup>\*</sup>House Price Index vs Nominal GDP Growth YoY (%) with vertical line represent the implementation of the 2015 LTV measure.