UNIVERSIDAD COMPLUTENSE DE MADRID
FACULTAD DE CIENCIAS ECONÓMICAS Y EMPRESARIALES

TESIS DOCTORAL

Three essays on macroprudential policy

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Alejandro Buesa Olavarrieta

Directores

Francisco Javier Población García
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No nos hemos perdido,
infinitas batallas nos preceden.
(Raúl Zurita)

Heureux qui comme Ulysse
a fait un beau voyage.
Heureux qui comme Ulysse
a vu cent paysages
et puis a retrouvé
après maintes traversées
le pays des vertes allées.
(Georges Brassens)

Agradecimientos

Resulta muy difícil condensar las vivencias que conducen a la conclusión de una tesis doctoral en unos pocos párrafos. En mi caso, la redacción de esta tesis fue fruto de infinitos encuentros y coincidencias vitales alineadas en la dirección adecuada.

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Las Delicias (Arganzuela), Madrid, 1 de julio de 2021.

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Summary

This doctoral thesis gathers three studies on different aspects of macroprudential policy and financial stability. The research questions featured in each of its parts are to be seen as complementary: one chapter concentrates on mortgage credit markets, another one explores the business decisions of banking institutions, while the remaining one considers the potential international implications of borrower-based measures.

The first paper introduces a simplified picture of the mortgage credit market and its behaviour under regulatory constraints related to borrower-based macroprudential policies. More precisely, the chapter presents an assessment of the effects of loan-to-value (LTV) ratio caps for housing mortgages using an agent-based model. Sellers, buyers and banks interact within a computational framework that enables the application of LTV caps to a one-step housing market. The initial exercise, which relies upon simulated distributions of buyers and sellers, is followed by a more realistic setup calibrated through actual European data from the Household Finance and Consumption Survey. In both cases, the application of an LTV cap results in a modified distribution of buyers along property values, bidding prices and properties sold, depending on the shape of the probability distributions of the LTV ratio, wealth and debt-to- income ratios considered. The results are of similar magnitude to other studies in the literature embodying other analytical approaches and suggest that this methodology can potentially be used to gauge the impact of common macroprudential measures.

The purpose of the second paper is to analyse how the evolution of credit risk measurement, having transitioned from the incurred to the expected loss approach, can affect the provisioning decisions of banking institutions as well as their profitability. To that end, it compares the cyclical behaviour of various credit impairment accounting regimes, namely IAS 39, IFRS 9 and US GAAP. The impact of credit impairments on the Profit and Loss (P&L) account is modelled under all three regimes. The results suggest that, although IFRS 9 is less procyclical

than the previous regulation in place (IAS 39), it remains substantially more procyclical than US GAAP because it merely requests to provision the expected one-year loss under Stage 1 (initial category) exposures. Instead, since US GAAP prescribes that lifetime expected losses are fully provisioned at inception, the amount of new loans originated is negatively correlated with realized losses. This leads to relatively higher (lower) provisions during the upswing (downswing) phase of the financial cycle. Nevertheless, the lower procyclicality of US GAAP seems to come at cost of a large increase in provisions. When synthetic, alternative paths are considered for defaults and the flow of new credit -mimicking different business cycles-, under our assumptions provisioning is larger during cycles with a longer contractionary phase. In terms of procyclicality, the length and shape of the cycle appears to matter much more under IFRS 9.

The third paper aims to expand the set of aggregate data available on credit quality across countries while also exploring the international dimensions of macroprudential policy. The paper describes a novel methodology of measuring risky and conservative mortgage credit using household survey data for 17 European Union countries and the United Kingdom. In addition, time series for both types of credit are constructed and embedded into a global vector autoregressive (GVAR) model, so as to study how shocks to both variables affect domestic output and propagate across countries through cross-border banking exposures. The results show that a decrease in risky credit can have long-lasting positive effects on GDP, both in the originating country and its most exposed peers, while a fall in conservative credit is detrimental. In some geographies, negative shocks to both types of credit reduce output, a feature linked to the lower relevance of homeownership which implies that mortgage credit plays a less prominent role in the domestic economy.

The views and opinions expressed in each of the chapters of this Doctoral Thesis are solely the authors' and do not necessarily represent those of the European Central Bank, Banco de España or the Eurosystem.

Resumen

Esta tesis doctoral agrupa tres estudios sobre diferentes aspectos de la política macroprudencial y la estabilidad financiera. Las cuestiones planteadas en cada una de sus partes han de considerarse como complementarias: una parte se centra en el mercado de crédito hipotecario, otra explora las decisiones empresariales de las entidades bancarias y la última considera la posible dimensión internacional de aquellas medidas impuestas sobre los prestatarios.

El primer artículo introduce una visión simplificada del mercado de crédito hipotecario y sus dinámicas en presencia de restricciones regulatorias. Más en concreto, el capítulo presenta una evaluación de los efectos de los límites sobre la ratio préstamo-valor (LTV) para hipotecas ligadas a la vivienda por medio de un modelo basado en agentes. Compradores, vendedores y bancos interactúan en un marco computacional que permite imponer límites a la ratio LTV sobre un mercado de un período. El ejercicio inicial, que utiliza distribuciones simuladas para vendedores y compradores, se complementa con un escenario más realista calibrado a través de microdatos de la encuesta europea sobre el consumo y las finanzas de los hogares (HFCS). En ambos casos, la aplicación de un límite a la ratio LTV induce cambios en la distribución de precios, ofertas y propiedades vendidas, dependiendo de las características de las distribuciones de la ratio LTV y otras medidas. Los resultados arrojan magnitudes similares a las mostradas en otros estudios de la literatura que utilizan metodologías alternativas, y sugieren que este modelo tiene el potencial de usarse para evaluar el impacto de las medidas macroprudenciales más comunes.

El propósito del segundo estudio es analizar cómo la evolución en la medición del riesgo de crédito, tras la transición desde el modelo de pérdida incurrida al de pérdida esperada, puede afectar a las decisiones de provisionamiento de las entidades financieras así como a su rentabilidad. Para ello, se compara el comportamiento cíclico de distintos regímenes contables: IAS 39, IFRS 9 y US GAAP. El impacto de las pérdidas sobre la cuenta de pérdidas y ganancias (P&L) se modela para los tres casos: los resultados sugieren que, aunque IFRS

9 es menos procíclico que la regulación previa (IAS 39), sigue siendo considerablemente más procíclico que US GAAP puesto que solo requiere provisionar las pérdidas de exposiciones tipo Stage 1 a un año vista. En contraste, US GAAP prescribe que al origen de la exposición ha de provisionarse la pérdida esperada para todo el horizonte temporal; esto conduce a provisiones relativamente mayores (menores) durante la fase expansiva (contractiva) del ciclo. En todo caso, la menor prociclicidad de US GAAP parece venir acompañada de un notable aumento de las provisiones. Cuando se consideran sendas alternativas para los incumplimientos crediticios y el ciclo económico, el provisionamiento es mayor en ciclos con una fase contractiva más larga. En términos de prociclicidad, la longitud y forma del ciclo parecen ser de mayor importancia bajo IFRS 9.

El tercer y último artículo pretende expandir el conjunto de datos agregados sobre calidad crediticia disponible en la actualidad, al tiempo que explora la dimensión internacional de las políticas macroprudenciales. El artículo describe una novedosa metodología para la medición del crédito hipotecario "riesgoso" y "conservador" utilizando datos de encuestas para 17 países de la Unión Europea junto con el Reino Unido; además, se construyen series temporales para ambas magnitudes y se insertan en un modelo autorregresivo global (GVAR), con el fin de estudiar cómo perturbaciones en éstas pueden afectar a la economía doméstica y propagarse a otros países por vía de las exposiciones bancarias. Los resultados muestran que una caída en el crédito riesgoso puede tener efectos positivos y persistentes sobre el PIB, tanto en la economía doméstica como en las más expuestas, mientras que una caída en el crédito conservador tiene efectos negativos. En algunas geografías, perturbaciones negativas a cualquiera de ambos tipos de crédito reducen el producto, un fenómeno ligado a la menor relevancia de la vivienda en propiedad, que implica que el crédito hipotecario juega un papel menos prominente en la economía doméstica.

Los puntos de vista expresados en cada uno de los capítulos de esta tesis doctoral son los de sus respectivos autores y no representan necesariamente los del Banco Central Europeo, el Banco de España o el Eurosistema.

Chapter 1

Introduction

In the wake of the 2008 global financial crisis, banking institutions were forced to adapt to a new environment of lower interest rates and muted credit provision to the real economy, an evolved *statu quo* with the potential of compromising the viability of at least a segment of the financial sector. As a consequence of the latter -and the crisis itself-, tackling financial systemic risk became of paramount importance. In most cases, international authorities and national regulators did not have the necessary tools to prevent the build-up of risks, both at the systemic and the institution level: this void gave rise to the blossoming of micro- and macroprudential policies. The first are conceived in a bottom-up, exogenous fashion, as their mandate is to tackle problems or manage risks in individual institutions; in contrast, macroprudential measures have a top-down nature because they address systemic conditions. This doctoral thesis will concentrate on the latter -or rather, a subset of those, which will be bounded later in this Introduction.

In the EU, a major milestone for macroprudential policy was the creation of the European Systemic Risk Board (ESRB) at the end of 2010, for it constituted a centralised body at the Union level entrusted with macroprudential oversight of Member States as well as, in a broader sense, safeguarding financial stability from systemic risks. The legal framework for macroprudential policy came four years later, in 2014, with the finalisation and entry into force of the Capital Requirements Directive IV (CRD IV) and the Capital Requirements Regulation (CRR), both providing Member States with a unified set of instruments to address and manage systemic risk in the banking sector. While instruments contemplated in the CRD have to be transposed into national law, those in the CRR become EU Community Law with immediate effects.

According to the ESRB, financial stability is to be achieved through a set of intermediate objectives: First, to prevent excessive credit growth -which has proven to fuel most major financial crises- and excessive leverage -which is a long-standing catalyst of the former. Second, to avoid large concentration of credit/market risk exposures, because of the associated increase in the vulnerability to system-wide shocks. Third, to address misaligned incentives issues, e.g. by making large (systemic) banking institutions less prone to moral hazard because of the implicit government support that they benefit from. Finally, to minimise mismatches in maturity of financial assets and market illiquidity, both of which can originate from short-term, unstable funding sources, among other factors. Each of these intermediate goals can be achieved through a variety of macroprudential instruments (see Table 1.1) which can also overlap in scope or be implemented simultaneously.

Risk to tackle	**Associated policies**
Excessive growth & leverage	Countercyclical Capital Buffer (CCyB) Systemic Risk Buffer (SRB) Capital Conservation Buffer (CCoB) Borrower-based measures (limits on loan/borrower characteristics) Sectoral requirements Leverage ratios Macroprudential use of Pillar 2*
Large exposure concentration	SRB Limits in exposure amounts (possibly sectoral)
Excessive maturity mismatch	Net stable financing ratio (NSFR) Liquidity Coverage Ratio (LCR), (Pigouvian) liquidity surcharges Loan-to-Deposit (LTD) ratios
Misaligned incentives	Systemically important institution (G-SII,O-SII) capital buffers SRB, CCoB

Source: European Systemic Risk Board.
(*) Pillar 2 instruments, such as capital surcharges (requirements—P2R or guidance—P2G) are usually considered microprudential measures as they are bank-specific.

Table 1.1: Macroprudential measures by intermediate financial stability objectives.

This doctoral thesis aims to explore a subset of the macroprudential universe: borrower-based measures (henceforth BoBMs). These instruments impose limits on the volume of credit granted by financial institutions to the real economy. When considering the scope of the limitations, one first natural classification of these measures arises: In a first group, only the characteristics of a loan (e.g. amount, collateral value, maturity) are evaluated to impose the limit; this is the case for caps on the loan-to-value (LTV) ratio, maximum maturities or amortisation requirements. A second set of BoBMs includes those formulated using borrower-specific variables: the most prominent examples are limits on loan-to-income (LTI) ratio or the debt-service-to-income (DSTI) ratio.

According to economic theory, there are a number of channels through which BoBMs might accomplish their main goal, that is, to preserve financial stability by maintaining indebtedness and the flow of credit at reasonable levels. On one hand, BoBMs act as a hedge against pervasive idiosyncratic shocks to borrowers' income, thus lowering the probability of loan defaults throughout the debt's life cycle; on the other, lenders benefit from lower credit risk as loan losses and risk exposure amounts are a function of the probability of default (PD) and the loss given default (LGD) for each asset class; in general, both parameters decrease following the application of BoBMs. As a matter of fact, this type of measures can be combined in order to increase their effectivneess: for instance, an LTV limit can reduce the PD while a cap in the DSTI ratio -with a pronounced intertemporal nature- would lower the LGD, regardless of the date at which default took place.

BoBMs are particularly known to the general public because of their strong link to real estate markets. Most measures in place within the European Union target residential real estate (RRE) credit exposures in the form of mortgage loans, with commercial real estate (CRE) being included only in some countries. This feature is not unexpected since mortgage credit represents the lion's share of loans by banking institutions to the private sector in most geographies[1]. As a result, limiting the flow of credit secured by immovable property has a direct effect on the housing market, possibly by reducing demand and lowering house prices. Moreover, owing to their ability to tweak the access to housing and alter the homeownership-rental equilibrium, BoBMs are sensitive instruments as their misuse or inadequate calibration might lead to increased economic inequality. **Chapter 2 of this Thesis analyses the effects of a limit in the LTV ratio on the provision of mortgage credit and real estate prices for a broad set of European countries.**

As useful as the application of BoBMs might prove for preserving financial stability, it might endogenously pose a downside risk lest credit provision be reduced to the point of hampering the lending institutions' financial soundness. For instance, were BoBMs to be implemented during the upswing phase of the economic cycle, the Profit and Loss (P&L) account could deteriorate against the counterfactual of no policy in place. On a different note, low-LTV loans have a negative accounting impact on capital requirements because they are associated with lower risk weights, so there might be an incentive to worsen the capital position of a banking institution. All of the former feeds further into the business model of

[1] See Section 3.3.

banks because regulatory parameters affected by BoBMs determine the stock of provisions accumulated to cope with faulty loans. In this vein, **Chapter 3 of this Thesis evaluates how forward-looking credit risk accounting might impact the provisioning of mortgage exposures and the P&L account of financial institutions.**

The design of BoBMs is subject to a number of measurement challenges. For instance, in the case of LTV limits, determining the value of the collateral is troublesome because banks tend to make a procyclical assessment, thus overpricing properties in the boom phase of the cycle. On a different note, LTI and DSTI limits require comprehensive income data from the borrowers, which is not always readily available, to be implemented effectively beyond the inception date of the loan. In general, the calibration of BoBMs would benefit from increased data availability: in many cases, the regulatory bodies lack detailed information at the individual loan level of the aggregate credit portfolio. By way of example, there are few datasets which allow to construct measures of loan quality and riskiness spanning a long period, beyond the well known non-performing loan (NPL) statistics, granular stress test information and, more recently, the Stage 1-2-3 classification in IFRS 9 impairment accounting[2]. In an attempt to help overcome this data gap, **Chapter 4 of the Thesis presents a novel methodology to construct aggregate measures of conservative and "risky" mortgage credit based on household survey data.** The exercise also tries to account for the potential leakages that may arise when implementing BoBMs: One of long-lasting tradition in the literature is the possibility of circumventing the LTV/LTI/DSTI limits by splitting up the loan and borrowing from more than one lender.

Last but not least, in the context of the European Union, a consequence of the regulatory "duality" between the CRD IV and the CRR is that BoBMs fall within the realm of national authorities, both in terms of their design and their effective implementation. In parallel, the increased interconnectedness -through branches and subsidiaries- of the European banking sector implies that macroprudential policies enacted in one country might have spillover effects in other geographies. From the standpoint of financial stability, both realities can only be reconciled through coordination of national authorities. **In addition to its methodological contribution, Chapter 4 uses a macroeconometric framework to illustrate how spillovers of BoBMs might be sizeable in foreign countries heavily exposed to the domestic banking sector.**

[2]...which is an *ex post* distinction made once the loan has been contracted, though it remains a valid proxy.

Chapter 2

Agent-based modelling for the assessment of LTV caps

*This chapter is joint work with Dimitrios Laliotis, Miha Leber and Javier Población. It was published as "An agent-based model for the assessment of LTV caps" in **Quantitative Finance 20(10)** (pp. 1721-1748) and the **ECB Working Paper Series** (#2294).*

2.1 Introduction

Housing markets are among the most important sectors of modern economies, probably the largest asset class in the world; owing to their relationship with macroeconomic dynamics, following the literature (see, for example, Reinhart and Rogoff (2013)), real estate bubbles and bursts characterize almost all financial crises, with the recent episode of the Great Recession being no exception.

However, because housing price characteristics such as illiquidity, locality, leverage or heterogeneity often render modelling demanding and difficult, researchers sometimes choose convenient shortcuts that represent a good approximation in most environments.

In this paper, we use an agent-based model (ABM) to assess loan-to-value (LTV) cap measures and determine the evolution of portfolio credit parameters, the impact on the provision of credit by banks and on the evolution of housing prices after the application of such caps.

The literature on housing markets is extensive. On the one hand, much conceptual work has started to appear related to macroprudential policy; some examples are Kuttner and Shim (2012), Nier et al. (2012), Kannan et al. (2012), and Christensen (2011). Mendicino (2012) shows that countercyclical LTV ratios in response to credit growth can smooth the credit cycle, whereas Unsal (2011) examines the link between monetary policy and macroprudential regulation in an open economy dynamic stochastic general equilibrium model with nominal and real frictions. The author finds that macroprudential measures can usefully complement monetary policy. A recent paper summarizing the experiences with *ex ante* impact assessments of macroprudential instruments can be found in BIS (2016).

On the other hand, research, though still scarce, is evolving on the empirical modelling side. Crowe et al. (2011) use state-level US data to find a positive relation between LTV at origination and subsequent property appreciation. Lim et al. (2011) evaluate the effectiveness of macroprudential instruments such as LTV caps in reducing systemic risk over time and across markets using data from 49 countries. Price (2014), as well as Bloor and McDonald (2013), use a Bayesian vector autoregression to conduct ex ante counterfactual analyses prior to the introduction of borrower-based policies in New Zealand. Building upon the same approach, Cussen et al. (2015) conduct a micro simulation exercise based on loan-level data to quantify the impact of various caps on loan volumes in Ireland[1]. Almeida et al. (2006) provide evidence that in countries with higher LTV ratios, house prices and demand for new borrowers are more sensitive to income shocks. Lamont and Stein (1999) find that in cities where a greater fraction of households have high LTV ratios, house prices respond more sensitively to economic shocks[2]. For Korea, Igan and Kang (2011) find that LTV and debt-to-income ratio caps help to contain house price growth. Finally, Lambertini et al. (2013) highlight the importance of an expectations channel developing a model of the housing market that incorporates expectations-driven cycles, then showing that countercyclical LTV rules responding to credit growth can reduce loan volatility and the loan-to-GDP ratio.

The contribution of our paper, seen against this strand of the literature, is to simulate a handful of simple models with agent-based techniques and to assess their efficiency in capturing the underlying dynamics. The intention is not to provide a fully-fledged analytical framework, rather a proof of concept on the suitability and efficiency of such behaviour-capturing models to contribute to the impact assessment of macroprudential measures of this type.

[1]Further related work for Ireland can be found in Hallissey et al. (2014), Lyndon and McCarthy (2013) and Kelly and O'Malley (2016).

[2]A list of related studies includes, with no intent of being exhaustive, Gerlach and Peng (2005), Nabar and Ahuja (2011), Wong et al. (2011), Funke and Paetz (2012), and Wong et al. (2016).

ABMs are not novel in the literature; some examples are Colander et al. (2008), LeBaron and Tesfatsion (2008), Gilbert et al. (2009), Farmer (2014) and Dawid et al. (2018). Our approach is based on Axtell et al. (2012), who proposed a new and comprehensive model of the housing market in Washington, DC. This particular modelling approach is innovative in the literature in the sense that micro-level data is used to calibrate behavioural equations instead of postulating theoretical top-down behavioural rules. The main focus of their work was on demonstrating the causal relationship between leverage and the formation of a housing bubble. Following the same overall approach in the use of multiple sources of micro data to elicit behaviours, Baptista et al. (2016) develop an ABM of the UK housing market to study the impact of macroprudential policies on key housing market indicators. This view enables them to tackle the heterogeneity in this market by modelling the individual behaviour and interactions of first-time buyers, home owners, buy-to-let investors and renters from the bottom up, as well as to observe the resulting aggregate dynamics in property and credit markets.

In line with these works, in our paper the housing market is viewed as a universe of interacting heterogeneous agents comprising sellers, buyers and banks. Following autonomous decision rules, these agents interact directly with one another and the economic environment, producing an overall economic outcome that emerges from complex interactions and that cannot be easily derived from the agents' objectives and behavioural rules. In this respect, Table 1 compares our framework with the two aforementioned closest references. Our approach is the simplest one because we do not envisage to predict housing prices but to assess the impact of the application of borrower-based macroprudential measures. That is the reason why we do not consider neither investors nor renters in our model.

Since they largely influence the choice of simplifications in our approach, there are two specific characteristics of the task of measuring the impact of macroprudential measures that should be noted. First, the results are relative in the sense that answers are sought on metrics (credit provision, housing prices) with or without the application of caps. Second, for the time being, one-time-step models are more critical to design, since our focus is on the impact related to the application of the macroprudential measure and not on the convergence of more complex multi-stage ABM that tend to focus on forecasting the housing cycle.

	Baptista et al. (2016) *Macroprudential policy in an agent-based model of the UK housing market*	**Axtell et al. (2014)** *Getting at systemic risk via an agent-based model of the housing market*	**Buesa, Laliotis, Leber and Población (2019)** *An agent-based model for the assessment of LTV caps*
Policy questions	(1) Booms and bust dynamics conditional on... ...size of rental/Buy-to-let sector ...different types of Buy-to-let investors (2) Qualitatively assess the effect of macro-prudential policies, such as a Loan-to-income limit	Housing price dynamics (booms and busts)	Impact of borrower-based macroprudential measures (LTV, LTI caps)
Agent types	Households, banks, central bank	Households, banks	Households, banks and regulators (could be a central bank or a government)
Household types	First-time buyers, buy-to-let investors, renters, owner-occupier	Home buyers and sellers, investors	Home buyers and sellers
Role of bank agents	Supply of mortgage loans	Supply of mortgage loans	Supply of mortgage loans
Role of central bank agents	Set LTV and LTI	-	Set LTV caps
Role of government	-	-	Set LTV caps
Role of non-financial firms	-	-	-
Markets in the model	Housing and rental market	Housing and rental market	Housing market, mortgage loan market
Demographic features for households	Age (related: birth, death and inheritance)	-	-
Empirical calibration	Micro calibration: Household survey, housing market data; macroeconomic indicators	Micro calibration: Household survey, real estate transactions data, mortgage loans series	Any micro-data source that covers the required inputs (possibly HFCS database for European countries)

Table 2.1: Comparison between this paper and its closest peers in the literature.

As a result, we initially present simulated results based on stylized, yet pragmatic assumptions. Subsequently, we calibrate the probability distributions from empirical data. We use the second wave of the European Central Bank's *Household Finance and Consumption Survey*, and a copula-based approach for the estimation of multivariate distributions of initial liquid wealth, debt-service-to-income ratios, LTV ratios and loan-to-income (LTI) ratios. Based on these real data probability distributions, we present the distributions of properties that are actually traded in the auctions pre- and post-application of an absolute LTV ratio cap, as well as under the assumption of a proportionate cap, where banks are allowed to exceed the imposed cap for a certain proportion of their newly originated exposures, i.e., some borrowers are indeed allowed to be granted loans in excess of the cap level, based on the banks' credit assessment. Finally, we divide the sample by country in order to present the results at the country level.

We compute the variation in house prices and mortgage credit under all the LTV cap specifications considered. Country estimates for real estate prices range from 5% increases to -12% contractions, whereas credit is shown to decrease within the 6%-12% interval. These results are are similar in magnitude to other studies in the literature adopting a variety of quantitative methods, showing that the approach is a useful and possibly complementary alternative to the existing analytical frameworks for assessing the impact of borrower-based macroprudential measures.

The remainder of our paper is organized as follows: In Section 2.2, we sketch an outline of the model and its components. In Section 2.3, we present the results, first from a series of simulations and subsequently based on a model calibration through real survey data to illustrate the impact of applying an LTV cap on mortgage lending. Section 2.4 concludes.

2.2 The agent-based model

Agent-based models (ABMs) are computational tools in which heterogeneous agents interact directly with one another and with their economic environment, following autonomous decision rules.

Our approach is based on a straightforward ABM where we model the interactions of sellers, buyers and banks within a computational framework that maps the economic environment, in the form of credit provision by banks and the applied LTV caps, into the emergence of a one-step housing market settlement state, where specific properties are sold at specific prices during the one-step time interval. Therefore, the ABM can be viewed as a set of parallel-run property auctions, one for each seller, on the properties offered by the universe of sellers, where the buyers' behavioural trends and the banks' imposed financing constraints define the demand side. Since the problem is that of assessing the impact of imposing LTV caps, the whole computational model has to be set up as a relative/differential model in the sense that the results should be compared in the pre- and post- LTV cap cases.

In that context, we restrict ourselves to a single time step - how the housing market *clears* for one period with or without the cap - and we ignore any multiple period aspects - how housing prices *evolve* over time and how this is linked to the formation of price imbalances. This consideration is relatively scarce in the ABM literature, where more often the target is to predict the long-term equilibrium for an entire housing cycle, that is, the multiple-stage evolution of house prices and the respective imbalances.

2.2.1 The seller agents

The model assumes that there are N sellers at the beginning of the period, each of them offering a single property in the market; for each seller, there is a parallel auction with all the buyers interested in buying the house. This implies that from a computational perspective, N parallel auctions would be needed in order to identify a final market clearing ratio, defined as the percentage of N that is finally sold in the market, and the "equilibrium" prices for those properties. The latter also entails the emergence of a settlement price for all properties: A transaction price for those sold and an average bid-ask price for those not sold.

The model is agnostic regarding the actual distribution of seller-asked prices. It only assumes that sellers uniformly cover the entire spectrum of the market, with no concentration on specific segments of buyers. More precisely, sellers can be ordered based on the asking price S_i, an ordering that is linked to the quality of the property, i.e. a higher price corresponds to a higher-quality property, with the term quality encompassing several features of the property such as location, size, age, and proximity:

$$S = S_1, S_2, \ldots, S_N,\ S_1 \leq S_2 \leq \cdots \leq S_N$$

Calibration includes the setting of initial asking prices at levels that would ensure uniformity across the distribution of buyers, although alternative and more complex distributions of starting asking prices for the seller agents can be incorporated relatively easily.

For the sellers, the model also assumes a passive behaviour in the sense that they start the auction with an asking price. If they are not "lifted", that is, if the transaction does not originate by a corresponding buyer willing to pay the asking price, they will lower their asking price with probability p_d^S, trying to match a buyer agent in the auction until a limit of a fixed factor r percentage points from the initial asking price S_i is reached. In other words, there is a probability p_d^S that a seller, if not matched by a buyer at the initiation of the auction process, will gradually mark down its asking price from S_i to $S_i \times (1-r)$ in an attempt to match a buyer: This is what we call an aggressive seller. Obviously p_d^S becomes important for calibration purposes, since it defines the supply side and the behavioural tendency of seller agents to mark down property prices.

2.2.2 The buyer agents

Buyer agents represent households seeking to buy a property. A liquid wealth distribution is assumed for each buyer, a percentage of which may be used for the down payment of a mortgage loan. Each buyer is assigned an original LTV ratio which, combined with the maximum preferred down payment, results in the highest value of property up to which the agent can bid. Therefore, we assume a set of bids B from M buyer agents:

$$B = B_1, B_2, \ldots, B_M,\ B_1 \leq B_2 \leq \cdots \leq B_M.$$

where

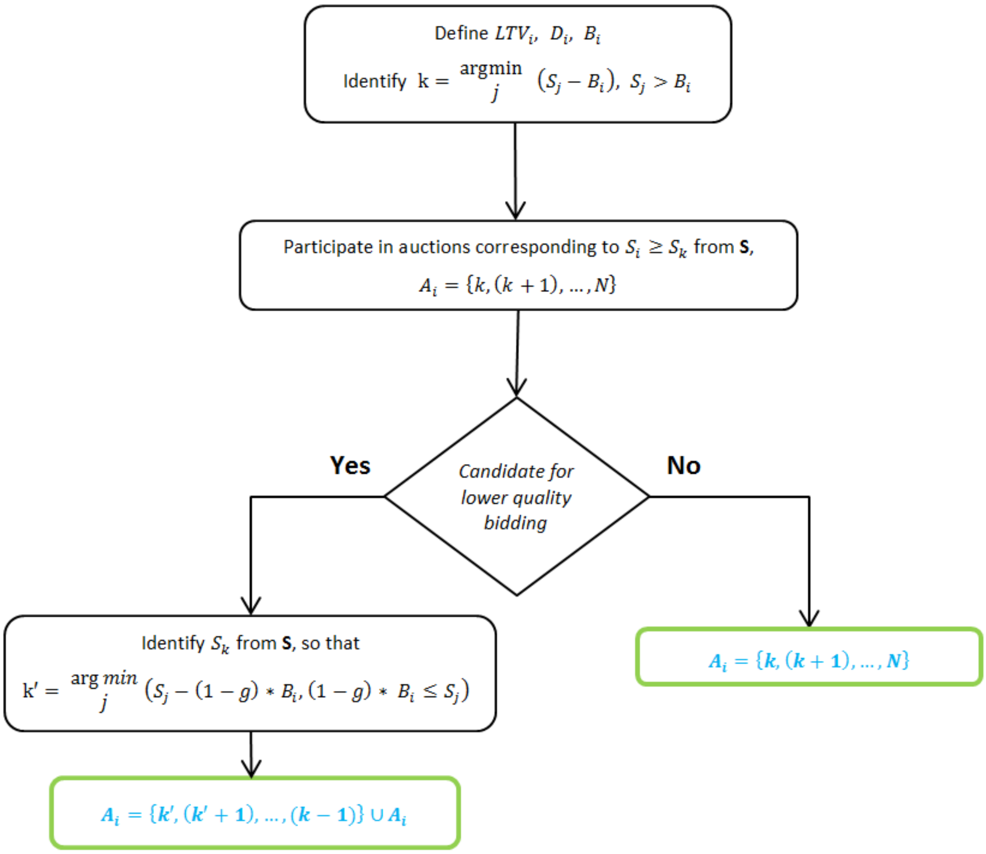
$$B_k = \begin{cases} \min\left\{\frac{D_k}{1-LTV_k}, a\times\omega_k\right\} & LTV_k < 1. \\ a\omega_k, & LTV_k \geq 1. \end{cases}$$

LTV_k represents the loan-to-value ratio associated with buyer agent k drawn from a probability distribution. Essentially, agents with an LTV ratio above 1 will bid as much as a multiple a of their liquid wealth ω_k. As for those having less than unity LTVs, they will choose between the latter amount and a multiple $1/(1-LTV)$ of the down payment D_k, which is randomly drawn as a fraction of liquid wealth in the range (a_1, a_2) or calibrated on the basis of an empirical distribution.

In principle, the model assumes that each buyer agent will always go for the highest quality property and bid in auctions for properties of higher value given the practical limitations imposed by its buying value price B_i. However, with probability p_d^B, buyer k will also decide to participate in auctions where the starting asking price of the seller is smaller (up to a fixed factor g) than its original buying price B_k. This gives buyers the opportunity to react to excessive demand and competition by participating in the auctions of lower quality properties, always within the limits of a given distance g from the maximum quality they can attain with their buying price. Therefore, as in the case of p_d^S for seller agents, p_d^B for buyers represents their tendency to also go for lower quality due to overcrowding conditions. A high value of

p_d^B reflects a higher density of buyer agents due to excessive demand.

The behaviour of a buying agent during the initial phase, when no LTV limits/caps are considered, can be summarized by the decision tree in Figure 2.1.



This figure shows the behaviour of a buyer during the initial phase if no LTV limits are considered.

Figure 2.1: Buyer's decision tree for the no-cap case.

For the case of the buyer's behaviour following the application of LTV caps, an additional option is modelled: The choice, with fixed probability q_d^B, to raise the down payment for the mortgage so that the buyer ends up competing for properties that were within his quality reach before the implementation of the LTV cap (increased own participation). In other words, when the cap constrains the buyer agents to participate in auctions with properties below the range they had been allowed prior to the cap, they may raise their down payment by increasing the part of household initial liquid wealth they consume in the purchase of the property. If such an increase does not allow them to participate in auctions for properties they would have participated in the no cap case, buyers remain inactive in the auctioning process.

Calibrating the value of q_d^B is a sensitive matter given that it is an artefact of our model through which buyers can liquefy their wealth. We assume that increasing the down payment is linked to a stable or improving financial situation; the European data used in the empirical exercise in Section 2.3.2 allows for some tentative calibration; more details can be found in Appendix 2B. With this addition, the buyer's behaviour under a cap in LTVs is summarized in Figure 2.2.

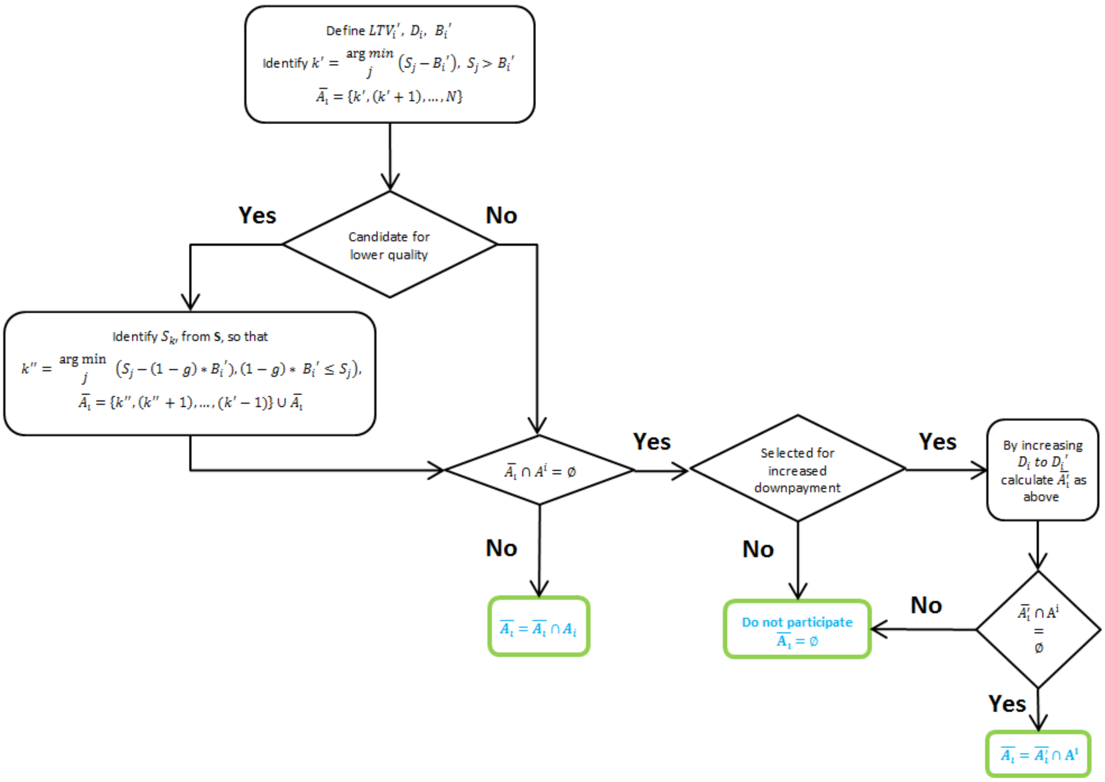


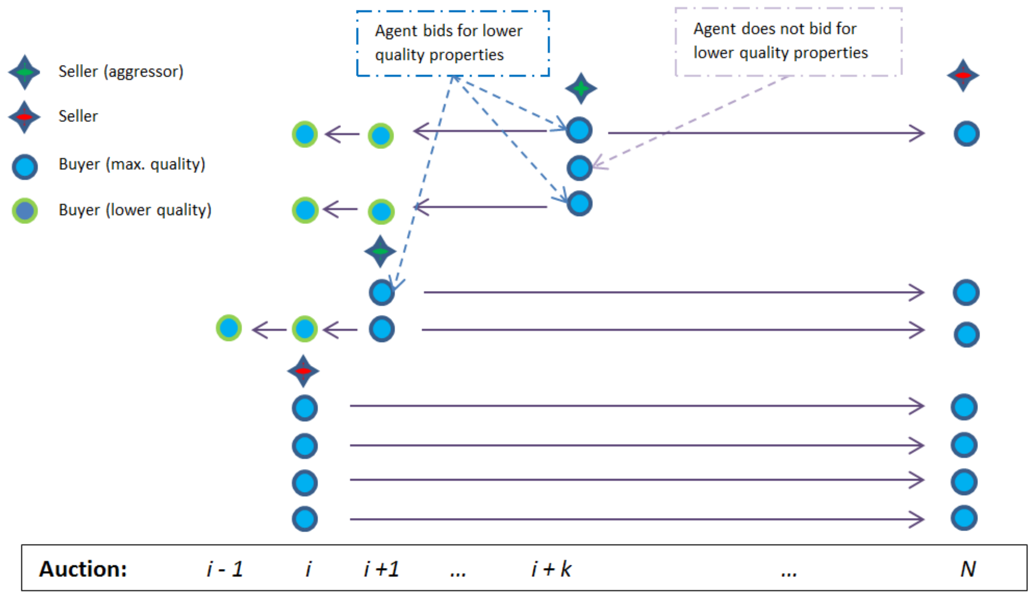
Figure 2.2: Buyer's decision tree if an LTV cap is in place.

2.2.3 The auction process

The N prices $S = S_1, S_2, \dots, S_N$, $S_1 \leq S_2 \leq \dots \leq S_N$ from the sellers are set in a way such that they are distributed across the entire spectrum of the buyer agents' bidding prices $B = B_1, B_2, \dots, B_M$. The easiest way to achieve this computationally is to divide the M buyers into N buckets, using N/M buyers for each bucket. By letting $B_i^*, i = 1, 2, \dots, N$ denote the maximum buying price within each bucket, the asking price of seller i is set as $S_i = B_i^* + \varepsilon$ where ε denotes a small positive constant.

Although such an assignment of asking prices is quite agnostic regarding the supply-side distributional characteristics, it corresponds to the relative strong assumption of a homogeneous market where sellers are distributed uniformly across the different quality segments. Based on the above description, Figure 2.3 schematically depicts the auctioning mechanism of N parallel auctions with the different types of sellers (aggressor and non-aggressor) and buyers (opting for lower-quality and non-opting ones).

The market clearing process can then be treated as a set of parallel auctions—one for each property—with the buyers' behavioural patterns fully defining the auctions' demand side. Computationally, this set of parallel auctions can be fully resolved by starting with the auction at the higher valued property and serially resolving lower-quality properties. This serialization enables the gradual clearance of both sellers and buyers, since buyers successful in bidding a higher valued property can be removed from lower quality auctions.



This figure depicts the auctioning mechanism of N parallel auctions with the different types of sellers (aggressor and non-aggressor) and buyers (opting for lower-quality and non-opting ones).

Figure 2.3: Schematic representation of the parallel auctioning process.

From the standpoint of the market mechanism, the cap case is treated exactly the same in the sense that buyers still have the option of increasing their down payment, bidding for cheaper properties or be subject to a seller that marks down the price.

The market clearing process is shown to converge for both cases, whether under a cap or not. Importantly, by controlling the number of buyers relative to that of sellers, the probability that sellers are willing to hit the bid of the best buyer if not lifted at the auction initiation, as well as the probability that a buyer mutates to the auctions of lower quality, can be used to calibrate the simulation process. They must be set to levels so that the desired clearing ratio (percentage of properties sold before the LTV cap) and demand uplift indicator (percentage of properties sold at a price higher than the one asked by the seller) are achieved.

It is relatively straightforward to calibrate control parameters so that the desirable clearing ratio and uplift ratio are attained in the no LTV cap case, and it is considered economically reasonable to restrain the initialization parameters to the two mentioned above. By way of the construction mechanism, the no LTV cap auction process results in an initial LTV distribution nearly identical to the desired one.

In this paper, we impose two different kinds of LTV caps: A simple absolute LTV cap and a more sophisticated one, the proportionate cap, in which banks are allowed to deviate from applying the cap only to a percentage of borrower exposures[3]. This second case requires the definition of a certain pecking order, based on which the deviation from the cap is applied to potential borrowers.

We have assumed three different types of pecking order[4]. The first proportional cap benefits those with higher total wealth, which are the more likely to be granted a loan with an LTV exceeding what is allowed by the cap. To be more realistic, we added stochasticity to this selection process, allowing for some degree of randomness: A buyer is allowed to exceed the LTV cap with a probability that is analogous to his/her total wealth level; after selecting those that may be allowed to exceed the imposed cap, they are ranked based on their respective total wealth, and starting from the top ones, a serial selection process identifies the prospective buyers with the most total wealth until the exposure limit of the proportionate LTV cap is reached.

In the second type of proportionate cap, buyers closer to the median in total wealth will have a higher probability of receiving a loan with an LTV ratio beyond the limit. In this case, the probability will be inversely proportional to $\frac{|Wealth_{Total} - Wealth_{Median}|}{Wealth_{Median}}$, where $|\cdot|$ represents the absolute value. In both types of proportionate cap, this process may also involve some trial-and-error simulations in order to identify the number of borrowers that would be needed in order to reach the exposure percentage above the cap.

Finally, we propose a third, more realistic version where the probability of exceeding the LTV limit is decreasing in the loan-to-income (LTI) ratio. The intuition is that agents for which the mortgage is a significant share (or even multiple) of total income are less solvent from the standpoint of the lending institution.

[3]Proportionate caps are common in OECD countries. See, for example, ESRB (2016).

[4]As a robustness check, we create a fourth implementation where households above the cap can beat it with random probability; the results are not shown in the paper but are available upon request.

2.3 Results

In this section, we elaborate on the results from our model. These results are important as a whole because they demonstrate that even simple ABMs that allow for the disaggregation of agents' basic behavioural characteristics may be used to assess significant issues that arise when demand and supply are treated in an average or aggregated manner.

A first exercise uses a collection of simulated probability distributions to study the main features of the responses and the sensitivities to selected parameters. In a second pass, we calibrate the distributions based on empirical European data extracted from the second wave of the Eurosystem's *Household Finance and Consumption Survey*, combined with a copula methodology which allows us to produce multivariate distributions of initial liquid wealth, total wealth, LTV ratio and property value at origination.

2.3.1 Simulated data

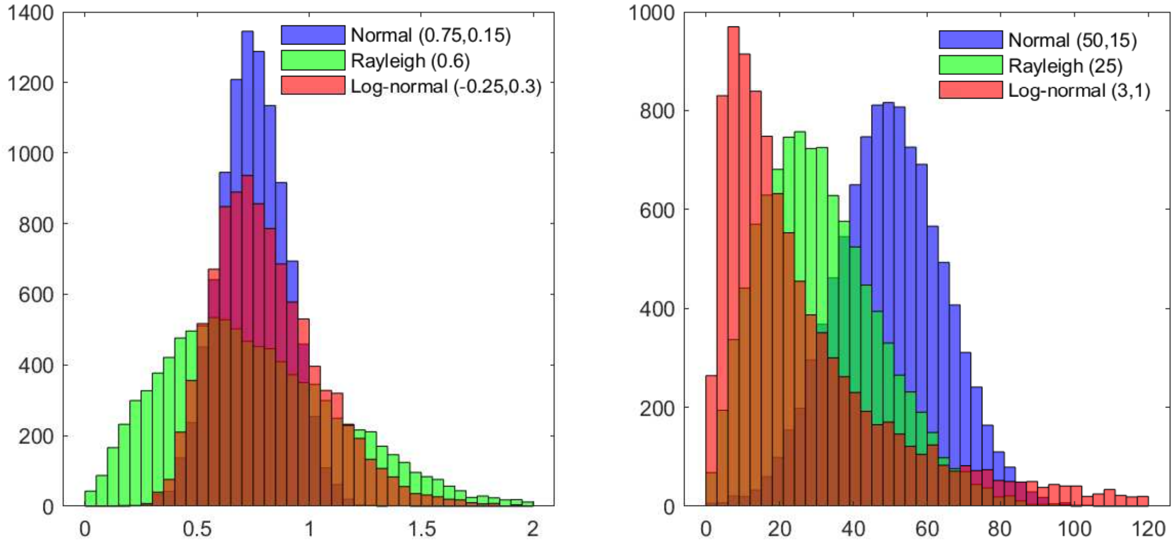
We carried out our study assuming that loan-to-value ratios and wealth follow three different types of probability distributions. The property value distribution function is derived from the LTV density.

Our starting points are Gaussian distributions with mean and standard deviation (0.75,0.5) and (50,15) for the loan-to-value ratio and liquid wealth, respectively. Based on the Gaussians, we find densities from the log-normal and Rayleigh[5] families which cover roughly the same range for both variables but exhibit different skewness and kurtosis. The chosen distributions are shown in Figure 2.4. The multiplicity of starting densities considered acts as a robustness exercise for our results; more importantly, it may be used to model groups of agents with different behaviour in empirical exercises where data is scarce. For instance, one can think of a sample of home buyers obtained from a country where wealth is more uniformly distributed around the median and agents do not contract mortgage loans with high LTVs, even in the absence of a cap, owing to cultural aversion for over-indebtedness.

The absolute LTV cap is set at 80 percent, a reasonable level for most jurisdictions; however, useful insights into relative market impact can be extracted[6] by comparing the results for different LTV caps, as will be discussed later in this section.

[5]The probability density function of a Rayleigh distribution with parameter ρ is $f(x,\rho) = \frac{x\exp\left(\frac{-x^2}{2\rho^2}\right)}{\rho^2}$.

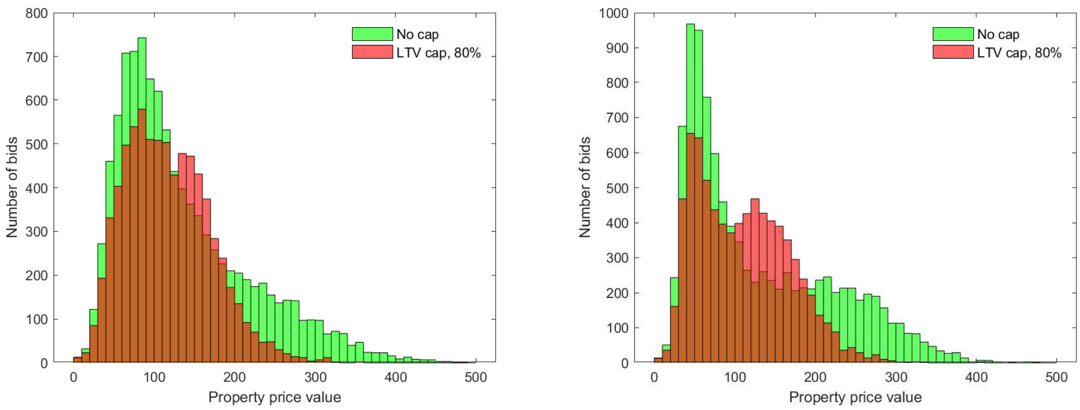
[6]Throughout this section and unless stated otherwise, we use the following calibration: $N = 7500$, $p_d^S = 0.1$, $p_d^B = 0.15$, $q_d^B = 0.3$, $r = 0.2$, $g = 0.1$, $a = 5$, $a_1 = 0.25$, $a_2 = 0.95$.



The brown area represents overlaps between the three distributions.

Figure 2.4: Probability distributions of LTV ratios (left) and liquid wealth (right).

The left hand side of Figure 2.5 summarizes the impact of the LTV cap on the distribution of 10000 buyers for the Gaussian case, which are allocated in buckets corresponding to the value of the property they are bidding for. The application of an LTV cap shifts the distribution of buyers' bids towards the lower end of the price range, since the cap becomes binding for a significant proportion of buyers if we also assume that there is no change in their household's liquid assets and their ability to come up with the required down payment. The inverse is true for higher-priced homes, where demand is relatively weak due to the cap application.

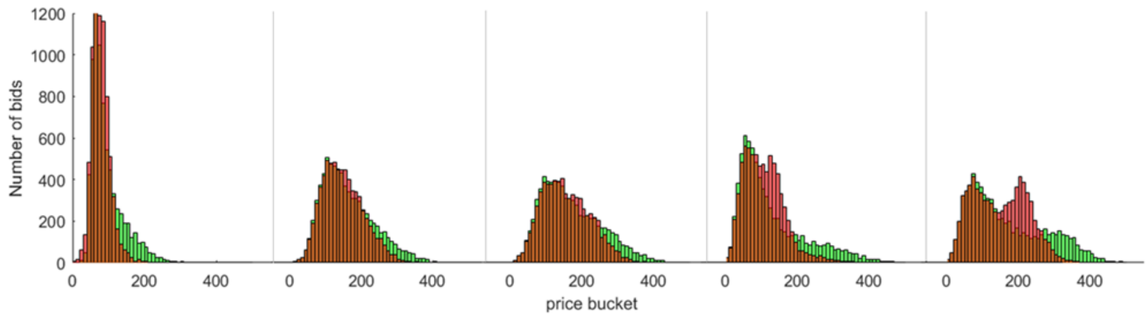


Case 1 (left): Gaussian density for LTV and liquid wealth; Case 2 (right) : Rayleigh density for LTV ratios and a Gaussian distribution for liquid wealth. The brown area represents overlaps between both distributions.

Figure 2.5: Pre- and post-cap distributions of buyer agents with simulated data.

One interesting effect arises when combining differently shaped distributions; on the right hand side of Figure 2.5 we exhibit the particular case of a Rayleigh density for LTV ratios and a Gaussian distribution for liquid wealth. As a consequence of the cap, a sizeable mass of buyers from the upper and lower end of the property range clusters more intensely around average-valued homes, in a behaviour mimicking that of a proportional cap penalizing buyers whose wealth is further from a centrality measure such as the median, as we will analyse later in this section.

From a statistical point of view, it is reasonable to reckon that the correlation between LTV and wealth distributions plays a major role in the shape of the results. Despite having agnostically assumed zero correlation in the previous exercise, most estimates for European countries from the HFCS yield values of -0.3 on average; we therefore decide to compare the distribution of buyers across property buckets for five different correlations, which we show in Figure 2.6. Using the zero case as a benchmark, a greater positive correlation naturally shifts the distribution of buyers towards lower price ranges, since the cap constraint becomes binding for a significant proportion of households under the assumption that there is no change in their household's liquid assets and their ability to come up with the required down payment. In the most extreme case (right corner) the distribution becomes bimodal, as if the market were more uniform, still slightly polarized around two types of representative property: One high-quality for the wealthy households who sign mortgages with high LTVs, and one low-quality for poor households who become prudent and borrow as little as possible. For the negative correlation cases, the effect seems to be much more marked: The average traded price decreases abruptly while low-tier buyers with high-LTV loans flood the auctions for the cheapest properties.



Histograms correspond, to correlations of {-0.75, -0.3, 0.0, 0.3, 0.75}. The green area represents the no LTV cap case, the red area the 80% LTV cap case and the brown area represents the overlap of both distributions.

Figure 2.6: Distribution of buyers for different correlations between LTV and liquid wealth.

Figure 2.7 sketches the ordered buyers (by bids) and the bidding prices before and after the introduction of the cap. It also displays the non-uniform effect on prices that is also observed by comparing the distributions of Figure 2.5. This suggests that different segments of the housing price curve would be affected differently. The magnitude of such effects would also depend on the households' initial liquid wealth distributions and the assumptions on their ability and willingness to increase down payments. Apart from the stylized approach used in the results presented here, where it is assumed that this behaviour does not change post-application of LTV caps, the use of more granular data to model possibly evolving behavioural patterns of buyers may result in significant changes in the way the demand side is comprised after the application of the cap.

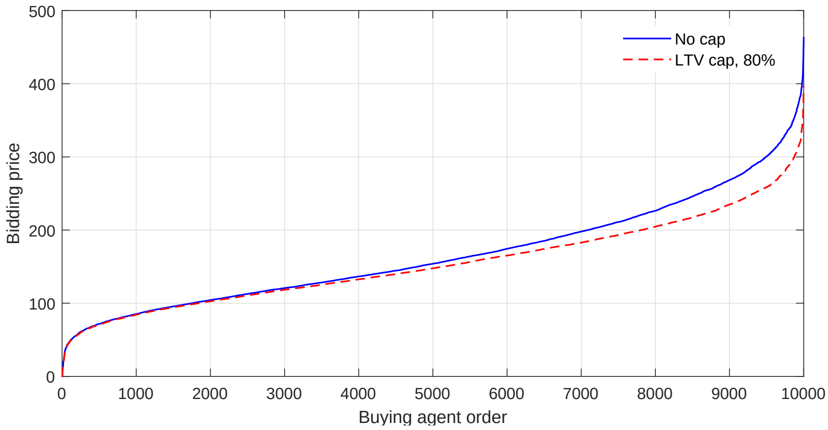
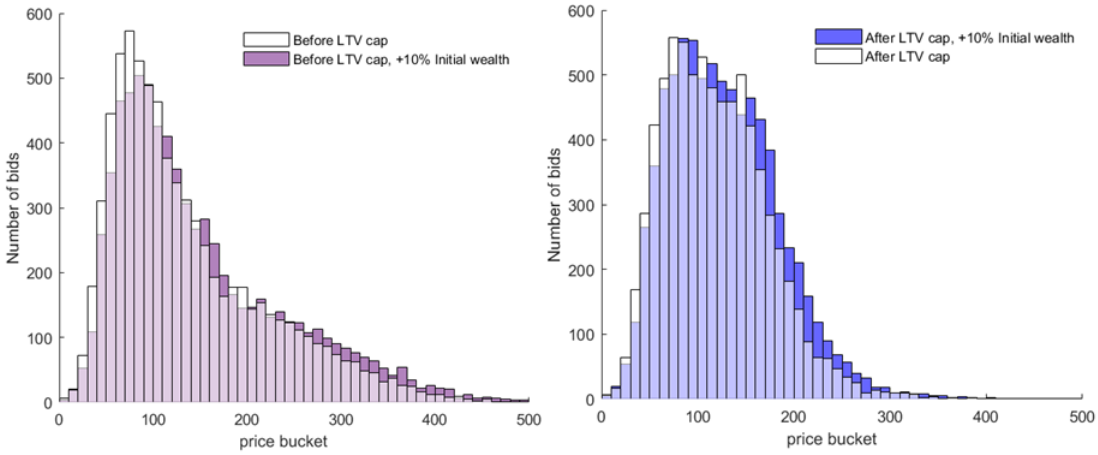


Figure 2.7: Ordered buyer bidding prices pre- and post-LTV cap.

Taking into account the results from Figure 2.7, it is clear that the number of sold properties increases, especially in the price buckets around the mean value, and decreases in the higher-valued properties. One last consideration for the benchmark exercise of an absolute cap relates to how the distribution of agents pre- and post-cap may vary if liquid wealth increases by the same amount for all buyers. Our ABM is not particularly sensitive with the benchmark calibration but is in line with intuition: As shown in Figure 2.8, if wealth uniformly increases by one tenth of the initial value, the same buyers will be placed in auctions for mildly more expensive properties. Graphically, this entails a shift from the left to the right edges of the distribution.

In addition to what has been presented above, a wider set of metrics and indicators can be collected and compared for the two cases in question. Table 2.2 summarizes the findings for simulated runs for different LTV cap values and market density parameters $(N/M, p_d^S, p_d^B)$. Simulation results are presented for several runs that represent different levels of LTV caps

(90, 85 and 80 percent). The results in different clearance ratios in the first column of the table segments can be used to determine the combination of parameters that would be closer to the real conditions of the housing market. In other words, for each city or country, it is possible to obtain yearly data on sold properties and the stock of unsold properties to infer the clearance ratio and market density (N/M). With real data from Table 2.2, one can infer p_d^S, p_d^B, and other model initialization parameters.



Distributions of buyers for an overall 10% increase in wealth before (left) and after (right) the imposition of an LTV cap. In both cases there is an area which represents the overlapping areas for both distributions.

Figure 2.8: Effect of a global 10% increase in initial wealth on the distribution of buyers.

The two segments of the table that refer to the cap and no cap cases also present statistics on the average traded price, the percentage of transactions that were secured by aggressive buyers, the percentage increase on the transaction price due to the aggressiveness of the buying agents and the split of the transaction price between bank credit and buyers' down payments.

Deriving metrics on the impact on housing prices is challenging due to the indexation process that might be required and the heterogeneity of the impact on different segments of the curve due to the "crude" way the LTV cap impacts the demand side of higher quality properties. On the other side, based on our assumptions, estimating the variation of banks' credit provision and increased own participation levels is a straightforward process due to the detailed available data associated with the individual agents of the simulated model.

Nevertheless, in Table 2.2 we present two of those metrics: The difference in credit provided by banks (capturing the credit supply impact) and the difference in property prices that were cleared in both cases through the auctioning process[7]. These two estimates may be

[7]We have to be careful when assessing the housing price decline figures, since what is presented here is the

used as a proxy to compare the impact of different LTV cap levels on both credit supply and housing prices. It is worth noting that in Table 2.2 differences in credit are much higher than differences in prices. This is because the difference in prices is estimated based on common sold properties (pre- and post-cap application), whereas difference in credit is taken from the whole sample.

LTV Cap	N/M	Pd_s	Pd_b	Clearing ratio (%)	Avg traded price	Aggressors (%)	Avg credit by bank	Avg down payment	Clearing ratio (%)	Avg traded price	Aggressors (%)	Avg credit by bank	Avg down payment	Buyers that increased down payment (%)	Credit diff (%)	Price diff in common cleared properties (%)
90%	0.75	0.2	0.1	29.7	140.1	11.9	114.1	26.5	29.9	140.6	11.2	111.4	28.7	100.0	-1.75	-0.01
			0.2	39.0	139.7	23.7	113.5	26.1	39.4	140.4	22.2	111.0	28.3	100.0	-1.10	-0.01
			0.3	49.1	139.1	36.2	112.3	27.0	49.5	139.7	33.7	110.1	29.0	100.0	-1.24	-0.01
		0.3	0.1	37.1	138.9	10.6	112.7	26.4	37.3	139.2	10.1	109.9	28.6	100.0	-2.17	0.00
			0.2	44.8	139.4	21.6	113.0	26.0	45.1	139.7	20.0	110.4	28.2	100.0	-1.69	-0.01
			0.3	55.1	139.9	35.0	113.4	26.4	55.4	140.3	32.3	110.9	28.6	100.0	-1.56	-0.01
		0.4	0.1	46.3	139.9	9.8	113.2	26.5	46.4	140.1	9.2	110.5	28.5	100.0	-2.27	-0.01
			0.2	51.8	138.5	20.1	112.2	26.4	52.0	138.8	18.7	109.6	28.5	100.0	-1.89	0.00
			0.3	59.5	138.1	31.8	112.0	26.2	59.8	138.5	29.3	109.5	28.3	100.0	-1.79	-0.01
	0.6	0.2	0.1	32.3	139.8	15.5	113.1	26.0	32.6	140.3	14.6	110.8	28.4	100.0	-1.17	0.00
			0.2	44.2	137.5	30.3	111.0	26.4	44.5	137.9	28.6	108.5	28.5	100.0	-1.49	-0.01
			0.3	57.2	139.6	47.6	113.2	26.4	57.8	140.6	44.5	111.2	28.5	100.0	-0.66	-0.02
		0.3	0.1	39.1	139.9	13.3	113.3	26.6	39.2	140.2	12.4	110.7	28.7	100.0	-1.95	0.00
			0.2	50.7	136.7	28.9	110.1	26.2	50.9	136.9	27.4	107.8	28.5	100.0	-1.76	0.00
			0.3	61.9	139.2	45.2	113.2	26.2	62.4	139.6	42.2	110.6	28.5	100.0	-1.49	-0.01
		0.4	0.1	48.2	137.6	12.8	111.4	26.4	48.4	137.9	12.1	108.7	28.6	100.0	-2.07	-0.01
			0.2	55.4	138.8	26.4	112.5	26.1	55.7	139.2	24.5	109.9	28.4	100.0	-1.84	-0.01
			0.3	66.2	137.4	44.2	111.4	26.1	66.5	137.8	40.8	108.8	28.2	100.0	-1.80	-0.01
85%	0.75	0.2	0.1	29.4	137.2	11.8	111.3	26.5	29.9	138.3	9.6	106.2	30.2	100.0	-3.05	-0.02
			0.2	38.0	137.3	23.3	110.6	26.3	38.9	139.0	19.5	106.5	29.9	100.0	-1.60	-0.03
			0.3	49.0	138.3	36.0	112.0	26.2	50.2	139.5	28.1	107.3	29.7	100.0	-1.92	-0.04
		0.3	0.1	37.4	139.4	10.2	113.0	26.2	37.6	139.5	8.3	106.9	30.0	100.0	-4.82	-0.03
			0.2	45.4	139.1	21.7	112.2	26.4	45.9	139.4	17.9	106.9	30.1	100.0	-3.62	-0.03
			0.3	54.1	138.8	34.6	112.4	26.7	55.0	139.5	27.1	107.2	30.1	100.0	-2.98	-0.05
		0.4	0.1	46.6	139.8	9.8	112.9	26.8	47.0	140.2	7.8	107.5	30.2	100.0	-4.00	-0.03
			0.2	52.8	139.4	20.3	113.4	26.1	53.4	140.0	16.5	107.7	29.7	100.0	-4.04	-0.03
			0.3	58.5	138.0	31.1	111.5	26.6	59.2	138.4	23.5	106.1	30.0	100.0	-3.78	-0.04
	0.6	0.2	0.1	32.6	137.8	15.5	111.4	26.7	33.0	138.8	13.1	106.5	30.2	100.0	-3.09	-0.02
			0.2	44.7	138.1	30.2	111.3	26.8	45.6	139.2	24.9	106.8	30.1	100.0	-2.01	-0.04
			0.3	57.7	138.9	47.4	112.2	26.2	59.0	139.7	37.8	107.0	30.0	100.0	-2.52	-0.03
		0.3	0.1	40.4	138.0	13.9	111.8	26.3	40.7	138.3	11.8	105.9	30.1	100.0	-4.40	-0.02
			0.2	50.5	141.8	29.6	115.5	26.3	51.4	142.7	23.9	110.0	30.1	100.0	-3.05	-0.03
			0.3	61.7	137.5	45.6	111.3	26.0	62.9	138.2	36.2	106.1	29.6	100.0	-2.90	-0.03
		0.4	0.1	48.1	134.7	13.3	108.1	26.6	48.4	135.1	11.5	103.1	30.0	100.0	-3.89	-0.02
			0.2	56.8	139.6	27.5	113.1	26.4	57.7	140.4	22.1	107.9	29.9	100.0	-3.07	-0.03
			0.3	65.7	140.1	42.0	113.6	26.4	66.7	140.6	33.0	108.2	30.1	100.0	-3.26	-0.04
80%	0.75	0.2	0.1	30.4	143.1	11.6	116.7	27.1	30.9	142.9	7.1	105.7	31.4	70.5	-8.10	-0.19
			0.2	37.8	139.0	22.4	112.5	26.5	38.7	137.2	14.1	101.2	31.3	69.9	-7.85	-1.22
			0.3	49.1	138.4	36.0	112.3	26.0	50.0	132.8	20.4	97.3	30.6	71.0	-11.68	-2.50
		0.3	0.1	36.5	138.9	10.4	112.4	26.0	36.9	137.3	6.5	101.3	30.9	69.6	-8.90	-1.46
			0.2	45.8	140.3	22.8	113.8	26.5	46.4	136.3	13.3	100.3	31.3	72.2	-10.66	-2.25
			0.3	53.6	139.9	33.6	113.8	26.6	54.4	131.4	17.6	96.1	31.0	69.5	-14.25	-3.46
		0.4	0.1	45.0	137.7	9.4	111.5	26.2	45.2	135.7	5.5	100.1	31.0	69.4	-9.90	-1.64
			0.2	52.1	138.9	20.0	112.5	26.4	52.6	133.1	11.1	97.5	30.9	70.5	-12.54	-3.07
			0.3	59.3	138.4	32.7	112.2	26.4	59.9	130.5	16.4	95.4	30.8	70.7	-14.17	-4.32
	0.6	0.2	0.1	32.2	139.1	14.8	112.7	26.7	33.0	139.0	9.5	102.4	30.9	57.3	-6.66	-0.26
			0.2	45.1	139.2	31.2	112.9	25.7	45.8	135.9	18.8	99.9	30.1	56.5	-10.13	-0.64
			0.3	57.8	138.9	47.0	112.3	26.3	58.8	133.1	25.8	97.6	30.9	57.8	-11.62	-3.72
		0.3	0.1	40.4	137.9	14.3	111.5	26.4	41.0	136.6	8.9	100.7	31.1	56.4	-8.42	-0.41
			0.2	51.0	139.7	28.8	113.6	26.4	51.9	135.3	16.9	99.5	30.6	57.9	-10.88	-1.14
			0.3	62.4	141.1	45.4	115.1	26.3	63.3	132.1	24.6	96.8	30.6	58.3	-14.70	-3.79
		0.4	0.1	48.0	140.0	12.5	113.7	26.6	48.4	136.5	7.4	100.5	31.0	58.2	-10.84	-0.95
			0.2	56.7	138.1	27.4	112.0	26.6	57.2	132.9	15.7	97.6	31.0	58.3	-12.05	-2.27
			0.3	66.0	140.8	43.8	114.5	26.8	66.7	131.5	22.0	96.2	31.2	56.4	-15.08	-4.35

Table 2.2: Simulation results for different calibrations of the model.

The first thing to note on Table 2.2 is that if we increase p_d^S and/or p_d^B, the clearance ratio increases because more houses are sold. It is interesting to note as well that, as expected, the higher the cap, the higher the percentage of buyers increasing down payments in order to buy a property. Conversely, if we increase p_d^B, the percentage of aggressors increases, but with a different intensity depending on the clearance ratio.

difference in prices for properties that were sold in both cases, ignoring the other effects of properties that could not be sold due to the LTV cap. Deriving meaningful house price metrics for assessing the impact on house prices of the application of the macroprudential measure may not be a trivial task; however, since all the activity is captured at the agent level, several measures may be assessed.

Differences in credit and price increases are more negative when there is a lower cap. This is unsurprising, since the lower the cap, the less credit is directed to buyers and, consequently, the less houses are sold. As explained above, the reduction in credit is much higher than the reduction in prices.

Note that although the actual cap level appears to be the dominant factor in determining the impact on the demand, density parameters do have some importance in some cases. Therefore, we tend to believe that calibrating the model using real data would reflect prevailing market dynamics —especially concerning LTV distributions and the dominance of buyers or sellers— which may significantly contribute to the accuracy of the results.

The effect of an increase in r and g before the introduction of the cap is negligible; however, following the cap, the effect on the clearing ratio and the number of aggressor buyers is more visible for low values of the parameters, then remains stable, suggesting that our auction mechanism is robust to both changes, as Figure 2.9 illustrates; r is the markdown on prices the seller is willing to accept with probability p_d^s while g is the maximum distance that, with probability p_d^b, one buyer will deviate below the auction for the most expensive property he can afford. Both parameters are flexibility metrics; it is unsurprising that if they increase, the clearing ratio grows as there is more room for matching of buyers and sellers. The percentage of aggressor buyers, on the other hand, is only a function of the probabilities p_d.

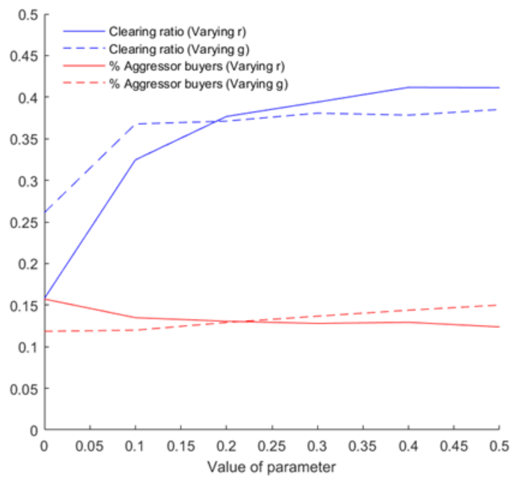


Figure 2.9: Sensitivity of key auction variables to changes in r and g.

A similar logic applies when looking deeper into the mechanisms behind p_d^s and p_d^b in Figure 2.10: The more likely buyers or sellers are to haggle around the transaction price, the more properties will be sold thus increasing the clearing ratio. Besides, if p_d^s increases a buyer will be more likely to find himself bidding for a property which in principle he could not afford, so the percentage of aggressors should fall because their desired effect is somehow coming from the supply side of the market. Finally, a larger p_d^b implies by definition more aggressor buyers, as seen in the first part of the red series on the left hand side; however, a non-linear effect arises after a threshold is reached, from where the number of aggressors falls, likely when the market is too saturated because of the rest of calibrated values. In any case, the results in Table 2.2 suggest that the auction mechanism is not largely affected by the calibration of these two probabilities if done within reasonable ranges.

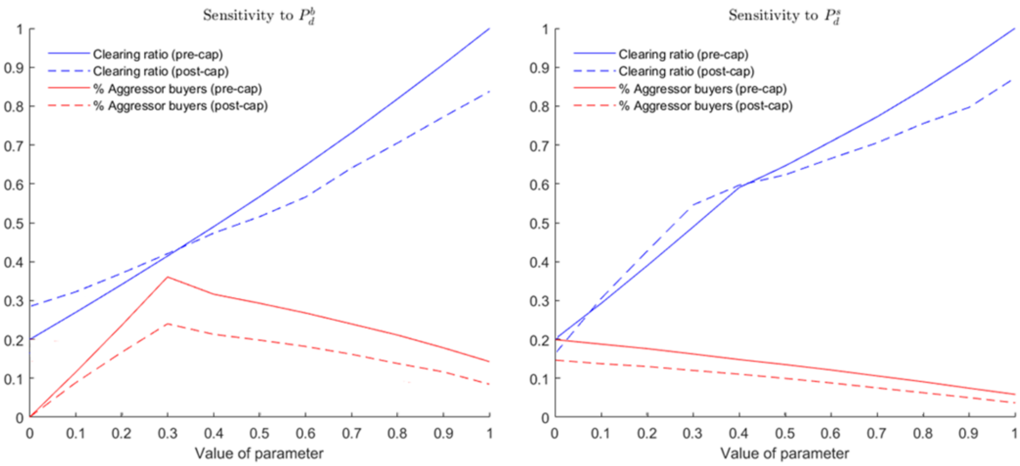


Figure 2.10: Sensitivity of key auction variables to probabilities p_d^s and p_d^b.

2.3.2 Survey data for European countries

In this subsection, we discuss the results based on the estimation of a multivariate distribution of initial liquid wealth, total wealth, LTV ratio and the loan-to-income ratio using a real data set. To this end, we resort to the *Household Finance and Consumption Survey* (HFCS), a compilation of household surveys from European countries unified and collected by the European Central Bank.

Participating institutions, which are national central banks or national statistical institutes, conduct their own wealth surveys[8]. The HFCS provides the Eurosystem with harmonized micro-level data on euro area households' finances and consumption. The survey is conducted every two or three years, the most recent one being 2016 (second wave) and our choice for this exercise.

[8]See `https://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_hfcn.en.html`. A number of studies use the survey data for the primary purpose of measuring household vulnerability. See, for example, Gross and Población (2017), May et al. (2004), Johansson and Persson (2006), Vatne (2006), Herrala and Kauko (2007), Holló and Papp (2007), Fuenzalida and Ruiz-Tagle (2009), Sugawara and Zalduendo (2011), Farinha and Costa (2012), Djoudad (2012), IMF (2012), Albacete and Lindner (2013), Albacete et al. (2014) and Ampudia et al. (2016).

The HFCS is composed of questions that refer to the household as a whole or to each of its members. Basic demographic information is requested in a personal questionnaire for all participating household members above sixteen years old. The survey part, covering household-level questions, encompasses real assets and their financing, liabilities and credit constraints, private businesses and financial assets, intergenerational transfers and gifts and consumption/savings. Questions to individuals cover employment, future pension entitlements and labour-related income[9].

However, even though data in the HFCS is harmonized, since macroprudential policies are implemented differently in each country, the empirical distributions might already be constrained by LTV, LTI and DSTI limits that each country has imposed[10]. This is a first limitation of our study because the framework would differ when imposing a tighter or looser LTV constraint in a country with existing caps. This issue cannot be solved because we cannot reconstruct the database assuming that there were no measures in place; fortunately, however, the active measures at the time of the survey were very few. We give more details in the country analysis section.

The second limitation of our empirical study comes from the fact that the HFCS is a survey on outstanding rather than new loans. Hence, there may be a bias to cover longer-maturity (and therefore larger) mortgages. The impact of an LTV limit would instead be on new loans and thus would not affect the entire distribution.

We use the well-known non-parametric, copula-based approach for the estimation of multivariate distributions of initial liquid wealth, debt-service-to-income ratios, LTV ratios and loan-to-income (LTI) ratios[11]. Figure 2.11 shows the bivariate densities for the LTV ratio combined with wealth and the LTI ratio, respectively.

Our implementation of the non-parametric approach is via an accept-reject algorithm that can be sketched as follows: We start by estimating a four-variate Kernel distribution function (using an Epanechnikov Kernel) for each combination of variables. The joint probability density function will be bounded by four pairs of minima and maxima. Uniform random numbers are strewn into these bounds, which delineate a four-dimensional polyhedron: Whenever a quartet of uniform random numbers falls under the joint probability density function, the quartet is accepted; otherwise, it is rejected. The resulting random numbers from the

[9] Other income sources are covered at the household level.
[10] See ESRB (2016) for some examples.
[11] We use *current* income as a proxy for calculating the LTI, as detailed in Appendix 2A.

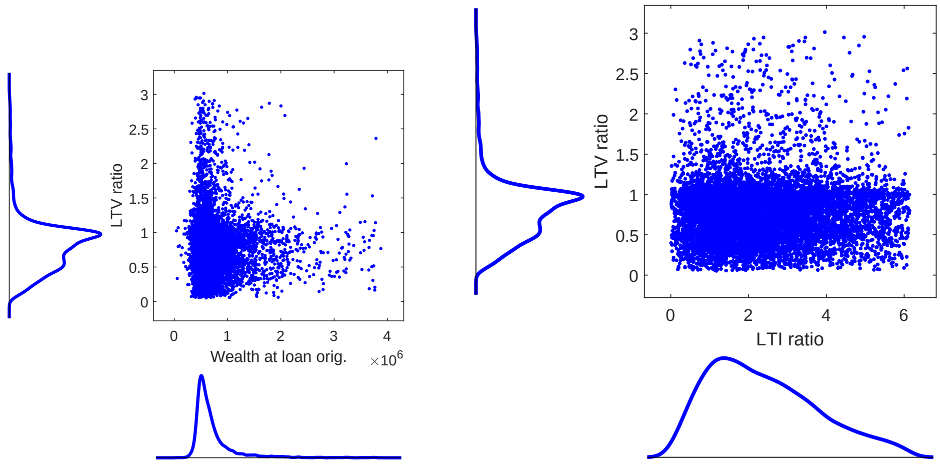


Figure 2.11: Bivariate probability distributions for aggregate HFCS data.

accepted draws will replicate the shape of the initial four-variate distribution[12]. Note that no distributional assumptions are imposed, neither on the marginal distributions nor on the copula that together constitute the joint distribution of the risk factors we examine.

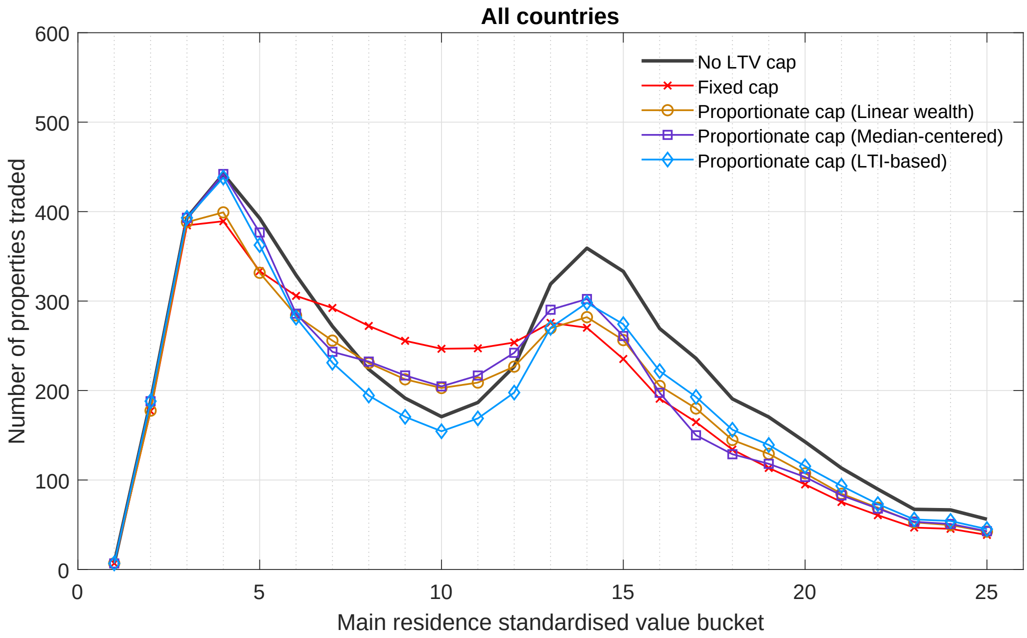
Based on this multivariate probability distribution function, Figure 2.12 illustrates the distributions of properties actually traded in the auctions before and after the introduction of an LTV cap. We consider an absolute 85 percent limit.

There are two housing segments that will be most impacted under an absolute LTV limit: In the next-to-cheapest properties, where less wealthy households with greater credit risk can have mortgages with high LTVs, the cap trims what can be regarded as sub-prime credit, although this idea will be discussed in greater detail in the following subsection. In parallel, wealthier agents with high LTVs will have to borrow less than they than intended, yet they have the capacity to shift to cheaper property buckets and purchase a house. In terms of our results, the latter entails a displacement of the transaction mass to the left of the distribution, which is observed in Figure 2.12. Both of these phenomena will be easier to observe when we discuss the results at a country level, where national heterogeneity on indebtedness habits plays a larger role in amplifying or damping the effects of the cap.

The application of a rigid LTV cap, therefore, may have different impacts across segments of the housing market, which can lead to undesirable consequences. That is why it is reasonable to consider the possibility of a proportionate cap instead, an alternative that allows for more precise implementation of the policy. As stated the previous section, this

[12]For details about this general technique, which is an alternative to inverse CDF transform-based methods; see, for instance, Joe (2014). The alternative to the so-called smooth bootstrap version we describe here is what one could call 'plain' bootstrap, which would not involve a univariate or multivariate Kernel estimator in the first step but would resample directly from historical data. The reason for considering a smooth bootstrap is to avoid replicating possibly fine though spurious details in the data, which is a concern in short samples.

type of cap requires the definition of a certain pecking order based on which it is applied to borrowers.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Fixed	0	-11	-9	-53	-59	-23	20	49	64	76	61	27	-43	-89	-98	-78	-71	-57	-57	-48	-38	-29	-20	-21	-18
Prop-linear	0	-11	-5	-43	-61	-45	-16	7	21	32	22	0	-49	-77	-77	-64	-56	-46	-41	-35	-29	-21	-15	-17	-14
Prop-median	0	0	0	0	-16	-43	-29	9	25	34	30	15	-29	-57	-72	-72	-86	-62	-52	-39	-30	-22	-14	-16	-13
Prop-LTI	0	0	0	-4	-30	-48	-41	-29	-21	-16	-18	-29	-49	-61	-59	-48	-43	-34	-31	-27	-20	-17	-11	-12	-11

The table reflects the absolute change in traded properties with respect to the no-cap case.

Figure 2.12: Distribution of prices for sold properties pre- and post-LTV cap - HFCS data.

In our first alternative, we have assumed that lending institutions show a preference for wealthier buyers. By doing so, banks comply with a simplification of the intuitive creditworthiness principle, that is: Potential borrowers with higher total wealth are more likely to be granted a loan with an LTV that exceeds the cap threshold as their probability of default is lower. This assumption relies on a short descriptive analysis using auxiliary variables in the HFCS sample[13]; it could, however, be challenged or sharpened using other empirical evidence.

In the second variant, buyers closer to the median in wealth will have a higher probability of receiving the loan with a higher LTV than the one allowed by the cap. This illustrates a more expansive policy for banks that are trying to distribute the excessive leverage to a larger number of potential borrowers of lower average wealth. Finally, in the third variant we rank borrowers subject to the cap according to their LTI ratio: Those for which the loan

[13] In particular, we use variables HC0400("*did not apply for credit in the last three years due to perceived credit constraints*") and HC1310("*was denied credit in the last three years*") and explore their relationship with net wealth (DN3001). For credit-constrained households, the distribution of wealth has considerably lower average.

is a smaller share of their total income will be more likely to obtain above-cap mortgages.

From Figure 2.11 we observe that in aggregate terms high wealth is related to moderate LTV values (seldom above 100%) whereas mid- and low-level wealth are linked with higher ratios. From the standpoint of our exercise, buyers with their LTV ratio in the medium range are the most likely to exceed the cap in the wealth-related proportionate case; such effect is likely to be present under a median-centered cap, too, but now buyers to the left of the median (not very wealthy, still with moderately high LTV) might also be allowed to beat the cap.

Country analysis

The aggregate HFCS results can be misleading in the sense that they abstract from country heterogeneity, which has proven to be notable and enriching within our agent-based framework. The survey comprises twenty countries. However, we do not have the same number of households with all the required information for each country; moreover, in some of them the number of data-sufficient households is too small to carry out a proper analysis so they were excluded[14]. Table 2.3 shows descriptive statistics for the main variables.

For the remaining countries, we compared the period of data collection for each national survey with applications of LTV caps by the relevant authority. Cyprus, Latvia and Poland introduced limits as the survey was taking place; only the Netherlands, for which data was gathered in January and February 2014, had a loan-to-value cap of 100% since 2012[15].

Before showing what our agent-based model has to say on the application of caps across countries, a closer look at the initial loan-to-value ratio distributions for each geography, shown in Figure 2.13, reveals notable differences in a number of dimensions; in terms of the third moments, densities are clearly left-skewed for Austria, Cyprus, Germany, and right-skewed for Spain, Ireland and Portugal; regarding kurtosis there are some cases of platykurtic distributions, most noticeably Poland and Slovakia, in contrast with Spain and Portugal which are more leptokurtic. These features, along with those of wealth distributions[16], will shape and cluster the results considerably.

[14]In the case of Finland, no households at all with all the required information are available.

[15]More precisely, the Netherlands introduced a cap of 106% in 2012 which progressively lowered 100% in 2018. Among the 589 valid households in the survey, only 4% contracted loans between 2012 and 2014.

[16]The differing supports and the similarity of shapes of wealth distributions render it difficult to extract information from plotting them in a way akin to Figure 2.13. The bivariate country distributions of wealth with LTV and LTI ratios are included in Appendix 2B.

Country	Valid HHs	Gross income (€)	House value (€)	Mortgage value (€)	LTV (%)	LTI (%)
Austria	372	62971	236329	120519	59	221
Belgium	508	75567	175239	120826	78	198
Cyprus	362	54841	242969	150019	81	326
Germany	827	104051	250628	138327	65	168
Estonia	307	39471	73260	55223	92	176
Spain	1016	57386	172679	129965	91	315
Finland	0	64294	-	-	-	-
France	2260	72599	225142	150228	77	241
Greece	198	30180	113288	75270	77	323
Hungary	41	10343	23130	13216	72	138
Ireland	1566	87121	257831	193923	87	276
Italy	546	51029	160900	110210	81	284
Luxembourg	507	139390	428148	296021	74	268
Latvia	33	40166	108228	65846	88	198
Malta	114	38014	116766	87578	85	263
Netherlands	589	66032	183362	145363	92	244
Poland	262	22372	67969	42875	76	221
Portugal	1756	34414	127865	98008	83	360
Slovenia	139	36432	127901	71054	63	250
Slovakia	192	20216	56591	36557	83	210

HH = Households. Rows in red represent discarded countries due to an insufficient number of observations.

Table 2.3: Descriptive statistics of country clusters in the HFCS.

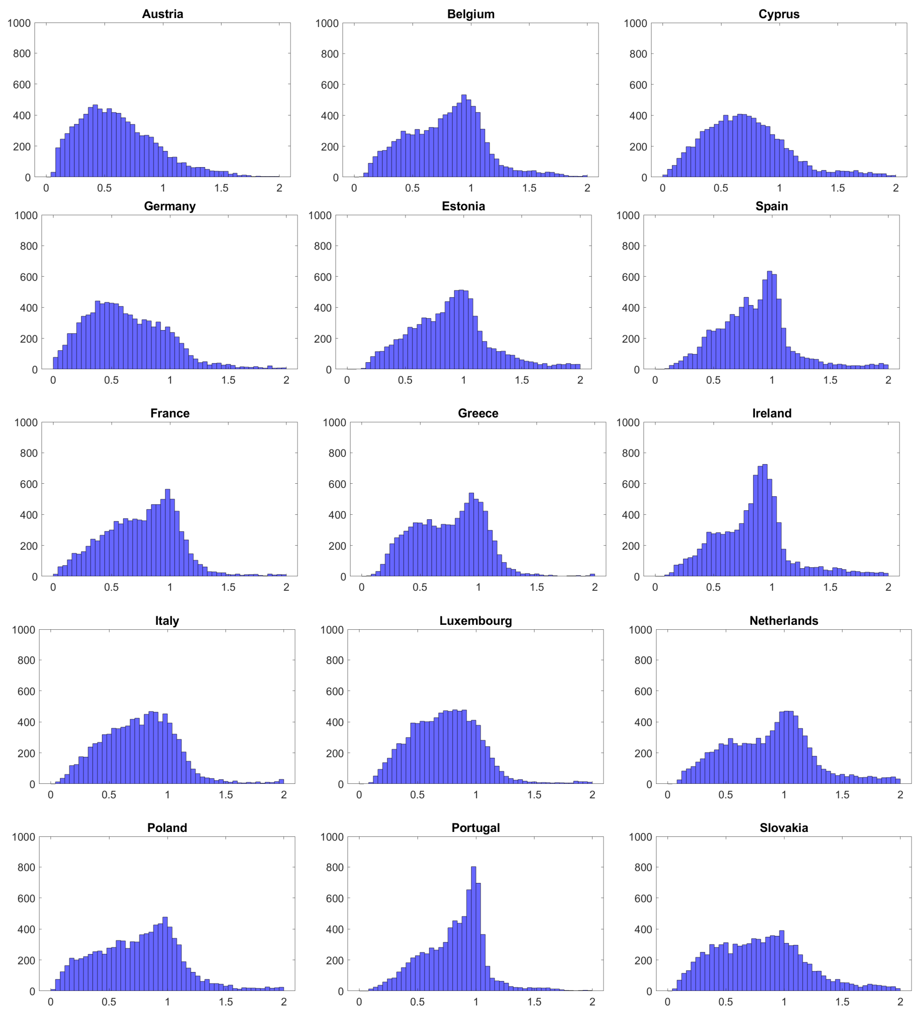


Figure 2.13: Generated loan-to-value ratio distributions by country.

We now discuss our results focusing on the two most relevant variables with policy implications, property price growth and credit growth, the latter being defined as the variation in the number of properties sold.

Starting with the behaviour of house prices, Table 2.4 shows the variation by country produced by our exercise with HFCS data. Under the fixed cap, prices decrease across all countries; given that this type of LTV limit affects all households beyond the threshold, regardless of their wealth or perceived creditworthiness proxied by any variable other than the LTV ratio, the mortgage market shrinks across all property price buckets and the supply effect prevails. For the proportionate caps, prices might behave differently owing to the differences in initial LTV distributions. Both the wealth- and LTI-based implementations target less wealthy buyers: Once they are ruled out of the market, the effect on prices will be less negative than in the fixed cap case, with the possibility of a positive reaction, as is seen for Austria and Germany. For these countries, the bivariate distributions of LTV with wealth and LTI ratios would show considerably less low-income households in relation to wealthy ones above the cap; Appendix 2B includes the relevant two-way density plots.

Country	Fixed cap	Proportionate cap		
		Wealth	Median	LTI
Austria	-5.74	0.30	2.31	4.09
Belgium	-8.92	0.25	-1.04	2.57
Cyprus	-9.76	-3.28	-0.08	0.60
Germany	-5.37	1.14	1.91	4.45
Estonia	-12.23	-3.70	-1.79	0.19
Spain	-9.11	-5.15	-2.86	0.73
France	-10.13	-5.24	-1.32	-0.51
Greece	-10.23	-1.41	-1.58	1.02
Ireland	-10.64	-3.75	-2.36	-0.03
Italy	-9.94	-3.06	-1.01	-0.28
Luxembourg	-9.31	-3.86	-0.99	-0.06
Netherlands	-11.17	-1.05	-1.62	1.71
Poland	-10.96	-2.93	-0.82	1.03
Portugal	-9.81	-7.20	-3.79	0.62
Slovakia	-11.16	-2.65	-0.29	0.56
All countries	-9.33	-3.00	-1.04	2.02

Table 2.4: Estimates of property price growth (%) with HFCS data.

Turning to the effects on mortgage credit, which are presented in Table 2.5, our estimates show that our model with the current calibration generates decreases in the vicinity of -10% for the majority of countries in all versions of the cap; the precise magnitude will depend on the distribution of households for the LTV ratio, wealth and the LTI.

One remark is in order: Recall that, with the mechanism underlying our agent-based model, an LTV cap does *not* imply that households above it will be granted zero credit: Such an assumption would generate unreal, dramatically large contractions in mortgage credit; instead, these households are constrained to borrow only up to the point allowed by the cap. This rationale justifies that the strength the effect of a fixed cap, which would be the largest if all credit above it were to be discarded, varies upon the country considered. From the standpoint of the lending institution, proportionate caps entail *a priori* that a residual share of households, the size of which depends on the type of cap, participate in the auction with an LTV above the limit; it is the auction itself and not the regulatory measure what ultimately determines the *a posteriori* effect on credit.

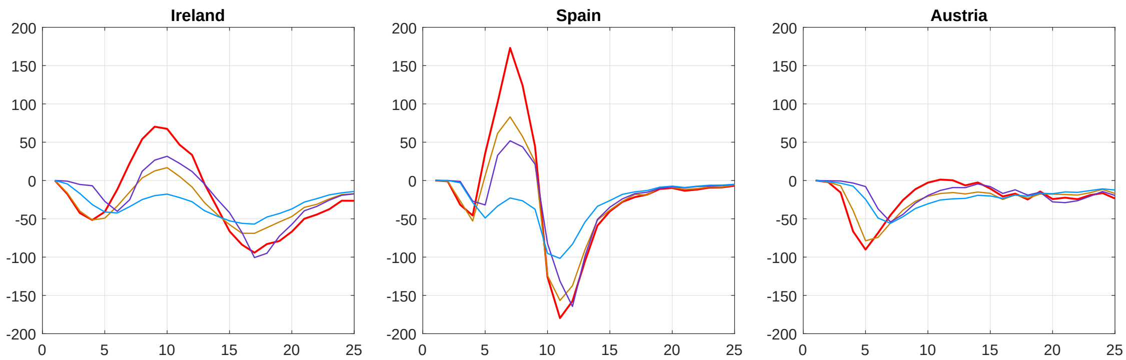
Country	Fixed cap	Proportionate cap		
		Wealth	Median	LTI
Austria	-10.55	-11.61	-8.43	-10.15
Belgium	-8.69	-12.14	-9.64	-11.63
Cyprus	-12.12	-14.48	-11.43	-13.86
Germany	-8.14	-9.28	-7.54	-9.30
Estonia	-10.22	-13.54	-12.79	-14.75
Spain	-7.79	-11.00	-11.19	-13.23
France	-11.29	-12.88	-11.08	-14.17
Greece	-10.44	-14.58	-10.82	-13.89
Ireland	-10.51	-13.58	-11.14	-14.14
Italy	-11.31	-14.06	-12.28	-14.89
Luxembourg	-12.22	-14.37	-12.18	-14.40
Netherlands	-3.83	-14.80	-10.26	-13.12
Poland	-10.56	-13.81	-11.34	-13.34
Portugal	-5.84	-11.35	-9.88	-12.54
Slovakia	-10.83	-14.31	-11.98	-14.46
All countries	-9.67	-11.75	-9.91	-12.14

Table 2.5: Estimates of mortgage credit growth (%) with HFCS data.

The previous two tables capture the considerable cross-country heterogeneity of the effects of all four types of caps, yet they do not display how the aggregate impacts are distributed across property buckets in each country. This dimension, however, is fundamental to draw a stylized picture of the mortgage credit markets in European countries, consistently with the phenomena observed in the probability distributions of households for wealth or LTVs.

One possibility to gain insights about the within-country transmission of an LTV limit is to look at the absolute variation for all property buckets in each country under the different

LTV caps, as is done in Figure 2.14. Among the 15 countries in the sample, we restrict our attention to three of them (Ireland, Spain and Austria) for the patterns they exhibit are very illustrative. Other countries behave similarly to the latter but it can be adventurous (and probably inaccurate) to create clusters of countries based only on visual information, lacking a detailed exploration of the socio-economic similarities that may justify the groupings. The full results, nonetheless, can be found in Appendix 2B.



Fixed cap (red), Wealth-linear proportionate (brown), Median-centered proportionate (purple), LTI-based proportionate (light blue). Results are presented in differences with respect to the no cap case.

Figure 2.14: Absolute variation in properties traded by bucket for selected HFCS countries.

Ireland is our first showcase. In our estimates, the absolute cap seems to reduce credit more sharply for wealthy households than for low-income ones; the rationale behind it is the following: While there are households with very high LTVs (say above 125%) in the low-price segment there are also many wealthy buyers, comparatively more, who contract mortgages with LTVs above the cap. It is unsurprising that, in a country where macroprudential policy is well-established, wealthy individuals dare to borrow at high LTVs because their repayment culture, along with the regulatory pressure, makes them confident that they will be able to fulfil their obligations. Another noticeable feature related to the former is the more uniform effect of the LTI-based proportionate cap; given that the LTI distribution across wealth and LTV levels is relatively uniform, the likelihood of beating the cap will be also more uniformly distributed, an effect visible also in the price bucket dimension.

We now turn to the effects of LTV caps in Spain. This case is similar to Ireland's in that low-income households suffer comparatively less from the measure than those above the median; however, the latter are located in cheaper property buckets and the cap seems to be almost neutral for those above the 15^{th} segment. We name this the *wannabe effect*: Very rich households bidding for a property will do so with a low LTV, almost surely below the cap;

instead, a large share of medium-high wealth households will try to purchase the property they want at the highest LTV possible, *as if* they were much wealthier. Such a behaviour was observed in the years preceding the 2008 financial crisis, when banks were more prone to grant high-LTV loans to customers with relatively high yet volatile, intermitent income.

Our last object of discussion is Austria, a somehow paradoxical case. By looking at Figure 2.14, it seems that the LTV cap in any of its forms is effective in tackling high-LTV credit granted to low-income households; in a country with low creditworthiness standards, this would be the optimal response to the policy, as the least favoured households are patronized by macroprudential regulation not to engage into transactions with high odds of becoming sub-prime credit[17] while the rest of agents remain largely unaffected by the measure. In contrast, Austria's retail banking sector has been traditionally very stable owing to the financial discipline of households; non-performing loan rates and defaulted credit risk exposures of assets secured on real estate are very low. Hence, like in the Irish case, low-income households will borrow as much as they need fully aware of the commitment to repay: The link between creditworthiness and wealth is more diffuse.

2.3.3 Empirical validation

The results we have presented so far concern quantitative artefacts of our agent-based model. Well aware of the variety of approaches that coexist within the literature of macroprudential measures, the following discussion aims to compare our estimates in the previous section with those found in those studies similar to ours.

As we went through the available literature to look for other estimates to benchmark our model against, we chose to mention only the studies that treat at least one of the countries in our sample, whether in an individual or aggregate fashion. Within this subset, the prevailing methodology uses panel data regression models over a set of countries.

The seminal work by Jacome and Mitra (2015) runs pooled regressions on six economies (among which Poland) to find that a 10% cut in the LTV limit has a maximum cumulative impact on mortgage credit of -0.7%. Later, Cerutti, Claessens and Laeven (2017) widen the scope of their exercise to 119 countries (31 advanced, 64 emerging, 24 developing) over the time span 2000-2013; following the introduction of an LTV limit, the aggregate impact on credit growth is -14pp and real estate prices fall by -1.5pp. Finally, Nymoen, Pedersen

[17]Here again, recall that for simplification we assume that wealth explains a large share of how credit scores are allocated.

and Sjalberg (2018) use a sample of 10 advanced open economies, among which Ireland and the Netherlands; they find that the introduction of an LTV limit impacts credit growth in -0.5±3.2 percentage points and house prices in -1±3.2 pp.

There are, however, other quantitative approaches in the literature. For instance, Crowe et al. (2011) use DSGE modelling to estimate that a 10% tightening in the LTV ratio increases nominal house prices by 13 percent; a permanent reduction in the LTV also decreases credit by -0.3 pp on impact. For the Portuguese economy, Basto, Gomes and Lima (2018) build a DSGE model where a permanent instantaneous shock to the LTV ratio decreases loans by -10% on impact and prices fall by roughly 4%; they also conduct an exercise for the euro area as a whole where credit contracts by -6% and prices by -3%. Similarly, de Jong and de Veirman (2019) study the effect of a LTV cap in the Netherlands by looking at the cross-sectional LTV distributions in a VECM framework; their findings suggest that the average LTV ratio decreases by 2 percentage points, while the long-run effect on prices ranges from -5% to -8%. Finally, a recent study by Morgan et al. (2019) relies on panel data methods, but assembling a bank-level dataset for 46 countries, finding that the imposition of an LTV cap reduces credit by -5.9% after one year.

In general, most of the papers with an intent similar to ours yield effects on credit and property prices which are reasonably akin in magnitude to what our agent-based model produces, in spite of following completely different approaches.

2.4 Conclusions

In this paper, we propose a simple model relying upon agent-based techniques to assess the impact of a cap in the loan-to-value ratio. Results based on simulated data are presented first, assuming that initial liquid wealth, total wealth, LTV at origination and property value parameters follow three types of probability distributions in which initial liquid wealth and LTV at origination can be positively or negatively correlated. The application of an LTV cap naturally shifts the distribution of buyers towards lower price ranges, since the cap constraint becomes binding for a significant proportion of households under the assumption that there is no change in their household's liquid assets and their ability to come up with the required down payment. The inverse is true for higher-priced properties, where demand is relatively weak due to the cap.

After this simulation exercise, the relevant probability distributions are calibrated on actual European data. In that context, the second wave of the *Household Finance and Consumption Survey* (HFCS) is used. We also deploy a copula-based approach for the estimation of multivariate distributions of initial liquid wealth, debt-service-to-income ratios, LTV and LTI ratios.

When LTV cap impacts are calculated country by country, considerable heterogeneity arises owing to the peculiarities of the distributions for wealth and LTV ratios. The effects of the fixed and proportionate variants of the cap affect different property price segments in different magnitudes and shapes; nevertheless, we obtain estimates for property price growth and credit growth which are in line with other studies in the literature.

As stated above, based on the results, we think that the approach is a useful and complementary alternative to the existing analytical framework for assessing the impact of macroprudential borrower-based measures such as LTV caps. The major benefits are the very few assumptions our method has to make on the functional/distributional forms of observed credit lending parameters and its ability to incorporate, even in a probably unsophisticated fashion, features related to the behavioural response of borrowers to such measures. Moreover, due to the simplicity of the model, many simple extensions can be added. For example, sharper sequential mechanisms for the property auctions or more than one time step. The vast amount of empirical data available may also allow for more precise country-level calibration.

Besides, clear macroprudential implications arise; our findings stress the need for careful implementation of policies, regardless of their simplicity, the effects of which can vary across agents considerably as a function of their endowments (say wealth), appetite for credit (say LTV) or flexibility of their preferences (say willingness to accept purchasing lower-quality housing).

Appendix 2A. Details on the HFCS data

2A.1. Data cleaning and preparation

In a first step (say "quality assurance"), we remove from the sample every observation for which any of the following is true:

- DL2100i (Has mortgage payments) is not 1.
- DA1110i (Has main residence) is not 1.
- fHB0800 (Flag for property value at acquisition) is "not imputed", "originally not collected" or "originally no answer".
- fHB1401 (Flag for initial amount borrowed) is "not imputed", "originally not collected" or "originally no answer".
- DN3001 (Net wealth) is blank.
- HB0800 (Property value at acquisition) is blank.
- DL2110 (Mortgage payments for main residence, flow) is blank.
- DA1110 (Value of main residence) is blank.

Once the data is free from blanks and missing values, we define the initial LTV ratio as the quotient between variables HB1401 (Main residence mortgage: Initial amount borrowed) and HB0800 (Property value at the time of acquisition); The LTI ratio is proxied using current income as the quotient between HB1401 and DI2000 (Total household gross income). Finally, the debt-service-to-income ratio is defined as DL2110 (flow of mortgage payments for main residence) divided by one twelfth of DI2000 (because the latter is annual and the former is monthly). As a next step, we filter the observations that:

- Have an LTV ratio over 300%.
- Have a debt service-to-income ratio above 50% or below 0%.

After the data cleaning process, we are left with 11,595 out of 84,500 valid observations.

2A.2. Calibration of q_d^B

q_d^B represents the probability of a buyer increasing his down payment; we deem reasonable to assume that this will only happen if its financial situation is sufficiently stable or, moreover, likely to improve. For this purpose, we use four indicator variables:

- HNB1700 ("Household makes extra mortgage payments over contractual amount").
- HNK0400 ("Household expects the overall economic situation to improve).
- HNI0700 ("Household expects to have more savings next year").
- (**1**-PNE2800x) ("Household expects the work situation *not* to worsen in the near future").

We calculate the probabilities of positive responses conditional on data availability for all 4 variables, then set q_d^B equal to their average. We obtain a value of 0.3024, which is what we use in the paper.

Appendix 2B. Detailed country results

The following tables show the absolute change in traded properties for all three cap cases by standardised residence value bucket. Note that the colour of each cell shows the magnitude of the decrease *within the row*, that is, within each country distribution.

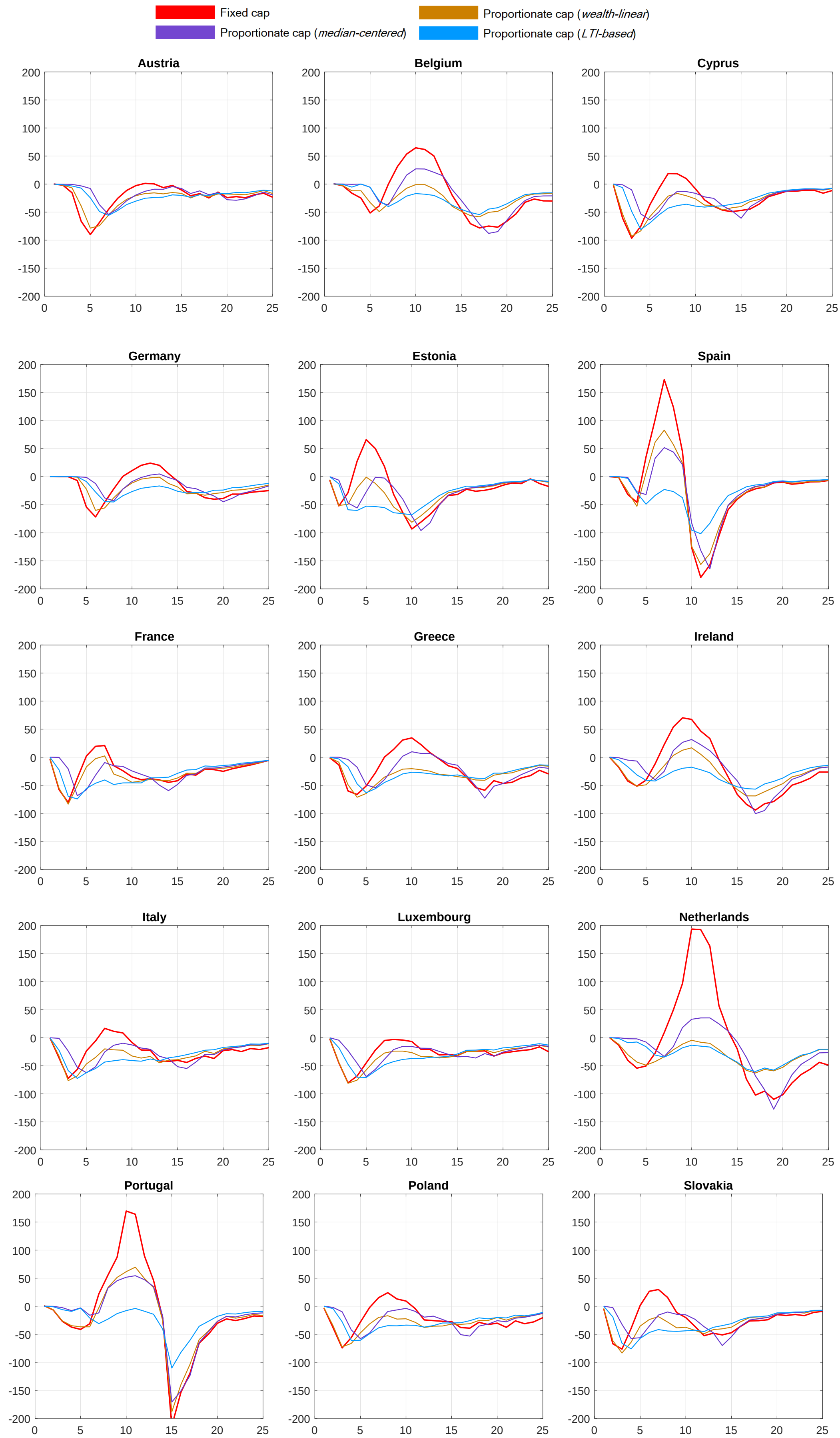
Absolute	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	-2	-16	-66	-90	-69	-45	-26	-11	-3	1	0	-6	-3	-11	-21	-17	-25	-14	-24	-22	-24	-19	-16	-24
Belgium	0	-3	-16	-25	-52	-39	0	31	53	65	62	50	14	-20	-46	-71	-78	-75	-77	-66	-53	-32	-27	-30	-30
Cyprus	-2	-61	-97	-75	-37	-8	19	18	10	-9	-28	-40	-47	-49	-47	-45	-36	-23	-18	-13	-13	-11	-11	-16	-12
Germany	0	0	0	-7	-54	-72	-46	-22	1	11	20	24	20	6	-8	-27	-29	-38	-40	-39	-31	-31	-28	-26	-25
Estonia	-6	-52	-29	28	66	50	18	-31	-64	-93	-81	-67	-50	-33	-32	-22	-26	-24	-21	-15	-11	-12	-4	-12	-17
Spain	0	-1	-32	-46	35	102	173	124	44	-126	-180	-157	-106	-59	-40	-28	-22	-18	-11	-10	-13	-12	-9	-9	-7
France	-3	-58	-81	-37	2	19	21	-15	-24	-35	-40	-38	-40	-45	-42	-30	-32	-21	-22	-25	-21	-17	-14	-10	-6
Greece	-1	-14	-60	-66	-51	-28	0	14	31	34	23	8	-3	-15	-20	-36	-54	-59	-42	-47	-45	-37	-33	-23	-30
Ireland	0	-18	-42	-52	-41	-12	23	54	70	67	47	33	-5	-35	-66	-84	-94	-83	-79	-67	-50	-44	-37	-26	-26
Italy	0	-36	-73	-56	-23	-6	17	12	9	-8	-22	-22	-41	-42	-40	-44	-37	-33	-37	-23	-21	-25	-19	-21	-18
Luxembourg	-2	-45	-80	-68	-45	-22	-5	-3	-4	-7	-21	-21	-31	-30	-32	-25	-24	-23	-33	-27	-25	-23	-21	-16	-25
Netherlands	0	-13	-40	-54	-50	-27	9	50	97	194	193	163	57	12	-20	-74	-102	-95	-110	-102	-81	-66	-56	-44	-49
Poland	-3	-38	-74	-56	-28	-2	15	24	13	9	-4	-24	-26	-27	-27	-38	-39	-29	-33	-30	-38	-26	-31	-28	-20
Portugal	1	-7	-27	-37	-41	-31	22	56	87	170	164	90	46	-21	-214	-154	-119	-66	-50	-30	-23	-26	-22	-17	-18
Slovakia	-4	-67	-76	-40	2	27	30	16	-11	-20	-36	-53	-48	-51	-47	-36	-26	-26	-24	-15	-16	-15	-17	-11	-9

Proportional, linear on wealth	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	-2	-7	-39	-79	-74	-55	-39	-27	-21	-17	-16	-18	-15	-17	-25	-19	-23	-18	-18	-18	-19	-16	-12	-17
Belgium	0	-3	-12	-12	-33	-49	-35	-20	-8	-1	-1	-9	-21	-40	-49	-56	-58	-51	-49	-41	-30	-21	-18	-17	-17
Cyprus	-1	-53	-93	-83	-58	-40	-22	-17	-21	-26	-38	-38	-46	-42	-40	-31	-27	-19	-15	-13	-11	-9	-9	-11	-8
Germany	0	0	0	-1	-22	-60	-56	-38	-22	-11	-4	-2	-1	-12	-18	-31	-30	-33	-30	-28	-24	-23	-21	-19	-15
Estonia	-5	-51	-49	-20	-1	-12	-29	-54	-66	-81	-70	-56	-41	-29	-26	-21	-20	-19	-16	-12	-10	-10	-5	-7	-10
Spain	0	-1	-27	-53	6	62	83	57	24	-124	-157	-137	-91	-52	-39	-27	-18	-19	-9	-9	-12	-11	-8	-8	-6
France	-3	-55	-84	-51	-17	-3	2	-30	-36	-45	-42	-40	-41	-42	-37	-28	-29	-21	-19	-20	-18	-15	-12	-10	-6
Greece	-1	-9	-49	-71	-65	-50	-35	-29	-21	-20	-22	-25	-30	-32	-35	-37	-41	-41	-32	-29	-28	-23	-18	-15	-16
Ireland	0	-16	-40	-51	-49	-33	-15	3	13	17	5	-9	-29	-44	-58	-69	-69	-62	-54	-47	-35	-31	-24	-18	-17
Italy	0	-33	-76	-68	-47	-35	-20	-21	-22	-32	-36	-33	-45	-40	-39	-36	-32	-24	-28	-20	-18	-16	-13	-14	-11
Luxembourg	-1	-44	-81	-76	-57	-39	-27	-24	-24	-26	-33	-33	-36	-35	-32	-24	-25	-21	-27	-22	-20	-18	-15	-14	-16
Netherlands	0	-11	-30	-43	-49	-43	-34	-21	-11	-4	-8	-10	-21	-35	-45	-58	-63	-56	-59	-53	-41	-33	-27	-21	-21
Poland	-3	-35	-73	-66	-48	-32	-20	-17	-23	-22	-29	-38	-36	-35	-32	-32	-31	-25	-26	-20	-25	-19	-18	-16	-13
Portugal	1	-7	-26	-35	-37	-37	-3	33	51	62	70	49	33	-25	-188	-140	-103	-59	-44	-27	-18	-21	-19	-15	-17
Slovakia	-4	-61	-83	-64	-35	-24	-19	-28	-39	-38	-43	-49	-42	-40	-37	-28	-20	-21	-20	-14	-12	-11	-12	-8	-8

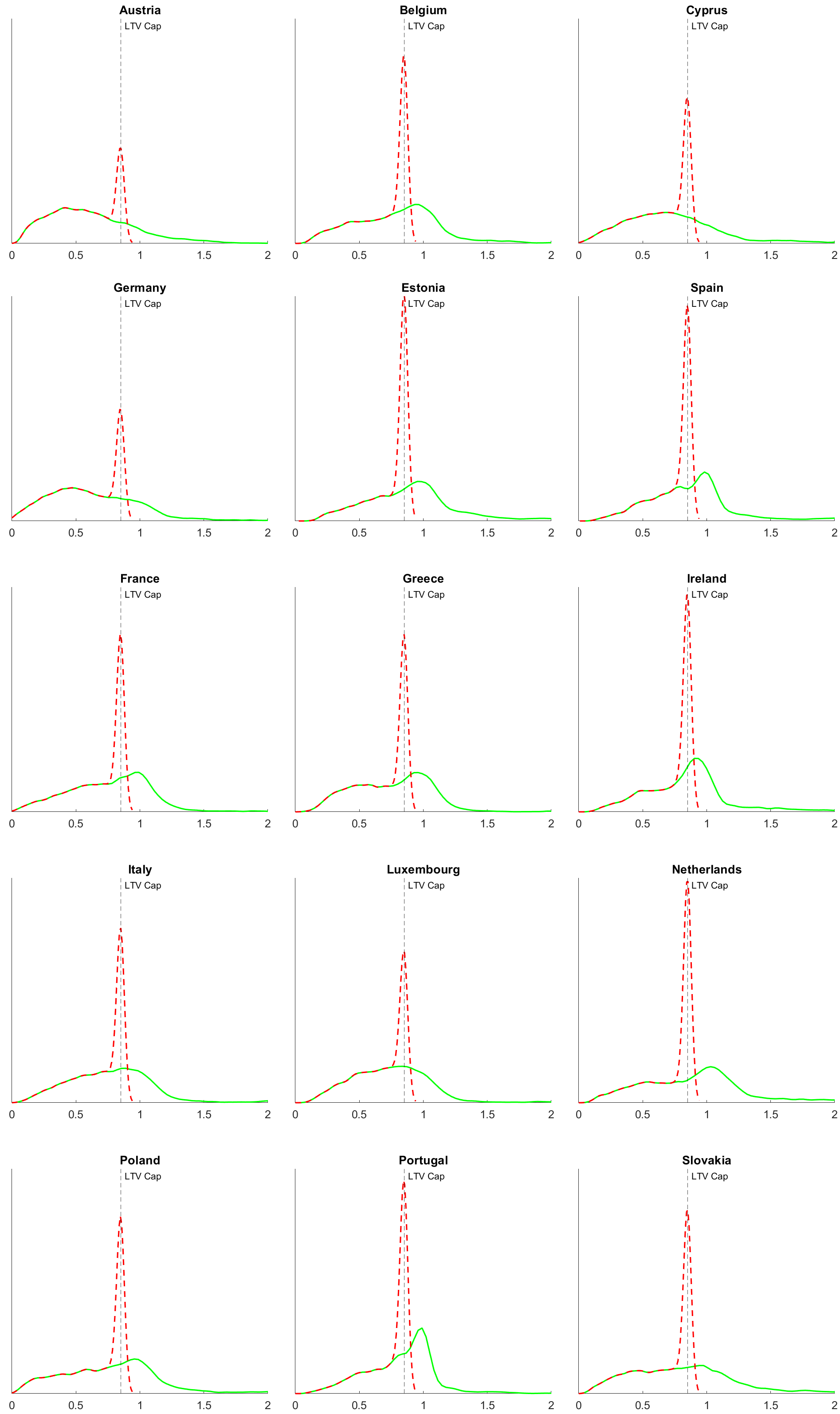
Proportional, median-centered	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	0	-1	-3	-8	-37	-54	-44	-30	-20	-13	-9	-9	-4	-8	-17	-12	-19	-15	-28	-29	-26	-21	-14	-19
Belgium	0	0	-1	0	-6	-32	-37	-10	16	27	27	21	15	-10	-29	-50	-72	-88	-85	-64	-44	-29	-22	-21	-21
Cyprus	0	-1	-10	-53	-64	-50	-26	-13	-13	-17	-23	-26	-39	-48	-61	-40	-31	-21	-15	-13	-11	-9	-9	-10	-8
Germany	0	0	0	0	-1	-12	-38	-43	-22	-9	-1	3	5	-2	-7	-19	-21	-28	-35	-45	-38	-30	-26	-21	-17
Estonia	0	-6	-47	-56	-27	-1	-2	-19	-40	-70	-96	-82	-51	-33	-27	-21	-19	-17	-15	-11	-9	-9	-5	-7	-9
Spain	0	0	-1	-27	-32	33	52	44	21	-82	-131	-164	-99	-51	-35	-24	-17	-15	-10	-8	-10	-8	-7	-7	-5
France	0	0	-21	-69	-58	-32	-9	-15	-16	-24	-30	-36	-50	-60	-48	-32	-30	-19	-19	-17	-15	-12	-11	-8	-6
Greece	0	0	-4	-18	-49	-54	-40	-18	2	10	7	7	-2	-11	-14	-32	-51	-73	-52	-47	-39	-31	-24	-18	-20
Ireland	0	-1	-5	-7	-27	-40	-25	12	27	32	22	12	-5	-24	-42	-68	-101	-95	-73	-57	-40	-34	-26	-19	-17
Italy	0	-1	-24	-53	-62	-52	-25	-13	-10	-13	-18	-20	-33	-37	-52	-55	-43	-30	-30	-22	-18	-16	-12	-13	-10
Luxembourg	0	-4	-23	-45	-69	-56	-38	-21	-15	-16	-19	-19	-24	-30	-34	-33	-36	-28	-33	-25	-22	-19	-15	-13	-15
Netherlands	0	0	-2	-2	-8	-21	-33	-16	18	33	35	35	25	12	-8	-35	-68	-93	-127	-97	-66	-47	-37	-27	-26
Poland	0	-2	-10	-42	-58	-48	-28	-9	-7	-4	-9	-19	-18	-24	-30	-51	-53	-35	-32	-26	-28	-21	-20	-16	-13
Portugal	0	0	-3	-8	-3	-16	-12	32	45	52	54	47	35	-18	-171	-151	-123	-65	-46	-27	-18	-19	-15	-13	-12
Slovakia	0	-2	-32	-58	-56	-35	-16	-10	-14	-15	-23	-36	-47	-70	-54	-35	-24	-22	-20	-14	-13	-11	-11	-8	-8

Proportional,LTI	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Austria	0	-1	-4	-7	-25	-49	-56	-47	-37	-30	-25	-24	-23	-19	-20	-23	-19	-20	-17	-17	-15	-15	-13	-11	-12
Belgium	0	-1	-5	0	-6	-30	-40	-32	-22	-17	-18	-20	-28	-38	-45	-51	-55	-45	-42	-35	-27	-19	-17	-16	-16
Cyprus	0	-6	-49	-81	-69	-55	-43	-38	-36	-39	-41	-40	-39	-36	-34	-28	-22	-16	-14	-11	-10	-8	-8	-9	-7
Germany	0	0	0	0	-9	-27	-44	-45	-34	-27	-21	-18	-17	-20	-26	-29	-28	-29	-24	-24	-20	-19	-16	-14	-12
Estonia	0	-13	-59	-60	-53	-53	-55	-64	-66	-68	-56	-45	-34	-26	-21	-17	-17	-15	-13	-10	-9	-8	-5	-7	-8
Spain	0	0	-3	-29	-49	-33	-23	-27	-37	-95	-102	-83	-54	-34	-26	-18	-15	-13	-9	-7	-9	-7	-6	-6	-5
France	0	-23	-70	-74	-56	-46	-41	-49	-46	-46	-46	-37	-36	-36	-29	-23	-22	-16	-16	-15	-14	-11	-9	-7	-5
Greece	0	-3	-17	-47	-63	-56	-45	-38	-30	-27	-28	-29	-31	-33	-32	-35	-37	-38	-28	-28	-24	-20	-17	-14	-14
Ireland	0	-4	-17	-32	-41	-42	-34	-25	-20	-18	-22	-28	-39	-47	-53	-56	-57	-48	-43	-37	-28	-24	-19	-16	-14
Italy	0	-22	-59	-73	-62	-55	-43	-41	-39	-41	-42	-38	-41	-36	-34	-30	-26	-22	-21	-17	-16	-14	-11	-11	-9
Luxembourg	0	-18	-47	-70	-71	-59	-48	-43	-39	-37	-37	-35	-34	-33	-29	-22	-22	-21	-22	-18	-17	-15	-13	-10	-13
Netherlands	0	-1	-9	-8	-16	-31	-34	-27	-18	-13	-15	-17	-26	-34	-43	-56	-60	-54	-58	-49	-40	-31	-28	-20	-20
Poland	0	-4	-28	-61	-61	-49	-39	-35	-35	-34	-34	-37	-34	-30	-30	-29	-26	-21	-23	-20	-21	-16	-17	-15	-11
Portugal	0	-1	-6	-9	-3	-21	-31	-23	-13	-8	-4	-9	-14	-41	-110	-82	-61	-36	-27	-18	-13	-14	-11	-10	-10
Slovakia	0	-19	-66	-76	-57	-47	-42	-44	-45	-44	-43	-45	-38	-35	-31	-24	-19	-19	-17	-12	-12	-10	-10	-7	-7

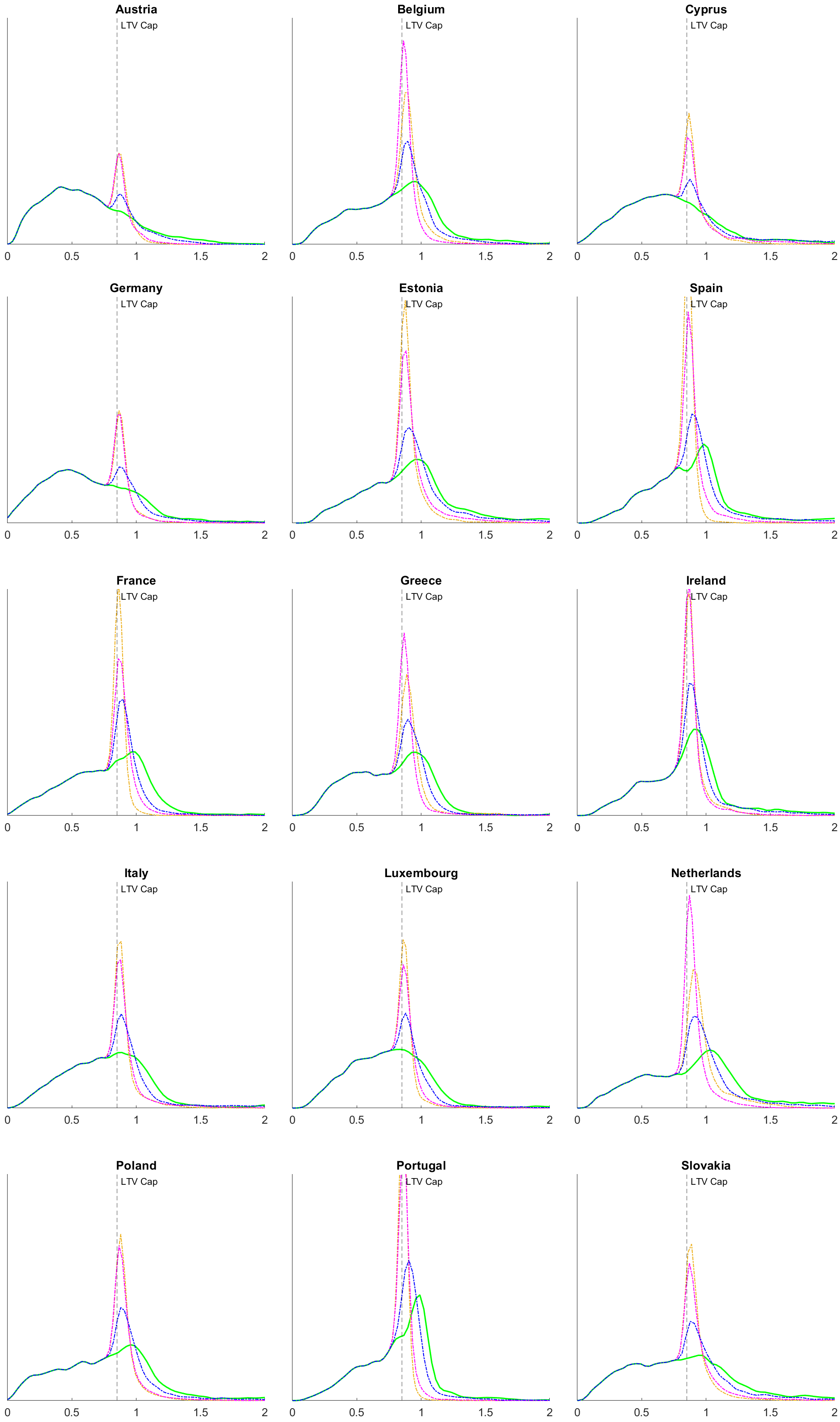
We also present the information in the table above by country, as in Figure 2.14.



The following graphs show the effect of the fixed and proportionate caps on the *a priori* LTV distributions.



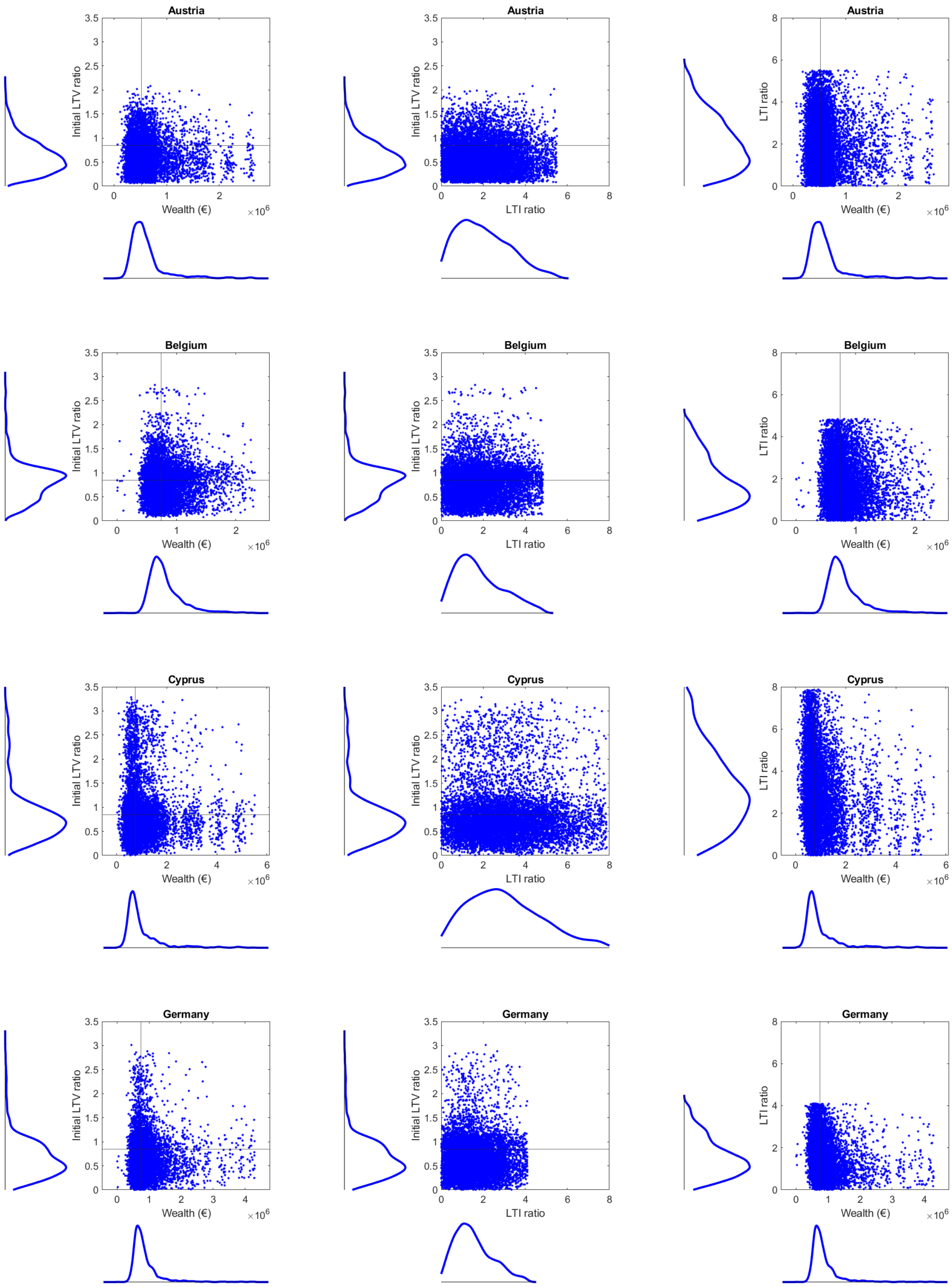
In this figure we show the effect of the fixed cap (red) on the initial LTV ratio distributions (green).

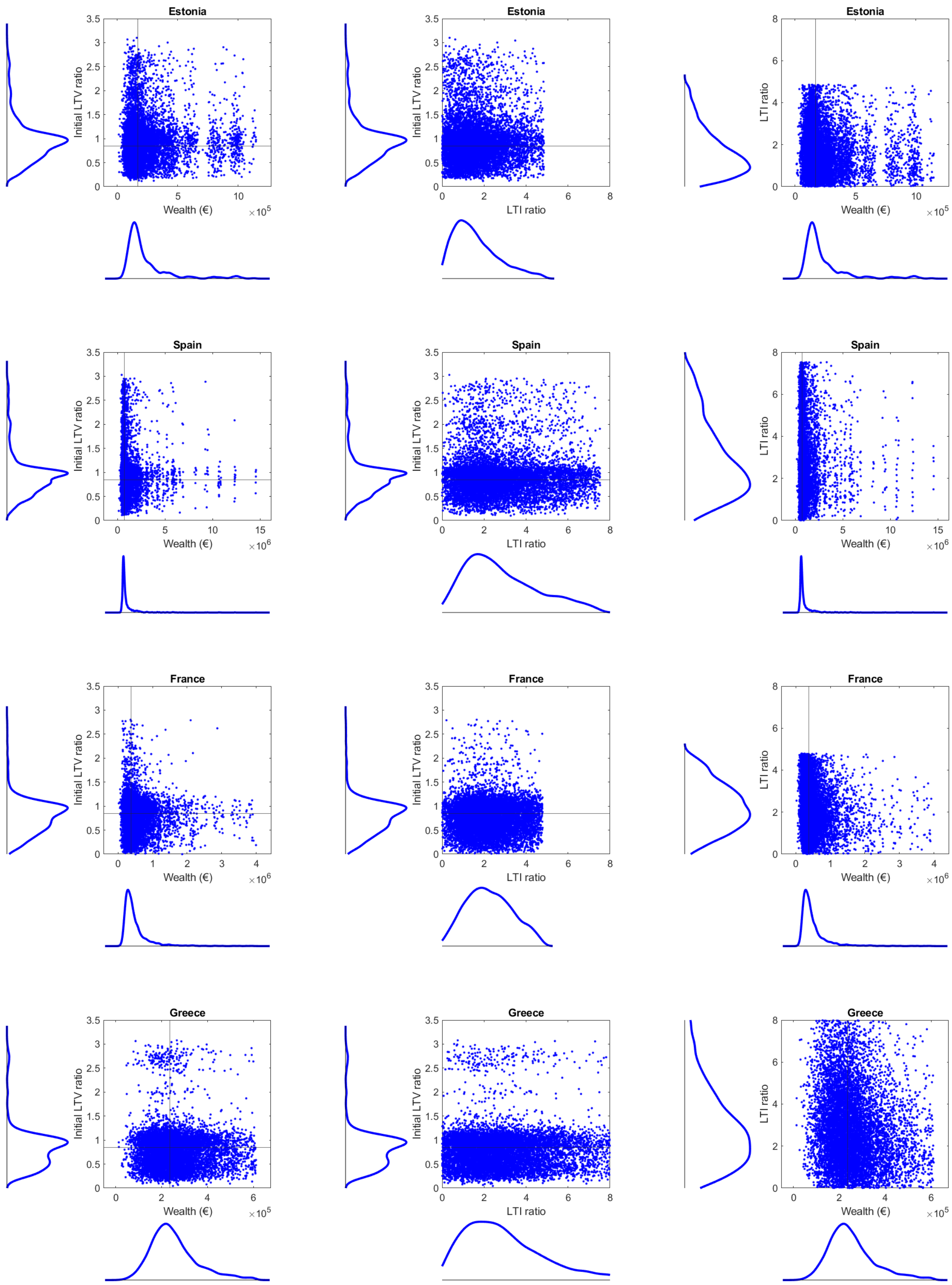


Initial LTV distribution (green), wealth-linear cap (orange), median-centered (magenta) and LTI-based (blue).

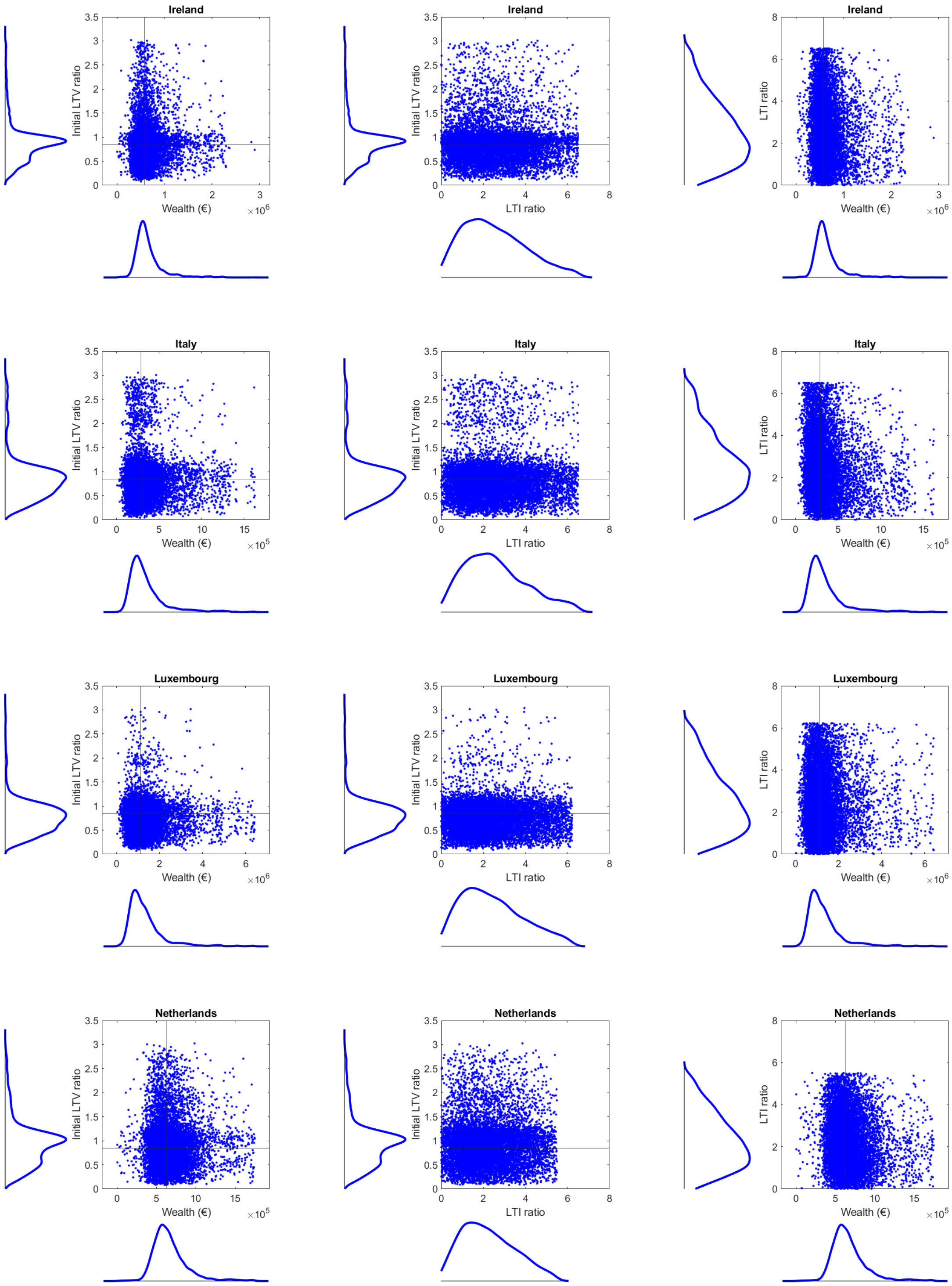
Finally, in order to better understand the extent to which the densities of wealth, LTV and LTI ratios alter the effects of each type of cap by country, the following matrix of graphs depicts three bivariate probability distributions: Wealth vs. LTV, LTI vs. LTV and wealth vs. LTI.

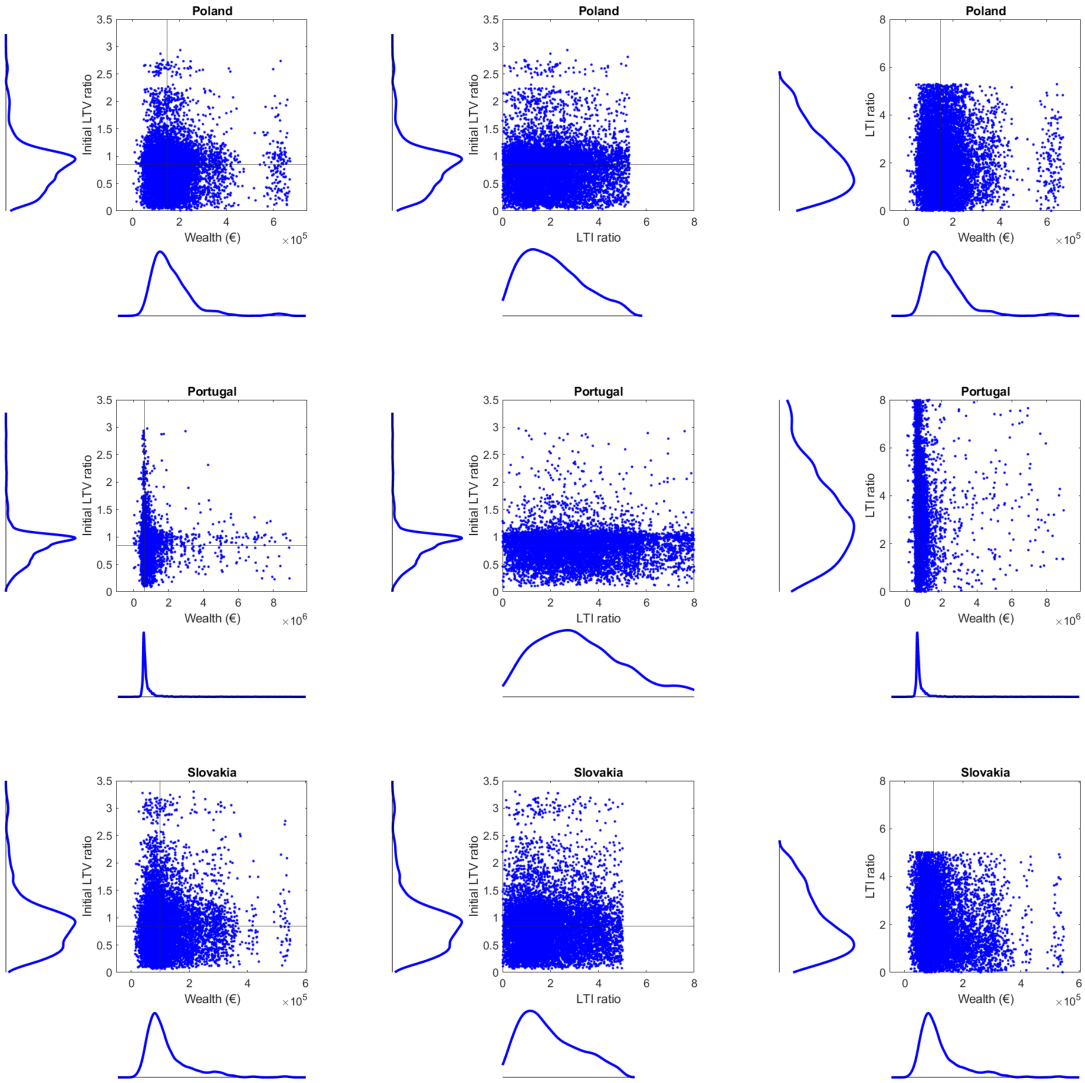
Vertical lines indicate the median of the wealth distribution; horizontal lines show the 85% cap.





Estonia
Initial LTV ratio
Wealth (€)
×10^5
LTI ratio
Spain
×10^6
France
Greece


Ireland
Initial LTV ratio
Wealth (€)
LTI ratio
Italy
Luxembourg
Netherlands


Poland
Initial LTV ratio
Wealth (€)
×10^5
Poland
Initial LTV ratio
LTI ratio
Poland
LTI ratio
Wealth (€)
×10^5
Portugal
Initial LTV ratio
Wealth (€)
×10^6
Portugal
Initial LTV ratio
LTI ratio
Portugal
LTI ratio
Wealth (€)
×10^6
Slovakia
Initial LTV ratio
Wealth (€)
×10^5
Slovakia
Initial LTV ratio
LTI ratio
Slovakia
LTI ratio
Wealth (€)
×10^5

Chapter 3

The procyclicality of impairment accounting

This chapter is joint work with Javier Población and Javier Tarancón. It was published with the title "Measuring the procyclicality of impairment accounting regimes: a comparison between IFRS 9 and US GAAP" in the ***Banco de España Working Paper Series*** *(#2003) and the* ***ECB Working Paper Series*** *(#2347).*

3.1 Introduction

In the early years of the 21st century, the accounting of financial assets was still guided by International Accounting Standard 39 (IASB, 2004), which prescribed the use of the incurred loss model for the recognition of credit losses in the profit and loss (P&L) account. If there was objective evidence that an impairment loss on a loan had been incurred, the amount of the loss needed to be calculated; however, losses expected as a result of future events were not recognized. As stated by the Basel Committee on Banking Supervision in BCBS (2015a), following the financial crisis of the late 2000s, concerns were raised about this method, particularly about the timeliness of banks'recognition of loan loss expenses. More concretely, recognizing losses after they have been incurred on a financial asset has been widely criticized for being "*too little, too late*", as detailed in Gaston and Song (2014).

Procyclicality in banks'financial soundness and credit supply is a well-known issue with many roots, such as the tendency to make a more lenient assessment of risk in good times than in bad ones, the amplification of shocks led by varying collateral valuations, the inclination of financial institutions to show herd behavior, and deterioration in managerial ability; A non-exhaustive set of references is Rajan (1994), Berger and Udell (2004), Lepetit et al. (2008), Jiménez and Saurina (2006) or Kiyotaki and Moore (1997), among others. Moreover, an extensive literature stresses the links between the accounting treatment of credit portfolios and procyclicality in lending and risk-taking[1]. Moreover, Norden and Stoian (2013), Koch and Wall (2000), Laeven and Majnoni (2003), Bushman and Williams (2015) and Ahmed et al. (1999) argue that banks have incentives for using discretion in establishing loan loss provisions to manage reported capital and earnings.

In response to such concerns, the G20 leaders issued a clear mandate to reform international prudential and accounting standards, reducing complexity and procyclicality and increasing coordination among the various standards used, as stated in G20 (2009). The G20 endorsed the Financial Stability Forum's report on addressing procyclicality in the financial system (FSF, 2009), according to which *"earlier recognition of loan losses could have dampened cyclical moves"* and *"earlier identification of credit losses is consistent both with financial statement users'needs for transparency regarding changes in credit trends and with prudential objectives of safety and soundness"*. The report also recommended the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) to replace the incurred loss method of loan loss provisioning with alternative approaches that *"incorporate a broader range of available credit information"*, i.e. with a more forward-looking expected loss method using statistical information to identify probable future losses. The result has been the publication of International Financial Reporting Standards 9 (IFRS 9) "Financial Instruments" in July 2014 (IASB, 2014) and the US GAAP in July 2016 (FASB, 2016). The primary difference between the two approaches is the method for impairment calculation (full lifetime in US GAAP vs. staging in IFRS 9)

This paper contributes to the literature that aims at establishing whether forward-looking accounting standards are actually more procyclical. There is a lack of consensus among the research conducted so far on this issue. Earlier literature as well as policymakers agreed on the fact that forward-looking provisioning would reduce procyclicality; some examples are Balla and McKenna (2009), Laeven and Majnoni (2003), Wezel et al. (2012), FSF (2009) and BCBS (2009). Conversely, more recent contributions point in the opposite direction: Two prominent examples are Barclays (2017) and Abad and Suárez (2018). In particular, the latter find that under the two forward-looking accounting standards, the impact of an exogenous increase

[1]See, for example, BCBS (2015), Beatty and Liao (2011), Studener et al. (2014) or Bushman and Williams (2012).

in substandard loans on P&L and capital is greater than under the incurred loss approach (with the IFRS 9 impact being the greatest). They conclude, therefore, that forward-looking approaches may amplify the effect of an unexpected increase in risk, since they concentrate the impact on P&L of future losses at the beginning of a contractionary phase of the credit or business cycle, possibly determining negative feedback effects on credit supply just as economic conditions start to worsen.

In this paper, we will focus exclusively on the dynamics of P&L impact under different accounting standards (IAS 39, IFRS 9 or US GAAP) with a simulated mortgage portfolio. More precisely, we investigate the degree of contemporaneous correlation with GDP as well as realized losses. Our results suggest that, in order to reduce the cyclicality of impairments, it is preferable to use an accounting method that takes into consideration the expected loss of credit portfolios over the entire lifetime of the asset, i.e., the approach followed by US GAAP.

In the latter case, since for each loan provisions made at the origination date account for its lifetime expected credit loss (ECL), overall provisions tend to increase with the flow of newly originated loans, *ceteris paribus*. Given that the latter is negatively correlated with default rates, two opposite effects influence the dynamics of provisions: While a higher new loan origination rate tends to increase provisions during credit cycle's boom phases (and vice versa during crises), it is also possible that lifetime ECL is underestimated during credit booms, leading to insufficient provisioning at inception and subsequent adjustments in the provisions held for loans originated in previous periods. Thus, the degree of cyclicality (in the sense previously defined of contemporaneous correlation with the evolution of credit quality) of the impact on P&L under the US GAAP framework, and how it compares with IFRS 9, cannot be disentangled beforehand but depends on which effect is larger.

We model the impact of credit impairments on P&L under different accounting regimes in a historical scenario for default rates and newly originated loans, under different assumptions on how financial institutions incorporate information in the expectation for lifetime losses. We alternatively assume that banks are able to correctly forecast future defaults -so that no underestimation of ECL is possible- and that their perfect forecasting ability is limited to a fixed horizon, after which the loss rate is assumed to revert to its historical average. In the latter case, underestimation of ECL at inception is possible and implies adjustments in the provisions for older loans as new information becomes available.

As expected, the impact on P&L under IFRS 9 appears less procyclical than under the previous regime (IAS 39, where it just coincided with realized losses), but still likely to hit financial institutions when a contractionary phase of the credit or business cycle has already started. Provisions under US GAAP appear to be less cyclical then those required under IFRS 9 under all scenarios considered. The lower procyclicality of US GAAP, however, comes at the cost of holding a larger stock of provisions at all times.

We also depart from the baseline case by constructing synthetic, alternative business cycles of varying length and severity in each of their phases, so that the extrapolation of our results to other historical scenarios becomes more straightforward. In our setup, when the new series for defaults and the flow of credit enter the two forward-looking accounting systems, provisioning is shown to be larger during cycles with a longer contractionary phase. Additionally, a higher level of provisions is maintained for cycles short upswings, while the latter decreases in those with short bonanza periods. In terms of procyclicality, the length and shape of the cycle appears to matter much more for the IFRS 9 regime, under which short downturns or long upswings induce higher correlations. The results for US GAAP are less heterogeneous, probably because lifetime provisioning at inception is mandatory and this renders the initial stage of the cycle much more relevant than its full shape.

The remainder of this paper is structured as follows: Section 3.2 presents a brief review of the most important accounting regimes for credit instruments; in Section 3.3, we describe our data sources. The methodology used in the paper is detailed in Section 3.4. Our main results and the associated robustness checks constitute Section 3.5. Finally, Section 3.6 concludes.

3.2 Regulation

In this section, we present a brief review of alternative accounting treatments – IAS 39, IFRS 9 and US GAAP – for credit portfolios.

3.2.1 IAS 39

IAS 39 adopts an incurred loss approach for impairment accounting, i.e. after the initial recognition of the asset it requires, at least, a loss event to occur for any impairment to be recognized (IASB, 2004). A non-comprehensive list of loss events is provided, but the crucial aspect is that expected losses stemming from future events cannot be accounted for. IAS 39 also allows to recognize collective provisioning or “incurred but not reported” (IBNR) losses[2]:

[2]See IAS 39, AG 89 and 90.

Statistical evidence can be used to work out the level of loss events already incurred, although not yet recognized, in a loan portfolio. However, this proved insufficient both because of the divergent application across countries and because the use of statistical evidence was limited to the existence of trigger events after origination (ECB, 2014). Following the distress unleashed by the financial crisis in the late 2000s, the incurred loss approach was broadly deemed "*too little, too late*" (BCBS, 2015b). Among the measures adopted to mitigate the procyclicality of IAS 39, it is worth to mention the generic provision scheme adopted in Spain, implemented in Banco de España (2004)[3] . This approach stemmed from IBNR collective provisioning (Saurina, 2009) and its objective was to accumulate allowances in the boom years of the cycle for subsequent use during crises[4]. However, it did not cover the full amount of specific provisions accumulated by banks during crisis years, as detailed in Trucharte and Saurina (2013) and Banco de España (2017).

3.2.2 IFRS 9 and Current Expected Credit Loss (CECL)

IASB published its final IFRS 9 implementation guidelines in July 2014 after several reviews and failed efforts to converge with US GAAP. The most fundamental change concerned the impairment accounting regime for financial instruments, which implies a shift in paradigm moving from incurred to expected losses.

According to the new standard, the bank needs to recognize the expected loss for any financial asset valued at amortized cost or fair value through other comprehensive income. The degree to which the expected credit loss (henceforth, ECL) has to be recognized depends, however, on the severity of credit quality deterioration. At origination or purchase of the asset, and as long as the condition for classification other stages does not subsist, the value correction has to account for the expected loss for the following 12 months (Stage 1). However, if there has been a significant increase in the risk (Stage 2) or default (Stage 3) since its inception, the institution will recognize the expected loss for the full expected lifetime[5].

[3]Prior to the modification via CBE 4/2016, which increased alignment with IAS 39.

[4]This was done determining generic provisions via the following formula:

$$\Delta Generic provision_t = \sum_{k=1}^{N} \left(\alpha_t^k \Delta c_t^k + \beta^k C_t^k - Specific provision_t^k \right)$$

where C_t^k is the stock of loans in portfolio k at time t. The coefficients α and β represent respectively the rate of credit losses in a cyclically neutral year and the average specific provision for loans in a specific portfolio k, estimated on the basis of historical data for Spanish banks.

[5]In order to move an asset from Stage 1 to Stage 2, thus recognizing a significant increase in default risk, the entity should evaluate the variation in the probability of default (PD) for the asset's lifetime. However, an increase in the twelve-month PD might be a good proxy for lifetime PD (IFRS 9, B5.5.13).

A generalized significant increase in risk due, for example, to a deterioration of the economic cycle, may determine a sharp rise (*"cliff effect"*) in the required provisions (IASB, 2013). Although there is a certain degree of discretion in the recognition of a significant increase in risk, some indications are provided; in particular, there is an assumption (rebuttable by the financial institution) that a significant increase in risk exists in case of exposures which are past due for more than 30 days. Additionally, IFRS 9 enumerates a non-exhaustive list of example criteria to recognize increases in risk, notably the criterion based on loan pricing, which suggests a comparison between the prices of existing and new portfolios as a proxy for risk increases[6].

As previously noted, after several failed attempts at convergence the FASB published its own financial instrument accounting standard, which is known as Current Expected Credit Loss (CECL) and tries to prevent under-provisioning by immediately recognizing, at the moment of origination or purchase of the asset, the full amount of credit losses expected over the assets'foreseeable lifetime (FASB, 2016, Novotny-Farkas et al., 2015 and O'Hanlon, 2015). In terms of IFRS 9, this would be similar to recognizing every asset directly in Stage 2. The FASB approach would also be conceptually close to the late Spanish collective provision with the only nuance of the automatic mechanism both for accumulating and releasing provisions, as explained in Trucharte and Saurina (2013).

The updated weighted averages of the expected credit losses (with the weights being the respective probabilities of default) are defined as the updated differences between expected and contractual payments. The expected loss must be estimated taking into account the weighted probability of default, the expected recovery rate, the time value of money and all the available information. The proceeds from collateral must be included when calculating the expected cash flows once execution costs have been deducted. Finally, the rate used to actualize shortages in payments will be the original rate at inception; thus, subsequent changes in interest rates after a loan's inception are not relevant for the calculation of provisions.

3.2.3 Linkages between accounting and regulatory provisions

The main goal of accounting standards is not to reduce procyclicality but to depict a truthful representation of the company's financial condition. This is the reason why the cyclicality of the provisioning regime is mitigated via prudential capital requirements. Nevertheless, the results of accounting and regulatory provisions are not independent from each other and the

[6] Also mentioned in EBA (2017), paragraph 107.

FSF (2009) report recommended accounting standard setters to replace the incurred losses approach with an expected losses one, arguing that *"earlier identification of credit losses is consistent both with financial statement users' needs for transparency (...) and with prudential objectives"*.

Accounting and regulatory provisions, however, still differ under several perspectives, and to avoid any undue shock in solvency, the first implementation of the ECL approaches is to be mitigated via transitional arrangements (see BCBS, 2017). In this section, we explore the primary differences between accounting and regulatory expected losses from the P&L perspective. In this line, it is reasonable to expect that credit parameters used for regulatory purposes be the basis for calculating accounting parameters; however, these parameters will be adjusted for the different purposes of each view (as mentioned in both the EBA and Basel guidelines).

For prudential purposes, the probabilities of default (PD) estimates are based on long-run averages (through the cycle approach, TTC) of one-year default rates. For accounting purposes, the PD is the point-in-time (PiT) value appropriate for each reporting period. Again, the time horizon greatly depends on the accounting standard, full lifetime for US GAAP and the 3-stage approach in IFRS 9.

In the same manner, for regulatory purposes, loss given default (LGD) estimates are expected to consider an economic downturn if this leads to more conservative estimates than the long-run average. However, for accounting purposes the best point-in-time estimation is chosen to avoid any bias.

Prudential regulation might be able to partly mitigate procyclicality. Firstly, discrepancies in accounting and regulatory expected losses will be considered in regulatory capital[7]. Besides, the level of provisions must be factored in during the Supervisory Review and Evaluation Process to determine Pillar 2 capital requirements (EBA, 2014). These elements might be used to mitigate the potentially procyclical impact of the new accounting regime. However, one should bear in mind that accounting is crucial for incentives to managers (impact on dividends, bonuses, market reputation...); for this reason, it is of utmost importance to assess the cyclical aspects of accounting regimes.

[7] According to the CRR, for IRB banks deficits accounting provisions, deficit will be deducted from Core Equity Tier 1 (CET1) capital while surplus will be included as Tier 2 capital (with a cap of 1.25% of the total risk exposure amount stemming from credit risk).

3.2.4 Comparison between the different methods

One of the main issues that we want to address is the procyclicality of conditions for moving from Stage 1 to Stage 2. Most of the events that may trigger the reclassification from Stage 1 to Stage 2, such as changes in internal and external ratings, value of collateral, pricing of the credit risk or financial soundness of the borrower, are highly correlated with the business cycle. A widespread concern is that the "cliff effect" may therefore exacerbate the increases in provisions due to the simultaneous deterioration of credit quality for a significant portion of the portfolio. Abad and Suárez (2018) find that the impact on P&L of an exogenous increase in substandard loans under an IFRS 9 regime would be particularly concentrated at the beginning of a contractionary phase of the credit or business cycle, with negative feedback effects on credit supply. In the next sections, we conduct a similar analysis showing that, while IFRS 9 does not seem to be able to decisively solve the issue of procyclicality, in contrast with the results of Abad and Suárez (2018) the impact of the "cliff effect" is likely to be small and not determine an excessive concentration of provisions at the turning point of the cycle. The other framework we study, US GAAP, seems better suited in comparison to smooth future losses over time.

We share some of the criticisms on the FASB accounting approach. The CECL approach, by frontloading all the future expected losses, implies the recognition of a significant amount of day-one losses. This also reduces comparability among portfolios and institutions since riskier loans will present higher initial losses, while their net present value is not lower if risk premiums are correctly set. However, in this paper we analyze only the cyclical behavior of the two methods, disregarding the comparison from a pure accounting perspective.

3.3 Data

In Section 3.5, we will propose an exercise which simulates provisions and losses under different regimes for a fictional portfolio composed only of mortgages with 20-year maturity over the years 2006-2018. This section describes the data used to feed the simulation, its sources and some methodological choices.

Average default rates for mortgages are estimated from the Italian central credit register (*Centrale dei Rischi*, CR). We consider loans with a predetermined maturity granted to households: given the minimum threshold of 30,000 euros for inclusion in the dataset, these loans are mostly constituted by mortgages. In order to estimate default rates, we divide the amount of loans in default at the end of each period by the amount that were performing at the beginning of the quarter. Quarterly default rates are then seasonally adjusted through the X-13 procedure. Information on defaulted loans compatible with the current harmonized EBA definition of non-performing loans is available from 2006 (Figure 3.1).

The probability of default, however, is not constant over the life of a loan; while various idiosyncratic events may intervene, default probability tends to be lower at the very beginning of a loan's lifecycle (when the information under which it was granted is more likely to still hold true) and for older loans (i.e. 'survivors' are likely to have idiosyncratic characteristics that make them more resilient). We are particularly interested in modeling the dependence between default rates and the age (i.e., the time since origination) of a loan, for it strengthens the link between credit dynamics and credit risk.

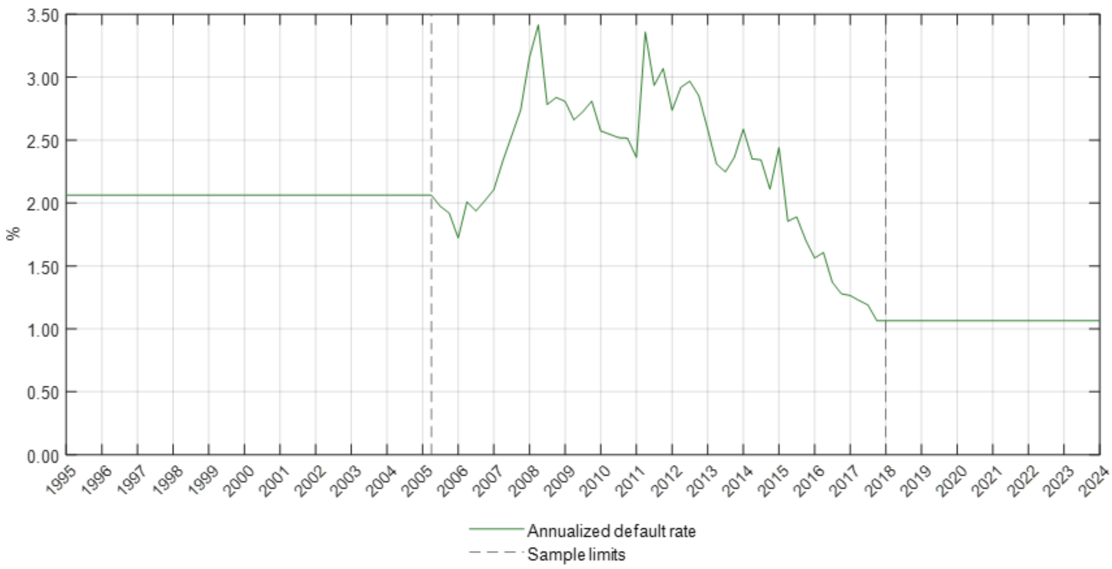
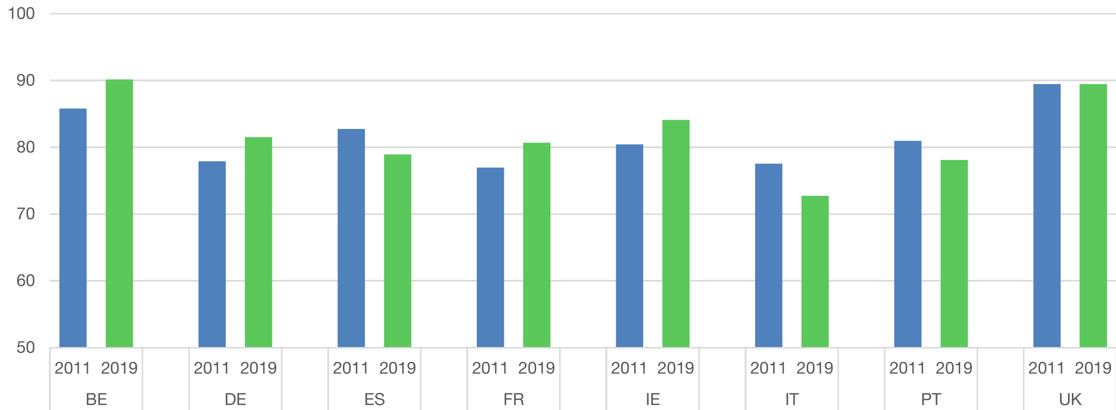


Figure 3.1: Annualized default rates for mortgage loans

In our Italian data from the CR, unfortunately, it is not possible to separately identify multiple exposures toward the same subject nor the contractual maturity of mortgages at origination, which makes it difficult to estimate the relation between default rates and loan age. We therefore obtain the latter using data from the *European Data Warehouse (EDW)*, composed of circa 10 million loans that are part of residential mortgage-backed securities (RMBS) from several European countries. For each loan, the dataset contains the date of origination, the date of maturity, and where applicable, the date of default[8].

[8]Institutions report information on securitisation deals that have not reached maturity (as is usually the case) and begin reporting significantly after the creation of the product, providing only information on the current status of the underlying pool of loans (i.e., omitting information on loans originally included in the

We acknowledge that resorting to EDW data restricts the analysis to a subsample of total loans -residential mortgages- underlying the securities in the pool. However, this loan category plays a very prominent role in total lending by banking institutions to the private non-financial sector, constituting around 80% of credit to households in those European countries for which the EDW has information. Figure 3.2 shows that this share has not varied significantly over the last decade. Anyhow, the classification of loans into Stages 1, 2 and 3 is uniform across loan types in IFRS 9 (whether mortgages or not), thus rendering our exercise easily extrapolable to other categories.



Sources: Statistics from the national central banks (NCBs).

Figure 3.2: Share (%) of residential mortgages in household loans for selected countries.

The EDW dataset has the benefit of providing a wide cross-country sample for European loans but also some shortcomings that can introduce bias in the estimation of default probabilities (PDs). The reason is twofold: First, even though the available evidence does not clearly point to a systematic presence or even a clear direction of a selection bias in securitized pools of loans in Europe[9], we reckon that its existence is plausible. Second, the EDW dataset does not include a complete history for each cohort of loans originated at a given date (origination cohort) since institutions can start reporting the status of the loans included in a securitization well after the date when it was initially created. When this is the case, information on loans initially included in the securitized pool but defaulted or matured before the first date of reporting is generally not reported, since it is not mandatory.

pool but that have since reached maturity, or that have defaulted and all the recovery procedures have been concluded so that no further cash flows are expected). This creates some issues in the estimation of probability of default, as explained in Section 3.4.

[9]For an analysis of the impact of securitization on screening and monitoring activity and a summary of the relevant literature, see Albertazzi et al. (2011).

Because of the potential presence of these two biases, we will only use this sample to characterize the relative PD level changes as a function of the age of a loan because we assert that it is not affected by these biases, even if the average PD is over- or underestimated. However, since the PD for a given age must be estimated using default rates from cohorts whose origination date is not successive to the current date minus the specific age, the PD for higher age buckets would be affected by a downward survivorship bias. This effect can be removed by excluding from the sample those loans originated before the first date of information reporting of the securitisation deal to which they belong. However, this solution is unsuitable for our purposes, since it would leave us with the possibility of studying the evolution of PD only within a small number of years from origination. Instead, we decided to accept the presence of some bias but, to mitigate the problem, we exclude from the sample the loans originated before 2000 or after 2010, for which underestimation of PD is more likely.

In a nutshell, we will use the Italian credit register to obtain the average PD for each period and the EDW database for establishing the relationship between the age of a loan (i.e., the time from origination) and its probability of default[10].

According to the IFRS 9 dispositions, a rebuttable presumption exists that the 30-day past due status represents a significant increase in the risk qualifier for loans. Unfortunately, this information is not available. However, we know the share of non-performing loans that are 90-days past due at the end of each quarter; if payments stop with uniform probability within each quarter, approximately two thirds of the 90-day past due loans at the end of the quarter would already be 30-days past due by the end of the previous quarter. Therefore, we approximate the amount of loans with significant risk increase in t[11] with

$$SRI_t = \frac{2}{3} PastDue90_{t+1} \tag{3.1}$$

Data on new loans for house purchases in Italy is extracted from the MFI Interest Rate Statistics (MIR), available at the European Central Bank's Statistical Data Warehouse[12]. In

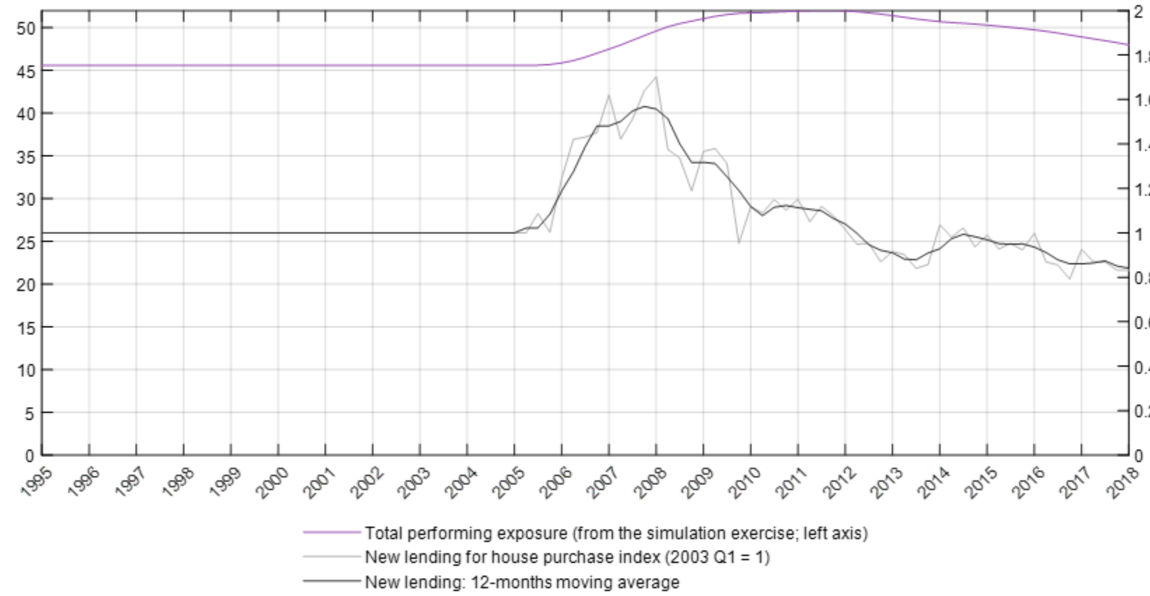
[10] Notice that if the PD is estimated conditional on the number of years from origination, right-censoring is not a source of bias: loans for which, at the sample cut-off date, neither default has been observed nor maturity has been reached are not considered part of the pool of loans alive at ages above the age they possess at the cut-off date. This is not true for the average default rate, which must be calculated removing from the sample right-censored observations to avoid a downward bias.

[11] This proxy is likely to slightly underestimate the amount of 90-day past due loans, since it excludes those exposures which enter and exit the status within the 90 days.

[12] More precisely, the series contains new business related to *"lending for house purchase, excluding revolving loans and overdrafts, convenience and extended credit card debt"* (MIR.M.IT.B.A2C.A.B.A.2250.EUR.N).

our simulation exercise, in each period new loans are originated for a normalized amount that tracks the historical series of new loans for house purchases, as depicted in Figure 3.3.

The dynamics of the overall stock of (performing) loans are therefore determined by the difference between the speed at which new loans are originated, which is inversely correlated with credit quality, the outflows deriving from regular repayments, following the amortization schedule in equation (2) below, and defaults[13].



The dynamics of the overall stock of performing loans (left axis), which is an index, are determined by the difference between the speed with which new loans are originated and the outflows deriving from regular repayments and defaults.

Figure 3.3: New loans and simulated stock of loans.

Other relevant information for modeling the effect of various impairment accounting rules is represented by the residual maturity of the loans in the portfolio. Impairment accounting rules indeed differ regarding the moment at which provisions must be made: under US GAAP, provisions are set aside at origination so that they tend to increase during credit cycle upswings when the portfolio contains younger loans and vice versa[14]. In addition, both the PD and the LGD, as detailed in Section 3.4, depend on the age of the loan measured since its origination. For LGD, we model this dependence deterministically.

[13]Notice that the overall stock of outstanding loans reported in aggregate statistics such as MIR includes NPLs instead.

[14]This effect can be compensated by lower estimates for PD and LGD during credit cycle upswings. In the following, we will in fact analyse both the case of perfect forecasting ability for all future periods — where the underestimation of risk parameters is absent by assumption — and the case where the forecast horizon is limited to one year forward, where underestimation of future risk at origination is possible. We also introduce stochastic forecast errors in Section 3.5.3.

3.4 Methodology

In this section, we model a simplified version of the accounting regimes detailed in the previous part. In Section 3.4.1 we start at the highest level describing the impact in P&L of loan loss provisioning. In Section 3.4.2 we work down to the details describing how we model the specific parameters.

For simplification purposes, we will not allow for multiple default events or the possibility that defaulted exposures return to performing status[15]. In addition, once the default status is triggered, the LGD is deterministic and depends on the loan-to-value (LTV) ratio. Finally, to focus on the differences between accounting regimes, we remove uncertainty from the model by assuming that credit models are perfect in the sense that they can exactly predict future outcomes.

3.4.1 Impact on P&L: provisions and realized losses

In calculating the impact on the profit and loss account we follow the approach defined by the accounting practice (GPPC, 2016), that is, we calculate provisions and realized losses through the PD, LGD and exposure at default (EAD) for each year. In this section, the basis time unit t is the quarter and financial institutions are supposed to account for provisions and losses on a quarterly basis.

IAS 39

Under IAS 39 there are no provisions, neither at inception nor for any given year; each period's total negative impact on the profit and loss account (PL_t) is required to equal realized losses. Assuming that the loss appears when there is a default, the P&L under IAS 39 would be:

$$PL_t^{IAS\,39} = EAD_t \cdot DR_t \cdot LGD_t \tag{3.2}$$

where DR_t is the realized default rate in t. However, since the loss appears well after the default, this formula is just an approximation. As we will state afterwards, for simplicity in this paper we will assume that the loss from a default is split equally across the following six years.

[15]This simplification assumptions have been chosen in line with standard practices; see, for example, the stress testing methodology in EBA (2016).

IFRS 9

Under the perfect forecast assumption, losses in each period are fully compensated with previous year provisions. Again, assuming the loss appears when there is a default, the negative impact on P&L from Stage 1 loans would be just equal to the losses expected for the following year:

$$PL_t^{S1} = EL_{t+1,t+4}^{S1} = \sum_{s=t+1}^{t+4} EL_s^{S1} = \sum_{s=t+1}^{t+4} EAD_s^{S1} \cdot LGD_s \cdot PD_{s|\mathcal{F}_t} \cdot (1+r)^{-(s-t)} \tag{3.3}$$

If there is a significant risk increase, loans pass to Stage 2 status and the full lifetime expected loss must be recognized. We use a proxy of the 30-day past due status as a trigger for the transition from Stage 1. According to IFRS 9 dispositions, a (rebuttable) presumption exists that 30-days past due status represents a significant increase in the risk qualifier for loans. Unfortunately, data on payments past due less than 90 days is not available from the Italian Credit Register. However, assuming that payments become past due with uniform probability within each quarter, approximately two thirds of the 90-day past due loans at the end of a quarter would already be 30-day past due by the end of the previous quarter. We assume as a rough approximation that 2/3 of the loans to be defaulted in $t+1$ show a significant risk increase in t, i.e.:

$$EAD_t^{S2} = \frac{2}{3} \cdot EAD_{t+1}^{S3}$$

However, this assumption does not embrace loans that temporarily shift from Stage 1 to Stage 2 and vice-versa; in subsequent sections of the paper, we explore alternative formulations that account for migrations from and to Stage 2. Assuming the loss is discovered when there is a default, the impact on P&L from loans in Stage 2 is:

$$\begin{aligned} PL_t^{S2} &= \sum_{s=t+1}^{M} EL_s^{S2} = \sum_{s=t+1}^{M} EAD_s^{S2} \cdot LGD_s \cdot PD_{s|\mathcal{F}_t} \cdot (1+r)^{-(s-t)} \\ &= \sum_{s=t+1}^{M} EAD_s^{S2} \cdot LGD_s \cdot PD_s \prod_{k=t}^{s-1} (1-PD_k) \cdot (1+r)^{-(s-t)} \end{aligned} \tag{3.4}$$

where M is the exposure maturity and $\mathcal{F}_t$ the information set in t.

The impact on P&L from Stage 1 and Stage 2 exposures comes therefore in terms of provisions for future losses:

$$PL_t^{S1} + PL_t^{S2} = Prov_t^{IFRS\,9} \tag{3.5}$$

For loans in Stage 3 default is certain ($PD_t = 1$), and a loss must be accounted for in P&L. The corresponding provisions already made in the previous periods, on the other hand, must be cancelled. Under the assumption of perfect forecast, in every period realized losses correspond to the expectations of the previous periods and the two quantities offset each other.

$$PL_t^{S3} = Loss_t - Prov_{\text{Previous periods}}^{IFRS\,9} = 0 \tag{3.6}$$

Since we have assumed perfect forecasting ability, the sum of losses realized in any period will exactly offset previous year's provisions, short of a difference due to discount unwinding[16]. For the sake of simplicity, we assume that there is no flow of loans back from Stage 2 to Stage 1. Under these assumptions the impact in P&L from Stage 3 is zero.

Summing up, under our assumption the impact on P&L in each period under IFRS 9 is therefore equal to the sum of one-year expected losses for loans in Stage 1 and of lifetime expected losses for loans in Stage 2:

$$PL_t^{IFRS\,9} = Prov_t^{IFRS\,9} + \left(Loss_t - Prov_{\text{Previous periods}}^{IFRS\,9}\right) = PL_t^{S1} + PL_t^{S2} \tag{3.7}$$

US GAAP

In order to replicate the approach devised by the FASB we recognize the full lifetime expected loss of each loan at inception. We model the impact on P&L under US GAAP under three different assumptions on how financial institutions incorporate new information in the estimates for lifetime ECL:

[16] Future losses must be discounted using the effective interest rate determined at inception (IFRS 9, par. B5.5.44). When cash flows are actualized to calculate the provision, the mere passage of time creates income because one year less is actualized. This effect is known as "discount unwinding".

1. Future loss rates are known ("*perfect forecast*");
2. Future loss rates are known up to a one-year horizon in the future, after which they are assumed to revert to the sample average;
3. Future loss rates are known up to a one-year horizon in the future, after which they are assumed to revert to the average of the previous five years.

When we assume that financial institutions can perfectly forecast future losses, the sum of realized losses in the subsequent periods will exactly offset the provisions in year one. Therefore, the impact on P&L in each period will equal to the lifetime expected loss for the newly originated loans and is obtained by replacing the EAD with the volume of new loans in equation (3).

Under the alternative assumptions where the perfect forecast horizon is limited to one year[17] (after which financial institutions either assume that PD will revert to the historical sample average levels or to the average of the last five years), in addition to the provisions for new loans in each period there will be a positive or negative impact from the provisions on older loans, for which the expectation on the loss for the residual lifetime changes in response to the new information available. The new value of the lifetime ECL for old loans tends to increase during crisis times, partially offsetting the reduction in overall provisions implied by the lower flow of new loans.

Which of the two effects will prevail is crucially contingent upon how financial institutions update their expectations on future losses. Under our assumption an increase in loss rates is seen as transitory and the latter are assumed to revert to some average value, which results in a limited effect that only partially offset the opposite dynamic driven by the provisions on new loans. If financial institutions assume longer persistence of loss rates values, the changes in provisions for old loans tend to prevail.

3.4.2 Parameters

We construct provisions and realized losses through the computation of PD, LGD and EAD for the various years. In this subsection, we explain the assumptions made to calculate these parameters.

With a slight abuse of notation, we use a single subscript t to denote the one-period time span $[t-1, t]$. PD_t and LGD_t are, respectively, the probability of default and the applicable

[17] We keep one year of perfect forecast in order to ease the comparison with the results for IFRS 9.

loss given default between $t-1$ and t. For simplicity we assume that the exposure does not change between t and the moment of default, so that EAD_t is constant throughout the period.

Exposure at default

We model the evolution of EAD according to a constant annuity amortization schedule with a fixed interest rate and annual coupon payments. The residual exposure EAD_t is[18]:

$$EAD_t = L \cdot [\frac{(1+r)^M - (1+r)^t}{(1+r)^M - 1}] \tag{3.8}$$

where L is the loan amount at inception, r is the interest rate and M is the original maturity of the loan. Figure 3.4 shows the EAD variation with the age of the loan, assuming $r = 3\%$ and M equal to 20 years for all loans.

Loss given default

Following the literature[19], in modeling loss given default we use a simplified structural model that represents LGDs as a deterministic function of the loan-to-value (LTV) ratio, that is, the ratio of the exposure value (EXP) to the value of the collateral C, and the residual exposure at a given time. Clearly, there is a positive relation in time between recovery rates and the reduction of LTV following the progressive reimbursement of the loan. If the LTV ratio is smaller than the sales ratio SR (which is the quotient between the present value of the sale price and the value C of the collateral), the entire value of the exposure can be recovered. In addition, we introduce a cost of recovery procedures CR that is proportional to EAD and equal to 5%. This effectively imposes an LGD floor of 5% even when $LTV_t \leq SR$. Our formula for LGD reads as follows[20]:

$$LGD_t \equiv LGD\left(EXP_t\right) = CR + \max\left\{0, \frac{EXP_t - C \cdot SR}{EXP_t}\right\} = CR + \max\left\{0, \frac{LTV_t - SR}{LTV_t}\right\} \tag{3.9}$$

[18] The proof of this result can be found in standard financial mathematics textbooks.

[19] See, for example, Qi and Yang (2009), Greve and Hahnenstein (2014) or Ross and Shibut (2015).

[20] We consider loan-to-value ratios within the $(0, 1]$ range, which is a reasonable modelling assumption, though not crucial to any of the results presented.

We make the simplifying assumptions of no uncertainty and no changes along the life horizon of the loan for recovery costs CR, the collateral value C and the sales ratio SR: Fixing these variables, the LTV ratio is just a constant share of the residual exposure at time t, and LGD a deterministic concave function of it. Since the loan is progressively reimbursed during his lifetime, given the assumptions LTV ratios and LGD will progressively decrease with the age of the loan, as shown in Figure 3.4.

We have set the SR value to 50% in this exercise and the initial LTV at 80% to obtain an average LGD of 16.8%, broadly in line with historical empirical values for residential mortgages[21].

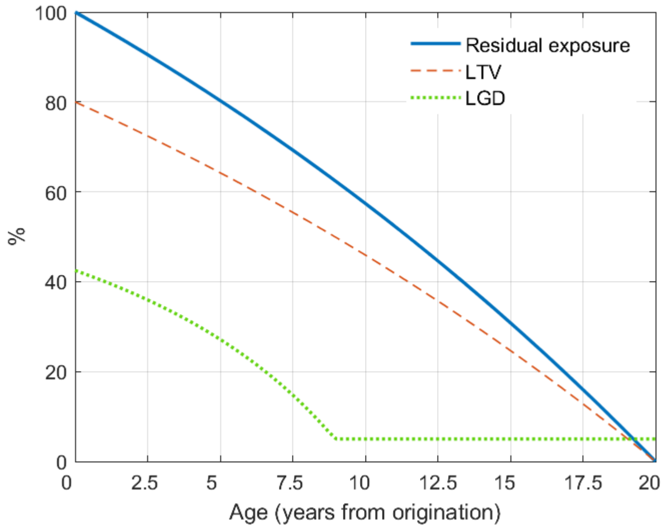


Figure 3.4: EAD and LGD vs. age of the loan.

Probability of default

As explained above, we need to estimate the relationship between the age of a loan (i.e., the time from origination) and its probability of default. To do so, we need to observe cohorts of loans with the same origination date over their entire lifetime (i.e., until each of them defaults or comes to maturity).

With this information, we can estimate the probability of default PD_t for each year following origination using the default rate for age t, calculated as the number of defaults in the period over the number of loans that either have not yet reached maturity or have defaulted at the beginning of the period:

[21] See, for example, EBA (2013).

$$\hat{PD}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} D_{i,t} \tag{3.10}$$

$$N_t = N_{t-1} - \sum_{i=1}^{N_{t-1}} D_{i,t-1} - \sum_{i=1}^{N_{t-1}} M_{i,t-1} \tag{3.11}$$

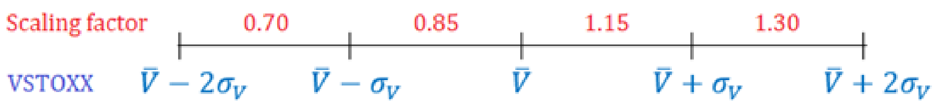
where $D_{i,t}$ and $M_{i,t}$ are binary variables for the default and maturity of loan i at age t and N_t is the number of loans survived.

In order to be consistent with the IFRS 9 framework and the rationale behind expected loss provisioning, we have also included forward-looking information in the calculation of PDs using information from the ECB's Bank Lending Survey. The series *BLS.Q.IT.ALL.Z.H.H.F3.ST.S.FNET* is available from 2003Q1 and collects the answers to the question *"Please indicate how you expect your bank's credit standards as applied to the approval of loans to households to change over the next 3 months"*; a negative (positive) value implies a perceived easing (tightening) of credit standards. If BLT_t is the value of the bank lending tightening series in period t, we rescale PDs so that

$$PD_t^* = \hat{PD}_t \times \left(1 + \frac{BLT_t}{BLT_{max} - BLT_{min}}\right) \tag{3.12}$$

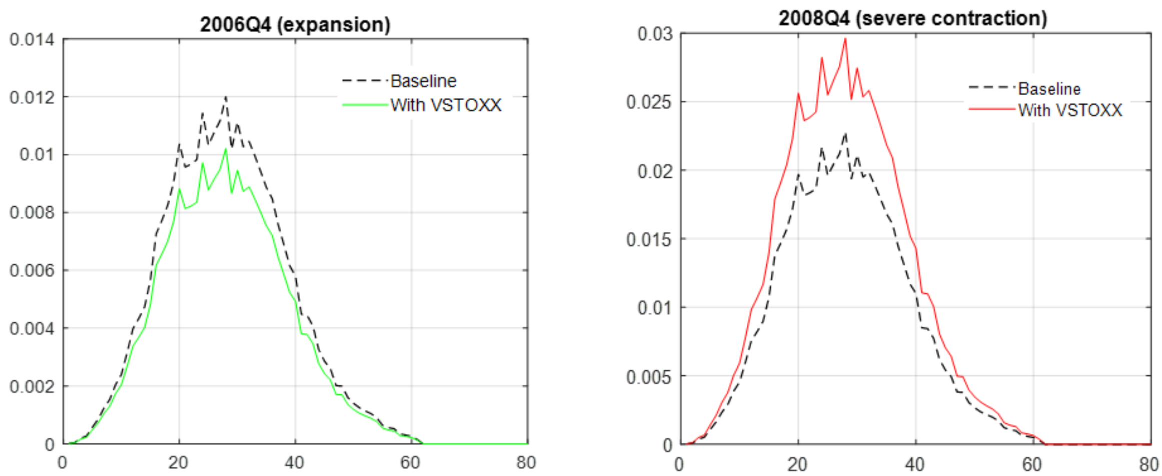
Moreover, in the calculation of default probabilities, Kröger, Rösch and Scheule (2018) account for macroeconomic information for the US economy using the VIX volatility index as a proxy, owing to its leading nature for the economic juncture[22]. We mimic this approach using the VSTOXX time series which is the VIX equivalent built upon the Dow Jones EUROSTOXX 50 Index.

Using the historical average $\overline{V}$ and the volatility σ_V of the VSTOXX from 2006 to 2018, we rescale the PDs so that both the magnitude and the sign of the index influence the probability of default:



[22] As detailed, among other works, in Bloom (2009) and Jo and Sekkel (2019).

We illustrate the effect of applying this correction by looking at the 1-year PD curves as a function of the age of the loan in two different points of the sample: on one hand, a moment of economic bliss (2006Q4) at which the value of the volatility index was below its historical average (but not further away than one standard deviation); on the other, we choose 2008Q4 as an example of severe economic downturn as the VSTOXX reached its maximum value within the time span considered. Figure 3.5 confirms that the inclusion of macroeconomic information has non-negligible effects on the calculation of expected losses. Note that linking the calculation of losses to the evolution of a macroeconomic variable in such a way implicitly introduces some degree of procyclicality, although not linked to the nature of impairment accounting regime, as we will discuss in subsequent sections of this paper.



PD curves assuming loans with 20-year maturity for two different points of the economic cycle.

Figure 3.5: Effect of macroeconomic information on 1-year PDs.

To calculate the lifetime expected loss in t we need, for each future period s until maturity, the probability of default conditional on a unique non-default event in previous periods between t and s. Indicating with D_k a default event in period k, the probability of a default in a future period s conditional on the information set $\mathcal{F}_t$ available at time $t < s$ is as follows:

$$PD_{s|\mathcal{F}_t} = p\left(D_s = 1, D_k = 0; t \leq k \leq s\right) = PD_s \prod_{k=t}^{s-1} (1 - PD_k) \tag{3.13}$$

The lifetime PD in t is simply the probability of observing a default in any of the future time periods, conditional on the information in t:

$$PD_t^{Life} = \sum_{s=t}^{M} PD_{s|\mathcal{F}_t} = PD_t + \sum_{s=t+1}^{M} PD_s \prod_{k=t}^{s-1} (1 - PD_k) \tag{3.14}$$

It follows immediately that the lifetime PD is always higher than the single-period PD and converges to it as the loan approaches maturity.

Accordingly with the logic above, PD_t is calculated for each age of a loan using EDW data (as in Figure 3.6). Given the limited number of defaults in the EDW dataset, we lack the amount of data necessary to calculate how this relation changed over time and assume a single curve for all periods.

The PDs for each age are subsequently multiplied in each period by a coefficient which ensures that the weighted average PD of the portfolio equals the default rate calculated from the Italian central credit register.

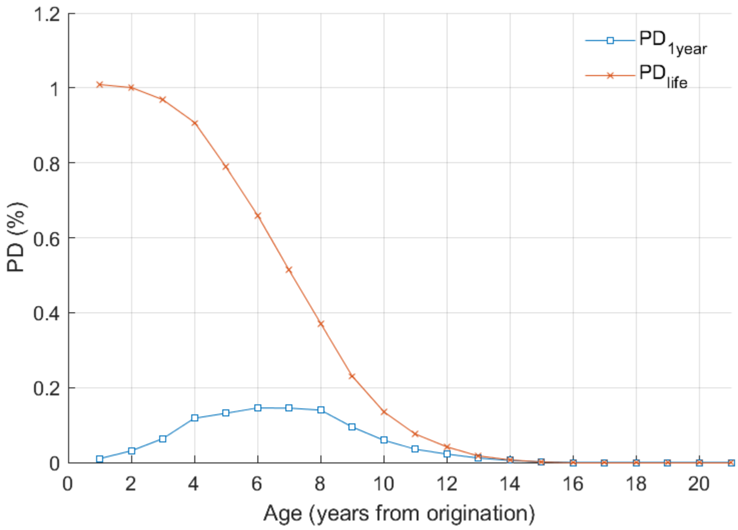


Figure 3.6: Lifetime versus one-period PD.

Expected loss

The one-period expected loss is defined as the product of the exposure times the PD and the LGD. However, in calculating lifetime provisions, the lifetime expected loss (using the proper discount rate) is the suitable measurement. Following the same logic as in the PD case, the lifetime expected loss in period t for a loan with contractual maturity M is merely defined as the sum of current and future one-period expected losses.

To calculate the lifetime expected loss in t we need, for each future period s until maturity, the probability of default conditional on no default event in previous periods between t and s[23]. The formula for the expected loss over the residual lifetime of the loan can then be written as:

$$\begin{aligned} EL_{t+1,M} \equiv \sum_{s=t+1}^{M} EL_s &= \sum_{s=t+1}^{M} EAD_s \cdot LGD_s \cdot PD_{s|\mathcal{F}_t} \cdot (1+r)^{-(s-t)} \\ &= \sum_{s=t+1}^{M} EAD_s \cdot LGD_s \cdot PD_s \prod_{k=t}^{s-1} (1-PD_k) \cdot (1+r)^{-(s-t)} \end{aligned} \tag{3.15}$$

As in the case of the PD, compared to the one-period EL, the lifetime EL not only is higher but monotonically decreasing as the loan ages (see Figure 3.7).

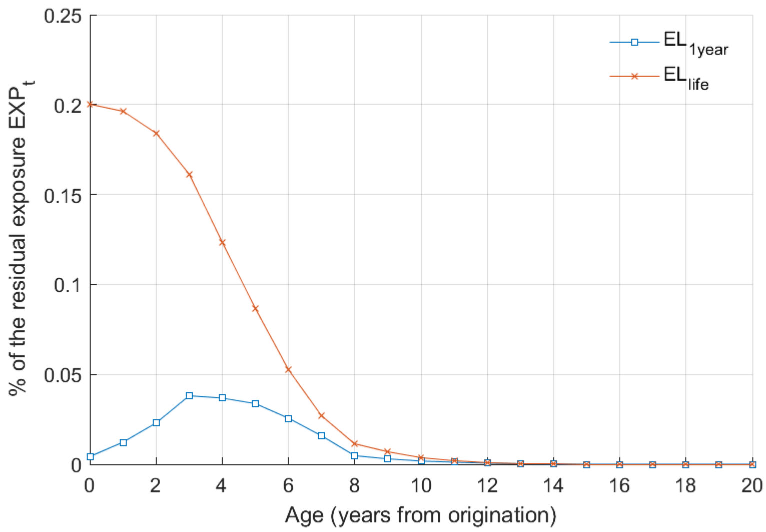


Figure 3.7: Lifetime versus one-period expected loss.

3.4.3 Methodological assumptions

In order to calculate the impact on procyclicality we were forced to make a number of assumptions to simplify our model. Although they have already been mentioned, in this section we explore the most relevant ones highlighting their potential impact. Besides, we would like all these restrictions to be borne in mind when extrapolating policy conclusions from our paper. We also perform several robustness checks in Section 3.5.3 to gauge how the results depend on these assumptions.

[23]Here again, we exclude the possibility of multiple defaults.

Stage 2 and "cliff effect"

As mentioned, when designing the impact of the significant increase in credit risk and its cliff effect we were forced to make two consecutive simplifications. We link the Stage 1 to Stage 2 transition to the 30-day past due rebuttable assumption. This simplification is heavily rooted on the IFRS 9 being the only common and purely objective criterion. Thus, regulation itself assumes the delay in payments as the most evident predictor of the rest of triggers (e.g. forbearance, increase in PD...).

Since our database did not have any information on which loans were 30 days past due we were forced to use a proxy. We assumed an even distribution of the 90 days past due loans as described in the previous section. This is another difference with respect to Abad and Suárez (2018) since they model the cliff effect by means of the transition matrix. Based on their data we have every reason to believe that the delay in payment will be even more procyclical than default itself.

Perfect forecast

Since we use an *ex post* database including observations from the latest economic crisis, one of the modelling options we compare is based on perfect forecast. That is, we test the different accounting regimes assuming that provisioning models can exactly predict future outcomes. We fully acknowledge that actual models will be subject to real data availability and thus, perfect forecast is not compatible with "real life". However, for comparison purposes we see merit in removing all other practical considerations from credit risk models.

Lag between default events and loss recognition

The timing with which credit losses are recognized can be constrained to a varying degree by accounting rules, but also depends on the actual speed with which the loss associated with a non-performing exposure becomes known, on the length of recovery procedures, and to some extent on discretion. There is abundant evidence in the literature on the tendency for financial intermediaries to procrastinate loss recognition in the context of crises, as shown in Norden and Stoian (2013), Basel Committee on Banking Supervision (2015a) and IMF (2015). Modelling how these factors affect the timing of loss recognition is beyond the scope of this paper. For simplicity, we assume that it takes some time to realise the full extent of the loss on a non-performing loan (this can be interpreted as a progressive deterioration in credit quality): If required to recognise realised losses, under this assumption a financial intermediary would split the loss equally across the six years following the default event[24].

Independence between accounting regime and loan supply

For modelling purposes, we assume independence between the accounting regime and loan supply. This hypothesis is established in order to be able to compare the two models and because there is no clear knowledge on how much the accounting model will impact credit supply. However, we fully acknowledge that the different P&L impacts might tailor banks'behavior. In fact, one of the conclusions of this paper is the different cyclical impact of the accounting regimes.

3.5 Results

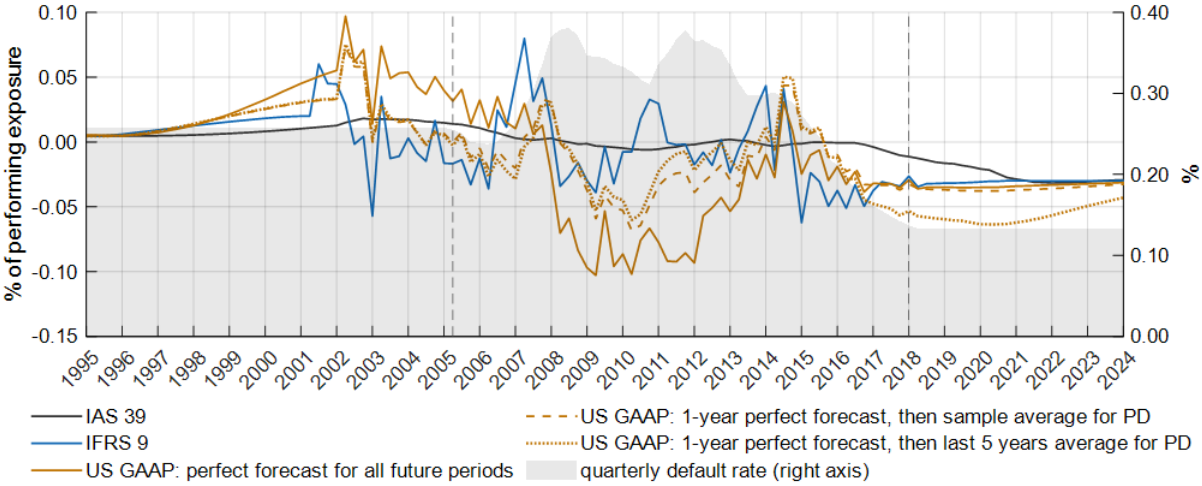
Based on the methodology and parameters described, in this section we have simulated what the shapes of provisions plus realized losses would have been for a fictional portfolio of Italian mortgages from 2006 to 2018. Additionally, we generate alternative scenarios for the default rate and new credit as a function of the length and severity of the oscillations in the financial cycle, in order to ease extrapolation to scenarios other than the Italian baseline. We do not assess the impact of regulatory changes given the current conditions of the financial system; instead, we study the dynamics of provisions and losses in a scenario where the effects of the transition to the new rules have been completely absorbed[25]. As regards PD, we will use average default rates from the Italian credit register, whereas the relationship between the PD and the age of the loan is estimated from the European Data Warehouse (EDW).

Using this fictional portfolio, Figure 3.8 depicts the sum of realized losses plus net provisions, i.e. the impact on P&L in each period under all three accounting regimes. Under the perfect forecast assumption, for US GAAP realized losses are always provisioned in advance (at loan origination). If there were no delay between default and write-off, the realised losses curve also would correspond to the total impact on P&L in each period under IAS 39. However, since this delay exists and we have assumed that the loss from a default is split equally across the following six years, under IAS 39 losses are recognized well after default.

[24] This number of years is roughly coherent with evidence on the average time needed to obtain the recoverable value in foreclosures procedures in Italy; see Carpinelli et al. (2016).

[25] In this spirit, Figure 3.8 does not show the provisions made in the first period of existence of the fictional portfolio, which correspond to the initial value of the stocks of provisions.

With IFRS 9, provisions anticipate default by one year (Figure 3.8). Under the perfect forecast assumption, in fact, Stage 1 provisions represent exactly the following year's realized losses if losses took place at the same time of default, whereas under our assumptions the amounts of exposure in Stage 2 have a relatively small effect[26]. Moreover, as we will analyze below, IFRS 9 seems much less procyclical than the previous IAS 39 regime (in the sense of contemporaneous correlation with realized losses). This is a major improvement with respect to IFRS 9 since under IAS 39 losses are recognized once they take place, sometimes too long *after* default, whereas under IFRS 9 they are recognized one year *before* default. However, the impact on P&L barely anticipates actual losses by one year, which may be an insufficient amount of time to build up reserves and the business cycle may already have entered the downturn phase. Anyhow, the concept of timeliness need not be intertwined with procyclicality as loan losses can be a signal of both credit quality *and* macroeconomic conditions.[27]



Variation of P&L (realized losses plus net provisions) under the different accounting regimes, over an historical scenario for mortgage defaults and new loan volumes

Figure 3.8: Impact on P&L.

[26]This point marks a significant difference with respect to the results of Abad and Suárez (2018). We use quarterly frequency in the model and assume that uncertainty on the status of assets classified into Stage 2 is solved (with passage to default) within one quarter. Since Stage 1 provisions account for the expected loss over the next four quarters, provisions for Stage 2 loans tend to be much less than those for loans in Stage 1. Abad and Suárez (2018), instead, divide time in discrete periods which implicitly represent years, assuming *de facto* that loans stay in Stage 2 for at least one year. In addition, their model allows a prolonged permanence in that status. The "cliff effect" from Stage 2 loans in their model is therefore much bigger and determines a strong response of IFRS 9 provisions to shifts in credit quality.

[27]In fact, by "smoothing" the expected credit losses from a loan portfolio, forward-looking accounting standards could decrease timely information in the loan loss portfolio about unexpected deteriorations in macroeconomic conditions on loan portfolios.

Our set of assumptions entails that the impact of the "cliff effect" from Stage 2 provisions is almost negligible, since the assets migrate toward a different stage within one quarter. More conservative assumptions about the conditions to classify assets in Stage 2 may lead to a higher amount of provisions being frontloaded when credit quality starts deteriorating. However, to the best of our knowledge, it seems that the cliff effect will always be close in time to defaults, which may worsen rather than reduce the procyclical effects of losses. So, based on these results it appears that while IFRS 9 is an advance with respect to previous regulation (IAS 39), there could be some room for improvement.

Under US GAAP, due to the fact that we have assumed independence between the accounting regime and loan supply, since provisions are granted at inception and there is a clear negative correlation between volumes of new granted loans and default rates, the impact on P&L is negatively related to contemporaneous default rates. The reason behind this result is that under US GAAP provisions tend to be accumulated during boom phases of the credit cycle, when new loans volumes are higher: losses that will occur during crises are recognized in advance and provisions are progressively released when credit quality deteriorates. The effect described above is stronger with perfect forecast, while when loss rates are estimated to be more persistent in time (the other two cases for US GAAP, indicated by the dotted and the dashed line in Figure 3.8) the effect of updating expectations on future losses for older loans tends to compensate the decrease in new loans. Without perfect forecast, in fact, losses in times of crisis could exceed provisions granted at inception based on the lifetime expected loss, if the future default and recovery rates were severely underestimated. Nevertheless, even if the perfect forecast horizon is limited to one-year, cyclicality under US GAAP is much lower than under IFRS 9. The results, thus, appear still valid under the assumption that expectations are overly optimistic in risk assessments during boom times.

Finally, notice that the level of provisions (see Figure 3.9) is much higher under US GAAP (between 1.5 and 2.5% of performing exposure) than under IFRS 9 (approximately 0.25%). This is not surprising since under US GAAP the entire expected lifetime loss is provisioned at inception, whereas in IFRS 9 financial institutions are required to provision only the following year expected loss plus the lifetime expected loss for the loans that show a significant increase in risk.

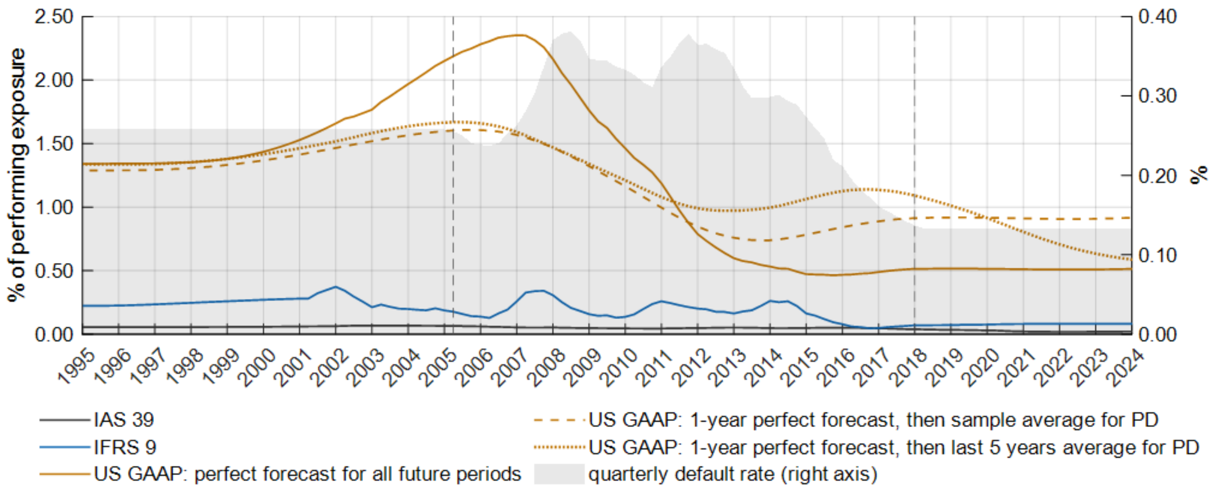


Figure 3.9: Stock of provisions.

To confirm these intuitions, in the following subsection we present a statistical procedure to measure procyclicality. However, it is worth noting that our results are based on our assumptions and, although these are reasonable and robustness checks will be carried out below, we should be cautious about the policy conclusions that can be extracted from these results.

3.5.1 Procyclicality

In the context of this paper, procyclicality is defined as the correlation with the contemporaneous evolution of credit quality, proxied by realised losses. However, procyclicality can also be defined in terms of correlation with macroeconomic variables, usually with GDP. Credit quality, in turn, tends to be strongly related to credit supply and the business cycle so we do not expect significant differences in both calculations, which justifies our use of the word "procyclical" in the former sense.

Following Paredes et al. (2014), we use dynamic cross-correlation functions to measure procyclicality. It can be inferred from the previous section that the impact in P&L from IFRS 9 presents positive and strong contemporaneous correlation with realized losses and increases to roughly 55% with four lags (one year). Consequently, as stated above, IFRS 9 appears less procyclical than the previous IAS 39 regime, which is perfectly correlated with realized losses by construction. Instead, confirming the results in the previous section, the impact in P&L from US GAAP and realized losses presents negative and non-negligible contemporaneous correlation in case (a), entailing a negative correlation with the business cycle, which is a desirable property. In cases (b) and (c) contemporaneous correlations are positive, but still significantly lower than under IFRS 9 except for some leads in (c). These results are not totally unexpected since the purpose of the introduction of ECL was to reduce procyclicality and US GAAP requires fully ECL recognition since inception[28].

We mentioned that credit quality tends to be strongly related to the business cycle; therefore, if we repeat the exercise using Italian GDP instead of realized losses, we expect no major differences. In general terms, Table 2 confirms this intuition. Firstly, taking into account lags and forwards, IFRS 9 tends to be procyclical in the sense that realized losses net of provisions tend to be higher when GDP is lower. However, as expected, under US GAAP with perfect forecast realized losses net of provisions tend to be higher when output is higher, which is a desirable property. Results related to US GAAP cases (b) and (c) are not totally unexpected : Updating expectations on future losses for older loans in bad times compensates the fact that during bad times banks grant less loans, creating a situation in which realized losses net of provisions tend to be higher when GDP is lower.

Lags/Leads	IFRS 9	US GAAP (a)	US GAAP (b)	US GAAP (c)
-8	45.2	6	16.6	34.8
-7	48.4	5	17.9	36.6
-6	51.6	3.9	19.8	38.8
-5	53.9	2.8	21.8	41.1
-4	55.3	1.9	24.1	43.6
-3	56.1	1.2	26.6	46.3
-2	55.5	0.4	29	48.8
-1	53.7	-0.6	30.6	50.6
0	52.3	-0.9	31.9	51.9
1	50.3	-2.3	31.1	51.5
2	48.8	-3.1	30	50.8
3	48.1	-3.2	29.1	50
4	48.1	-3.2	28.4	49.3
5	48.2	-2.8	28	48.6
6	48.7	-2	28	48.1
7	50.2	-0.8	28.7	48.2
8	50.3	-0.1	29.6	48.2

(a) Future loss rates known ("perfect forecast"); (b) Future loss rates known up to a 1-year horizon in the future, then revert to the sample average; (c) Future loss rates known up to a 1-year horizon in the future, then revert to average of previous 5 years.

Table 3.1: Cross-correlation functions: P&L with realized losses.

[28] See, for example, FSF (2009).

Lags/Leads	IFRS 9	US GAAP (a)	US GAAP (b)	US GAAP (c)
-8	-23.5	43.3	19.3	2.6
-7	-29	38.2	11.3	-4.6
-6	-31.9	33.8	3.1	-12
-5	-31.6	30.3	-4.3	-18.8
-4	-29.2	26.3	-11.9	-25.8
-3	-22	23.2	-17.7	-31.1
-2	-14.5	20.1	-21.6	-34.8
-1	-6.2	17.4	-22.6	-35.8
0	0.6	13.9	-21.1	-34.2
1	3.6	9.1	-19	-31.8
2	5.1	3.4	-17.2	-29.2
3	4.9	-3.7	-16.7	-27.3
4	3.4	-11.3	-18	-26.5
5	1.3	-18.1	-20.2	-26.5
6	-1.1	-23.9	-22.8	-26.6
7	-2.8	-28.8	-25.6	-26.8
8	-4.2	-33.8	-29.3	-27.8

(a) Future loss rates known ("perfect forecast"); (b) Future loss rates known up to a 1-year horizon in the future, then revert to the sample average; (c) Future loss rates known up to a 1-year horizon in the future, then revert to average of previous 5 years.

Table 3.2: Cross-correlation functions: realized losses with GDP.

3.5.2 Alternative business cycle dynamics

One potential caveat of our exercise is that the constraint imposed by the choice of Italian default rates new credit flows between 2006 and 2018, the evolution of which might not be comparable to other scenarios. In order to facilitate the extrapolation of our results to a variety of countries and periods, we construct alternative dynamics for the default rate and new credit by varying the length of the economic cycle as well as the depth of its expansionary and contractionary phases. This subsection describes our methodology and reviews the main findings on procyclicality for these synthetic scenarios.

We start by assuming that the economic cycle has four stages: downturn (D), trough (T), upswing (U) and peak (P). The length L of each phase can be short, medium or long. Moreover, we allow the magnitude of downturns and upswings to be low or high. A schematic version of our artificial cycle is shown in Figure 3.10.

We model the evolution of the default rate starting from an initial value def_0 with constant growth rates during downturns and upswings. This growth rate can be high or low, depending on the severity of the cycle. The default rate remains constant during peaks and troughs, that is:

$$def_t = \begin{cases} def_0(1+g_{D,i})^t & t_0 < t \leq L_D \\ def_0(1+g_{D,i})^{L_D} = def_D & L_D < t \leq L_T \\ def_D(1+g_{U,j})^t & L_T < t \leq L_U \\ def_D(1+g_{U,j})^{L_U} & L_U < t \leq L_P \end{cases} \quad i,j \in \{Hi, Lo\} \tag{3.16}$$

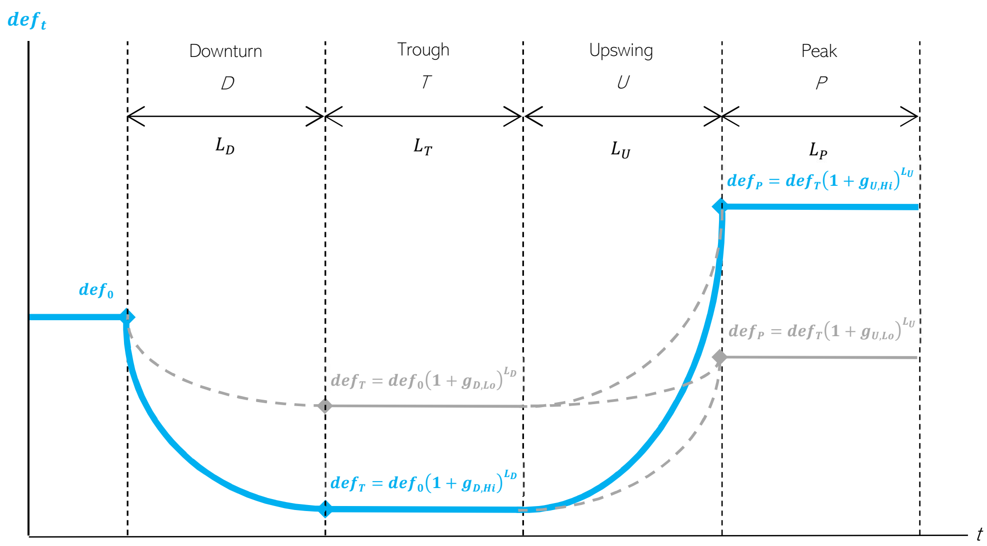


Figure 3.10: Definition of artificial business cycles.

Our sample for the Italian default rate and new credit is 52 quarters long between 2006 and 2018. For the sake of simplicity, we assume that one full synthetic cycle lasts 40 quarters; each of its phases can span 4 (short), 10 (medium) or 16 (long) quarters:

$$\begin{gathered} \{L_D, L_T, L_U, L_P\} \in \{4, 10, 16\}^4 \\ L_D + L_T + L_U + L_P = 40 \end{gathered} \tag{3.17}$$

We set the initial default rate def_0 to the value of the Italian time series in 2006Q1 and leave it constant for 2 years, so that t_0 =2007Q4. For the calibration of high and low severity of the cycles, we use the median rise μ_{rise} and fall μ_{fall} in the data between 2006 and 2018:

$$g_{D,Hi} = 1.25\mu_{fall} \quad g_{U,Hi} = 1.25\mu_{rise}$$
$$g_{D,Lo} = \mu_{fall} \qquad g_{U,Lo} = \mu_{rise} \tag{3.18}$$

Conditions (17) and (18) allow for a vast number of possible paths for the synthetic default rate. We restrict our analysis to a subset of 28 combinations which are depicted in Table 3.3.

Phase length: Long(L), medium (M), short (S)
Downturn/upswing magnitude: High (Hi), low(Lo)
Cycle structure {Downturn, Trough, Upswing, Peak}

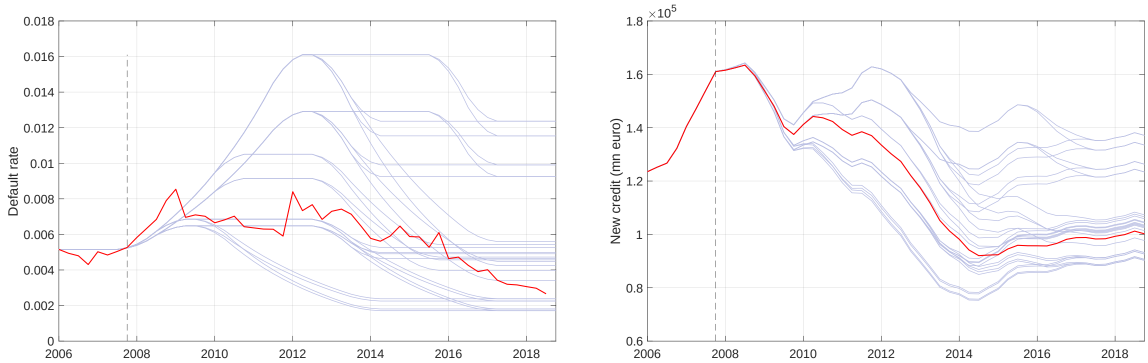
$L^{Hi}LS^{Hi}S$	$L^{Hi}SL^{Hi}S$	$L^{Hi}SS^{Hi}L$	$S^{Hi}SL^{Hi}L$	$S^{Hi}LS^{Hi}L$	$S^{Hi}LL^{Hi}S$	$M^{Hi}MM^{Hi}M$
$L^{Hi}LS^{Lo}S$	$L^{Hi}SL^{Lo}S$	$L^{Hi}SS^{Lo}L$	$S^{Hi}SL^{Lo}L$	$S^{Hi}LS^{Lo}L$	$S^{Hi}LL^{Lo}S$	$M^{Hi}MM^{Lo}M$
$L^{Lo}LS^{Hi}S$	$L^{Lo}SL^{Hi}S$	$L^{Lo}SS^{Hi}L$	$S^{Lo}SL^{Hi}L$	$S^{Lo}LS^{Hi}L$	$S^{Lo}LL^{Hi}S$	$M^{Lo}MM^{Hi}M$
$L^{Lo}LS^{Lo}S$	$L^{Lo}SL^{Lo}S$	$L^{Lo}SS^{Lo}L$	$S^{Lo}SL^{Lo}L$	$S^{Lo}LS^{Lo}L$	$S^{Lo}LL^{Lo}S$	$M^{Lo}MM^{Lo}M$

Table 3.3: Combinations for the synthetic default rate considered in this exercise.

Finally, if the evolution of the default rate is tweaked to accomodate different shapes of the business cycle, it is reasonable to adjust the flow of credit accordingly; to this end, we fit the latter to an autoregressive, distributed lag (ARDL) regression of new credit on its lag, contemporaneous and lagged default rates and contemporaneous real GDP[29]. Our smoothed synthetic series for the default rate and new credit are shown in the two panels of Figure 3.11.

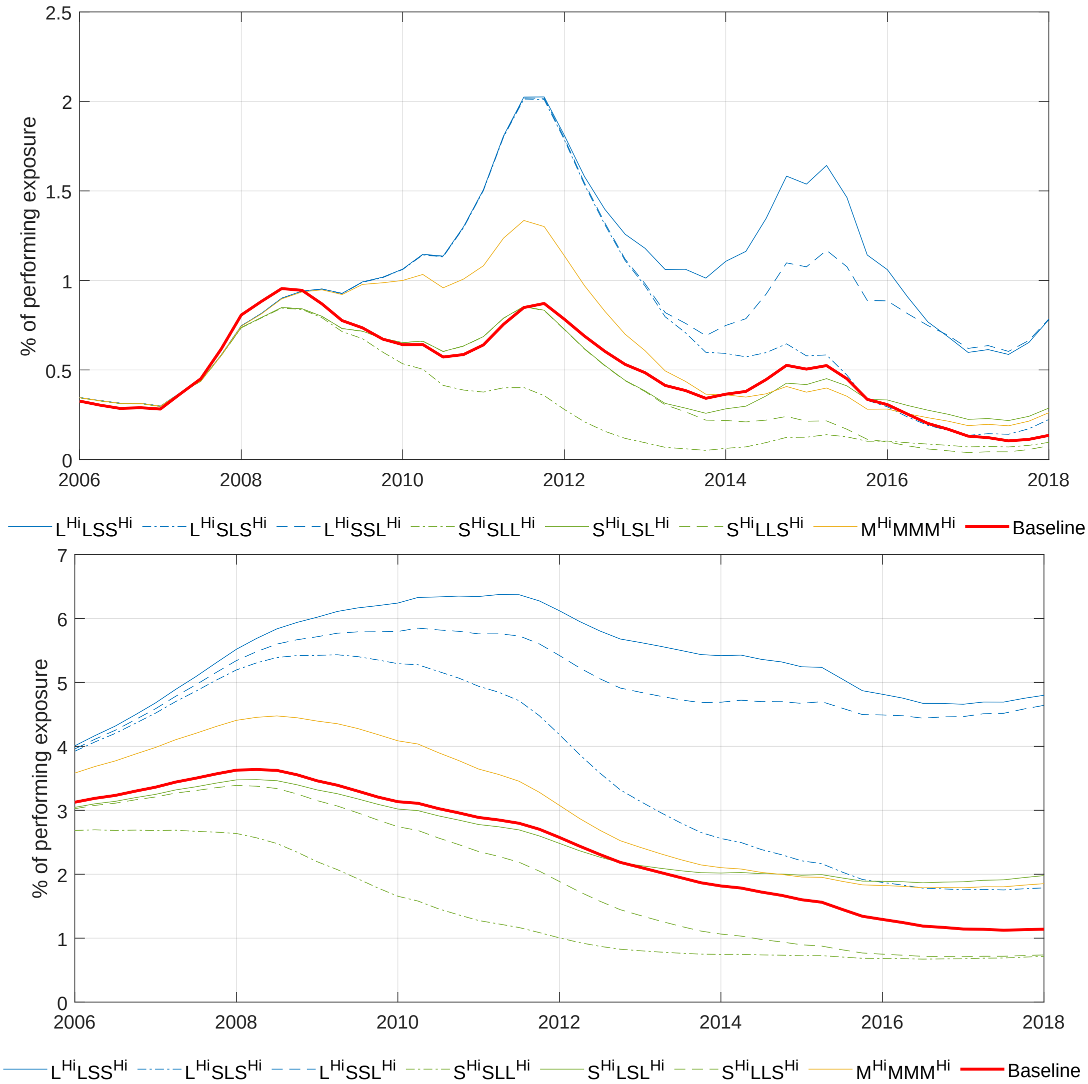
When the new paths for default and new credit are plugged into the expected loss accounting equations, considerable heterogeneity arises, as illustrated by Figure 3.12. Although building an intuition on the procyclicality of both regimes would require to plot the default rate along with the stock of provisions for each case -in the spirit of Figure 3.9-, two phenomena are appreciable: First, with our simulated setup, provisions tend to be much larger in cycles for which the contractionary phase -especially the downturn- is longer (case $L^{Hi}LS^{Hi}S$); second, a higher level of provisions is maintained for cycles with a short expansionary phase ($S^{Hi}LS^{Hi}L$), in contrast to those with short bonanza upswings in which the provisioning rate falls much more quickly ($S^{Hi}LL^{Hi}S$). The individual results for all combinations are available in Appendix 3A.

[29] Although this regression might seem to induce procyclicality by construction, we computed the correlation coefficient between the new credit series and GDP and verified that this was not the case. In fact, the new credit estimates from an ARDL without the output term exhibited much higher correlation than our specification.



Light blue lines denote the 28 scenarios described in Table 3. The red line is the baseline case (original Italian default rate and the associated flow of new credit as estimated by the auxiliary ARDL model). The dashed line represents the start of the synthetic business cycles..

Figure 3.11: Default rates and flows of new credit obtained using synthetic business cycles.



Note: On the grounds of clarity, only cycles with high magnitude for downturns and upswings are displayed.

Figure 3.12: Stock of provisions under IFRS 9 (top) and US GAAP/CECL (bottom).

Turning to the analysis of cross-correlations, Figure 3.13 complements the former intuition with the behavior of P&L under different business cycle shapes. Under IFRS 9, procyclicality tends to be much lower if the downturn phase is short-lived; were it not the case, the length of the upswing also would matter as longer expansionary phases are linked to higher cross-correlation. One interesting fact is that these observations do not hold under the US GAAP regime: On one hand, shorter downturns favor prociclicality; on the other, the distinction between the rest of phases appears much less relevant as the divergences narrow sharply while the correlation pattern is similar in all cases. The latter is probably related to the fact that provisioning for the asset's entire lifetime at inception is mandatory under US GAAP, thus rendering the start of the cycle much more relevant than the remaining phases.

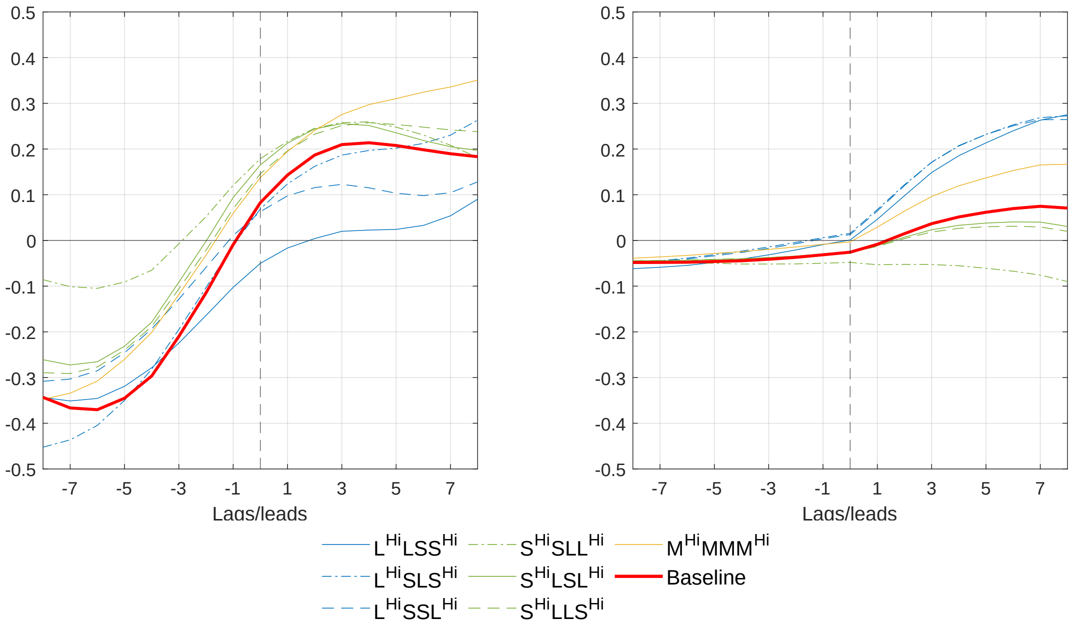


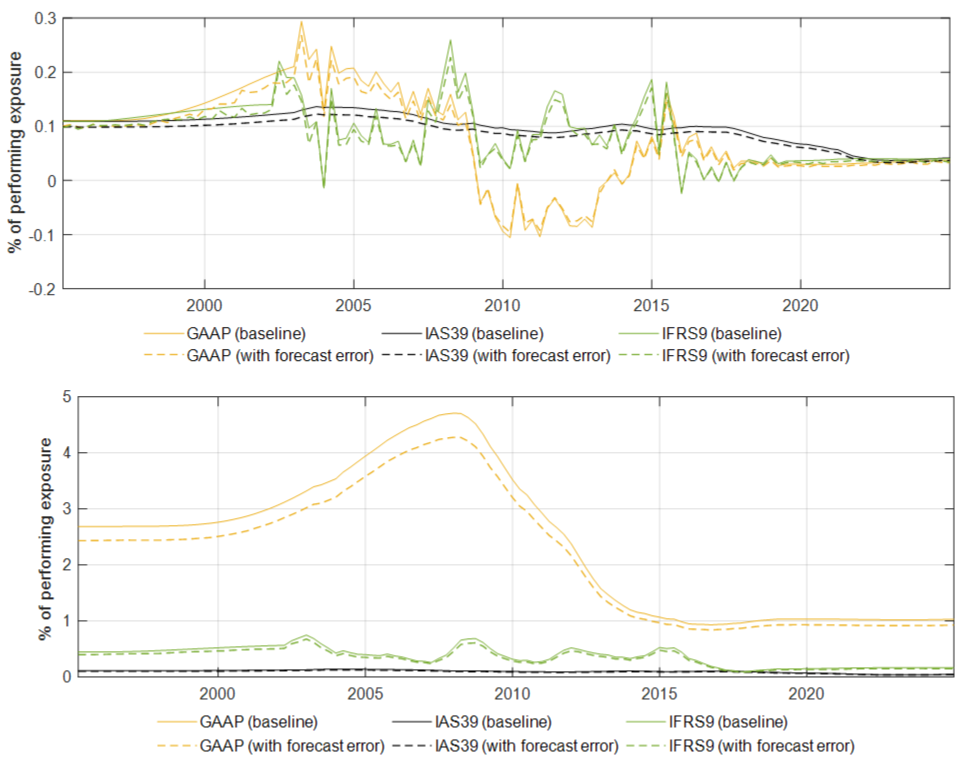
Figure 3.13: Cross-correlations of P&L with GDP: IFRS 9 (left), US-GAAP/CECL (right).

3.5.3 Robustness checks

The previous sections have clarified that, in order to calculate the impact on procyclicality, we were forced to make several assumptions to simplify our model. Although all the assumptions are reasonable and in line with regulation, we present a set of robustness checks in order to understand how results depend on the assumptions.

Allowing for forecast errors in expected losses

The first assumption that we will challenge is the ability of credit institutions to perfectly forecast expected losses up to a one-year horizon. In the alternative setup, 1-year-ahead PDs across the sample span are subject to a stochastic forecast error drawn from a uniform distribution over the interval $(75\%, 105\%)$. It is reasonable to assume that, in general, there is a tendency to underestimate the probability of default more often than being overly cautious, hence the choice of the interval. Introducing such biased noise in the computations results in lower expected losses, which ultimately entails a reduction of the stock of provisions, as illustrated by Figure 3.14. However, the main conclusion of the paper would not have changed had this effect been in place.

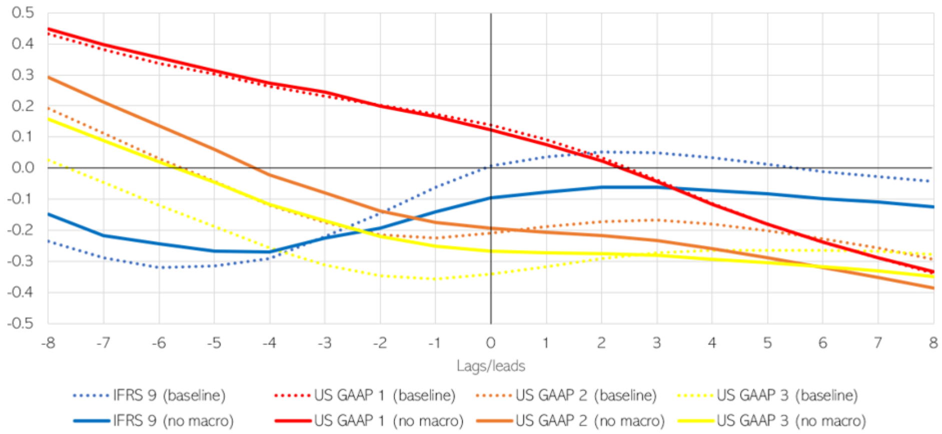


Profit and Loss (upper panel), stock of provisions (lower panel).

Figure 3.14: Effect of the inclusion of stochastic forecast errors.

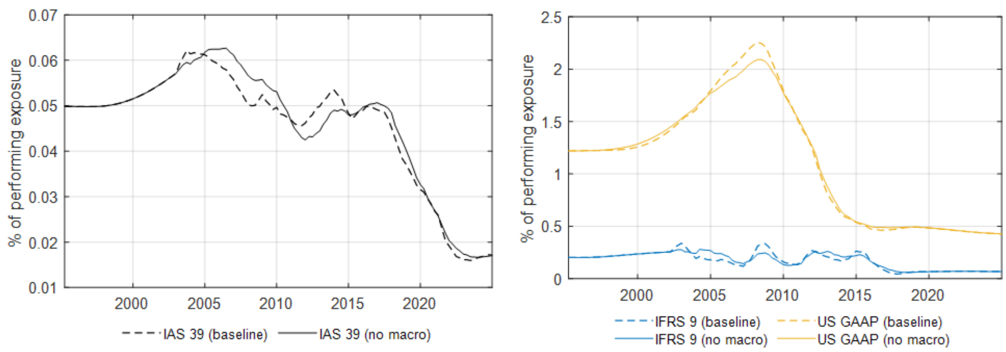
Ruling out macroeconomic information

The simulations conducted in our baseline specification account for the interaction of default probabilities with the economic cycle, the latter proxied through the VSTOXX index. In previous sections, we have pointed out that this feature implicitly introduces some procyclicality in the calculation of loan losses. Figure 3.15 plots the cross-correlation functions from Table 1 in the baseline and "no macro" scenario; it appears that discarding macroeconomic information reduces the procyclicality of P&L with respect to GDP in both the IFRS 9 and GAAP accounting regimes, in line with our intuition. Regarding the ultimate impact on provisions, where we also look at the IAS 39 case, Figure 3.16 illustrates that the shape of the series varies notably; for IFRS 9, in particular, the reduction in procyclicality can also be observed in the smoother oscillations in the neighbourhood of the 2008 recession.



GAAP 1: Future loss rates are known ("perfect forecast"); GAAP 2: Future loss rates known up to a one-year horizon in the future, then revert to the sample average; GAAP 3: Future loss rates known up to a one-year horizon in the future, then revert to the average of the previous five years.

Figure 3.15: Cross-correlations of P&L and GDP: Effect of macroeconomic information.



The US GAAP series refers to the perfect forecast case.

Figure 3.16: Stock of provisions: Effect of macroeconomic information.

A second look at Stage 2 transitions

In our baseline simulations, we link the Stage 1 to Stage 2 transition to the 30-day past due rebuttable assumption. Exploring the existing literature along with other data sources has provided us with two alternatives for the modelling of $S1 \leftrightarrow S2$ transitions.

The work by Abad and Suárez (2018) is our first source of inspiration as the authors compute transition probabilities from S1 to S2 (TR_{12}) and from S2 to S1 (TR_{21}) in expansions and contractions of the economic cycle. We take the averages in both points to obtain proxies of the two TRs. With this information, we can calculate the Stage 1 and Stage 2 exposures at default accounting for migrations within both states:

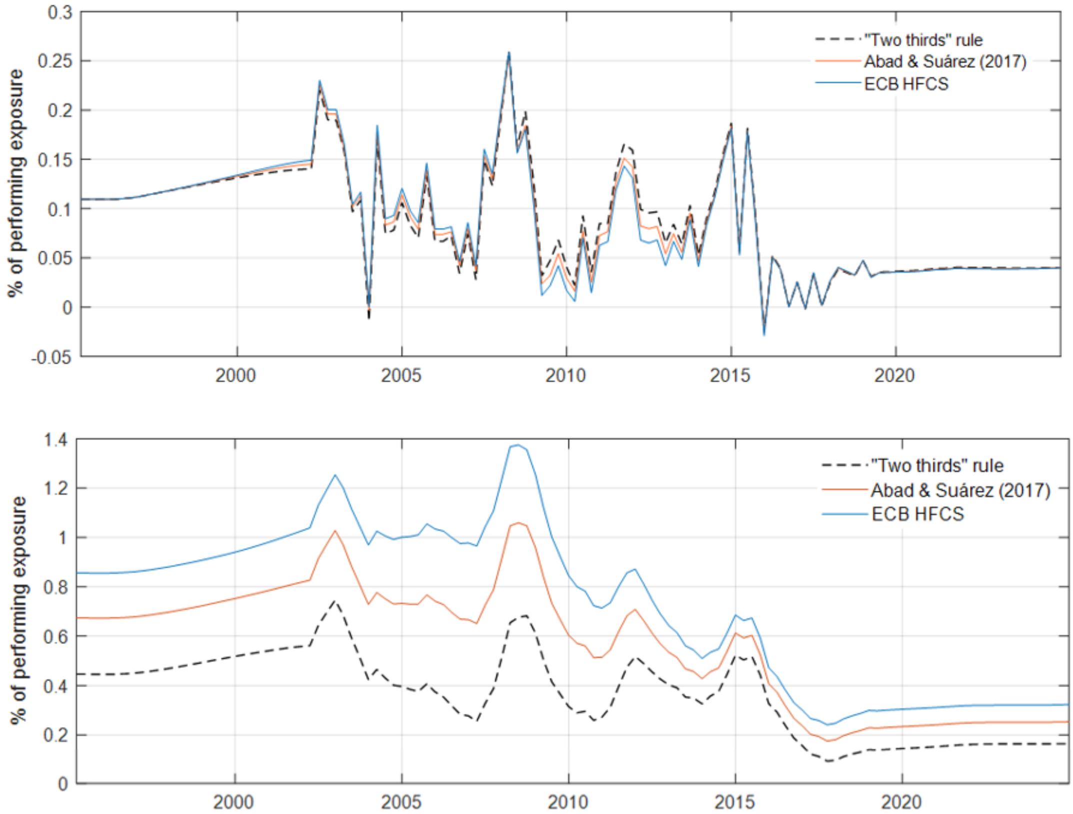
$$\begin{aligned} EAD_{t+1}^{S1} &= (1 - TR_{12}) \times EAD_t^{S1} + TR_{21} \times EAD_t^{S2} \\ EAD_{t+1}^{S2} &= (1 - TR_{21}) \times EAD_t^{S2} + TR_{12} \times EAD_t^{S2} \end{aligned} \tag{3.19}$$

In this case we obtain $TR_{12} = 5.65\%$ and $TR_{21} = 8.8\%$.

Besides, the European Central Bank's Household Finance and Consumption Survey (HFCS) contains information on late or missed payments on loans and mortgage payments from households across the euro area. In particular, variable HNC0125 collects the answers to the question *"Thinking of all the various loan or mortgage payments due in the last twelve months: were all the payments made the way they were scheduled, or were payments on any of the loans sometimes made later or missed?"*. The possible answers are: 1 (All payments as scheduled), 2 (It happened once or more that I was late with or missed some of the payments) and 3 (Household did not have loans in the last 12 months). We use this variable as a proxy for the transition probability TR_{12} with the intuition (and the strong assumption) that impaired repayments imply a deterioration in the credit quality of the loan:

$$TR_{12}^{HFCS} = \frac{\sum(\text{HNC0125} = 2 \mid \text{Italian household})}{\sum(\text{Italian household})} = \frac{1274}{8156} = 15.62\% \tag{3.20}$$

To the best of our knowledge, however, none of the survey variables sheds any light on how to approximate the transition probability from S2 to S1; therefore, we decide to use the same value for TR_{21} than in the previous case. Both the effect on P&L and the differences in provisioning under the three migration regimes are shown in Figure 3.17. While similar in shape, provisions are higher when one allows for loans switching between Stages 1 and 2.



Profit and Loss (upper panel), stock of provisions (lower panel).

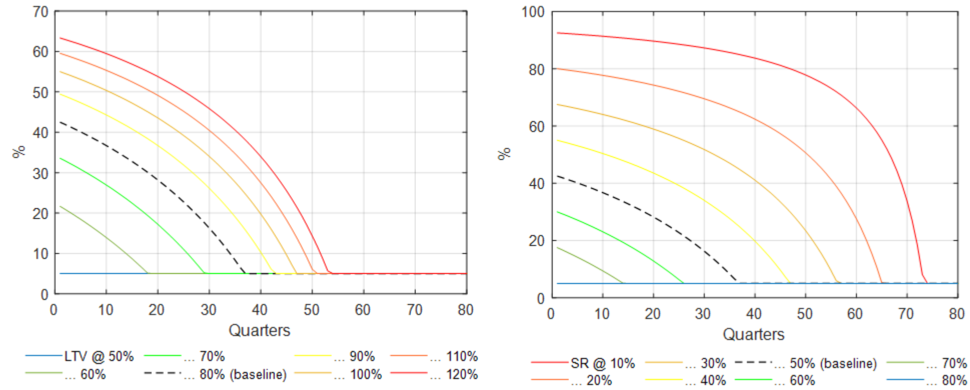
Figure 3.17: Comparison of different Stage 2 migration assumptions.

Comparative statics on key parameters

As an additional check on the suitability of our approach, we perform two sensitivity exercises: Firstly, we gauge the responsiveness of loss given default to different values of the loan-to-value ratio (LTV in our equations) and the sales ratio SR, that is, the ratio between the present value of the sale price and the value of the collateral; secondly, we depart from a loan maturity of 20 years to evaluate the consequences in the P&L account and the provisions.

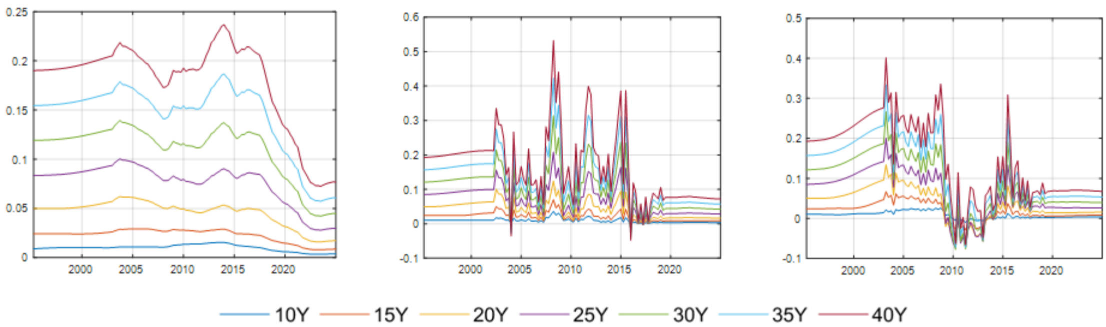
Starting with loan-to-value ratios, it is straightforward that a higher exposure-to-collateral value induces greater losses through the LGD identity and, hence, provisions will also increase. The opposite occurs with the sales ratio: If the (discounted) sale price represents a large share of the collateral, losses will be more contained and so LGD is decreasing in SR. Figure 3.18 shows how loss given default, plotted against the age of the loan, varies for different values of the two parameters of reference; the effects, as expected, are not linear. In terms of impact on provisions and the P&L account, we provide the full set of time series for each of the accounting regimes in Appendix 3B.

Regarding the effects of loan maturity M in our results, we relax the 20-year assumption to allow for shorter and longer mortgage horizons. The results are plotted in Figures 3.19 and 3.20: longer-term loans imply a larger stock of provisions for all the maturities considered.



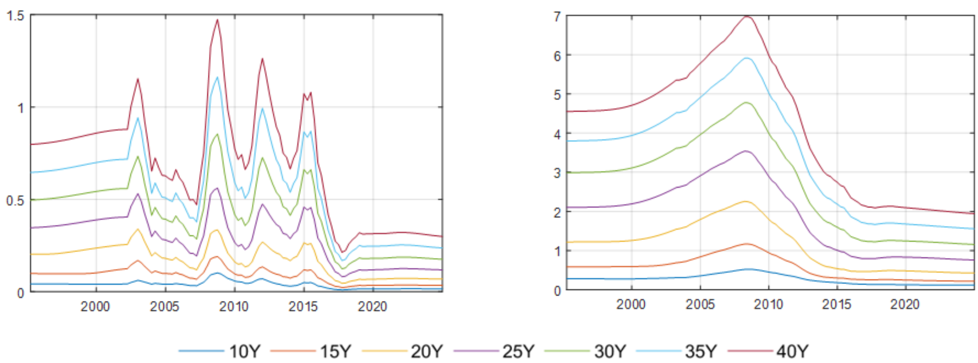
The dashed black line represents the baseline for the simulations.

Figure 3.18: LGD (%) vs. loan age for selected LTV (left panel) and SR (right panel) values.



IAS 39 (left panel), IFRS 9 (center panel), US GAAP (right panel).

Figure 3.19: P&L as a % of performing exposure for different loan maturities.



IFRS 9 (left panel), US GAAP (right panel).

Figure 3.20: Provisions as a % of performing exposure for different loan maturities.

3.6 Conclusions

The purpose of this paper is to present an assessment of the procyclicality of credit impairments under various accounting regimes. We elaborate on the recent evolution of financial instrument accounting systems, namely, IAS 39, IFRS 9 and US GAAP. Under IAS 39, the expected losses stemming from future events cannot be recognized. Consequently, under this accounting regime financial institutions are required to deal with losses only when a negative turn in the business cycle is already affecting credit quality.

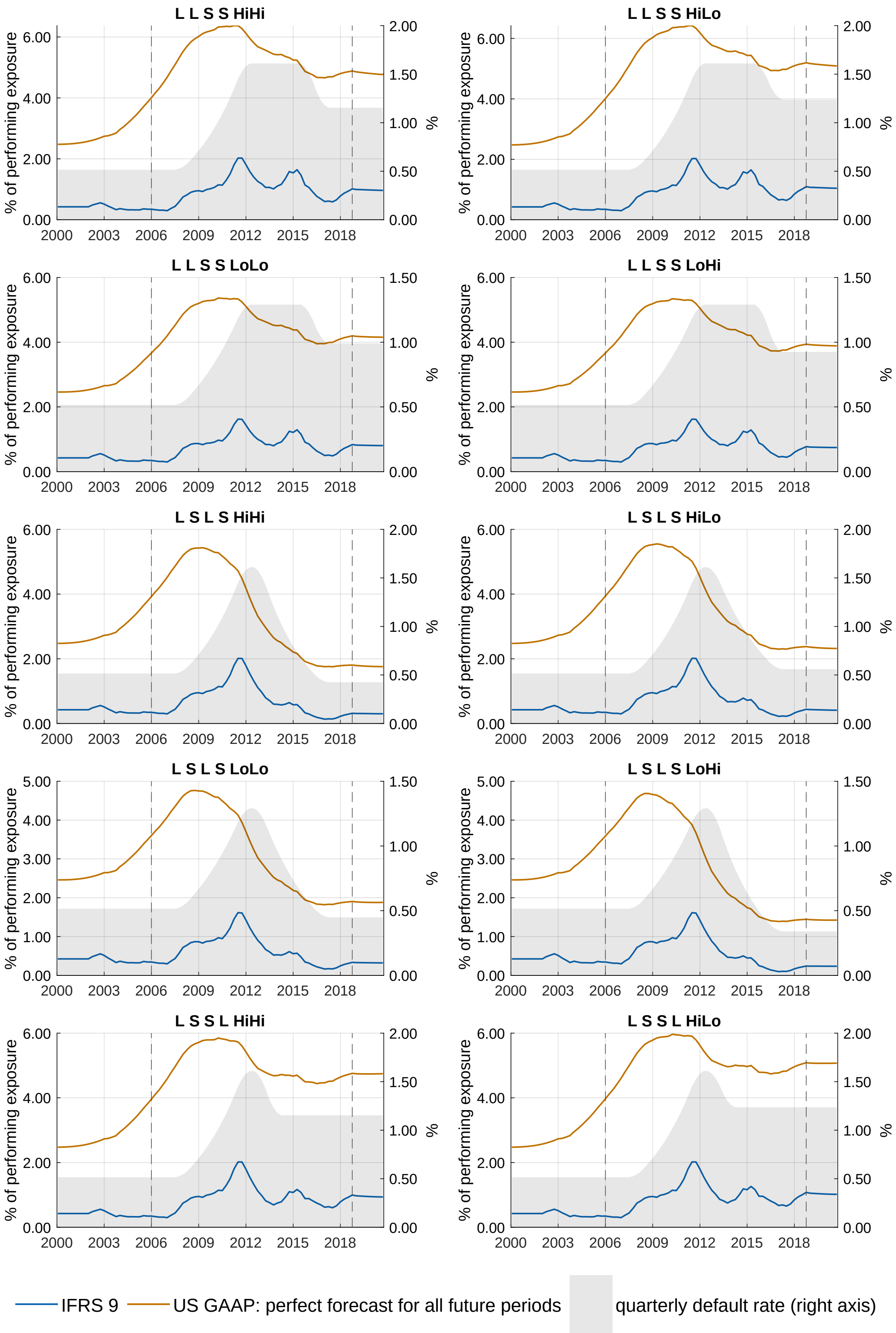
The recently introduced IFRS 9 and US GAAP mark a paradigm shift from incurred loss to expected loss but differ in the moment at which expected losses are recognized. While US GAAP requires the recognition of lifetime losses at origination or purchase of an asset, IFRS 9 only demands to account for the expected losses in the next 12 months as long as the asset does not show a significant increase in risk, which triggers the recognition of the ECL for the remaining lifetime.

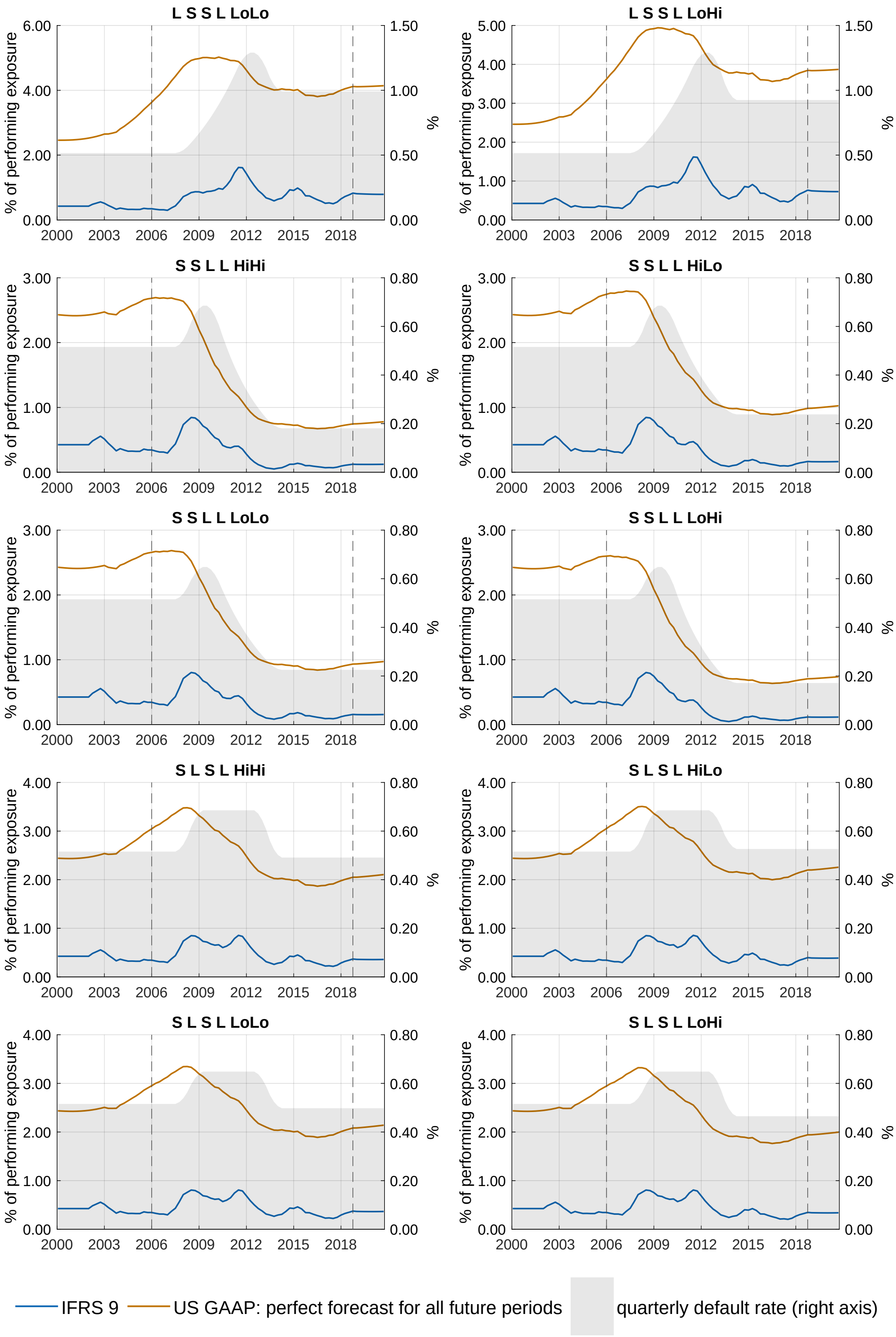
We model the impact of credit impairments on P&L under different accounting regimes in an historical scenario under different assumption on the how financial institutions estimate ECL. Our results indicate that IFRS 9 is much less procyclical than the previous regulation (IAS 39). Nevertheless, it presents a substantial degree of procyclicality because, even if financial institutions had the ability to exactly forecast future losses, their impact would be anticipated by just one year, and therefore would still be likely to hit financial institutions when a contractionary phase of the credit or business cycle is already started. Under US GAAP, since future expected losses are fully provisioned from inception, the realized impact on P&L instead tends to be anticipated and smoothed out in time. The US GAAP therefore seems more likely to reduce the procyclical effects of credit quality deterioration. However, the level of provisions is much higher under US GAAP than under IFRS 9. Therefore, the lower procyclicality of US GAAP seems to come at the cost of a larger stock of provisions.

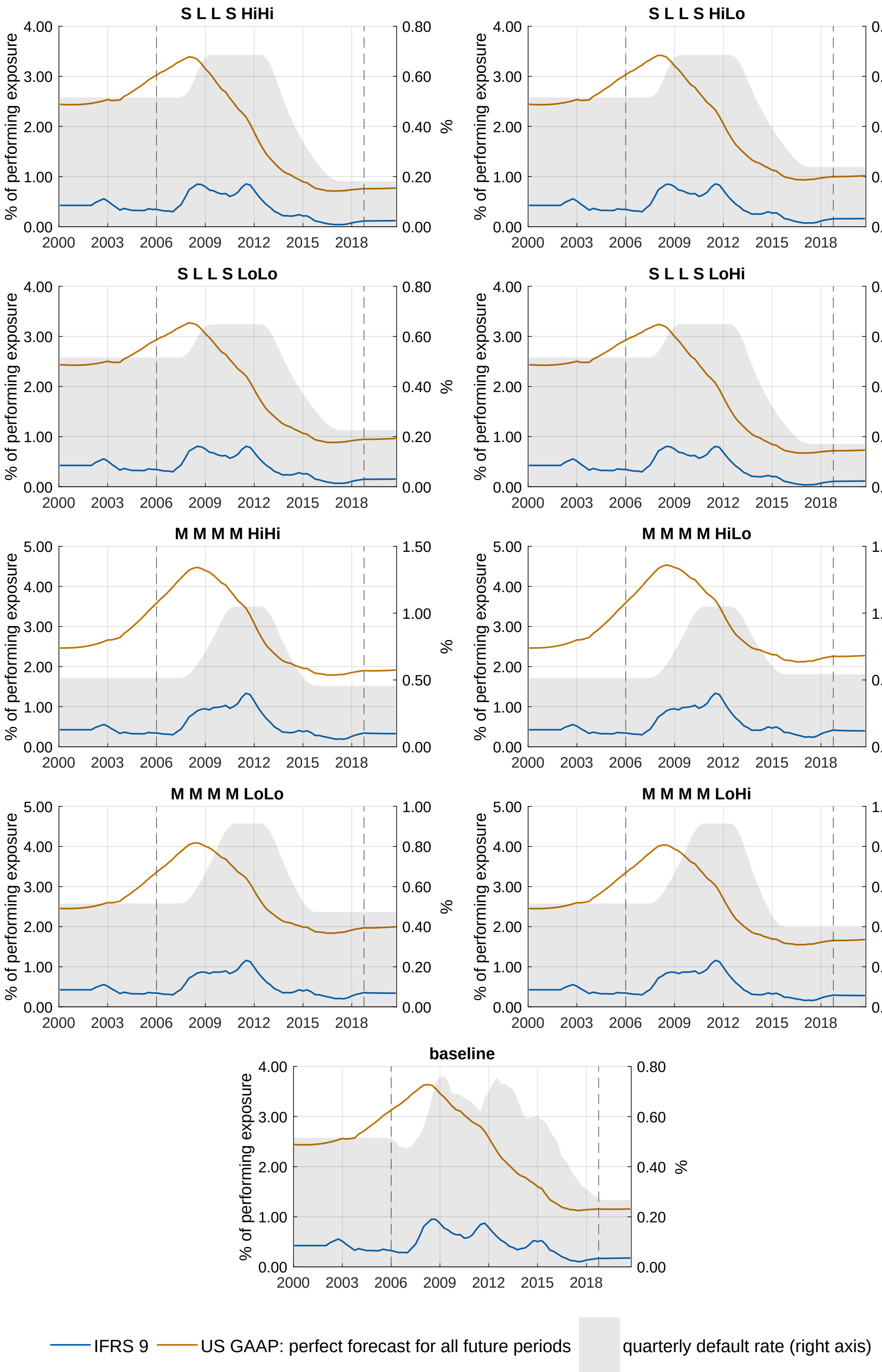
An alternative set of scenarios for defaults and new credit, which tries to mimic other types of business cycles, allows us to extract additional stylized facts for provisioning and procyclicality. In our setup, provisions are larger during cycles with longer busts and for those with short booms. Besides, under IFRS 9 short downturns or long upswings induce higher procyclicality. The results for US GAAP are more homogeneous, partly due to mandatory lifetime provisioning of loan losses which renders the initial stage of the cycle much more relevant than the rest of it.

Appendix 3A. Synthetic business cycles — detailed results

Each graph corresponds to a cycle {Downturn, Trough, Upswing, Peak} with {Downturn severity, Upswing severity}. Each phase has {Long (L), Medium(M), Short(S)} span and severity can be {High, Low}.



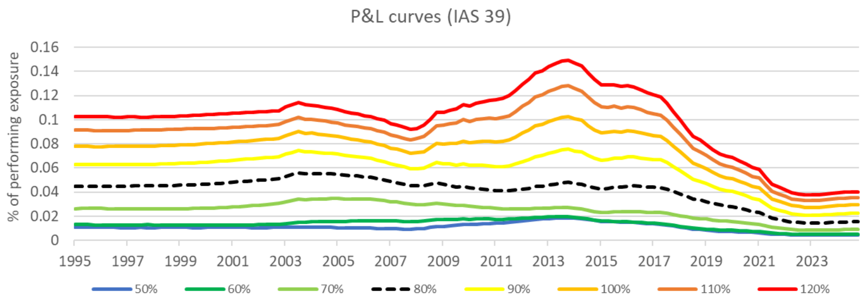

L S S L LoLo
L S S L LoHi
S S L L HiHi
S S L L HiLo
S S L L LoLo
S S L L LoHi
S L S L HiHi
S L S L HiLo
S L S L LoLo
S L S L LoHi
% of performing exposure
%
2000
2003
2006
2009
2012
2015
2018
IFRS 9
US GAAP: perfect forecast for all future periods
quarterly default rate (right axis)

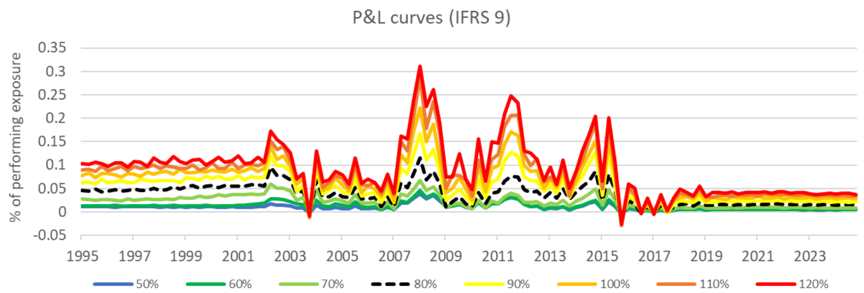

S L L S HiHi
S L L S HiLo
S L L S LoLo
S L L S LoHi
M M M M HiHi
M M M M HiLo
M M M M LoLo
M M M M LoHi
baseline
% of performing exposure
%
2000 2003 2006 2009 2012 2015 2018
IFRS 9
US GAAP: perfect forecast for all future periods
quarterly default rate (right axis)

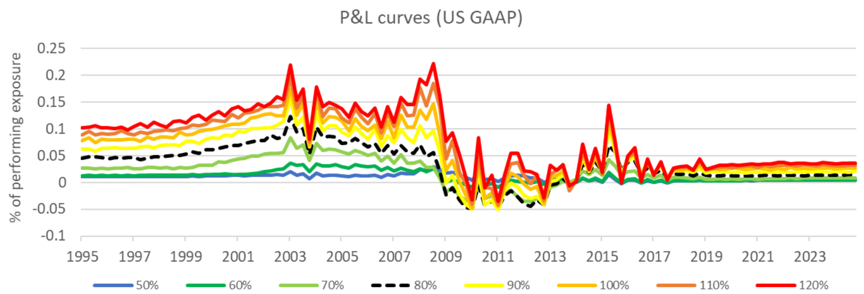
Appendix 3B. Robustness checks — detailed results

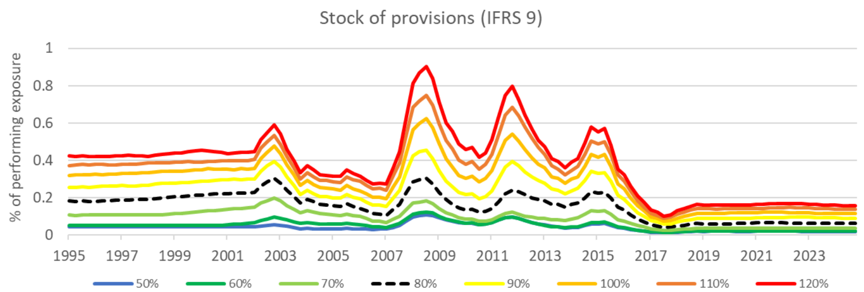
3B.1. Comparative statics on the loan-to-value ratio, *LTV*

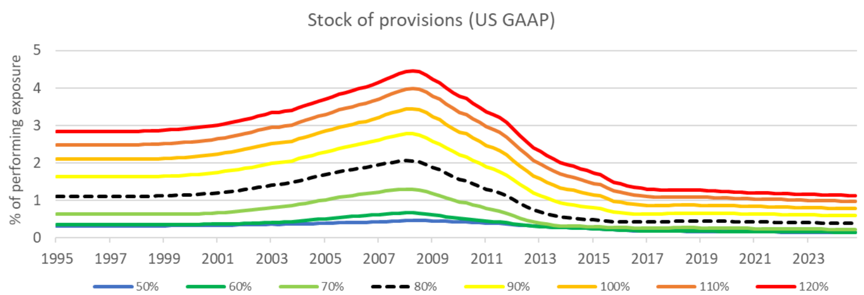
(The black dashed line represents the baseline for our simulations)





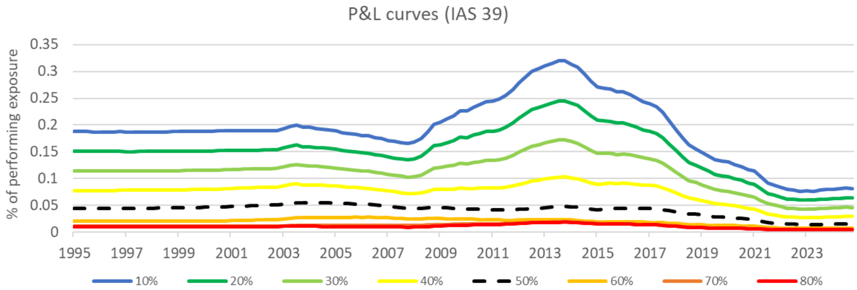


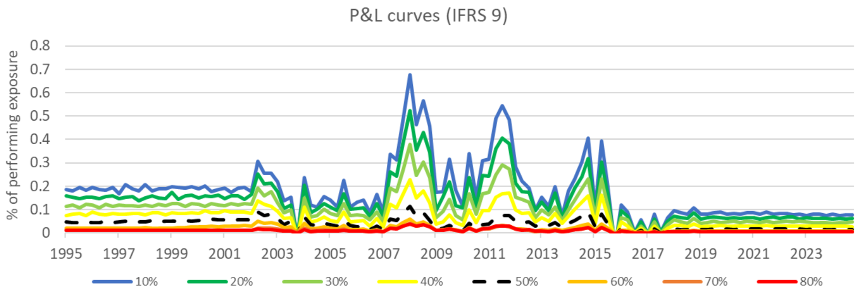


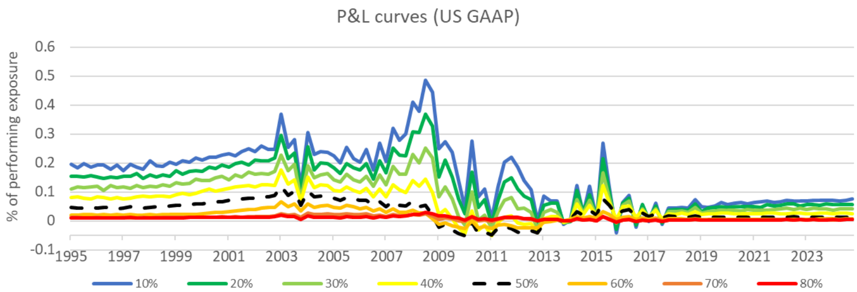


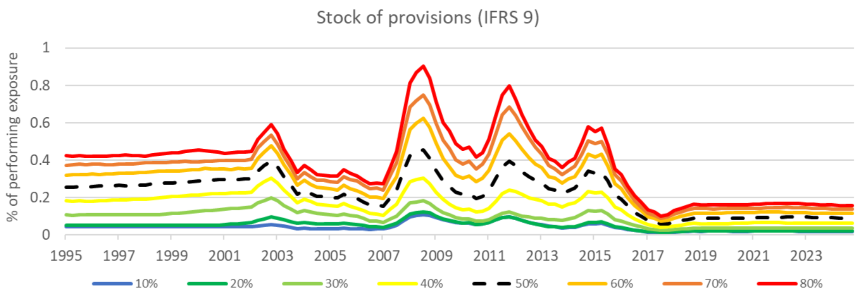
3B.2. Comparative statics on the sales ratio, SR

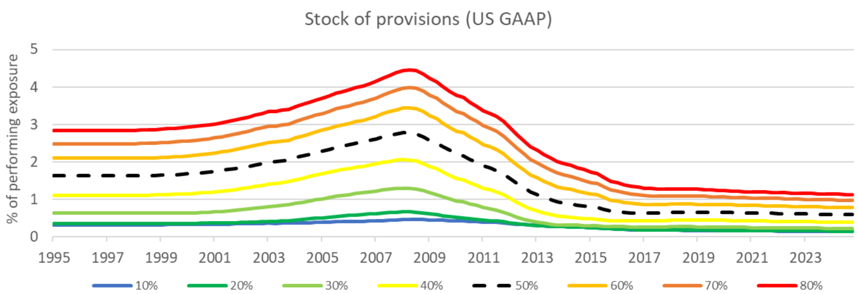
(The black dashed line represents the baseline for our simulations)











Chapter 4

Risky mortgages, credit shocks and cross-border spillovers

This chapter is joint work with Alicia de Quinto and Javier Población. It is accepted and forthcoming in the ***ESRB Working Paper Series****.*

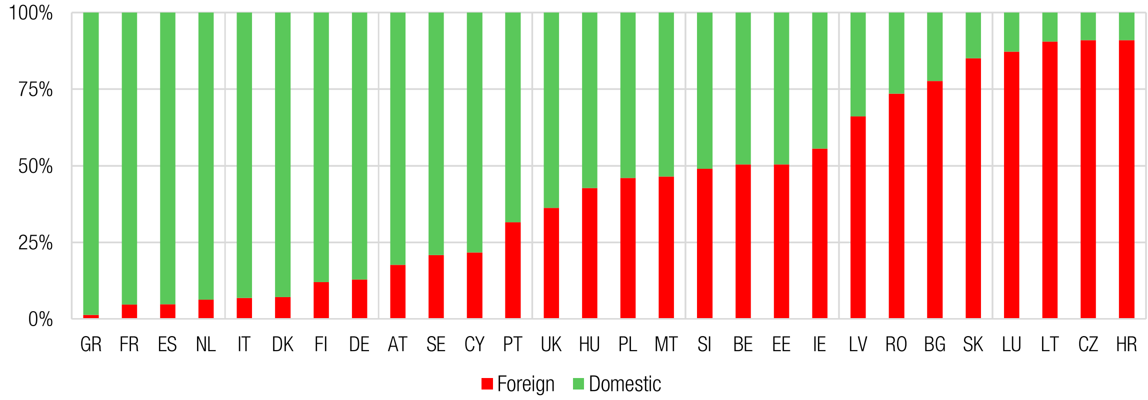
4.1 Introduction

In recent years, topics related to macroprudential policy have been high on the agenda, with an emphasis on the need to prevent fluctuations in financial cycles. This trend has given rise to a number of policy instruments aimed at preserving financial stability. In the European Union, macroprudential instruments have been well anchored in the Capital Requirements Regulation (CRR), whereby some measures are directly embedded in the Union's legal system, and the Capital Requirements Directive (CRD IV), which depicts a second set of instruments to be transposed into national law. The scope of macroprudential policies is very broad and encompasses four main financial stability risks[1]: misaligned incentives and moral hazard (e.g. capital buffers for significant banking institutions), concentration of credit risk (e.g. exposure limits), market illiquidity (e.g. liquidity ratios) and -last but not least- excessive credit growth and leverage (e.g. the countercyclical capital buffer).

Within the latter, so-called borrower-based measures are particularly known to the general public as they directly determine the access to bank financing and its volume. The epitomes of borrower-based instruments are limits on the loan-to-value (LTV), loan-to-income (LTI) or debt-service-to-income (DSTI) ratios for loans to the private sector, typically on mortgages. In general, borrower-based measures are understood as effective if they succeed in reducing the volume of low-quality credit, with banks engaging in transactions for which credit risk is lower; at some point, the behavior of borrowers might also shift towards demanding loans with more reasonable conditions (e.g. with lower LTV ratios).

[1]Following the classification in ESRB (2019).

In parallel, economies around the world are becoming increasingly interlinked through the bank lending channel. Financial integration is apparent, for instance, by looking at cross-border ownership of assets by banking institutions. For EU countries, this phenomenon is particularly relevant: as displayed in Figure 4.1, eleven out of 28 territories have more than half of their bank assets in the hands of foreign institutions. Abstracting from the potential gains from integration, two major risks arise: firstly, the transmission of financial shocks in such an environment becomes much more difficult to track; secondly, banking systems largely dependent on foreign institutions to supply credit could "import" a funding shortfall or tighter financing conditions.



Source: ECB Statistical Data Warehouse, DD dataset. Foreign banking groups include branches and subsidiaries.

Figure 4.1: Total consolidated bank assets by bank ownership (2019).

It follows that the effects of macroprudential measures implemented in one country may spill over other geographies: for instance, they might induce regulatory arbitrage, whereby banking groups - through their foreign branches and subsidiaries- benefit from either not being subject to the same local macroprudential regulation as domestic banks or these policies being laxer than in the country where the parent is located. In consequence, transnational implications shall be accounted for when gauging the effectiveness of any policy action.

Measuring potential cross-border spillovers requires information on individual banking institutions in order to quantify credit risk exposures via branches and subsidiaries. In the EU, national regulators as well as the ECB can resort to supervisory reporting (FINREP/COREP) where information is consistent across countries and banks, although there are some limitations which might lead to underestimation of the true volume of cross-border transactions[2]. However, the only feasible alternative with public data is to use the results from the EBA supervisory stress tests; the exercises include a subsample of banks from each country, in a way such that circa 70% of total consolidated banking assets in the EU are covered but substantial heterogeneity across countries prevails[3]. The

[2]In the current COREP setting, banks only have to report cross-border exposure if the latter exceeds 10% of total exposure, although national supervisors may set a lower threshold for banks established in their jurisdiction. Besides, institutions with material focus on the domestic market are not required to report.

[3]For example, Germany counts 350+ savings banks (*Sparkassen*) making up over 25% of total bank assets, but all of them are less significant institutions (LSIs) and thus not covered by the EBA stress test.

time series dimension remains unusable as only three rounds of the exercise are available to date (2014, 2016, 2018) and the disaggregation level is not uniform across them.

However, there is an additional dimension that not even supervisory data captures comprehensively: loan quality within non-deteriorated credit. For instance, while the volume of non-performing exposures is known for each loan segment, country, institution and reporting period, no information exists on the LTV ratio distribution within performing exposures; individual banks will certainly calculate it internally yet it falls out of the scope of regulatory data submissions. The implementation of IFRS 9 accounting standards shed some light as a distinction now exists between Stage 1 (ordinary) and Stage 2 (with a significant increase in credit risk) assets; in fact, the 2020 EBA stress test templates include information on LTV ratios for S1 and S2 assets, but the exercise has been postponed to 2021 due to the Covid-19 health crisis. Nevertheless, the S1/S2 distinction is a posteriori, as risk is measured with respect to the moment that the loan entered into the bank's balance sheet. Therefore, at present it is unfeasible to create a proxy for "conservative" and "risky" credit granted by banking institutions, whether through public or supervisory information, let alone build a uniform measure for a number of countries. This data gap has important implications, as the conclusions of any empirical model will be drawn on the grounds of broad credit aggregates lacking the required degree of granularity.

The situation becomes even more apparent in the realm of dynamic macro models. Consider a multivariate time-series setup built to calculate the dynamic response of GDP to a negative shock in credit, the latter originating due to a borrower-based macroprudential measure. Ideally, conservative credit -which encourages sustainable economic growth- should remain unaffected, while risky credit should fall: the effect on output should then be transient and manageable. Unfortunately, this distinction is very difficult to make due to the aforementioned data gap.

The purpose of this paper is twofold. Firstly, we construct measures of "conservative" and "risky" mortgage credit for a number of EU countries Specifically, we use the Eurosystem's Household Finance and Consumption Survey (HFCS) to extract LTV, LTI and DSTI ratios for each loan in the sample, and then calculate time-varying shares of conservative/risky credit using thresholds in line with the borrower-based measures in place in most European countries. These shares are applied to aggregate mortgage lending data from the BIS to construct the final time series. Secondly, we use our measures of conservative and risky mortgages along with real output in a Global Autoregressive (GVAR) framework, in order to have a first check on the validity of our artefacts. In particular, we profit from this setup as well as cross-country banking exposures data to evaluate the potential spillover effects of borrower-based macroprudential measures within the Euro Area countries.

The results of our simulation exercise show that a negative shock to risky credit can increase real output in the long run while the effect of a contraction in conservative credit is pervasive, in line with our intuition. Nevertheless, in some geographies a contraction in credit, whether conservative or risky, increases real output. These countries are found to have a different homeownership structure with a more prominent role of the rental market, in a way such that the positive long-run effect of deleveraging on output prevails.

The remainder of the paper is organized as follows: a brief literature review can be found in Section 4.2; Section 4.3 describes the construction of conservative and risky mortgage weights. Section 4.4 depicts the structure of the GVAR model, the data used and our specification, then presents the main results. Finally, Section 4.5 concludes.

4.2 Related literature

To the best of our knowledge, no study exists to date analysing conservative and risky credit from a time series perspective. The literature on macroprudential policy employs aggregate credit statistics or supervisory data, but the two have not yet been combined to study differences in credit quality among performing borrowers, and how the latter feeds into macroeconomic variables. Our methodology, though simple and constrained by data availability, constitutes an initial attempt to be perfected in future research.

Having said this, by exploring the cross-border propagation of credit shocks induced by borrower-based macroprudential measures, our paper echoes several strands of literature which have been active in recent years. The first one is the conceptual work related to capital- and borrower-based macroprudential policies, and the channels through which they are expected to work (e.g. Cerutti et al., 2017 or IMF, 2013). Focusing on the latter, Mendicino (2012) develops a business cycle model with credit frictions and shows that countercyclical LTV ratios in response to credit growth can smooth the credit cycle. Precisely, a number of early studies such as Lamont and Stein (1999) or Almeida et al. (2006) had find evidence that the business cycle is more sensitive to house price movements if LTV ratios are higher.

On the policy evaluation front, Lim et al. (2011) assess the efficiency of macroprudential tools, such as LTV caps, in reducing systemic risk using data from 49 countries. Crowe et al. (2011), using data from the US, find a positive relationship between LTV and price appreciation. Ravn (2016) highlights that LTV caps are an effective macroprudential policy tool in order to reduce the additional volatility caused by endogenous changes in lending standards; this is an important result as it is well known that banking margins are countercyclical[4]. By geographical areas, impact assessments are also abundant for individual countries[5], yet only a few studies include a multinational dimension: Kim and Mehrotra (2018) analyse four countries in the Asia-Pacific region, while Richter et al. (2019) construct a panel of 56 countries. For the Euro Area, Gross and Población (2017) develop an integrated micro-macro model framework to assess the efficacy of borrower-based instruments and quantify the macroeconomic feedback effects. In doing so, they employ household-level data from the Household

[4]See, for example, Aliaga-Diaz & Oliveiro (2011).

[5]See Gerlach and Peng (2005) or Wong et al. (2016) for Hong Kong, Cussen et al. (2015) for Ireland, Price (2014) for New Zealand, or Tillmann (2015) and Kim et al. (2020) for Korea.

Finance and Consumption Survey (HFCS) that is also the cornerstone of our study; however, the objects of study are regulatory parameters (Default probabilities and losses given default -PD and LGD) rather than credit volumes.

Turning to the implications of cross-border banking, the 2008 financial crisis gave rise to a strand of literature studying how foreign branches and subsidiaries altered their lending behaviour contingent on the parent institutionś: two prominent examples are Cerutti and Claessens (2017) and Hoggarth et al. (2013). The relative importance of foreign business for the banking group also affects credit supply in these markets, a feature studied in Cetorelli and Goldberg (2012). In the case of the Euro Area, ESRB (2019) is a comprehensive reference on this issue.

Finally, the advances in macroprudential regulation in latest years have prompted a deeper examination of the potential cross-border spillovers of these policies, with conceptual frameworks deployed as in FSC, Kok and Reinhardt (2020). The workhorse of the vast majority of them is a DSGE model: Rubio (2020) or Darracq Pariès, Kok and Rancoita (2019) present a two-country setup -the euro area versus the rest of the world-, similarly to Rubio (2020) where calibration is done for the US. Kang et al. (2017) use the 40-country DSGE in Kang et al. (2017) which includes a parsimonious financial intermediation sector with cross-border spillovers through trade flows, exchange rates and other financial variables; all studies conclude that these effects are significant, although their magnitude is strongly dependent upon the pair of countries considered and the business structure of the individual banking institutions. In a different vein, Kok, Gross and Zochowski (2016) use a mixed cross-section GVAR model to assess the effect of bank capital shocks (i.e. capital-based macroprudential measures) on different Euro area countries, an approach which we rely on by adding two contributions: disentangling the effects of high- and low-quality credit and using an up-to-date, more refined country weighting scheme with information from FSC (2020) or Cantone, Wildmann and Rancoita (2019). This is in the spirit of the broader work by Sgherri and Galesi (2009), who study the transmission of financial shocks across European economies linked through financial weights, although in their work asset prices play a prominent role.

Lastly, concerning the regulatory dimension, most studies suggest that foreign affiliates of domestic banks will increase lending in their host countries if macroprudential regulation is laxer than in the parent, a phenomenon known as regulatory arbitrage. This phenomenon is examined in Avdjiev et al. (2017), Caccavaio et al. (2017), Hills et al. (2017), Ohls et al. (2017), Reinhardt et al. (2015) or Aiyar et al. (2014).

4.3 Risky versus conservative mortgages

A limitation of most papers is that they use data at the aggregate level and rely on the use of average indicators in their cross- or single-country analysis. Therefore, they miss the intricate effects of LTV limits on borrower behavior in the credit and housing markets, a feature which can only be tested accounting for intra-country borrower-specific variation. In this paper, we use comprehensive loan-level data on mortgages to distinguish between two types of credit, which we dub "risky" and "conservative".

We start by extracting loan-level data from the Household Finance and Consumption Survey (HFCS), a joint initiative of all the Eurosystem national central banks, the central banks of three EU countries that have not yet adopted the euro, and several national statistical institutes aimed at collecting comparable micro-level data on households' balance sheets. The HFCS is therefore a unique and harmonized survey that provides detailed information on households' socio-economic and demographic background, liabilities, consumption, income, and wealth across 19 euro area countries as well as Croatia, Hungary and Poland.

Our dataset includes the three available HFCS survey waves which took place mainly during 2010, 2014 and 2017, and covers 17 of the aforementioned countries, as some key variables are missing for Croatia, Finland, Hungary, Lithuania, and Malta. It contains information on housing characteristics for the household main residence (HMR) and other real estate properties, as well as mortgages or loans using such properties as collateral taken out by a total of 40,686 households.

The data refers to the initial mortgage and subsequent refinancing. For the HMR, we calculate the LTV at loan inception using the property value at the time of acquisition and the initial mortgage. Otherwise, where the loan has been refinanced, information relates to the total amount refinanced and the year the current loan was most recently refinanced; but the collateral value at that given year is unknown as respondents are asked to price their residence only at the time of purchase and when the survey comes about. In such cases, we estimate the collateral's value using residential property price statistics from the Bank for International Settlements. For properties other than the HMR, the collateral value is only available for the year at which the survey took place; therefore, we extrapolate it using property prices back to the year when the loan was contracted.

One important observation is that borrowers might have an incentive to take out more than one mortgage backed by the same collateral, whether because they want to circumvent the regulatory limits to LTV ratios -if in place- or benefit from more favorable lending conditions. Therefore, in order to avoid misclassification, when households engage in more than one mortgage during the same year we calculate the factual LTV by adding the total amounts borrowed.

In a final step, we discard all mortgages with an LTV ratio below 10% or above 200%[6] and restrict our analysis to the year 2000 onwards, as data for the GVAR model is only available since that point

[6] After visual inspection of the dataset, we discovered that loans out of the range [10%,200%] are frequently misreported, with missing or extra zeros in the amounts leading to errors in the LTV ratio.

in time. After all the aforementioned transformations, we are left with 162,756 loans. A summary of available mortgages for each country and year is shown in Table 4.1.

Once we have calculated and adjusted the LTV for each mortgage in our sample, we classify the mortgage as "risky" -as opposed to "conservative"- if it exhibits an LTV ratio beyond a preset value. We use three alternative cutoffs (85, 90 and 95 percent) in line with the regulatory limits in place in most European countries, as described in Appendix 4A. This allows us to compute the shares of risky credit for using two different measures: by taking the volume of risky mortgages over the total amount borrowed in one country at a given year, or by plainly counting the number of risky loans over the total number of mortgages.

Year	AT	BE	CY	DE	EE	ES	FR	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	174	336	168	384	552	948	612	306	480	372	216	*0*	348	*6*	1242	*6*	78
2001	186	318	126	318	348	738	660	180	510	486	234	*0*	408	*18*	1560	*6*	*24*
2002	186	342	228	342	486	888	768	204	558	444	348	*0*	276	*42*	1698	*6*	60
2003	162	498	342	480	618	954	1056	216	834	576	264	*0*	324	54	1218	*6*	108
2004	276	426	444	486	648	1002	1320	438	1284	660	294	*6*	252	90	1290	*36*	138
2005	282	564	510	666	870	1182	1722	444	1842	684	336	*36*	324	72	1362	66	198
2006	342	528	666	702	972	1074	1896	336	2124	648	384	*12*	498	108	1176	90	204
2007	294	648	912	846	912	810	2250	384	1986	714	480	108	696	258	1626	162	222
2008	312	504	816	948	498	468	1908	354	1704	618	414	150	690	438	1638	138	240
2009	300	612	474	1110	186	672	1974	192	960	588	420	168	744	348	1998	120	222
2010	330	606	438	1044	246	582	3186	144	822	600	564	120	738	378	1374	132	210
2011	330	312	204	1038	222	276	3012	*24*	372	306	396	54	588	330	1446	156	132
2012	198	342	264	1146	222	174	2430	*30*	552	246	456	*30*	498	414	1362	198	246
2013	198	318	306	1170	222	54	2508	*18*	318	234	402	60	372	480	378	96	306
2014	132	330	192	996	180	114	2904	*12*	300	252	408	66	396	330	180	54	156
2015	96	516	60	840	444	*18*	5124	*0*	366	150	282	72	342	306	144	*36*	114
2016	108	456	54	684	360	*0*	6552	*0*	276	120	348	*48*	342	306	138	*36*	216
2017	*0*	90	*6*	378	150	*0*	4578	*6*	270	*0*	378	*6*	384	*0*	144	*18*	*48*

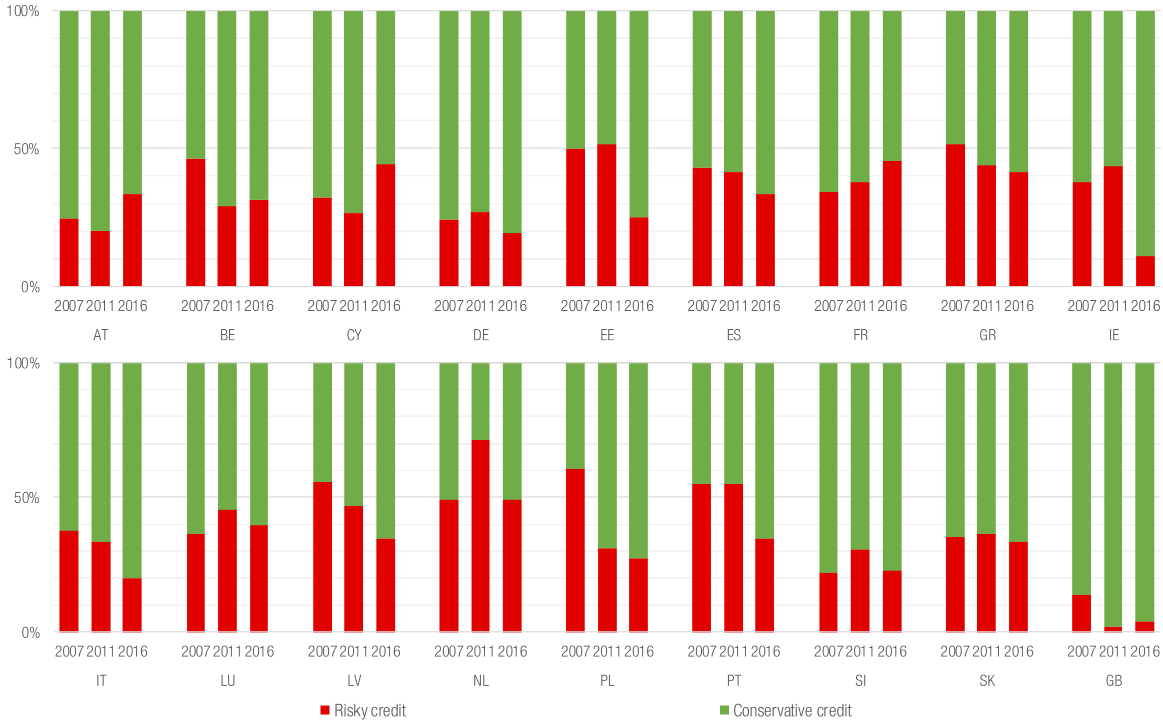
Note: Red cells indicate less than 50 observations available.

Table 4.1: Number of available mortgages in the sample by country and year

In addition, we create matrices for risky and conservative credit based on debt-service-to-income (DSTI) as well as loan-to-income (LTI) ratios, which are extensively used in recently announced measures. To this end, we profit from two derived variables in the HFCS dataset which register mortgages with DSTI ratios over 40% and LTI ratios with an income multiple over 3. Once again, these cutoff values are in line with those in place in Europe to date. In this case, the sample of mortgages is larger, with 254,000 observations.

Because of its relevance for banking systems across the European Union -as analysed subsequently in this paper- it makes sense to include the United Kingdom in our country sample. However, as neither the Office for National Statistics nor the Bank of England are members of the HFCS cluster, we have computed risky and conservative credit shares relying upon other data sources. In particular, the Financial Conduct Authority (FCA) publishes the quarterly statistics on Mortgage Lending and Administration Return (MLAR) which feature a distribution of mortgage loans by LTV ratio and income multiple (i.e. the LTI ratio); we are thus able to compute the share of loans with LTV ratios above 90%, on one hand, and with LTI ratios greater than 3, on the other[7].

Last but not least, it may occur that too few mortgages are available in our dataset for a given country and year to compute meaningful shares of risky and conservative credit. When the number of observations falls below our *ad hoc* threshold of 50, we fill the missing values by taking moving averages of the following (resp. preceding) years, if this happens at the beginning (resp. end) of the sample, or by using linear interpolation, if the blanks lie within two available observations. For 2018 and 2019, which are not available in the HFCS sample because the 3^{rd} wave took place in 2017, we use the last computed value.



Results for the 90% LTV ratio threshold, using the number of mortgages (baseline case).

Figure 4.2: Conservative and risky credit by country in 2007, 2011 and 2016.

The full matrices with conservative and risky credit shares for all countries in the period 2000-2019 can be found in Appendix 4B; a graphical summary is depicted in Figure 4.2. With our methodology, risky credit appears to constitute a smaller share of total mortgages than conservative loans. This said, substantial heterogeneity prevails across countries; in particular, economies most hit by the 2008 financial crisis (e.g. Spain, Ireland, Italy, Portugal) seem to have reduced more clearly the share of risky credit over time.

[7]More concretely, this information is contained in MLAR Table 1.31. We use the total of regulated plus unregulated mortgages; for the LTI threshold, we consider both single and joint income.

4.4 An application: Cross-border spillovers of LTV limits

This section presents a simple exercise where we embed our estimates of conservative and risky credit into a multivariate time series framework, allowing us to gauge how credit shocks induced by borrower-based macroprudential measures can propagate to foreign economies via cross-border exposure of banking institutions. We start by describing our workhorse, the GVAR model, then narrate how our data and the econometric specification are constructed in the abridged spirit of Sgherri and Galesi (2009); finally, we discuss our results.

4.4.1 The GVAR model

The GVAR approach was originally proposed by Pesaran et al. (2004)[8] and since the very first moment after its appearance, it has been very well accepted and echoed among researchers and practitioners. The GVAR is a simple but effective methodology of modelling interactions in a system with many dimensions such as the global economy avoiding the curse of dimensionality (see, for example, Chudik et al. (2011)).

GVAR modelling can be seen as a two-stage procedure. In the first step, country-specific models are estimated conditional on the rest of the world, which enters the equations in the form of weighted cross-section averages of foreign variables that are treated as weakly exogenous. The latter are generated from the domestic variables using a weight matrix that can reflect trade volumes (the original formulation of GVAR), banking sector features or any other desired cross-country interaction. In the second step, individual country models are stacked and solved simultaneously as one global, reduced-form VAR model. The solution can be used for shock scenario analysis and forecasting as in an ordinary low-dimensional VAR.

We present a succinct mathematical formulation of the model following Kok, Gross and Zochowski (2016). Initially, consider an ordinary VARX structure (possibly with a deterministic trend) with exogenous variables for each of the countries $i = 1, 2, ..., N$. Assume there are d_i endogenous variables grouped in a vector $\boldsymbol{y}_{i,t}$ and f_i foreign variables in a vector $\boldsymbol{y}^*_{i,t}$. While domestic variables enter the model with P lags at most, foreign variables are considered both contemporaneously and with up to R lags:

$$y_{it} = \boldsymbol{a}_{i,0} + \boldsymbol{a}_{i,1}t + \sum_{p=1}^{P} \boldsymbol{\Phi}_{i,p}\boldsymbol{y}_{t-p} + \sum_{r=0}^{R} \boldsymbol{\Gamma}_{i,r}\boldsymbol{y}^*_{t-r} + \boldsymbol{\varepsilon}_{i,t} \tag{4.1}$$

where $\boldsymbol{\varepsilon}_{i,t} \sim iid(0, \boldsymbol{\Sigma}_i)$. Note that there exists the possibility of contemporaneous cross-country dependence of shocks, that is, $E\left[\boldsymbol{\varepsilon}_{i,t}\boldsymbol{\varepsilon'}_{j,t}\right] = \operatorname{cov}\left(\boldsymbol{\varepsilon}_{i,t}\boldsymbol{\varepsilon'}_{j,t}\right)$.

Foreign variables for the N countries are constructed using an $N \times N$ weight matrix $\boldsymbol{W}$ in which the relevance of country j for country i is captured by element w_{ij} and the main diagonal of $\boldsymbol{W}$ is zero,

[8] It was also developed in seminal contributions by Pesaran and Smith (2006), Pesaran et al. (2006) and Dées et al. (2007).

meaning that $\boldsymbol{y}_i^* = \sum_{j=1}^{N} \boldsymbol{y}_j$ and $\sum_j w_{ij} = 1$. Within each country VARX model, one key assumption is weak exogeneity of the foreign variables, which entails that short-run interaction between domestic and foreign variables is permitted but the former cannot influence the latter in the longer term.

Now assume $P = R$ for simplicity, stack all of the country variables in a single vector $z_{i,t} = \left(y_{i,t}\, y_{i,t}^*\right)'$ sized $(d_i + f_i) \times 1$ and rewrite the country models as:

$$\boldsymbol{A}_{i,0}\boldsymbol{z}_{i,t} = \boldsymbol{a}_{i,0} + \boldsymbol{a}_{i,1}t + \sum_{p=1}^{P} \boldsymbol{A}_{i,p}\boldsymbol{z}_{i,t-p} + \boldsymbol{\varepsilon}_{i,t} \tag{4.2}$$

where $\boldsymbol{A}_{i,0} = (\boldsymbol{I}_{d_i}, -\boldsymbol{\Gamma}_{i,0})$ and $\boldsymbol{A}_{i,p} = (\boldsymbol{\Phi}_{i,p}, \boldsymbol{\Gamma}_{i,p})$.

If the endogenous variables in the cross-section are stacked into one global vector $\boldsymbol{y}_t$ of dimension $d = d_1 + ... + d_N$, we can establish a mapping of the domestic variable vectors $\boldsymbol{z}_{i,t}$ into the global vector by means of a series of link matrices L_i of dimension $(d_i + f_i) \times d$, so that $\boldsymbol{z}_{i,t} = \boldsymbol{L}_i\boldsymbol{y}_t$. This allows the model to be reformulated as:

$$\boldsymbol{A}_{i,0}\boldsymbol{L}_i\boldsymbol{y}_t = \boldsymbol{a}_{i,0} + \boldsymbol{a}_{i,1}t + \sum_{p=1}^{P} \boldsymbol{A}_{i,p}\boldsymbol{L}_i\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_{i,t} \tag{4.3}$$

The global model can now be constructed by stacking the the country-specific models:

$$\boldsymbol{G}_0\boldsymbol{y}_t = \boldsymbol{G}_0^{-1}\left(\boldsymbol{a}_0 + \boldsymbol{a}_1 t + \sum_{p=1}^{P} \boldsymbol{G}_p\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t\right) \tag{4.4}$$

$$\boldsymbol{G}_i = \begin{pmatrix} \boldsymbol{A}_{01}\boldsymbol{L}_1 \\ \boldsymbol{A}_{02}\boldsymbol{L}_2 \\ \vdots \\ \boldsymbol{A}_{0N}\boldsymbol{L}_N \end{pmatrix}, \boldsymbol{G}_p = \begin{pmatrix} \boldsymbol{A}_{p1}\boldsymbol{L}_1 \\ \boldsymbol{A}_{p2}\boldsymbol{L}_2 \\ \vdots \\ \boldsymbol{A}_{pN}\boldsymbol{L}_N \end{pmatrix} \tag{4.5}$$

This is the model that will be used for simulation and impulse response analysis. It is important to bear in mind that the GVAR produces generalized IRFs in the sense that it allows error terms to be correlated.

Aside from the weak exogeneity of foreign variables in each country model, there are three additional conditions that the GVAR has to satisfy in order to be valid and well-behaved: Firstly, the eigenvalues of the matrices $\boldsymbol{H}_p = \boldsymbol{G}_0^{-1}\boldsymbol{G}_p$ have to be smaller or equal than one in module to ensure stability; secondly, the elements ot W have to be relatively small. Finally, the cross-dependence of the idiosyncratic shocks must be sufficiently low.

4.4.2 Data and estimation

By combining the annual risky/conservative credit[9] weights described in the previous section with aggregate household credit statistics from the Bank of International Settlements, we are able to create time series of risky and conservative credit, assuming that their sum equals the aggregate figure reported by the BIS[10]. We apply country-specific correction factors to scale down aggregate credit depending on the relevance of mortgages, as detailed in Appendix 4D.

The domestic block of each country model includes three quarterly time series spanning from 2000Q1 to 2019Q2: real GDP, risky and conservative credit, the latter both deflated by the consumer price index. All variables enter the model in logs; the details of the series can be found in Appendix 4D. We conduct Augmented Dickey-Fuller tests (ADF) on both domestic and foreign variables so as to ascertain whether the series have a unit root[11]. The test is run on levels, first and second differences; as shown in Tables 4.2 and 4.3, most variables in our model are found to be I(1).

In order to construct the foreign variables for each country, we use two weight matrices: For GDP, we resort to the traditional trade approach where cross-country weights are derived from bilateral imports/exports; in contrast, for the credit variables we build a matrix based on the information in FSC (2020), which includes information on cross-border bank exposures built upon supervisory reporting at the highest level of consolidation for end-2018, for a sample of circa 400 banks supervised by the SSM. Because of data availability in the construction of our credit aggregates, we must recompute the individual weights excluding Finland, Lithuania, Malta and Sweden. Final weight matrices are provided in Appendix 4C.

As regards the individual country VAR specification, we incorporate a maximum of two lags for each domestic variable -with the lowest AIC as the decision rule- and only one for foreign terms. Regarding the latter, de-activate foreign risky credit for all countries: the rationale for this choice is that, while an increase in risky credit might have immediate financial stability consequences for the host economy, it is likely that the impact on foreign economies through cross-border banking exposures will happen through changes in the business model or the amount of loans granted, which is more visible in conservative credit[12].

[9] Henceforth, we use "credit" and "mortgages" indistinctly.

[10] Weights from the HFCS are computed annually while the BIS statistics are quarterly; we thus multiply each quarter in the year for the same weight. An alternative would be to interpolate quarterly weights.

[11] The lag order of the test statistics is determined by minimizing the Akaike IC with a limit of 2 lags.

[12] We also rule out conservative credit for Cyprus, Greece, Latvia and Slovenia, owing to the reduced availability of data to compute weights in the HFCS sample.

	y(t)	y	Δy	Δ^2y	cons(t)	cons	Δcons	Δ^2cons	risk(t)	risk	Δrisk	Δ^2risk
Cr.Val.	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-3,45**	**-2,89**	**-2,89**	**-2,89**
AT	-2,63	-0,67	-3,85	-5,31	-1,35	-1,96	-6,41	-12,2	-4,61	-2,36	-5,85	-9,63
BE	-2,64	-0,78	-5,02	-6,69	-1,65	-0,98	-5,78	-7,34	-2,42	-2,16	-5,85	-6,10
CY	-2,37	-1,98	-2,08	-10,7	-1,18	-1,90	-5,11	-8,24				
DE	-2,83	-0,12	-4,65	-6,50	-2,40	-2,35	-6,00	-9,03	-2,49	-1,79	-6,17	-11,7
EE	-2,36	-1,64	-2,67	-10,6	-0,66	-2,35	-4,05	-7,29	-1,15	-2,92	-2,78	-7,76
ES	-2,02	-1,47	-2,23	-8,26	-1,32	-1,96	-5,06	-4,85	-2,38	-2,51	-6,30	-4,64
FR	-2,45	-0,65	-3,82	-7,11	-0,95	-1,23	-5,52	-10,9	-2,26	-1,75	-6,02	-7,82
GB	-2,89	-1,28	-4,35	-6,10	-1,25	-2,18	-5,82	-8,31	-1,33	-1,18	-5,72	-10,5
GR	-1,94	-1,24	-2,17	-12,4	-0,54	-2,40	-5,01	-10,7				
IE	-0,60	0,64	-6,30	-9,50	-1,09	-2,56	-4,90	-9,30	-1,04	-1,24	-5,59	-10,5
IT	-2,59	-2,47	-4,49	-6,10	-1,40	-1,68	-5,60	-9,91	-2,48	-2,61	-6,10	-10,8
LU	-2,79	-0,44	-4,91	-8,74	-2,12	-0,82	-5,56	-9,98	-1,24	-1,54	-5,90	-8,18
LV	-2,36	-1,95	-2,35	-9,90								
NL	-1,83	-0,28	-4,26	-7,34	-3,19	-2,67	-5,92	-9,42	-1,99	-2,11	-6,00	-5,35
PL	-1,63	0,21	-4,14	-9,46	-1,72	-1,74	-5,58	-10,8	-1,12	-1,77	-5,66	-9,55
PT	-1,43	-1,05	-4,01	-9,41	-1,48	-2,25	-5,57	-8,13	-1,74	-1,85	-6,08	-10,8
SI	-1,89	-1,27	-3,82	-8,35	-0,97	-1,19	-4,87	-7,06				
SK	-1,23	-1,44	-6,03	-9,58	-1,36	-1,26	-5,57	-10,8	-1,36	-0,79	-5,11	-9,59

Table 4.2: Unit root tests (ADF) for the domestic variables at the 5% significance level.

	y(t)	y	Δy	Δ^2y	cons(t)	cons	Δcons	Δ^2cons	risk	Δ^2risk
Cr.Val.	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-3,45**	**-2,89**	**-2,89**	**-2,89**	**-2,89**	**-2,89**
AT	-2.94	-0.41	-4.32	-8.37	-1.39	-1.73	-5.56	-9.23	-2.27	-11.4
BE	-2.49	-0.41	-3.87	-7.34	-1.59	-1.63	-5.67	-8.98	-1.93	-12.8
CY	-1.92	-1.94	-3.36	-9.05	-0.77	-2.14	-5.26	-9.59	-1.77	-12.3
DE	-2.38	-0.64	-3.94	-6.03	-1.21	-1.69	-5.40	-8.82	-2.02	-12.0
EE	-3.01	-1.22	-2.63	-6.71	-1.47	-1.69	-5.60	-9.03	-2.01	-12.3
ES	-2.78	-0.65	-4.03	-7.16	-1.28	-1.64	-5.55	-8.90	-1.87	-12.7
FR	-2.62	-0.67	-4.02	-7.34	-1.38	-1.89	-5.32	-8.36	-1.52	-12.9
GB	-2.09	-0.24	-3.91	-7.97	-1.15	-1.87	-4.97	-8.75	-1.93	-5.15
GR	-2.48	-0.69	-3.83	-7.13	-1.13	-1.71	-5.37	-9.00	-1.88	-12.5
IE	-2.84	-0.78	-3.92	-6.63	-1.05	-1.78	-5.44	-9.01	-1.45	-9.84
IT	-2.56	-0.57	-3.89	-7.27	-0.98	-1.44	-5.34	-9.75	-1.88	-12.0
LU	-3.16	-0.48	-4.30	-7.44	-1.10	-1.46	-5.51	-9.60	-1.89	-12.3
LV	-2.62	-0.85	-3.62	-7.42	-1.15	-1.80	-5.32	-8.62	-1.84	-11.9
NL	-2.98	-0.49	-4.12	-7.53	-1.07	-1.58	-5.41	-9.65	-1.75	-12.1
PL	-2.80	-0.55	-4.18	-8.03	-1.35	-1.85	-5.32	-8.64	-1.84	-5.56
PT	-2.22	-0.92	-3.65	-7.38	-1.22	-1.90	-4.96	-9.12	-2.30	-4.77
SI	-2.75	-0.67	-3.97	-7.35	-1.02	-1.73	-5.74	-10.8	-2.12	-10.4
SK	-3.01	-0.36	-3.86	-7.29	-1.04	-1.79	-5.93	-11.3	-2.20	-9.92

Table 4.3: Unit root tests (ADF) for the foreign variables at the 5% significance level.

The individual country VARX* models are estimated in error-correcting form (VECMX*). The number of cointegrating relationships is determined through the reduced-rank regression procedure[13] and is reported in Table 4.4 along with the selected lag orders; note that country models with zero cointegration rank are estimated in differences.

[13]Both the trace and maximum eigenvalue statistics are derived by letting the intercept coefficients to be unrestricted in levels and not including a deterministic trend in the reduced rank regressions.

For each country model, we test whether the foreign variables are weakly exogenous by evaluating the joint significance of the foreign terms in each VECMX*; for countries where the cointegration rank is zero, foreign variables are directly considered weakly exogenous. The test results, which are presented in Table 4.5, show that weak exogeneity is assured for all series except for GDP in Slovakia; we thus consider our setup sufficiently well-grounded for the analysis.

		VARX* order		# Coint. Rel.
		p (domestic)	q (foreign)	
Austria	AT	1	1	0
Belgium	BE	1	1	0
Cyprus	CY	2	1	1
Germany	DE	1	1	1
Estonia	EE	1	1	1
Spain	ES	2	1	1
France	FR	1	1	0
United Kingdom	GB	2	1	1
Greece	GR	1	1	1
Ireland	IE	1	1	0
Italy	IT	1	1	0
Luxembourg	LU	1	1	0
Latvia	LV	1	1	0
Netherlands	NL	1	1	0
Poland	PL	1	1	0
Portugal	PT	1	1	0
Slovenia	SI	2	1	1
Slovakia	SK	1	1	1

Table 4.4: Country VARX* models: Lag order and cointegration rank.

Country		F-test	Critical value	Real GDP	Conservative credit
Austria	AT	*F(0,69)*	-	-	-
Belgium	BE	*F(0,69)*	-	-	-
Cyprus	CY	*F(1,69)*	**3.98**	1.04	0.04
Germany	DE	*F(1,68)*	**3.98**	0.01	0.94
Estonia	EE	*F(1,68)*	**3.98**	0.00	0.02
Spain	ES	*F(1,68)*	**3.98**	1.22	2.93
France	FR	*F(0,69)*	-	-	-
United Kingdom	GB	*F(1,68)*	**3.98**	0.86	1.54
Greece	GR	*F(1,69)*	**3.98**	1.57	0.04
Ireland	IE	*F(0,69)*	-	-	-
Italy	IT	*F(0,69)*	-	-	-
Luxembourg	LU	*F(0,69)*	-	-	-
Latvia	LV	*F(0,71)*	-	-	-
Netherlands	NL	*F(0,69)*	-	-	-
Poland	PL	*F(0,69)*	-	-	-
Portugal	PT	*F(0,69)*	-	-	-
Slovenia	SK	*F(1,69)*	**3.98**	0.72	1.39
Slovakia	SI	*F(1,68)*	**3.98**	***5.86***	2.15

Results at the 5% significance level. Order of regression equations: (1,1) for (d,f) variables.

Table 4.5: Weak exogeneity test for the foreign variables.

Aside from the weak exogeneity, the rest of conditions needed to ensure stability of the global model are verified in our setup: The elements of the financial weight matrix are sufficiently small and the all the model eigenvalues lie on or within the unit circle. An additional way of checking model stability is to look at the persistence profiles (PPs), which gauge the effect of shocks on the long-run (cointegrating) relationships. The PPs should converge relatively fast to zero, something that happens for our model, as Figure 4.3 shows.

As a last condition, the system's idiosyncratic shocks must be weakly correlated, so that the shocks to both conservative and risky credit employed in our analysis can be considered idiosyncratic and country-specific. In a way, the foreign variables in each country VECMX* model act as common latent factors which help reducing the dependence among all domestic variables in the GVAR; therefore, the residuals of foreign variables should exhibit low correlation. We compute the pairwise cross-country correlations for foreign output and conservative credit, which are displayed in Table 4.6, reporting the values for the series in levels and first differences as well as for the country VECMX* residuals. The calculations show that the dependence, initially high in levels, dampens considerably after taking differences and shrinks further in the equation residuals to generally negligible values. Only risky credit series exhibit a slightly higher -though still very low- correlation.

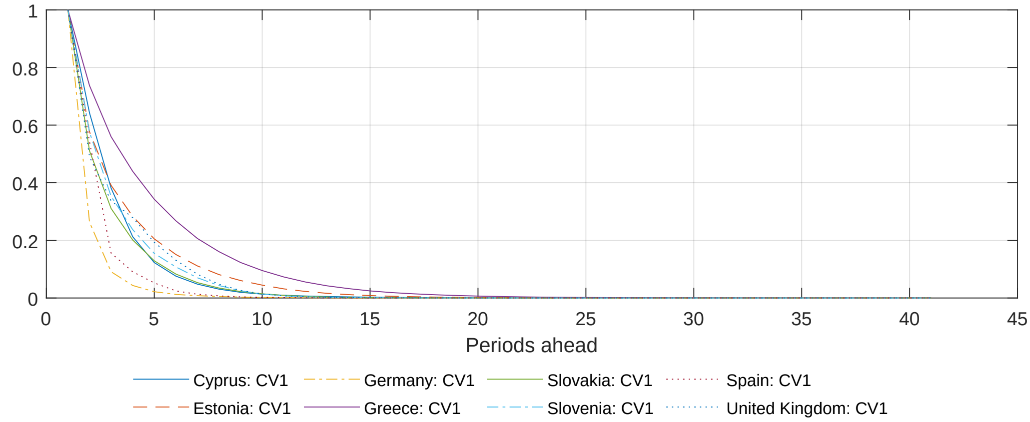


Figure 4.3: Persistence profiles for the cointegrating vectors: Median bootstrap estimates.

		Real GDP			Conservative credit			Risky credit		
		Levels	1st diff.	Res.	Levels	1st diff.	Res.	Levels	1st diff.	Res.
Austria	AT	0.79	0.48	0.05	0,79	0,28	0.02	0.20	0.02	-0.09
Belgium	BE	0,78	0,48	0,05	0,86	0,25	0,07	0,48	0,02	***-0,12***
Cyprus	CY	0,77	0,35	0,00	0,85	0,32	-0,04			
Germany	DE	0,73	0,43	***-0,18***	0,78	0,40	-0,03	-0,03	0,14	***0,13***
Estonia	EE	0,79	0,40	0,05	0,91	0,36	-0,04	0,61	0,23	***0,16***
Spain	ES	0,80	0,54	0,04	0,87	0,34	-0,04	0,54	0,16	***0,18***
France	FR	0,79	0,53	-0,01	0,90	0,43	-0,01	0,49	0,20	***0,15***
United Kingdom	GB	0,78	0,45	-0,03	0,85	0,41	0,06	-0,38	-0,06	-0,07
Greece	GR	-0,20	0,29	0,00	0,91	0,43	0,06			
Ireland	IE	0,74	0,17	-0,02	0,91	0,38	0,00	0,47	0,25	***0,16***
Italy	IT	0,09	0,55	0,03	0,90	0,37	-0,06	0,45	0,15	***0,19***
Luxembourg	LU	0,77	0,29	-0,01	0,85	0,32	0,05	0,52	0,16	0,09
Latvia	LV	0,78	0,31	-0,05						
Netherlands	NL	0,80	0,50	-0,02	0,78	0,22	-0,08	0,54	0,11	***0,11***
Poland	PL	0,75	0,15	-0,01	0,84	0,09	0,09	0,54	0,10	-0,04
Portugal	PT	0,57	0,41	0,00	0,85	0,28	0,01	0,43	0,10	0,01
Slovenia	SI	0,82	0,53	0,03	0,90	0,30	0,04			
Slovakia	SK	0,78	0,35	-0,03	0,84	0,18	0,00	0,50	0,12	-0,01

Res: Residuals for the VECMX individual country models.*

Table 4.6: Average pairwise cross-section correlations: variables and residuals.

4.4.3 Results

In this subsection, we present selected dynamic features of our GVAR specification. In particular, we are interested in measuring how economies respond to shocks in risky and conservative credit and how the latter propagate across foreign countries. With our methodology to build risky and conservative credit, more stringent borrower-based macroprudential measures such as LTV ratio limits are univocally linked to a reduction in risky credit; moreover, cross-border spillovers of macroprudential policy imply that the contraction might feed to other geographies where the banking institutions of the home country are exposed via branches or subsidiaries. In our simplified GVAR setup, we would expect all of the former to manifest in two simultaneous ways: Firstly, a negative shock to risky credit favours output in the long run by preventing an excessive build-up of credit risk for financial institutions; conversely, a fall in conservative credit hampers the country's economy by weakening the leverage-growth channel. Secondly, this behavior will affect the banking systems of other geographies where parent institutions affected by domestic shocks play a significant role.

We choose to illustrate our results using pairs of countries with significant cross-border bank exposures, measured by the weight matrices found in Appendix 4C. In particular, we use the simulation suite by Galesi and Smith (2014) focusing on three cases in which the share of domestic credit granted by foreign institutions is large: The exposure of Spanish banks in Portugal (74%) and the UK (40%), of Italian banks in Austria (54%) and of French banks in Belgium (53%), Italy (61%) and Luxembourg (58%). Figure 4.4 shows generalized impulse response functions (GIRFs) of real GDP to negative, one-standard deviation shocks to risky and conservative credit in Spain and Italy. Output reacts in a distinct fashion to both perturbations, in line with our intuition: conservative credit has a persistent positive effect on domestic output while risky credit has negative consequences. Regarding the magnitude, both types of credit induce a similar behavior of GDP in absolute value for the case of Spain, while in Italy the response to risky mortgages is twice as large as for conservative mortgages. Cross-border effects are also sizeable for countries significantly exposed to the Spanish and Italian banking sectors, although varying across geographies: for instance, the reaction of output in the UK is more muted than the domestic reaction in Spain, while for Portugal some amplification is at play; this might be due to foreign GDP being weighted by trade flows in the GVAR as trade linkages between Spain and Portugal are particularly strong.

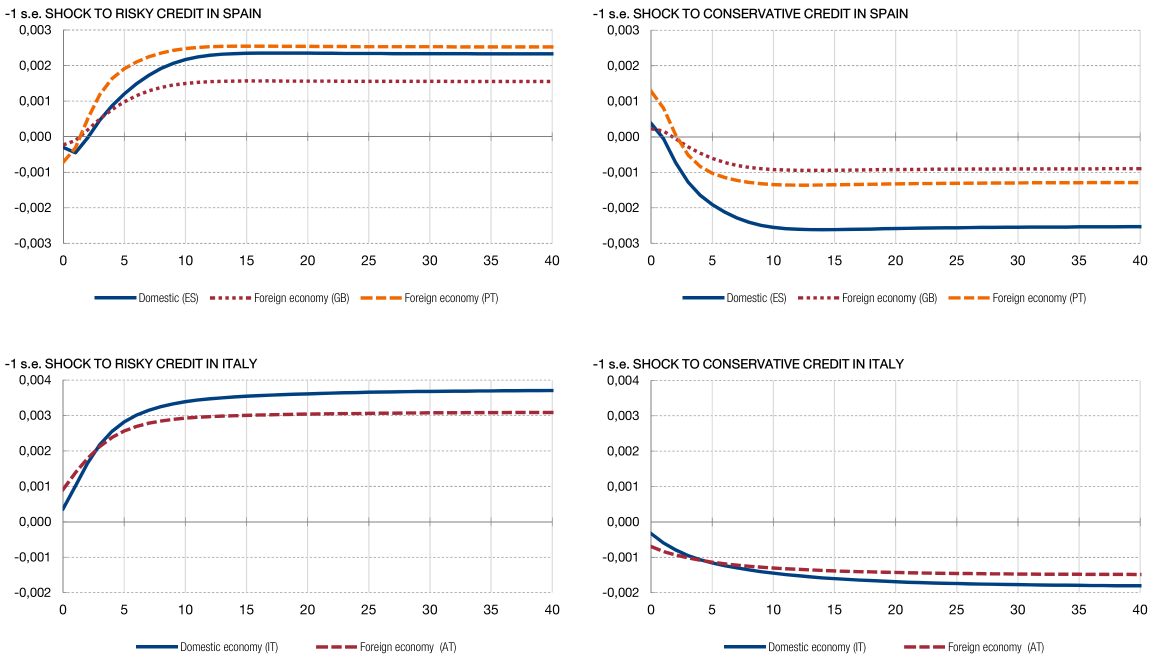


Figure 4.4: GDP responses to credit shocks in Spain and Italy.

However, not all countries exhibit behaviors in line with our intuition. Figure 4.5 plots the domestic impulse responses to credit shocks in France: the results are at odds with those observed for Spain and Italy as the domestic response of GDP is similar in magnitude and has a positive sign for both risky and conservative deleveraging, thus suggesting that *any* reduction in credit will favor output in the long run. The cross-country effects are, again, contingent upon the relevance of cross-border ties in terms of trade flows and financial exposure; moreover, it appears that the range of amplification effects is broader for conservative credit. One plausible explanation arises by looking at the weight matrices: the share of conservative mortgages in Luxembourg and Italy, which exhibit the largest amplification, is much larger than in France[14].

[14]The divergence in responses to credit shocks in Spain, illustrated in Figure 4.4, also fits into this hypothesis.

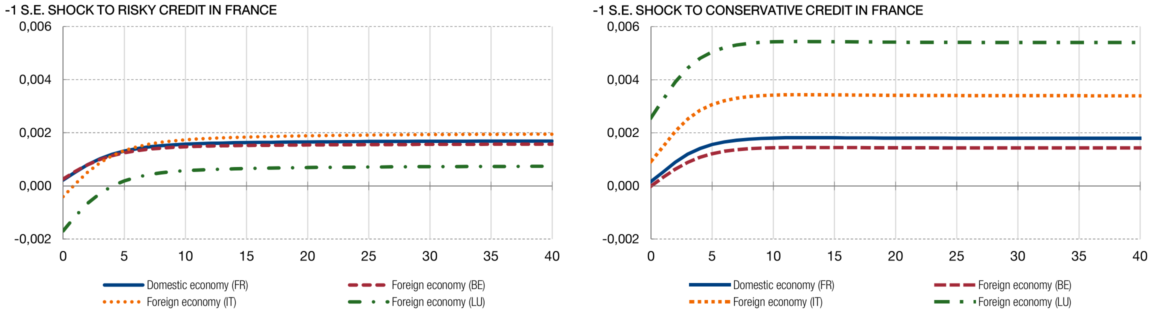
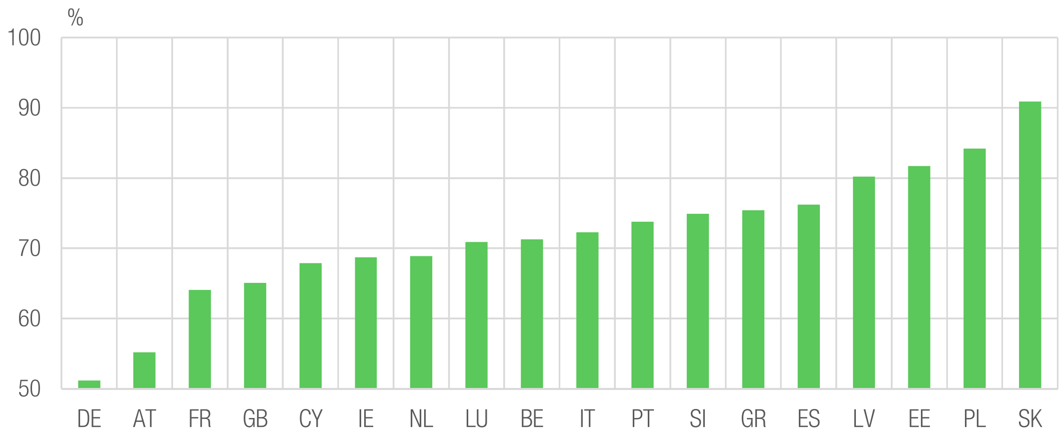


Figure 4.5: GDP responses to credit shocks in France.

In order to understand why output might expand due to a reduction in conservative credit, the flow of which should be beneficial for an economy, we explore the homeownership structure across geographies in the model: where rental plays a more important role, mortgage credit should be less relevant as its bulk is devoted to house purchase and, more broadly, secured on immovable property. In such cases, the distinction between risky and conservative mortgages could become secondary in favor of the beneficial effects of deleveraging for the aggregate economy. As shown in Figure 4.6, Spain and Italy -where the response of risky credit is distinct- have a much higher homeownership rate than France.



Source: Eurostat, ilc_lvho02 *dataset.*

Figure 4.6: Homeownership rate (2019) in the GVAR countries.

4.4.4 Robustness checks

We verify the soundness of our results using credit shocks in Spain as a benchmark. Firstly, we use alternative cutoff values of the LTV ratio to compute country weights and the resulting conservative/risky credit time series to be inserted in the GVAR. Figure 4.7 illustrates that responses to credit shocks under different LTV thresholds preserve the sign of the baseline case, with magnitude varying non-linearly: decreasing the cutoff has more-than-proportional effects on the GIRFs.

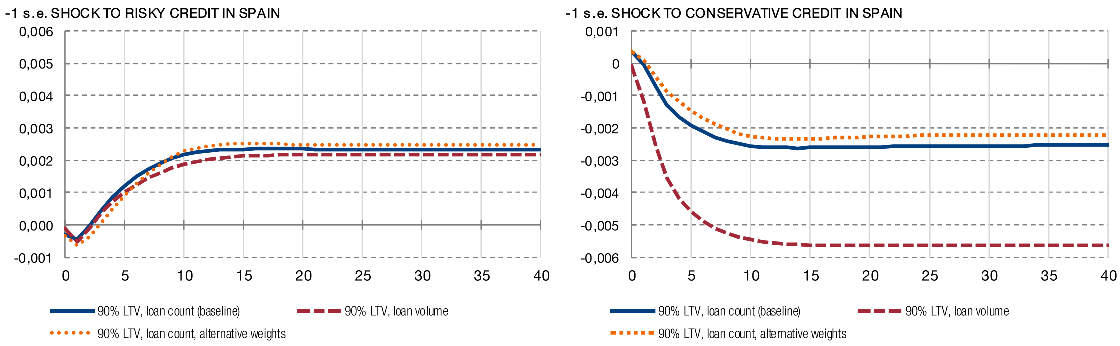


Figure 4.7: Spain: GDP response to domestic credit shocks under alternative LTV cutoffs.

Secondly, we compute the shares of conservative and risky weights by country and year by considering the volume of mortgage credit, rather than the number of mortgages, above the LTV cutoff value. The response of GDP to a shock in volume-based risky credit are very similar to the baseline case using the number of loans, whereas the reaction of output to a shock in conservative credit is amplified considerably. Finally, we employ an alternative weight matrix for the creation of foreign credit variables in the GVAR, relying on the work on direct or branch-directed cross-border bank exposures by Cantone, Wildmann, and Rancoita (2019). Again, we have to adjust the data to exclude some countries not present in our GVAR specification. A correlation analysis with the baseline matrix, which can be found in Appendix 4C, suggests that the country-specific distribution of exposures is very similar in the majority of cases. As Figure 4.8 depicts, the impulse responses in our model appear robust to the choice of financial weight matrices.

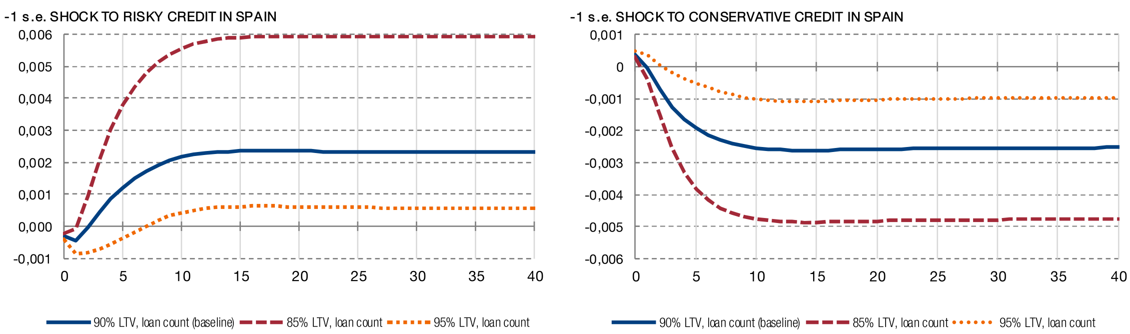


Figure 4.8: Spain: GDP response to domestic credit shocks under alternative weightings.

4.5 Conclusions

In this paper, we introduce a novel, simple methodology to fill an existing gap in publicly available macro-financial data: time-series information of loan quality within performing mortgage credit in European countries. For that purpose, we classify mortgage credit into "risky" and "conservative" by exploiting loan-level data from harmonized household surveys at the European level. In order to do so, given that borrower-based macroprudential measures are widely used in most European countries, we compute LTV, DTI and LTI ratios for individual mortgages, which we use as cutoff values for our classification.

We frame our contribution in the context of increasing financial linkages across countries by considering cross-border banking exposure data. The latter allows us to quantify the potential outward spillover effects of borrower-based measures. To this end, we construct a GVAR model to evaluate how shocks to both types of credit -related to a tightening of the macroprudential stance- can potentially affect output, both domestically and in other countries.

Our results suggest that a decrease in risky credit can have long-lasting positive effects on GDP, both in the originating country and its most exposed peers, while a fall in conservative credit is detrimental. In some geographies, negative shocks to both types of credit reduce output, a feature linked to the lower relevance of homeownership which implies that mortgage credit plays a less prominent role in the domestic economy.

Appendix 4A. Borrower-based measures in Europe

Table 4A.1 presents a simplified overview of the borrower-based macroprudential measures implemented in European countries, based on the European Systemic Risk Board's database in December 2020. For the sake of our argument, we do not distinguish between enforceable limits and guidelines, neither do we include the particular cases (e.g. first-time buyers, second residence...) which tweak the headline limit upwards or downwards.

Country	LTV ratio	DSTI ratio	DTI ratio
Austria	80%	30 – 40%	..
Belgium	90%	50%	9
Cyprus	70 – 80%	80%	..
Czech Republic	80 – 90%	45 – 50%	9
Denmark	95%	..	4 – 5
Estonia	85 – 90%	50%	..
Finland	90 – 95%	..	..
France	..	33%	..
Hungary	80%	25 – 60%	..
Iceland	85 – 90%	..	..
Ireland	80 – 90%	..	3.5
Latvia	95%	40%	6
Lithuania	85%	40 – 60%	..
Malta	85%	40%	..
Netherlands	100%	..	..
Norway	60 – 85%	..	5
Poland	85 – 90%	40 – 50%	..
Portugal	80 – 90%	50%	..
Romania	60 – 85%	40%	..
Slovakia	80 – 90%	60%	8 – 9
Slovenia	80%	50 – 76%	..
Sweden	85%	..	..
United Kingdom	..	..	4.5

Table 4A.1: Borrower-based measures active in European countries.

Appendix 4B. Risky and conservative credit: Full matrices

Risky credit: Proportion of loans with **LTV ratio** > **90%**:

year	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	0,38	0,38	0,29	0,39	0,38	0,47	0,35	0,14	0,35	0,41	0,31	0,33	0,51	0,57	0,29	0,51	0,28	0,54
2001	0,29	0,49	0,19	0,40	0,47	0,43	0,39	0,14	0,37	0,32	0,25	0,38	0,52	0,60	0,26	0,53	0,28	0,28
2002	0,26	0,39	0,37	0,35	0,51	0,49	0,49	0,14	0,41	0,37	0,39	0,38	0,51	0,59	0,26	0,51	0,30	0,30
2003	0,41	0,35	0,12	0,19	0,43	0,47	0,49	0,14	0,50	0,35	0,32	0,43	0,51	0,50	0,33	0,41	0,28	0,22
2004	0,28	0,37	0,23	0,30	0,49	0,42	0,45	0,14	0,40	0,36	0,45	0,31	0,52	0,50	0,20	0,44	0,26	0,30
2005	0,13	0,39	0,33	0,30	0,46	0,46	0,39	0,14	0,53	0,37	0,32	0,30	0,50	0,69	0,25	0,51	0,36	0,36
2006	0,26	0,49	0,26	0,32	0,51	0,47	0,41	0,14	0,50	0,36	0,46	0,28	0,51	0,39	0,39	0,53	0,20	0,38
2007	0,24	0,46	0,32	0,24	0,50	0,43	0,34	0,14	0,52	0,38	0,38	0,36	0,56	0,49	0,60	0,55	0,22	0,35
2008	0,19	0,37	0,29	0,32	0,51	0,32	0,38	0,08	0,44	0,35	0,27	0,38	0,44	0,66	0,45	0,59	0,22	0,38
2009	0,20	0,43	0,20	0,31	0,52	0,32	0,43	0,02	0,50	0,51	0,26	0,54	0,54	0,51	0,43	0,62	0,15	0,35
2010	0,20	0,40	0,16	0,22	0,49	0,32	0,37	0,02	0,38	0,42	0,32	0,44	0,55	0,54	0,56	0,57	0,27	0,34
2011	0,20	0,29	0,26	0,27	0,51	0,41	0,38	0,02	0,44	0,44	0,33	0,45	0,47	0,71	0,31	0,55	0,31	0,36
2012	0,21	0,37	0,11	0,22	0,41	0,21	0,33	0,02	0,41	0,34	0,10	0,36	0,38	0,46	0,48	0,52	0,24	0,44
2013	0,18	0,21	0,22	0,25	0,38	0,56	0,31	0,02	0,42	0,43	0,23	0,37	0,30	0,66	0,44	0,43	0,25	0,53
2014	0,41	0,25	0,22	0,24	0,40	0,26	0,38	0,04	0,41	0,22	0,36	0,38	0,36	0,52	0,40	0,17	0,22	0,58
2015	0,38	0,24	0,30	0,17	0,30	0,41	0,40	0,04	0,42	0,25	0,24	0,43	0,33	0,54	0,41	0,38	0,24	0,42
2016	0,33	0,32	0,44	0,19	0,25	0,34	0,46	0,04	0,42	0,11	0,20	0,40	0,35	0,49	0,27	0,35	0,23	0,33
2017	0,35	0,33	0,37	0,17	0,32	0,37	0,45	0,04	0,42	0,16	0,22	0,30	0,34	0,52	0,34	0,38	0,23	0,25
2018	0,35	0,33	0,37	0,17	0,32	0,37	0,45	0,04	0,42	0,16	0,22	0,30	0,34	0,52	0,34	0,38	0,23	0,25
2019	0,35	0,33	0,37	0,17	0,32	0,37	0,45	0,05	0,42	0,16	0,22	0,30	0,34	0,52	0,34	0,38	0,23	0,25

Risky credit: Proportion of loans with **DSTI ratio** > **40%**:

year	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	0,05	0,05	0,26	0,05	0,10	0,14	0,04	0,14	0,07	0,09	0,10	0,10	0,09	0,08	0,21	0,11	0,17	0,16
2001	0,08	0,08	0,17	0,02	0,15	0,17	0,08	0,14	0,15	0,12	0,04	0,10	0,09	0,10	0,07	0,11	0,19	0,21
2002	0,02	0,03	0,38	0,05	0,18	0,13	0,10	0,14	0,12	0,07	0,05	0,09	0,09	0,05	0,09	0,09	0,17	0,17
2003	0,04	0,07	0,36	0,07	0,13	0,16	0,08	0,14	0,16	0,10	0,08	0,03	0,09	0,08	0,06	0,07	0,17	0,04
2004	0,03	0,05	0,33	0,05	0,15	0,12	0,10	0,14	0,19	0,09	0,11	0,04	0,08	0,10	0,04	0,08	0,24	0,18
2005	0,01	0,10	0,40	0,03	0,19	0,19	0,08	0,14	0,14	0,13	0,07	0,11	0,10	0,08	0,05	0,11	0,20	0,17
2006	0,06	0,07	0,37	0,07	0,11	0,18	0,09	0,14	0,12	0,12	0,09	0,15	0,07	0,07	0,05	0,11	0,17	0,11
2007	0,14	0,09	0,39	0,07	0,09	0,15	0,10	0,14	0,14	0,10	0,10	0,06	0,08	0,07	0,11	0,09	0,13	0,07
2008	0,06	0,07	0,42	0,07	0,14	0,15	0,10	0,08	0,21	0,12	0,14	0,13	0,08	0,11	0,11	0,11	0,09	0,14
2009	0,05	0,08	0,47	0,05	0,13	0,08	0,08	0,02	0,18	0,12	0,09	0,03	0,11	0,13	0,12	0,07	0,09	0,07
2010	0,13	0,05	0,36	0,04	0,05	0,16	0,09	0,02	0,19	0,10	0,11	0,08	0,14	0,10	0,07	0,11	0,20	0,04
2011	0,18	0,07	0,45	0,05	0,05	0,12	0,08	0,02	0,30	0,07	0,09	0,10	0,07	0,08	0,10	0,12	0,17	0,09
2012	0,02	0,09	0,50	0,04	0,02	0,26	0,11	0,02	0,15	0,05	0,07	0,16	0,07	0,11	0,12	0,12	0,13	0,05
2013	0,03	0,04	0,47	0,07	0,02	0,35	0,10	0,02	0,17	0,13	0,07	0,07	0,07	0,10	0,14	0,09	0,17	0,08
2014	0,03	0,06	0,45	0,04	0,05	0,04	0,09	0,04	0,17	0,09	0,03	0,11	0,09	0,09	0,16	0,09	0,18	0,06
2015	0,06	0,06	0,33	0,05	0,03	0,20	0,10	0,04	0,17	0,03	0,12	0,08	0,09	0,10	0,06	0,09	0,17	0,09
2016	0,09	0,05	0,48	0,07	0,04	0,12	0,10	0,04	0,17	0,07	0,22	0,12	0,09	0,15	0,13	0,08	0,18	0,04
2017	0,07	0,05	0,41	0,10	0,04	0,16	0,09	0,04	0,17	0,07	0,17	0,12	0,08	0,31	0,10	0,08	0,18	0,04
2018	0,07	0,05	0,41	0,10	0,04	0,16	0,09	0,04	0,17	0,07	0,17	0,12	0,08	0,31	0,10	0,08	0,18	0,04
2019	0,07	0,05	0,41	0,10	0,04	0,16	0,09	0,05	0,17	0,07	0,17	0,12	0,08	0,31	0,10	0,08	0,18	0,04

Risky credit: Proportion of loans with **LTI ratio** > **3**:

year	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
2000	0,17	0,05	0,33	0,08	0,12	0,19	0,07	0,14	0,16	0,17	0,09	0,15	0,19	0,41	0,14	0,29	0,15	0,32
2001	0,17	0,09	0,20	0,12	0,21	0,23	0,09	0,14	0,22	0,15	0,08	0,15	0,19	0,43	0,07	0,34	0,14	0,14
2002	0,11	0,08	0,47	0,21	0,32	0,31	0,09	0,14	0,14	0,13	0,10	0,16	0,19	0,34	0,04	0,33	0,17	0,06
2003	0,08	0,07	0,49	0,21	0,27	0,35	0,10	0,14	0,26	0,14	0,15	0,08	0,19	0,39	0,06	0,34	0,14	0,12
2004	0,19	0,12	0,46	0,17	0,28	0,38	0,17	0,14	0,26	0,26	0,11	0,18	0,19	0,44	0,07	0,44	0,12	0,30
2005	0,20	0,18	0,48	0,13	0,31	0,55	0,20	0,14	0,39	0,31	0,16	0,30	0,19	0,45	0,09	0,49	0,19	0,17
2006	0,21	0,20	0,52	0,19	0,32	0,53	0,23	0,14	0,41	0,39	0,35	0,35	0,11	0,48	0,11	0,56	0,14	0,19
2007	0,23	0,19	0,54	0,23	0,28	0,51	0,27	0,14	0,45	0,40	0,23	0,32	0,16	0,42	0,24	0,51	0,13	0,22
2008	0,23	0,20	0,63	0,20	0,29	0,50	0,27	0,08	0,50	0,39	0,27	0,37	0,21	0,56	0,21	0,55	0,13	0,32
2009	0,24	0,23	0,61	0,17	0,21	0,52	0,31	0,02	0,50	0,44	0,37	0,45	0,22	0,59	0,18	0,60	0,15	0,20
2010	0,33	0,21	0,57	0,14	0,18	0,61	0,27	0,02	0,31	0,38	0,34	0,46	0,14	0,44	0,16	0,58	0,20	0,21
2011	0,39	0,19	0,61	0,12	0,08	0,56	0,32	0,02	0,20	0,32	0,27	0,56	0,13	0,53	0,18	0,56	0,24	0,23
2012	0,38	0,23	0,57	0,17	0,08	0,60	0,32	0,02	0,38	0,23	0,25	0,55	0,03	0,48	0,21	0,51	0,21	0,16
2013	0,30	0,26	0,74	0,21	0,06	0,50	0,29	0,02	0,17	0,25	0,27	0,51	0,04	0,42	0,21	0,51	0,25	0,35
2014	0,49	0,28	0,79	0,20	0,07	0,40	0,32	0,04	0,20	0,19	0,27	0,48	0,14	0,47	0,15	0,39	0,23	0,23
2015	0,19	0,28	0,43	0,24	0,08	0,45	0,28	0,04	0,18	0,19	0,16	0,54	0,10	0,42	0,19	0,42	0,24	0,25
2016	0,35	0,35	0,60	0,21	0,15	0,43	0,33	0,04	0,19	0,26	0,49	0,52	0,06	0,62	0,17	0,46	0,23	0,34
2017	0,27	0,28	0,51	0,25	0,24	0,44	0,42	0,04	0,19	0,27	0,32	0,56	0,17	0,66	0,18	0,50	0,24	0,40
2018	0,27	0,28	0,51	0,25	0,24	0,44	0,42	0,04	0,19	0,27	0,32	0,56	0,17	0,66	0,18	0,50	0,24	0,40
2019	0,27	0,28	0,51	0,25	0,24	0,44	0,42	0,05	0,19	0,27	0,32	0,56	0,17	0,66	0,18	0,50	0,24	0,40

Appendix 4C. GVAR Weight matrices

Figure 4C.1 shows the weight matrices used in the construction of the GVAR foreign variables: the baseline and alternative for credit variables, and the trade-based one for GDP weighting.

Weight matrix: Based on FSC (2020)

	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
AT		0,00	0,06	0,06	0,00	0,02	0,02	0,01	0,03	0,02	0,01	0,01	0,05	0,03	0,04	0,00	0,33	0,46
BE	0,02		0,00	0,06	0,00	0,06	0,13	0,05	0,03	0,12	0,06	0,03	0,06	0,13	0,01	0,04	0,02	0,15
CY	0,00	0,00		0,01	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DE	0,27	0,06	0,14		0,32	0,23	0,33	0,17	0,24	0,21	0,16	0,21	0,33	0,33	0,24	0,07	0,05	0,04
EE	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13	0,00	0,00	0,00	0,00	0,00
ES	0,02	0,01	0,00	0,08	0,03		0,16	0,40	0,05	0,05	0,09	0,03	0,00	0,07	0,21	0,74	0,00	0,00
FR	0,06	0,53	0,07	0,25	0,15	0,28		0,17	0,30	0,19	0,61	0,58	0,01	0,29	0,22	0,11	0,23	0,03
GB	0,00	0,00	0,00	0,00	0,00	0,00	0,06		0,00	0,31	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
GR	0,00	0,00	0,47	0,00	0,00	0,00	0,00	0,01		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IE	0,01	0,01	0,01	0,02	0,00	0,02	0,04	0,07	0,05		0,00	0,01	0,00	0,05	0,00	0,00	0,03	0,01
IT	0,54	0,02	0,10	0,25	0,12	0,18	0,09	0,04	0,16	0,03		0,05	0,29	0,07	0,02	0,01	0,34	0,29
LU	0,01	0,01	0,01	0,01	0,03	0,01	0,02	0,01	0,00	0,01	0,00		0,01	0,02	0,01	0,00	0,00	0,00
LV	0,00	0,00	0,01	0,00	0,32	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00
NL	0,07	0,36	0,12	0,25	0,03	0,15	0,13	0,07	0,08	0,07	0,06	0,09	0,08		0,16	0,02	0,00	0,02
PL	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00
PT	0,00	0,00	0,00	0,00	0,00	0,05	0,01	0,00	0,03	0,00	0,01	0,00	0,01	0,01	0,09		0,00	0,00
SI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04	0,00	0,00	0,00		0,00
SK	0,00	0,00	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	

Weight matrix: Alternative based on Cantone, Wildmann and Rancoita (2020)

	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
AT		0,02	0,08	0,09	0,00	0,02	0,02	0,01	0,00	0,02	0,02	0,01	0,06	0,03	0,06	0,01	0,56	0,10
BE	0,05		0,00	0,08	0,00	0,08	0,06	0,06	0,03	0,01	0,06	0,04	0,05	0,14	0,06	0,11	0,05	0,04
CY	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DE	0,55	0,20	0,19		0,21	0,17	0,33	0,25	0,24	0,22	0,21	0,18	0,32	0,32	0,28	0,18	0,15	0,16
EE	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13	0,00	0,00	0,00	0,00	0,00
ES	0,02	0,02	0,00	0,05	0,03		0,13	0,24	0,03	0,04	0,13	0,02	0,00	0,05	0,11	0,37	0,00	0,02
FR	0,14	0,38	0,09	0,38	0,21	0,28		0,17	0,32	0,25	0,45	0,61	0,02	0,32	0,14	0,20	0,04	0,13
GB	0,05	0,10	0,00	0,16	0,00	0,00	0,16		0,00	0,35	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00
GR	0,00	0,00	0,34	0,00	0,00	0,00	0,00	0,01		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IE	0,02	0,03	0,01	0,04	0,03	0,03	0,04	0,10	0,08		0,01	0,01	0,00	0,05	0,00	0,01	0,10	0,02
IT	0,03	0,04	0,11	0,07	0,16	0,20	0,09	0,05	0,16	0,02		0,05	0,28	0,06	0,13	0,04	0,08	0,43
LU	0,01	0,03	0,01	0,01	0,00	0,01	0,03	0,01	0,00	0,01	0,00		0,01	0,02	0,00	0,01	0,01	0,02
LV	0,00	0,00	0,01	0,00	0,32	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00
NL	0,13	0,18	0,14	0,11	0,05	0,18	0,13	0,09	0,08	0,08	0,10	0,07	0,07		0,16	0,06	0,01	0,07
PL	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00	0,00
PT	0,00	0,01	0,00	0,00	0,00	0,04	0,01	0,01	0,05	0,00	0,02	0,00	0,02	0,01	0,06		0,00	0,00
SI	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04	0,00	0,00	0,00		0,01
SK	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	

Weight matrix: Traditional using IMF DOTS trade weights

	AT	BE	CY	DE	EE	ES	FR	GB	GR	IE	IT	LU	LV	NL	PL	PT	SI	SK
AT		0,01	0,01	0,09	0,02	0,01	0,02	0,02	0,02	0,01	0,05	0,02	0,02	0,02	0,04	0,01	0,15	0,13
BE	0,03		0,04	0,10	0,05	0,06	0,14	0,10	0,05	0,15	0,08	0,27	0,04	0,18	0,05	0,04	0,03	0,03
CY	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DE	0,56	0,24	0,10		0,22	0,22	0,27	0,26	0,22	0,19	0,28	0,31	0,21	0,39	0,46	0,19	0,31	0,38
EE	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,22	0,00	0,00	0,00	0,00	0,00
ES	0,02	0,04	0,06	0,06	0,03		0,13	0,07	0,10	0,04	0,10	0,03	0,03	0,04	0,05	0,37	0,04	0,03
FR	0,05	0,20	0,04	0,15	0,07	0,23		0,13	0,10	0,08	0,19	0,16	0,05	0,10	0,08	0,15	0,08	0,09
GB	0,03	0,09	0,10	0,10	0,05	0,09	0,09		0,06	0,32	0,08	0,03	0,10	0,12	0,07	0,06	0,02	0,05
GR	0,00	0,00	0,33	0,01	0,00	0,01	0,01	0,01		0,01	0,02	0,00	0,00	0,01	0,00	0,00	0,02	0,00
IE	0,00	0,04	0,01	0,02	0,00	0,01	0,03	0,09	0,02		0,01	0,01	0,01	0,02	0,01	0,01	0,00	0,00
IT	0,10	0,07	0,16	0,11	0,05	0,13	0,13	0,08	0,20	0,05		0,04	0,05	0,06	0,08	0,07	0,20	0,07
LU	0,00	0,02	0,00	0,01	0,00	0,00	0,01	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,00
LV	0,00	0,00	0,01	0,00	0,25	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,01	0,00	0,00	0,00
NL	0,06	0,24	0,08	0,19	0,11	0,08	0,11	0,17	0,10	0,12	0,08	0,09	0,09		0,09	0,07	0,05	0,04
PL	0,05	0,03	0,03	0,11	0,12	0,03	0,04	0,04	0,04	0,02	0,05	0,03	0,15	0,04		0,02	0,06	0,14
PT	0,00	0,01	0,01	0,01	0,01	0,11	0,02	0,01	0,01	0,01	0,02	0,01	0,01	0,01	0,01		0,01	0,01
SI	0,03	0,00	0,01	0,01	0,01	0,00	0,00	0,00	0,01	0,00	0,02	0,00	0,00	0,00	0,01	0,00		0,02
SK	0,06	0,00	0,01	0,03	0,01	0,01	0,01	0,01	0,01	0,00	0,01	0,01	0,02	0,01	0,04	0,01	0,04	

Figure 4C.1: Weight matrices for the GVAR foreign variables.

In order to verify the consistency between the baseline and alternative weighting for credit variables and to illustrate the considerable divergence with respect to the traditional trade-based matrix, we provide country (i.e. row) correlations in Figure 4C.2.

	AT	BE	CY	DE	EE	ES	FR	GB	GR
r (TFSE,Cantone et al.)	0,421	0,893	0,963	0,666	0,944	0,981	0,933	0,908	0,989
r (TFSE,Trade)	0,515	0,743	0,908	0,778	0,858	0,914	0,962	0,513	0,777
r (Cantone et al.,Trade)	0,956	0,872	0,859	0,672	0,782	0,855	0,921	0,800	0,721

	IE	IT	LU	LV	NL	PL	PT	SI	SK
r (TFSE,Cantone et al.)	0,954	0,969	0,998	0,999	0,995	0,861	0,873	0,669	0,586
r (TFSE,Trade)	0,937	0,676	0,519	0,547	0,821	0,630	0,887	0,579	0,230
r (Cantone et al.,Trade)	0,841	0,802	0,495	0,548	0,781	0,848	0,967	0,495	0,397

Figure 4C.2: Weight matrices: Correlation coefficients for countries.

Appendix 4D. Data sources

The time series for GDP and total credit are originally extracted from the IMF's International Financial Statistics and the BIS's Credit Statistics, respectively, as shown in Table 4D.1:

Country	**GDP**	**Total credit to households**
AT	IMF/IFS/Q.AT.NGDP_R_K_SA_IX	BIS/total_credit/Q.AT.H.A.M.USD.A
BE	IMF/IFS/Q.BE.NGDP_R_K_SA_IX	BIS/total_credit/Q.BE.H.A.M.USD.A
CY	IMF/IFS/Q.CY.NGDP_R_K_SA_IX	Directly from National Bank of Cyprus
DE	IMF/IFS/Q.DE.NGDP_R_K_SA_IX	BIS/total_credit/Q.DE.H.A.M.USD.A
EE	IMF/IFS/Q.EE.NGDP_R_K_SA_IX	Directly from Eesti Pank
ES	IMF/IFS/Q.ES.NGDP_R_K_SA_IX	BIS/total_credit/Q.ES.H.A.M.USD.A
FR	IMF/IFS/Q.FR.NGDP_R_K_SA_IX	BIS/total_credit/Q.FR.H.A.M.USD.A
GB	Directly from ONS: YBEZ	BIS/total_credit/Q.GB.H.A.M.USD.A
GR	IMF/IFS/Q.GR.NGDP_R_K_SA_IX	BIS/total_credit/Q.GR.H.A.M.USD.A
IE	IMF/IFS/Q.IE.NGDP_R_K_SA_IX	BIS/total_credit/Q.IE.H.A.M.USD.A
IT	IMF/IFS/Q.IT.NGDP_R_K_SA_IX	BIS/total_credit/Q.IT.H.A.M.USD.A
LU	IMF/IFS/Q.LU.NGDP_R_K_SA_IX	BIS/total_credit/Q.LU.H.A.M.USD.A
LV	IMF/IFS/Q.LV.NGDP_R_K_SA_IX	Directly from Latvijas Bankas
NL	IMF/IFS/Q.NL.NGDP_R_K_SA_IX	BIS/total_credit/Q.NL.H.A.M.USD.A
PL	IMF/IFS/Q.PL.NGDP_R_K_SA_IX	BIS/total_credit/Q.PL.H.A.M.USD.A
PT	IMF/IFS/Q.PT.NGDP_R_K_SA_IX	BIS/total_credit/Q.PT.H.A.M.USD.A
SI	IMF/IFS/Q.SI.NGDP_R_K_SA_IX	Directly from Banka Slovenije
SK	IMF/IFS/Q.SK.NGDP_R_K_NSA_IX	Directly from Narodna Banka Slovensko

Note: Values for IE until 2001Q4 are extrapolated using the BIS series for bank credit to non-financial private sector.

Table 4D.1: GDP and credit time series mnemonics.

As detailed in Section 4.3, We extract LTV data from the HFCS at loan level and use the information to create shares of "risky" and "conservative" credit by country and year. However, given that we use *mortgage* data from a *household* survey, we multiply aggregate household credit values from the BIS to account by the ratio of mortgage loans to total household loans. For that purpose, we resort to the ECB's CBD2 dataset, available through the Statistical Data Warehouse; we compute the average ratios for the period 2018Q1-2019Q3.

Country	**Mortgage loans to Households**
AT	CBD2.Q.AT.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
BE	CBD2.Q.BE.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
CY	CBD2.Q.CY.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
DE	CBD2.Q.DE.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
EE	CBD2.Q.EE.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
ES*	CBD2.Q.ES.W0.67._Z._Z.A.F.A1135._X.ALL.CA._Z.LE._T.EUR
FR	CBD2.Q.FR.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
GB*	CBD2.Q.GB.W0.67._Z._Z.A.F.A1135._X.ALL.CA._Z.LE._T.EUR
GR	CBD2.Q.GR.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
IE*	CBD2.Q.IE.W0.67._Z._Z.A.F.A1135._X.ALL.CA._Z.LE._T.EUR
IT	CBD2.Q.IT.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
LU	CBD2.Q.LU.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
LV	CBD2.Q.LV.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
NL	CBD2.Q.NL.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
PL	CBD2.Q.PL.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
PT	CBD2.Q.PT.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
SI	CBD2.Q.SI.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR
SK	CBD2.Q.SK.W0.67.S1M._Z.A.F.A1131._X.ALL.CA._Z.LE._T.EUR

Note: For countries marked with (*), loans for house purchase were used due to data availability.

Table 4D.2: Mortgage-to-total loans ratios: Numerator.

Country	**Total loans to Households**
AT	CBD2.Q.AT.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
BE	CBD2.Q.BE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
CY	CBD2.Q.CY.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
DE	CBD2.Q.DE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
EE	CBD2.Q.EE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
ES	CBD2.Q.ES.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
FR	CBD2.Q.FR.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
GB	CBD2.Q.GB.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
GR	CBD2.Q.GR.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
IE	CBD2.Q.IE.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
IT	CBD2.Q.IT.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
LU	CBD2.Q.LU.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
LV	CBD2.Q.LV.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
NL	CBD2.Q.NL.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
PL	CBD2.Q.PL.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
PT	CBD2.Q.PT.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
SI	CBD2.Q.SI.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR
SK	CBD2.Q.SK.W0.67.S1M._Z.A.F.A1100._X.ALL.CA._Z.LE._T.EUR

Table 4D.3: Mortgage-to-total loans ratios: Denominator.

Chapter 5

Conclusions

This thesis aims to analyse the functioning and impact of certain types of macroprudential measures directed to preserve financial stability: On one hand, actions conceived to curtail the access of certain types of borrowers to the mortgage market; on the other, the implementation of accounting standards embedding the provisioning of *expected* loan losses. Both approaches are deeply intertwined due to the prominent role that housing -or more generally, immovable property- plays in the balance sheets of both contracting parties. For the non-financial sector, it constitutes the main purpose of large mortgage loans while being the most common kind of collateral. From the standpoint of financial institutions, housing mortgages make up for a non-negligible, usually very large share of loans to households and firms. Beyond the balance sheet, nevertheless, borrower-based macroprudential measures have much deeper implications for borrowers and lenders.

From the borrowers' side, imposing caps on the loan-to-value (LTV) or other similar ratios on mortgages ultimately determines the access to financing for house purchase: the results in this thesis show that the number and volume of loans contracted decreases following the application of these limits. Moreover, the distribution of house prices across properties is also altered. More broadly, the second-round effects of such measures are potentially sizeable: Firstly, because they might stress the dichotomy between rental and homeownership, which in turn affects the intertemporal consumption and investment decisions of households; secondly, because access to housing is strongly linked to inequality, although the latter nexus is not explored in this dissertation.

From the lenders' side, the variation -usually reduction- of credit to the non-financial sector associated to the phasing-in of a borrower-based measure can have ambiguous effects: While the profit and loss account might be hampered, e.g. through lower net fee and commission income (NFCI), the introduction of LTV limits and alike reduces the volume of loans with traditionally higher probability of default (PD) or those for which the loss given default (LGD) is larger, with a positive effect on credit risk. In order to disentangle these effects in a more accurate fashion, the distinction between "risky" and "conservative" credit becomes fundamental: the results in the second paper of this thesis show that a contraction in the two types of lending can have opposite effects.

In a more international perspective, the increasing linkages between financial institutions across the globe -for instance, through branches and subsidiaries- entail that domestically implemented macroprudential measures might feed onto other countries and generate undesirable spillovers. In order to prevent policy leakages, where possible, or to isolate them and internalize them in a consistent fashion, regulatory coordination between prudential authorities is of the utmost importance. Furthermore, data integrity and broad availability also allow policymakers and scholars to better gauge the depth of spillovers and their control.

All in all, the results in this dissertation stress the need for careful fine-tuning and implementation of macroprudential measures directed towards borrowers or with a straightforward impact on the latter, as a means to guarantee that no tradeoff arises between financial stability and fairness, whether geographical, social or economic.

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