A Thesis submitted for the degree of Doctor of Philosophy in Economics

Essays on empirical macroeconomics

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Abstract

Motivated by the desire to inform macroeconomic policy-makers in order to make decisions, this dissertation consists of a compilation of three essays devoted to three different economic questions using three diverse econometric methods. In particular, Chapter 1 proposes a Markov-switching model to estimate the probability of being in a state characterized by a *housing boom fueled by credit* (HBFC), that is a housing boom not justified by fundamentals, but by a credit boom. I do so to better enable policy makers to understand the state of the housing sector in order to potentially prevent the appearance of a housing bubble financed by credit, a well known source of macroeconomic instability. Estimated with US data, such model proved consistency in identifying HBFC preceding housing bubbles as estimated in the literature. Chapter 2 is devoted to a thick modeling tool to forecast residential investment. Housing investment is known to be an important leading indicator of economic activity, so its forecast seems key for policymaking. Estimated with euro area (EA) and EA largest five countries data, this tool proved successful in beating benchmark models, while also highlighting the importance of including building permits in housing investment models. Finally, Chapter 3 estimates the effects of monetary policy shocks to subcomponents of GDP and other key macroeconomic variables in the euro area. Additionally we evaluate whether such effects have changed in the last two decades. To perform such analysis we use an extended version of the SVAR model of Jarocinski and Karadi (2020) and a Proxy-SVAR model. I find that purely monetary policy shocks have significantly negative effects on consumption, housing and business investment, having the largest impact on the latter. By contrast, the effects on prices are quite modest, consistent with the literature. Finally, our evidence suggest that the effects of purely monetary policy shocks have changed over time in the euro area. In particular, while during the 2000s the effects are the conventional contractionary ones, during the 2010s it seems that the capacity of the ECB to affect economic variables such as business and housing investment and unemployment has been critically weakened.

1 Housing booms fueled by credit

The aim of this paper is to empirically identify housing booms not justified by fundamentals, but by a credit boom. The current literature on housing overvaluation has focused on identifying explosive behaviors in house prices, i.e. bubbles, neglecting the importance of the coexistence with credit booms and the fact that such detection does not allow for macroprudential policy, shortcomings that this paper addresses by using a regime-switching model. The research question is when is the economy in a state that combines a housing boom not justified by fundamentals, but fueled by a credit boom. I do so to better enable policy makers to understand the state of the housing sector in order to potentially prevent the appearance of a housing bubble financed by credit, a well known source of macroeconomic instability. Applying a three states Markov switching model to the case of the US from 1984 to 2019, I identify four episodes of *housing booms fueled by credit*. First, one in the late 80s, from January 1986 to February 1987. Second, in the preceding boom before the Great Recession, from February 2000 to February 2006, before the detection of a rational bubble by other authors using alternative methods. Third, a short booming period in the late 2009. Fourth, a discontinuous span from March 2012 to May 2018. The significance of this study is that it informs policy makers about the risk of an overvaluation in housing prices fueled by credit without requiring explosive price behavior, i.e. before a housing bubble might appear, therefore allowing policy makers to implement truly macroprudential policy in a timely manner.

Keywords: Housing prices, non-linear modeling, Markov switching model, housing demand, household debt.

JEL Classification: C22, C24, G51, R21, R31.

1.1 Introduction

The recent Great Recession and the related literature on the financial interlinkages between housing and credit made clear that what makes a housing boom economically dangerous is being financed by a credit boom. As many economists acknowledge, bubbles with leverage have emerged as a threatening phenomenon able to critically increase macroeconomic and financial risks. In this context, trying to identify housing bubbles has become a standard target in the literature. However, a bubble identification can not prevent their appearance, therefore it would come always late. This is one key limitation that policymakers still face, because identifying housing bubbles after the fact do not allow for macroprudential policy, but just *mitigating policy*.

Consequently, this paper does not try to find bubbles explicitly but identifying the state of the economy in which macroeconomic risks coming from the housing sector might be building up due to a housing boom financed by credit. In this way, it may be truly possible for policymakers to have enough time to evaluate the housing markets, identify the sources of overvaluation, analyze possible economic policy and implement it. This approach may be more useful in macroprudential terms than finding bubbles itself, which is necessary but insufficient for a *real time policy-maker*.

This paper addresses this issue by estimating a three states Markov switching model in which housing prices are explained by standard demand fundamentals plus mortgage debt, which is the state-dependent variable that drives the transitions between each state. This approach exploits two empirical findings. First, the crucial role of credit in driving housing prices during booms (Kindleberger, 1978 and Geanakoplos, 2009, *inter alia*). Second, indirectly exploits the *momentum* observed in housing prices (Guren, 2014; Glaeser and Nathanson, 2017), as the formation of excessive price growth expectations requires some past positive dynamics, which may be identified before becoming a rational bubble. Therefore, identifying housing booms fueled by credit should be a previous step before identifying housing bubbles, which in turn may be a crucial improvement from a macroprudential point of view.

In the empirical literature about housing overvaluation the point of interest is typically the identification of rational bubbles, i.e. finding periods of time in which asset prices deviate from fundamentals, in such a way that asset prices are thought to be driven only by price expectations. This analysis has its roots on applications in the stock market and has some empirical challenges (see Gürkaynak, 2008), however recently there seems to be an agreement among academics and central bankers on this issue by means of detecting mildly explosive behaviors in time series of asset prices. In spite of the importance of these tools, they are not enough to avoid bubbles for at least three reasons. First, they typically test a price-fundamental ratio that may leave aside other important housing fundamentals. Second, they do not take into account credit. Third, even if bubbles are correctly identified, their identification can't avoid their appearance. That is, in terms of macroprudential policy, for such identification to be useful it has to arrive before the fact.

The contributions of this study are the following. First, it provides a tool for the identification of states characterized by housing booms not justified by standard fundamentals, but by mortgage debt. Second, for doing so I use a non-linear approach that has not been exploited yet for that particular purpose. Third, by providing an application of such methodology to the housing sector in the US from 1984 to 2019, I show that the identification of housing booms fueled by credit are previous than rational bubbles, and therefore they give more time to policymakers to implement the macroprudential policy that may prevent the appearance of bubbles.

Related literature. This paper relates to several strands of literature. Empirically, this analysis is complementary to the studies that target the identification of rational bubbles in housing prices. After decades of debate among economists in order to find a tool to identify rational bubbles[1], it seems to be a certain degree of agreement in the profession by means of the mildly explosive behavior tests introduced by Phillips, Wu and Yu (2011) and extended afterwards[2]. Despite the limitations of this tool[3], it is used to identify asset price bubbles in different environments, including the housing market. However, in spite of the importance of this family of tests, they provide a warning signal that ideally arrives when the bubble is already in place, i.e. not allowing macroprudential policy to avoid such bubble.

The papers that use mildly explosive behavior tests applied to the US housing sector are Phillips and Yu (2011), Martínez-García, Pavlidis, Yusupova, Paya, Peel, Mack and Grossman (2016), the *Exuberance Indicators* reported by the Dallas Fed in their website[4] and Shi (2017), which are briefly summarized in Table 1.1. The first three are methodologically quite homogeneous, as they test for mildly explosive behavior in price-fundamental ratios, while Shi (2017) tests an estimate of the non-fundamental component of such ratios. Despite the methodological differences, I use the results of these tests as a benchmark to measure the capacity of the Markov switching model described in this paper to precede the identification of housing bubbles.

Table 1.1: Tests of mildly explosive behavior in the US housing literature.

	PY (2011)	Martínez-García et al. (2016)		Dallas Fed	Shi (2017)
Sample size	1990:M1 - 2009:M1	1985:Q1 - 2013:Q2		1981:Q3 - 2019:Q2	1978:H1 - 2015:H2
Frequency	Monthly	Quarterly	Quarterly	Quarterly	Semiannually
Tested variable	HP/R ratio	HP/R ratio	HP/I ratio	HP/I ratio	HP/R ratio Residual
Price index	S&P C–S C-10	FHFA	FHFA	FHFA	FHFA
Fundamental(s)	Rents (LILP)	Rents (OECD)	Income (PDIPC)	Income (PDIPC)	Rents (BLS) Interest rates Income Population Employment Housing supply
SADF test	2002:M2 - 2007:M12			2002:Q3 - 2006:Q4	
GSADF test		2000:Q2 - 2006:Q2	2003:Q4 - 2006:Q4		2004:H1 - 2005:H2*

Notes: Dallas Fed stands for the *Exuberance Indicators* published by the Federal Reserve Bank of Dallas in their website, that employs the methods explained by Martínez-García, Pavlidis, Yusupova, Paya, Peel, Mack and Grossman (2016), which builds on Phillips, Wu and Yu (2011) and Phillips, Shi and Yu (2015). To this regard, exuberance signals of lower or equal lengths than 2 periods (that is, the log of their sample size, 152 observations, specifically, 2.18) are not reported. S&P C–S C-10 stands for the S&P Case–Shiller Composite-10 index, which Phillips and Yu (2011) use as a house price index. LILP means Lincoln Institute of Land Policy, the source of Phillips and Yu (2011) for rents, after which they subtract estimated utilities expenses following Davis, Lehnert, and Martin (2008) and interpolate linearly to a monthly frequency. OECD stands for Organisation for Economic Co-operation and Development. PDIPC is the NIPA Real personal disposable income per capita. FHFA stands for Nationwide house price index for existing single-family houses, issued by the US Federal Housing Finance Agency. The SADF is the supremum ADF test proposed by Phillips and Yu (2011), while the GSADF is the Generalized SADF test implemented by Phillips, Shi and Yu (2015). H1 and H2 mean first and second semester, respectively. Shi (2017) identifies mildly explosive behavior from 2004:H1 to 2005:H2 when testing for the residual component, instead from 1998:H2 to 2007:H2 when testing for the price to rent ratio.

[1] See Himmelberg, Mayer and Sinai (2005), Gürkaynak (2008), Homm and Breitung (2012) and Davis and Van Nieuwerburgh (2015) for surveys.

[2] Phillips, Wu and Yu (2011) is extended by Phillips and Yu (2011), Phillips and Shi (2014), Phillips, Shi and Yu (2015) and Phillips and Shi (2018).

[3] Two important limitations of this approach are the following. First, it tests a price-fundamental ratio, therefore leaving some important fundamental aside is always possible. Second, in the particular case of housing, not including mortgage credit may be an important exclusion.

[4] See the International House Price Database of the Dallas Fed at https://www.dallasfed.org/institute/houseprice.aspx.

Second, this paper is also related to the empirical studies that analyze the effect of credit growth on house prices and on the economy after a burst. The results of papers pointing out to the crucial role of credit in driving upwards housing prices are fundamental in this paper[5], as credit is essential in the design of the Markov switching model that is presented in subsection 1.3.5. On the other hand, the studies that find excessive debt as a key risk factor for the economy[6] greatly justify the approach taken in this paper implying that it is of interest from a macroprudential point of view.

In particular, the channels through which credit affects housing and the aggregate economy are reportedly numerous, powerful and potentially damaging. First, the credit conditions at which financial institutions provide finance to homebuyers generate strong effects on housing prices (see e.g., Adelino, Schoar and Severino, 2012 and Greenwald, 2017). Second, the role of houses as a collateral is much larger than the one assumed in earlier standard literature focusing on information asymmetries or limited contract enforcement. Indeed, past house appreciation is positively related to the supply of mortgage credit, generating additional overshooting in housing purchasing power (see Dell'Ariccia, Igan and Laeven, 2008; Geanakoplos, 2009 and Adrian and Shin, 2010). Other channels by which the collateral has amplification effects is by using mortgage refinancing and equity extraction (Bhutta and Keys, 2016). Third, an adaptive price expectation mechanism employed by the housing demand overshoots the behavior of prices beyond fundamentals, where different authors estimate this mechanism as being best explained by roughly four years of past housing price growth (see Duca, Muellbauer and Murphy, 2012 and Muellbauer, 2012). While some theorists model this expectation formation as homebuyers making small errors in managing information from past prices (Glaeser and Nathanson, 2017), others provide a foundation based on social contagion by which optimistic agents convince less optimistic ones to change their beliefs (see Burnside, Eichenbaum and Rebelo, 2016). Fourth, financial innovations have a vital role in the housing sector. In particular, credit scoring and securitization foster the financing of new mortgages, inducing an upward shift in credit supply and an easing in lending standards (see e.g., Duca, Muellbauer and Murphy, 2010; Keys, Mukherjee, Seru and Vig 2010 and Maddaloni and Peydró, 2011). Fifth, housing credit cycles can generate both crowding-out and crowding-in effects (Martín, Moral-Benito and Schmitz, 2018). At first, a housing boom is able to attract credit into household mortgages and to real estate and construction firms. At a later stage, it also generates a crowding-in effect by stimulating credit growth in all sectors of the economy.

Finally, this paper also relates to work on macroprudential policy in scenarios of housing and credit booms. Despite the fact that it is still unanswered how to deal with a housing boom fueled by credit[7], what is clear is that for any possible policy to be effective, a policymaker needs time to identify the phenomenon and the sources, evaluate different policies, overcome the expected political obstacles, implement them and wait some time until the policy materializes[8]. Therefore, finding a tool that identifies a housing boom fueled by credit as soon as possible is essential for maximizing the success of a macroprudential policy tool, regardless the chosen device. Thus, this paper is intended to give a clue to macroprudential studies in order to identify the moment

[5]See, e.g., Jordà, Schularick and Taylor (2015) and Cerutti, Dagher and Dell'Ariccia (2015).

[6]The *debt-deflation theory of great depressions* of Fisher (1933) and the *financial instability hypothesis* of Minsky (1986, 1992) are early contributions to this topic. For recent empirical studies see, e.g., Mian and Sufi (2010), Schularick and Taylor (2012), Jordà, Schularick and Taylor (2012).

[7]The inaction of the Federal Reserve and the ECB during the mid-2000s regarding the important increases in house prices and mortgage debt volumes exhibited a policy-making choice based on a *laissez-faire* approach. The argued reasons for that were basically three (see Roubini, 2006). First, the uncertainty regarding the bubble identification. Second, the uncertainty about the negative effects of a bubble on the economy. Third, the possibility that trying to burst a bubble may generate a recession. After the Great Recession, and even if these uncertainties are nowadays much reduced, the policy approach has been mostly focused on the increase in capital requirements for the banking system, while bank leverage and provisioning remain procyclical.

[8]Choi, Kodres and Lu (2018) show that even a set of coordinated macroprudential policies on the housing market of highly interlinked countries take substantial time to materialize.

during a housing boom where it may be justified to intervene for avoiding the appearance of a housing bubble.

The structure of this paper is as follows. In section 1.2 are shown the stylized facts and findings that characterize the housing market developments in the US. Section 1.3 defines the theoretical framework which represents the starting point in the analysis, shows the data and the macroeconometric modeling approach that is used, with a prevalent role for the Markov-Switching model of house prices. Section 1.4 presents the empirical results which include a set of robustness checks in subsection 1.4.6. Finally, section 1.5 concludes.

1.2 Stylized facts and findings on US housing

The following ten points describe certain regularities observed in the US housing sector which are important in this paper both to motivate its target and to define the research choices taken.

Stylized fact 1: Residential investment exhibits higher volatility than GDP and than non-residential investment.

Real residential fixed investment growth exhibits more variability than real GDP growth (0.0345% versus 0.0234%, respectively) and almost twice as volatility than real non-residential fixed investment growth (0.0180%) from 1984 Q1 to 2019 Q2. This regularity is fairly standard in advanced economies (see Kohlscheen, Mehrotra and Mihaljek, 2018).

Stylized fact 2: Residential investment is a leading indicator of economic activity.

Real residential investment growth tends to lead the business cycle by fluctuating before output, therefore becoming an important series in forecasting economic aggregate variables. In particular, residential investment is a key contributor to recessions (Leamer, 2007), a feature that is also reportedly standard in advanced economies (see Kohlscheen, Mehrotra and Mihaljek, 2018).

Stylized facts 1 and 2 together explain why housing is important in macroeconomics, despite the relatively low weight of residential investment to GDP, on average a 4.29% from 1984 Q1 to 2019 Q2.

Stylized fact 3: Housing prices are serially correlated, i.e. exhibit *momentum*.

In the literature of housing markets, the autocorrelation in aggregate housing price time series is referred as the so-called *momentum*, since the pioneering work of Case and Shiller (1989). As Cho (1996) surveys, such feature is robust for different samples and methodologies, also to the sample I use in this paper (see the autocorrelation tests results in Appendix A.2). However, the order of autocorrelation, i.e. the length of momentum I find is lower compared to some authors[9].

The main explanations found for this phenomenon are extrapolative expectations about price appreciation and gradual spread optimism when house prices increase beyond fundamentals (see Burnside, Eichenbaum and Rebelo, 2016). In particular, an average rate of appreciation of 4 years in US housing prices fits well in a model of user costs (Duca, Muellbauer and Murphy, 2011)[10].

Stylized fact 4: House prices changes are negatively correlated with inventory levels, i.e. the so-called *housing Phillips curve*.

House prices changes and housing inventory levels exhibit a strong negative correlation, as observed by many authors. There are different explanations for that relationship, stemming

[9] Guren (2014) finds serial correlation in US house prices for 2 to 3 years, while the results in this paper exhibit about one year of pricing momentum. See the autocorrelation tests results in Appendix A.2

[10] Similar conclusions are found in the literature when analyzing the housing sector of other economies, as the UK (see Cameron, Muellbauer and Murphy, 2006) and France (see Chauvin and Muellbauer, 2013).

from the role of financing constraints (see Stein, 1995), behavioral explanations as a result of sellers' risk aversion (Genesove and Mayer, 2001) and interpretations of the housing market as a search and matching market (see Han and Strange, 2015 for a survey). Despite the different possible natures of this stylized relationship, it is not a modern feature (Korevaar, 2018).

Finding 5: The standard asset pricing model fails to explain housing prices.

The excess volatility of housing prices with respect to fundamentals is a major challenge for economic models. In particular, the standard present value model of asset pricing is unable to explain the large movements that are observed in house prices (see Mayer, 2011 for a survey). In consequence, standard models have been extended with additional features such as expectations formation, liquidity constraints and lending cycles.

Finding 6: Credit supply conditions in the mortgage market are a key housing demand shifter.

The importance of credit supply conditions in the housing market is well established in the literature, along different dimensions. First, the softening of credit conditions for households facilitates the expansion of household leverage (Mian and Sufi, 2009 and Greenwald, 2017). Second, most borrowers tend to determine their housing demand at the top of their loan-to-value (LTV) limit and their monthly debt payment-to-income (PTI) limit, in such a way that such features exercise a crucial amplification mechanism to house prices (Greenwald, 2017; Greenwald and Guren, 2019; Duca, Muellbauer and Murphy, 2011), much along the lines of Geanakoplos (2009). Third, the easing of credit conditions is amplified by securitization and weak supervision for bank capital (Maddaloni and Peydró, 2011).

Finding 7: Housing finance stimulate leverage cycles through the mortgage market.

In the empirical literature it is widely acknowledged the strong relationship between credit and real estate booms. In particular, about two-thirds of the housing booms happen as a result or during periods of fast economic growth and high credit growth (see Cerutti, Dagher and Dell'ariccia, 2015). Importantly, Favara and Imbs (2015) show that it exists a causal link between the exogenous increases in mortgage credit and housing prices, consistent with Geanakoplos (2009)[11], Mian and Sufi (2014b) and Di Maggio and Kermani (2017). Additionally, the home equity–based borrowing channel also plays an important role (see Mian and Sufi, 2011).

Finding 8: Mortgage loans over households' liabilities, banks' assets and GDP are substantial. In consequence, housing leverage is an endogenous source of financial instability and potential economic costs.

After the subprime crisis in the US, the empirical evidence relating leverage, financial instability and economic costs has become sizable (see Mian and Sufi 2009, 2014a, 2018; Geanakoplos, 2009; Schularick and Taylor, 2012; Cerutti, Dagher and Dell'ariccia, 2015; Jordà, Schularick and Taylor, 2015, 2016; Crowe, Dell'Ariccia, Igan and Rabanal, 2013; and Freixas, Laeven and Peydró, 2015, *inter alia*). Indeed, similar considerations are performed by Eichengreen and Mitchener (2003) in their analysis of the Great Depression. The main mechanism to link leverage and the real economy is the bank-lending channel, which propagates financial shocks through the credit supply. The reasons for that are at least four. First, housing represents the largest share over households' liabilities (from 1987 to 2019, on average the 72.1%). Second, housing lending stands for a large fraction over commercial banks' total assets[12]. Third, most of the mortgage debt is collaterallized with the real estate property itself. Fourth, mortgage loans represents a large fraction over GDP in advanced economies[13]. All in all, even if at the times of

[11] Geanakoplos (2009) defines leverage as the ratio between the price of the asset over the down payment made in order to borrow the difference.

[12] The sum of real estate loans plus mortgage-backed securities represents on average a 37.7% over commercial banks' total assets from July 2009 to December 2019 according to Board of Governors of the Federal Reserve System data (no available data on these securities before 2009).

[13] According to Jordà, Schularick and Taylor (2017) data, mortgage loans to non-financial private sector represents the 91% of GDP in advanced economies from 1984 to 2016. It is important to remark that the crucial

Minsky (1986) his *hypothesis* about the endogeneity of the financial system as a macroeconomic risk was not mainstream, nowadays it is well respected.

Finding 9: Financial innovations expand mortgage debt, boosting housing purchase capacity and credit risk.

The importance of financial innovations in housing is well known in the literature. Banking practices as securitization affect negatively the incentives of lenders to properly screen credit risk, allowing that securitized portfolios with greater ease of securitization default significantly more than similar portfolios with a lesser ease (Keys, Mukherjee, Seru and Vig, 2010), becoming an amplification mechanism that tends to ease credit conditions (Maddaloni and Peydró, 2011) and facilitate speculation (Mian and Sufi, 2019). Additionally, other innovations as complex mortgages are also mostly used during housing booms, becoming instruments with significantly higher delinquency rates (Amromin, Huang, Sialm and Zhong, 2013).

Finding 10: Mortgages defaults and foreclosures are explained both by negative equity and cash flow tensions, i.e. the so-called *double trigger hypothesis*.

One of the common consequences of a housing burst is the increase in delinquency rates, impairing the balance sheets of the banking system, which may end up finally in foreclosure. Despite previous strategic theories suggesting that rational borrowers default because of negative equity, that is when mortgage debt is higher than the value of the collateral, Bhutta, Dokko and Shan (2010), among others, show that negative equity is a necessary condition for defaulting but not sufficient. Instead, households having cash-flow tensions is also a necessary condition.

All in all, the magnitude of the interlinkages between the housing sector and the macroeconomy clearly encourage both governments and central banks to carefully monitor housing developments and to use systematically greater macroprudential policy mechanisms. With that respect, the good news is that the leading behavior of housing and credit with respect to potential posterior damaging economic developments is a key feature to exploit. This crucial point should provide economists the necessary time to analyze the economic conjuncture and to implement the appropriate macroprudential policy in a timely fashion.

1.3 Model specification

1.3.1 Theoretical framework

Consistent with the main target of this study, i.e. identifying states in the economy characterized by a potential build-up of macroeconomic risks by means of housing booms financed by credit, the ingredients we require to a theoretical framework are the following. First, it has to include a housing sector, so a household sector that holds housing assets and pays a price for such good. Second, there must be a banking sector that provides credit to the households in order to purchase the housing assets. Third, such a framework has to provide a plausible theory of booms and busts and demand excesses. Along these lines, a reasonable literature strand to follow is in the Minskian tradition, after the contributions of Minsky (1986, 1992) and his financial instability hypothesis[14].

A reference that fits on the defined purpose is Ryoo (2016), who proposes a theory of housing boom-bust cycles in which the interaction between household debt accumulation and housing price dynamics can generate long expansions followed by an acute downturn[15]. In this subsection

role of the mortgage market in advanced economies is the result of the so-called *financialization* long-run trend observed in advanced economies from the post-WWII period, as shown by Jordà, Schularick and Taylor (2016).

[14] Note that statistical tests for identifying bubbles by means of testing explosiveness or non-stationarity in housing prices series do not meet these criteria. See Homm and Breitung (2012) for a survey of such tests.

[15] Other models that might fit our purposes are surveyed in Guerrieri and Uhlig (2016).

we offer a brief explanation of the household block of the model as a theoretical foundation for the Markov switching model of housing prices that is proposed in subsection 1.3.5[16].

Households can be workers or capitalists, i.e. bankers. The former gets a wage, consumes, owns housing wealth only and can get bank loans for financing housing. Instead, the latter holds stocks and makes deposits. The aggregate budget constraint of workers, in physical capital units[17], is as follows:

$$c(t) = [1 - \pi(t)]u^d - rm(t) + nm(t) + \dot{m}(t) \tag{1.1}$$

where $c(t)$ is consumption in period t, $\pi(t)$ is the gross profit of firms, u^d is the capital utilization in the economy, r is the real interest rate which is set exogenously by the capitalists, $m(t)$ is the outstanding housing debt of workers, $\dot{m}$ denotes the new housing debt of workers and n is the fixed growth rate of the labor force, which in turn proxies the steady growth rate of the economy. The first term in the right hand side refers to the working income that the workers gets out of the firms profits $\pi(t)$, the second term constitutes the credit costs that workers pay to the capitalists for the mortgage loans m(t). Importantly, the third term refers to the steady growth path of housing debt, while the fourth term is the out of the steady growth path housing debt, which might be positive, negative or zero.

The workers face a credit constraint imposed by the capitalists, i.e. the bankers, so the level of workers' consumption is limited by the availability of credit. The amount of new household borrowing $\dot{m}(t)$ depends on workers' income $y^w(t)$ and net worth $\omega^w(t)$, which represents essentially a credit supply function such that:

$$\dot{m}(t) = \mu(y^w(t), \omega^w(t)); \mu_y > 0, \mu_\omega > 0 \tag{1.2}$$

where:

$$y^w(t) \equiv [1 - \pi(t)]u^d - rm(t) \tag{1.3}$$
$$\omega^w(t) \equiv h^w(t) - m(t) \tag{1.4}$$

where $h^w(t)$ is the value of housing wealth. Bankers use as an indicator of creditworthiness workers' income net of interest paid, and in case of any change in credit risk adjust credit supply instead of interest rates. In this specification, in the jargon of Minsky (1996) the effect of net workers' income $y^w(t)$ on credit supply captures the *fundamental margin of safety*, which is the excess expected income over the payment committed by debt contracts. Additionally, the effect of net worth $\omega^w(t)$ on household borrowing represents the so-called *collateral effect*, by which houses can serve as collateral so they relax workers' credit constraints, which in turn becomes another margin of safety for bankers when granting loans.

The consumption of workers is then determined by equations (1.1) and (1.2) such that:

$$c^w(t) = y^w(t) + nm(t) + \mu(y^w(t), \omega^w(t)) \tag{1.5}$$

which means that consists of working income $y^w(t)$, steady growth borrowing, i.e. second term and possibly an out of steady growth new borrowing, i.e. the last term. So, an income increase stimulates consumption directly and also indirectly through debt, while a net worth increase stimulates also consumption by relaxing the credit constraint.

Building from the assumption that workers have a desired ratio of housing stock to consumption, the demand for housing stock $H^d(t)$ is given by:

[16] For additional details on this model, please see Ryoo (2016).

[17] Following the notation of Ryoo (2016), variables are in general in capital letters, while its counterpart in physical capital units is found by dividing by capital. For instance, housing wealth in physical capital units is such that $h^w(t) \equiv p^h(t)H^w/p(t)K(t)$.

$$H^d(t) = \frac{\eta(\rho^e(t))p(t)C^w(t)}{p^h(t)}; \eta' > 0 \tag{1.6}$$

where $\rho^e(t)$ is the housing price expectations, $p(t)$ are prices and $p^h(t)$ is the housing price. Ryoo (2016) follows a disequilibrium approach to asset prices so that assumes that the excess demand in the housing market causes price inflation, instead of vanishing immediately, such that:

$$\widehat{p^h(t)/p(t)} = n + \kappa \left(\frac{H^d(t) - H^w}{H^w} \right), \kappa > 0 \tag{1.7}$$

where n is the real house price inflation required to sustain a steady growth path, and the second term constitute deviations of the rate of housing price inflation from the steady state driven by excess demand in the market.

Considering the value of housing wealth $h^w(t)$ and using equations (1.6) and (1.7) we can define new housing wealth as:

$$\dot{h}^w(t) = \kappa[\eta(\rho^e(t))c^w(t) - h^w(t)] \tag{1.8}$$

Therefore, the dynamics in housing wealth are a gradual adjustment to th desired level. The households' expectations on capital gains $\dot{\rho}^e(t)$ are assumed to follow an adaptative mechanism such that:

$$\dot{\rho}^e(t) = \nu[\rho(t) - \rho^e(t)], \nu > 0 \tag{1.9}$$

where $\rho(t)$ is the real housing price inflation. Then, using the value of housing wealth $h^w(t)$ the rate of housing price inflation is defined as:

$$\rho(t) = n + \frac{\dot{h}^w(t)}{h^w(t)} \tag{1.10}$$

Finally, considering the model version of Ryoo (2016) that includes both debt and pricing expectations dynamics and its definition of $\dot{h}^w(t)$, real housing price inflation $\rho(t)$ can be rewritten as:

$$\rho(t) = n + \frac{G(m(t), h^w(t), \rho^e(t))}{h^w(t)} \tag{1.11}$$

where n is the housing price inflation required to support a steady growth path with a constant housing-capital ratio[18], $m(t)$ is the housing debt outstanding, $h^w(t)$ is the value of housing wealth and $\rho^e(t)$ are the housing prices expectations. The general interpretation of this pricing equation is that the deviations of housing prices growth rates from steady state are driven by an excess demand in housing, which in turn is guided by mortgage debt and house price expectations. This equation (1.11) is the theoretical housing price equation used as reference in our Markov switching model.

The rest of this section is organized as follows. In the next subsection I present the data that is used. And, before estimating the Markov switching model in the last subsection, I describe previous empirical exercises which are used to motivate its design, namely explosiveness tests of mortgage debt and securitization, dynamic factor models of demand and supply and linear models of housing prices and overvaluation.

[18] Assuming n as being a constant may be over simplistic. In the empirical application with Markov regime switches, the steady state growth of housing prices is assumed to be driven by standard housing demand variables.

1.3.2 Data

The sample size starts in January 1984, such that it coincides with the beginning of the *Great Moderation*, in order to avoid possible issues coming from the structural break in aggregate volatility[19], until June 2019.

The house price index that is mainly used in this paper is the S&P Case-Shiller home price index, where the alternatives are the house price index computed by the Federal Housing Finance Agency (FHFA, henceforth), and the 10-City and 20-City composites also offered by S&P Case-Shiller. The reasons for using the S&P Case-Shiller home price index as the standard US housing price time series are twofold. First, because it is a nationwide measure, which fits the pretended scope in this paper. Second, because the data source they use for computing the index relies on the records that are registered in local government deeds recording offices (see S&P Dow Jones Indices, 2019) instead of records in a particular banking institution, which would make the index a function of the decision making of such firm at different levels such as the lending standards, refinancing and securitization policies[20].

Beyond housing prices, the principal time series that are used in this paper are the variables that can be understood either as being fundamental drivers of housing demand or those related to housing finance. As part of the first block, I consider a measure of employment (*all employees: total non-farm payrolls*, noted by E), wages (*gross domestic income: compensation of employees, paid: wages and salaries*, noted by W) and housing rental prices (*CPI for urban consumers: rent of primary residence*, noted by R), which are standard measures of income and purchasing capacity commonly used in the literature. In the second group of variables I consider a measure of mortgages debt (*mortgage debt outstanding, individuals and other holders*, noted by D). Table 1.2 lists all these time series together with other variables used in the paper.

[19] McConnell and Pérez-Quirós (2000) show that the output fluctuations in the United States structurally declined starting the first quarter of 1984.

[20] The house price index computed by the Federal Housing Finance Agency relies on the records obtained by reviewing repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac (see www.fhfa.gov).

Table 1.2: Time series data.

Variable		Source	Data availability	Data transfor.
S&P Case-Shiller home price index	HP	S&P	1975 M1 - 2020 M1	R, L, D
Nationwide house price index for existing single-family houses	-	FHFA	1975 Q1 - 2019 Q4	-
Urban primary residence rent index	R	BLS	1981 M1 - 2020 M2	R, L, D
Working age population: aged 15-64	P	OECD	1977 M1 - 2020 M2	L, D
Employees, non-farm payrolls	E	BLS	1939 M1 - 2020 M3	L, D
Compensation of employees	W	BEA	1959 M1 - 2020 M2	R, L, D
30 year fixed rate mortgage average	F	FM	1971 M4 - 2020 M3	-
Balance on current account	C	BEA	1947 Q1 - 2019 Q4	M
Mortgage debt outstanding, all holders	D	BG	1949 Q4 - 2019 Q3	SA, M, R
Real personal income excluding current transfer receipts	I	BEA	1959 M1 - 2020 M2	L, D
Real estate loans owned and securitized	S	BG	1970 M6 - 2020 M1	R
Real GDP growth	G	BEA	1947 Q2 - 2019 Q4	M
New private housing building permits	B	CB	1960 M1 - 2020 M2	L, D
Housing starts	T	CB	1959 M1 - 2020 M2	L, D
New one family houses sold	N	CB	1963 M1 - 2020 M2	L, D
Spread between 10 - 2 years treasury bills	Z	BSL	1976 M6 - 2020 M3	-

Notes: In the last column, *L* means that logs have been taken, *D* means taking one difference, *R* means that the variable has been transformed into real terms by applying the CPI, *M* means that the series have been transformed to a monthly frequency by linear interpolation. Decisions on differentiation are made after implementing stationarity tests (see Appendix A.1). Regarding the sources of the data, S&P means Standard & Poor's, BLS means Bureau of Labor Statistics, BEA means Bureau of Economic Analysis, CB means the Census Bureau, BG stands for Board of Governors of the Federal Reserve System, BSL means Federal Reserve Bank of St. Louis, OECD stands for Organization for Economic Cooperation and Development and FM means Freddie Mac. FHFA stands for Federal Housing Finance Agency.

In order to check the explosiveness of housing finance variables, I perform a mildly explosive behavior test as implemented by Phillips, Wu and Yu (2011) to *mortgage debt outstanding D to income I ratio* and *real estate loans securitized* S[21]. The results of these tests are shown in Table 1.3. First observation is that both time series show evidence of explosiveness in quite similar periods than the price-fundamental ratios seen in the literature, supporting the view that both mortgage credit and securitization played an important role in the rising-up of housing prices during such periods. Second, there is agreement between both variables in dating explosiveness in the late 80s and during the years preceding the Great Recession, consistent with Shi (2017), among others.

[21] Regarding the specification of the mildly explosive behavior tests, the testing equations include a constant, the information criteria employed is the AIC, the number of lags is 1, the initial window size is 36 and the number of replications of simulations is 1,000.

Table 1.3: Tests of mildly explosive behavior in housing finance.

	D/I ratio	S
SADF	1985:M4 - 1991:M11	1984:M8 - 1990:M12
	2002:M3 - 2011:M1	1991:M4 - 1991:M9
		1996:M6 - 2009:M8
GSADF	1985:M1 - 1989:M11	1984:M7 - 1990:M12
	1991:M2 - 1991:M5	1996:M6 - 2015:M11
	2001:M7 - 2010:M11	
	2014:M6 - 2014:M11	
	2019:M2 - 2019:M6	

Notes: D means real mortgage debt outstanding, I stands for real personal income excluding current transfer receipts and S are the real estate loans owned and securitized. Mildly explosive behavior signals of lower or equal lengths than 3 periods are not reported (Phillips, Shi and Yu, 2015 suggest as a threshold for identification the log of the sample size, which in this case is 2.66).

1.3.3 Factor models of housing demand and supply

In order to construct measures of housing price overvaluation, first two dynamic common factor models are estimated to proxy the unobservables housing demand and supply, respectively. Such measures of overvaluation will be used later with two purposes. First, evaluating the explanatory power of standard housing fundamentals and financial variables to house price overvaluation. Second, to better assess the outcomes of the Markov switching model.

The general structure of the proposed dynamic factor model builds on Stock and Watson (1991) and is common for both demand and supply specifications. The assumptions we implicitly make in this exercise are the following. First, housing demand and supply are unobservables, and we assume they might be better tracked by summarizing several proxies than just using one variable to proxy each of the unobservables. Second, we assume that the fundamentals we include in each of the models are reasonable proxies, as commonly used in the literature, so that they can summarize the state of housing demand and supply, respectively. Third, we assume that the comovements between the multiple time series in each model arise from the single common factor.

Let y_t denote an $i\times 1$ vector of monthly housing fundamentals in stationary form and standardized, the proposed dynamic common factor model of unobserved housing demand (or supply) yields:

$$y_t = \gamma c_t + e_t \tag{1.12}$$

where c_t is the common factor which follows an autorregressive structure of order 2 such that:

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + w_t \tag{1.13}$$

where $w_t \sim iid$ N(0, σ_w^2) and the errors $e_{i,t}$ in e_t above yield:

$$e_{i,t} = \psi_{i,1} e_{i,t-1} + \psi_{i,2} e_{i,t-2} + \epsilon_{i,t} \tag{1.14}$$

where $\epsilon_{i,t} \sim iid$ N(0, σ_i^2).

The selected housing demand fundamentals in log-differences are working age population (aged 15-64 years old), compensation of employees, non-farm employees and the CPI of rents of primary residence, which are standard measures of housing demand commonly used in the literature[22]. In particular, studies evaluating the explosiveness of a housing price-fundamental

[22]See Girouard, Kennedy, Van den Noord and André (2006) for a review of studies on housing prices and fundamentals in OECD countries.

ratio (i.e. testing for housing bubbles) choose one variable as fundamental of housing prices which typically is rents or income (see Table 1.1). Instead, in this study we prefer to construct a proxy of housing demand out of several commonly used variables than to rely on only one measure[23].

Alternatively, the factor model of housing supply include three variables in logs, which are new one family houses sold, building permits and housing starts, which are commonly used in the literature to track housing supply developments[24].

Both housing demand and supply models are estimated using maximum likelihood, and the systems are updated by using the Kalman filter. The output of these estimations is a common factor c_t, i.e. a time series representing the common evolution of the variables included in the model. After standardizing this factor and applying the mean and standard deviation of log-differenced housing prices HP_t, we get the common factor of the fundamental variables in a housing prices-comparable fashion that we call f_t. Then, as deviations from house prices growth we get a measure of overvaluation O_t, such that:

$$O_t = HP_t - f_t \tag{1.15}$$

Finally, this time series of overvaluation O_t is used to generate a binary indicator of overvaluation IO_t such that:

$$IO_t(O_t) = \begin{cases} 1 & \text{if } O_t > 0 \text{ and } HP_t > 0 \\ 0 & \text{otherwise} \end{cases} \tag{1.16}$$

This measure of overvaluation is denoted as IO_D or IO_S depending upon it refers to the overvaluation measure with respect to demand or supply side proxy, respectively. The logic behind the overvaluation measure IO_D is that observing housing prices growing faster than demand fundamentals might be the result of an excess of demand fueled by credit, hypothesis that is tested using the models defined in next subsection. Alternatively, overvaluation IO_S may be a symptom of rigidities in the supply of new housing in the real estate sector.

1.3.4 Linear models of overvaluation and housing prices

Having generated a binary indicator of overvaluation IO_t in the previous subsection, in this one we estimate a probit model in order to analyze the significance of housing fundamentals candidates in explaining overvaluation in house prices. This is performed by estimating a linear probability model for binary response IO_t such that[25]:

$$p(IO_t = 1|O_t) = IO_t = \Phi(x_{i,t}\beta) \tag{1.17}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, $x_{i,t}$ is an $i \times 1$ vector of explanatory variables and IO_t is the dependent binary variable, which again can be demand or supply-driven, that takes the value of 1 if there is evidence of overvaluation and 0 otherwise, according to the results obtained in subsection 1.3.3.

The choice of explanatory variables included in such model is based partly on the theoretical model of housing booms and busts explained in subsection 1.3.1, particularly regarding the definition of housing prices inflation, which is pinned down as a function of the steady state growth path, i.e. the rate of the labor force n, and an out-of-equilibrium excess of demand possibly fueled by credit. Therefore, we include a number of housing fundamentals as working age population, employees, wages and rents, and financial variables such as mortgage interest

[23] In fact, subsection 1.4.3 shows that real wages growth is not statistically significant in explaining either housing prices or overvaluation. This result reinforces our preference for constructing a proxy out of several housing demand indicators rather than choosing one.

[24] See Hilbers, Hoffmaister, Banerji, and Shi (2008).

[25] A similar exercise is done by Martínez-García, Pavlidis, Yusupova, Paya, Peel, Mack and Grossman (2016).

rates, a proxy of the yield curve and mortgage debt outstanding. Additionally, real GDP growth and balance on current account are added as controls. All variables are in stationary form (see Table 1.2 for details).

The results of the probit model are compared with the analogous one obtained by estimating OLS and Cochrane-Orcutt regressions in which log-differenced housing price is instead the dependent variable.

1.3.5 Markov switching model of housing prices

The Markov switching model of house prices adopted in this paper is an extension to Markov chains with time-varying transition probabilities, drawing from Hamilton (1989) and Pérez-Quirós and Timmermann (2000) applied in the real estate sector. The motivation for using such model is threefold. First, house prices and mortgage credit undergo episodes in which its behavior change dramatically, as was seen during the 2000s in the US. Second, the change in regime in such variables does not seem to be regarded to the outcome of a perfectly foreseeable event, but instead as a random variable that we might call *state*. Third, the target in this study is finding a state characterized by a housing boom financed by credit, while controlling for standard determinants of house prices, and a Markov switching model seems to be flexible enough for that purpose. Indeed, such precise regime might constitute an episode in which macroeconomic risks are building up, which potentially might lead to price overvaluations, credit and investment excesses, unreasonable price expectations and maybe later messy implosions. It is along these lines that the identification of housing booms financed by credit might constitute an early warning of potential future severe macroeconomic costs.

In particular, let HP_t be the log-difference of the nationwide house prices index in period t, let X_t be a vector of state independent variables, let Y_t be a vector of state dependent variables and s_t be the latent state variable that defines the state of the real estate sector such that:

$$HP_t = \phi_{0,s_t} + \phi_1' X_t + \phi_{2,s_t}' Y_t + \epsilon_t \tag{1.18}$$

where $\epsilon_t \sim (0,\, h_{s_t})$.

For simplicity, let's assume that there are two states, denoted 1 and 2, so that $s_t = 1$ or $s_t = 2$. Therefore, depending on the state, the coefficients and variance of the state-dependent terms can be either $(\phi_{0,1},\, \phi_{2,1},\, h_1)$ or $(\phi_{0,2},\, \phi_{2,2},\, h_2)$.

The state transition probabilities are assumed to follow a first-order Markov chain such that:

$$p_t = P(s_t = 1 | s_{t-1} = 1, \omega_{t-1}) = p(\omega_{t-1}) \tag{1.19}$$

$$1 - p_t = P(s_t = 2 | s_{t-1} = 1, \omega_{t-1}) = 1 - p(\omega_{t-1}) \tag{1.20}$$

$$q_t = P(s_t = 2 | s_{t-1} = 2, \omega_{t-1}) = q(\omega_{t-1}) \tag{1.21}$$

$$1 - q_t = P(s_t = 1 | s_{t-1} = 2, \omega_{t-1}) = 1 - q(\omega_{t-1}) \tag{1.22}$$

where ω_{t-1} is a vector of variables that are known in period $t-1$ that affect the state transition probabilities in period t. The standard formulation of the Markov switching model assumes that these transition probabilities are constant. However, I follow the approach of Van Norden, Shaller (1993) where in analyzing stock market returns the probability of transitioning from one regime to another depends on an economic variable.

The parameters of this model are obtained by maximum likelihood estimation. Let θ be the vector of parameters entering the likelihood function for the data and supposing that the density conditional on being in state $j, \eta(HP_t \mid s_t = j, X_t, Y_t; \theta)$ is Gaussian:

$$\eta(HP_t \mid \Omega_{t-1}, s_t = j; \theta) = \frac{1}{\sqrt{2\pi h_j}} \exp\left(\frac{-(HP_t - \beta_{0,s_t} - \beta_1' X_t - \beta_{2,s_t}' Y_t)^2}{2h_j} \right) \tag{1.23}$$

for j = 1,2. The information set Ω_{t-1} contains X_{t-1}, Y_{t-1}, HP_{t-1}, ω_{t-1} and lagged values of these variables, such that: $\Omega_{t-1} = \{X_{t-1}, Y_{t-1}, HP_{t-1}, \omega_{t-1}, \Omega_{t-2}\}$.

Notice that in this formulation I assume a constant relationship between the conditioning factors Y_t and house prices within each state, but allow these coefficients to vary between states. Alternatively, the relationship between the conditioning factors X_t and house prices is constant.

The log-likelihood function takes the form:

$$\ell(HP_t \mid \Omega_{t-1};\theta) = \sum_{t=1}^{T} \ln(\phi(HP_t \mid \Omega_{t-1};\theta)) \tag{1.24}$$

where the density $\phi(HP_t \mid \Omega_{t-1};\theta)$ is obtained by summing the weighted probability state densities, across the two possible states, such that:

$$\phi(HP_t \mid \Omega_{t-1};\theta) = \sum_{j=1}^{2} \eta(HP_t \mid \Omega_{t-1}, s_t = j;\theta) P(s_t = j \mid \Omega_{t-1};\theta) \tag{1.25}$$

being $P(s_t = j \mid \Omega_{t-1};\theta)$ the conditional probability of being in state j at time t given information set Ω_{t-1}.

The conditional state probabilities can be obtained recursively such that:

$$P(s_t = i \mid \Omega_{t-1};\theta) = \sum_{j=1}^{2} P(s_t = i \mid s_{t-1} = j, \Omega_{t-1};\theta) P(s_{t-1} = j \mid \Omega_{t-1};\theta) \tag{1.26}$$

Finally, by Bayes' rule the conditional state probabilities can be written as:

$$P(s_{t-1} = j \mid \Omega_{t-1};\theta) = P(s_{t-1} = j \mid HP_{t-1}, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta) \tag{1.27}$$

$$= \frac{\eta(HP_{t-1} \mid s_{t-1} = j, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta) P(s_{t-1} = j \mid X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta)}{\sum_{j=1}^{2} \eta(HP_{t-1} \mid s_{t-1} = j, X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta) P(s_{t-1} = j \mid X_{t-1}, Y_{t-1}, \omega_{t-1}, \Omega_{t-2};\theta)} \tag{1.28}$$

In particular, two models are specified. First, let HP_t be the S&P Case-Shiller home price index in month t, let the variables wages W_t, employment E_t and rents R_t be state-independent fundamental variables of housing demand and mortgage debt D_t be the state-dependent variable which affects non-linearly housing prices[26], the three states Markov switching baseline model is such that[27]:

$$HP_t = \beta_{0,s} + \beta_1 W_t + \beta_2 E_t + \beta_3 R_t + \beta_{4,s} D_t + \epsilon_t \tag{1.29}$$

where $\epsilon_t \sim N(0, h_{st})$. In this way is captured the idea of Geanakoplos (2009) that endogenous leverage cycles can simultaneously lead growth in debt and housing prices[28]. Equation (1.29) is the empirical counterpart of the housing price inflation equation of Ryoo (2016) in which we assume that the steady growth path of house prices is well approximated by standard fundamentals of housing demand and *dividends* such as wages, employment and rents, while we also assume that the possible excess of demand might be caused only by credit[29].

The conditional variance of HP_t is given by:

$$\ln(h_{st}) = \lambda_{0,s} \tag{1.30}$$

[26]It is standard in the literature to employ measures of income and rental prices as fundamental variables of housing demand and also assuming non-linear effects of credit on housing prices (see IMF, 2019; Gürkaynak, 2008, among others). To that respect, the model can be considered pretty standard and parsimonious.

[27]The choice for determining the number of states in the baseline model depends on two elements. First, considering the target of this model it is assumed that the minimum number of states that should be present are three, which may potentially correspond to normal times, booms and bursts. Second, adding additional states increases quickly the number of parameters in the model, so a parsimonious approach has been taken. See subsection 1.4.6 for a robustness check by estimating the baseline model with 2 and 4 states, all else equal.

[28]It may be that the contributions between mortgage debt and house prices are bidirectional, as already shown in the empirical literature on housing. However, as the target in this model is to capture a state with both high housing prices and debt, disentangling possible reverse causality is not addressed.

[29]Alternative specifications are also checked for robustness in subsection 1.4.6.

The state transition probabilities are specified as follows:

$$p_t = prob(s_t = 1 \mid s_{t-1} = 1, \Omega_t) = \Phi(\pi_{0,p} + \pi_{1,p} D_t) \tag{1.31}$$
$$q_t = prob(s_t = 2 \mid s_{t-1} = 2, \Omega_t) = \Phi(\pi_{0,q} + \pi_{1,q} D_t) \tag{1.32}$$
$$z_t = prob(s_t = 3 \mid s_{t-1} = 3, \Omega_t) = \Phi(\pi_{0,z} + \pi_{1,z} D_t) \tag{1.33}$$

The second estimated model adds a securitization dummy Sd_t which is defined using the results obtained when testing for mildly explosive behavior in the time series of real estate loans securitized[30]. Therefore, model (2) yields:

$$HP_t = \beta_{0,s} + \beta_1 W_t + \beta_2 E_t + \beta_3 R_t + \beta_{4,s} D_t + \beta_5 Sd_t + \epsilon_t \tag{1.34}$$

where Sd_t is a state-independent variable dummy of real estate loans securitized, which is defined such that:

$$Sd_t = \begin{cases} 1 & \text{if } ADF_{S_t} > cv_{S_t} \\ 0 & \text{otherwise} \end{cases} \tag{1.35}$$

where ADF_{S_t} and cv_{S_t} are the corresponding t-statistic and critical values, respectively, obtained in the SADF test for mildly explosive behavior in real estate loans securitized. Therefore, dummy Sd_t is 1 when there is mild explosiveness in such time series and 0 otherwise. The rest of model (2) is unchanged with respect to the baseline model (1).

1.4 Empirical results

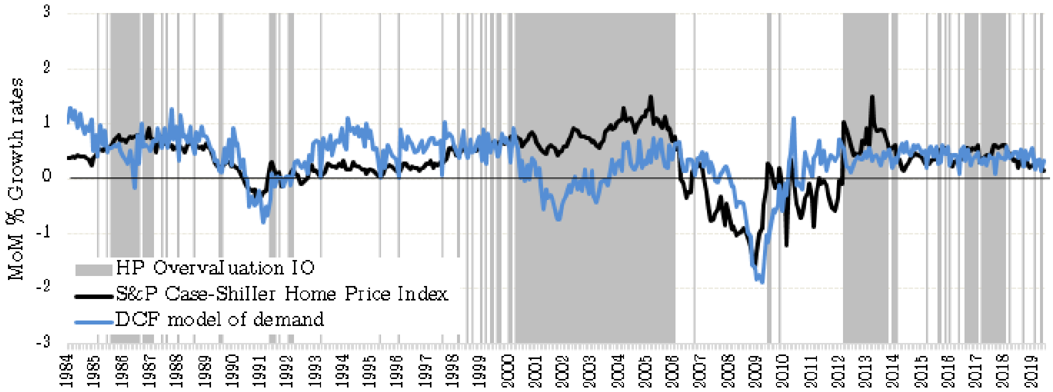
The following subsections show the individual results regarding the dynamic common factor models of housing demand and supply, the linear models of housing prices and overvaluation and the Markov switching model. In particular, the fifth subsection analyzes more transversally the identified *housing booms fueled by credit* comparing it with earlier results on overvaluation.

1.4.1 Common factor of housing demand

The evolution of the dynamic common factor of housing demand is plotted in Figure 1.1, which summarizes the common path of the four included housing demand fundamentals (blue line) compared with the S&P Case-Shiller home price index (black line), where the correlation coefficient between the two series is 44.31%. The four longest periods of overvaluation are the following. First, one that lasted 13 months from August 1985 to August 1986. Second, the longest overvaluation interval lasting 70 months that occurred from April 2000 to January 2006, which corresponds to the years before the Great Recession, what is consistent with the literature that widely interprets the housing boom of the 2000s as the result of a booming demand fostered by credit[31]. Additionally, there were previous discontinuous signals of overvaluation already from March 1998. Third, a period from March 2012 to October 2013, which lasted 20 months. Fourth, an overvaluation period of 17 months ranging from August 2016 to January 2018, discontinued in February 2017.

[30] See subsection 1.3.2.
[31] See a comparison of these results together with the Markov switching model ones in subsection 1.4.5.

Figure 1.1: Common factor of housing demand vs S&P Case-Shiller home price index.

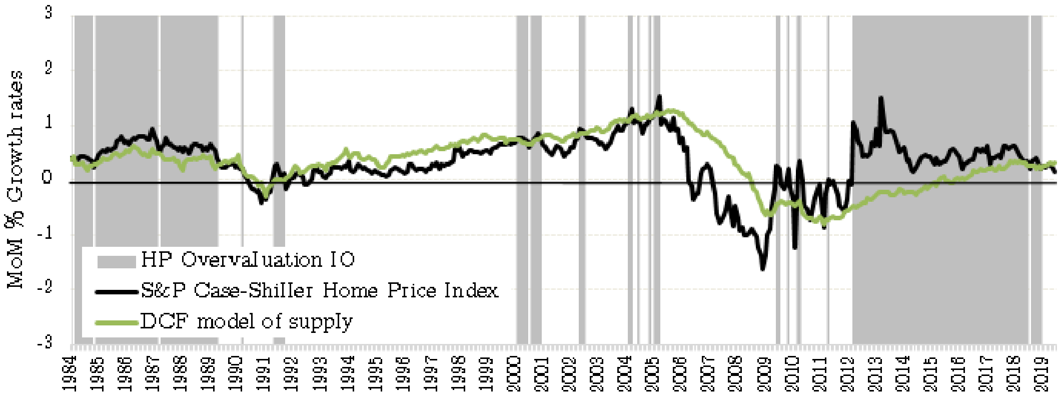


Notes: The included housing demand fundamentals are *working age population (aged 15-64 years old) P*, *compensation of employees W*, *total non-farm employees E* and *CPI of rents of primary residence R*. See subsections 1.3.2 and 1.3.3 for a detailed description.

1.4.2 Common factor of housing supply

Figure 1.2 plots the dynamic common factor composed by supply variables (green line), as defined in subsection 1.3.3. In this case, we can observe that the fit compared with the S&P C-S home price index growth (black line) is pretty good until 2006, while the correlation coefficient between the two series for the whole sample is 54.06%. According to this setup, there are two periods of overvaluation. First, from January 1984 to April 1989, including a couple of discontinuities. Second, a period starting in March 2012 until December 2018, also with one discontinuity. This result is consistent with the housing market commentators which argue that the low inventory available after the Great Recession may have an important role in facilitating prices to go up.

Figure 1.2: Common factor of housing supply vs S&P Case-Shiller home price index.



Notes: The included housing supply proxies are *new one family houses sold N*, *building permits B* and *housing starts T*. See subsections 1.3.2 and 1.3.3 for a detailed description.

1.4.3 Linear regression models

The results of the estimated OLS, Cochrane-Orcutt and probit models are shown in Table 1.4, models (1), (2) and (3), respectively. In the three cases, the explanatory variables are analogous, while the dependent variable is different. Indeed, the dependent variable in models (1) and (2) is the real housing prices growth, and in model (3) is the binary variable IO_t, an index of overvaluation in housing prices[32]. The Cochrane-Orcutt model, labeled as model (2) in Table 1.4, has been estimated after an autocorrelation analysis of model (1), in which it is found strong evidence of 11th order serial autocorrelation at the 95% level of significance, meaning that real housing prices growth exhibits *momentum*[33].

The first round of observations on Table 1.4 regards on the role of the standard demand fundamentals versus financial variables in significantly explaining real housing prices growth. First, in model (1) both standard fundamentals and financial variables are individually statistically significant, with the exception of working age population growth and real wages growth. In fact, they are both also jointly significant (see the joint significance tests results in Table 1.5). Second, after correcting for autocorrelation and estimating model (2), only real rents growth remains as being statistically significant, while none of the financial variables are significant. Indeed, standard fundamentals are still jointly significant while financial variables are not (see Table 1.5). Third, the fact that real rents growth is the only standard fundamental or financial variable statistically significant in both models (1) and (2) is consistent with the literature that uses rents to test for bubbles. However, it also warns that not taking into account additional fundamentals and financial variables as mortgage debt may make a model incomplete, which in turn is consistent with Shi (2017). These findings may suggest that the serial correlation exhibited by real housing prices growth could be related to the role of financial variables, such as mortgage debt growth. In other words, they may suggest that mortgage debt finances the *momentum* of house prices growth, and in turn, the discrepancy between housing prices and demand fundamentals, as proxied by the index of overvaluation, which is consistent with Mian and Sufi (2009)[34].

[32]See subsection 1.3.4.

[33]See the autocorrelation tests results in Appendix A.2.

[34]Mian and Sufi (2009) show that in US subprime ZIP codes between 2002 and 2005 the expansion of mortgage credit occurred in spite of decreasing relative income growth.

Table 1.4: Linear regression models estimates.

	(1) OLS		(2) CO		(3) Probit		(4) Probit	
Dependent variable	Real HP growth		Real HP growth		IO_D		IO_S	
Standard fundamentals								
Working population gr.	0.033	(0.14)	-0.120	(0.08)	0.139	(0.75)	-2.374**	(0.96)
Employees growth	0.870***	(0.13)	0.037	(0.09)	-2.093***	(0.65)	2.766***	(0.63)
Real wages growth	0.031	(0.03)	0.014	(0.01)	-0.003	(0.09)	-0.101	(0.11)
Real rents growth	0.803***	(0.07)	0.755***	(0.04)	0.291	(0.28)	0.844***	(0.26)
Financial variables								
Mortgage interest rates	-0.101***	(0.01)	0.028	(0.03)	-0.241***	(0.04)	0.001	(0.03)
Yield curve proxy	0.121***	(0.02)	0.051	(0.06)	0.354***	(0.09)	0.159	(0.86)
Mortgage debt growth	0.316***	(0.02)	0.014	(0.03)	0.818***	(0.09)	-0.055	(0.08)
Control variables								
Real GDP growth	0.035***	(0.01)	0.020***	(0.01)	0.074*	(0.05)	-0.003	(0.04)
Current account balance	0.000***	(0.00)	-0.000	(0.00)	0.001*	(0.00)	0.000	(0.00)
Number of observations	426		425		426		426	
R^2	0.590		0.539		-		-	
Pseudo R^2	-		-		0.216		0.093	
Prob > F	0.000		0.000		-		-	
Prob > chi^2	-		-		0.000		.	
Log pseudolikelihood	-		-		-225.174		-261.354	

Notes: Robust standard deviations between brackets. Significance levels at 1%, 5% and 10% are represented by ***, **, * asterisks, respectively. Results on the constant coefficient are omitted. CO stands for the Cochrane-Orcutt estimation and IO means index of overvaluation (see subsection 1.3.3 for a detailed description).

The second round of observations are related to the role of standard demand fundamentals versus financial variables in significantly explaining overvaluation. First, standard fundamental variables of housing demand have a hard time in explaining demand-driven overvaluation in model (3), where the only significant coefficient is the one associated to employees growth, and the sign is negative i.e. at odds with an *a priori* guess. Indeed, considering fundamental variables jointly they are statistically significant, but leaving employees aside, they are not (see Table 1.5). Second, the three financial variables included in model (3) are both individually and jointly statistically significant in explaining overvaluation. These two findings suggest that while demand-based variables can be relevant to explain real housing prices growth, financial variables are the ones that significantly explain demand-driven overvaluation. Third, in model (4) housing demand fundamentals are jointly statistically significant in explaining supply-driven overvaluation (see Table 1.5), while employees growth and rents are individually statistically significant and have the positive expected sign. Fourth, interestingly financial variables are in the case of model (4) not significant, neither individually nor jointly. Therefore, it is noticeable that supply-driven overvaluation exhibits a pattern characterized by a significant role of employment and rental markets, but not significantly boosted by credit. This finding suggests that depending upon the nature of overvaluation, the macrofinancial risks coming from the mortgage market can be substantially different.

Table 1.5: Joint significance tests.

	(1) OLS	(2) CO	(3) Probit	(4) Probit
Dependent variable	Real HP growth	Real HP growth	IO_D	IO_S
Standard fundamental variables				
Including employees growth	0.000	0.000	0.021	0.000
Not including employees growth	0.000	0.000	0.756	0.001
Financial variables	0.000	0.664	0.000	0.233
Control variables	0.000	0.047	0.023	0.868

Notes: OLS and CO results refer to the p-values obtained, while in the case of the probit model results refer to the Prob > chi2. The models labeled in this table correspond to the models which results are shown in Table 1.4.

1.4.4 Markov switching model of housing prices

The summary of the results of the three states Markov switching models specified in subsection 1.3.5 is provided in Table 1.6, where columns (1) refer to the baseline specification and (2) correspond to the model including the securitization dummy S_d. Regarding model (1), the following features are well noticeable. First, the state dependent elements in the estimation are statistically significant at the 1% significance level. Second, the three states dependent coefficients of mortgage debt outstanding growth are positive, suggesting that an increase in such variable has a positive effect on housing prices growth independently of the state, hinting its critical importance in explaining prices in any circumstance. Third, the constant in state 2 is the only one having a positive coefficient, so giving a first hint that state 2 may be understood as a *housing boom* state. Fourth, the constant in state 3 is negative and far more negative than the constant in state 1, which suggest that state 3 may be an *implosion* state[35]. Then, state 1 might be understood as being *normal times*. Fifth, the coefficients of employment E and rents R are positive and statistically significant at 1%, while the coefficient of wages is not statistically significant. This result is relevant considering that wages are for most households the ultimate funds source for repaying housing debt. With regard to model (2), we can observe that the securitization dummy S_d is statistically significant at 1% and slightly negative. This may be a consequence of the binary nature of the dummy variable, which is unable to capture the similar trends that housing prices and securitization followed during the considered time period[36].

[35] An alternative label for state 3 might be *bust* state, as also commonly named in the literature. Below in this section I provide evidence that state 3 is the only one exhibiting negative average growth in real house prices, housing starts, new building permits, new one family houses sold, new homes under construction and real cement production.

[36] For instance, from June 1996 to August 2009, when the securitization dummy is always one, housing prices growth shows a positive path only until the mid-2006.

Table 1.6: Markov switching model estimates.

	(1)		(2)	
Mean parameters				
Constant, State 1	-0.0018***	(0.000)	-0.0018***	(0.000)
Constant, State 2	0.0024***	(0.000)	0.0036***	(0.000)
Constant, State 3	-0.0074***	(0.000)	-0.0076***	(0.001)
Wages (W)	0.0062	(0.014)	0.0057	(0.019)
Employment (E)	0.6098***	(0.069)	0.9069***	(0.073)
Rents (R)	0.3845***	(0.039)	0.5491***	(0.048)
Mortgage debt (D), State 1	0.5382***	(0.031)	0.5921***	(0.048)
Mortgage debt (D), State 2	0.3959***	(0.045)	0.3607***	(0.055)
Mortgage debt (D), State 3	0.6315***	(0.085)	0.5921***	(0.094)
Securitization (S_d)			-0.0012***	(0.000)
Variance parameters				
Constant, State 1	0.0000***	(0.000)	0.0000***	(0.000)
Constant, State 2	0.0000***	(0.000)	0.0000***	(0.000)
Constant, State 3	0.0000***	(0.000)	0.0000***	(0.001)
Time Varying Transition Probabilities				
p(1,1)(1)	1.5468***	(0.239)	1.7687***	(0.224)
p(1,1)(2)	143.77***	(64.17)	137.802***	(67.368)
p(1,2)(1)	-1.9276***	(0.273)	-1.673***	(0.256)
p(1,2)(2)	-43.2782	(71.677)	-60.552	(54.577)
p(1,3)(1)	-1.3849***	(0.328)	-1.3754***	(0.3454)
p(1,3)(2)	-88.847	(69.35)	-104.687	(71.019)
p(2,1)(1)	9.897	(137.77)	10.3328	(116.688)
p(2,1)(2)	2458.828	(3.4e+4)	2459.2037	(28531.2)
p(2,2)(1)	1.993***	(0.316)	2.0835***	(0.408)
p(2,2)(2)	35.6849	(62.47)	19.2679	(66.753)
p(2,3)(1)	-2.2306	(1.8724)	-2.1232	(1.999)
p(2,3)(2)	-150.701	(466.25)	-137.0596	(459.701)
Final Log likelihood value	2002.43		1994.11	
Akaike Information Criterion	-3.96e+03		-3.94e+03	
Bayesian information criterion	-3.86e+03		-3.84e+03	
Number of estimated parameters	24		25	

Notes: Standard deviations between brackets. Significance levels at 1%, 5% and 10% are represented by ***, **, * asterisks. Standard errors calculated using the first partial derivatives of the log likelihood, i.e. the outer product matrix. Model (1) is the baseline and model (2) adds a securitization dummy.

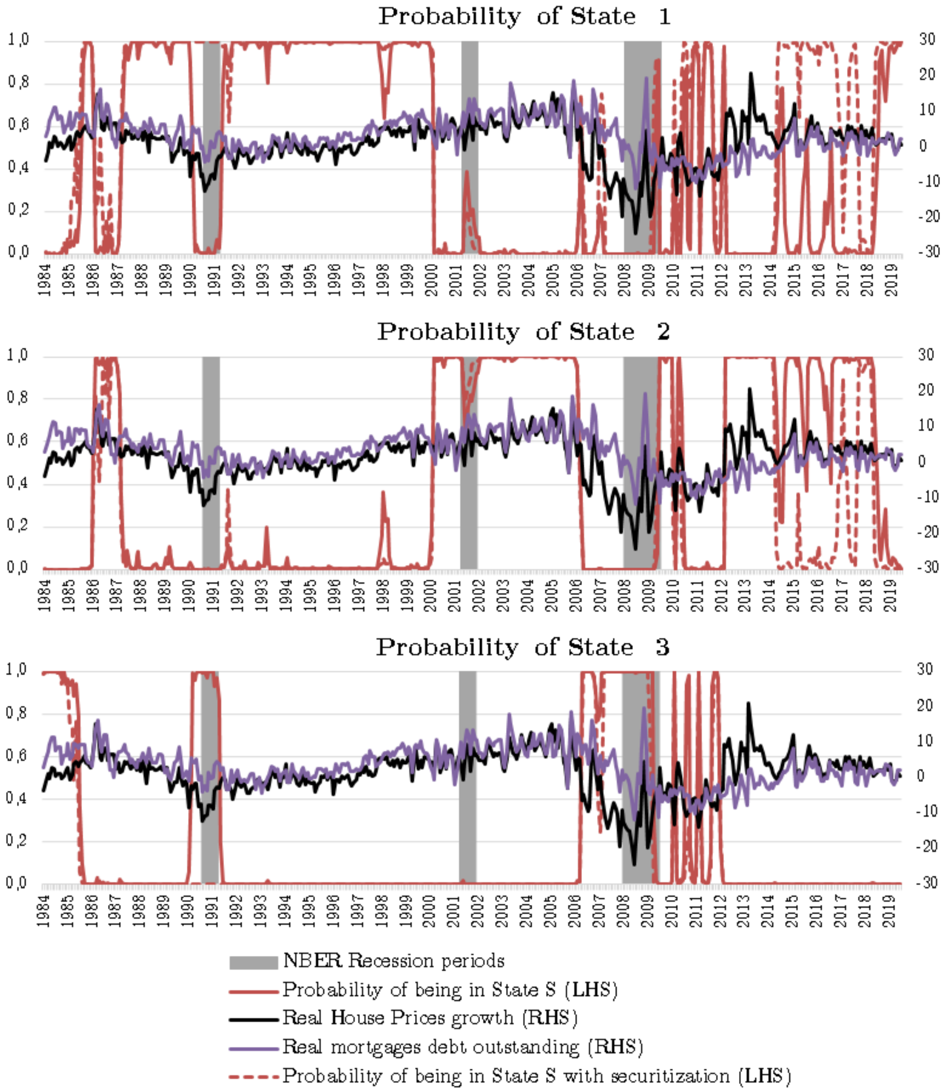
The filtered Markov switching probabilities of being in each state are shown in Figure 1.3, in which the solid red line corresponds with the baseline model (1) probabilities, and the dashed red line refers to model (2)[37], i.e. including securitization. As already introduced in the explanation of Table 1.6 and further upheld later in this subsection I argue that the identified three states may correspond with *normal times*, *housing boom fueled by credit* and *implosion*, respectively. According to this correspondence, there appear four episodes of housing booms fueled by credit[38]. First, one in the late 80s, from January 1986 to February 1987. Second, a

[37] The smoothed Markov switching probabilities according to model (1) are shown in Appendix A.4.

[38] A specific and commonly agreed definition of housing booms and credit booms is rather missing in the literature, where typically such empirical definitions are quite ad-hoc. For instance, Crowe, Dell'Ariccia, Igan and Rabanal (2013) define a real estate boom as a period in which real house price appreciation is above a threshold of 1.5 percent or the annual real house price appreciation rate exceeds the country-specific historical annual appreciation rate. Also, they define a credit boom as a period in which the growth rate of bank credit to the private sector in % of GDP is more than a 20 percent or it exceeds the rate implied by a country-specific,

long episode in the preceding boom before the Great Recession, from February 2000 to February 2006. Third, a short period from June 2009 to May 2010. Fourth, a discontinuous case from March 2012 to May 2018. Interestingly, when controlling for securitization, the last boom is shortened in such a way that the period between 2014 and 2018 is mainly classified as being *normal times*. Moreover, the *implosion* state identified by model (1) in 1990 turns out to be *normal times* when adding securitization.

Figure 1.3: Filtered Markov switching probabilities of being in each state.



The latest transition probabilities matrix of model (1) is presented in Table 1.7[39]. Interestingly, these results show that in order to get into an *implosion* state period it is typically necessary to be first in a *housing boom fueled by credit*, as the probability of jumping from state 1 to state 3 is very close to zero, which seems reasonable.

backward-looking, cubic time trend by more than one standard deviation. In the course of this section I provide evidence that during state 2 both housing prices and mortgage credit grow significantly over the average in the full sample, and also significantly more than in states 1 and 3.

[39]Additionally, the latest transition probabilities matrix of model (2) is shown in Appendix A.5.

Table 1.7: Latest transition probabilities matrix, model (1).

		State in t-1		
		1	2	3
State in t	1	0.9695	0.0214	0.0563
	2	0.0305	0.9600	0.0048
	3	0.0000	0.0186	0.9390

Table 1.8 shows the expected duration in each state for each of the two estimated models. Consistent with Figure 1.3, the expected duration of *housing booms fueled by credit* in a model with securitization is lower, while the expected duration of *normal times* is higher, while in the case of the *implosion* state it remains quite similar.

Table 1.8: Expected duration in each state.

	(1)	(2)
State 1	19.80	30.11
State 2	24.29	18.60
State 3	13.09	12.63

Notes: Expected duration is expressed in the number of time periods, which is the expected number of months.

In order to better characterize the nature of each of the three states shown in Figure 1.3 corresponding to model (1), Table 1.9 shows the growth rates averages of some macroeconomic and financial variables of interest depending upon the state in which the economy is estimated to be according to the results of the baseline model in each period. These calculations have been done taking into account the results with smoothed probabilities, as the target is to get a historical picture from this data and the differences are not critical. Some interesting observations can be drawn from these results. First, the S&P Case-Shiller home price index growth evolves as expected, such that during *housing booms fueled by credit* (state 2) the average price growth is the highest (0.47% per month), while it is modest but positive during *normal times* (0.06%) and negative during *implosion times* (-0.53%). Second, mortgages debt outstanding shows the highest average growth during *housing booms fueled by credit*, as expected. Third, rental prices show a marked different path compared with home prices. Indeed, rents growth is positive in the three states, and the difference between the first and second state is tiny, so the distinctive effect of housing booms fueled by credit on rental prices is low, consistent with the fact that rents are usually not funded by debt, but with salaries. Fourth, the standard fundamentals exhibit the highest growth averages during *normal times* and *housing booms fueled by credit*. Fifth, macroeconomic and financial variables typically display the best performance during states 1 or 2. Sixth, real estate market indicators exhibit the highest average growth during *housing booms fueled by credit*, while also showing the worst performance in *implosion times*, which is the expected outcome according to the argued interpretation of states.

With regard to the second moments of the same variables of interest exhibited in the previous table, Table 1.10 shows the standard deviations of such time series. First, we can notice that the house price index exhibits the highest volatility during *implosion times* (state 3), as it happens with the rent prices index as well. Second, the job market also exhibits more volatility during state 3, both in terms of non-farm employees and unemployment rate. Third, regarding the financing of real estate investments, mortgages debt outstanding displays the highest variability during *housing booms fueled by credit* and *implosion* times, as expected. Indeed, it is interesting to observe that in the case of real estate loans the difference in volatility between states 1 and 3 is even higher, suggesting that being in state 3 has even a larger effect to the construction sector than on the mortgages market. Fourth, in the case of the real estate loans securitized the largest variability is instead in state 1. Fifth, interest rates exhibits more volatility in state 3, both in terms of the Fed funds and the 30-year fixed rate mortgage average. Sixth, the variables measuring aggregate economic activity as real GDP, industrial production and sales have more variability during *implosion times*, specially in the case of the former. Also, this is the case of the balance on current account, which exhibits the largest distance between the variability in state 1 and state 3 of all the time series. Eighth, regarding public finance proxied by public expenditures, tax receipts and public debt we can observe that the largest variability is shown in state 3. Finally, real estate indicators show dual paths. That is, measures of initial construction as housing starts, new homes under construction and cement production show more variability in state 3. However, proxies of the outcome of the construction process as houses sold and supply of houses exhibit more volatility during state 1.

Overall, these descriptive statistics shown in Tables 1.9 and 1.10 are consistent with the assumption of state 1 being *normal times*, state 2 resembling *housing booms fueled by credit* and state 3 being *implosion* times.

Table 1.9: Summary statistics in each state: growth averages (%).

	Full Sample	State 1	State 2	State 3
Housing Prices				
Real S&P Case-Shiller home price index	0.1136	0.0594	0.4660	-0.5305
Real urban primary residence rent index	0.0598	0.0168	0.0977	0.0754
Fundamentals				
Non-farm employees	0.1163	0.1779	0.0868	0.0471
Real wages	0.1791	0.2694	0.1643	0.0053
Real disposable personal income	0.1597	0.2098	0.1589	0.0471
Working age population (aged 15-64)	0.0765	0.0747	0.0783	0.0767
Financial variables				
Real mortgages debt outstanding	0.2740	0.2319	0.3316	0.2449
Real savings deposits	0.4026	0.2126	0.6597	0.2760
30-year fixed rate mortgage average	7.0565	8.0053	5.5724	8.1257
Fed funds	3.7958	4.9413	1.9553	5.1928
Real real estate loans	0.3997	0.3559	0.4414	0.4090
Real real estate loans securitized	0.2484	0.6425	-0.0002	-0.1093
Macroeconomic variables				
Real GDP	2.7445	3.5125	2.5273	1.4653
Real industrial production	0.1696	0.3261	0.1263	-0.0935
Real manufacturing and industries sales	0.2132	0.3325	0.2366	-0.1103
Unemployment rate	5.9737	5.9045	5.9018	6.2885
Real balance on current account	0.0301	-0.2945	-0.8974	2.7925
Yield curve proxy (10y - 2y spread)	1.1132	0.9345	1.3927	0.9116
Real government total expenditures	0.1893	0.1648	0.1916	0.2401
Real government current tax receipts	0.1907	0.3001	0.1912	-0.0603
Real public debt	0.4307	0.3593	0.3764	0.7120
Other real estate indicators				
Housing starts	0.2141	0.3487	0.9741	-1.7494
New building permits	0.0692	0.2730	0.8151	-2.0218
New one family houses sold	0.2335	0.4937	0.8847	-1.7795
Supply of houses	0.3402	0.0670	0.1287	1.4249
New homes under construction	0.0359	0.0318	0.5928	-1.1687
Real cement production	0.0994	0.1799	0.3647	-0.6624

Notes: These summary statistics refer to the percentage average of the growth rates experienced during each subset of data, except in the case of interest rates, in which the reported numbers are the average of the variable in levels. Government total expenditures, government current tax receipts and public debt have been linearly interpolated in order to get a monthly time series.

Table 1.10: Summary statistics in each state: standard deviations.

	Full Sample	State 1	State 2	State 3
Housing Prices				
Real S&P Case-Shiller home price index	0.5224	0.2747	0.3727	0.5715
Real urban primary residence rent index	0.2758	0.1787	0.2944	0.3852
Fundamentals				
Non-farm employees	0.1601	0.1192	0.1262	0.2394
Real wages	0.7333	0.9320	0.4747	0.6531
Real disposable personal income	0.7525	0.7231	0.7789	0.7573
Working age population (aged 15-64)	0.0976	0.0684	0.1098	0.1241
Financial variables				
Real mortgages debt outstanding	0.4413	0.3472	0.4936	0.5008
Real savings deposits	0.7739	0.8145	0.6553	0.7701
30-year fixed rate mortgage average	2.5787	2.0926	1.8941	3.2653
Fed funds	2.9713	2.3386	2.3000	3.4724
Real real estate loans	0.6894	0.5248	0.6575	1.0163
Real real estate loans securitized	3.4688	4.1698	3.3273	1.2325
Macroeconomic variables				
Real GDP	2.0644	1.4398	1.5423	3.2266
Real industrial production	0.6093	0.5028	0.5133	0.8710
Real manufacturing and industries sales	0.8375	0.8454	0.7547	0.9153
Unemployment rate	1.5019	1.4364	1.5132	1.5994
Real balance on current account	5.3443	1.4189	4.7449	9.6815
Yield curve proxy (10y - 2y spread)	0.8400	0.8042	0.8181	0.8074
Real government total expenditures	0.4367	0.2987	0.3784	0.7274
Real government current tax receipts	0.8155	0.6215	0.8906	0.9751
Real public debt	0.5457	0.3967	0.5276	0.7566
Other real estate indicators				
Housing starts	7.6036	6.3262	7.6152	9.7269
New building permits	5.1667	4.3107	3.3273	1.2325
New one family houses sold	7.0067	7.3297	6.6612	6.7004
Supply of houses	7.9944	8.6956	7.3815	7.6088
New homes under construction	1.5030	1.3146	1.3631	1.5044
Real cement production	3.9032	3.0311	4.1637	4.9155

Notes: These summary statistics refer to the standard deviations of the growth rates (in percentage) experienced during each subset of data, except in the case of interest rates, in which the reported numbers are the standard deviations of the variable in levels. Government total expenditures, government current tax receipts and public debt have been linearly interpolated in order to get a monthly time series.

1.4.5 Housing booms fueled by credit versus overvaluation signals

The probabilities of being in a *housing boom fueled by credit* (state 2) are graphed again in Figure 1.4 (red lines), together with the overvaluation signals (gray areas) coming from the demand side (upper graph), from the supply side (middle chart) and the mildly explosive behavior test results of Shi (2017) in the lower graph (brown area)[40]. The first *housing boom fueled by credit* according to the baseline Markov switching model with filtered probabilities is dated from January 1986 to February 1987. In this period, it can be observed overvaluation signals both

[40] Shi (2017) investigates the existence of bubbles in the US national and regional housing markets over 1978–2015. The results of this study regarding the tests of the nationwide non-fundamental component of house prices are arguably the most comparable mildly explosive behavior ones in the literature compared to this paper, as it uses a set of fundamental variables instead of relying only on a price-fundamental ratio.

from the demand and from the supply side common factor models, while the nationwide mildly explosive behavior test of Shi (2017) is silent. However, this author finds bubble behavior in some US regional markets in the late 80s, so giving some support to the Markov switching findings[41]. On the other hand, Ball (1994) suggests that the 1980s property boom was mainly due to technical change in key service industries, together with consequential employment developments, while housing debt acted as a demand booster, along the lines of the BIS (1992) and consistent with the results of this paper[42]. The supply pressures evidenced by the common factor model are also consistent with the results of Glaeser and Gyourko (2018), which find the highest density of households falling in the left hand side of the price-to-cost ratio distribution during the late 80s.

Secondly, the baseline model registers a *housing boom fueled by credit* from February 2000 to February 2006, corresponding to the years previous to the Great Recession. In this case, the common factor model of supply is almost mute, while from the demand side there are solid signals of overvaluation during all this booming period. These results are consistent with the literature, which widely interprets the housing boom of the 2000s as the result of booming demand fostered by credit (see Duca, Muellbauer and Murphy, 2010; Favara and Imbs, 2015; Di Maggio and Kermani, 2017; Adelino, Schoar and Severino, 2017; *inter alia*). Interestingly, Shi (2017) identifies a mildly explosive behavior in housing prices from the first semester of 2004 to the second semester of 2005, which coincides with the final two years of this *housing boom fueled by credit*, consistent with the hypothesis that for a rational bubble to appear, first a housing boom has to be present in order to generate a distortion in price growth expectations. This is also consistent with Muellbauer (2012), who finds overvaluation signals from future price appreciation expectations, peaking in 2005[43].

Third, the baseline model identifies a short and discontinuous *housing boom fueled by credit* from June 2009 to May 2010 in (until December 2009 according to model (2)), a period characterized by a stimulus-supported recovery in the US (see IMF, 2010), in which housing prices were stabilizing and credit conditions were attractive while the labor market was still weak. Therefore, it may be strictly considered as a false signal coming from a housing sector stabilization not explained by an improvement in the job market, and better defined as a *housing recovery fueled by credit*. Along these lines, none of the common factor models identify overvaluation in this period. However, the fact that this recovery was at a high pace, which may have become the beginning of a boom, leave the consideration of this state 2 identification as a *false signal* open to debate, as the difference between a recovery and a boom is ex-ante almost imperceptible[44].

The fourth *housing boom fueled by credit* arises from March 2012 to April 2014 and discontinuously to May 2018 in the case of the baseline model (solid red line). Instead, the model extended to include securitization (model (2), dashed red line) does not identify a booming phase from April 2014 to August 2017. Between 2012 and 2014, the common factor model of demand exhibits signals of overvaluation, while from the supply side they are identified from 2012 on, a time span in which the explosiveness test of Shi (2017) is silent. Indeed, from 2012 to 2018 it has been strong growth in nationwide housing prices, specially in areas as Los Angeles, San Francisco, San Diego and Seattle, while after 2018 the market has gradually slowed down. Again, the findings of Glaeser and Gyourko (2018) are consistent with the supply side overval-

[41] Shi (2017) identifies mildly explosive behavior in bubble residuals in seven metropolitan statistical areas such as Boston, New York, Philadelphia, San Francisco, Los Angeles, Honolulu, and Seattle in the late 80s.

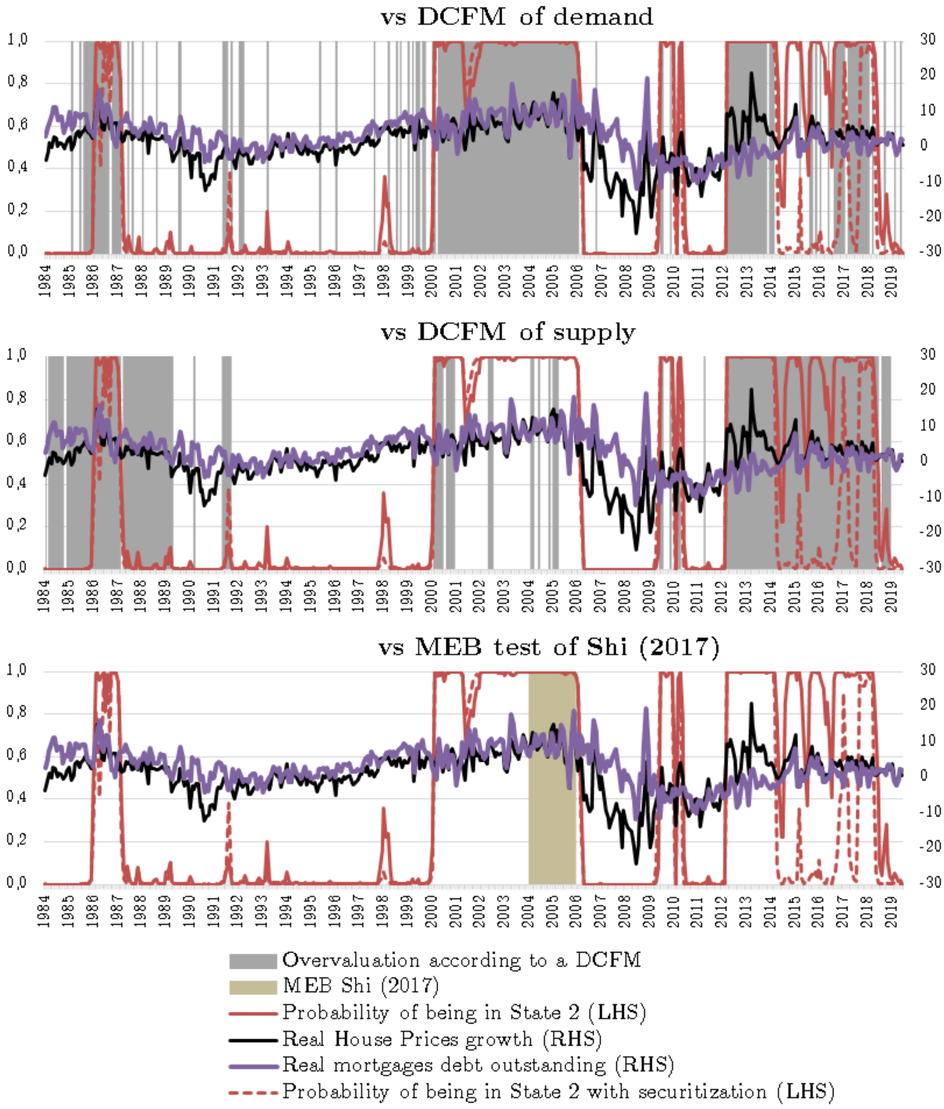
[42] Additional explanations are related to demographics and extrapolative expectations (see Poterba, 1991).

[43] Muellbauer (2012) shows that a measure of overshooting due to extrapolative expectations is crucial to explain the difference between the user cost term by its estimated coefficient in the long run solution for real house prices versus the average historical appreciation from 1980 to 2012.

[44] Indeed, it may be argued that under the interpretation of this Markov switching model as an early warnings model, the identification of this *housing boom fueled by credit* may be a lower bound of housing booming risk, instead of a mistaken signal.

uation signals exhibited by the common factor model of supply. In that regard, it is recognized by housing market analysts that the low inventory available from the Great Recession may have an important role in facilitating prices to go up (see JCHS, 2018 and Sharga, 2019, among others), as supported by the series of monthly supply of houses.

Figure 1.4: Housing booms fueled by credit.



Overall, the results found in this paper seem to be consistent with those shown in the literature. Moreover, the timing of the mildly explosive behavior identified by Shi (2017) together with the *housing boom fueled by credit* preceding the Great Recession are consistent with the hypothesis that before a rational housing bubble appears there should be a booming phase which may generate the economic conjuncture that allows the distortion of prices growth expectations. Whether a *housing boom fueled by credit* end up in a rational bubble is ex-ante unknown, however being able to detect such a state gives an opportunity to macroprudential policy to act when it is still possible to avoid the housing bubble. It is still an open debate whether a central bank or a government should burst the bubble or not, but being able to identify the potentially previous state before a housing bubble arises should generate a more informed position regarding such decision.

1.4.6 Robustness checks

In order to confirm the robustness of the results obtained in the Markov switching model (subsection 1.4.4) and support the choices made in its estimation, some alternative model specifications are performed in this subsection[45]. First, I estimate model (1) and model (2) by using a different series of housing prices growth, i.e. instead of using the *S&P Case–Shiller home price index* I use the *nationwide house price index for existing single-family houses* issued by the FHFA (see Table 1.2). Both models (1) and (2) deliver similar results, which regarding the probabilities of being in *implosion times* are roughly analogous to those obtained in subsection 1.4.4. However, the distinction between *normal times* and *housing booms fueled by credit* becomes less clear, as there appear multiple changes of state.

Second, in order to mitigate the risk that considering different time intervals may bias the estimation of the Markov switching model, both model (1) and (2) are estimated using alternative time horizons. In particular, the models are estimated beginning in 1992 instead of 1984 in order to avoid an initial booming subperiod, and alternatively are estimated from 1984 to June 2007 to avoid the impact of the Great Recession. In all of these four alternative cases, the log likelihood is much lower than using the complete dataset (between 1200 and 1500). Additionally, while in model (1) both time horizons deliver probabilities of being in each state which are pretty similar to the baseline, when adding securitization again the distinction between *normal times* and *housing booms fueled by credit* is unclear.

Third, the Markov switching model is also estimated using an alternative measure of income. In particular, using *real disposable personal income* instead of *real wages* (see Table 1.2) the results resemble the ones obtained in subsection 1.4.4 both in the case of model (1) and 2.

Fourth, in order to verify the convenience of estimating the Markov switching model (1) with 3 states, it is estimated again using an alternative number of states, which are either 2 or 4, leaving the rest of the specification unchanged. When the number of states are 2, one of the states agglutinates the identifications of *normal* and *implosion times*, while the other state proxies the standard *housing booms fueled by credit*. Therefore, choosing 2 states generates an informative loss. Alternatively, when the number of states is set to be 4, one of the states is silent, while the difference between *normal times* and *housing booms fueled by credit* is less robust. However, the probabilities associated to *implosion times* are analogous to the standard version of the model, while the *housing booms fueled by credit* that are still identified are those from 2004 to 2006 and from 2012 to 2014. Additionally, the obtained log likelihood is lower in both models.

Fifth, I estimate the Markov switching model (2) using a different measure of securitization than the used in subsection 1.4.4, such that the variable *real estate loans owned and securitized* in growth rates (see Table 1.2). The results obtained in this case are similar to model (2), where the differences are that the *housing boom fueled by credit* during the 2000s has a short switch to state 1 in 2001 - 2002 and that from 2014 to 2018 the state 2 identification gets closer to the model (1).

Sixth, a measure of house price growth expectations is introduced in the baseline model in order to better meet the pricing equation of Ryoo (2016), commented in subsection 1.3.1. This addition is performed in the form of 1, 2, 3 or 4 years of house price growth lags of the main price series *S&P Case–Shiller home price index* as a state-independent variable. In this way is introduced the result of Duca, Muellbauer and Murphy (2012) that an adaptive price expectation mechanism employed by the housing demand overshoots the behavior of prices beyond fundamentals. This exercise does not seem to improve the estimation of probabilities of being in any particular state as the interpretation of the results becomes unclear, while in some cases one of the three states becomes silent, fixing the probabilities results at zero (lags of 1, 2

[45] The results of these robustness checks are available upon request.

and 3 years). These results support the modeling choice made in subsection 1.3.5 in avoiding the introduction of house price expectations in the Markov switching model.

1.5 Conclusions

The evidence that relates excessive leverage, housing prices growth and financial instability has accumulated over the last decade. The aim of this paper is to empirically identify housing booms not justified by standard fundamentals, but by a credit boom, i.e. *housing booms fueled by credit*. The target in doing so is to better enable policy makers to identify the state of the housing sector in order to potentially prevent the appearance of a rational housing bubble and its consequences.

The main conclusions of this paper are the following. First, standard fundamental factors of demand can explain house prices, but not demand-driven overvaluation. Second, financial variables instead explain demand overpricing, specially mortgage debt. Third, supply-driven overvaluation has a different pattern, which is not explained by financial variables. Fourth, dynamic common factor models can help in identifying the sources of overvaluation, and then, policy making. Fifth, mortgage debt outstanding and securitization exhibit explosiveness. Consequently, standard asset pricing models of housing without debt are incomplete, and also the mildly explosive behavior tests derived from them. Sixth, *housing booms fueled by credit* are consistent with the exuberance periods dated in the literature, and importantly, precede housing bubbles when they arise.

The significance of this study is that it informs policy makers about the risk of an overvaluation in housing prices as soon as data becomes available, that is before a rational housing bubble arises, truly allowing for macroprudential policy. Consequently, identifying *housing booms fueled by credit* may give an opportunity to macroprudential policymakers in avoiding housing bubbles and the potential damage that may come afterwards. This usage may be specially of interest for economists in institutions that wish to *lean against the wind* instead of taking the risk of increasing the likelihood of major future macroeconomic disruptions, along the lines of Roubini (2006), Geanakoplos (2010), Mishkin (2011) and Mian and Sufi (2014b), among others. However, the particular policy to implement after the identification of a *housing boom fueled by credit* is well beyond the scope of this study.

The limitations of this research are mainly two. First, there is the possibility that a short period of volatility in housing prices generate a false signal of *housing boom fueled by credit*, while instead is a fast *recovery*. This risk is mitigated by estimating dynamic factor models and evaluating whether in case of a housing boom signal there are also overvaluation signals coming either from the demand or supply side. However, in any case a fast recovery identification may serve also as an early warning signal. Second, international investments in housing have not been introduced in the model because there is only yearly data on that series. However, finding a good proxy of such source of demand and including it in the Markov switching model would certainly give further insights to the analysis.

Future research along the lines of this paper may go in the following directions. First, this model may be applied to any economy and be used by analysts and policy makers to identify *housing booms fueled by credit* in other countries. Second, by using a general equilibrium model including a housing sector it may be analyzed which set of policies are able to effectively avoid a housing bubble as soon as the Markov switching model presented in this paper identifies a *housing boom fueled by credit*. Third, the Markov switching model may be enlarged to include additional features, such as foreign investments in housing, among others.

Appendices

A.1 Stationarity tests

The stationarity tests are performed by employing augmented Dickey–Fuller tests applied to four alternative functional forms to each considered time series: without deterministic terms (column X), with a constant (column C), with a trend (column T) and with both constant and trend (column CT). The number of lags are chosen by minimizing an information criteria, either the Akaike Information Criteria (AIC row) or the Bayesian (or Schwarz) Information Criteria (BIC row), in which the maximum number of lags have been set at 12. These tests are applied both to the time series in log levels and in first differences.

The results of these stationarity tests are reported in Table A.1, in which $\hat{t}$ are the t-statistics associated to each test of hypotheses, and the critical values are shown in the last row of the table. From such results can be noted that all the time series are integrated of order 1.

Table A.1: Stationarity tests results.

			Log levels				1 Difference			
			X	C	T	CT	X	C	T	CT
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HP	AIC	lags	12	12	12	12	12	12	12	12
		$\hat{t}$	0.51	-2.23	-3.64	-2.30	-2.47	-2.57	-2.64	-2.65
	BIC	lags	4	4	4	4	3	3	3	3
		$\hat{t}$	0.84	-1.50	-2.32	-1.52	-3.61	-3.72	-3.75	-3.75
W	AIC	lags	12	12	12	12	11	12	12	12
		$\hat{t}$	2.23	-0.83	-2.47	-0.86	-2.77	-3.74	-3.88	-3.86
	BIC	lags	12	12	12	12	11	11	0	11
		$\hat{t}$	2.23	-0.83	-2.47	-0.86	-2.77	-3.59	-23.59	-3.69
I	AIC	lags	4	4	4	4	11	3	3	3
		$\hat{t}$	7.03	-0.66	-1.75	-0.67	-3.60	-14.16	-14.29	-14.29
	BIC	lags	3	3	3	3	0	2	2	2
		$\hat{t}$	6.72	-0.66	-1.92	-0.66	-24.77	-16.48	-16.58	-16.59
E	AIC	lags	4	4	4	4	3	3	3	3
		$\hat{t}$	1.97	-1.15	-2.39	-1.16	-2.84	-3.47	-3.49	-3.50
	BIC	lags	3	3	3	3	2	2	2	2
		$\hat{t}$	2.21	-1.23	-2.26	-1.24	-3.16	-3.87	-3.90	-3.90
R	AIC	lags	12	12	12	12	11	11	11	11
		$\hat{t}$	2.17	0.92	-0.71	0.95	-4.78	-5.27	-5.63	-5.42
	BIC	lags	1	1	1	1	0	0	0	0
		$\hat{t}$	2.86	0.70	-0.63	0.70	-12.75	-13.17	-13.26	-13.20
D	AIC	lags	12	12	12	12	12	12	12	12
		$\hat{t}$	0.72	-1.23	-2.54	-1.27	-1.55	-1.62	-1.68	-1.67
	BIC	lags	10	10	11	10	9	9	9	9
		$\hat{t}$	0.74	-1.30	-2.88	-1.33	-1.73	-1.85	-1.92	-1.89
S	AIC	lags	9	9	9	9	8	8	8	8
		$\hat{t}$	0.27	-1.51	-0.54	-1.55	-3.97	-3.98	-4.73	-4.07
	BIC	lags	2	2	0	2	1	1	0	1
		$\hat{t}$	0.80	-1.91	0.37	-1.83	-11.51	-11.55	-19.25	-11.60
Critical Values			-1.95	-2.89	-3.43	-1.64	-1.95	-2.89	-3.43	-1.64

Notes: AIC accounts for the Akaike Information Criterion and BIC stands for the Bayesian Information Criteria. Lags are the optimal number that minimizes the information criteria and $\hat{t}$ are the corresponding t-statistics associated to each test. See a complete description of these variables in Table 1.2. The sample size used in these tests in the case of variable D is 1984 M1 to 2019 M6.

A.2 Autocorrelation tests

As commented in subsection 1.4.3, real housing prices growth exhibits autocorrelation when estimated in model (1) of Table 1.4. Table A.2 shows that using different tests such as the t-test on the AR(1) coefficient on the residuals in model (1), the Durbin-Watson test, the Breusch-Godfrey test and the Cumby-Huizinga test overwhelmingly reject the null of no serial correlation. In addition, the Cumby-Huizinga test lag order 12 can not reject the null of serial correlation up to an eleventh order at the 95% significance level, meaning that real housing prices growth in model (1) of Table 1.4 exhibits autocorrelation at lags 1–11, i.e. roughly one year.

Table A.2: Autocorrelation tests results.

	Statistic	(1) OLS Real HP growth
Residuals AR(1) regression test	p-value	0.000
Durbin-Watson test	DW d-statistic	0.589
Breusch-Godfrey test		
Order 1	Prob > chi2	0.000
Order 24	Prob > chi2	0.000
Cumby-Huizinga test		
Order 1	p-value	0.000
Order 11	p-value	0.029
Order 12	p-value	0.056
Order 13	p-value	0.084
Order 14	p-value	0.179

Notes: The Cumby-Huizinga test for autocorrelation allows for predetermined regressors and is robust to heteroskedasticity.

A.3 Linear regression models

Table A.3 exhibits the analogous estimations of those shown in Table 1.4 (see subsection 1.4.3) after recursive elimination of not significant variables, except for the controls.

Table A.3: Linear regression estimates.

	(1)		(2)		(3)		(4)	
	OLS		CO		Probit		Probit	
Dependent variable	Real HP growth		Real HP growth		IO_D		IO_S	
Standard fundamentals								
Working population g.							-2.495***	(0.95)
Employees growth	0.898***	(0.13)			-2.056***	(0.63)	2.672***	(0.61)
Real wages growth								
Real rents growth	0.827***	(0.07)	0.763***	(0.04)			0.763***	(0.25)
Financial variables								
Mortgage interest rates	-0.101***	(0.01)			-0.243***	(0.04)		
Yield curve proxy	0.121***	(0.02)			0.351***	(0.09)	0.157*	(0.08)
Mortgage debt growth	0.316***	(0.02)			0.830***	(0.09)		
Control variables								
Real GDP growth	0.036***	(0.01)	0.020***	(0.01)	0.063*	(0.04)	-0.007	(0.04)
Current account balance	0.000***	(0.00)	-0.000	(0.00)	0.001*	(0.00)	0.000	(0.00)
Number of observations	426		425		426		426	
R^2	0.588		0.533		-		-	
Pseudo R^2	-		-		0.2194		0.0900	
Prob > F	0.000		0.000		-		-	
Prob > chi^2	-		-		0.000		0.000	
Log pseudolikelihood	-		-		-225.174		-262.170	

Notes: Robust standard deviations between brackets. Significance levels at 1%, 5% and 10% are represented by ***, **, * asterisks, respectively. Results on the constant coefficient are omitted. CO stands for the Cochrane-Orcutt estimation and IO means index of overvaluation (see subsection 1.3.3 for a detailed description).

A.4 Markov switching models: smoothed probabilities

The smoothed Markov switching probabilities of being in each of the three states according to model (1) and (2) are shown in Figure A.1 (blue solid line and blue dashed line, respectively), where the interpretation of states is analogous to the one with filtered probabilities (detailed in subsection 1.4.4). Indeed, the results are quite similar after introducing the smoothing, as it can be seen in Figure A.2, that compares the Markov switching model (1) probabilities of both filtered (red line) and smoothed (blue line) approaches.

Figure A.1: Smoothed Markov switching probabilities of being in each state.

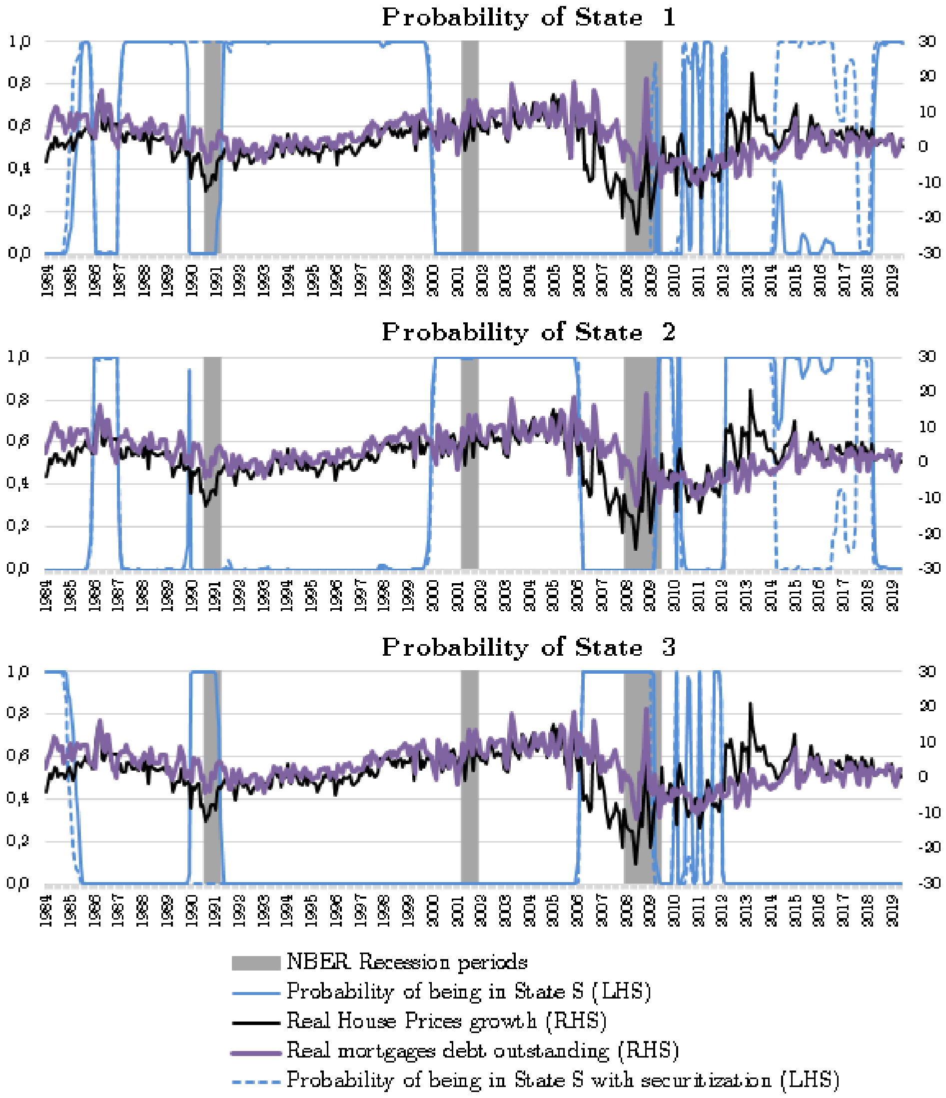
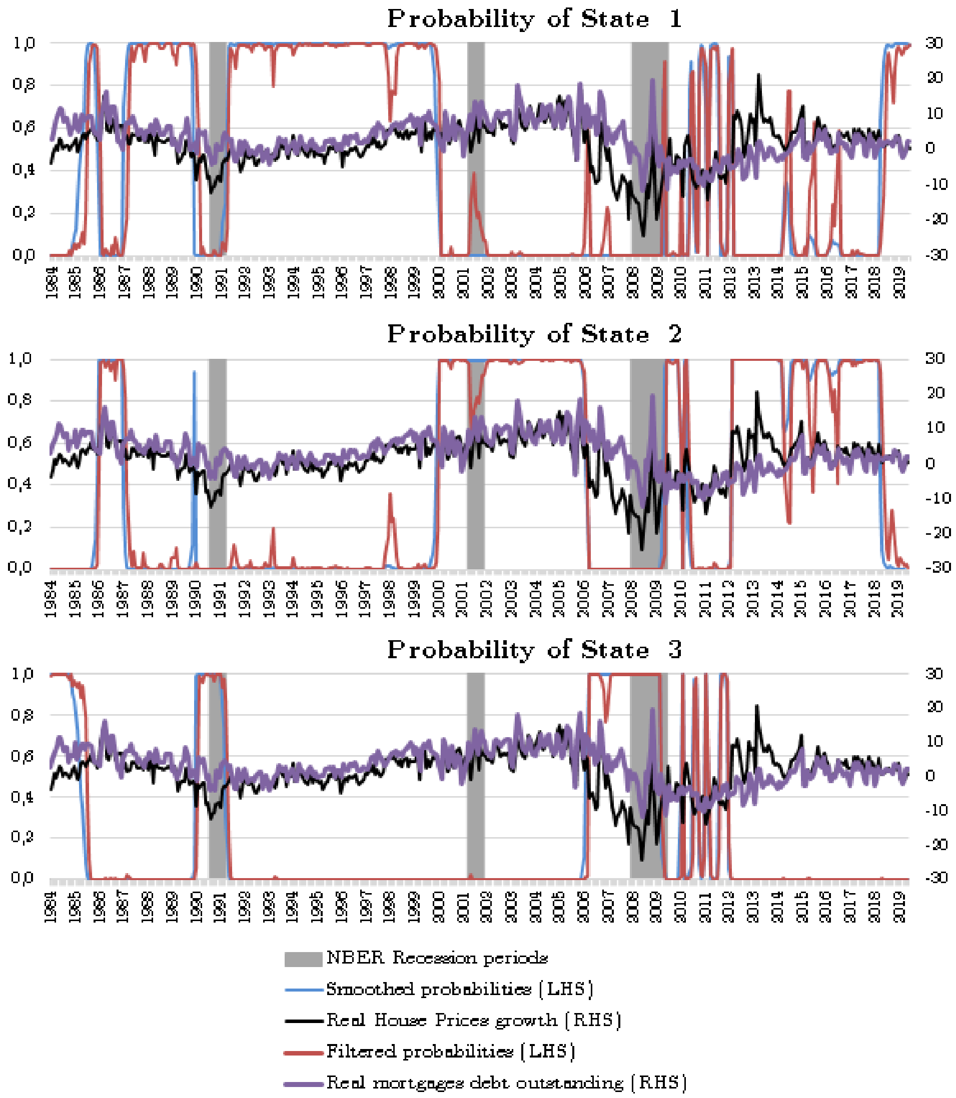


Figure A.2: Filtered vs. smoothed probabilities, model (1).



A.5 Markov switching model (2): with securitization

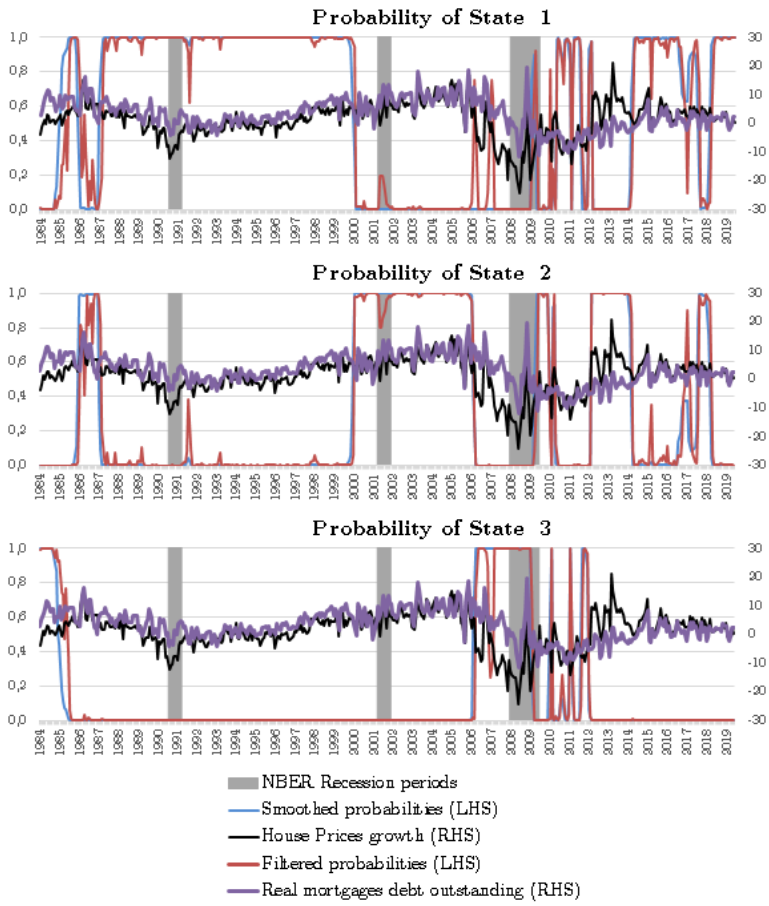
Table A.4 shows the latest transition probabilities of model (2):

Table A.4: Latest transition probabilities matrix, model (2).

		State in t-1		
		1	2	3
State in t	1	0.9813	0.0351	0.0533
	2	0.0187	0.9488	0.0071
	3	0	0.0161	0.9396

Figure A.3 shows the comparison of filtered (red line) versus smoothed (blue line) Markov switching probabilities of being in each of the three states according to model (2). It is noticeable that results are quite similar in both approaches.

Figure A.3: Filtered vs. smoothed probabilities, model (2).



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2 Thick modeling housing investment

This study empirically models housing investment in the largest euro area countries and the euro area. It applies a model averaging approach that selects error correction specifications based on in-sample and out-of-sample selection criteria and using a wide set of short and long-run investment determinants. In-sample estimates confirm marked country heterogeneity in the drivers of housing investment. The role of Tobin's Q, income and credit are found to be country specific. The out-of-sample model averaging forecasts outperform autoregressive and building permits benchmarks. These findings call for a country heterogeneous implementation of investment policy measures and for future applications of the model averaging tool to exploit its conditional forecast potential.

Keywords: Housing investment, model averaging, Tobin's Q, euro area, country heterogeneity.

JEL Classification: C22, C51, C52, C53, E17, E22, E27.

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2.1 Introduction

Housing investment is widely monitored by analysts and policymakers across the globe due to the importance of housing for the business cycle, including for predicting recessions. The latter has been extensively studied particularly for the US (Nguyen, 2013; Leamer, 2015; Piazzesi and Schneider, 2016; Kohlscheen et al., 2018; Aastveit et al., 2019; and Huang et al., 2020). Yet, the literature neither provides a clear-cut commonly agreed theoretical framework to model housing investment nor an agreement on its empirical determinants. One plausible reason for that may be the rather persistent housing investment cycles which might diverge across countries. This study empirically models housing investment in the five largest euro area countries and compares the country results with those for the aggregated euro area level.

Modelling housing investment across the largest euro area countries proves rather challenging. First, housing markets across these countries have undergone divergent developments during the past two decades. Second, there are profound structural differences across housing markets in these countries. For example, the share of owner-occupied accommodation ranges between 50% in Germany to around 80% in Spain, while it takes around 80 years for the average dwelling in Germany to change ownership compared to just 40 years in the Netherlands. Against the background of these modelling challenges, we apply a uniform empirical framework that nevertheless allows for country heterogeneity. The same set of model selection criteria using a common and large set of potential investment determinants are applied to the five largest euro area countries and the euro area. Moreover, model averaging is applied, because averaging over a large set of models often leads to better predictive performance (Moral-Benito, 2015; Aye et al., 2016; Steel, 2019; Bobeica and Hartwig, 2021). To the best of our knowledge it is for the first time that such a flexible and encompassing model averaging tool is applied to housing investment in the euro area countries. In contrast to other euro area country studies, a housing affordability index and uncertainty measures are also considered as potential drivers of housing investment. The empirical framework model is closely related to a model averaging application to private consumption (de Bondt et al., 2019 and 2020).

In more detail, this study sets out with a search for robust long-run relationships among three key long-run housing investment determinants. Once robust cointegration relationships have been established, a wide set of short-run investment determinants is added to enrich these models and to generate many estimated models. The applied model averaging tool selects error-correction model (ECM) specifications from in- and out-of-sample selection criteria. Two alternative ECM specifications are explored. The first specification considers equations where both long-term and short-term determinants are freely estimated. The former group includes various measures of Tobin's Q, household income and mortgage credit. The latter includes mortgage interest rates, a set of macroeconomic variables, uncertainty measures, demographics and wealth. The only difference made in the second specification is the assumption of a unit coefficient in the long term for Tobin's Q measures and income variables. This assures that housing investment behaves in line with Tobin's Q theory in the long run and that the investment-income ratio is constant in the long run. For both approaches, the same in- and out-of-sample selection criteria are applied using an identical set of short-term investment determinants.

Two main conclusions emerge from our model averaging tool. Firstly, it confirms the necessity to take euro area country heterogeneity into account for modelling housing investment. Tobin's Q and income are not necessarily selected as key long-run drivers of housing investment at the country level versus the aggregated euro area level. Tobin's Q has been a key long-term investment determinant since 1999 in the Netherlands and to a lesser extent in Germany and Spain, but not at all in France and Italy. Income has been a key long-term driver of investment in Germany and the Netherlands and to some extent in Spain, whereas this has not been the case in France and Italy. In contrast to other euro area country studies, we find that credit or housing affordability matters for housing investment in the long run. Credit has played a decisive supportive long-run role for housing investment in France and Italy and housing affordability in Spain and the Netherlands. In Germany we find consistently a negative long-run relation between housing investment and credit. The investment-credit relationship is found to be significantly positive in the short run. Secondly, the out-of-sample performance of the top 50 selected equations from the unrestricted and restricted specifications is telling. The former outperforms in all cases an autoregressive benchmark model and the latter even in all cases a benchmark model using building permits. The latter is expected to provide clear leading signals about housing investment as it takes a couple of quarters for building permits to be translated into housing investment. It is interesting that the top 50 selected restricted equations consistently rank better than the building permits-based benchmark model. The reported outperformance of the building permits benchmark is a surprising and promising result. An out-of-sample application including the first three COVID-19 quarters in 2020 shows that housing investment in all countries derived from our model averaging tool is despite the unprecedented sizeable COVID-19 shock relatively close to the actual housing investment level in the 2020Q3, the last observation of our sample. Having said this, the results also make clear that the model averaging outcomes help in conditional forecasting the underlying housing investment level developments, but they are less suitable for capturing short-run swings in quarterly growth rates. The latter often rebounds from one quarter to the next and typically relate to events not part in our set of model variables, such as weather conditions, tax and regulatory changes.

This paper is structured as follows. Section 2.2 reviews the literature, focusing on the determinants of housing investment. Section 2.3 describes the model averaging methodology and section 2.4 the data. Section 2.5 reports the results in terms of numbers of selected equations, estimates, contributions and out-of-sample performance. Section 2.6 concludes.

2.2 Literature review

Empirical studies of housing investment in euro area countries and the euro area are surprisingly limited, given the consensus view of the economic importance of housing. Many studies analyse house prices, but studies focusing on housing or residential investment are comparatively rare. Table 2.1 summarises the housing investment studies we found (2 to 3 per country), focusing on the empirical estimates of long-run housing investment determinants. Five remarks emerge.

The first and main conclusion is that almost all studies explore an error correction type of model, but there is no clear-cut agreement on the long-run drivers of housing investment. There is thus common agreement among modellers to distinguish between short and long-run effects and no general opinion about which factors drive housing investment in the long run. The exceptions are a panel study of Rodríguez Palenzuela and Dees (2016) and Bulligan et al. (2017) which both estimate a level specification for a housing investment ratio to real GDP, respectively, to wealth. Estimates of the long-run housing investment determinants can of course only be included if a long-run cointegration relation exist. For example, Kajuth (2020) find no support for a long run Tobin's Q relation in Germany. Vermeulen and Rouwendal (2007) don't find a cointegration relationship for the Netherlands.

Secondly, among the long-run determinants often house or land prices are considered, and less frequently other prices relevant for the cost of housing. Yet, following Tobin's Q theory, house prices might not necessarily matter per se, but rather in relative terms compared to prices capturing the replacement costs of housing. Like for other investment a Tobin's Q concept makes sense for housing investment. After the influential work of Jorgenson (1963) and Tobin (1969), many authors have used the notion of Tobin's Q in the context of modelling business investment. Tobin (1969) defines Q as the value of capital relative to its replacement cost, which assumes it should be related to the rate of investment, i.e. the speed at which investors wish to increase the capital stock. Building on this usage, housing researchers have used Tobin's Q, with heterogeneity on how q is empirically measured: ratio between house prices and price of alternative construction projects (Poterba, 1983); ratio between existing to new-home prices (Jud and Winkler, 2003); and ratio between house prices and a measure of construction costs (Antipa and Lecat, 2009; Bulligan et al. 2017; Kajuth, 2020). Noteworthy is that the estimated long-run house price and Tobin's Q effects (negative coefficient expected for housing costs variables) are quite homogeneous, fluctuating around 1, in line with Tobin's Q theory.

Thirdly, household income is a long-run determinant in only about one-third of the studies. In most of the cases where household income is not a driver of investment, macroeconomic proxies such as real GDP or private consumption are considered instead. Put differently, in all most all cases investment is scaled by some type of income or output. In a couple of cases this scaling variable is restricted to one, implying a constant investment-income ratio in the long run. In the three cases of a freely estimated income elasticity, it is twice clearly below 1 and once above. The household income measure studied is total disposable income. It can, however, be questioned, whether all components of disposable income are expected to be used for funding housing investment. Labour income and wages appear particularly relevant.

Fourthly, the availability or the cost of credit is part of most studies. Most often the cost of credit as captured by real interest rates or more detailed cost of capital measures including taxes or subsidies. The availability of credit is not so often studied. This surprises us, because households and particularly first-time buyers will only decide on their housing project once they have made sure that sufficient credit is being granted. In fact, the cost of credit might be relevant only to the extent that they determine the access to credit. Estimates report positive as well as negative long-run credit effects. Negative long-term credit effects, albeit *prima facie* counterintuitive, are in line with historical (1913-2016) evidence across 17 countries (Kohl, 2020). This cross-country study shows that the explosion of mortgages since the 1970s is associated not with a proportional expansion in new construction, but rather with construction-depressing effects.

The fifth and final remark is that occasionally other factors have been analyzed as long-run housing investment determinants[1]. One group consists of macro factors, another of demographics and wealth and a rest category. The first group captures the general environment in which housing investment decisions take place: real GDP (economy-wide output measure and business cycle), private consumption (broader based proxy for household income) and employment (labour market situation). Demographic data are typically analysed by modelling real housing investment per capita or households (Dümmler and Kienle, 2010; Bulligan et al., 2017). Other studies focus on population or certain age cohorts. Household wealth, housing stock and capital are occasionally studied as long-run housing investment determinants. The rationale for this approach is an assumed long-run target level for the ratio between housing investment and wealth, stock or capital. The final group of other long-run determinants are considered only in one study. Regarding housing starts and building permits, their use as independent model variable can be questioned, because others (e.g. Jud and Winkler, 2003) use both series as alternative measures of housing investment and thus treat them as dependent variable. The limited use of housing starts is no surprise due to limitations in availability. We use building permits, which are available for the five largest euro area countries, to benchmark our out-of-sample forecasts of housing investment and thus treat permits as an alternative measure of housing investment.

[1] For a summary of more qualitative characteristics on the different housing markets in the five largest euro area countries see Table B.1 in the Appendix.

Table 2.1: Overview of estimated long-run housing investment determinants.

	Germany			France			Italy	
Study	[1]	[2]	[3]	[4]	[5]	[3]	[3]	[6]
Model type	VECM	VECM	ECM	VECM	ECM	ECM	ECM	Level
Sample	1980 2007	1975 2009	1970 2012	1984 2006	1980 2008	1970 2012	1970 2012	1982 2012
Tobin's Q								
House prices		0.76***			0.80***			0.06***
Land price			1.15***			0.50***	0.38***	
Housing investment deflator								x
Construction costs					-0.63***			
Income	0.21	0.26***						
Credit availability and costs								
Debt								
Credit (access)								
Debt-to-disposable income								
Real interest rates			-1.88***			-2.22***	-0.51***	-0.00***
User cost of housing capital	-4.94***							
Depreciation rate								x
Taxes				-0.09				-0.31***
Subsidies				0.31***				
Macro								
Real GDP			0.99***			-0.00	0.06*	
Consumption				1.09***				
Employment in construction								
Inflation gap	-2.32*							
Demographic and wealth								
Population	x	1.56***						x
Homeowners over population								
Wealth	0.41							1
Housing stock								0.38***
Housing capital to inv. ratio								
Others								
Liquid financial assets								
Consumer confidence								
Housing starts								
Building permits								
Adjustment coefficient	-0.03	-0.07**	-0.06***	-0.10**	-0.04**	-0.11***	-0.10***	-0.23***

Notes: [1] = Dümmler and Kienle (2010); [2] = Knetsch (2010); [3] = Gattini and Gannoulis (2012); [4] = Antipa and Schalck (2010); [5] = Antipa and Lecat (2010); [6] = Bulligan et al. (2017). ***, ** and * denote significance of coefficient at 1%, 5%, respectively, 10% level. "x" means that the variable is present in the model but does not have a specific estimated coefficient.

Table 2.1 (cont.): Overview of estimated long-run housing investment determinants.

	Spain			**Netherlands**		**Euro area**	
Study	[4]	[3]	[7]	[3]	[8]	[9]	[10]
Model type	ECM	ECM	VECM	ECM	ECM	Level	ECM
Sample	1982 2007	1970 2012	1995 2014	1970 2012	1980 2016	2000 2012	1995 2016
Tobin's Q							
House prices	0.28***						1.06***
Land price		0.11**		0.14***			
Housing investment deflator					x		x
Construction costs							
Income			1.54				
Credit availability and costs							
Debt						2.96*	
Credit (access)			0.03				
Debt-to-disposable income						-0.02*	
Real interest rates	-0.06***	-2.16***	-0.04	-1.87***	x	-0.12	
User cost of housing capital					0.11***		-0.16**
Depreciation rate					0.02		x
Taxes							
Subsidies							
Macro							
Real GDP		1.21***		0.42***		1.00***	1
Consumption					1		
Employment in construction							
Inflation gap							
Demographic and wealth							
Population						2.45***	
Homeowners over population						0.12**	
Wealth			0.04				
Housing stock							
Housing capital to investment ratio							3.22***
Others							
Liquid financial assets						-5.97**	
Consumer confidence						0.05**	
Housing starts	0.46***						
Building permits					0.45***		
Adjustment coefficient	-0.21***	-0.03	-0.03	-0.29**	-0.11		-0.10

Notes: [3] = Gattini and Gannoulis (2012); [4] = Antipa and Schalck (2010); [7] = Arencibia et al. (2017); [8] = Berben et al. (2018); [9] = Rodríguez Palenzuela and Dees (2016); [10] = Angelini et al. (2019). ***, ** and * denote significance of coefficient at 1%, 5%, respectively, 10% level. "x" means that the variable is present in the model but does not have a specific estimated coefficient.

2.3 Empirical methodology

2.3.1 Specification

Our starting point is a housing capital stock-adjustment process with all variables in log real terms, i.e. deflated by the private consumption deflator. Denoting k_t as the housing stock in period t, and following the common assumption that housing investment is non-stationary in levels but stationary in growth terms (I(1)), the stock variable obeys the following process, where τ is the rate of depreciation[2]:

$$k_t \equiv (1-\tau)k_{t-1} + i_t \tag{2.1}$$

Because the optimal housing stock k^* is unobserved, it must be inferred from the data. The desired housing stock is written as a linear function of its determinants x_t:

$$k_t^* = f(x_t) \tag{2.2}$$

Regarding the long-run determinants, we include the widely applied determinants of Tobin's Q, q, (house price relative to another price index), income, y, and credit, c[3]. Various measures for each determinant are considered to acknowledge uncertainty about its measurement: four measures of Tobin's Q, always the residential property price but relative to different other price indices; and five measures of income: real disposable income per household, labour income, total compensation, compensation per employee and a housing affordability index. The latter is calculated in line with an index published by the National Association of Realtors and combines the joint impact of income, house prices and mortgage rates in one variable[4]. The credit group contains three measures: mortgages, mortgage credit to disposable income ratio and loan to value ratio. The latter is calculated as the ratio between mortgages and housing wealth. The long-run specification for housing investment is then formulated as follows:

$$i_t = \gamma_1 + \gamma_2 q_t + \gamma_3 y_t + \gamma_4 c_t + \gamma_5 k_{t-1} + \epsilon_t \tag{2.3}$$

A priori expectations for the coefficient signs are: γ_1, γ_4 can be any sign; γ_2, $\gamma_3 > 0$ and $\gamma_5 < 0$. The long-run model residual ϵ measures the deviation from the long-run relationship and is a mean zero stochastic innovation. In equation (2.2) the optimal housing capital stock is optimally adjusted without any time lag, but in a housing capital stock adjustment principle there are lags in this adjustment process (Lee, 1999). While equation (2.3) characterizes the long-run behaviour of housing investment, short-run dynamics are also important and therefore short-run determinants x are additionally considered, resulting in the following specification:

$$\triangle\, i_t = \beta_1 + \beta_2 \triangle q_t + \beta_3 \triangle y_t + \beta_4 \triangle c_t + \beta_5 \triangle i_{t-1} + \epsilon_{t-1} + \delta_i \triangle x_{i,t-j} + \mu_t \tag{2.4}$$

A wide range of potential short-run determinants is considered, divided into four categories: (i) mortgage interest rates, mr; (ii) macroeconomic indicators, ma; (iii) demographics and wealth, w; and (iv) unemployment rate and uncertainty measures, un. Mortgage rates are always included, whereas this is not necessarily the case for the other categories. Within each

[2] This general specification is along the lines of Demers (2005).

[3] The long-run variables we define are commonly used in the literature, either by empirical or theoretical studies (see Table 2.1). However, there is no general agreement on the variables that have to be used in the analysis of housing supply, while country heterogeneity is a widely accepted feature of housing markets. These are reasons for us to prefer a flexible specification in which we let data speak, so maximizing the chances of finding sets of equations that perform well in forecasting housing investment without imposing a priori theory that may not fit for all countries we study. This choice is also consistent with our thick modeling approach.

[4] The Housing affordability index is calculated as follows: Housing affordability index (HAFI) = 100 * monthly household income (PYNH) / monthly qualifying income (PYNQ), with PYNH calculated using Eurostat data on the number of households, and PYNQ calculated as 4 * monthly down-payment (derived assuming an initial down-payment of 20% and applying the composite interest rate on house purchases. See https://www.nar.realtor/research-and-statistics/housing-statistics/housing-affordability-index/methodology.

category between 3 to 4 series are considered. Table B.2 in the Appendix provides the details about these short-run model variables. Three uncertainty measures are, to the best of our knowledge for the first time for euro area countries included. They are calculated as the volatility of the stock market, unemployment, respectively, disposable income. Theoretically, increased uncertainty should lower housing investment. Empirically, finding a proxy for uncertainty has proven problematic, but results for the US indicate that uncertainty indeed has a negative impact on housing starts (Miles, 2009). The unemployment rate is not only a labour market indicator, but it has a close link with consumer confidence.

Equation (2.4) is an ECM type of specification. The term error-correction relates to the fact that the previous period deviation from the long-run equilibrium, the error, influences its short-run dynamics. ECMs directly estimate the speed at which housing investment returns to equilibrium after a change in other variables. This framework is useful for estimating both short-run and long-run effects of one time series on housing investment. We prefer to estimate equation (2.4) in a vector-based Johansen system, implying a 3-variable VECM, where our focus is on the housing investment equation. Besides common practice, multivariate models seem better equipped to deal with large variations in some variables, for example due to COVID-19 (Bobeica and Hartwig, 2021). We uniformly apply 2 lags, as more lags are too demanding for the comparatively short sample. The estimated unrestricted (UN) specification reads then as follows:

$$\begin{aligned}\triangle i_t = {} & \alpha_0 + \alpha_1 \triangle mr_t + \alpha_2 \triangle ma_t + \alpha_3 \triangle w_t + \alpha_4 \triangle un_t + \beta_{2,1} \triangle q_{t-1} + \beta_{2,2} \triangle q_{t-2} + \\ & + \beta_{3,1} \triangle y_{t-1} + \beta_{3,2} \triangle y_{t-2} + \beta_{4,1} \triangle c_{t-1} + \beta_{4,2} \triangle c_{t-2} - \gamma_0 \gamma_2 q_{t-1} - \gamma_0 * 1 * \gamma_0 \gamma_3 y_{t-1} - \\ & - \gamma_0 \gamma_4 c_{t-1} + \gamma_0 i_{t-1} + \delta_1 \triangle i_{i,t-1} + \delta_2 \triangle i_{i,t-2} + \mu_t \end{aligned} \tag{2.5}$$

We not only fully let the data speak as is the case in equation (2.5), but also explore another avenue that puts structure on the long-run co-integration relation by restricting the long-term coefficients of Tobin's Q and income to one. Tobin's Q coefficient is in the long term restricted to one to assure a theoretically plausible long-run supply adjustment. Similarly, the long-run income elasticity is restricted to one for a plausible long-term demand adjustment. The income restriction to one is like studies that analyse the housing investment ratio to real GDP as it is the case in the euro area country panel study of Rodríguez-Palenzuela and Dees, 2016) and in the ECB-BASE model (Angelini et al., 2019) or to wealth (Bulligan et al., 2017). The long-run coefficient of credit remains freely estimated, because credit can be viewed as a positive funding source for investment as well as a negative constraint or housing market risk measure.

2.3.2 Selection of equations

After estimating all possible equations given the considered categories and variables per category explained in last subsection, a four-step selection process is applied to filter those specifications per country that fulfill three in-sample selection criteria and one out-of-sample criterion. The selection process broadly follows the one used in earlier applications to private consumption (De Bondt et al., 2019; 2020).

S1) The first selection criterion is a co-integration test. The starting point is a search among all possible combinations of long-run relationships with up to three long-run determinants (in total 119 combinations) without any short-run determinant. The error correction coefficient (γ_0) should be statistically significant with a t-statistic of at least 3 (5% augmented Dickey-Fuller critical value) to ensure that housing investment is co-integrated with its long-run determinants.

S2) The second selection criterion focuses on residual autocorrelation as a sign of model misspecification using the P-values of the Ljung-Box Q-statistics. The probabilities should be larger than 0.05 for lags 1 to 4. This criterion thus tests for significant departures over the first four lags. Given the short sample, testing for more lags appears problematic as the test loses its predictive power against low degrees of freedom.

S3) The third selection tests for positive and significant long-run coefficients with respect to Tobin's Q as well as income. It hence aims at avoiding economically implausible negative long-run effects. The 5% significance level using the F-statistic is applied. This criterion is only relevant for the unrestricted specifications. We do not impose any restrictions on the estimated coefficients for credit variables.

S4) The fourth and final selection criterion examines recursively the out-of-sample performance. The root mean squared out-of-sample forecast error (RMSE) on average over one, two, up to eight quarters ahead should be at least 10% lower as those from an AR(1) benchmark model. At each recursive step, the RMSE for each equation is calculated based on forecasts for between 1 and 8 quarters ahead. RMSEs are then averaged across all steps for each equation. The ECM equations are sorted according to their average RMSE from the lowest to the highest. In addition, the relative average RMSEs against an AR(1) benchmark model are computed and only specifications with a RMSE 10% lower than the AR benchmark model are selected.

The benchmark is an AR(1) model, because it is often used and well-known to be hard to beat. The out-of-sample outcomes are also compared to a second benchmark model using building permits. Building permits are expected to be closely related to national accounts data on housing investment, particularly to the housing construction component (the other main component is housing renovation) as new construction can only start after a building permit has been granted. For Canada Demers (2005) finds that the best out-of-sample model is a leading indicator model using building permits and housing starts. For the US Lunsford (2015) shows the value added of a forecast tool based using housing starts and completions. Building permits are the first clear signal regarding future housing investment. After they are issued by municipalities, it usually takes a couple of quarters for building permits to translate into housing starts followed by housing investment. Both benchmark models read as follows, respectively.

$$\triangle i_t = c_0 + c_1 \triangle i_{t-1} + e_t \tag{2.6}$$

$$\triangle i_t = \mu_0 + \mu_1 \triangle bp(ma4)_{t-1} + \epsilon_t \tag{2.7}$$

where bp(ma4) denotes the four-quarter moving average of building permits excluding residences.

Out of the selected equations that have passed the four selection criteria, the focus is on the top 50 equations in terms of out-of-sample performance. We do not rely on a single "best" model specification but prefer to apply model averaging. This method is an important tool in economics, particularly in empirical settings with large numbers of potential specifications and relatively limited numbers of observations (Moral-Benito, 2015). Averaging over a large set of models often leads to better predictive performance (Steel, 2019). Averaging over 50 models is in our view sufficiently large in practice. For example, model averaging using the Occam's window reduces in many practical cases the number of models to fewer than 25 (Clyde, 1999). We set the number of model equations at two times 25. We thus construct estimates by "averaging" estimated coefficients across 50 different models to address the problem of model uncertainty inherent in the selection of housing investment determinants. Our model averaging application is closely related to Stadelmann (2010) Bayesian model averaging application to Swiss house prices. The modelling spirit is the same, as both approaches take account of uncertainty concerning the model variables and perform an exhaustive search over the whole model space. A difference is that we use unweighted averages of classical estimates (Sala-i-Martín et al., 2004) rather than weights to individual regressions derived from a Bayesian information criterion.

2.4 Data

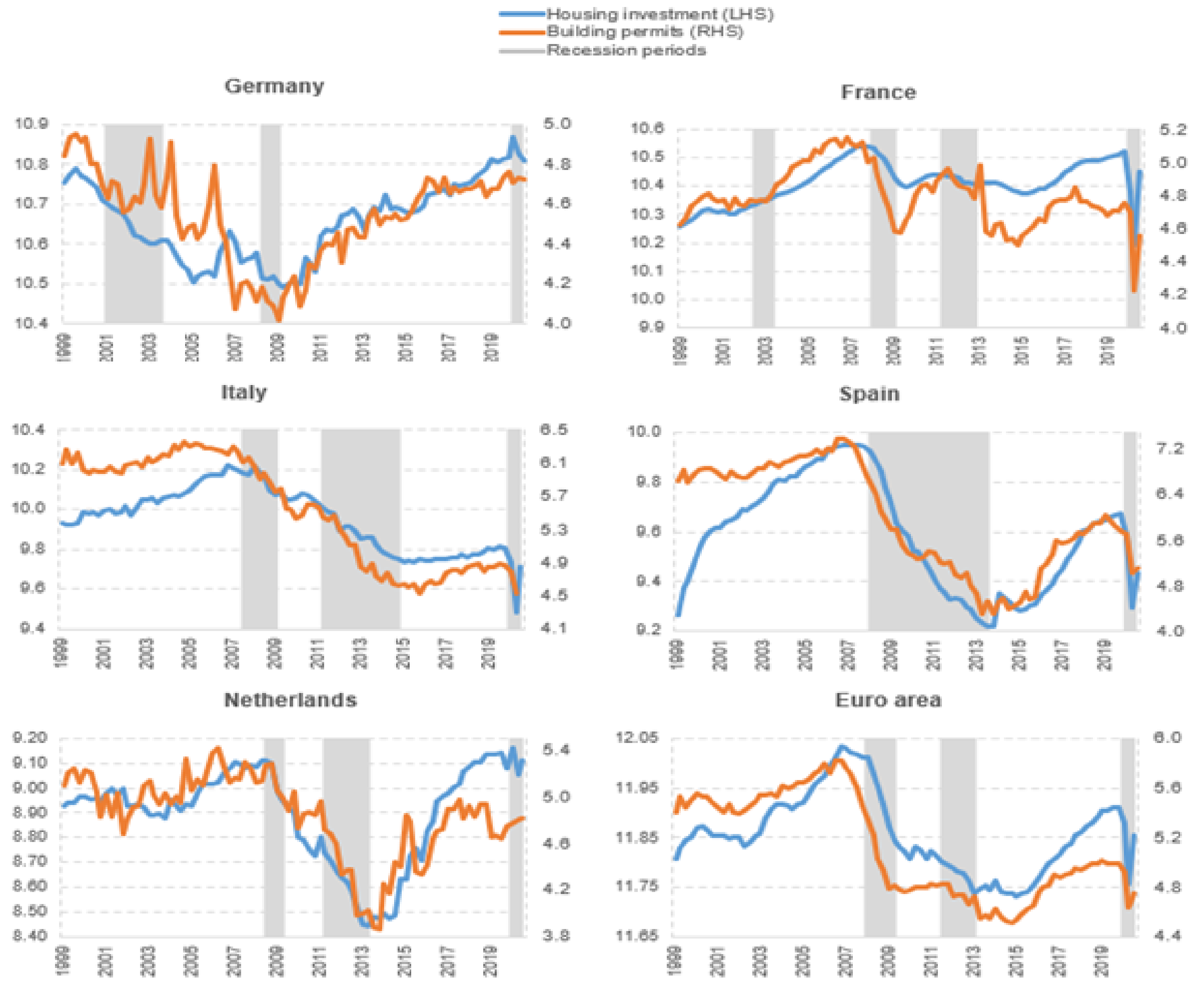
The sample period starts in the first quarter of 1999, which has the advantage that true euro area data as well as sector account data are used. The latter provide consistent harmonised quarterly data on household balance sheet stock and flows, such as income and wealth components. The sample period ends in 2020Q3. All variables, unless stated otherwise, are retrieved from the European Central Bank's projection database, which, in turn, extract the data from the ECB Statistical Data Warehouse with Eurostat as main underlying data source. Included are also the number of households from the Eurostat database and housing stock data, which evolve closely in line with quarterly seasonally adjusted data for housing wealth. All explanatory variables (except ratios) have been deflated using the private consumption deflator and if needed seasonally adjusted using X12-Arima and transformed into log levels and differences according to unit root tests. Table B.2 in the Appendix provides an overview of all the variables considered.

Figures B.6 to B.5 in the Appendix show the evolution of the main determinants of housing investment in the euro area and the euro area five largest countries. Additionally, in Appendices B.4 to B.6 we can observe summary statistics of the main determinants of housing investment, the tests of the order of integration of the variables used, and the cross-correlations between residential investment and leads and lags of the main determinants, respectively.

For the reported in-sample estimates the sample period ends in 2019Q4 to ensure that the results are not affected by the COVID-19 pandemic. The first three quarters of 2020 are used to evaluate the out-of-sample performance of our selected top 50 equations during the COVID-19 pandemic. Regarding the out-of-sample period as used for the fourth selection criterion, equations are estimated recursively with end-dates ranging from 2012Q4 to 2017Q4 to generate conditional forecasts for quarterly consumption growth for up to 8 quarters ahead, i.e. over the pseudo out-of-sample period spanning 2013Q1 to 2019Q4.

Figure 2.1 plots housing investment together with building permits in log level real terms. The former is the relevant series for the cointegration relation. Building permits are also plotted, because they are used for a fundamental based benchmark model. The figure shows country heterogeneity in housing investment. During the 2002-2003 recession in Germany and France, housing investment declined in Germany, whereas it increased in France. Before the outbreak of the global financial crisis housing investment clearly peaked in all euro area countries, except in Germany. During the corona recession housing investment in Germany and the Netherlands was hardly affected, whereas it plummeted in the other euro area countries.

Figure 2.1: Housing investment and building permits in the euro area, log real terms.



Notes: Shaded areas are recessions as dated by the Economic Cycle Research Institute (ECRI) for Germany, France, Italy and Spain and by the Centre for Economic Policy Research (CEPR) for the euro area. For the Netherlands, recessions correspond to technical recessions, i.e. periods with at least two consecutive quarters of quarterly contractions in real GDP. It is assumed that the euro area countries entered a recession in 2020Q1 as communicated for the euro area by the CEPR.

2.5 Empirical results

This section describes the empirical results from the applied model averaging approach. It reports the number of selected equations following the selection criteria. Focusing on the top 50 selected equations, it provides details about the in-sample estimates and fit as well as the out-of-sample performance, including during the COVID-19 pandemic.

2.5.1 Selected equations

The four selection criteria result in a varying number of selected equations across countries and the restrictiveness of the criteria differs also across countries and between unrestricted and restricted specifications. Table 2.2 summarises the number of selected equations after each selection criterion for the unrestricted (upper panel) and restricted specifications (lower panel).

After the first selection criterion on cointegration, the number of selected cointegration relations vary between 1 selected cointegration relation (1% of the total considered) for the Netherlands based on the unrestricted model specifications and 53 selected long-run relations for the euro area using the restricted model specifications (45% of the total). Consequently, the number of estimated equations including the short-run variables vary between 376 for the former and almost 62 thousand for the latter. Only a minority of the equations, often around 10% to 20%, fulfill the cointegration criterion, suggesting that the comparatively strong short-term swings in housing investment prevent finding stable long-run relations. All selected equations in this step are jointly significant at the 5% level. The selection criterion on autocorrelation test is not binding at all for Germany and Italy, slightly for Spain and to some extent for France. Autocorrelation is particularly an issue for the euro area, with 60% to 74% of the equations remaining, and the Netherlands, where only 18% to 14% of the equations remain. The individual significance test for Tobin's Q and income for the unrestricted model specifications is restrictive in all cases and most markedly in Spain where 23% of the equations are still selected. The out-of-sample selection criterion is not restrictive for the Netherlands, whereas at the other end of the spectrum is Italy where the number of selected equations declines by 55 percentage points for the unrestricted model and by 75 percentage points for the restricted model. Finally, the number of equations that outperform a building permits-based benchmark model vary a lot. Only a handful of the selected equations outperform the building permits benchmark for the unrestricted model specifications in Spain, whereas almost 14 thousand equations for the restricted model specifications in Germany. In all cases there are more equations selected that outperform the building permits benchmark for the restricted model specifications than for the unrestricted ones.

Table 2.2: Number of selected equations after each selection criterion.

	Germany		France		Italy	
Unrestricted model						
All estimated long-run equations	119	100%	119	100%	119	100%
S1: after cointegration test	39	33%	12	10%	8	7%
All estimated equations adding short-run variables	32,289	100%	22,887	100%	16,883	100%
S2: after autocorrelation test	32,283	100%	14,563	64%	16,883	100%
S3: after individual significance test	21,252	66%	9,047	40%	12,578	75%
S4: after at least 10% outperformance vs. AR(1)	6,762	21%	4,605	20%	3,237	19%
Equations outperforming building permits benchmark	4,935	15%	929	4%	202	1%
Restricted model						
All estimated long-run equations	119	100%	119	100%	119	100%
S1: after cointegration test	28	24%	21	18%	24	20%
All estimated equations adding short-run variables	26,278	100%	30,771	100%	27,399	100%
S2: after autocorrelation test	26,273	100%	21,647	70%	27,399	100%
S4: after at least 10% outperformance vs. AR(1)	17,610	67%	13,055	42%	6,825	25%
Equations outperforming building permits benchmark	13,766	52%	2,972	10%	263	1%

Notes: S1-S4 refers to the respective selection criterion (see subsection 2.3.2).

Table 2.2 (cont.): Number of selected equations after each selection criterion.

	Spain		Netherlands		Euro area	
Unrestricted model						
All estimated long-run equations	119	100%	119	100%	119	100%
S1: after cointegration test	14	12%	1	1%	39	33%
All estimated equations adding short-run variables	10,514	100%	376	68%	44,289	100%
S2: after autocorrelation test	9,918	94%	68	18%	26,425	60%
S3: after individual significance test	2,442	23%	30	8%	12,486	28%
S4: after at least 10% outperformance vs. AR(1)	1,368	13%	30	8%	10,789	24%
Equations outperforming building permits benchmark	5	0%	27	7%	21	0%
Restricted model						
All estimated long-run equations	119	100%	119	100%	119	100%
S1: after cointegration test	13	11%	14	12%	53	45%
All estimated equations adding short-run variables	11,638	100%	10,889	100%	61,553	100%
S2: after autocorrelation test	11,628	100%	1,574	14%	45,382	74%
S4: after at least 10% outperformance vs. AR(1)	7,198	62%	1,401	13%	39,559	64%
Equations outperforming building permits benchmark	2,496	21%	1,103	10%	1,009	2%

Notes: S1-S4 refers to the respective selection criterion (see subsection 2.3.2).

2.5.2 Estimated coefficients

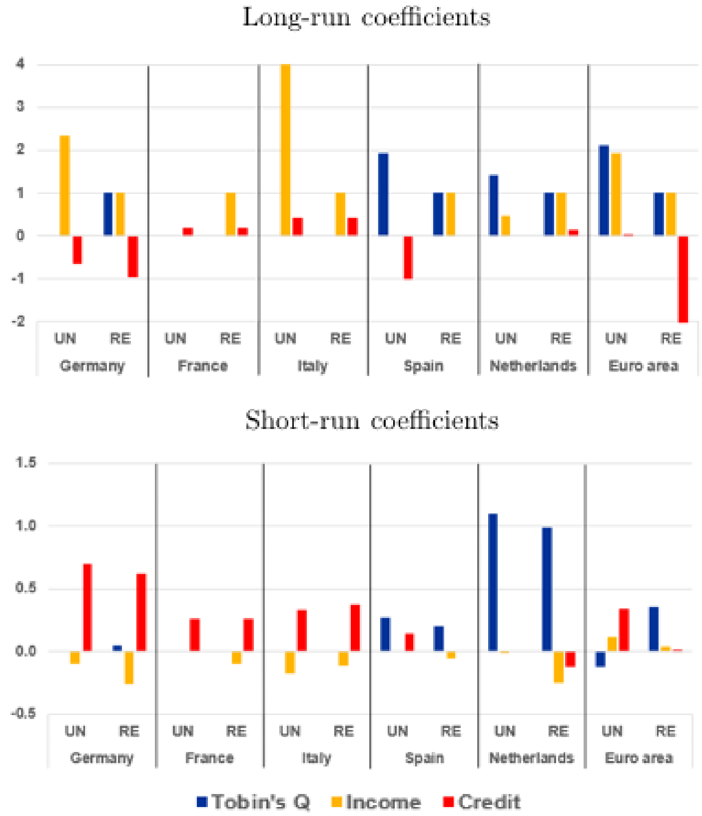
A closer look at the average estimates of the top 50 selected equations reveals one main conclusion of striking country differences in the estimates (see Fig. 2.2)[5]. Regarding the long-run, the three long-run determinants considered are not always selected for the unrestricted model specifications. Tobin's Q is not selected in the long run for Germany, France and Italy, income not for France and Spain and credit not for the Netherlands and the euro area. The average coefficients for Tobin's Q and income are estimated to be larger than one in all cases except for income in the Netherlands. In the latter case the income measure selected is the housing affordability index which depends not only on income but also on house prices and mortgage rate. Credit is estimated to be (slightly) positive in France and Italy and negative in Germany and Spain[6]. Looking at the estimates for the restricted specification, the country heterogeneity in the estimates remains. Tobin's Q still doesn't play a role in France and Italy and the credit sign variation is divided. For Spain and the Netherlands in all cases the income measure selected is the housing affordability index (for the detailed estimation results, see in the Appendix Table B.6). In both countries the cost of credit thus matters via the housing affordability index. The short-run estimates show also striking cross-country differences. Again, no role for Tobin's Q in France and Italy, whereas it is an important short-run driver in Spain and the Netherlands. Short-run income elasticities are small and only positive in the euro area.

Noteworthy is a positive short-run credit effect in all countries except for Spain and the Netherlands. In both countries, however, the cost of credit has a short-run positive effect via the housing affordability index (see Table B.7 in the Appendix). A sign reversal between the short and long-term credit effects suggests that mortgage growth supports housing investment growth in the short term, but a high level of outstanding credit hampers investment in the long term. The latter reflects debt overhang and a need to deleverage. Our long-run negative credit estimates are consistent with a theory of indebted demand (Mian et al., 2021). This theory captures the idea that a large debt burden lowers demand. Expansionary policies generate a debt-financed short-run boom at the expense of indebted demand in the future. Our finding of a sign reversal between the short and long-term credit effects is also consistent with the results from Carrington and Madsen (2011). They show that house prices for the US and for a panel of eight OECD countries are positively related to credit in the short run and negatively in the long run.

[5]This conclusion is also derived looking at the selected long-run investment drivers after the first selection criterion on cointegration (see Table B.6 in the Appendix). Among the four Tobin's Q measures there is no clear preferred measures, except for the Netherlands where only the house price relative to the private consumption deflator is selected. For income all income measures are part of one of the selected cointegration relations, apart from Spain where neither real disposable income per household nor labour income is selected. Noteworthy is that the housing affordability index (not considered by other studies) is the most selected income measure in all countries and the euro area for the restricted specification. For credit there is also country heterogeneity in the measures selected. The loan to value ratio is never selected for the Netherlands. Most often loans to households for house purchase are part of the cointegration relations, but for Spain the most selected credit measure is the loan to value ratio for the unrestricted specification and the loan to income ratio for the restricted specification.

[6]Negative coefficients on credit measures might be suggestive of debt overhang, so suggestive of a possible previous phase of perhaps excessive housing loaning. To assess this possibility, in a robustness check we include in the top 50 equations a dummy that is intended to capture periods of housing booms fueled by credit. In this vein, this dummy is one in one particular quarter when three conditions hold at the same time. First,the growth of housing loans to households is higher than income growth. Second, house prices growth is higher than income growth. Third, house prices growth is higher than rental prices. After introducing this dummy in the top 50 equations and evaluate the average results per region, we observe in the Euro area and largest five countries that the dummy coefficient is typically very close to zero, and statistically not significant.

Figure 2.2: Estimated Tobin's Q and income coefficients.

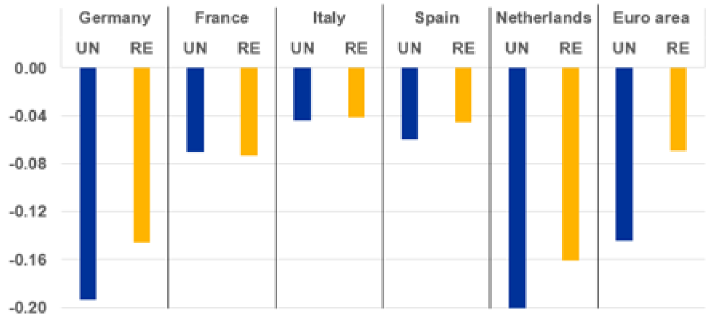


Notes: Average of the top 50 selected equations estimated up to 2019Q4 and the average coefficient of all series within a group. UN refers to unrestricted model specification and RE to restricted specification.

The average estimated error correction coefficients vary between about -0.05 in Italy and Spain and around -0.20 in Germany and the Netherlands (both cases unrestricted model), suggesting marked difference in the speed of adjustment to the cointegration relation (see Fig. 2.3). Consequently, the half-life of disequilibrium is estimated to vary between 3 quarters (within one year) and 14 quarters (three and a half years). The estimates are consistent with the range of error-correction coefficients reported in Table 2.1, with the slowest adjustment speed of -0.03 reported for Spain and the fastest one of -0.29 for the Netherlands (see Gattini and Ganoulis, 2012). The estimated adjustment speed is faster for the unrestricted model specifications than for the restricted ones for Germany, Spain, the Netherlands and the euro area. The adjustment speed is broadly unchanged between the two model specifications for France and Italy[7].

[7]In subsection 2.5.4 we perform and extension of the model by including building permits. In this extended model results we observe that the speed of adjustment to the long-run equilibrium is faster than in the baseline model. See subsection 2.5.4 for the detailed results.

Figure 2.3: Estimated error correction coefficient.

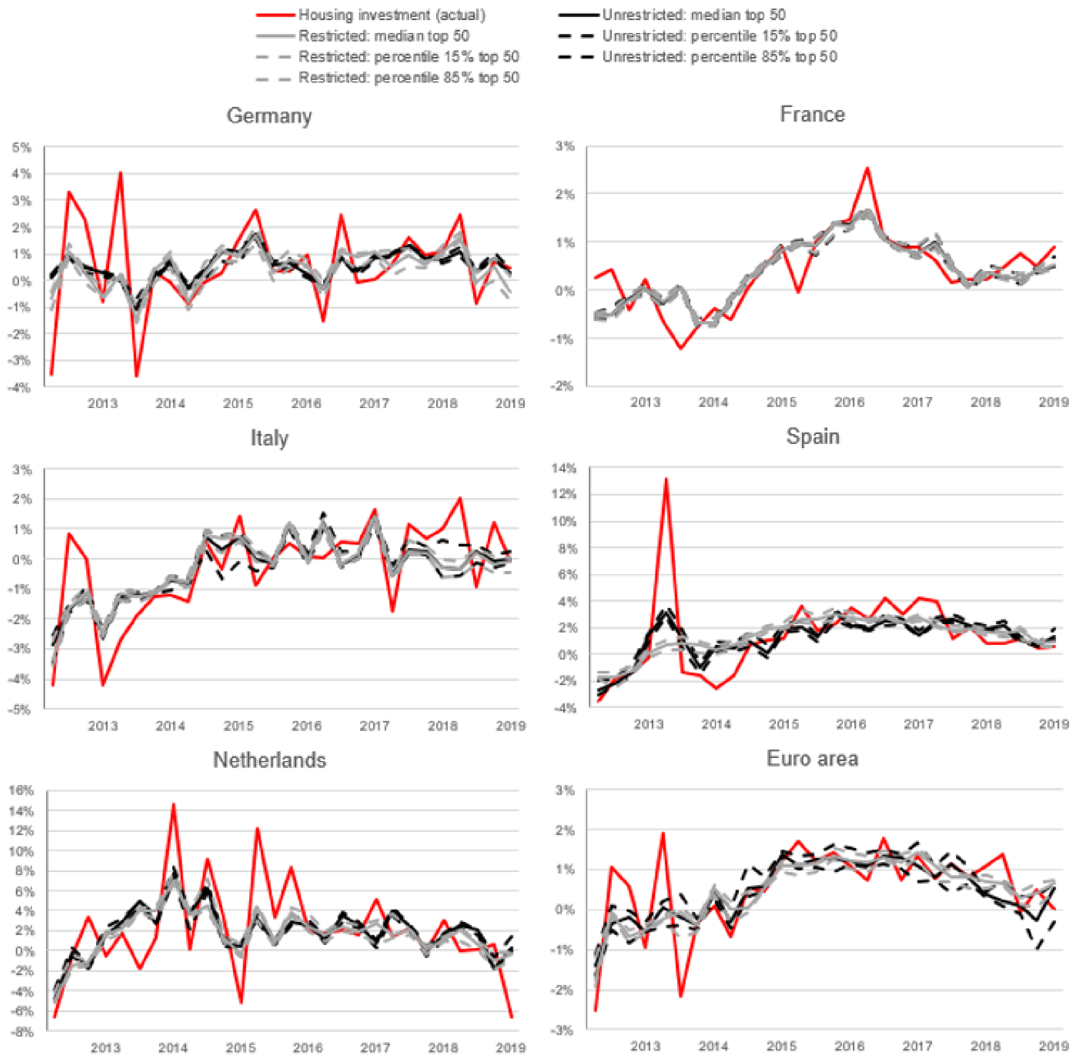


Notes: Average of the top 50 selected equations estimated up to 2019Q4.

A couple of observations emerge from the estimates of the short-run variables, which are all included in terms of quarterly changes (see Table B.6 in the Appendix for the detailed results). Mortgages interest rates significantly negatively affect housing investment growth in France and Italy, the two countries where credit plays a key role in the long run. In the other large euro area countries and the euro area the estimated coefficients for mortgages interest rates are not statistically different from zero. The macroeconomic group plays a statistically significant role. Real GDP growth is found to be a significant short-run determinant for all countries and real private consumption growth for Germany and the Netherlands. In almost all cases the estimated coefficients are larger than 1, suggesting an accelerator effect. Foreign demand is significant for the euro area. Total employment is found to be a significant determinant in Germany, Spain and the euro area. The unemployment rate is also found to be a significant driver of housing investment, as its coefficient is significant in Germany, France and Spain. In contrast, demographics and wealth hardly play a significant role. The number of households only significantly matters in Germany and population is never found to be significant. The housing stock is only found to be significant in Italy and financial assets in the Netherlands. Turning to uncertainty, a similar picture emerges. The only significant case is found for stock market volatility in France. This finding suggests that the lack of uncertainty measure in other studies is no reason for being concerned. In sum, the macro environment, including the unemployment rate does particularly play a role for housing investment in the short run.

Turning to the overall in-sample fit, it becomes clear that the selected top 50 equations capture well underlying housing investment growth but not necessarily its short-run volatility. Fig. 2.4 shows for the period 2013-2019 that actual housing investment fluctuates far more than the growth derived from the selected equations, irrespective whether it is the unrestricted or restricted specification. Actual spikes in housing investment growth are substantial and driven by factors, such as weather conditions, strikes, tax or regulatory changes, which are not part of our set of model variables. Consequently, our model averaging tools does not capture well short-run swings in the quarterly change in housing investment. Often a high or low change in one quarter rebounds in the next quarter. The figure also reveals growth volatility differences across countries, as captured by different y-scales. The standard deviation of the quarterly change in housing investment times 100 is over 1999 to 2019 comparatively low in France (1.3) and the euro area 1.5, high in Spain (3.3) and the Netherlands (4.2) and in between in Germany and Italy (2.3).

Figure 2.4: In-sample fit.

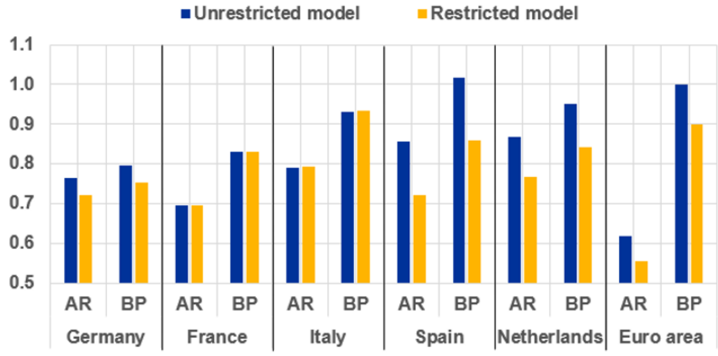


Notes: Actual quarterly changes in housing investment and median, 15% and 85% percentiles of the top 50 selected equations for unrestricted as well as restricted model specifications.

2.5.3 Out-of-sample performance

The out-of-sample performance of our model averaging tool is promising, most striking is that the selected restricted model specifications on average consistently have outperformed the building permit-based benchmark model. Fig. 2.5 plots the RMSE of the top 50 selected equations relative to those from the AR and building permits-based benchmark models. In all cases, except two, the selected top 50 equations outperform the two benchmark models. The two exceptions are for the unrestricted model specifications in Spain and the euro area. In both cases they show a similar out-of-sample performance as the building permits benchmark. This is still a very satisfactory outcome, given the strong link between building permits and housing investment. It is therefore no surprise that the forecast gains of the model averaging approach are always stronger compared to the AR benchmark (between 15% and 45%) than relative to the building permits-based benchmark. A comparison between the performance of the unrestricted model specifications and the restricted ones reveals that the differences are marginal for France and Italy and that the restricted model specifications perform better than the restricted ones in the other cases. The latter is most markedly visible for Spain, with an additional forecast gain against the building permits benchmark of 16 percentage points.

Figure 2.5: Out-of-sample performance.



Notes: Out-of-sample performance over all eight forecast horizons. Average RMSE of top 50 selected equations relative to AR benchmark and building permits (BP) benchmark.

Looking at the out-of-sample forecast performance across forecast horizon, the value added of the applied model averaging approach is confirmed, particularly at forecast horizons longer ahead. For at least five out of the eight forecast horizons the model averaging tool outperforms the two benchmark models (see Table 2.3). This outperformance is often significant, except for Italy and Spain where it is only significant at one forecast horizon. Qualitatively, there are no large differences in results between the unrestricted and restricted models. The most marked significant outperformance across horizons is recorded for Germany.

Table 2.3: Out-of-sample performance across forecast horizon.

	Unrestricted model				Restricted model			
	RMSE	RSR	AR RRMSE DM	BP RRMSE DM	RMSE	RSR	AR RRMSE DM	BP RRMSE DM
Germany								
1Q ahead	1.84	1.20	0.91	0.97	1.64	1.07	0.81**	0.86
2Q ahead	1.53	1.00	0.82	0.87**	1.46	0.95	0.78**	0.83***
3Q ahead	1.41	0.92	0.82***	0.84***	1.33	0.87	0.78***	0.80***
4Q ahead	1.41	0.82	0.85***	0.86***	1.26	0.82	0.76***	0.77***
5Q ahead	1.29	0.84	0.75**	0.76***	1.24	0.81	0.72***	0.74***
6Q ahead	1.02	0.67	0.70***	0.68***	0.91	0.59	0.62***	0.61***
7Q ahead	0.80	0.52	0.62***	0.66**	0.74	0.48	0.58***	0.61***
8Q ahead	0.83	0.54	0.65***	0.69*	0.77	0.50	0.60***	0.64
France								
1Q ahead	0.63	0.76	1.01	0.90	0.63	0.76	1.01	0.90
2Q ahead	0.64	0.78	0.88	0.94	0.64	0.78	0.89	0.94
3Q ahead	0.55	0.67	0.70	0.79	0.55	0.67	0.70	0.79
4Q ahead	0.61	0.74	0.69	0.87	0.61	0.74	0.68	0.87
5Q ahead	0.56	0.68	0.61*	0.91	0.56	0.68	0.60*	0.90
6Q ahead	0.47	0.57	0.51*	0.72	0.47	0.57	0.50*	0.71
7Q ahead	0.40	0.48	0.45***	0.63**	0.40	0.48	0.44***	0.62***
8Q ahead	0.44	0.54	0.50*	0.69*	0.44	0.54	0.50*	0.68*
Italy								
1Q ahead	1.12	0.91	0.67	0.75	1.09	0.89	0.66	0.74
2Q ahead	1.09	0.89	0.75	0.85	1.09	0.89	0.75	0.85
3Q ahead	0.90	0.73	0.62	0.74	0.90	0.73	0.62	0.74
4Q ahead	0.91	0.74	0.61	0.74	0.92	0.75	0.61	0.74
5Q ahead	1.02	0.83	0.79	0.97	1.04	0.85	0.81	0.98
6Q ahead	1.00	0.82	0.85**	0.99	1.03	0.84	0.87*	1.02
7Q ahead	1.04	0.85	0.91	1.05	1.09	0.88	0.94	1.10
8Q ahead	1.03	0.84	0.91	1.07	1.08	0.88	0.96	1.12

Notes: RSR = Median RMSE of top 50 selected equations standard deviation ratio; RRMSE = Median RMSE of top 50 selected equations relative to AR benchmark and building permits (BP) benchmark. DM = two-sided Diebold, Mariano (1995) tests corrected using the Harvey et al. (1997) approach, with ***, ** and * denoting 1%, 5%, respectively, 10% significance.

Table 2.3 (cont.): Out-of-sample performance across forecast horizon.

	Unrestricted model				Restricted model			
	RMSE	RSR	AR RRMSE DM	BP RRMSE DM	RMSE	RSR	AR RRMSE DM	BP RRMSE DM
Spain								
1Q ahead	3.50	1.15	0.88	0.88	3.32	1.09	0.95	0.95
2Q ahead	3.48	1.15	0.87***	0.87	3.19	1.05	0.91	0.91
3Q ahead	3.76	1.24	0.93	0.93	2.96	0.97	0.92	0.92
4Q ahead	3.69	1.21	0.91	0.92	2.83	0.93	0.89	0.90
5Q ahead	3.65	1.20	0.95	0.93	2.79	0.92	0.85	0.84
6Q ahead	1.98	0.65	0.80	1.13	1.81	0.59	0.62	0.88
7Q ahead	2.02	0.66	0.80	1.17	1.64	0.54	0.56	0.81
8Q ahead	2.09	0.69	0.83	1.35	1.51	0.50	0.50**	0.81***
Netherlands								
1Q ahead	4.91	1.03	0.85*	0.91	4.67	0.98	0.81	0.87
2Q ahead	4.72	0.99	0.83**	0.88	4.25	0.89	0.75**	0.80
3Q ahead	4.75	1.00	0.83*	0.87	4.25	0.89	0.74**	0.78
4Q ahead	4.67	0.98	0.81*	0.87	4.37	0.92	0.76**	0.81
5Q ahead	4.64	0.97	0.81***	0.88***	4.20	0.88	0.73***	0.79**
6Q ahead	4.77	1.00	0.83	0.91	4.39	0.92	0.76	0.84*
7Q ahead	4.72	0.99	0.81	0.91*	4.28	0.90	0.74	0.83***
8Q ahead	5.15	1.08	0.86	0.97	4.58	0.96	0.76	0.86
Euro area								
1Q ahead	0.92	1.02	0.71***	0.96	0.98	1.09	0.76***	1.02
2Q ahead	0.81	0.90	0.71***	0.92*	0.90	1.00	0.78*	1.02
3Q ahead	0.77	0.85	0.67	0.88	0.85	0.95	0.75	0.98
4Q ahead	0.80	0.89	0.64*	0.99	0.82	0.90	0.66	1.01
5Q ahead	0.77	0.85	0.62*	0.93**	0.77	0.85	0.62	0.93
6Q ahead	0.62	0.69	0.53**	0.95	0.56	0.62	0.47*	0.84
7Q ahead	0.49	0.55	0.44***	0.88**	0.37	0.41	0.33***	0.66**
8Q ahead	0.46	0.51	0.41**	0.84	0.37	0.41	0.33***	0.68***

Notes: RSR = Median RMSE of top 50 selected equations standard deviation ratio; RRMSE = Median RMSE of top 50 selected equations relative to AR benchmark and building permits (BP) benchmark. DM = two-sided Diebold, Mariano (1995) tests corrected using the Harvey et al. (1997) approach, with ***, ** and * denoting 1%, 5%, respectively, 10% significance.

Interesting is that the RMSE declines over the forecast horizon in all countries, apart from Italy and the Netherlands. This finding suggests an important steering role of the cointegration relation, irrespective whether it is the unrestricted or restricted long-run relation. It can also be viewed that the selected determinants have more difficulties capturing short-run swings, which might be more determined by unpredictable surprises such as weather conditions. The size of the RMSE in absolute terms vary a lot across countries. They are below 1 for France and the euro area, around 1 for Germany and Italy and much higher in Spain (between 1.5 and 3.5) and the Netherlands (close to 5). The absolute RMSE are also scaled by the standard deviation of household investment changes over the out-of-sample period to improve the country comparison. The RMSE standard deviation ratio (RSR) show comparatively outstanding performance of a RSR of about 0.5 for 7 and 8 quarters ahead for Germany, France, Spain (restricted specification) and the euro area, whereas the performance is poor with a RSR of about 1.0 across the board for the Netherlands and at short forecast horizons for the Germany, France, Spain and the euro area.

2.5.4 Extension of the baseline model with building permits

Experience suggests building permits as other natural candidate for being a long-run variable in the model. Figure 2.1 illustrates the leading role of building permits for the Euro area and five largest Euro area countries. Building permits is the leading component that is insightful for the Euro area business cycle as well as Euro area inflation cycle (De Bondt et al., 2018, 2020). For Canada the best out-of-sample model for housing investment is a leading indicator model using building permits and housing starts (Demers, 2005).

Therefore, we also report results of an extended specification where building permits have been added to the set of housing investment determinants to the top 50 equations selected and commented in subsection 2.3. Table 2.4 reports such results, from which we can extract a couple of observations. First, the extended version results in a quicker adjustment to the long-run co-integration relation (ECM coefficient with BP versus baseline columns). This is in a way not surprising as building permits are a precondition for starting housing investment, however it is a remarkable result as most of the studies in the literature do not include building permits, so the adjustment to the long-run equilibrium might be faster than what we thought so far. According to our results this downward speed of adjustment bias would apply to the euro area and largest five Euro area countries except the Netherlands. Second, in most of the countries, including building permits in the model also results in a consistent improvement of the forecast performance (relative RMSE versus baseline model column). For instance, in the case of the euro area, the forecast gain is in the range between a 6% and 21%, depending upon whether we consider the unrestricted or the restricted version of the model. It has to be highlighted that these forecasts improvement should be thought as a lower bound, as we might also include lagged functions of building permits, which show even higher correlations *vis a vis* housing investment.

Table 2.4: Results of the top 50 equations extended with building permits.

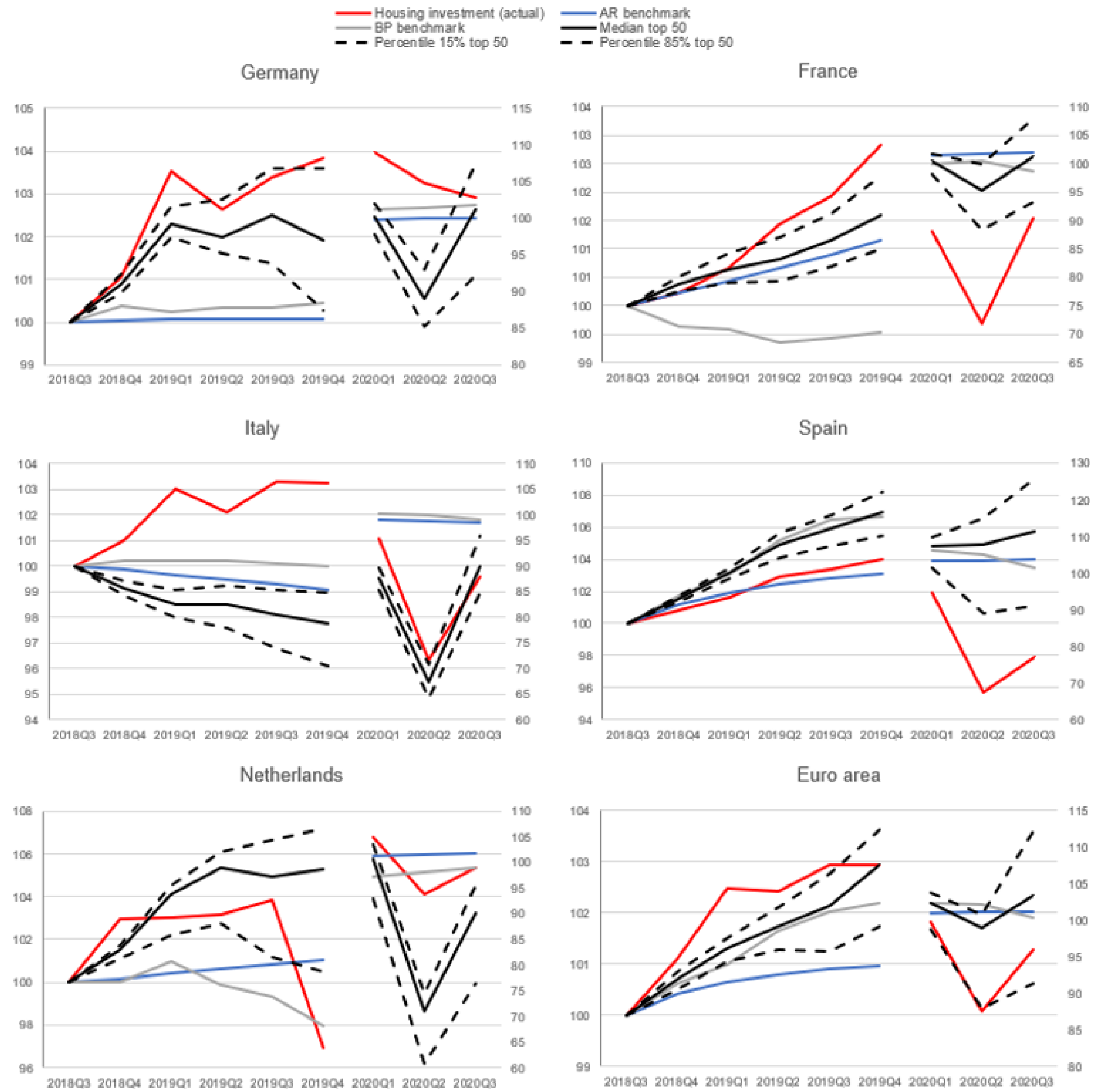
	Unrestricted model			**Restricted model**		
	ECM coefficient		**Relative RMSE**	**ECM coefficient**		**Relative RMSE**
	Baseline	**with BP**	**vs baseline**	**Baseline**	**with BP**	**vs baseline**
Germany	-0.19	-0.31	0.90	-0.15	-0.22	0.87
France	-0.07	-0.11	0.99	-0.07	-0.12	1.03
Italy	-0.04	-0.31	0.95	-0.04	-0.31	0.95
Spain	-0.06	-0.12	1.04	-0.05	-0.06	1.15
Netherlands	-0.20	-0.21	1.08	-0.16	-0.16	0.94
Euro area	-0.14	-0.27	0.94	-0.07	-0.10	0.79

Notes: ECM results refer to the average of the resulting top 50 equations. The relative RMSE refers to the ratio between the extended model over the baseline, in terms of the respective median absolute RMSE results.

2.5.5 COVID-19 pandemic

The out-of-sample performance of the model averaging tool is further evaluated by applying it to the final eight quarters of our sample, which includes the first three quarters of 2020 which had been affected by the COVID-19 pandemic. The country charts in Fig. 2.6 is split into two parts due to the large size of the pandemic shock. It plots the outcomes for the restricted specification as the previous section shows that it performs at least as well as the unrestricted specification. Looking at the first five quarters up to 2019Q4, the model-based forecasts from the top 50 selected equations are broadly in line with actual housing investment in Germany, France till 2019Q1, Netherlands (note that in 2019Q4 many building projects were put on hold due to CO-2 regulation discussion), and the euro area (with some deviation in 2019Q1). They were consistently too high in Spain and too low in Italy. The top 50 selected equations often outperform the benchmark models. The exceptions are both benchmark models for Italy, the AR benchmark for France and Spain and the building permits benchmark for the euro area. Turning to the first three quarters of 2020, the most striking observation is that actual housing investment in 2020Q3 is close to the model averaging outcome in 2020Q3 in all countries except Spain. It is within the model range in Germany, Italy and the euro area. For the latter even for all three quarters. In France and the Netherlands, actual housing investment is in 2020Q3 close to the model range. The unrestricted model specification appears to deal even better with large shocks (see Fig. B.7 in the Appendix). In 2020Q3 housing investment is within the model range in Germany, Italy, Netherlands and the euro area and close to the lower range for France and Spain. These findings illustrate the benefits of the model averaging tool also in case of sizeable unexpected developments and particularly for the longer term. However, in the near term large forecast errors can occur. The COVID-19 pandemic also illustrates country heterogeneity. Housing investment has been resilient to the major shocks originating from COVID-19 in Germany and the Netherlands, whereas France, Italy and Spain faced double-digit declines in housing investment due to COVID-19. Historical evidence suggests that these strong movements following an epidemic can be expected to be transitory (Francke and Korevaar, 2020).

Figure 2.6: Out-of-sample forecasts for 2018Q4 – 2020Q3, restricted model.



Notes: Based on top 50 selected restricted model equations estimated over 1999Q1 – 2018Q3. Housing investment level in 2018Q3 = 100.

2.6 Conclusions

This study empirically models housing investment in the largest euro area countries and the euro area. A uniform set of in- and out-of-sample criteria selects among tens of thousands of error-correction specifications. The focus is on model averaging across the top 50 selected equations to address the problem of model uncertainty inherent in the choice of model variables. We hope that our model averaging approach inspires others to follow a similar route. Housing investment studies remain rare compared to those analysing house prices, a gap that needs to be filled.

Our model averaging results have important implications. Firstly, for policy makers the country heterogeneity in the drivers of housing investment makes a strong call for country specific policy measures. Or put differently, common policy measures are expected to result in different country impacts. For example, the positive long-term credit coefficients suggest that credit stimulating measures through accommodative monetary policy or an easing of macroprudential rules could foster housing investment in France and Italy. Similarly, income supporting measures are estimated to stimulate especially housing investment in Germany. Policy measures that result in comparatively strong house price increases and upward pressure to Tobin's Q could bolster housing investment especially in Spain and the Netherlands. During crisis periods like the COVID-19 pandemic the type of policy support package can make a key difference. Secondly, for forecasters our results call for using this tool to generate conditional forecasts of housing investment. The reported out-of-sample results illustrate the benefits of the applied model averaging tool both compared to an autoregressive and building permits-based benchmark models. The latter is not trivial as gauged by the fact that building permits are included in composite leading indicators across the globe.

Some research avenues we might find interesting are the following. First, considering a model of residential investment in which credit is added non-linearly, specially to account for different time-varying risk-taking behaviour by the banking system during our sample horizon. Second, given the importance of considering building permits for forecasting residential investment, we think that it would be worth it to devote more research effort to generate reliable forecasts of building permits.

Appendices

B.1 Characteristics across euro area housing markets.

Table B.1: Characteristics across euro area 5 housing markets, according to literature.

Country	Characteristics	References
	1) "Own" housing cycle	De Bandt (2010), [1], [2]
	2) Population having a key role in driving housing investment	Knetsch (2010)
	3) Housing supply is highly elastic to house prices	Knetsch (2010), [3], [4]
DE	4) Importance of construction costs	[3]
	5) Greatly influenced by the 1991 reunification	Knetsch (2010)
	6) User costs affect housing demand	[5]
	7) Credit amplifies the user costs of housing	[5]
	8) Lowest homeownership ratio	[2]
	1) Importance of subsidies for housing investment	Antipa and Schalck (2010)
	2) Housing leads the business cycle	Ferrara and Vigna (2010)
	3) Housing supply is highly elastic to house prices	[4], [6]
FR	4) High persistence of housing investment	[3]
	5) Downward price rigidity	[6]
	6) Housing cycle highly correlated with Spain	[1], Álvarez et al. (2010)
	7) Labour as a limiting factor	[2]
	1) Very low effect of house prices on housing investment	Bulligan et al. (2017)
	2) Almost insignificant impact of GDP on housing investment	[3], Bulligan (2010)
	3) Low effect of interest rates in driving housing investment	[3]
IT	4) Insignificant persistence of housing investment	[3]
	5) Low credit to households (and to GDP)	De Bandt (2010)
	6) Bad performance in dealing with building permits	World Bank (2020)
	7) High correlation with the German housing investment	Álvarez et al. (2010), EC (2019a)
	1) Housing leads the business cycle	[3], De Bandt (2010)
	2) Mortgage credit having a key role	De Bandt (2010), [6], [7]
	3) High housing wealth to wealth ratio	De Bandt (2010), [8]
	4) Bad performance in dealing with building permits	World Bank (2020), EC (2020a)
ES	5) Construction costs irrelevant for housing investment	[3]
	6) Demographics play a key role	González and Ortega (2013)
	7) High preference for homeownership	De Bandt (2010), [2]
	8) Downward price rigidity	[6]
	9) housing investment precede most other countries	Álvarez et al. (2010)
	1) Housing supply is inelastic to house prices	[3], [4], [9]
	2) High degree of government intervention	[4], [9]
	3) Full tax deductibility of interest rates	[4]
NL	4) Very high LTV ratios	[4], Badarinza et al. (2016)
	5) Construction costs are irrelevant for housing investment	[3], [4]
	6) Building permits is the main driver of housing investment	Berben et al. (2018)
	7) Bad performance in dealing with building permits	World Bank (2020), EC (2019b)

Notes: [1] = Ferrara and Koopman (2010); [2] = Battistini et al. (2018); [3] = Gattini and Ganoulis (2012); [4] = Swank et al. (2002); [5] = Dümmler and Kienle (2010); [6] = Antipa and Lecat (2010); [7] = Arencibia et al. (2017); [8] = Badarinza et al. (2016); [9] = Vermeulen and Rouwendal (2007). EC stands for European Commission.

B.2 Overview of model variables.

Table B.2: Overview of model variables.

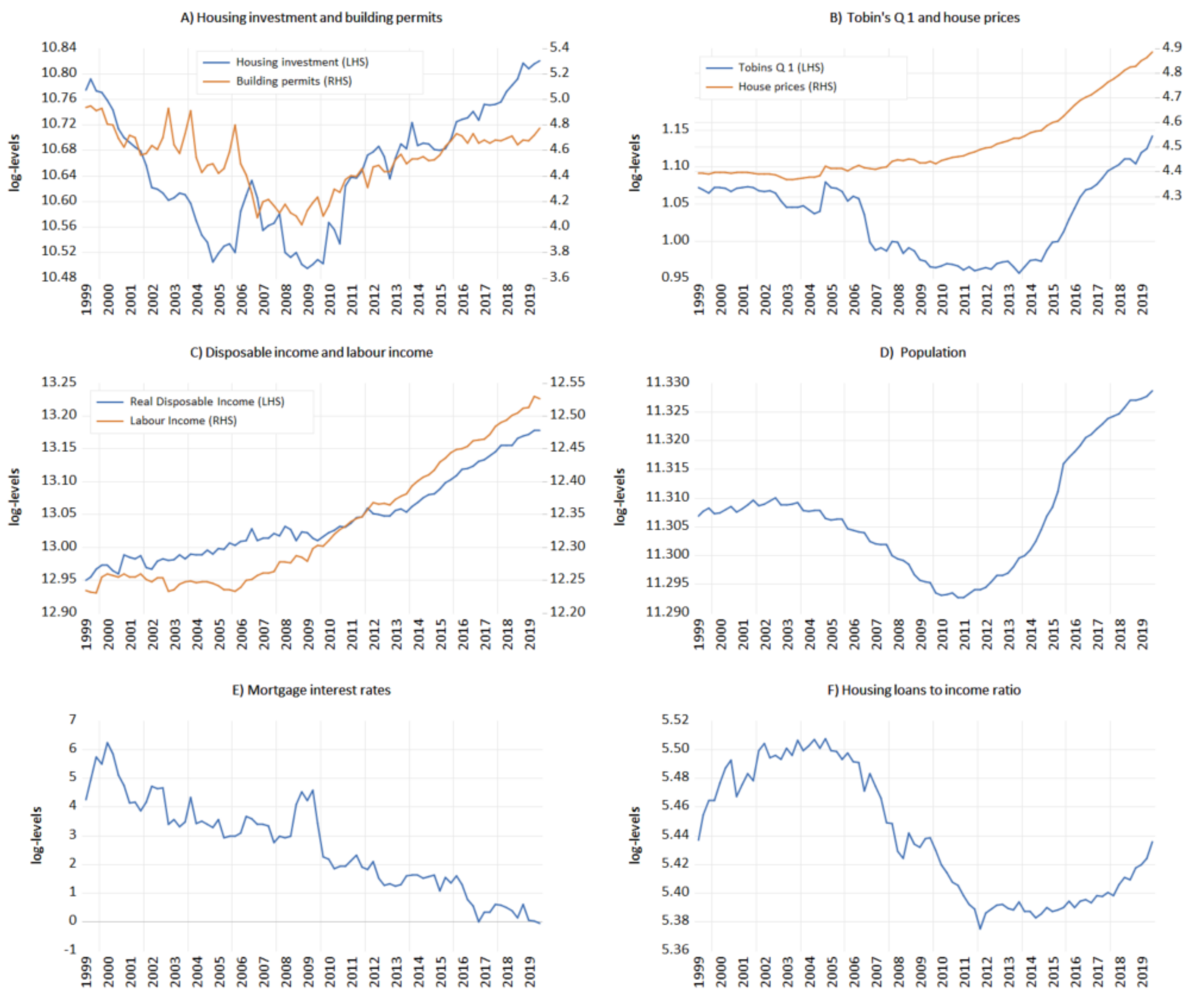
Block	Category	Variable	Definition
Long and short-term (3 groups)	**Tobin's Q**	TQ1	House price index / residential investment deflator
		TQ2	House price index / total investment deflator
		TQ3	House price index / private consumption deflator
		TQ4	House price index / non-housing investment deflator
	Credit	LHPR	Loans for house purchase, real
		LHPI	Loans for house purchase to disposable income
		LTV	Loans for house purchase to net non-financial assets
	Income	PYNHR	Real disposable income per household
		LABY	Labour income
		WINR	Total compensation
		CEXR	Compensation per employee
		HAFI	Housing affordability index
Short-run (4 groups)	**Mortgage interest rates**	TTHOUR	Composite interest rate for house purchase, real
		STHOUR	Short-term interest rate for house purchase, real
		LTHOUR	Long-term interest rate for house purchase, real
	Macroeconomic indicators	YER	Real GDP
		PCR	Real private consumption
		LNN	Total employment
		FOD	Foreign demand
	Unemployment and Uncertainty	STOVOL	Stock market volatility
		URXVOL	Unemployment volatility
		PYRVOL	Income volatility
		URX	Unemployment rate
	Demographics and wealth	PRHH	Number of private households
		POP	Total population
		HGHS	Gross housing stock
		HNFA	Net financial assets

Notes: All variables in log real terms, except Tobin's Q, the two credit ratios, mortgage rates and uncertainty measures.

B.3 Main variables in log-levels.

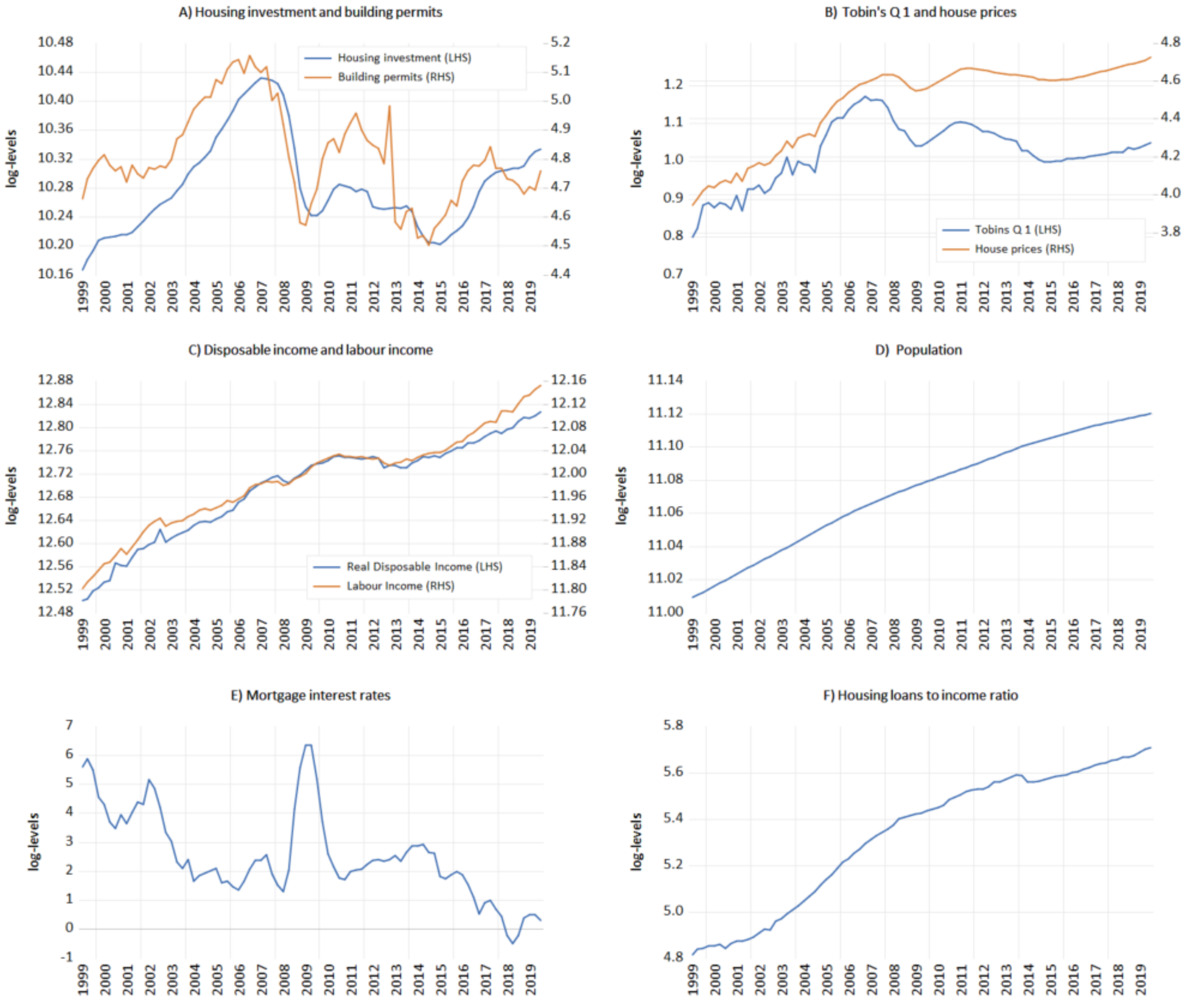
Germany

Figure B.1: Main variables in log-levels, Germany.



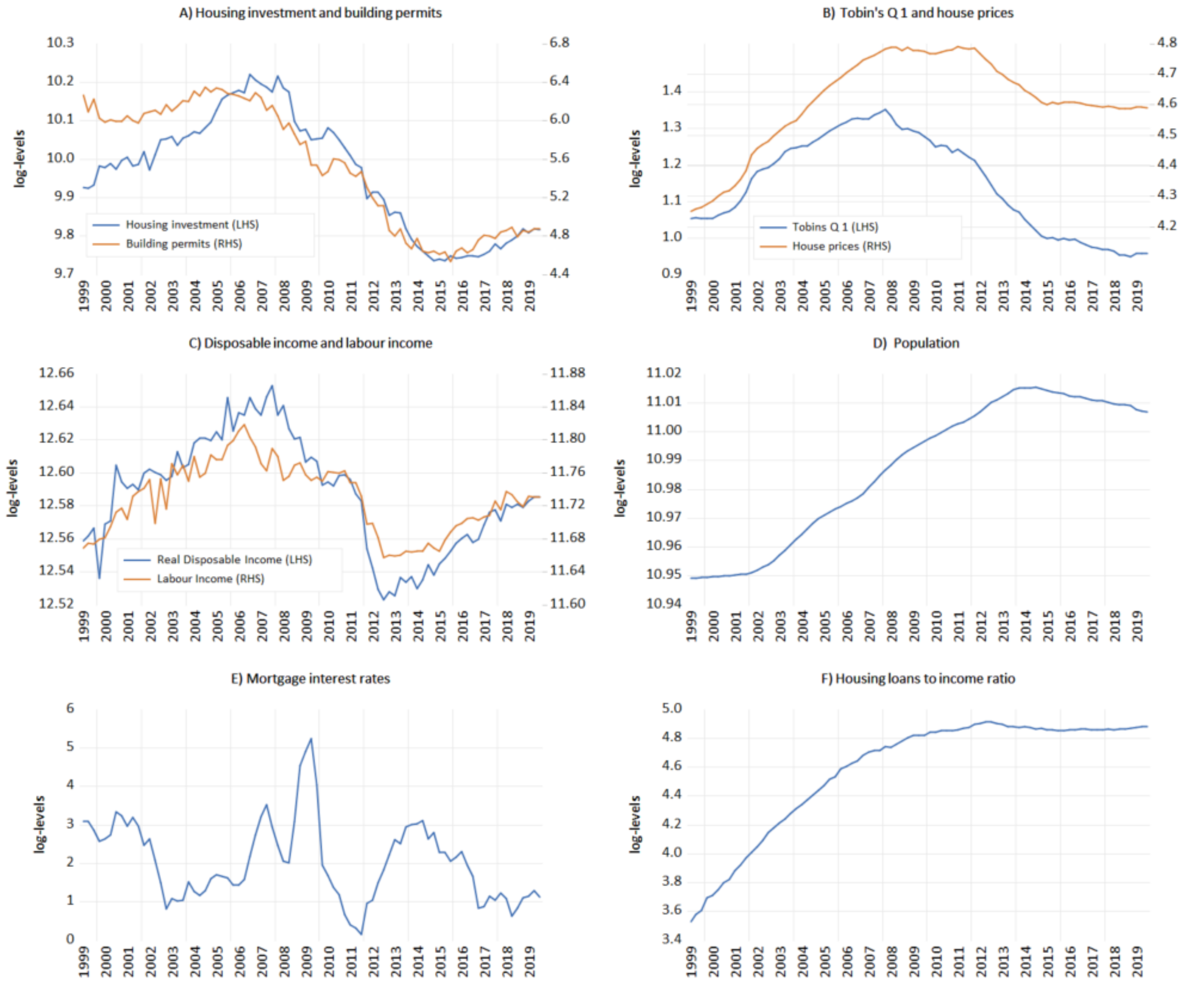
France

Figure B.2: Main variables in log-levels, France



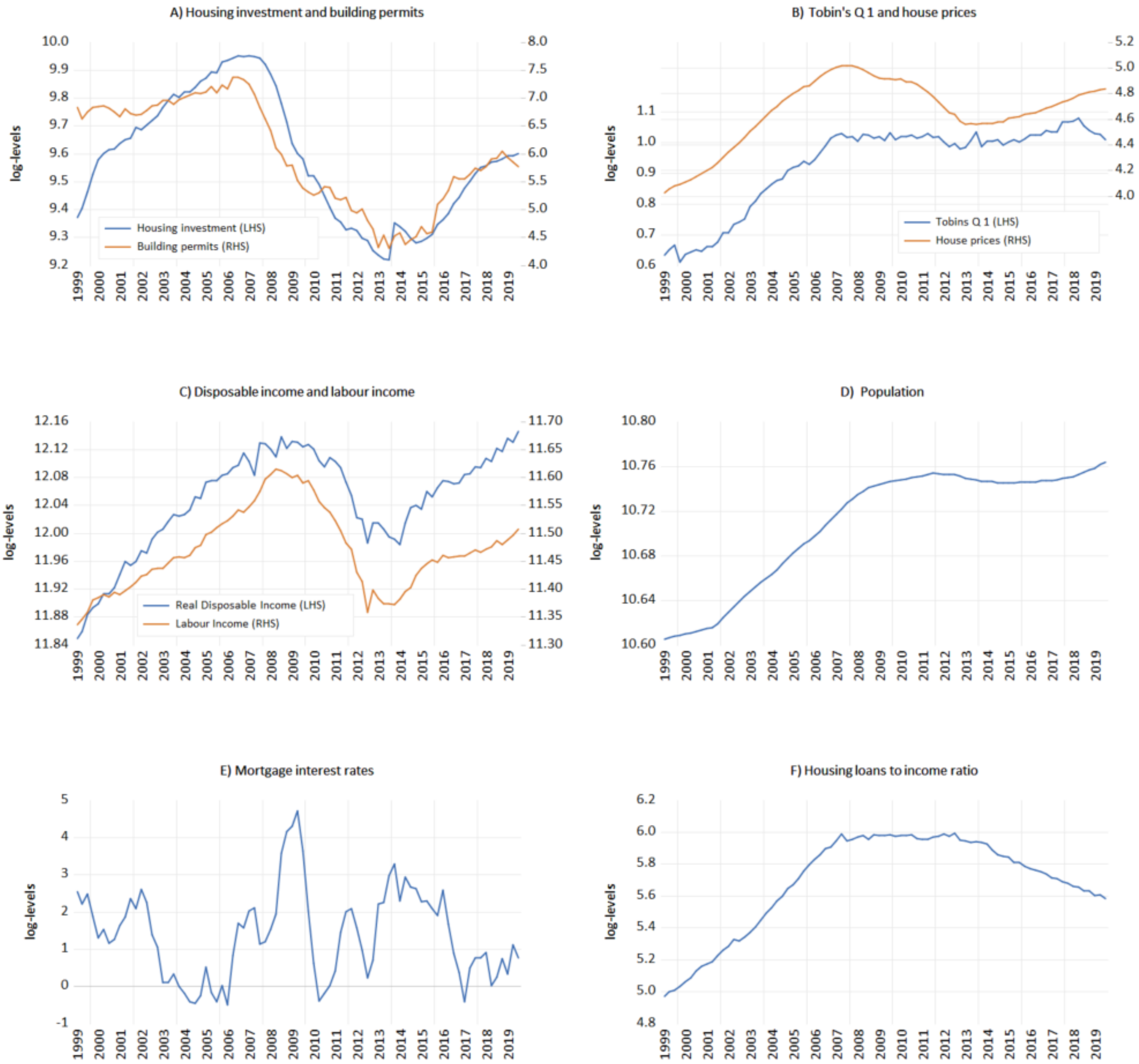
Italy

Figure B.3: Main variables in log-levels, Italy.



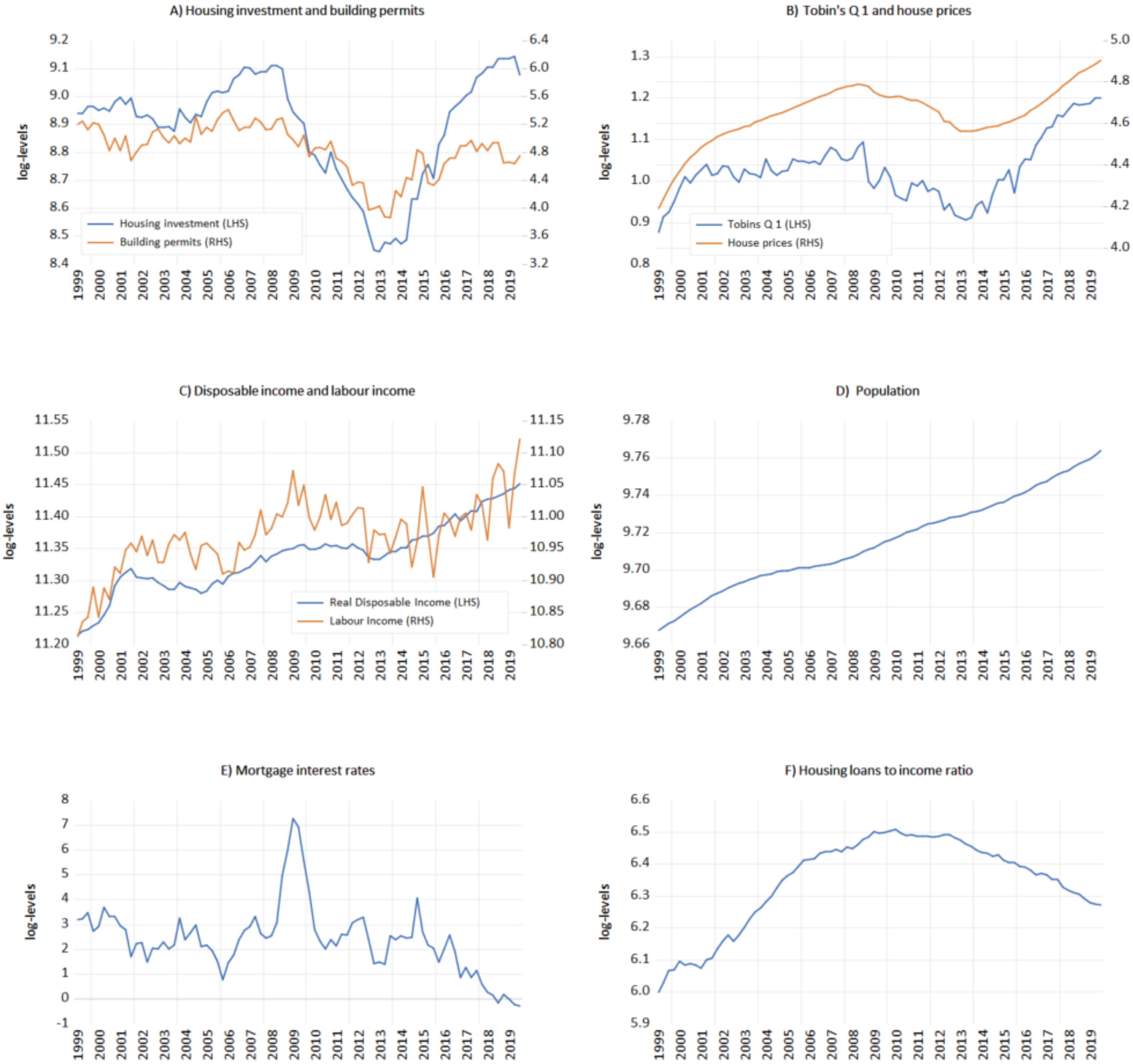
Spain

Figure B.4: Main variables in log-levels, Spain.



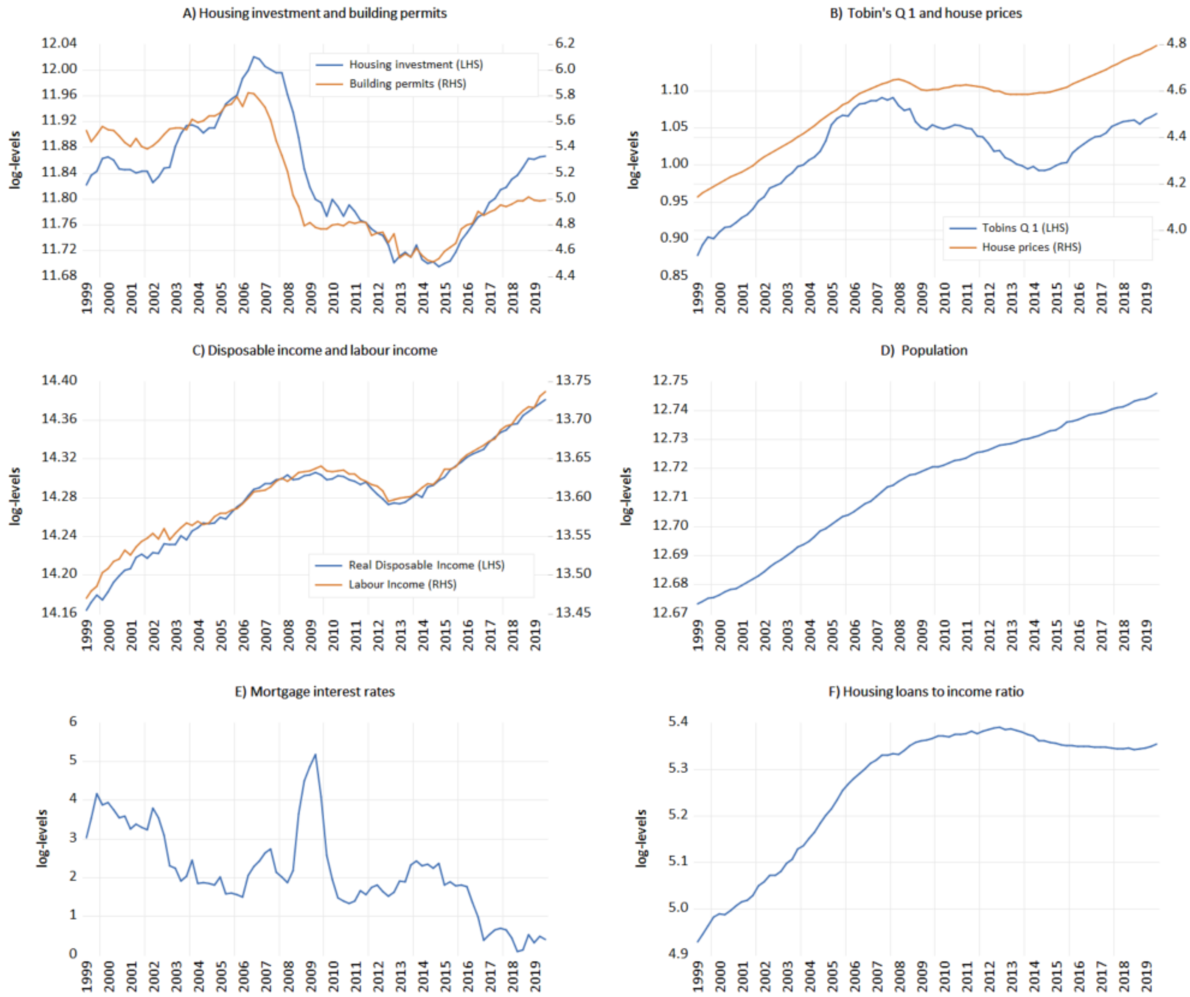
Netherlands

Figure B.5: Main variables in log-levels, Netherlands.



Euro area

Figure B.6: Main variables in log-levels, euro area.



B.4 Summary statistics of housing investment and its main determinants.

Table B.3: Summary statistics of housing investment and its main determinants.

	DE	FR	IT	ES	NL	EA
d(real housing investment)						
Average * 100	0.08	0.22	-0.13	0.41	0.18	0.08
Average standard deviation * 100	2.32	1.26	2.29	3.31	4.19	1.54
Correlation coefficient vs EA	0.58	0.69	0.58	0.68	0.48	1
d(Tobin's Q 1)						
Average * 100	0.09	0.29	-0.11	0.51	0.43	0.25
Average standard deviation * 100	0.96	1.95	1.18	1.70	2.46	0.65
Correlation coefficient vs EA	0.24	0.41	0.56	0.56	0.45	1
d(real disposable income)						
Average * 100	0.27	0.39	0.06	0.37	0.29	0.27
Average standard deviation * 100	0.73	0.68	1.05	1.39	0.69	0.43
Correlation coefficient vs EA	0.23	0.48	0.54	0.44	0.33	1
d(real labour income)						
Average * 100	0.36	0.42	0.06	0.19	0.36	0.28
Average standard deviation * 100	0.64	0.54	1.58	1.35	3.15	0.51
Correlation coefficient vs EA	0.36	0.46	0.62	0.53	0.57	1
d(population)						
Average * 100	2.66	13.53	6.94	19.20	11.80	8.83
Average standard deviation * 100	10.48	3.86	8.55	19.82	5.30	4.27
Correlation coefficient vs EA	0.13	0.50	0.45	0.75	0.07	1
d(real mortgage interest rates)						
Average * 100	-0.07	-0.06	-0.03	-0.02	-0.04	-0.05
Average standard deviation * 100	0.43	0.54	0.49	0.67	0.66	0.43
Correlation coefficient vs EA	0.80	0.92	0.81	0.72	0.67	1
d(housing loans to income ratio)						
Average * 100	0.02	1.11	1.67	0.77	0.37	0.54
Average standard deviation * 100	0.85	1.01	2.05	2.40	1.42	0.76
Correlation coefficient vs EA	0.17	0.52	0.71	0.76	0.77	1
d(real house prices)						
Average * 100	0.59	0.93	0.42	1.01	0.91	0.80
Average standard deviation * 100	0.94	2.03	1.25	2.34	1.58	0.84
Correlation coefficient vs EA	0.08	0.47	0.69	0.88	0.73	1
d(building permits)						
Average * 100	-0.07	0.16	-1.40	-1.07	-0.42	-0.50
Average standard deviation * 100	10.35	6.98	7.81	14.28	16.42	6.25
Correlation coefficient vs EA	0.30	0.55	0.19	0.79	0.16	1

Notes: Tobin's Q 1 is defined as housing prices divided by the residential investment deflator. Sample size: 1999Q1 – 2019Q4. *d* means first differences.

B.5 Tests of the order of integration of the variables used.

Table B.4: Tests of the order of integration of the variables used, Euro area.

Variable	Transformation	Integration order					
		DE	FR	IT	ES	NL	EA
Long-run variables							
Tobin's Q							
Tobin's Q 1		I(1)	I(0)	I(1)	I(0)	I(1)	I(1)
Tobin's Q 2		I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Tobin's Q 3	Real	I(1)	I(1)	I(1)	I(0)	I(1)	ns
Tobin's Q 4		I(1)	I(0)	I(1)	I(0)	I(1)	I(1)
Income							
Real disposable income per household	Log, real	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Real Labour income	Log, real	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Total compensation	Log, real	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)
Compensation per employee	Log, real	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)
Housing affordability index	Log	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)
Credit							
Loans for house purchase (LHPR)	Log, real	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
LHPR to income ratio	Log	I(0)	I(1)	I(0)	I(1)	I(1)	I(1)
LHPR to financial assets ratio		I(0)	I(1)	I(0)	I(1)	I(1)	I(1)
Short-run variables							
Mortgage interest rates							
Composite interest for house purchase	Real	I(0)	I(0)	I(0)	I(0)	I(1)	I(0)
Short-term interest for house purchase	Real	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)
Long-term interest for house purchase	Real	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)
Macroeconomic indicators							
Real GDP	Log	I(1)	I(0)	I(0)	I(1)	I(1)	I(1)
Private consumption	Real	I(1)	I(0)	I(1)	I(1)	I(1)	I(1)
Total employment	Log	I(1)	I(1)	I(0)	I(1)	I(1)	I(1)
Foreign demand	Real	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Unemployment and uncertainty							
Unemployment rate		I(1)	I(0)	I(1)	I(1)	I(1)	I(1)
Stock market volatility		I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Unemployment volatility		I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Income volatility		I(1)	I(0)	I(1)	I(1)	I(0)	I(1)
Demographics and wealth							
Total population	Log	I(0)	I(0)	I(1)	ns	I(1)	I(0)
Number of private households	Log	I(1)	I(1)	I(0)	I(0)	I(1)	I(0)
Gross housing stock	Log, real, 1 period lag	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Net financial assets	Log, real, 1 period lag	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)

Notes: Short-run variables enter the error correction model in differences. *ns* means non stationary in first-differences.

B.6 Cross-correlations between housing investment and leads and lags of main determinants.

Table B.5: Cross-correlations between housing investment and leads and lags of determinants.

	d(real housing investment)								
	-4	**-3**	**-2**	**-1**	**t**	**+1**	**+2**	**+3**	**+4**
Germany									
d(Tobin's Q 1)	-0.06	0.06	0.13	0.07	0.09	0.01	-0.11	-0.11	0.09
d(real disposable income)	-0.04	0.00	0.03	0.16	0.12	0.03	0.18	-0.11	0.10
d(real labour income)	-0.13	0.09	0.03	-0.02	0.32	0.16	0.03	0.09	0.16
d(population)	0.07	0.06	0.05	0.11	0.11	0.10	0.05	0.05	0.17
d(real mortgage interest rates)	-0.11	-0.04	-0.08	-0.07	0.10	0.03	-0.04	-0.02	0.07
d(housing loans to income ratio)	-0.05	-0.04	-0.03	-0.14	-0.06	0.07	-0.11	0.09	-0.04
d(real house prices	-0.06	0.09	0.24	0.03	0.16	0.19	0.04	0.08	0.23
d(building permits)	-0.05	0.25	0.27	0.05	0.02	0.04	-0.04	0.00	-0.11
France									
d(Tobin's Q 1)	0.21	0.33	0.39	0.42	0.40	0.35	0.25	0.15	0.05
d(real disposable income)	0.12	0.22	0.18	0.12	0.10	0.06	0.12	0.08	0.08
d(real labour income)	0.17	0.26	0.28	0.24	0.20	0.08	0.02	-0.04	-0.05
d(population)	0.09	0.10	0.12	0.14	0.16	0.17	0.17	0.17	0.17
d(real mortgage interest rates)	0.01	-0.11	-0.30	-0.50	-0.51	-0.41	-0.19	0.02	0.19
d(housing loans to income ratio)	0.02	-0.03	0.07	0.17	0.29	0.27	0.17	0.17	0.12
d(real house prices	0.10	0.20	0.32	0.43	0.48	0.47	0.37	0.26	0.16
d(building permits)	0.27	0.35	0.38	0.40	0.39	0.22	0.05	-0.10	-0.08
Italy									
d(Tobin's Q 1)	0.27	0.25	0.37	0.34	0.29	0.29	0.30	0.35	0.44
d(real disposable income)	0.11	0.12	0.19	0.15	0.01	0.23	0.13	0.12	0.14
d(real labour income)	0.23	-0.05	0.22	0.10	0.17	0.10	0.05	0.15	0.08
d(population)	-0.19	-0.15	-0.13	-0.18	-0.13	-0.06	-0.03	-0.05	0.00
d(real mortgage interest rates)	0.17	0.01	0.02	-0.08	-0.35	-0.15	-0.08	-0.02	0.12
d(housing loans to income ratio)	0.24	0.21	0.27	0.20	0.31	0.20	0.18	0.29	0.22
d(real house prices	0.24	0.27	0.30	0.24	0.28	0.34	0.37	0.29	0.43
d(building permits)	0.09	0.33	0.17	-0.07	0.34	0.21	0.18	0.10	0.29

Notes: Tobin's Q 1 is defined as housing prices divided by the residential investment deflator. Sample size: 1999Q1 – 2019Q4.

Table B.5 (cont.): Cross-correlations between housing investment and leads and lags of determinants.

	d(real housing investment)								
	-4	**-3**	**-2**	**-1**	**t**	**+1**	**+2**	**+3**	**+4**
Spain									
d(Tobin's Q 1)	0.14	0.23	0.29	0.19	0.13	0.16	0.14	0.04	0.12
d(real disposable income)	0.34	0.28	0.18	0.18	0.17	0.19	0.29	0.23	0.23
d(real labour income)	0.35	0.19	0.17	0.32	0.25	0.35	0.19	0.17	0.21
d(population)	-0.16	-0.11	-0.06	0.02	0.05	0.11	0.15	0.16	0.22
d(real mortgage interest rates)	-0.01	0.13	-0.11	-0.04	-0.16	-0.24	-0.01	-0.08	0.09
d(housing loans to income ratio)	-0.05	0.07	0.13	0.19	0.21	0.21	0.15	0.17	0.18
d(real house prices	0.27	0.42	0.51	0.50	0.53	0.51	0.50	0.49	0.44
d(building permits)	0.39	0.24	0.50	0.29	0.46	0.29	0.20	0.25	0.12
Netherlands									
d(Tobin's Q 1)	0.19	-0.01	0.18	-0.03	0.49	0.28	0.03	0.22	-0.05
d(real disposable income)	-0.07	0.02	0.05	0.14	0.39	0.15	0.15	0.15	0.07
d(real labour income)	-0.06	-0.13	0.02	0.09	0.05	-0.02	0.11	-0.02	0.11
d(population)	-0.08	-0.07	-0.06	-0.07	-0.04	0.08	0.06	0.08	0.11
d(real mortgage interest rates)	0.00	-0.28	-0.10	0.03	0.00	0.09	0.01	-0.05	0.06
d(housing loans to income ratio)	-0.01	-0.09	-0.12	-0.02	-0.18	-0.10	-0.03	-0.06	0.05
d(real house prices	0.12	0.23	0.26	0.28	0.30	0.37	0.36	0.36	0.34
d(building permits)	0.12	0.23	-0.06	0.30	0.15	0.09	0.15	-0.04	0.05
Euro area									
d(Tobin's Q 1)	0.27	0.37	0.50	0.41	0.51	0.47	0.34	0.23	0.26
d(real disposable income)	0.15	0.21	0.21	0.29	0.23	0.27	0.23	0.20	0.23
d(real labour income)	0.15	0.03	0.16	0.14	0.32	0.18	0.10	0.07	0.10
d(population)	0.00	-0.01	0.05	0.02	0.10	0.12	0.15	0.09	0.23
d(real mortgage interest rates)	-0.03	0.13	-0.29	-0.30	-0.30	-0.27	-0.09	-0.01	0.13
d(housing loans to income ratio)	0.07	0.10	0.10	0.13	0.19	0.13	0.20	0.15	0.15
d(real house prices	0.20	0.33	0.49	0.49	0.59	0.62	0.56	0.43	0.45
d(building permits)	0.58	0.42	0.51	0.49	0.46	0.37	0.23	0.14	-0.11

Notes: Tobin's Q 1 is defined as housing prices divided by the residential investment deflator. Sample size: 1999Q1 – 2019Q4.

B.7 Long-run variables included after the cointegration test (S1).

Table B.6: Long-run variables included after the cointegration test (S1).

	Germany		France		Italy		Spain		Netherlands		Euro area	
	UN	**RE**	**UN**	**RE**	**UN**	**RE**	**UN**	**RE**	**UN**	**RE**	**UN**	**RE**
Tobin's Q												
Tobin's Q 1	11	6	2	3	1	4	4	3	0	0	9	16
Tobin's Q 2	8	5	2	3	1	5	3	5	0	0	6	11
Tobin's Q 3	5	4	1	3	2	4	3	1	1	14	13	8
Tobin's Q 4	7	5	1	3	1	5	3	2	0	0	5	9
Income												
Real disposable income	13	6	2	2	2	1	0	0	0	3	6	7
Labour income	8	3	8	2	2	1	0	0	0	1	13	2
Real total compensation	8	3	1	2	3	6	0	2	0	1	6	6
Real compensation per employee	7	4	0	1	0	1	12	0	0	3	7	11
Housing affordability index	0	10	0	13	0	14	0	9	1	3	0	16
Credit												
Loans for house purchase (LHPR)	21	17	8	10	6	13	4	2	0	4	19	26
LHPR to disposable income	7	3	4	7	2	7	4	5	0	4	10	16
LHPR to net non-financial assets	7	1	0	3	0	0	5	3	0	0	2	2

B.8 Estimates of long and short-run coefficients.

Table B.7: Estimates of long and short-run coefficients of Tobin's Q, income and credit.

	Number of equations		Long-run				Short-run			
			Coefficients		t-statistics		Coefficients		t-statistics	
	UN	RE	UN	RE	UN	RE	UN	RE	UN	RE
Germany										
Tobin's Q	0	22		1				0.05		0.2
Tobin's Q 1	0	0								
Tobin's Q 2	0	3		1				-0.06		-0.2
Tobin's Q 3	0	0								
Tobin's Q 4	0	19		1				0.07		0.2
Income	50	31	2.35	1	3.5***		-0.09	-0.26	-0.2	-0.6
Labour income	0	26		1				-0.32		-0.8
Real disposable income per HH	50	3	2.35	1	3.5***		-0.09	0.11	-0.2	0.2
Real total compensation	0	2		1				0.06		0.1
Real compensation per employee	0	0								
Housing affordability index	0	0								
Credit	50	36	-0.64	-0.96	-1.5	-1.8*	0.70	0.62	1.1	1.0
Loans for house purchase (LHPR)	38	36	-0.63	-0.96	-1.5	-1.8*	0.77	0.62	1.1	1.0
LHPR to disposable income	12	0	-0.66		-1.2		0.49		0.8	
LHPR to net non-financial assets	0	0								
France										
Tobin's Q	0	0								
Tobin's Q 1	0	0								
Tobin's Q 2	0	0								
Tobin's Q 3	0	0								
Tobin's Q 4	0	0								
Income	0	3		1				-0.10		-0.8
Labour income	0	3		1				-0.10		-0.8
Real disposable income per HH	0	0								
Real total compensation	0	0								
Real compensation per employee	0	0								
Housing affordability index	0	0								
Credit	50	50	0.20	0.20	3.4***	3.4***	0.26	0.26	1.9*	1.9*
Loans for house purchase (LHPR)	50	50	0.20	0.20	3.4***	3.4***	0.26	0.26	1.9*	1.9*
LHPR to disposable income	0	0								
LHPR to net non-financial assets	0	0								

Notes: Coefficients and t-statistics refer to median results for the top 50 selected equations estimated up to 2019Q4. ***, ** and * denote 1%, 5%, respectively, 10% significance. HH means household.

Table B.7 (cont.): Estimates of long and short-run coefficients of Tobin's Q, income and credit.

	Number of equations		Long-run				Short-run			
			Coefficients		t-statistics		Coefficients		t-statistics	
	UN	RE	UN	RE	UN	RE	UN	RE	UN	RE
Italy										
Tobin's Q	0	0								
Tobin's Q 1	0	0								
Tobin's Q 2	0	0								
Tobin's Q 3	0	0								
Tobin's Q 4	0	0								
Income	12	13	4.04	1	2.1**		-0.18	-0.12	-1.0	-0.7
Labour income	12	9	4.04	1	2.1**		-0.18	-0.13	-1.0	-0.9
Real disposable income per HH	0	0								
Real total compensation	0	0								
Real compensation per employee	0	4		1				-0.07		-0.3
Housing affordability index	0	0								
Credit	50	50	0.43	0.43	1.5	1.6	0.33	0.38	1.3	1.6
Loans for house purchase (LHPR)	50	50	0.43	0.43	1.5	1.6	0.33	0.38	1.3	1.6
LHPR to disposable income	0	0								
LHPR to net non-financial assets	0	0								
Spain										
Tobin's Q	50	50	1.94	1	2.1**		0.27	0.21	1.7*	1.1
Tobin's Q 1	50	0	1.94		2.1**		0.27		1.7*	
Tobin's Q 2	0	0								
Tobin's Q 3	0	48		1				0.21		1.1
Tobin's Q 4	0	2		1				0.24		1.8*
Income	0	50		1				-0.05		-0.6
Labour income	0	0								
Real disposable income per HH	0	0								
Real total compensation	0	0								
Real compensation per employee	0	0								
Housing affordability index	0	50		1				-0.05		-0.6
Credit	50	0	-1.01		-2.5**		0.15		0.8	
Loans for house purchase (LHPR)	8	0	-1.00		-2.7***		0.14		0.4	
LHPR to disposable income	42	0	-1.01		-2.5**		0.15		0.9	
LHPR to net non-financial assets	0	0								

Notes: Coefficients and t-statistics refer to median results for the top 50 selected equations estimated up to 2019Q4. ***, ** and * denote 1%, 5%, respectively, 10% significance. HH means household.

Table B.7 (cont.): Estimates of long and short-run coefficients of Tobin's Q, income and credit.

	Number of equations		Long-run Coefficients		Long-run t-statistics		Short-run Coefficients		Short-run t-statistics	
	UN	**RE**	**UN**	**RE**	**UN**	**RE**	**UN**	**RE**	**UN**	**RE**
Netherlands										
Tobin's Q	30	50	1.43	1	3.0***		1.10	0.98	2.2**	2.1**
Tobin's Q 1	0	0								
Tobin's Q 2	0	0								
Tobin's Q 3	30	50	1.43	1	3.0***		1.10	0.98	2.2**	2.1**
Tobin's Q 4	0	0								
Income	30	33	0.47	1	2.3**		-0.01	-0.25	0.0	-0.5
Labour income	0	0								
Real disposable income per HH	0	29		1				-0.30		-0.6
Real total compensation	0	0								
Real compensation per employee	0	0								
Housing affordability index	30	4	0.47	1	2.3**		-0.01	0.12	0.0	0.7
Credit	0	50		0.13		0.5		-0.12		-0.1
Loans for house purchase (LHPR)	0	0								
LHPR to disposable income	0	50		0.13		0.5		-0.12		-0.1
LHPR to net non-financial assets	0	0								
Euro area										
Tobin's Q	24	25	2.11	1	4.9***		-0.12	0.36	-0.4	1.2
Tobin's Q 1	24	25	2.11		4.9***		-0.12	0.36	-0.4	1.2
Tobin's Q 2	0	0								
Tobin's Q 3	0	0								
Tobin's Q 4	0	0								
Income	5	50	1.93	1	2.2**		0.12	0.04	0.4	0.1
Labour income	0	0								
Real disposable income per HH	5	8	1.93	1	2.2**		0.12	0.04	0.4	0.1
Real total compensation	0	0								
Real compensation per employee	0	0								
Housing affordability index	0	42		1				-0.04		-0.6
Credit	42	50	0.03	-10.93	0.3	-0.8	0.34	0.01	0.9	0.3
Loans for house purchase (LHPR)	37	25	0.00	0.02	0.0	0.1	0.30	0.25	0.8	0.7
LHPR to disposable income	5	0	0.28		2.3**		0.62		1.6	
LHPR to net non-financial assets	0	25		-21.87		-1.8*		-0.22		-0.2

Notes: Coefficients and t-statistics refer to median results for the top 50 selected equations estimated up to 2019Q4. ***, ** and * denote 1%, 5%, respectively, 10% significance. HH means household.

B.9 Estimates of short-run coefficients.

Unrestricted model

Table B.8: Estimates of short-run coefficients, unrestricted model.

	Germany			France			Italy		
	N	coeff.	t-stat	N	coeff.	t-stat	N	coeff.	t-stat
Mortgage interest rates	50	0.42	0.8	50	-0.46	-3.0***	50	-1.17	-2.5***
Composite interest for house purchase	11	0.30	0.6	21	-0.50	-3.3***	20	-1.20	-2.5***
Short-term interest for house purchase	29	0.50	1.0	9	-0.50	-3.1***	25	-1.20	-2.6***
Long-term interest for house purchase	10	0.30	0.5	20	-0.40	-2.6**	5	-0.90	-1.9*
Macroeconomic indicators	4	1.39	2.4**	36	-0.17	0.2	50	1.64	4.4***
Real GDP	0			10	0.35	1.9*	50	1.64	4.4***
Real private consumption	3	1.04	2.5**	6	0.14	0.8	0		
Total employment	1	2.46	2.2**	20	-0.53	-0.9	0		
Foreign demand	0			0			0		
Population and wealth measures	27	-2.15	-2.0**	5	0.00	-0.1	19	-0.27	-0.4
Number of private households	27	-2.15	-2.0**	0			3	-1.52	-1.4
Total population	0			0			16	-0.03	-0.3
Gross housing stock (-1)	0			0			0		
Net financial assets (-1)	0			5	0.00	-0.1	0		
Unemployment rate and uncertainty	27	0.01	0.0	38	-0.20	-1.1	38	0.90	1.5
Unemployment rate	0			23	-0.60	-1.7*	0		
Stock market volatility	8	-0.20	-0.4	2	-0.30	-2.0**	0		
Unemployment volatility	0			10	0.10	0.5	38	0.90	1.5
Income volatility	19	0.10	0.1	3	0.10	0.7	0		
Lagged housing investment growth	50	-0.01	-0.5	50	2.27	0.5	50	-1.26	-0.3
Housing investment (-1)	50	0.00	-0.1	50	0.49	0.1	50	-0.22	-0.1
Housing investment (-2)	50	-0.02	-0.9	50	4.05	0.8	50	-2.31	-0.6

Notes: Coefficients and t-statistics refer to median results for the top 50 selected equations estimated up to 2019Q4. ***, ** and * denote 1%, 5%, respectively, 10% significance.

Table B.8 (cont.): Estimates of short-run coefficients, unrestricted model.

	Spain			Netherlands			Euro area		
	N	**coeff.**	**t-stat**	**N**	**coeff.**	**t-stat**	**N**	**coeff.**	**t-stat**
Mortgage interest rates	50	-0.21	-0.5	30	0.03	0.1	50	-0.26	-0.6
Composite interest for house purchase	15	-0.20	-0.4	10	0.00	0.0	18	-0.30	-0.7
Short-term interest for house purchase	15	-0.10	-0.3	10	0.10	0.2	10	-0.10	-0.2
Long-term interest for house purchase	20	-0.30	-0.7	10	0.00	-0.1	22	-0.30	-0.7
Macroeconomic indicators	49	1.44	-2.7***	30	2.52	3.3***	42	1.98	3.2***
Real GDP	30	1.55	-2.9***	0			0		
Real private consumption	5	0.68	1.5	30	2.52	3.3***	0		
Total employment	14	1.47	2.7***	0			21	3.73	4.7***
Foreign demand	0			0			21	0.23	1.8*
Population and wealth measures	2	0.44	0.9	18	-9.58	-1.6	19	-0.98	-0.8
Number of private households	1	0.79	0.8	3	-7.21	-1.1	16	-1.21	-0.9
Total population	0			12	-12.50	-1.4	1	0.71	0.2
Gross housing stock (-1)	0			0			0		
Net financial assets (-1)	1	0.08	1.0	3	-0.29	-3.0***	2	-0.01	-0.2
Unemployment rate and uncertainty	44	0.90	1.6	24	0.84	0.6	35	-0.33	-1.4
Unemployment rate	0			0			0		
Stock market volatility	44	0.90	1.6	9	0.40	0.4	29	-0.50	-1.7*
Unemployment volatility	0			9	1.90	1.3	1	0.00	0.2
Income volatility	0			6	-0.10	-0.1	5	0.60	0.4
Lagged housing investment growth	50	0.07	0.8	30	-0.08	0.2	50	0.17	0.4
Housing investment (-1)	50	0.01	0.1	30	-0.02	0.0	50	0.03	0.1
Housing investment (-2)	50	0.12	1.4	30	-0.15	0.4	50	0.30	0.8

Notes: Coefficients and t-statistics refer to median results for the top 50 selected equations estimated up to 2019Q4. ***, ** and * denote 1%, 5%, respectively, 10% significance.

Restricted model

Table B.9: Estimates of short-run coefficients, restricted model.

	Germany			France			Italy		
	N	**coeff.**	**t-stat**	**N**	**coeff.**	**t-stat**	**N**	**coeff.**	**t-stat**
Mortgage interest rates	50	0.35	0.6	50	-0.47	-3.0***	50	-1.26	-2.6***
Composite interest for house purchase	12	0.30	0.5	24	-0.50	-3.2***	20	-1.20	-2.6***
Short-term interest for house purchase	26	0.40	0.7	9	-0.50	-3.1***	29	-1.30	-2.7***
Long-term interest for house purchase	12	0.30	0.5	17	-0.40	-2.6***	1	-0.01	-2.9***
Macroeconomic indicators	48	1.09	2.3**	34	-0.23	0.0	50	1.70	4.5***
Real GDP	0			8	0.32	1.7*	50	1.70	4.5***
Real private consumption	45	0.99	2.3**	5	0.14	0.8	0		
Total employment	3	2.67	2.3**	21	-0.53	-0.9	0		
Foreign demand	0			0			0		
Population and wealth measures	23	-2.12	-2.1**	6	0.17	0.5	19	0.31	0.3
Number of private households	23	-2.12	-2.1**	0			0		
Total population	0			0			16	-0.03	-0.3
Gross housing stock (-1)	0			1	1.05	3.3***	3	2.12	3.2***
Net financial assets (-1)	0			5	0.00	-0.1	0		
Unemployment rate and uncertainty	29	-0.54	-0.4	40	-0.34	-0.9	50	0.80	1.5
Unemployment rate	5	-3.10	-2.0**	2	-0.30	-2.0**	0		
Stock market volatility	3	-0.10	-0.2	11	0.10	0.5	0		
Unemployment volatility	3	0.60	0.7	3	0.10	0.7	50	0.80	1.5
Income volatility	18	-0.10	-0.1	24	-0.60	-1.7**	0		
Lagged housing investment growth	50	0.33	-0.6	50	2.27	0.5	50	-1.19	-0.3
Housing investment (-1)	50	0.07	-0.1	50	0.49	0.1	50	-0.21	0.0
Housing investment (-2)	50	0.59	-1.0	50	4.05	0.8	50	-2.17	-0.5

Notes: Coefficients and t-statistics refer to median results for the top 50 selected equations estimated up to 2019Q4. ***, ** and * denote 1%, 5%, respectively, 10% significance.

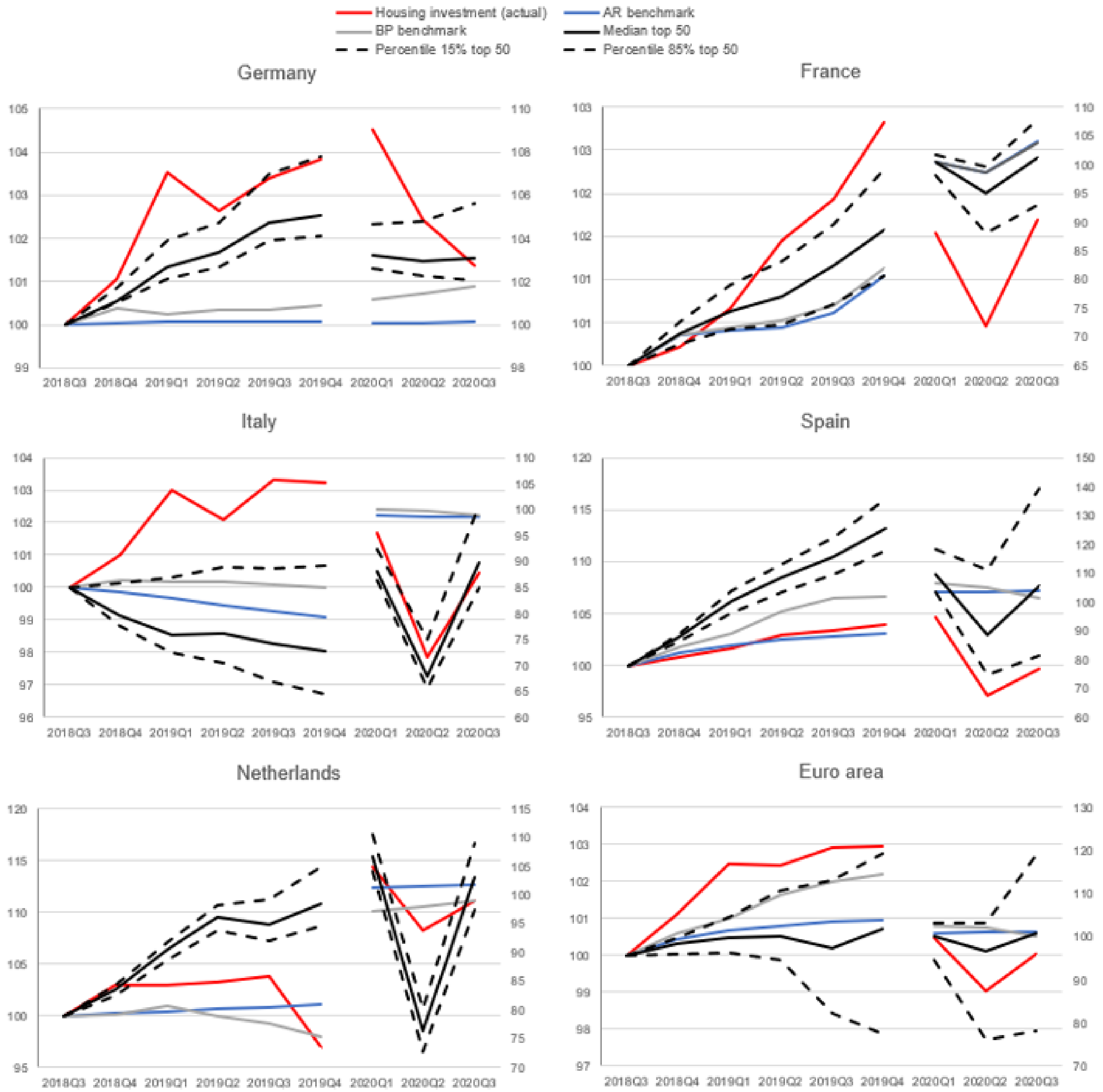
Table B.9 (cont.): Estimates of short-run coefficients, restricted model.

	Spain			Netherlands			Euro area		
	N	**coeff.**	**t-stat**	**N**	**coeff.**	**t-stat**	**N**	**coeff.**	**t-stat**
Mortgage interest rates	50	-0.07	-0.2	50	0.03	0.1	50	-0.06	-0.1
Composite interest for house purchase	16	-0.10	-0.1	19	0.10	0.2	17	0.00	-0.1
Short-term interest for house purchase	15	0.00	-0.1	14	0.20	0.3	15	-0.20	-0.4
Long-term interest for house purchase	18	-0.10	-0.3	17	-0.20	-0.3	18	0.00	0.1
Macroeconomic indicators	29	0.28	0.4	50	2.91	4.2***	50	0.39	2.6**
Real GDP	3	0.78	1.1	30	3.12	4.9***	8	1.04	3.9***
Real private consumption	16	0.47	0.9	20	2.60	3.3***	0		
Total employment	0			0			0		
Foreign demand	10	-0.18	-0.6	0			42	0.27	2.3**
Population and wealth measures	39	-0.05	0.3	16	-0.17	-0.3	14	-0.08	-0.1
Number of private households	0			0			7	-0.14	-0.1
Total population	0			0			0		
Gross housing stock (-1)	18	-0.20	-0.4	16	-0.17	-0.3	0		
Net financial assets (-1)	21	0.08	0.9	0			7	-0.01	-0.2
Unemployment rate and uncertainty	19	0.14	0.3	38	0.42	0.3	23	0.02	0.1
Unemployment rate	10	0.90	1.4	2	-1.50	-0.5	2	-0.80	-0.6
Stock market volatility	0			8	0.60	0.6	21	0.10	0.1
Unemployment volatility	0			16	1.40	1.0	0		
Income volatility	9	-0.70	-0.9	12	-0.70	-0.6	0		
Lagged housing investment growth	50	0.90	0.2	50	0.23	0.4	50	0.06	0.0
Housing investment (-1)	50	0.19	0.2	50	0.04	0.1	50	0.01	0.0
Housing investment (-2)	50	1.62	2.4**	50	0.42	0.8	50	0.10	0.1

Notes: Coefficients and t-statistics refer to median results for the top 50 selected equations estimated up to 2019Q4. ***, ** and * denote 1%, 5%, respectively, 10% significance.

B.10 Out-of-sample forecasts for 2018Q4 – 2020Q3, unrestricted model.

Figure B.7: Out-of-sample forecasts for 2018Q4 – 2020Q3, unrestricted model.



Notes: Based on top 50 selected unrestricted model equations estimated over 1999Q1 – 2018Q3. Housing investment level in 2018Q3 = 100.

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3 The effects of monetary policy in the euro area

This paper estimates the effects of monetary policy and central bank information shocks to subcomponents of GDP and other key macroeconomic variables in the euro area. Additionally, we evaluate whether such effects have changed in the last two decades. To perform such analysis we use an extended version of the SVAR model of Jarocinski and Karadi (2020) and a Proxy-SVAR model. The main findings in this study are as follows. First, purely monetary policy shocks have significantly negative effects on consumption, housing and business investment, having the largest impact on the latter. By contrast, the effects on prices are quite modest, consistent with the literature. Finally, our evidence suggest that the effects of purely monetary policy shocks have changed over time in the euro area. In particular, while during the 2000s the effects are the standard contractionary ones, during the 2010s it seems that the capacity of the ECB to affect economic variables such as business and housing investment and unemployment has been critically weakened.

Keywords: Monetary policy shocks, VARs, external instruments, euro area.

JEL Classification: C11, C32, C36, C38, E32, E52, E58.

3.1 Introduction

The measurement of the effects of monetary policy shocks on the macroeconomy is a classic topic of discussion in both academia and research-oriented institutions. However, despite the substantial efforts done in the literature to measure their transmission in the last decades, there is still not a conclusive consensus (see Ramey, 2016; Wolf, 2020), specially in the case of the euro area, for which there is typically less evidence available than for the US. Nowadays, this topic is even more relevant than usually at least for the following reasons. First, after almost a decade with mostly flat and near to zero reference rates and the increasing importance of unconventional monetary policy tools (Hartmann and Smets, 2018), studying the effects of purely monetary policy shocks is arguably even more challenging than before. Second, the recent excess savings experienced during the Covid-19 pandemic and its posterior inflation risks calls for a necessary analysis of the effects of a potential increase in reference interest rates. Third, the risk of stagflation in the euro area together with a possible gradual tapering of unconventional monetary measures might require an increased care in the understanding of the macro outcomes after interest rates hikes. Fourth, anomalies found in the monetary policy transmission (Giannone, Lenza and Reichlin, 2019) also suggest the need for analyzing whether such transmission might have suffered changes over time.

The first target of this paper is to estimate the effects of monetary policy shocks to subcomponents of GDP, i.e. private consumption and business and housing investment in the euro area. This is motivated by the fact that usually the monetary policy literature tends to focus on the effects on aggregate output and in the US data, leaving the subcomponents of GDP and the euro area relatively understudied. The second objective in this paper is to evaluate whether the effects of monetary policy have changed across time. This aspect is relevant because during the last decade monetary policy in the euro area has experienced extremely low interest rates and employed unconventional monetary policy after experiencing important downturns, i.e the financial crisis and the sovereign-debt crisis, which arguably might have modified to some extent the effects of standard monetary policy on the economy.

Such analysis is performed by estimating two econometric models employing different identification strategies available in the literature using high frequency monetary policy instruments. First, we estimate an extended Jarocinski and Karadi (2020) SVAR model, which combines sign restrictions and high frequency instruments to identify both the interest rate and central bank information shocks. Second, we estimate two Proxy-SVARs (Stock and Watson, 2012, 2018; Mertens and Ravn, 2013) using as external instruments surprises in pure monetary policy shocks and central bank information shocks, respectively, by exploiting the EA-MPD database of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019).

Against this background, four main conclusions emerge from the results in this paper. First, purely monetary policy shocks have significantly negative effects on consumption, housing and business investment, having the largest impact on the latter. Second, the effects on HICP are modest, consistent with the literature, which calls for caution when dealing with upward inflation risks. Third, the estimation of the effects of monetary policy including 2020 data and an heteroskedasticity approach along the lines of Ferroni and Canova (2021) and Lenza and Primiceri (2020) generates apparently too strong negative effects in some variables while others are unaffected, which suggests that an approach to dealing with heteroskedasticity that allows for heterogeneous effects across variables might be more desirable. Fourth, it turns out that the effects of purely monetary policy shocks have changed over time in the euro area. In particular, while during the 2000s the effects are the conventional contractionary ones found for the full sample, during the 2010s it seems that the capacity of the ECB to affect economic variables as business and housing investment and unemployment has been substantially weakened.

Given the current context of inflationary risks provoked by the excess savings generated during the Covid-19 pandemic in the euro area, these results seem specially relevant because they highlight the fact that a potential increase in interest rates might have a tiny impact on prices while having bigger costs for households and firms. Moreover, in an economic environment characterized by a depressed fiscal space, huge GDP losses due to the pandemic and energy shocks we might expect that the actual effects of a potential contractionary monetary policy shock might be even higher than estimated in this study. Therefore, alternatives to increasing interest rates might also be explored in managing inflationary risks.

Literature review. The effects of monetary policy have been massively studied using structural VARs since the pioneering work of Sims (1980). Since then, virtually all papers in that literature have faced the same identification challenge, that is finding an empirical method to plausibly identify exogenous monetary policy shocks and then estimate its impact on macroeconomic variables. Several issues might appear while working on this enterprise. First, there is the risk that a model leaves relevant information aside so that might generate *omitted variable bias*, which authors as Bernanke, Boivin and Eliasz, 2005 mitigate by using a factor-augmented VAR model. Second, our monetary policy shock of interest might be confused with other shocks in the system (Wolf, 2020). Third, it is debatable that macroeconomic aggregates are informative enough to capture hidden structural shocks, i.e. the *non-invertibility problem* (Nakamura and Steinsson, 2018). Initially, economists dealt with this identification challenges by employing *internal instruments* (Stock and Watson, 2018), i.e. by imposing restrictions on elements inside the system that is estimated. Classic examples are the recursive identification and zero and sign restrictions (Uhlig, 2005; 2017). The controversial assumptions behind these methods and counterfactual results such as *output* and *price puzzles* led to further identification developments.

Indeed, more recently two additional methods have been proposed in the literature to improve the identification of structural shocks. First, as introduced by Stock (2008) *external instruments* can be used for SVAR shock identification, method that robustly estimate the true effects of monetary policy shocks (Stock and Watson, 2018; Wolf, 2020) and which has been largely used in monetary policy studies in the last decade (Stock and Watson, 2012; Mertens and Ravn, 2013; Gertler and Karadi, 2015 among others). Briefly speaking, an external instrument is a variable that is correlated with the shock of interest, but not with other shocks, so that such instrument captures exogenous variation in the shock of interest[1]. Second, as shown by Antolín-Díaz and Rubio-Ramírez (2018) narrative sign restrictions can also be used to sharpen the identification of structural shocks in SVARs. This type of restrictions entails imposing sign restrictions on the structural shock of interest, instead of restricting the response of a variable in the system[2].

Besides alternative methodological approaches to estimate the monetary transmission mechanism, the studies focusing on the euro area are comparatively less numerous than those using US data, specially regarding euro area individual countries. Table 3.1 summarizes the monetary policy studies that recently have covered the euro area[3]. The following remarks emerge from that review. First, most of them use small or medium-scale VARs, being Corsetti, Duarte and Mann (2020) and Giannone, Lenza and Reichlin (2019) the exceptions. Second, most of them use external instruments to identify the monetary policy shock. Third, only Durante, Ferrando and Vermeulen (2020) and Corsetti, Duarte and Mann (2020) report results for the euro area

[1] Alternatively, the interested researcher might use the external instrument to estimate directly structural impulse responses directly, i.e. without estimating an SVAR but using a local projection (see Jordà, Schularick and Taylor, 2015).

[2] Given the *external* nature of the narrative to impose narrative sign restrictions, one might consider this method as an external instrument.

[3] Studies using a recursive structural identification method or with data samples before 2015 are excluded. Some remarkable examples are Boivin, Giannoni and Mojon (2008) and Blaes (2009). Also, Andrade and Ferroni (2021) study the effects of forward guidance in the euro area using high frequency information. Instead, Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) estimate a SVAR with financial variables only.

countries. Fourth, only Corsetti, Duarte and Mann (2020) and Durante, Ferrando and Vermeulen (2020) for the case of investment provide impulse responses results for subcomponents of GDP, which might confirm the interest in observing such disaggregated results instead of just the impulse responses of output or industrial production.

Our paper complements these studies in several dimensions, beyond providing estimates on a larger sample. First, we provide results on the effects of a purely monetary policy and central bank information shock on subcomponents of GDP, so providing a more comprehensive answer on the monetary policy transmission to consumption, business and housing investment. Second, we provide evidence on the changes in the monetary policy transmission mechanism in the euro area during the last two decades. Third, we also estimate the effects of monetary policy shocks including 2020 data by employing an heteroskedasticity treatment tool along the lines of Ferroni and Canova (2021) and Lenza and Primiceri (2020).

The remainder of this paper proceeds as follows. Section 3.2 describes the different econometric models and identification strategies that are employed. Section 3.3 shows the obtained empirical results. Finally, section 3.4 concludes and suggests some policy implications and research avenues.

Table 3.1: Overview of studies on standard monetary policy effects in the euro area

	[1]	[2]	[3]	[4]	[5]
Sample	1999	1999	2000	1992	2007
	2016	2016	2016	2008	2020
Model	FAVAR	SVAR	OLS-LP	SVAR	SVAR
Linear	Yes	Yes	Yes	Yes	Yes
Identification	EI	SR + EI	EI	SR	EI
External instrument	OIS 1y.	OIS 3m.	OIS 3m.	-	OIS 1m.
Frequency	Q	M	Q	M	M
Variables	179*	7	**	28	20
Volatility treatment	No	No	No	No	No
UMP variables	No	No	No	No	Yes
Policy tool shocked	EONIA	1y. bund	EONIA	Euribor 3 m.	Euribor 1 m.
Shock	+25 b.p.	+1 s.d.	+1 b.p.	+1 s.d.	+25 b.p.
IRFs effect (+1 year) on:					
GDP	-0.5%	-0.2%			
Industrial production				-0.4%	-2%
Consumption	-0.2%				
Investment	-1%		-0.3%		
Public spending	n.s.				
Imports	-1.5%				
Exports	-1.8%				
Wages	n.s.				
Prices	n.s.	-0.05%		-0.05%	-0.5%
House prices	-0.4%				
Unemployment	0.01%			0.01%	n.s.
Stock index		n.s.		n.s.	n.s.
Mortgages				-0.2%	-0.5%
Saving deposits				-0.4%	

Notes: [1] = Corsetti, Duarte and Mann (2020); [2] = Jarocinski and Karadi (2020); [3] = Durante, Ferrando and Vermeulen (2020); [4] = Giannone, Lenza and Reichlin (2019); [5] = Martínez-Hernández (2020). UMP variables refer to the inclusion in the model of explanatory variables proxying unconventional monetary policy. IRFs refers to impulse responses effects. EI identification means external instruments while SR means sign restrictions. OIS is the Overnight Index Swap, i.e. the EONIA swap rate index. Frequencies M and Q refer to monthly and quarterly. The reported IRFs effects on the selected variables refer to the percentage change of such variables after a contractionary monetary policy shock after 1 year. The IRF results of Martínez-Hernández (2020) refer to her Target responses. * Corsetti, Duarte and Mann (2020) use 179 variables for factor extraction, which include both the euro area and 11 euro area countries, for which they also provide results not reported here to save space. ** Durante, Ferrando and Vermeulen (2020) use micro data corresponding to more than 1 million firms, which in total yields more than 9 million observations, so this is the only study in this Table not using macro data. These authors also provide analogous results for Germany, France, Italy and Spain, not reported here to save space (which are roughly similar one year after the shock, but more heterogeneous both on impact and two years after the shock). b.p. means basis points, s.d. stands for standard deviations and n.s. refers to not significant at the 5% significance level.

3.2 Modeling frameworks

3.2.1 The Jarocinski and Karadi (2020) SVAR model

First, we consider the Jarocinski and Karadi (2020) model in order to estimate the effects of monetary policy shocks in the euro area. These authors estimate an SVAR which includes directly external high frequency instruments as additional explanatory variables in the model. In particular, their baseline model is a monthly VAR with a y_t vector of N_y macro and financial variables, a vector m_t of monetary policy surprises in N_m financial instruments and the restriction that such m_t does not depend on the lags of either itself or y_t and has zero mean. Such model reads as follows:

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} 0 & 0 \\ B^p_{YM} & B^p_{YY} \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} 0 \\ c_y \end{pmatrix} + \begin{pmatrix} u^m_t \\ u^y_t \end{pmatrix}, \begin{pmatrix} u^m_t \\ u^y_t \end{pmatrix} \sim N(0, \Sigma) \quad (3.1)$$

where the m_t vector of surprises includes two high frequency instruments for proxying the two structural monetary policy shocks and the y_t vector of macro and financial variables includes 5 indicators: real GDP, the GDP deflator, a stock prices index, the 1 year German bond rate (as a measure of a *safe* asset rate) and the BBB bond spread. With these ingredients, Jarocinski and Karadi (2020) identify two structural monetary policy shocks by using a mixture of sign restrictions and external instruments, i.e. a *monetary policy shock* and a *central bank information shock*.

The SVAR model defined in equation (3.1) is estimated in one step, instead of using the instruments in a Proxy-SVAR or in a local projection, making the inference simpler. The VAR parameters are estimated using standard Bayesian priors following Litterman (1986) and they generate draws from the posterior distribution using the Gibbs sampler[4].

Regarding the identification scheme to identify the monetary policy shocks in this framework, we consider the *poor man's sign restrictions* of Jarocinski and Karadi (2020). This approach combines sign restrictions and external instruments from high-frequency information to identify a purely monetary policy shock and a central bank information shock. To isolate both, the authors make the following two assumptions (summarized in Table 3.2):

1. The surprises m_t are only affected by the two monetary shocks (i.e. the purely monetary shock and the central bank information shock) and not by other shocks.
2. Sign restrictions. A purely monetary policy shock is associated with an increase in interest rates and a decline in stock prices. On the contrary, a central bank information shock is associated with a rise in both interest rates and stock prices.

Table 3.2: Identifying *poor man's sign restrictions* in Jarocinski and Karadi (2020)

Variables	**Monetary policy shock**	**CB information shock**	**Other shocks**
Interest rate	+	+	0
Stock index	-	+	0
Low frequency variables	•	•	•

Notes: Restrictions on the contemporaneous responses of variables to shocks +, -, 0 and • denote positive, negative, zero and unrestricted responses, respectively.

[4] For more details on the estimation of the SVAR see Jarocinski and Karadi (2020).

3.2.2 The Proxy-SVAR model

Secondly, we consider a Proxy-SVAR (or SVAR-IV) model as introduced in the literature by Stock (2008) and used since then by Stock and Watson (2012), Mertens and Ravn (2013), Gertler and Karadi (2015) and increasingly more economists. The main idea behind an *external instrument* or *Proxy-SVAR* is that the interested researcher might use information *outside* the VAR for identifying the shock of interest, for instance a monetary policy shock as in our particular case, assuming that such external series is a valid proxy of the true shock.

Let Y_t be an $n \times 1$ vector of observable variables, we assume their dynamics can be described by a system of linear simultaneous equations such as a vector autorregressive model with p lags, i.e. a VAR(p) denoted as:

$$Y_t = \sum_{j=1}^{p} \delta_j Y_{t-j} + B\epsilon_t \tag{3.2}$$

where δ_j are $n \times n$ coefficient matrices, $j = 1, ..., p$, B is a non-singular $n \times n$ matrix of coefficients, and ϵ_t is the $n \times 1$ vector of structural shocks with $E[\epsilon_t] = 0$, $E[\epsilon_t \epsilon_t'] = I$, $E[\epsilon_t \epsilon_s'] = 0$ for $s \neq t$ being I the identity matrix[5]. Alternatively, we might express the system as $A(L)Y_t = u_t$, where $B = A^{-1}$, u_t are the reduced form residuals and L denotes the lag operator. Given that Y_t is second-order stationary, $A(L)$ is invertible[6].

Crucially, the reduced form residuals u_t are related to the structural shocks ϵ_t such that:

$$u_t = B\epsilon_t \tag{3.3}$$

where we assume that the number of variables n in the VAR is equal than the number of shocks m. Then, the classical SVAR identification problem is to identify the matrix B as it allows us to disentangle our structural shock of interest in ϵ_t from the reduced form residuals u_t. Then, if equation 3.3 holds, the SVAR impulse response function displays the dynamic causal effects. We tackle the SVAR identification by employing external instruments.

Let Z_t be a proxy candidate of a monetary policy shock under scrutiny, ϵ^{mp} is the structural monetary policy shock and ϵ^{nmp} any other structural shock different than the monetary policy one, such series Z_t is a valid proxy for identifying our structural monetary policy shock of interest if two conditions hold:

$$(i) \;\; E[Z_t \epsilon^{mp}] \neq 0 \tag{3.4}$$

$$(ii) \;\; E[Z_t \epsilon^{nmp}] = 0 \tag{3.5}$$

where condition *(i)* refers to the *relevance condition* of the instrumental variable and instead *(ii)* refers to the *exogeneity condition* with respect to other contemporaneous shocks. That is, the external instrument Z_t must be correlated contemporaneously with the structural monetary policy shock but contemporaneously uncorrelated with the other structural shocks. These are key assumptions that translate into restrictions on the elements of B.

Once we have a valid external instrument, a Proxy-SVAR model is estimated by two-stage least squares equation-by-equation using the instrument Z_t (see Mertens and Ravn, 2013).

[5]The VAR(p) description in equation 3.6 omits deterministic trends and exogenous regressors for simplicity.

[6]The system invertibility assumption, i.e. that the structural shocks can be expressed as linear combinations of the VAR innovations is a standard assumption in the literature.

3.3 Empirical assessment

3.3.1 Data

In order to feed our SVAR models we use monthly data from January 1999 to December 2019, while we allow also the inclusion of 2020 data only in an extension explained in subsection 3.3.6[7]. Our baseline specifications use the 1 year German bond as the measure of the policy rate, the blue-chip Euro Stoxx 50 index as the stock price index and subcomponents of GDP such as private consumption, business and housing investment and imports and exports of goods. As a measures of prices, we include the HICP and the commodity price index PCE. Finally, we also include the unemployment rate. Additionally, in some robustness exercises we alternatively use the EONIA overnight interest rate as the policy rate and include a measure of the excess bond premium, either the original BBB spread of Jarocinski and Karadi (2020) or the credit spread of De Santis (2016), which in turn follows Gilchrist and Zakrajšek (2012)[8,9]. All variables enter in the models in log-levels per 100 except interest rates and credit spreads that are in levels. All variables are in real terms[10].

Our dataset includes quarterly variables that we have converted into monthly frequency. In these cases, i.e. the subcomponents of GDP, we use the Chow and Lin (1971) interpolation method to estimate the series at the monthly frequency, which entails using monthly indicators to obtain the monthly estimates of the quarterly variables. See Table C.2 in Appendix C.2 for a description of the monthly indicators that we use in the interpolation for each interpolated quarterly variable.

With regard to the construction of the external instruments of monetary policy shocks, we use the EA-MPD dataset of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019), which provides the high frequency data on changes in OIS rates at different maturities and other financial assets around the European Central Bank policy announcements[11]. In order to compute our monthly series of surprises, we sum up the surprises at one month in case there are more than one announcements in one particular month, while we set at zero the surprises in months where there is no announcement.

3.3.2 The external instruments of Jarocinski and Karadi (2020)

First, we compute two external instruments as proxies of the monetary policy shocks that we use in our Proxy-SVARs and in combination with sign restrictions in an extended Jarocinski and Karadi (2020) model. In particular, we use the dataset of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) to compute the external instruments along the lines of Jarocinski and Karadi (2020), who extract them using high-frequency information[12].

[7] All the results explained in this section refer to our baseline data sample, i.e. from January 1999 to December 2019 to initially avoid dealing with the Covid-19 related surge in volatility. However, an extended sample up to December 2020 is used in subsection 3.3.6 when also employing the heteroskedasticity treatment of Lenza and Primiceri (2020).

[8] Roberto De Santis nicely shared his updated excess bond premium series with us.

[9] See Figure C.1 in Appendix C.3 for a graphical comparison of these three measures of the excess bond premium.

[10] See Table C.1 in Appendix C.1 for a detailed description of the time series used in this paper with their transformations and sources.

[11] See the most updated version of the EA-MPD database of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) at https://www.ecb.europa.eu/pub/pdf/annex/Dataset_EA-MPD.xlsx.

[12] The usage of high-frequency information to compute external instruments dates back to Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005).

Indeed, Jarocinski and Karadi (2020) compute a purely *monetary policy shock* and a *central bank information shock* from March 1999 to December 2016 by exploiting the surprises in the 3-month EONIA interest rate (OIS) swaps and the Euro Stoxx 50[13]. Their main intuition is that, as in any monetary policy event there is both an interest rate decision and also information that is provided by the central bank during the press conference, so for identifying a purely monetary policy shock, i.e. an interest rate shock, one should disentangle the effect of the information provided by the monetary institution. For that purpose, they record changes in the 3-month EONIA interest rate (OIS) swaps and the Euro Stoxx 50 in a 30 minutes window around press statements and in a 90 minutes window around press conferences for each monetary event during the time span they consider, while they sum up the responses in the two windows whenever there is a press conference after a press statement. Then, the *monetary policy shock* is the series that contains each monthly average of changes in the 3-month EONIA interest rate swap that shows a negative comovement with the average monthly change in the Euro Stoxx 50, zero otherwise[14]. On the contrary, a *central bank information shock* is the series containing each monthly average of changes in the 3-month EONIA interest rate swap that shows a positive comovement with the average monthly change in the Euro Stoxx 50, zero otherwise. The reasoning for that is prosaic: a pure monetary policy tightening lowers stock market valuation[15], while the opposite might be read as an information shock from the signals provided by the central bank.

To visualize whether the apparently puzzling positive comovement between surprises in policy rates and stock prices is relevant we can have a look at Figure 3.1, which shows a scatterplot with the surprises in the Euro Stoxx 50 (y-axes) versus those in the 3-month OIS rate (x-axis) around monetary events windows between January 1999 and December 2020. As predicted by economic theory, in quadrants II and IV we observe monetary events in which there is a negative comovement between surprises in stock prices and OIS rates. However, as shown by Jarocinski and Karadi (2020), there are many monetary events in which we observe apparently wrong-signed responses: positive surprises in stock prices after positive surprises in interest rates (quadrant I) and vice versa (quadrant III)[16]. These surprises, which account for the 42% of the ECB announcements from January 1999 to December 2020, motivate the need for disentangling information shocks from purely monetary policy shocks in order to estimate their effects in the economy.

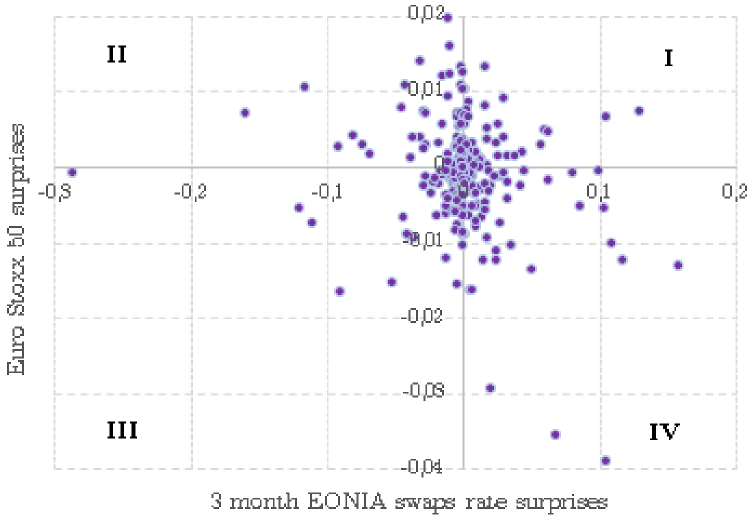
[13] The EONIA is the rate at which banks can lend unsecured money to each other overnight, i.e. at a maturity of 1 day. Then, an x-period EONIA swap rate, or x-period Overnight Index Swap (OIS) rate, is the fixed rate at which a bank can swap the daily rate over an x-period. Movements in this rate are understood as the markets' expectation of movements in the central bank policy rate in the next x-period ahead. On the other hand, the Euro Stoxx 50 is the reference stock prices index for the eurozone, that includes the stock prices of the 50 blue-chip companies from 11 euro area countries.

[14] Average changes refer to the average across the possibly more than one monetary events occurred during one month.

[15] There are two reasons for expecting a decline in stock prices after an interest rate hike. First, higher interest rates lower the expected future dividends of a given company, then reducing its discounted value or theoretical price. Second, higher interest rates increase the discount rate at which future dividends are discounted.

[16] Interestingly, there is certain degree of concentration of quadrant III wrong-signed responses during the financial crisis and sovereign-debt crises (2007-2009 and 2012), accounting for the 34% of the total quadrant III wrong-signed responses.

Figure 3.1: Scatterplot of surprises in Euro Stoxx 50 vs 3-month OIS rate, euro area



Notes: Own calculation according to the method for calculating surprises of Jarocinski and Karadi (2020) using the EA-MPD dataset of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019). Each dot represents a month in which there was at least one ECB announcement from January 1999 to December 2020.

The monetary policy shocks of Jarocinski and Karadi (2020), i.e. red dashed line, together with our replication using the Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019), i.e. blue solid line, and an analogous instrument using the 1 year OIS rates changes as the underlying financial contract around the press release window, i.e. black dashed line, are plotted in Figure 3.2[17]. The largest negative (accommodative) monetary policy shock appear in May 2001, which is consistent with the ECB announcing a cut in its policy interest rates by a 25 basis points on May 10th 2001 (Duisenberg, 2001a). Instead, the two largest positive (contractionary) monetary policy shocks take place in October 2011 and November 2008. First, on the 6th October 2011 the ECB decided to keep the interest rates unchanged while the market expected a rate cut (Trichet, 2008a), so the unchanged rates were understood as contractionary. Conversely, in November 2008 the ECB decreased policy rates by 50 basis points (ECB, 2008). This is interesting because at the same time we observe a decrease in policy rates and a hike in the OIS rates, which seems to be due to the market expecting a higher decline in interest rates in a context of increasing tensions from the financial sector (Trichet, 2008b).

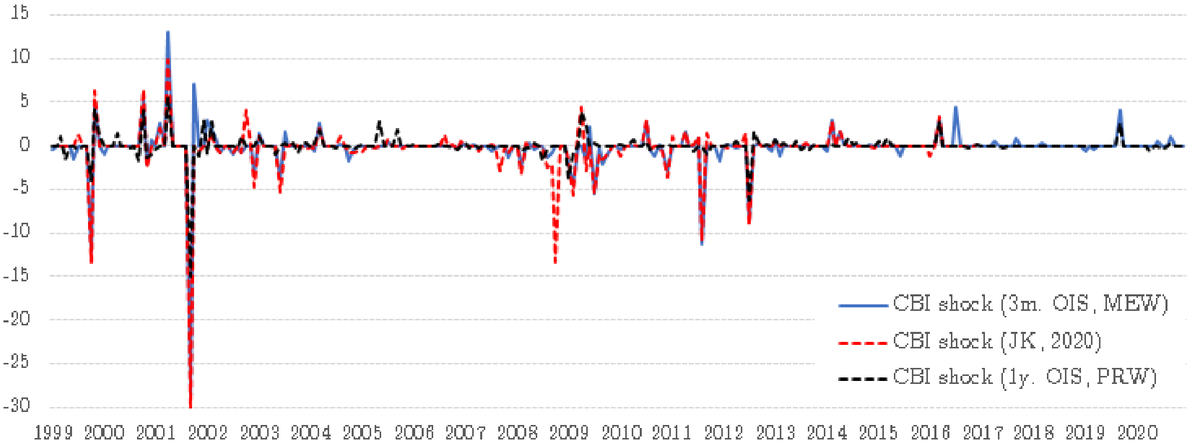
On the other hand, the analogous external instruments but in the central bank information shock case, i.e. showing positive comovement with changes in the Euro Stoxx 50 index, are plotted in Figure 3.3. The largest negative (accommodative) information shock happened in September 2001, a time in which the ECB announced that cut policy interest rates by 0.5 percentage points in a joint movement with the Federal Reserve after the 9/11 terrorist attacks in the US (ECB, 2001). On the contrary, the largest positive (contractionary) information shock takes place in April 2001 when the ECB kept interest rates unchanged while the market expected a cut, so the messages of Duisenberg (2001b) seemed to be hawkish.

[17] The largest discrepancy in our replication (blue line) versus those of Jarocinski and Karadi (2020) refers to the shock identified in October 2008, in which case they record that contractionary surprise as central bank information shock while we identify it as monetary policy shock. The difference is due to the fact that they record a decline in the Euro Stoxx 50 at this monetary event while with the Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) data we record a rise in the index price. Such difference might be due by the fact that those studies record changes in stock prices using slightly different timings and methods. Indeed, Jarocinski and Karadi (2020) use a 30 minutes and 90 minutes window around press release and press conference, respectively, in both cases 10 minutes before and 20 minutes after the event. On the contrary, Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) first take median prices on 10 minutes windows before and after the events prior to calculating the changes in prices. See Appendix C.4 for a detailed scheme comparing the timings at which these two studies record their high frequency data vis a vis the ECB policy communication timeline.

Figure 3.2: Monetary policy shocks in the euro area

Notes: Surprises are aggregated to the monthly frequency. The y-axis defines monetary policy (MP) shocks in basis points changes in OIS rates around policy announcements. The "MP shock (JK, 2020)", i.e. red dashed line, is the original series used by Jarocinski and Karadi (2020) as MP shock. The "MP shock (3m. OIS, MEW)", i.e. the solid blue line is our replication of the Jarocinski and Karadi (2020) shock using the EA-MPD dataset of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019), which uses the 3 months OIS rates around the full monetary event window. The "MP shock (1y. OIS, PRW)" is the analogous shock but using the 1 year OIS rate around the press release window.

Figure 3.3: Central bank information shocks in the euro area



Notes: Surprises are aggregated to the monthly frequency. The y-axis defines central bank information (CBI) shocks in basis points changes in OIS rates around policy announcements. The "CBI shock (JK, 2020)", i.e. red dashed line, is the original series used by Jarocinski and Karadi (2020) as CBI shock. The "CBI shock (3m. OIS, MEW)", i.e. the solid blue line is our replication of the Jarocinski and Karadi (2020) shock using the EA-MPD dataset of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019), which uses the 3 months OIS rates around the full monetary event window. The "CBI shock (1y. OIS, PRW)" is the analogous shock but using the 1 year OIS rate around press release window.

3.3.3 Evaluation of the external instruments

In this subsection we test the relevance of alternative external instruments to proxy for monetary policy shocks. First, we estimate a small-scale VAR similar to that used by Miranda-Agrippino and Ricco (2021) for tackling the same purpose. The vector of endogenous variables includes a policy rate, an industrial production index, the unemployment rate, the HICP index and the commodity price index PCE. As interest rate, we consider three alternatives such as the EONIA overnight rate, the 1 year German bond and the Wu and Xia (2017) shadow interest rate. We estimate such VAR models by OLS from January 2000 to December 2019 with 12 lags and then finally we regress the reduced-form innovations on each candidate instrument. Table 3.3 reports the evaluation results considering the external instruments computed using the surprises on OIS rates at 1 month, 3 months and 1 year maturities covering the press release, press conference and monetary event windows exploiting the EA-MPD database of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019). As external instruments candidates for monetary policy shocks we focus on maturities between 1 month and 1 year for two reasons. First, because our main target is to estimate the effects of purely monetary policy shocks, so we prefer short maturity rates to avoid confusions with other monetary policies. Second, because for identifying monetary policy shocks we still need to disentangle them from central bank information shocks so we also need to consider maturities capturing information, which are larger than 1 month[18].

Table 3.3: Evaluation of external instruments based on direct OIS rates surprises

	(1) OIS 1m	**(2) OIS 3m**	**(3) OIS 1y**	**(4) OIS 1m**	**(5) OIS 3m**	**(6) OIS 1y**	**(7) OIS 1m**	**(8) OIS 3m**	**(9) OIS 1y**
Contract	OIS	OIS	OIS	OIS	OIS	OIS	OIS	OIS	OIS
Maturity	1 m.	3 m.	1 y.	1 m.	3 m.	1 y.	1 m.	3 m.	1 y.
Window	PRW	PRW	PRW	PCW	PCW	PCW	MEW	MEW	MEW
Observations	240	240	240	240	240	240	240	240	240
A) Policy tool: EONIA overnight rate									
P-value	0.00	0.02	0.14	0.29	0.18	0.49	0.00	0.01	0.15
R^2	0.075	0.065	0.036	0.009	0.014	0.004	0.089	0.083	0.026
F-statistic	19.18	16.51	8.97	2.23	3.40	0.97	23.30	21.54	6.42
B) Policy tool: German bond, 1 year rate									
P-value	0.00	0.00	0.00	0.64	0.00	0.00	0.00	0.00	0.00
R^2	0.068	0.073	0.088	0.003	0.060	0.072	0.102	0.126	0.137
F-statistic	17.43	18.85	22.97	0.64	15.24	18.34	27.05	34.23	37.71
C) Policy tool: Wu and Xia (2017) rate									
P-value	0.99	0.89	0.97	0.84	0.78	0.83	0.92	0.90	0.81
R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
F-statistic	0.00	0.06	0.01	0.02	0.05	0.04	0.03	0.05	0.11

Notes: P-values, observations, R^2 and F-statistics refer to the results concerning the first stage regression of the reduced-form innovations on each alternative instrument. m and y maturities refer to months and years. PRW, PCW and MEW windows are the press release window, the press conference window and the monetary event window, which includes both the press release and the press conference window.

From the results in Table 3.3 we can extract the following observations. First, considering the press release window (columns 1 to 3), the three considered OIS maturities provide relevant instruments in the case of the EONIA (panel A) and the 1 year German bond rate (panel B) as policy rates, given that their associated F-statistics are above the 8.96 threshold[19]. Second, focusing on the press conference window (columns 4 to 6), only the 3 months and the 1 year OIS

[18]See Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019).

[19]The threshold F-statistic at the 5% significance level for testing for an instrument relevance is 8.96 when considering one only instrument, and 11.59 when including 2 instruments. See Stock, Wright and Yogo (2002).

surprises on the 1 year German bond rate exhibits relevance. Third, considering the monetary event window (columns 7 to 9), the three maturities considered are relevant in the case of the EONIA and the German bund, except the 1 year OIS rate on the EONIA. Finally, no instrument among this panel is relevant when considering as policy tool the Wu and Xia (2017) shadow interest rate (panel C), which might be due to the fact that such rate also captures the effects of unconventional monetary policies after reaching the zero lower bound.

Additionally, Table 3.4 shows the analogous relevance tests results considering two additional groups of proxy candidates. First, we evaluate the type of monetary policy proxies considered by Jarocinski and Karadi (2020) in which they disentangle between purely monetary policy shocks and central bank information shocks as detailed in subsection 3.3.2. In particular, columns 1 and 3 consider two purely monetary policy shocks, i.e. those that comove negatively with stock price reactions, denoted in the headers as "JK -". By contrast, column 2 and 4 consider testing jointly the purely negative monetary policy shocks and the central bank information shocks, i.e. those that comove positively with stock price reactions, denoted in the headers as "JK ∘". Second, we also evaluate refined instruments along the lines of Miranda-Agrippino and Ricco (2021) reported in columns 5 to 7, which are *informationally-robust* such that they are orthogonal to central bank's economic projections, and their revisions to forecasts while also accounting for the slow absorption of information by agents[20].

Table 3.4: Evaluation of external instruments based on transformed OIS rates surprises

	(1) JK -	**(2) JK ∘**	**(3) JK -**	**(4) JK ∘**	**(5) MPI**	**(6) MPI -**	**(7) MPI ∘**
Contract	OIS*	OIS*	OIS*	OIS*	OIS**	OIS**	OIS**
Maturity	3 m.	3 m.	1 y.	1 y.	3 m.	3 m.	3 m.
Window	MEW	MEW	PRW	PRW	MEW	MEW	MEW
Observations	204	204	240	240	212	212	212
A) Policy tool: EONIA overnight rate							
P-value	0.63	0.65	0.60	0.60	0.16	0.63	0.64
R^2	0.005	0.111	0.007	0.050	0.018	0.003	0.031
F-statistic	0.96	12.60	1.67	6.17	3.94	0.56	3.39
B) Policy tool: German bond, 1 year rate							
P-value	0.04	0.05	0.02	0.02	0.00	0.00	0.00
R^2	0.027	0.146	0.034	0.096	0.097	0.044	0.106
F-statistic	5.62	17.24	8.35	12.57	22.63	9.64	12.43
C) Policy tool: Wu and Xia (2017) shadow rate							
P-value	0.59	0.58	0.62	0.62	0.78	0.28	0.27
R^2	0.007	0.021	0.006	0.019	0.001	0.019	0.042
F-statistic	1.34	2.12	1.43	2.24	0.24	4.08	4.53

Notes: P-values, observations, R^2 and F-statistics refer to the results concerning the first stage regression of the reduced-form innovations on each alternative instrument. m and y maturities refer to months and years. PRW and MEW windows are the press release window and the monetary event window, which includes both the press release and the press conference window. In case there are two external instruments being evaluated, the P-value refers to the coefficient of the monetary policy shock proxy.

According to our relevance tests results shown in Table 3.4 we notice the following points. First, the purely monetary policy shock instrument of Jarocinski and Karadi (2020) (column 1), which builds on the 3 months OIS rate surprises and the stock market reactions around monetary event windows[21], does not pass the relevance test. However, when considering in the

[20] See Appendix C.5 for a detailed explanation of our calculation of informationally-robust instruments.

[21] In this case, the instrument used for the test is literally the series used and circulated by Jarocinski and Karadi (2020), not an update of their measure calculated in this study. For this reason, the data sample is shorter, as their proxy series starts in March 1999 and ends in December 2016.

test both the monetary policy shock proxy and also the central bank information instrument (column 2) the relevance test is passed when using the EONIA and also the 1 year German bond as policy tools. Second, when testing the analogous *JK-style* proxies but employing the 1 year OIS rates surprises around the press release window as the underlying contract (columns 3 and 4), the relevance test is passed only vis a vis the 1 year German bond as policy rate. Third, the informationally-robust instrument MPI that best resembles the baseline MPI proxy of Miranda-Agrippino and Ricco (2021), i.e. column (5), passes the relevance test when using the 1 year German bond as policy tool. Therefore, the instruments that pass the relevance tests just described are valid candidates for proxying a monetary policy shock.

3.3.4 The extended Jarocinski and Karadi (2020) model

We start examining the effects of monetary policy shocks in the euro area by estimating an extended version of the Jarocinski and Karadi (2020) SVAR monthly model identified using their poor man's sign restrictions (see the full description of their model and their identification strategy in section 3.2.1) from January 1999 to December 2019[22]. In this SVAR model, we include the 1 year German bond as the policy tool, the Euro Stoxx 50 index, private consumption, business and housing investment, the HICP index, the price commodity index PCE, the unemployment rate and imports and exports of goods. As an underlying monetary policy proxy, we use the surprises in the 1 year OIS rates changes around the press release window from which we compute the monetary policy and central bank information shocks making use of the EA-MPD database of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019), which passed the relevance test as shown in subsection 3.3.3. We use 12 lags in the VAR and estimate the model by using the same Bayesian techniques that Jarocinski and Karadi (2020) use and report the results based on 2,000 draws from the Gibbs sampler[23].

Therefore, the differences of our extended model with respect to the baseline Jarocinski and Karadi (2020) one are an updated data sample ending in December 2019, an alternative underlying external instrument, additional economic variables, the usage of the HICP instead of the GDP deflator and the exclusion of the BBB spread[24]. We choose external instruments to be computed on the changes around the press release window instead of the entire monetary event window to focus the attention on the interest rates changes, so that we avoid a potential confounding effect with other policies and discussions during the press conference.

Figure 3.4 shows that such model rises impulse responses that are along the lines of the original results of Jarocinski and Karadi (2020), which are shown in Appendix C.6. Therefore, a one standard deviation positive monetary policy shock (left column of responses) is a conventional monetary policy tightening such that it depresses consumption, business investment, housing investment, the HICP, commodity prices PCE, imports and exports, and increases unemployment. Alternatively, the responses to a positive central bank information shock (right column of responses in the same Figure) have on impact the opposite effects in the case of stock prices, business investment and prices, looking like a positive news shock about the economy to which the central bank is responding. However, in the cases of consumption, business and housing investment, unemployment and imports and exports, the responses are not expansionary. So,

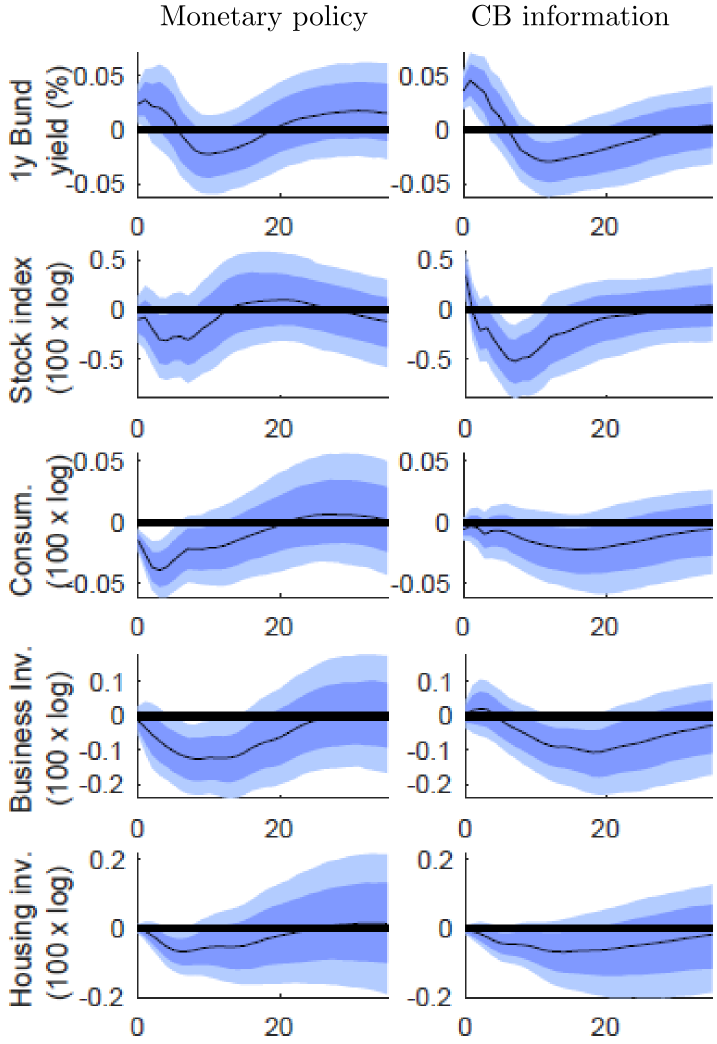
[22]The estimations of the extended Jarocinski and Karadi (2020) model in this paper have been performed using modified versions of their code, available at https://www.aeaweb.org/articles?id=10.1257/mac.20180090.

[23]Jarocinski and Karadi (2020) use standard Bayesian priors for the VAR parameters, following Litterman (1986), such that the prior about B and Σ is independent normal-inverted Wishart. We follow their exact estimation method and discard the first 2,000 draws and keep every fourth of the next 8,000.

[24]We exclude a measure of the excess bond premium because the BBB spread is not available for us beyond December 2016, and the inclusion of the measures of De Santis (2016) provide impulse responses for the monetary policy shock such that the spread decreases. See Figure C.4 in Appendix C.7 for observing the impulse responses of the monetary policy shocks in the Jarocinski and Karadi (2020) SVAR model extended until December 2019 feed with our data.

overall, the monetary policy shock delivers responses that seem more consistent than those of the central bank information shock.

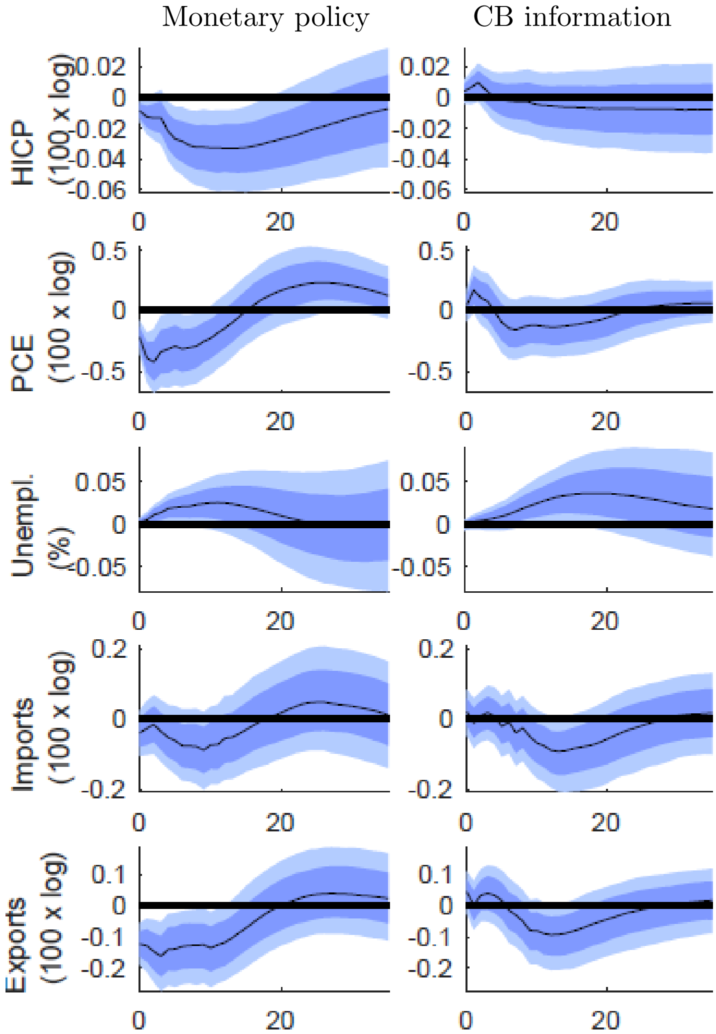
Figure 3.4: Extended Jarocinski and Karadi (2020) model, poor man's sign restrictions



Notes: Impulse responses to a 1 standard deviation shock. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band). Months on the horizontal axis. Own elaboration using the codes of Jarocinski and Karadi (2020).

The impact of the monetary policy shock is quantitatively along the lines of those found in the literature. The decline in consumer prices is relatively small, around a significant 0.03% after a year. Commodity prices instead decrease a 0.4% after few months. Regarding economic activity, consumption decreases after a quarter around a 0.04%, returning to zero after 20 months. The responses of business and housing investment are smoother but more pronounced, reaching declines of respectively 0.12% and 0.05% after half a year. Roughly after this time span imports and exports decline a 0.1% and 0.15% respectively. Unemployment increases around a 0.02% after a year.

Figure 3.4 (cont.): Extended Jarocinski and Karadi (2020) model, poor man's sign restrictions



Notes: Impulse responses to a 1 standard deviation shock. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band). Months on the horizontal axis. Own elaboration using the codes of Jarocinski and Karadi (2020).

Robustness exercises in which we estimate this extended Jarocinski and Karadi (2020) model using other external instruments, such as the updated version of the one they originally use, i.e. the 3 months OIS rates changes around the full monetary event window, or another using the 1 year OIS rates around press release window deliver impulse responses with output and price puzzles. This lack of robustness plus being susceptible to the critique of Baumeister and Hamilton (2020) on the sign restrictions algorithm gives us leverage to look at an alternative model as the Proxy-SVAR.

3.3.5 The Proxy-SVAR model

A natural alternative to the estimation of the Jarocinski and Karadi (2020) model as in the previous subsection is to estimate a Proxy-SVAR model using the external instruments for the purely monetary policy shock and the central bank information shock one at a time[25]. Therefore, in this subsection we report the results obtained after estimating a monthly Proxy-SVAR model including the same vector of endogenous variables as in the last subsection with 12 lags from January 1999 to December 2019. For the Bayesian estimation we use conventional Minnesota priors which are common to all the Proxy-SVARs we estimate in this study[26]. Our results are based on 3,000 draws from the posterior distribution, while robustness checks doubling this number do not affect them. The two stage IV (2SLS) regression estimation follows Mertens and Ravn (2013) while the impulse responses are constructed along the lines of Miranda-Agrippino and Ricco (2021)[27].

Also common to all next Proxy-SVAR results is that we employ the same series of monetary policy surprises that we use in our extension of the Jarocinski and Karadi (2020) model, i.e. the 1 year OIS rate surprises around the press release window which gives rise to the purely monetary policy shocks and central bank information shocks depending upon its comovement with the changes in the Euro Stoxx 50 index (see section 3.3.2).

Monetary policy shock

Figure 3.5 depicts the impulse responses to a 1 percentage point increase in the monetary policy shock in our Proxy-SVAR model. These responses are qualitatively similar to those obtained after estimating our extended Jarocinski and Karadi (2020) model, however in our Proxy-SVAR are somewhat more pronounced and persistent. The HIPC index declines around a 0.05% after a year and the effect does not fade out during the three years horizon that we show in our impulse responses. Also, the commodity price index PCE declines about 0.8% after half a year, when it troughs. Regarding the components of GDP, private consumption follows a similar pattern than prices and it declines roughly a 0.06% after a year and the effect persists. Alternatively, the effects on investment are quantitatively more acute. Business and housing investment decline after the monetary policy shock and trough after a year by about a 0.2% and 0.12%, respectively. The declines of imports and exports are even more marked as they decrease already on impact a 0.2% and 0.4%, respectively. Instead, unemployment does not move on impact but increases a 0.04% peaking after 18 months after increasing around a 0.05%.

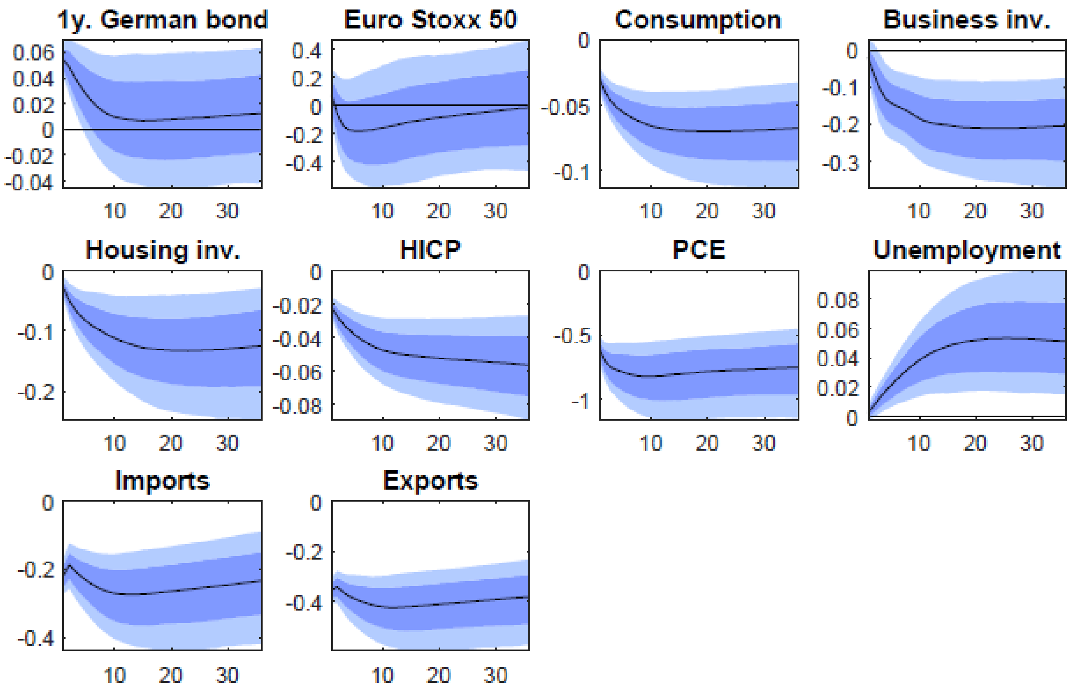
These results are roughly in line with the literature, however the declines in economic activity seem to be lighter. First, it is a conventional result that consumer prices decline only modestly after a monetary policy shock, as reported by Jarocinski and Karadi (2020) and Giannone, Lenza and Reichlin (2019). Corsetti, Duarte and Mann (2020) reports a non-significant movement of prices after a monetary policy shock. With regard to economic activity variables, we report declines in consumption and investment that are lower than showed by Corsetti, Duarte and Mann (2020) (-0.2% and -1% after a year, respectively), while our investment decline estimate is closer to that reported by Durante, Ferrando and Vermeulen (2020) (-0.3% after a year).

[25]The Proxy-SVAR models in this paper have been estimated using modified versions of the codes of Ferroni and Canova (2021). See the latest version of their toolbox at https://github.com/naffe15/BVAR_.

[26]The values of our Minnesota priors are shown in Appendix C.8.

[27]For more details on the estimation of our Proxy-SVAR and the computation of the impulse responses, see Ferroni and Canova (2021), Appendix A.6.

Figure 3.5: Proxy-SVAR, monetary policy shock

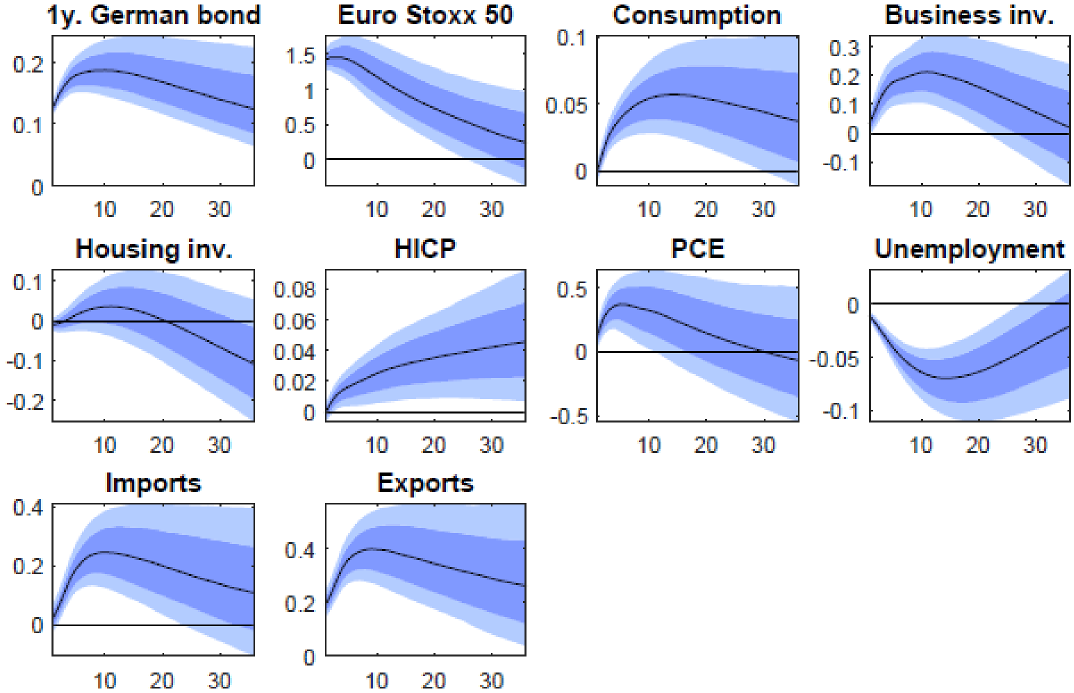


Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

Central bank information shock

The impulse responses to a 1 percentage point increase in the central bank information shock in our Proxy-SVAR are shown in Figure 3.6. They are qualitatively consistent with the conclusion of Jarocinski and Karadi (2020) that such a shock looks like a positive news shock about the economy to which the central bank is responding. Indeed, after the shock the HICP increases persistently (+0.03% after a year), while consumption and business investment also grow (+0.05% and 0.2% after 12 months respectively) and unemployment decreases. These dynamics are also present in external trade variables, such that imports and exports of goods increase a 0.2% and 0.4% three quarters after the information shock. Instead, housing investment does not move significantly after the shock, though the bulk of the draws lies on the positive side.

Figure 3.6: Proxy-SVAR, central bank information shock



Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

Comparing the impulse responses of our Proxy-SVARs with those obtained in our extended Jarocinski and Karadi (2020) model we notice the following two main differences. First, while the responses to the monetary policy shock are qualitatively similar, the Proxy-SVAR shows somewhat larger and more persistent responses. Second, the responses to the central bank information shock delivered by our Proxy-SVAR seem more consistent and plausible.

3.3.6 Proxy-SVAR model with heteroskedasticity treatment

The next target in our analysis is to allow our data sample to incorporate Covid-19 observations, i.e. data after March 2020, and so attached the extreme values observed in economic and financial time series after the outbreak of the global Covid-19 pandemic. Consequently, we need to add to our model an additional heteroskedasticity treatment ingredient in order to equip it with the capacity to deal with such extreme observations, which pose significant challenges to time series models (see Bobeica and Hartwig, 2021). Otherwise, our results become unreliable, as it can be acknowledged by looking at the impulse responses that would be obtained estimating our baseline Proxy-SVAR model including 2020 data for identifying both monetary policy and central bank information shock in Appendix C.9.

In order to estimate the effects of monetary policy shocks in the euro area including 2020 data we estimate a Proxy-SVAR model exactly as in 3.3.5 but extending the data sample from January 1999 to December 2020 and arming it with an heteroskedasticity treatment along the lines of the one proposed by Lenza and Primiceri (2020). Essentially, their approach is to parameterize the residual covariance matrix of the VAR during the period of the pandemic and scale it up exploiting the fact that the time at which the volatility in economic series burst is known, i.e. March 2020[28]. Similarly, we follow Ferroni and Canova (2021) and allow our VAR(12) to be specified as:

$$Y_t = \sum_{j=1}^{p} \delta_j Y_{t-j} + s_t B \epsilon_t \tag{3.6}$$

where the new element is s_t, a parameter that take a value equal to 1 during all the months previous to March 2020, while it takes a value higher than 1 from March 2020. In this way, the innovation of the VAR is scaled up so that is *corrected* for heteroskedasticity. In our application, we choose a value for s_t equal to 10 from March to December 2020 under the assumption that all these months were subject to the pandemic-driven increase in residual volatility.

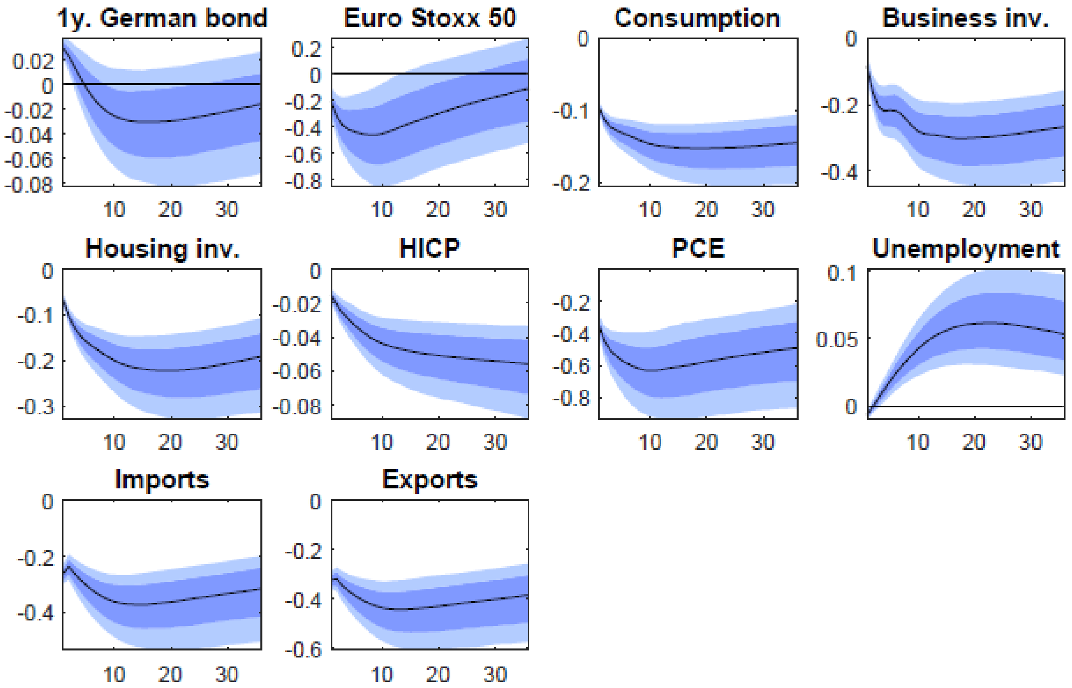
Monetary policy shock

Figure 3.7 shows the impulse responses to a 1 percentage point increase in the purely monetary policy shock including 2020 data and the heteroskedasticity treatment explained above. First observation is that the responses remain stable and reasonable, and similar to those obtained in section 3.3.5, as we would expect after adding just few additional observations in a data sample. However, we can notice that, while the responses of some variables are mainly unchanged (such as HICP and commodity prices PCE, unemployment and imports and exports), other variables react more strongly to the monetary policy shock. In particular, the responses of private consumption, business and housing investment and the stock price index are now more pronounced, roughly doubling the decline observed in the model not including 2020 data[29].

[28] Alternative approaches to handle extreme values in time series are also available. Two of such contributions are Álvarez and Odendahl (2021) and Carriero, Clark, Massimiliano and Mertens (2021).

[29] Setting a value of 5 in our parameter s_t yield similar results.

Figure 3.7: Proxy-SVAR-LP, monetary policy shock

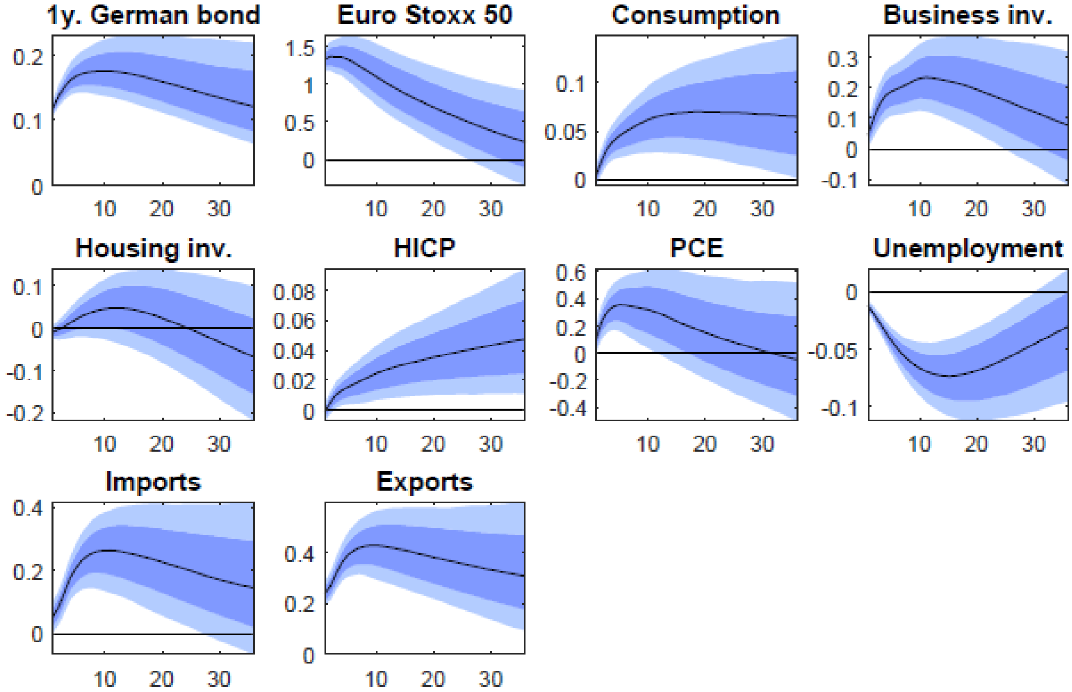


Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

Central bank information shock

Regarding the information shock case, Figure 3.8 depicts the analogous impulse responses to a 1 percentage point increase in the central bank information shock including 2020 data and the same heteroskedasticity treatment. In this application we notice that no meaningful difference is found with respect to the baseline data sample Proxy-SVAR results, not observing any abnormal difference in the responses.

Figure 3.8: Proxy-SVAR-LP, central bank information shock



Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

The results shown in this subsection suggest the following findings. First, the reescaling approach of Ferroni and Canova (2021) and Lenza and Primiceri (2020) for dealing with extreme observations seems valid and robust when estimating central bank information shocks. However, in the case of the purely monetary policy shock, it turns out that some macroeconomic variables are specially affected by the inclusion of Covid-19 observations, notably the main components of real GDP. This observation might suggest that the implicit modeling assumption that the increase in volatility during the pandemic is common across economic variables might be too strong for private consumption, investment and stock prices. Finally, it also suggests that the ability of the central bank to affect prices did not change during the pandemic in the euro area.

3.3.7 Changes in the effects of monetary policy shocks over time

Over the last 20 years, the euro area has witnessed dramatic economic changes in the region. Without being extensive, we might recall three of these changes. First, economic activity followed marked economic cycles including an initial period of fast growth at the beginning of the 2000s, the financial crisis, a sovereign-debt crisis and lately a global pandemic. Second, as a result of such events, the ECB monetary policy has become more complex than ever, reaching the zero lower bound and launching several new policy tools coexisting with the classic interest rates setting such as liquidity injections, forward guidance, quantitative easing and asset purchases (Hartmann and Smets, 2018). Third, credit markets, notably in the housing sector, have evolved from a booming initial phase during the 2000s to a freezing shock during the financial crisis, followed by a slow deleveraging stage. In this evolution, the framework regulating commercial banks have also changed with the implementation of Basel III (BIS, 2010), as well as with changes in the ownership and governance of several banks hardly affected by the financial crisis which were forced to consolidate. All these sensitive changes suggest that the monetary transmission mechanism might have arguably changed over time in the euro area during the last 20 years.

Previous economists have already analyzed whether the monetary transmission mechanism has changed in the euro area. Boivin, Giannoni and Mojon (2008) evaluated this issue in a factor-augmented VAR (FAVAR) framework reporting an overall reduction in the effects of monetary shocks for the period 1999 - 2007 compared to the overall 1988 - 2007 time span.

In order to evaluate whether the transmission of monetary policy has changed in the euro area since 1999 using our framework, we estimate a stylized Proxy-SVAR model compared to our baseline used in subsection 3.3.5 but splitting the sample in two: from January 1999 to June 2009 and from June 2008 to December 2019. In particular, the model we consider here excludes imports and exports for decreasing the number of parameters to estimate. In this exercise we also abstract from 2020 data to avoid heteroskedasticity issues.

Monetary policy shock

The impulse responses to a 1 percentage point increase in the monetary policy shock in our stylized Proxy-SVAR estimated from January 1999 to June 2009 are shown in Figure 3.9, left hand side. There we can observe that such responses are quite similar to the ones reported in section 3.3.5 when estimating our baseline Proxy-SVAR with the sample ending in December 2019. However, looking at the responses to the same monetary policy shock but estimated over the sample 2009 - 2019 (Figure 3.9, right hand side) we see a different picture. While for variables as prices and consumption the responses do not change much, now the responses of business and housing investment and unemployment are not significantly different than zero. Therefore, two conclusions emerge from that results. First, the monetary policy transmission mechanism that we observe when estimating VARs using the full sample starting in 1999 draws a transmission mechanism that is apparently more representative of the one in place during the decade previous to the financial crisis than that after it. Second, according to this evidence, it turns out that after the financial crisis the ECB seems to have lost its capacity to influence investment and unemployment via reference interest rates, while still keeping the ability to affect prices.

Central bank information shock

A similar pattern emerge when focusing on the information shock. Indeed, the impulse responses to a 1 percentage point increase in the central bank information shock in our stylized Proxy-SVAR estimated with the January 1999 to June 2009 sample (Figure 3.10, left hand side) we observe similar responses to those obtained for the full sample in subsection 3.3.5. However, when focusing on the responses obtained when using only the second decade in our sample (Figure 3.10, right hand side) we observe that generally the effects of a positive central bank information shock to consumption, business investment and HICP are still of a positive sign, but significant only for few months after the shock. In the case of housing investment, the effect is actually negative. An explanation for that change in signs might be that after the financial crisis large indebtedness in the housing sector and weaker housing demand might have triggered more caution among real estate builders, so that positive information shocks, might be enough for cooling down housing investment plans. An another change of signs is found in the commodity prices index PCE, which declines significant and persistently after the information shock.

Therefore, according to the evidence shown in this subsection it turns out that the capacity of the ECB to affect economic activity in the euro area has weakened after the financial crisis. Two reasons why this would be the case are the following. First, the higher indebtedness level in the economy, which might weaken the credit channel of monetary policy. Second, the extremely low levels in reference interest rates, as the main refinancing operations rate reached zero in 2016. This weakened ability to affect economic activity though conventional interest rates policy is consistent with the ECB launching unconventional monetary policy programs during its second decade of existence, including injections of liquidity, quantitative easing, forward guidance and asset purchases (Hartmann and Smets, 2018).

Figure 3.9: Proxy-SVAR, monetary policy shock, split sample

Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals. The impulse response of the 1 year German bond is excluded for saving space.

Figure 3.10: Proxy-SVAR, central bank information shock, split sample

Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals. The impulse response of the 1 year German bond is excluded for saving space.

3.3.8 Robustness checks

We have performed several robustness checks on our baseline Proxy-SVAR model shown in subsection 3.3.5 for estimating the effects of a purely monetary policy shock. After separately experimenting with using the EONIA overnight rate instead of the 1 year German bond rate as the policy rate, including the two excess bond premium measures of De Santis (2016), and generating 6,000 draws from the posterior distribution (instead of 3,000) we find no significant differences. We have also estimated the model using alternative external instruments as the 1 week, 1 month, 3 months and 1 year OIS rates around the press release window finding some output and price puzzles. Using as an external instrument the proxy of Jarocinski and Karadi (2020) updated using with the EA-MPD dataset of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) we find very similar results compared to those with our baseline proxy, except for a stock price puzzle (positive response after a contractionary monetary policy shock)[30]. Also, using as external instrument the updated Jarocinski and Karadi (2020) one but refined along the lines of Miranda-Agrippino and Ricco (2021), i.e. *informationally-robust*[31], we find output and price puzzles.

Regarding our baseline Proxy-SVAR for estimating the effects of central bank information shocks, we have done analogous robustness exercises finding similar results. First, an alternative policy rate, the addition of an excess bond premium and the generation of the double number of generated draws from the posterior do not alter our baseline results. Also, using as external instrument the updated proxy of Jarocinski and Karadi (2020) deliver identical results as ours. However, using instruments refined as in Miranda-Agrippino and Ricco (2021) leads to some output and price puzzles.

[30] See Appendix C.10 for observing the impulse responses to a monetary policy and central bank information shock in our baseline Proxy-SVAR identified using the updated instruments of Jarocinski and Karadi (2020).

[31] See Appendix C.5 for a detailed explanation of our informationally-robust refinements of our proxies along the lines of Miranda-Agrippino and Ricco (2021).

3.4 Conclusions

The target of this study is twofold. First, we estimate the effects of purely monetary policy shocks and central bank information shocks to key macroeconomic variables in the euro area, notably subcomponents of GDP, which are relatively understudied compared with GDP or industrial production. Second, we wonder whether such effects have changed during the last two decades. To perform this analysis we use the SVAR model of Jarocinski and Karadi (2020) and a Proxy-SVAR model, therefore identifying in both cases monetary policy shocks using high frequency instruments.

The main findings in this study are the following. First, purely monetary policy shocks have significantly negative effects on consumption, housing and business investment, having the largest impact on the latter. Second, the effects on HICP are modest, consistent with the literature, which calls for caution when dealing with upward inflation risks, as the costs in terms of investment contraction might be higher than the benefits in cooling down inflation. Third, the estimation of the effects of monetary policy shocks including 2020 data and an heteroskedasticity approach along the lines of Lenza and Primiceri (2020) and Ferroni and Canova (2021) generates apparently too strong negative effects in some variables while others are unaffected, which suggest that an approach to dealing with heteroskedasticity that allows for heterogeneous effects across variable might be more desirable. Fourth, it turns out that the effects of purely monetary policy shocks have changed over time in the euro area. In particular, while during the 2000s the effects are the conventional contractionary ones typically found for the 1999 to 2019 sample, during the 2010s it seems that the capacity of the ECB to affect economic variables such as business and housing investment and unemployment has been dramatically weakened.

Two policy implications emerge from the highlighted findings in this study. A backward-looking one is that in the context of the weakened capacity to affect activity and unemployment that the ECB suffered during the 2010s, alternative monetary policies might have to be put in place. This is consistent with the set of unconventional monetary policy tools that the ECB have used during the last years as liquidity injections in the banking system, quantitative easing, forward guidance and asset purchases. A forward-looking implication is related to the management of inflationary risks via standard monetary policy. Indeed, in the current context of upward inflationary risks in the euro area combined with weak growth and increased public debt due to the pandemic, a careful cost-benefit analysis on the possibility of increasing interest rates has to be performed as it turns out that the effects of a positive monetary policy shock on inflation are relatively modest compared to the contractionary effects on economic activity.

Some research avenues that seem worth it are the following. First, applying the models and instruments of monetary policy used in this study to the euro area countries and the US. Second, we might increase the data used in our models by estimating a Proxy-FAVAR model, also identified using high frequency instruments. Third, employing as an heteroskedasticity treatment device an approach allowing for different volatility degrees across economic variables, as it turns out that not all them have been affected by the Covid-19 shock up to the same degree. One such approach might be the one proposed by Álvarez and Odendahl (2021). Finally, a time-varying Proxy-SVAR might be estimated to account for the changes in the effects of monetary policy in the last decade. We leave these possibilities for future research.

Appendices

C.1 Macro and financial data used

Table C.1 shows a detailed description of the data used in our models together with the transformations we made and their sources.

Table C.1: Quarterly interpolated series, and their monthly indicators for interpolation

Variable	Description	Freq.	Transfor.	Source
Consumption	HH and NPISH final consumption expenditure	Q	Log, real	Eurostat
Business investment	Business investment	Q	Log, real	Eurostat
Housing investment	Housing investment	Q	Log, real	Eurostat
HICP	Harmonized index of consumer prices	M	Log	Eurostat
PCE	Commodity Price index	M	Log	ECB SDW
Stock prices	Euro Stoxx 50 Price Index	M	Log	Dow Jones
Unemployment	Unemployment rate, levels	M	Log	Eurostat
Imports	Imports of goods	M	Log, real	Eurostat
Exports	Exports of goods	M	Log, real	Eurostat
1 year German bond	1 year German bond, % yield	M	-	ECB SDW
EONIA	EONIA overnight rate	M	-	ECB SDW

Notes: HH and NPISH stand for households and non-profit institutions serving households.

C.2 Interpolated series and their monthly indicators

Table C.2 relates each quarterly variable used in this study with the monthly indicators that have been employed to estimate its analogous monthly time series by using the Chow and Lin (1971) interpolation method.

Table C.2: Quarterly interpolated series, and their monthly indicators for interpolation

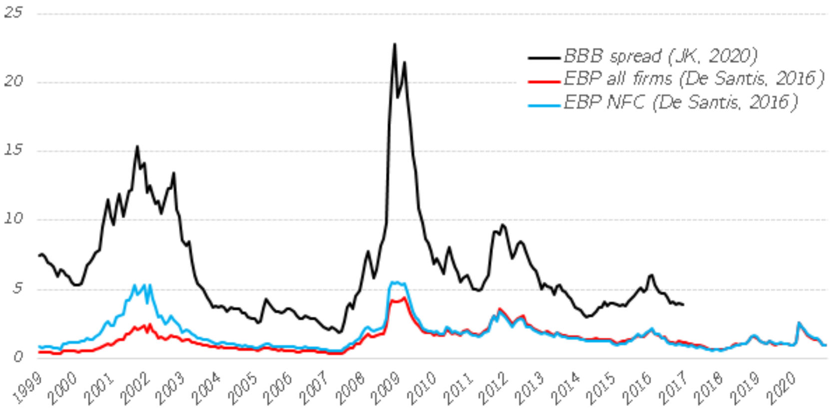
Quarterly series	Monthly indicators for interpolation
Real final consumption expenditures	HICP, URX
Real housing investment	CONCONF, URX
Real business investment	URX, HICP, MANCONF
GDP deflator	HICP, PPIT
Real GDP	JIP, URX

Notes: HICP is the harmonized index of consumer prices, URX stands for the unemployment rate, CONCONF means the Confidence indicator in the construction sector, MANCONF is the Confidence indicator in the manufacturing sector, JIP is the industrial production index and the PPIT stands for the Producer price inflation, total industry excluding construction. Final consumption expenditures are deflated using the GDP deflator.

C.3 Measures of the excess bond premium

Figure C.1 plots the original BBB spread used by Jarocinski and Karadi (2020) together with the two series of the excess bond premium computed by De Santis (2016), i.e. the all-firms and the non-financial corporations versions.

Figure C.1: Measures of the excess bond premium in the euro area

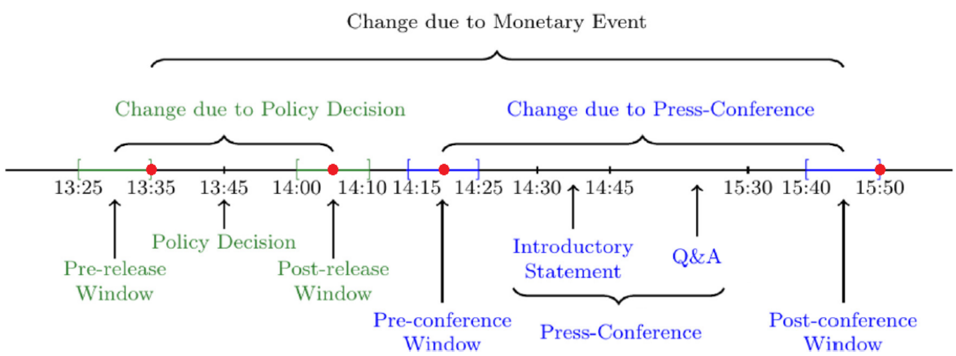


Notes: Y axis are spread points. The BBB spread extends until December 2016.

C.4 ECB policy communication timeline

Figure C.2 reproduces the ECB policy communication timeline as done by Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019), i.e. the typical policy communication structure during a day of the Governing Council policy meeting of the ECB. It also show the differences in information recording on financial contracts between Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) and Jarocinski and Karadi (2020).

Figure C.2: ECB policy communication timeline



Notes: Green and blue text refer to the time intervals used by Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) to record pre- and post-monetary policy events prices to compute price changes in financial assets, referring to the press release window and press conference window, respectively. Instead, the red dots refer to the time points chosen by Jarocinski and Karadi (2020) to perform the same task, which constitute the 10 (20) minutes before (after) the start (end) of press release and conference windows.

C.5 Informationally-robust instruments

We have refined some of our external instruments along the lines of the *informationally robust* proxy proposed by Miranda-Agrippino and Ricco (2021). Similarly as they do, we construct instruments for monetary policy shocks as the high frequency market surprises triggered by policy announcements that are orthogonal to central bank's economic projections and to past market surprises. In particular, we proceed in three steps.

First, we project our high frequency surprises in OIS rates at some particular maturity constructed from the EA-MPD database of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019) on the ECB nowcasts and forecasts from 1 to 8 months ahead of inflation and real GDP, which are quarterly series published in the ECB website as part of their Macro Projection Database (MPD)[1], which we convert to the monthly frequency[2].

$$OIS_t = \alpha_0 + \sum_{j=0}^{8} \theta_j F_t^{ecb} x_{m+j} + RES_t \tag{C.1}$$

where OIS_t denotes the monthly series of OIS rates high frequency surprises computed around a monetary announcements, F_t^{ecb} are the ECB nowcasts and forecasts for the vector of variables x, i.e. real GDP and inflation, at horizon $m+j$, where m denotes the current month.

Second, we project the residual in last equation, i.e. RES_t, on the ECB revisions to forecasts between consecutive months such that:

$$RES_t = \alpha_0 + \sum_{j=0}^{7} \vartheta_j [F_t^{ecb} x_{m+j} - F_{t-1}^{ecb} x_{m+j}] + \overline{MPI}_t \tag{C.2}$$

where $[F_t^{ecb} x_{m+j} - F_{t-1}^{ecb} x_{m+j}]$ are the series of revisions to forecasts between consecutive months. The residual $\overline{MPI}_t$ is the instrument for monetary policy shocks at the monthly frequency that controls to some extent for the transfer of information that happens during central banks' announcements.

Third, we account for the slow absorption of information by economic agents by removing the autorregressive component of the monthly surprises.

$$\overline{MPI}_t = \phi_0 + \sum_{j=1}^{12} \phi_j \overline{MPI}_{t-j} + MPI_t \tag{C.3}$$

where MPI_t is the resulting *informationally-robust* monetary policy instrument.

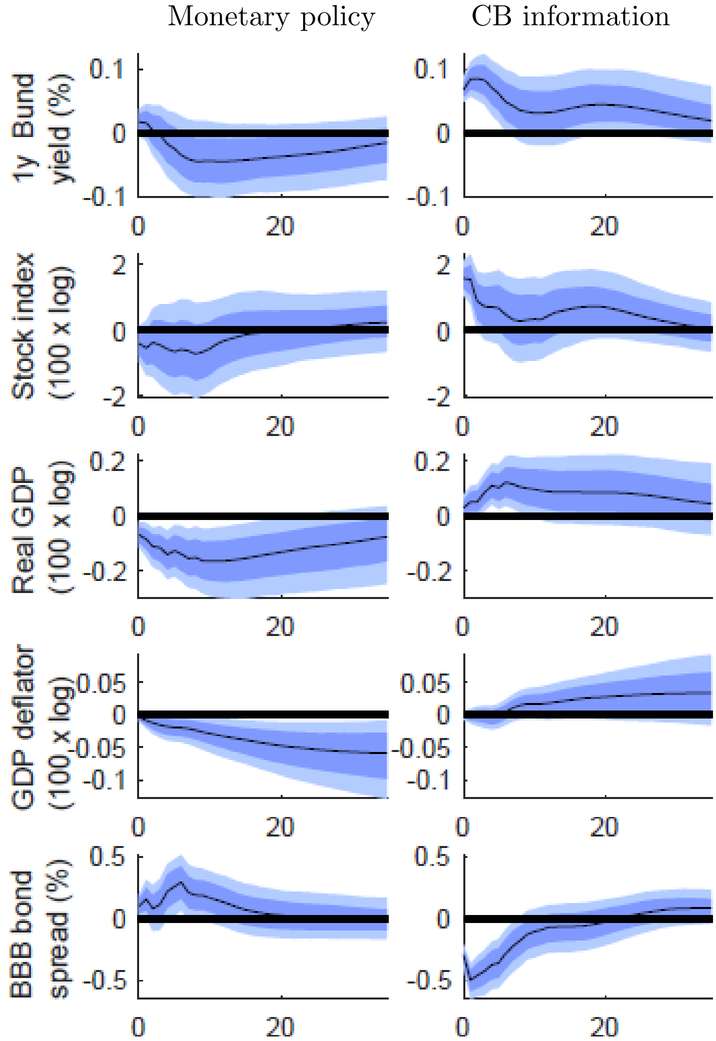
[1]See the most updated version of the ECB Macro Projection Database (MPD) at https://sdw.ecb.europa.eu/browseSelection.do?node=5275746.

[2]Given that the ECB forecasts series are quarterly, we convert them to the monthly frequency by using the quadratic conversion method available in Eviews, which provides a smooth conversion. Such conversion implies assuming that the ECB smoothly changes its forecasts each month, which might be a strong assumption in times of turning points and high forecast uncertainty.

C.6 Original results of Jarocinski and Karadi (2020), poor man's sign restrictions

Figure C.3 illustrates the original results of Jarocinski and Karadi (2020) when estimating the effects of monetary policy shocks in the euro area according to their poor man's sign restrictions on their 7 variables SVAR.

Figure C.3: Jarocinski and Karadi (2020), poor man's sign restrictions

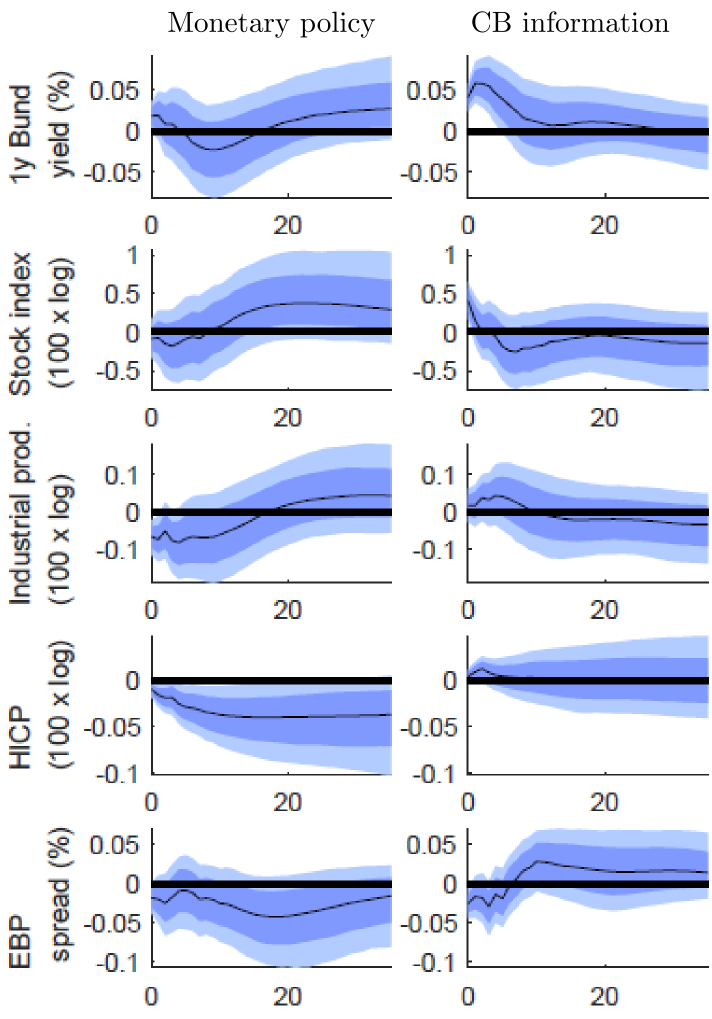


Notes: Impulse responses to a 1 standard deviation shock. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band). Months on the horizontal axis. Own elaboration using the codes of Jarocinski and Karadi (2020).

C.7 Jarocinski and Karadi (2020) model, poor man's sign restrictions, January 1999 - December 2019

Figure C.4 plots the impulses responses to a monetary policy shock in the Jarocinski and Karadi (2020) SVAR model identified with their poor man's sign restrictions, but estimated with data between January 1999 and December 2019, and using our baseline external instrument, i.e. the 1 year OIS rates around the press release window. It includes the excess bond premium (EBP) of De Santis (2016), all firms version, while using instead the non-financial corporations one does not significantly affect the results.

Figure C.4: Jarocinski and Karadi (2020) model, poor man's sign restrictions



Notes: Impulse responses to a 1 standard deviation shock. Median (line), percentiles 16-84 (darker band), percentiles 5-95 (lighter band). Months on the horizontal axis. Own elaboration using the codes of Jarocinski and Karadi (2020).

C.8 Proxy-SVAR priors

Table C.3 details the Minnesota priors parameters used in all the Proxy-SVAR models estimated and shown in this paper, which are rather standard and not specially tight.

Table C.3: Minnesota priors parameters in the Proxy-SVAR models

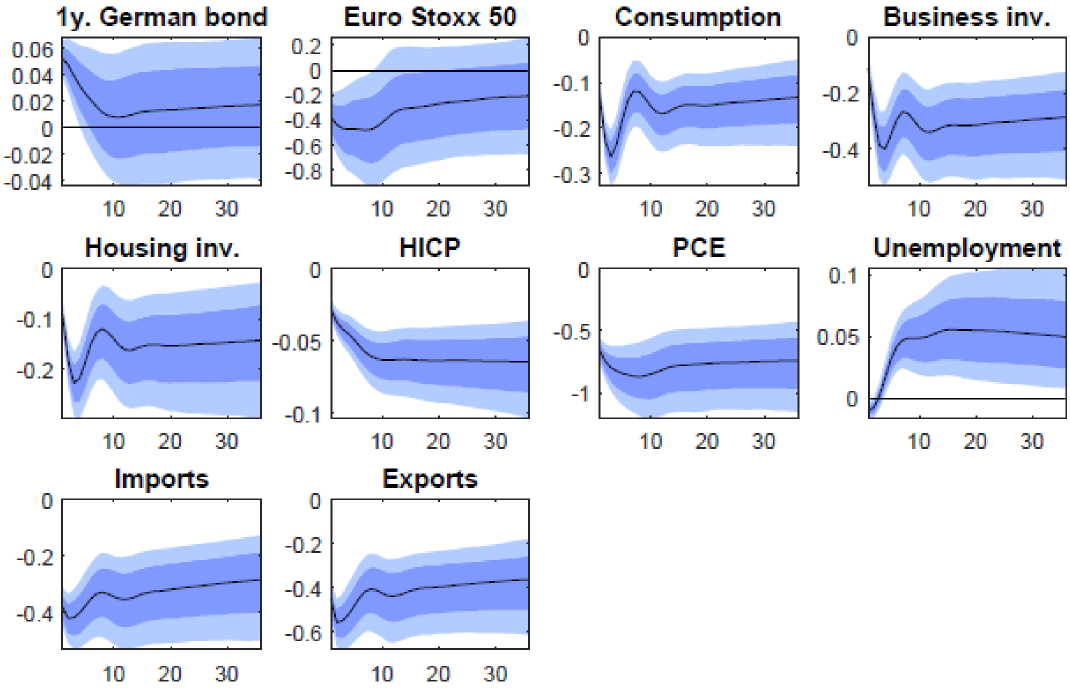
Parameter	Value
Prior tightness for the autorregressive coefficients of order one	3
Prior tightness for the autorregressive coefficients of higher lags	1.5
Sum-of-coefficients prior	5
Co-persistence prior dummy observations	2
Weight for the priors of the covariance matrix of innovations	2

C.9 Proxy-SVAR model using 2020 data

This Appendix shows the impulse responses for monetary and central bank information shocks corresponding to our baseline Proxy-SVAR model as explained in Section 3.3.5 but extending the data sample up to December 2020, notably without any heteroskedasticity treatment.

C.9.1 Monetary policy shock

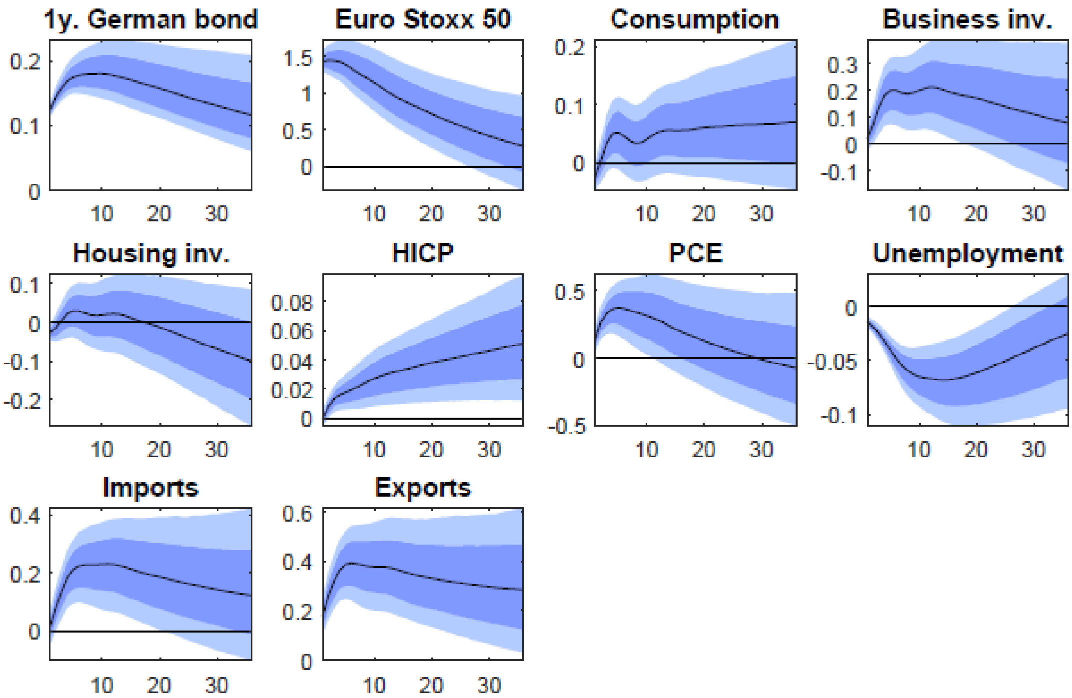
Figure C.5: Proxy-SVAR, monetary policy shock



Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

C.9.2 Central bank information shock

Figure C.6: Proxy-SVAR, central bank information shock



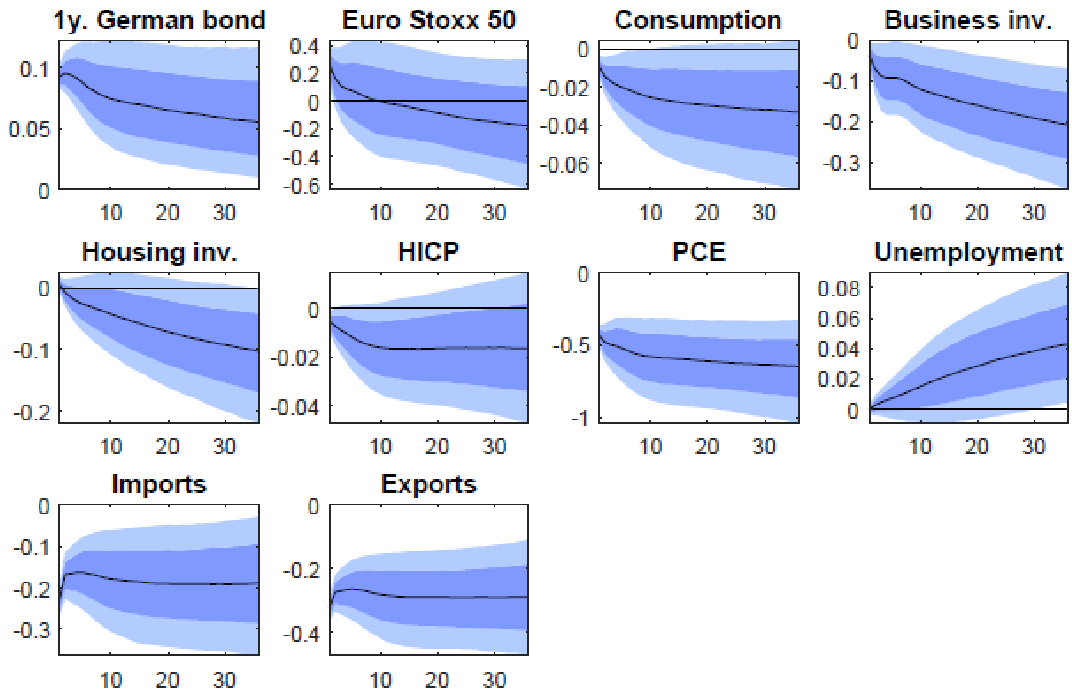
Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

C.10 Proxy-SVAR model using the updated Jarocinski and Karadi (2020) external instrument

This section shows the impulse responses to a contractionary monetary policy and central bank information shock using our baseline Proxy-SVAR model but identified using the external instrument of Jarocinski and Karadi (2020), i.e. the proxy using as underlying contract the 3 months OIS rates around the monetary policy events, updated using the EA-MPD dataset of Altavilla, Brugnolini, Gürkaynak, Motto and Ragusa (2019).

C.10.1 Monetary policy shock

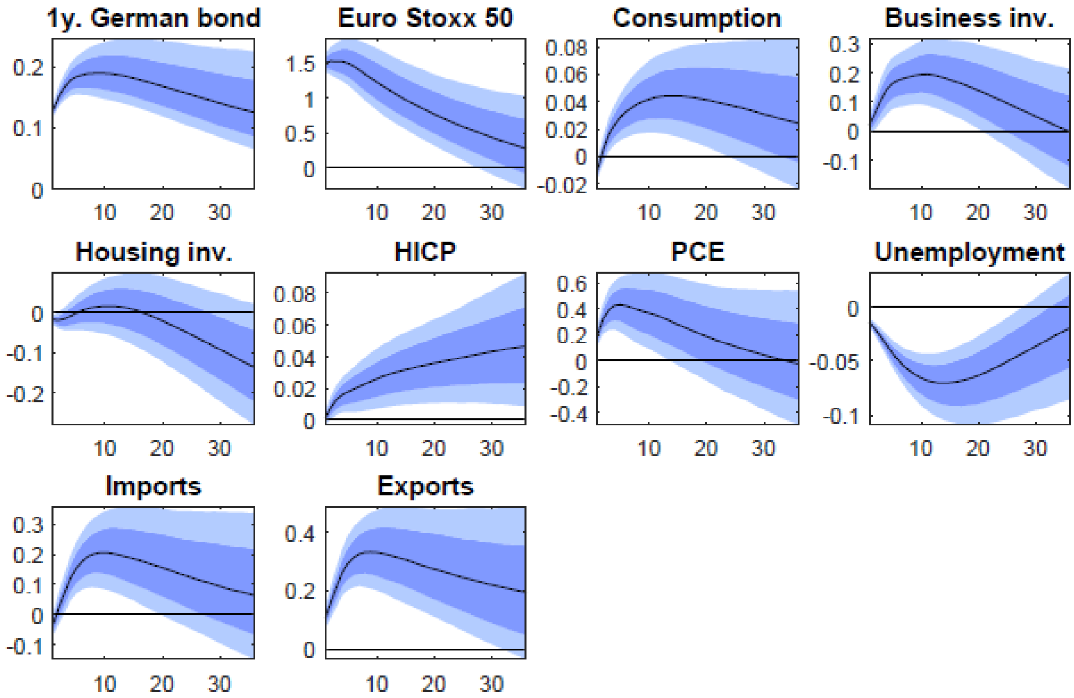
Figure C.7: Proxy-SVAR, monetary policy shock



Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

C.10.2 Central bank information shock

Figure C.8: Proxy-SVAR, central bank information shock



Notes: Impulse responses of a contractionary monetary policy shock of 1 percentage point increase in the shock. X axis denote months after the shock, Y axis denote percentage change in each variable. Shaded areas correspond with the 68% (dark) and 90% (light) credible confidence intervals.

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