Essays on Empirical Macroeconomics

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Chapter 1

Introduction

The thesis contains four essays, covering topics in the field of real-time macro-econometrics, forecasting and applied macroeconomics. The last decades have seen the flourishing of methods which permit us to efficiently extract information from large datasets in macroeconomics and finance. In this thesis, I make use of these state-of-the-art techniques in order to deal with matters which are relevant both for policy makers and financial markets participants.

In particular, in Chapter 2[1], I use methods developed in the "nowcasting" literature in order to analyse the macroeconomic news flow, proposing an econometric model to interpret the flow of data releases that are useful to assess the state of the Mexican economy. Understanding which are the macroeconomic indicators to look at in order to assess the state of the business cycle is a relevant question for policy makers, who make and implement decisions on the basis of the current state on the economy, and for market participants, who take it into account in making their investment decisions. GDP would be the natural indicator to consider. However, since it is published only quarterly and it has a significant publication delay, it is important to extract information from indicators that are available at higher frequency and in a more timely fashion, to have a reliable forecast (or "nowcast") of

[1] Published as Caruso, A. (2018). Nowcasting with the help of foreign indicators: The case of Mexico. Economic Modelling, 69, 160-168.

the current state of the economy that can be updated whenever a new data release is published. The general framework of the nowcasting approach has been introduced by Giannone et al. (2008), and recent developments have been surveyed by Banbura et al. (2011) and Banbura et al. (2013*b*). In the case of a small open economy, a related and important question is whether it is important to look at external data as well.

The main contributions of the chapter can be summarized as follows. First, reconstructing and interpreting the Mexican and US macroeconomic data flow, I evaluate the importance of each data release and the relevance of the information accessible to markets participants and policy makers in order to assess the state of the Mexican economy in real time. Second, I find that the information coming from US indicators has an important role in the updating process of a nowcasting model for Mexican GDP. Finally, I find that a nowcasting model constructed using a medium-scale dataset of real macroeconomic indicators from Mexico and from the US performs well out-of-sample with respect to tough benchmarks like Surveys of Professional Forecasters. Importantly, the Mexican example could be seen as a case study to analyse the relevance of foreign macroeconomic data in small open economies whose business cycles are highly synchronized with the one of a large trade partner.

Nowcasting methods can be used not only to assess the current condition of the business cycle, but the information extracted in real-time from the macroeconomic news flow can help in tackling other issues in which the state of the economy may matter, for example for markets' participants. In this perspective, in Chapter 3[2] I use nowcasting techniques to establish a novel link between macroeconomic news and asset prices, through a model that can help us interpret macroeconomic data and explaining markets' reaction to macroeconomic surprises. I show that a "Nowcasting Surprise Index", constructed aggregating forecast errors from a nowcasting model using model-based weights, resembles surprise indexes proposed in the recent literature or constructed by practitioners, which cumulate survey-based forecast errors weighting them using the average news effects on asset prices.

[2]Published as: Caruso, A. (2019). Macroeconomic news and market reaction: Surprise indexes meet nowcasting. International Journal of Forecasting, 35(4), 1725-1734.

Macroeconomic data are released every day, and are closely monitored by market participants: macroeconomic "news" move the markets (for a survey see Gürkaynak & Wright 2013). In this strand of literature the "market-based" news is constructed as the difference between the actual macroeconomic release and market expectations, available through surveys among market participants. One way to aggregate the news, in order to interpret this massive flow of heterogeneous information coming every day, is to assign some weights to the news and to construct "surprise indexes" that synthesize the unexpected information released in a certain window of time. Being a standard practice among practitioners, the relevance of a meaningful surprise index has been recently acknowledged in the economic literature, which shows that market operators filter and price the new macroeconomic information.

I construct a real time, model-based, surprise index that summarizes how a short term forecasting model has been surprised by macroeconomic developments in a rolling window of time. The construction of news and weights is based on the "nowcasting" approach, processing the releases and aggregating macroeconomic news looking at their impact on model updates of the assessment of the current state of the economy. The index is daily and can be updated at any macroeconomic release, and represents a rolling measure of the surprise component of the macroeconomic data flow, flexible and judgement free. I analyse the properties of the model-based forecasts, showing that they replicate well market expectations.

The Nowcasting Surprise Index has a similar behaviour to indexes constructed using market-based weights and news, showing good correlation with asset prices and in-sample predictive power, especially at quarterly frequency. On the one hand, this means that market news and model forecast errors are similar, meaning that a computer-based model fed with a large data set is able to replicate market expectations. Moreover, a model-based index is less costly than paying experts, and less susceptible to biases such as herding behaviour. On the other hand, it is useful to understand, in a coherent statistical framework, whether financial market operators react because a series of news events triggers an update about the current state of the economy. Therefore, the essay can be read as an attempt to bridge the high-frequency easier identification with the low frequency stronger links between macroeconomic information and asset prices, which has been documented for several asset classes and in different frameworks: for example, Altavilla, Giannone & Modugno (2017) find that aggregating macroeconomic news permits us to explain more than one third of bond yields fluctuations at quarterly frequency.

Notwithstanding these results, an explicit model between macroeconomic news and changes of the yield curve has not been yet constructed, and the underlying mechanism that drives the reaction of financial markets is still not well understood. In other words, we have quite a good understanding of what is the reaction of the markets to macroeconomic news, but why do they react?[3] And how to link and explain the reaction at high frequency with the stronger, persistent effect at lower frequencies? In a recent work, Gürkaynak et al. (2018) note that the standard high frequency identification of news effect measures only the reaction to headline news, while macroeconomic releases contain more information which can be measured.[4] They propose an estimator of a latent "missing" factor, which captures the news component of the releases beyond the headline surprises: they show that it helps explain the great majority of the variance of interest rates around the announcements. In any case, they explicitly state that their methodology cannot explain which are the drivers of the effects of macroeconomic surprises. For example, it has been argued that the impact on the term structure of interest rates is due to changes in expected future real short-term interest rates and/or real risk premia (Beechey & Wright 2009) or to the updating of steady state inflation beliefs (Gürkaynak et al. 2005). However, another suggestion on the direction of future research on the topic can be found from the work of Coroneo et al. (2016), in which the authors find that macroeconomic factors are not spanned by the cross-section of yields. An important issue is whether this result also holds using real-time data, with a proper handling of the characteristics of the macroeconomic data flow. If this is the case, then it is possible to combine this approach with nowcasting methodologies, which permit us to interpret the macroeconomic flow of information in real time: it would be possible

[3] A recent work by Gilbert et al. (2017) deals with a similar question. They define the "intrinsic value" of a release the ability of that announcement to nowcast GDP or other main indicators. However, what matters in our context is the unexpected part of the release (i.e. the "news"), not the announcement itself.

[4] An example of this additional information is the content of the employment report in the US, or the publication of the GDP components in correspondence of GDP releases.

to decompose and measure, in a novel way, the impact of the "news" component of macro releases on the yield curve factors and on assessment of the underlying state of the economy (i.e. the macroeconomic factors).

In the following essay the link between financial markets and macroeconomic data has been explored further in this direction. Indeed, in Chapter 4, a joint work with Laura Coroneo (University of York), we assess the relevance of real-time macroeconomic information to predict the future path of the yield curve of interest rates in the framework of Coroneo et al. (2016). Following the seminal work by Ang & Piazzesi (2003), there is a consensus in the literature that macroeconomic indicators are successful at predicting interest rates and excess bond returns. However, recent studies find limited evidence of predictive ability of real-time macroeconomic variables for excess bond returns: they argue that the result of the previous literature was an artefact coming from the use of revised data, instead of real-time macroeconomic data.

Our contribution is to make interest rate predictions based on the information set available to agents at each point in time, by taking into account all the characteristics of the real-time macroeconomic data flow: adequately specifying the information set available to agents in real-time, in fact, is particularly important when evaluating models in macroeconomics and finance. We specify a mixed-frequency macro-yields model in real-time that incorporates interest rate surveys and treats macroeconomic factors as unobservable components, which we extract simultaneously with the traditional yield curve factors á la Nelson & Siegel (1987). More specifically, our empirical model is a mixed-frequency dynamic factor model for Treasury zero-coupon yields, a representative set of real-time macroeconomic variables and interest rate surveys with restrictions on the factor loadings.

We find that real-time macroeconomic information is helpful to predict interest rates, especially short maturities at mid and long horizons, and that data revisions drive an increase in the predictive power of revised macro information with respect to real-time macro information. Moreover, during a period when a forward guidance policy is implemented, we find that incorporating interest rate surveys in the model significantly improves its predictive ability. Surveys, in fact, incorporate soft information about the future path of interest rates – that comes from policy announcements, for example – that cannot be taken into account by standard macroeconomic variables. The fact that macroeconomic data contains useful information for the future path of the yield curve even in real time, in the framework of Coroneo et al. (2016), can be the starting point of future research aimed at a better understanding of the link between macroeconomic data and asset prices, as stated in the previous paragraphs.

The last essay, in Chapter 5[5], is a joint work with Lucrezia Reichlin (London Business School, Now-Casting Economics, and CEPR) and Giovanni Ricco (University of Warwick, CEPR and OFCE-SciencesPo). We use other methods to take advantages of the information present in large datasets in macroeconomics, namely Bayesian Vector Autoregressions. We build a model to analyse the anomalous characteristics of the Euro Area 'twin crises', by contrasting the aggregate macroeconomic dynamics in the period 2009-2013 with the business cycle fluctuations of the previous decades.

We model the Euro Area as a single economy and the twin crises – the 2008 financial crisis and the 2012 sovereign debt crisis – as a potentially unique event. This to account for the highly integrated economic and financial features of the Euro Area, and for the possibly common chain of events linking the two recessions. Our analysis contributes to the literature on the special nature of financial crises as opposed to regular recessions. Much of the existing empirical literature in this area has investigated the path of a handful of macroeconomic variables by using a single regression approach, in which financial crises are identified by using a narrative dummy or a quantitative index.[6] A stylised fact emerging from this strand of research is that recessions that are associated to financial crises tend to be deeper, longer, and characterised by prolonged cycles of deleveraging which weigh on the economy.

Differently from this approach, we focus on the fallout of a single financial crisis but provide a landscape view over the economy by adopting a rich multivariate Vector Autoregression (VAR) model with real, nominal and financial variables to

[5] Published as: Caruso, A., Reichlin, L., & Ricco, G. (2019). Financial and fiscal interaction in the Euro Area crisis: This time was different. European economic review, 119, 333-355.

[6] Among others, see Reinhart et al. 2012, Jordà et al. 2013*b*, and Romer & Romer 2017.

capture the interdependence of business and financial cycles. Our Euro Area-wide VAR model makes use of historical quarterly time series data from 1983 to 2013 to jointly model the dynamic interaction of macro aggregates, several fiscal indicators, different spreads, and house prices.

Our model provides three sets of empirical results. First, we perform a model-based counterfactual exercise by estimating the model for the period 1983-2007 (pre-crisis sample) and computing forecasts for 2008-2013, based on the pre-crisis parameters and conditional on the realised (observed) paths of nominal GDP and inflation. This exercise can be interpreted as a test for the statement 'this time is different'.

Second, using results from the first exercise, we then study how two measures of public debt – the cumulative sum of the deficit and the observed debt incorporating stock-flow adjustments – deviated from its predicted measure conditional on the collapse in output. If the observed path of any variable is found to be significantly different from what observed in its 'stressed' scenario, we conclude that there is a departure from previous cyclical experiences. This exercise is at the core of this chapter, and highlights a novel set of results concerning the anomalous dynamics in fiscal variables, following the financial crisis.

Third, we study how the realised paths of the variables of interest deviated from the unconditional forecast and the implicit trends recovered by the model. This exercise provides a gauge on how much (or how little) correlation exists in the data between macro and financial variables. It also provides useful information on pre-crisis trends.

On balance, our results on fiscal debt-deficit dynamics support the observation that, in the Great Recession, the financial-fiscal interaction determined a deterioration of the budget and an increase in the stock of debt, beyond business cycle regularities. As recovery began, countries reacted to the unprecedented accumulation of the stock of debt by a severe fiscal consolidation which is likely to have negatively affected the recovery path. These observations lend support to proposals for reform of the Euro Area governance that would allow a slower fiscal consolidation in case of large negative shocks and would distinguish between that part of the government fiscal balance depending on the business cycle and that part that is explained by the reaction to the increase in the stock of debt.

Chapter 2

Nowcasting with the help of foreign indicators: the case of Mexico

I propose an econometric model to interpret the flow of macroeconomic data releases that are useful to assess the state of the Mexican economy. I estimate the relevance of both Mexican and US indicators for predicting Mexican GDP, using a nowcasting model that can be continuously updated as new data are released. The model produces forecasts that have better accuracy than Surveys of Professional Forecasters, and shows the high relevance of US data in the real-time process of forecast updating. These results encourage a more frequent use of external indicators in short-term GDP forecasting in small open economies.

JEL Classification: C32; C53; E37.

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2.1 Introduction

Which are the macroeconomic indicators to look at in order to assess the state of the business cycle? This is a relevant question for policy makers, who make and implement decisions on the basis of the current state on the economy, and for market participants, who take it into account in making their investment decisions. GDP would be the natural indicator to consider. However, since it is published only quarterly and it has a significant publication delay (usually weeks or months after the end of the reference quarter), it is important to extract information from indicators that are available at higher frequency and in a more timely fashion, to have a reliable forecast (or "nowcast") of the current state of the economy that can be updated whenever a new data release is published. In the case of a small open economy, a related and important question is whether it is important to look at external data as well. The Mexican example could be seen as a case study to analyse the relevance of foreign macroeconomic data in small open economies whose business cycles are highly synchronized with the one of a large trade partner. In the Mexican case, do US indicators help in detecting early signals about business cycle developments and to identify turning points? Are they useful in the process of forecast updating? Which are the relevant domestic and foreign variables to look at? To answer these questions, in this chapter I reconstruct the macroeconomic information flow from Mexico and from the US, and interpret it through the lens of a nowcasting model for Mexican GDP.

The general framework of the nowcasting approach has been introduced by Giannone et al. (2008), and recent developments have been surveyed by Banbura et al. (2011) and Banbura et al. (2013*b*). The issue is to assess the current state of the economy exploiting the information embedded in many macroeconomic variables which are more timely and at a higher frequency than a target variable usually released with a considerable delay (e.g. GDP), and to be able to update the forecasts in real-time whenever new macroeconomic data is released. Private and institutional sources provide a flow of macroeconomic data almost every day: the challenge is to interpret the new information properly, in a process of signal extraction that copes with its complexity. The complexity lies in dealing with a possibly large number of variables, which can have mixed frequencies, refer to different sectors of the economy, and are released in a non-synchronous way. Using a factor model is a parsimonious way to use a large number of macroeconomic variables exploiting their co-movement, see Forni et al. (2000) and Stock & Watson (2002). The problems of the mixed frequency and of the non-synchronicity of the releases are solved by casting the model in state space form and using Kalman filtering techniques.[1] Following Doz et al. (2012*a*), I estimate the model using Maximum Likelihood in an Expectation-Maximization algorithm initialized by principal components.

Some recent papers proposed short-term forecasting models for Mexican GDP, but none of them have analysed in depth the information flow available to the forecasters in real time and the importance of the information carried by US variables. Coutino (2005) presents a model based on several Mexican monthly indicators, but his technique does not allow either a real-time updating or an evaluation of the impact of different indicators. The VAR-based model presented in Guerrero et al. (2013) allows one to make an estimate of GDP that is more timely than the official release, but it can only be estimated at least 15 days after the end of the reference quarter, being a "backcast" rather than a "nowcast". The use of foreign indicators is a practice rarely found in the nowcasting literature. However, the empirical evidence of spillovers and synchronization between Mexican and US business cycles suggests that a forecasting

[1]The nowcasting methodology has been proven to be effective in many empirical applications, applied to many countries. Among others see Rünstler et al. (2009) and Giannone et al. (2009) for the Euro Area, Lahiri & Monokroussos (2013), Higgins (2014), and Grant et al. (2016) for the US, Barhoumi et al. (2010) for France, D'Agostino et al. (2008) and Liebermann (2012) for Ireland, Matheson (2010) for New Zealand, Marcellino & Schumacher (2010) for Germany, de Winter (2011) for the Netherlands, Siliverstovs & Kholodilin (2012) for Switzerland, Arnostova et al. (2011) and Rusnak (2016) for the Czech Republic, Aastveit & Trovik (2012) and Luciani & Ricci (2014) for Norway, Bragoli et al. (2015) for Brazil, Luciani et al. (2015) for Indonesia, Bragoli & Modugno (2017) for Canada, de Antonio Liedo (2014) for Belgium, Bragoli (2017) for Japan, Matheson (2013) for 32 economies, Porshakov et al. (2016) for Russia, Yiu & Chow (2010) for China, Bragoli & Fosten (2016) for India, Modugno et al. (2016) for Turkey. Moreover, the nowcasting methodology has also been used to track indicators different from GDP: see for example Modugno (2013) for inflation, D'Agostino et al. (2016) for trade variables, and Cimadomo et al. (2015) for forecasting fiscal variables using a mixed frequency Bayesian VAR.

model of the Mexican economy should take into account the relationship with the US. Among others, Torres & Vela (2003) document the synchronization of the US and Mexican business cycles and the role of trade, while Cuevas et al. (2002), Kose et al. (2004), Chiquiar & Ramos-Francia (2005), Lederman et al. (2005), Bayoumi & Swiston (2008) and Miles & Vijverberg (2011) evaluate the impact of NAFTA agreement on the synchronization, documenting its importance. Herrera Hernández (2004) finds a common trend and a common cycle between Mexican and US GDP and gains in forecasting Mexican GDP using a simple bivariate error correction model with US GDP. Evidence of the correlation between US and Mexican business cycles is confirmed in a later work by Mejía-Reyes & Campos-Chávez (2011). Regarding possible spillovers from the US to the Mexican economy, Sosa (2008) finds a high impact of US shocks on Mexico in the post-NAFTA period, with a major role played by US Industrial Production and by the indicators relating to the automotive sector. Liu et al. (2012) present nowcasting models for the GDP of several Latin American countries, including Mexico, obtaining the result that external indicators (8 US variables plus 11 commodity prices) do not help improve the accuracy of the nowcast for Mexican GDP in the sample 2005-2010. Dahlhaus et al. (2017) make a similar exercise on BRICS countries and Mexico finding a low impact of exogenous variables, but using only two variables about the real side of the US economy. Moreover, the last two works mimic the data available to the econometrician without reconstructing the exact calendar of data releases, they do not explicitly measure the specific weights of US indicators, and they do not compare the performance of their models to other than statistical benchmarks.

The main contributions of the present work can be summarized as follows. First, reconstructing and interpreting the Mexican and US macroeconomic data flow, I evaluate the importance of each data release and the relevance of the information accessible to markets participants and policy makers in order to assess the state of the Mexican economy in real time. Second, I find that the information coming from US indicators has an important role in the updating process of a nowcasting model for Mexican GDP. Finally, I find that a nowcasting model constructed using a medium-scale dataset of real macroeconomic indicators from Mexico and from the

US performs well out-of-sample with respect to tough benchmarks like Surveys of Professional Forecasters.

2.2 The model

The dynamic factor model used in this work can be described as follows. The variables are assumed to have a factor structure:

$$x_t = \Lambda f_t + \epsilon_t, \tag{2.1}$$

where x_t is a vector of standardized stationary monthly variables, f_t are r unobserved common factors with zero mean and unit variance, Λ are the factor loadings, and ϵ_t is a vector of idiosyncratic components of dimension N which is modelled as an $AR(1)$ process, uncorrelated with f_t at any leads and lags.

The dynamics of the factors are modelled as a stationary Vector Autoregressive process with p lags, in which $A_1, ..., A_p$ are rxr matrices of autoregressive coefficients:

$$f_t = A_1 f_{t-1} + ... + A_p f_{t-p} + u_t;\ u_t\ i.i.d. \sim \mathcal{N}(0, Q). \tag{2.2}$$

To deal with the mixed frequency of macroeconomic data I follow the approximation of Mariano & Murasawa (2003), including the quarterly variable in the model as a monthly partially-unobserved variable. For any variable y_t, defined at the highest frequency present in the model, define $y_t^{(k)}$ as its "counterpart" which is observed every k periods. That means that the observations of the lower frequency variables are periodically missing. In the case of the present work y_t is the difference of natural logarithms of GDP, and since the highest frequency of the model is monthly we have that its counterpart is $y_t^{(3)}$, which from now on can be defined as $y_t^{(Q)}$. Define as z_t the non-transformed series corresponding to y_t, in our example the level of GDP. The approximation is the following:

$$y_t^{(Q)} = log(z_t^{(Q)}) - log(z_{t-3}^{(Q)}) \approx y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4} \tag{2.3}$$

with $t = 3, 6, 9, \dots$.

I estimate the model using Maximum Likelihood estimation following Doz et al. (2012*a*), who have proven convergence properties in the case of factor models in large dimensions.[2] The authors also showed that the estimation is robust to different sources of misspecification, for example in the case of weak cross-correlation of the idiosyncratic components, and that Maximum Likelihood is computationally feasible and can be performed within an Expectation-Maximization algorithm initialized with principal components (PC). Precisely, in a first step PC are used for a preliminary extraction of the common factors, in the spirit of Forni et al. (2000) and Stock & Watson (2002), and the parameters are estimated by OLS treating the PC as if they were the true common factors. In a second step, the Kalman smoother is used to extract the common factors conditionally on the parameters estimates. If we stop here we obtain the two-step approach used by Giannone et al. (2008), see Doz et al. (2011) for an asymptotic analysis. The Maximum Likelihood estimation is obtained by iterating the procedure until convergence, and taking into account the uncertainty due to extraction of the factors.[3] The number of lags p is set to two. Determining the number of factors is still a debated question in the literature: I fix the number of factors to one, as being the simplest choice, which also permits to interpret the factor as a business cycle indicator.[4]

[2]Early examples of Maximum Likelihood estimation of small factor models with macroeconomic indicators can be found in Watson & Engle (1983), Stock & Watson (1989), and Mariano & Murasawa (2003); however, these models could handle just a few number of variables. More recent examples of Maximum Likelihood estimation of dynamic factor models in frameworks different from nowcasting can be found in Reis & Watson (2010), Luciani (2015), Delle Chiaie et al. (2015), Coroneo et al. (2016).

[3]I use the adaptation of the EM algorithm to the presence of missing data proposed in Banbura & Modugno (2014).

[4]The forecasting performance is robust to the use of more factors and to a change of the number of lags. Results are available on request.

2.3 Data

I decide which variables to include in the model following a market-oriented approach. I consider only surveys and real variables, since financial variables have been proven to be not effective in improving the precision of short-term forecasts of GDP in this framework (Banbura et al. 2013*b*). I take into consideration what market operators, statistical agencies, and the specialized press consider to be the key variables for assessing the condition of the Mexican economy. As a starting point I choose the variables reported on Bloomberg, one of the major sources of information for investors, traders and market operators. I also include some variables that were reported on Bloomberg in the past, given the importance they might have had in the eyes of market operators to assess the state of the Mexican economy (e.g. Truck Sales). For each variable Bloomberg reports a "relevance index", that is the ratio of alerts requested for new releases of that variable over the total number of alerts. The index could be seen as a measure of the importance assigned by financial market operators to that indicator. Moreover, I also take into consideration the variables that are perceived of being of "high impact" in ForexFactory.com, the most viewed forex-related website in the world. Finally, I consider the indicators that frequently appear in the debate about the Mexican economy in the main local media, and some variables that should be taken into account given their relevance in the analysis of the latest statistical reports of the INEGI (Instituto Nacional de Estadistica y Geografia) and of the Bank of Mexico.

Regarding Mexican surveys, I include Consumer Confidence, Producer Confidence, and a survey about Manufacturing Orders, all of which are very timely indicators. Moreover, I include two surveys about Business Climate conducted by the Instituto Mexicano de Ejecutivos de Finanzas (IMEF). Even though their Bloomberg relevance index is low, these two indicators (Manufacturing and Non-Manufacturing) are widely followed by economic commentators, in newspapers and specialized websites. They are the Mexican version of the "Purchasing Managers Index" published by the Institute for Supply Management in the US, as their construction explicitly follows the same methodology.

As for standard macroeconomic indicators about Mexican production and internal demand I consider Industrial Production and Retail Sales. It is worth noting that Industrial Production has a Bloomberg relevance index even higher than GDP. I include two indicators related to the automotive sector (Automobile Sales and Truck Sales), given the importance of the automotive sector for the Mexican economy and Mexican exports.[5] The trade sector is particularly important: the trade balance historically fluctuates around zero, but trade has a major role in the economy since exports represents 31.7% of GDP.[6] The main trade partner are the United States, which absorb 79% of Mexican exports: the trade surplus with the US amounts to 53,8 Billions of USD.[7] The largest shares of exports are represented by vehicles, electronic and mechanical components (often linked to the automotive sector), and oil. However, the trade balance relative to the first two categories is almost neutral. Therefore, in addition to Imports and Exports, I include in the model indicators for oil production and exports, vehicle production and exports, and the trade balance with the United States. The final list of Mexican variables consists of 18 indicators.

Regarding US data, I look at a set of variables considered standard in the forecasting literature and by practitioners assessing the behaviour of the US economy. As regards real variables I include Industrial Production, Capacity Utilization, Retail Sales, Housing Starts, and Employees on Non-Farm Payrolls. As regards surveys, I use the Purchasing Managers Index (Manufacturing), Consumer Confidence, and the Consumer Sentiment from the University of Michigan. Moreover, given the high importance of the automotive sector in the trade activity between Mexico and the US, I include three automotive-related variables that are commented on Bloomberg (Automotive Wholesale Sales, Car Imports and Truck Imports).

The dataset is composed of 28 monthly variables plus quarterly Mexican GDP, and is described in Table 2.1. The dimension of the dataset is consistent with the results of Banbura & Modugno (2014), who show that in the nowcasting framework small and medium scale models perform better than large scale ones. In Table 2.2 I report an example of the flow of macroeconomic releases included in the model for

[5] In 2016 Mexico was the 7th world producer of vehicles, 3rd for commercial vehicles. Source: Organisation Internationale des Constructeurs d'Automobiles (OICA).

[6] Data relative to 2010-2014, World Bank.

[7] Source: www.census.gov.

	Series	Source	Start date	Unit	Transf.	Lag
Mexico	IMEF Bus.Clim. Index: Mfg	IIEEM	Jan-04	INDEX	Level	3
Mexico	IMEF Bus.Clim. Index: Nonmfg	IIEEM	Jan-04	INDEX	Level	3
Mexico	Consumer Confidence	INEGI	Apr-01	INDEX	Level	4
Mexico	Producer Confidence Index	INEGI	Jan-04	Units	YoY	4
Mexico	Opinion Survey: Mfg. Orders	INEGI	Jan-04	INDEX	Level	4
Mexico	Total Vehicle Production	AMIA	Jan-91	Units	YoY	10
Mexico	Industrial Production	INEGI	Jan-91	INDEX	MoM	13
Mexico	Total Vehicle Exports	AMIA	Jan-91	Units	YoY	13
Mexico	Unemployment Rate	INEGI	Apr-00	%	M diff	22
Mexico	Petroleum Exports: Crude	INEGI	Jan-91	US$	MoM	24
Mexico	Imports	INEGI	Jan-91	US$	MoM	24
Mexico	Exports	INEGI	Jan-91	US$	MoM	24
Mexico	Production of Crude Petroleum	INEGI	Jan-91	Units	MoM	26
Mexico	Automobile Sales	AMIA	Jan-91	Units	MoM	37
Mexico	Truck Sales: Total	AMIA	Jan-95	Units	YoY	37
Mexico	Retail Sales	INEGI	Jan-94	INDEX	MoM	52
Mexico	Gross Domestic Product	INEGI	Jan-91	Mil.Pesos	QoQ	55
Mexico	Trade Balance: United States	INEGI	Jan-93	US$	YoY	57
US	UoM: Cons. Sentiment	Univ. of Mich.	Jan-91	INDEX	Level	-3
US	Conference Board: Cons. Conf.	CB	Jan-91	INDEX	Level	-3
US	ISM Mfg: PMI Composite Index	ISM	Jan-91	INDEX	Level	1
US	Employees on Nonfarm Payrolls	BLS	Jan-91	Units	M diff	5
US	Retail Sales	CENSUS	Jan-91	US$	MoM	13
US	Industrial Production	FRB	Jan-91	INDEX	MoM	16
US	Capacity Utilization	FRB	Jan-91	%	M diff	16
US	Housing Starts	CENSUS	Jan-91	Units	MoM	18
US	Wholesalers: Sales: Automotive	CENSUS	Jan-92	US$	MoM	40
US	Car Imports	CENSUS	Jan-91	US$	YoY	41
US	Truck Imports	CENSUS	Jan-91	US$	YoY	41

Table 2.1: The table describes the variables included in the model, the sources, the starting dates of their availability, the units of measure and the transformations. The "Lag" column indicates the average number of days between the macroeconomic announcement and the end of the reference period. IIEEM stands for "Indicador IMEF del Entorno Empresarial Mexicano", INEGI for "Instituto Nacional de Estadística Geografía e Informática", AMIA for "Asociación Mexicana de Industria Automotriz", CB for "The Conference Board", ISM for "Institute for Supply Management", CENSUS for "US Census Bureau", FRB for "Federal Reserve Board".

May 2013. In the first days of the month three surveys are released: the Mexican IMEF (Manufacturing and Non-Manufacturing) and the US PMI Manufacturing. On the same day of the IMEF surveys, data about Car and Trucks Imports in the

United States are released, but they refer to the month of March. Then other data about April are released, and then data about March again. This is an example of the ragged edge feature of the dataset, and of the importance of taking all the available information into account: using a balanced panel up to March, which would be completed only on the 26th May, in this example the forecaster would have neglected a lot of information relative to April given by important indicators which has a very high average impact on the nowcast of Mexican GDP (see section 2.4.2). Data has been downloaded from Haver Analytics on 1st June 2017. All the variables except the surveys have been transformed to monthly growth rates (or monthly differences when not applicable and in the case of Employment variables), and not seasonally adjusted variables have been transformed to yearly growth rates.

2.4 Results

2.4.1 Out-of-sample evaluation

In this section I present the results of the out-of-sample evaluation of the model, performing a pseudo real-time historical evaluation. It is called "pseudo" because it abstracts from data revisions, but in this framework the estimates are robust if the revision errors are weakly cross-correlated (Giannone et al. 2008). I evaluate two versions of the model: one in which I include all the variables and one in which I use just Mexican variables. I compare the forecasts of the two models to some benchmarks: an autoregressive model, the Surveys of Professional Forecasters reported monthly by the Bank of Mexico, the projections published in the OECD Economic Outlook in June and December of the reference year, and the forecasts published in the World Economic Outlook by the International Monetary Fund in April and October of the reference year.

The estimation sample starts in January 1991, and the out-of-sample evaluation goes from the first quarter of 2006 to the fourth quarter of 2016. Following the calendar of the data releases, at each release after 1st January 2006 the forecast (1-quarter ahead), nowcast (current quarter) and backcast (last quarter) are updated

Date	Country	Series	Average Lag	Ref. Period	Bloomberg Relevance
01-May	US	ISM Mfg: PMI Composite Index	1	April	94.7
02-May	Mexico	IMEF Index: Mfg	3	April	17.5
02-May	Mexico	IMEF Index: Nonmfg	3	April	12.5
02-May	US	Car Imports	41	March	
02-May	US	Truck Imports	41	March	
03-May	Mexico	Producer Confidence Index	4	April	
03-May	Mexico	Manufacturing Orders	4	April	
03-May	US	Employees on Nonfarm Payrolls	5	April	99.1
06-May	Mexico	Consumer Confidence	4	April	82.5
07-May	Mexico	Total Vehicle Production	10	April	37.5
07-May	Mexico	Total Vehicle Exports	13	April	30
08-May	Mexico	Automobile Sales	37	March	
08-May	Mexico	Truck Sales	37	March	
09-May	US	Automobile Sales	40	March	
10-May	Mexico	Industrial Production	43	March	92.5
13-May	US	Retail Sales	13	April	89.4
15-May	US	Industrial Production	16	April	86.7
15-May	US	Capacity Utilization	16	April	60.71
16-May	US	Housing Starts	18	April	88.5
24-May	Mexico	Unemployment rate	22	March	77.5
22-May	Mexico	Retail Sales	52	March	80
23-May	Mexico	Gross Domestic Product	55	Q1	87.5
26-May	Mexico	Imports	24	April	75*
26-May	Mexico	Exports	24	April	75*
26-May	Mexico	Trade Balance: United States	57	March	
26-May	Mexico	Oil Exports	24	April	
26-May	Mexico	Oil Production	26	April	
28-May	US	Consumer Confidence	-3	May	95.6
31-May	US	Univ. of Michigan: Cons. Sentiment	-3	May	92.9

Table 2.2: The table reports an example of the macroeconomic data flow in May 2013. The last three columns describe the average publication lag expressed in days from the end of the reference period, the reference period and the Bloomberg relevance index, which is the ratio of alerts requested for new releases of an indicator over the total number of alerts.
* Refers to Trade Balance.

using the information that is available at that point in time.[8] Since the variables are jointly modelled, it is important to note that the model produces a forecast for each variable in the dataset.

[8]The estimation is performed recursively.

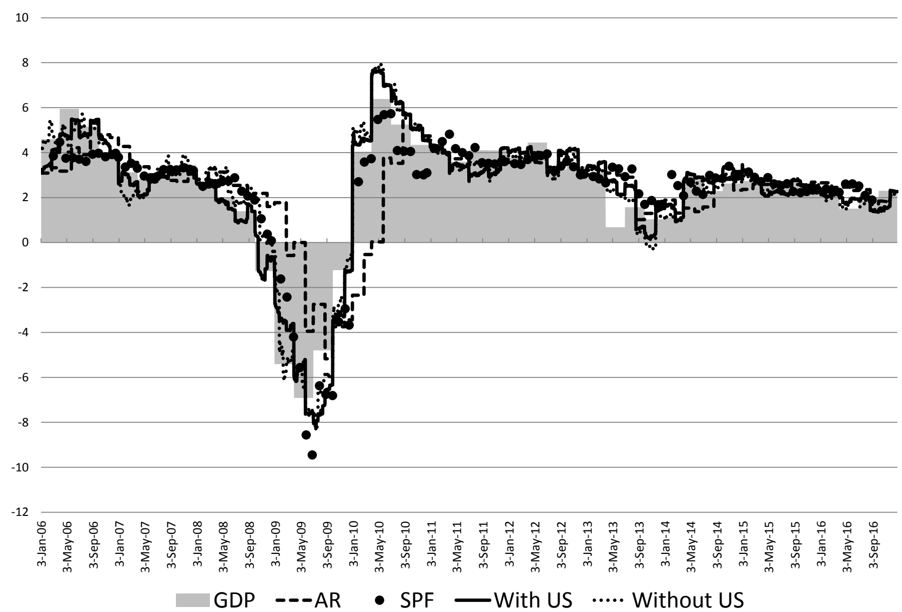


Figure 2.1: The chart shows the nowcast of the YoY growth rate of GDP produced by the model that includes US variables (With US) and the nowcast produced by the model that includes just Mexican variables (Without US). They are compared to the actual value (shaded area), with the forecast from an AR(1) model and with the Surveys of Professional Forecasters conducted by the Bank of Mexico.

The model tracks the quarter-on-quarter (QoQ) growth rate, aggregated also on a year-on-year (YoY) basis in order to compare the results with the benchmarks. Figure 2.1 shows a comparison between the nowcast of the YoY growth rate of Mexican GDP and the actual values. The nowcast tracks well the large crisis of 2009, the recovery, as well as more tranquil periods. The model performs very well in comparison to the nowcast from the Surveys of Professional Forecasters. Similar qualitative results hold for the nowcast of the quarter-on-quarter (QoQ) growth rate, in Figure 2.2, and for the nowcast of the calendar year growth rate, in Figure 2.3, compared to the performance of institutional forecasts coming from the IMF World Economic Outlook and the OECD Economic Outlook. In the QoQ case, we can note from the chart that the model that does not consider US variables forecasts better the severity of the crisis of 2009, but produces a nowcast which is more volatile than the one from the model with US variables.

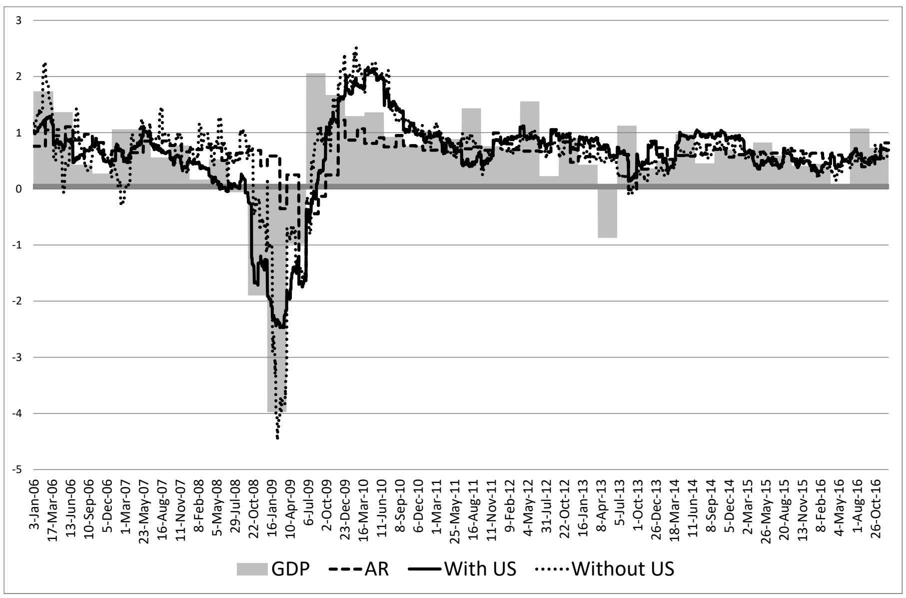


Figure 2.2: The chart shows the nowcast of the QoQ growth rate of GDP produced by the model that includes US variables (With US) and the nowcast produced by the model that includes just Mexican variables (Without US). They are compared to the actual value (shaded area) and with the forecast from an AR(1) model.

In Figures 2.4 and 2.5 I present the Root Mean Squared Forecast Error of the nowcast of the QoQ and the YoY growth rate in different points of the forecast period (from -90 to 0 days to the start of the reference quarter), the nowcast period

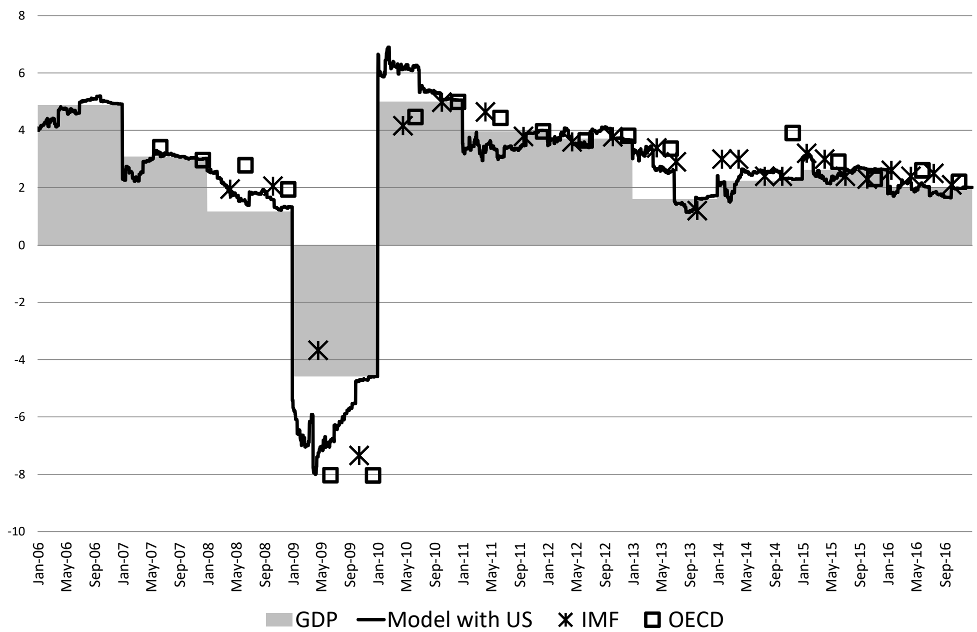


Figure 2.3: The chart shows the nowcast of the calendar year growth rate of GDP produced by the model that includes both US and Mexican variables, compared to the actual value (shaded area) and with the forecast published by the IMF and the OECD.

(from day 0 to day 90) and the backcast period (from day 90 onwards). The figures show the results obtained using the two versions of the model, including the US variables or with just Mexican ones. I compare these results to the performance of an AR(1) and of the Surveys of Professional Forecasters conducted by the Bank of Mexico.[9]

Focusing on the YoY case (Figure 2.5), the chart shows three main results. First,

[9]Only available in the YoY case.

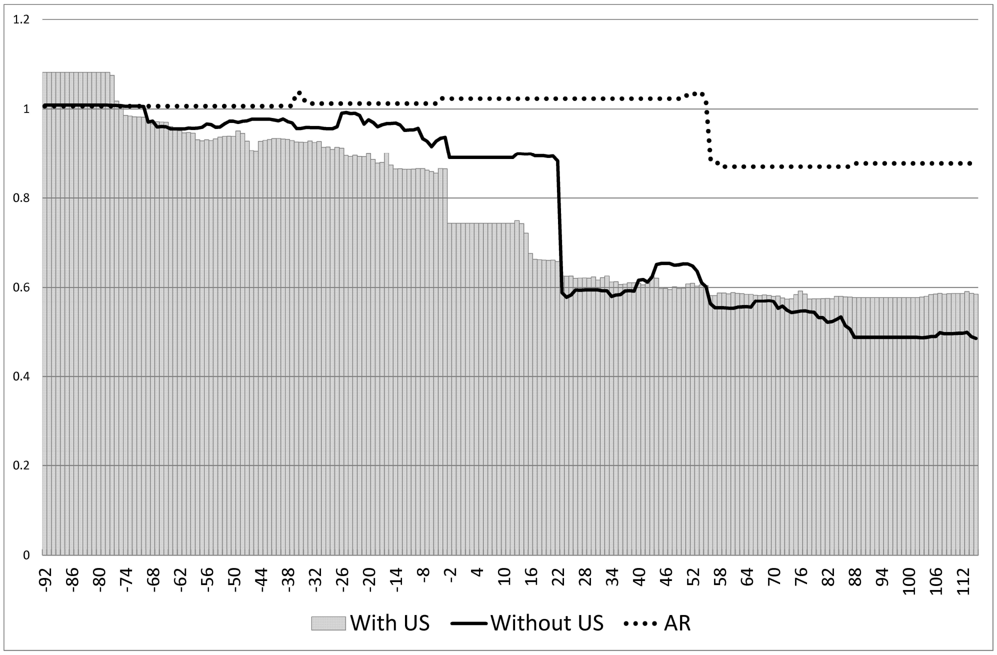


Figure 2.4: The chart shows the Root Mean Squared Forecast Error of the nowcasting models of the QoQ growth rate of GDP during the forecast period (from -90 to 0 days to the start of the reference quarter), the nowcast period (from day 0 to day 90) and the backcast period (from day 90 onwards). The horizontal axis reports the distance in days from the beginning of the reference quarter.

the reduction in RMSFE as new data arrives shows that the information coming from macroeconomic releases is effectively incorporated into the estimates of the GDP growth rate. Second, the model that includes US indicators performs uniformly better in the forecast period and in the beginning of the nowcast period, and slightly worse onwards. Third, the chart shows that the forecasts coming from such a mechanical model are comparable to those of professional forecasters, with the ad-

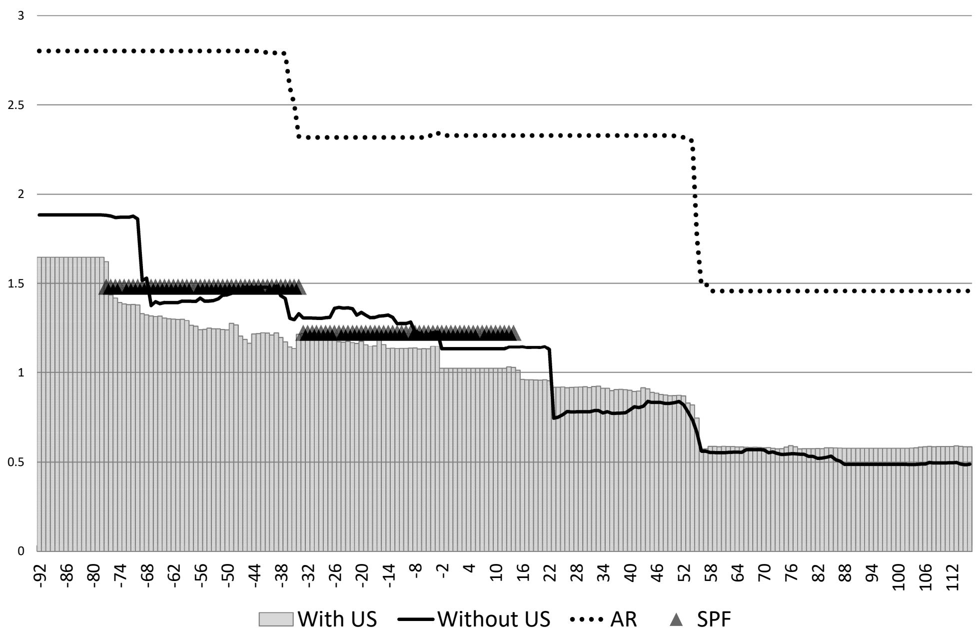


Figure 2.5: The chart shows the Root Mean Squared Forecast Error of the nowcasting models of the YoY growth rate of GDP during the forecast period (from -90 to 0 days to the start of the reference quarter), the nowcast period (from day 0 to day 90) and the backcast period (from day 90 onwards). The horizontal axis reports the distance in days from the beginning of the reference quarter. The chart also shows a comparison with the RMSFE of the forecasts of the Surveys of Professional Forecasters conducted by the Bank of Mexico.

vantages that the model can be updated in real time at any release and it is totally free of possible judgemental biases.

To test the performance of the models I perform a Diebold & Mariano (1995) test of equal predictive accuracy, applying the correction for small samples described in

Harvey et al. (1997).[10] Since the results of the Surveys of Professional Forecasters conducted by the Bank of Mexico are usually published at the end of the month, I evaluate the forecasting performance on the last day of each month of the out-of-sample period. Let us call the model that includes just Mexican variables "Small", and the model that includes Mexican and US variables "Large". I test the equal accuracy between the forecasts (i) from the Small model and from the Large, (ii) from the Large and from the AR(1), (iii) from the Small and from the AR(1). The null hypothesis is that the forecasts have the same predictive accuracy. I test the accuracy of the forecasts in the whole sample as well as in two sub-samples of 8 years, one which includes the 2008-09 crisis (from 2006:Q1 to 2013:Q4) and one which excludes it (from 2009:Q3 to 2016:Q4). The results are in Table 2.3 and in Table 2.4.

I first analyse the results relative to the whole sample. Comparing the nowcasts and forecasts produced by the nowcasting models with the forecasts produced by the AR(1), the test rejects the null hypothesis of equal predictive ability at the 99% confidence level in all the cases, except in the QoQ case for the Large model in the forecast period, in which the null hypothesis is rejected at 90%. Comparing the Small model with the Large, the null hypothesis cannot be rejected in the QoQ case and in the YoY case for the forecast, while it is rejected in favour of the Small at the 95% in the nowcast period. That confirms the results visible in Figure 2.5, in which we can see that the Large model outperforms the Small (but the advantage is not statistically significant) until the third week of the nowcast period. Looking at the results relative to the Surveys of Professional Forecasters, the null hypothesis is rejected in the case of both nowcasting models at the 99% or 95% confidence level, pointing out that the models perform better than professional forecasters.

Analysing the results in the two sub-samples, there is evidence of a statistically

[10] The loss function is specified in terms of squared forecast errors. A test for nested models of the type discussed in Clark & McCracken (2001) might be advocated. However, as discussed in Busetti & Marcucci (2013), such a test is oversized when the number of out-of-sample observations is small, and in case of a misspecified model. Moreover, Busetti & Marcucci (2013) show the lower power of the Diebold-Mariano test in case of nested model, therefore for the purpose of the present work it is more conservative than a Clark-McCracken test.

DM stat		2006-16	
		Nowcast	Forecast
QoQ	Small vs Large	-1.1	0.41
	AR vs Large	2.64***	1.33*
	AR vs Small	2.63***	2.73***
YoY	Small vs Large	-1.83**	0.88
	AR vs Large	3.78***	3.94***
	AR vs Small	3.89***	4.06***
	SPF vs Large	3.1***	3.43***
	SPF vs Small	3.2***	2.29**

Table 2.3: The table reports the results of Diebold-Mariano (1995) tests of equal predictive accuracy, at 99% (***), 95% (**), and 90% (*) level, applying the correction for small samples described in Harvey et al. (1997). The model written as the second is the one whose forecast are tested to be more accurate in the alternative hypothesis (e.g.: A vs B, H_1 is that forecasts from B are more accurate than forecasts from A). "Small" refers to the nowcasting model with just Mexican variables; "Large" to the model with Mexican and US variables; "AR" to the AR(1); "SPF" to the Surveys of Professional Forecasters conducted by the Bank of Mexico. The tests are based on 131 observations.

significant better predictive ability of the Large model in the sample which includes the crisis of 2008-09, while US indicators worsen the performance in the sub-sample 2009-16. In both sub-samples, the two models perform better than professional forecasters.

To sum up, the tests indicate a statistically significant advantage of the nowcasting models with respect to the AR(1) and with respect to professional forecasters. The gain in forecasting accuracy of including US indicators is not significant over the whole sample, while US variables improve the accuracy in the sub-sample including the crisis, maybe because they help in a timely way to identify recession episodes which have a global feature. In fact, it is interesting that US surveys like the PMI or Consumer Sentiment, which are very timely and closely followed by market participants also because of their informativeness, have a very large impact on the update of the nowcast, as analysed more in detail in the next section.

DM stat		2006-13	2009-16
		Nowcast	
QoQ	Small vs Large	2.05**	-2.93***
	AR vs Large	1.78**	2**
	AR vs Small	1.54*	2.32**
YoY	Small vs Large	1.5*	-3.18***
	AR vs Large	3.40***	3.29***
	AR vs Small	3.35***	3.49***
	SPF vs Large	4.21***	2.68***
	SPF vs Small	3.5***	2.93***

Table 2.4: The table reports the results of Diebold-Mariano (1995) tests of equal predictive accuracy, at 99% (***), 95% (**), and 90% (*) level, applying the correction for small samples described in Harvey et al. (1997). The model written as the second is the one whose forecast are tested to be more accurate in the alternative hypothesis (e.g.: A vs B, H_1 is that forecasts from B are more accurate than forecasts from A). "Small" refers to the nowcasting model with just Mexican variables; "Large" to the model with Mexican and US variables; "AR" to the AR(1); "SPF" to the Surveys of Professional Forecasters conducted by the Bank of Mexico. The tests are based on 95 observations.

2.4.2 News analysis

Banbura et al. (2011) explain how it is possible to extract model-based news in the nowcasting framework.[11] In our case, let y_t^Q be the GDP at time t, and Ω_ν the information set at time ν, where ν is a vintage of data. The nowcast is the projection of y_t^Q using the available data, $\mathbb{E}[y_t^Q|\Omega_\nu]$. At any release, abstracting from data revisions, the information set expands: $\Omega_\nu \subset \Omega_{\nu+1}$, and it is possible to decompose the new forecast in:

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}]}_{\text{new forecast}} = \underbrace{\mathbb{E}[y_t^Q|\Omega_\nu]}_{\text{old forecast}} + \underbrace{\mathbb{E}[y_t^Q|I_{\nu+1}]}_{\textit{revision}}, \tag{2.4}$$

where $I_{\nu+1}$ is the information in $\Omega_{\nu+1}$ orthogonal to Ω_ν. Therefore, it is possible

[11] For an earlier derivation see the working paper version of Banbura & Modugno (2014).

to express the revision as a weighted sum of news from the released variables, where $b_{j,\nu+1}$ are the weights:[12]

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}] - \mathbb{E}[y_t^Q|\Omega_\nu]}_{revision} = \sum_{j \in J_{\nu+1}} b_{j,\nu+1} \underbrace{\left(x_{i_j,t_j} - \mathbb{E}[x_{i_j,t_j}|\Omega_\nu]\right)}_{news}. \tag{2.5}$$

This methodology permits us to evaluate the marginal contribution of every release in the updating of the nowcast. In Figure 2.6 I report the average impact of the variables on the update of the nowcast, which is calculated as the the weight assigned by the model to a specific variable multiplied by the standard deviation of the model-based news. The main result of this analysis is that the nowcasting model attributes a very high importance to the variables relative to the US economy. The release of the US Purchasing Managers Index in the first month of the quarter has the second highest impact after Mexican GDP, followed by US Industrial Production, Mexican Producer Confidence, and US Non Farm Payrolls. In general, the model shows a high impact of both US soft (surveys) and hard variables. As expected, the variables that are released in the first half of the first month have the highest impacts, and this confirms that timeliness is indeed important. The ranking of the impacts is very similar if we look at the second month in the quarter. In the third month, US Industrial Production is the most important variable. The informational content of the indicators is also relevant, and not just their timeliness: the high impact of US Car and Truck Imports, which are released with a significant delay, confirms the importance of looking at the trade with the US, especially in the automotive sector. Among Mexican variables, it is worth noticing the predominant role of the Producer Confidence Index and of Imports and Exports. Overall, the analysis shows the importance of US variables in assessing the current condition of the Mexican economy. The high relevance of timely US variables like PMI, Consumer Confidence, and the Consumer Sentiment makes clear that early signals about the state of the US economy are important to assess the Mexican current economic condition.

[12]Essentially, the weights are the Kalman gains adapted to a staggered arrival of information.

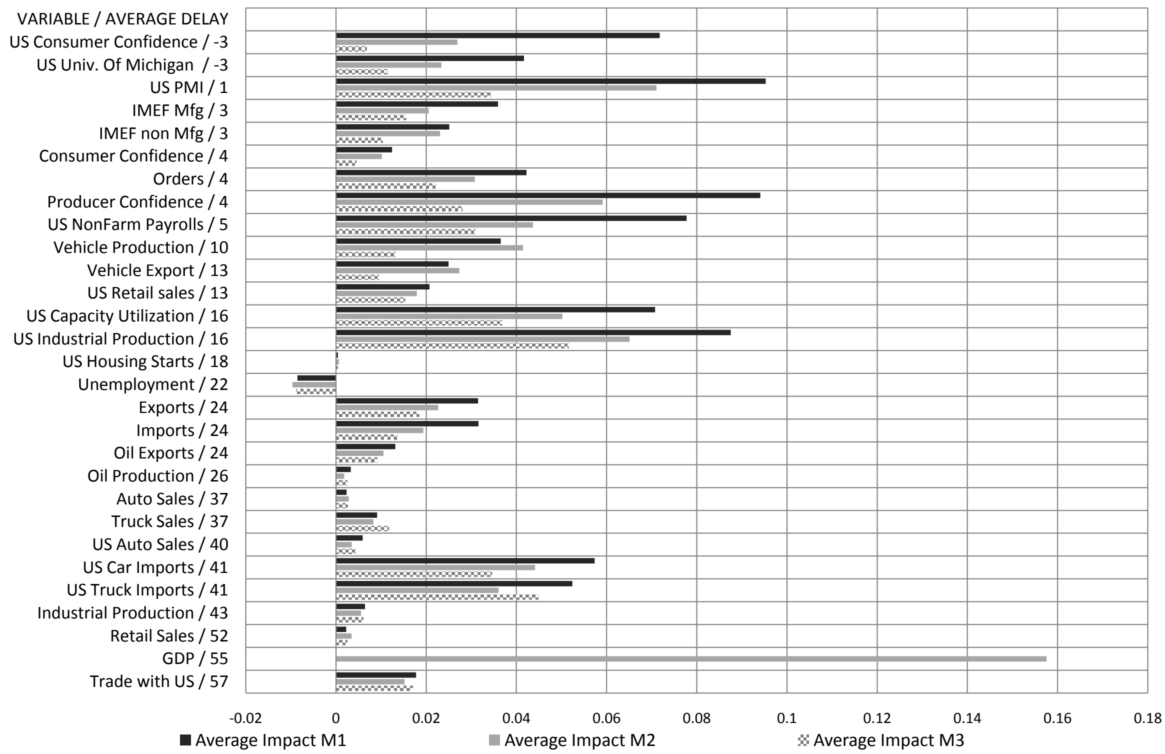


Figure 2.6: The chart shows the average impact of the variables on the update of the nowcast in the 3 months of the current quarter (M1, M2, M3). The impact is the product of the standard deviation of the model-based news and the weight that the model assigns to the variable in the updating process. The variables are ordered by average publication delay expressed in days, reported after the name of the variable.

2.5 Conclusions

This chapter studies the macroeconomic data relevant to assess the state of the Mexican economy. In particular, I exploit the information embedded in macroeconomic news from Mexico and from the United States in a model constructed to nowcast

Mexican real GDP, assessing the importance of including US variables. I use the nowcasting technique based on dynamic factor models and Kalman filters that has its grounds in Giannone et al. (2008), which permits us to evaluate the relevance of any single indicator used in the model. The results show the good predictive accuracy of the model when compared to institutional forecasts from the International Monetary Fund and the OECD, with the advantage that it is possible to update the nowcast at any macroeconomic release. The model outperforms the Surveys of Professional Forecasters conducted by the Bank of Mexico, both in nowcasting and in forecasting the Mexican GDP growth rate.

The work documents the important role of indicators about the US economy. In particular, the model indicates the usefulness of a group of "core" US variables in the process of forecast updating, like the Manufacturing Purchasing Managers Index, Non-Farm Payrolls, Capacity Utilization and Industrial Production. The improvements in forecasting accuracy given to the inclusion of US indicators are relevant in the forecast period (before the start of the reference quarter) and in the sub-sample which includes the crisis of 2008-2009. That indicates that early signals from the US can be useful as indicators of macroeconomic shocks which might have a global source. These results encourage a more frequent use of external indicators in short-term GDP forecasting of small open economies.

Chapter 3

Macroeconomic news and market reaction: Surprise indexes meet nowcasting

Market operators monitor a massive flow of macroeconomic information every day, and react to the unexpected component of the releases. Can we replicate in an automatic way market's pricing of macroeconomic news? In this work I show that a "Nowcasting Surprise Index", constructed aggregating forecast errors from a nowcasting model using model-based weights, resembles surprise indexes proposed in the recent literature or constructed by practitioners, which cumulate survey-based forecast errors weighting them using the average news effects on asset prices. This suggests that market operators and a nowcasting model filter the macroeconomic data flow in a similar way, and confirms the link between asset prices and news about macroeconomic indicators. Moreover, this work shows that a non-negligible part of asset prices behaviour can be associated to the recent cumulated news in macroeconomic data which carry information about the underlying state of the economy. These results also open a new route for algorithmic trading based on macroeconomic conditions.

JEL Classification: E37; E44; G12.

Keywords: Macroeconomic News; Macroeconomic forecasting; Surveys; Dynamic Factor Model; Asset Prices.

3.1 Introduction

Macroeconomic data are released every day, and are closely monitored by market participants: they need to filter the new information updating their view of the current state of the economy, given that the most comprehensive measures of economic activity have low frequency and are released only with a lag. If markets are efficient, market operators react when the actual releases are different from their expectations: macroeconomic "news" move the markets (for a survey see Gürkaynak & Wright 2013). This fact has been extensively documented in the literature looking at different asset classes (yields, stock prices, exchange rates) and frequencies (from tick-by-tick data to quarterly frequency).[1] To have an idea of the economic relevance of the phenomenon, macroeconomic news explain more than one third of bond yields fluctuations at low frequency, and their effect is statistically significant and persistent (Altavilla, Giannone & Modugno 2017).

In this strand of literature the "market-based" news is constructed as the difference between the actual macroeconomic release and market expectations, available through surveys among market participants. One way to aggregate the news, in order to interpret this massive flow of heterogeneous information coming every day, is to assign some weights to the news and to construct "surprise indexes" that synthesize the unexpected information released in a certain window of time. They are a cumulated weighted sum of these news, in which the weights are based on the effect of macroeconomic news on specific markets or on their predictive content for

[1]Among the others, for studies on yields and stocks see Hardouvelis (1988), Balduzzi et al. (2001), Andersen et al. (2003), Gürkaynak et al. (2005), Simpson et al. (2005), Pearce & Solakoglu (2007), Andersen et al. (2007), Faust et al. (2007), Kilian & Vega (2011), Goldberg & Grisse (2013), Swanson & Williams (2013), Gilbert et al. (2017); and for studies on exchange rates see Almeida et al. (1998), Galati & Ho (2003), Ehrmann & Fratzscher (2005), Caruso (2016).

economic activity. Being a standard practice among practitioners, the relevance of a meaningful surprise index has been recently acknowledged in the economic literature.[2] For example, Scotti (2016) constructs a surprise and an uncertainty index weighting market-based news using the contributions of the variables to common factors; Grover et al. (2016) relate GDP forecast errors to market-based news and from this build a nowcasting model; Altavilla, Giannone & Modugno (2017) aggregate and cumulate macroeconomic news using a measure of their high frequency impact on bonds, and show that their surprise index explain a relevant share of yields behaviour.

These studies show that market operators filter and price the new macroeconomic information: is it possible to use an automatic machine and replicate the market pricing of macroeconomic news? A positive answer would provide us with another perspective to try to understand the importance of fundamentals in driving asset prices. Moreover, it can inform whether there is scope to invest further in studying algorithmic trading strategies based on macroeconomic news. A model-based index is more flexible than a market-based one, since it can be constructed for any country of interest as it does not need survey expectations, which in some cases can be not available; moreover, survey expectations can be costly, prone to sentiment or herding behaviour, and could be affected by respondents giving strategic responses.

In this chapter I construct a real time, model-based, surprise index that summarizes how a short term forecasting model has been surprised by macroeconomic developments in a rolling window of time. The construction of news and weights is based on the "nowcasting" approach, processing the releases and aggregating macroeconomic news looking at their impact on model updates of the assessment of the current state of the economy (Giannone et al. 2008, Banbura et al. 2013*b*). The index is daily and can be updated at any macroeconomic release, and it is a weighted average of the forecast errors of the macroeconomic variables that enters a nowcasting model. The index represents a rolling measure of the surprise component of the macroeconomic data flow, flexible and judgement free. It is important to take into account the timeliness and quality of the variables which are part of the analysis:

[2]For examples among practitioners, see the Citi Economic Surprise Index or the SIREN Index constructed by Deutsche Bank.

the nowcasting approach permits us to do that using many macroeconomic variables. The weights represent the importance assigned by the model to a macroeconomic release in updating the assessment of the business cycle at each point in time. In particular, I use the weights assigned to macroeconomic news by a nowcasting model in order to calculate its updates of the nowcast, forecast, or backcast of GDP; then, to have a consistent rolling index, I weight these weights depending on the position of the index in the quarter. It is essential to remark that the weights refer to the macroeconomic news, which is what matters for market participants, and not to the variables. I analyse the properties of the model-based forecasts, showing that they replicate well market expectations. Moreover, I test the properties of bias and efficiency of model-based and market-based forecast, showing that they have similar properties and that the model is at least as efficient as market participants in forecasting individual macroeconomic variables.

The Nowcasting Surprise Index has a similar behaviour to indexes constructed using market-based weights and news, showing good correlation with asset prices and in-sample predictive power, especially at quarterly frequency. The fact that a model-based index can replicate market-based indexes is a remarkable result. On the one hand, that means that market news and model forecast errors are similar, meaning that a computer-based model fed with a large data set is able to replicate market expectations. Moreover, a model-based index is less costly than paying experts, and less susceptible to biases such as herding behaviour. On the other hand, it is useful to understand, in a coherent statistical framework, whether financial market operators react because a series of news events triggers an update about the current state of the economy.

3.2 Methodology and surprise indexes

3.2.1 Market-based news and weights

I define "market-based news" the difference between the actual release and the median survey forecast among leading practitioners, as the standard practice in the literature (see for example Balduzzi et al. 2001). I use the surveys collected by Bloomberg, considered a good benchmark for market expectations also in the recent related works constructing news indexes (Scotti 2016, Altavilla, Giannone & Modugno 2017). These surveys are available since a few days before the announcements and can be updated by the respondents up to one hour before the release. In line with Altavilla, Giannone & Modugno (2017) I define "market-based weights" W_i^{mkt} the estimated β_i of the following regression:

$$y_t = \alpha + \sum_{i=k}^{K} \beta_i X_{i,t} + \epsilon_t \tag{3.1}$$

Where y_t is the daily difference of the 10-year government bond yield and $X_{i,t}$ are the market-based news.[3] The news about variable i at time t is defined as $X_{i,t} \equiv x_{i,t} - \mathbb{E}[(x_{i,t}|Info_\nu)]$, where $x_{i,t}$ and $\mathbb{E}[(x_{i,t}|Info_\nu)]$ are the actual release and the median of the Bloomberg survey expectations among practitioners given their information set at vintage ν.

Then we can define the market based surprise index as:

$$SI_t^{mkt} \equiv \sum_{s=t-win}^{t} \sum_{i \in I} W_i^{mkt} X_{i,s}, \tag{3.2}$$

where the lenght of the window win in the present work is 66 working days (approximately one quarter).

3.2.2 Model-based news and weights

I order to extract model-based news I use a nowcasting model to predict the quarterly GDP growth rate of the United States. The nowcasting approach has its grounds in Giannone et al. (2008) and has been surveyed in Banbura et al. (2011, 2013*b*). A nowcasting model extracts the relevant information about the state of the economy contained in indicators that are more timely than GDP, taking into account the

[3] I standardize them to have mean zero and variance equal to 1.

characteristics of the macroeconomic data flow: a (potentially) large data set, the non-synchronicity of data releases and their mixed frequency. The information is funnelled into an estimate that can be updated at every data release. The solution adopted to deal with a large number of variables is to use a dynamic factor model, which compresses the information into a few unobserved factors that drive the co-movement of the macroeconomic variables in the model (see Forni et al. 2000, Stock & Watson 2002). The issues of the mixed frequency and the non non-synchronicity of the data releases is solved casting the model in state space form and using Kalman filters and smoothers.

Importantly, since the variables are jointly modelled, the technique allows us to have forecasts for any indicator of interest, and to calculate the "model-based news" as the difference between the forecast of the model at the moment of the release and the actual value. Banbura et al. (2011) explain how to extract model based news as the difference between the prediction of the model and the actual realization of the macroeconomic data. A nowcasting model also permits us to calculate a weight for each release of interest, which can be seen as the importance assigned by the model to that specific release in the updating process of the nowcast (estimate of the GDP of the current quarter), the backcast (previous quarter) and the forecast (following quarter). In other words, the weights express how much the model changes its "view" about the state of the economy after having incorporated a new piece of information represented by the unexpected part of a macroeconomic release. In our case, following Banbura et al. (2011), let y_t^Q be the GDP at time t, and Ω_ν the information set at time ν, where ν is a vintage of data. The nowcast is the projection of y_t^Q using the available data, $\mathbb{E}[y_t^Q|\Omega_\nu]$. At any release, ignoring revisions, the information set expands: $\Omega_\nu \subset \Omega_{\nu+1}$, and it is possible to decompose the new forecast in:

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}]}_{\text{new forecast}} = \underbrace{\mathbb{E}[y_t^Q|\Omega_\nu]}_{\text{old forecast}} + \underbrace{\mathbb{E}[y_t^Q|I_{\nu+1}]}_{\textit{revision}} \tag{3.3}$$

Where $I_{\nu+1}$ is the information in $\Omega_{\nu+1}$ orthogonal to Ω_ν. Therefore, it is possible to express the revision as a weighted sum of news from the released variables, where

$b_{j,t,\nu_{+1}}$ are the weights:

$$\underbrace{\mathbb{E}[y_t^Q|\Omega_{\nu+1}] - \mathbb{E}[y_t^Q|\Omega_\nu]}_{revision} = \sum_{j \in J_{\nu+1}} w_{j,t,\nu+1} \underbrace{(x_{i_j,t_j} - \mathbb{E}[(x_{i_j,t_j}|\Omega_\nu)]}_{news} \tag{3.4}$$

It would be wrong to use the GDP nowcast as a "Nowcasting Surprise Index", as it is a fixed event forecast and refers to GDP in a specific quarter. Moreover, also the weights represent the importance given by the model to a news in updating the projection about a specific quarter: the current one (nowcasting), the previous one (backcasting) or the following one (forecasting). Using the nowcast and just the weights relative to the nowcast update would not be correct, as the surprise index is a rolling concept while the weights are referred to a fixed time frame. For example, at the beginning of the quarter, the weights referring to the nowcast represent the importance given by the model to the news given the update of the assessment about the GDP in the near future (the next 3 months quarter). In the last day of the quarter, instead, the weights referred to the nowcast represent the importance given to the news in the update about the assessment of GDP in the near past (the last three months). In order to have an index which evolves in a rolling fashion, I use a consistent weighting scheme, weighting the weights relative to the backcast, nowcast and forecast depending on the position in the quarter.

Let $w_{i,t}^{BC}$, $w_{i,t}^{NC}$, $w_{i,t}^{FC}$ be the weights corresponding to the updates in the backcast, nowcast and forecast. I temporally weight them in order to have coherent rolling model weights $W_{i,t}^{mdl}$. Define d as the distance from the beginning of the reference quarter.

$$\text{If } 0 \leq d \leq 33, \text{ then } W_{i,t}^{mdl} = \tfrac{33+d}{66} * w_{i,t}^{NC} + \tfrac{33-d}{66} * w_{i,t}^{BC}$$
$$\text{If } 33 \leq d \leq 66, \text{ then } W_{i,t}^{mdl} = \tfrac{99-d}{66} * w_{i,t}^{NC} + \tfrac{d-33}{66} * w_{i,t}^{FC}$$

Then I construct a market-based and a model-based "Nowcasting Surprise Index" from a nowcasting model using these news and weights:

$$SI_t^{mdl} \equiv \sum_{s=t-win}^{t} \sum_{i \in I} W_{i,s}^{mdl} X_{i,s}. \tag{3.5}$$

A ”Nowcasting Surprise Index” has some key features. First, it can potentially include a large number of indicators, as the dynamic factor model assures dimensionality reduction, without needing survey expectations for each variable. Second, the weights are based on macroeconomic news, since what matters to market participants is the unexpected component of the releases, and not on the variables themselves (as in Scotti 2016). Third, it has a rolling reference period, not being based on a fixed event forecast (as the stardard nowcast or as in Grover et al. 2016), making nowcasting totally compatible with surprise indexes.

3.3 Data and nowcasting model

I consider a set of 13 variables relative to the US economy which are reported on Bloomberg with a high ”relevance index”, which is the ratio of alerts requested for new releases of that variable over the total number of alerts, and could be seen as a measure of the importance assigned by financial market operators to that indicator. They are also chosen to have an exact correspondence in the real-time data base of St. Louis Fed (ALFRED), which is the source of the real-time news extracted by a nowcasting model.

An extended dataset for a more comprehensive nowcasting model, used as a robustness check, consists of 26 variables, and includes indicators that are widely followed by practitioners or are often used in the forecasting literature, but with a limited availability or history of Bloomberg expectations. In order to have a fully real-time News Index, it is essential to reconstruct exactly the information set available at each point. I use all the real-time vintages of the releases since 2005 for any single indicator, and I use them reproducing the exact calendar of the releases. The variables are listed in Table 3.1. Starting from the 1st January 2005, the model updates its forecasts at any macroeconomic release. At each point in time, I use the real-time vintage for all the macroeconomic indicators available in that moment. This is the only way to exactly reconstruct the availability of the indicators included

Name	Bloomberg	Transformation
Building Permits	✓	MoM
Capacity Utilization	✓	Diff
Civilian Unemployment Rate	✓	Diff
Conference Board: Consumer Confidence	✓	Level
Consumer Price Index	✓	MoM
Housing Starts	✓	MoM
Industrial Production	✓	MoM
ISM Mfg: PMI Composite Index	✓	Level
Producer Price Index	✓	MoM
Real Gross Domestic Product	✓	MoM
Total Nonfarm Employment	✓	Diff
Trade balance	✓	MoM
University of Michigan: Consumer Sentiment	✓	Level
All Employees: Total Private Industries		MoM
Average Weekly Hours Mfg		MoM
Commercial and Industrial Loans		MoM
Disposable Personal Income		MoM
Inventories to Sales Ratio		Diff
M2 Money Stock		MoM
Mfg New Orders: Durable Goods		MoM
Mfg' New Orders: Nondefense Capital Goods Excl.Aircraft		MoM
Personal Consumption Expenditures		MoM
Personal Consumption Expenditures: Chain-type Price Index		MoM
Producer Price Index of Interm. Materials: Supplies and Components		MoM
Retail Sales		MoM
Total Business Inventories		MoM

Table 3.1: Data used in the analysis. The first 13 variables show an exact correspondence between ALFRED and Bloomberg. In the "Transformation" column, "Diff" stands for "monthly differences" and "MoM" for "month-on-month growth rate".

in the model to a market participant who is assessing the current economic conditions. Data on government bond yields (10-Year Treasury Constant Maturity Rate and the 3-Month Treasury Constant Maturity Rate to calculate the excess returns) and on stock prices (S&P 500 index) have been downloaded from the Federal Reserve Economic Data (FRED) website maintained by the St. Louis Fed.

The dynamic factor model used in this work can be described as follows. The variables are assumed to have a factor structure:

$$x_t = \Lambda f_t + \epsilon_t \tag{3.6}$$

Where x_t is a vector of standardized stationary monthly variables, f_t are unobserved common factors with zero mean and unit variance, Λ are the factor loadings, ϵ_t a vector of idiosyncratic components of dimension N which follow an $AR(1)$ process uncorrelated with f_t at any leads and lags.

The dynamics of the factors is modelled as a stationary Vector Autoregressive process with p lags, in which $A_1, ..., A_p$ are rxr matrices of autoregressive coefficients. I follow the approximation of Mariano & Murasawa (2003), including the quarterly variable in the model as a monthly partially-unobserved variable, in order to accommodate the mixed frequency nature of the dataset. Following Doz et al. (2012*a*), the model is estimated using Maximum Likelihood within an Expectation-Maximization algorithm.[4]

The estimation sample starts in 1991, and the evaluation period is 2005-2014. The specification of the factor model is with 1 factor which follows a $AR(2)$ process (results are robust to changes in the specification).

3.4 Results

In Figure 1 I plot the market-based surprise index against the model-based "Nowcasting Surprise Index". The indexes show a good correlation, meaning that the market participants and the model have been surprised in a similar way by the macroeconomic data flow. Moreover, that means that the impact that macroeconomic news had on 10-year bonds resemble the weights they have been assigned to the same news by the nowcasting model. That could shed some light on why market participants

[4] Banbura & Modugno (2014) adapt the algorithm to an arbitrary pattern of missing data.

reacted to macroeconomic news: their reaction is associated to the news that could change their assessment of the current state of the economy.

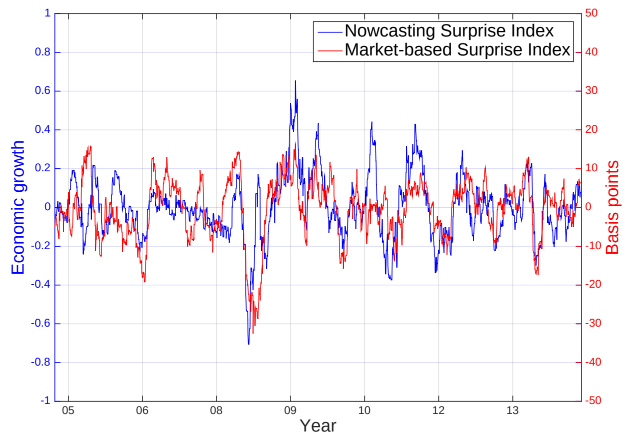


Figure 3.1: Standardized market-based and model-based surprise indexes (13 variables). Window=66 working days.

In Figure 2 I plot the Nowcasting Surprise Index against the S&P 500, and in Table 2 I show the correlation of the indexes with it at different frequency. As reported in Table 3.2, the correlation is notable and increases with the length of the window considered, confirming the result of Altavilla, Giannone & Modugno (2017) that the effect of macroeconomic news is permanent and amplified at lower frequency. The market-based index shows similar properties: the correlation with the asset prices considered is around 40% at quarterly frequency.

Then I estimate the following model using OLS with Newey-West s.e.:

$$\Delta^w AssetReturn_{i,t} = \alpha + \beta_i(Index_t^w) + \epsilon_{i,t} \tag{3.7}$$

Where w can be 22, 44 or 66 working days. For example, if $w = 22$, $AssetReturn_{i,t}^w$ is the monthly return of asset i. As reported in Table 3.3, the R^2 of the regressions using the model-based indexes are similar to the R^2 obtained using the market-based indexes.

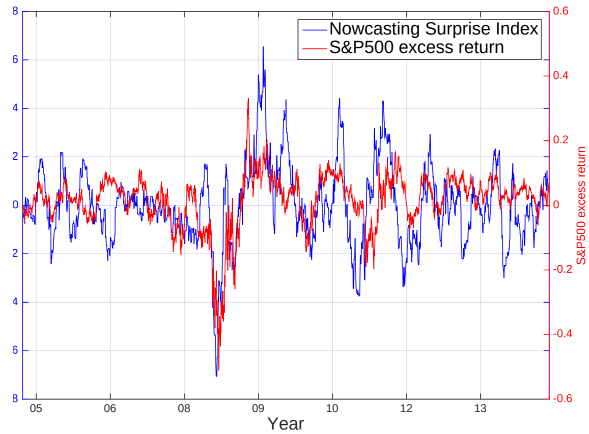


Figure 3.2: Standardized model-based surprise index (13 variables, window=66 working days) and quarterly excess returns of S&P 500.

Table 3.4 reports different correlations with S&P 500 using different combinations of market-based and model-based news and weights. If is worth noticing that if we simply use the nowcast as a surprise index, not using the temporal rolling weighting scheme proposed in this work, the correlation with S&P 500 drops dramatically from 0.42 to 0.25.

3.4.1 News analysis

It is important to study the properties of the market based and of the model-based forecast. Regarding the market-based forecast, some studies (Balduzzi et al. 2001, Andersen et al. 2003, Scotti 2016) show that they are not always efficient. I test the efficiency of forecasts for variable i, F_i (which can be the median of Bloomberg surveys or the model-based forecasts), testing for $\alpha_i = \beta_i = 0$ in the following regression:

$$News_{i,t} = \alpha_i + \beta_i F_{i,t} + \epsilon_{i,t} \tag{3.8}$$

In the spirit of Mincer & Zarnowitz (1969), if the coefficients are jointly significant, we can say that the forecast are not efficient. Table 3.5 reports the results of such

	Nowcasting Surprise Index		
Correlations	1-month	2-months	Quarterly
Change in 10y yields	0.23 / 0.19*	0.33 / 0.30*	0.36 / 0.41*
S&P 500 excess returns	0.23 / 0.23*	0.37 / 0.36*	0.42 / 0.45*

	Market Surprise Index		
Correlations	1-month	2-months	Quarterly
Change in 10y yields	0.33	0.40	0.45
S&P 500 excess returns	0.19	0.33	0.46

Table 3.2: Correlation of the market-based and the model-based indexes (13 variables) with S&P 500 at different frequencies. *Larger model with 26 variables

	Nowcasting Surprise Index		
OLS - R^2	1-month	2-months	Quarterly
Change in 10y yields	0.05 / 0.04*	0.11 / 0.09*	0.17 / 0.17*
S&P 500 excess return	0.04 / 0.05*	0.08 / 0.13*	0.18 / 0.21*

	Market Surprise Index		
OLS - R^2	1-month	2-months	Quarterly
Change in 10y yields	0.11	0.16	0.21
S&P 500 excess return	0.04	0.10	0.19

Table 3.3: Results of regression in equation (6). *Larger model with 26 variables

tests.

As it can be seen from the tables, there are some macroeconomic variables for which either market-based and model-based forecast are not efficient. However, for some important variables (notably, Non-Farm Payrolls, Unemployment rate, CPI), model-based news show better properties than market-based news.

The model-based news are also to replicate the forecasts of the markets in real

		News	
		Market	*Model*
Weights	*Market*	0.46	0.17
	Model	0.40	0.42 / 0.25*

Table 3.4: Correlation at quarterly frequency with S&P 500 excess return of indexes constructed using model or market weights. *Correlation using the nowcast.

Efficiency test - Bloomberg news

	α		β		F		F-pvalue
Industrial Production	-0.300	***	0.781	***	13.849	***	0.000
Capacity Utilization	-0.182	**	0.846	***	15.943	***	0.000
Housing Starts	0.019		0.058	***	8.047	***	0.005
Building Permits	0.022		0.042		1.482		0.226
Trade Balance	0.067		0.000		1.384		0.242
Change in Nonfarm Payrolls	-0.118		-0.001		1.403		0.239
U. of Mich. Sentiment	2.189	***	-0.024	***	8.369	***	0.005
Unemployment Rate	-0.207	**	2.581	***	7.884	***	0.006
CPI	-0.313	***	1.583	***	32.469	***	0.000
PPI	-0.119		0.862	***	34.695	***	0.000
Consumer Confidence Index	-0.072		0.001		0.088		0.767
ISM Manufacturing	1.276		-0.022		1.575		0.212
GDP	-0.041		-0.024		0.095		0.759

Table 3.5: Efficiency test for market-based news.

time. The exercise is particularly relevant and has been done using financial data by Ghysels & Wright (2009). The nowcasting framework permits us to do that even with macroeconomic variables, taking into account all the relevant information, the quality and the timeliness of macroeconomic releases.

In Table 3.7 I report the results of a forecast exercise of the median of the surveys conducted by Bloomberg at the moment of the release, using the model predictions

Efficiency test - Nowcasting news

	α	β		F		F-pvalue
Industrial Production	0.086	-0.610	***	17.067	***	0.000
Capacity Utilization	-0.067	-0.839	***	15.679	***	0.000
Housing Starts	0.020	-0.035		2.376		0.126
Building Permits	0.018	-0.102	*	3.228	*	0.075
Trade Balance	0.009	0.000		0.187		0.666
Change in Nonfarm Payrolls	-0.052	0.001		1.562		0.214
U. of Mich. Sentiment	0.837	-0.011		1.331		0.251
Unemployment Rate	-0.018	1.294		1.736		0.190
CPI	0.085	-0.442		0.532		0.467
PPI	0.099	-0.670	**	3.998	**	0.048
Consumer Confidence Index	0.321	-0.004		1.071		0.303
ISM Manufacturing	0.732	-0.014		0.590		0.444
GDP	0.090	-0.140		0.146		0.705

Table 3.6: Efficiency test for model-based news.

updated up to the previous macroeconomic release. The table shows that, for the majority of the variables, the nowcasting model is able to replicate survey-based forecasts reported by Bloomberg.

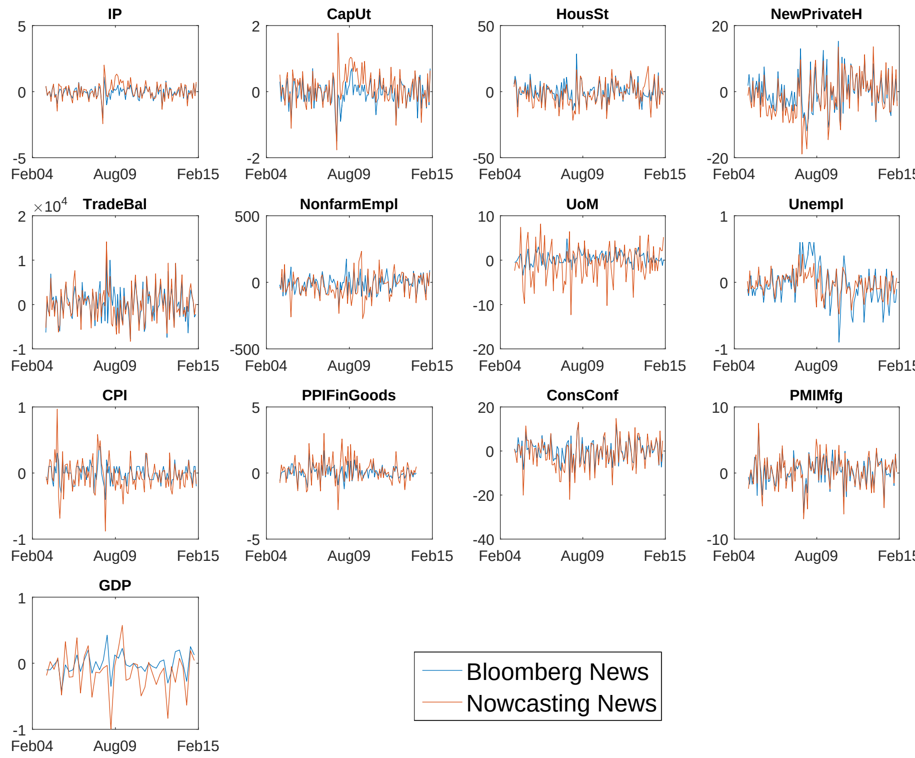


Figure 3.3: Model-based (13 variables) news and market-based news.

3.5 Conclusions

In this chapter I have constructed a real time model-based "Nowcasting Surprise Index", based on weighted forecast errors of macroeconomic variables produced by a nowcasting model for US GDP growth rate. The index behaves in a similar way than market-based news indexes, which are based on survey-based forecast errors weighted by their impact on asset prices: a nowcasting model and market operators filter the flow of macroeconomic data in a similar way. A model-based index has several advantages: it comes from a coherent model that is not prone to judgement, mood or strategic answers; it is cheaper than market-based ones; it can be applied to any country of interest, since it can be built without collecting surveys expectations. The "Nowcasting Surprise Index" shows a good correlation with asset prices

RMSFE relative to previous release	
Capacity Utilization	0.81
Housing Starts	0.67
Building Permits	0.72
Trade Balance	1.21
Change in Nonfarm Payrolls	0.87
U. of Mich. Sentiment	0.75
Unemployment Rate	0.73
CPI	0.63
PPI	1.09
Consumer Confidence Index	0.62
ISM Manufacturing	0.44
GDP	1.27

Real time out of sample, 2005-2014

Table 3.7: The table reports the RMSFE of the model-based forecast in forecasting the median of survey expectations reported by Bloomberg, relative to a forecast equal to the previous release.

at quarterly frequency, confirming the results of a recent literature that links asset prices behaviour at low frequency to a cumulated weighted stream of macroeconomic surprises: a large part of market reaction to macroeconomic news is due to their informational content about the current state of the economy. The results also open a new route to algorithmic trading based on macroeconomic information.

A. 3 Appendix

A.3.1 Other correlations

Table A.3.1 reports the correlations of asset prices with the market-based indexes constructed using as weights the betas of the regression on market-based news of the daily change of USD/EUR exchange rate and of the daily S&P 500 returns.

	Correlations		
	1-month	2-months	3-months
Market-based Index: weights from USD/EUR			
10y yields	0.23	0.29	0.33
S&P 500	0.09	0.17	0.26
USD/EUR	0.07	0.00	-0.11
Market-based Index: weights from S&P 500			
10y yields	0.25	0.30	0.33
S&P 500	0.07	0.18	0.32
USD/EUR	0.03	0.10	0.18

Table A.3.1: Correlation at different frequencies of differences of the 10-year bond yield, S&P 500 returns and change of the USD/EUR exchange rate with the market-based indexes constructed using different weights.

A.3.2 Four different surprise indexes

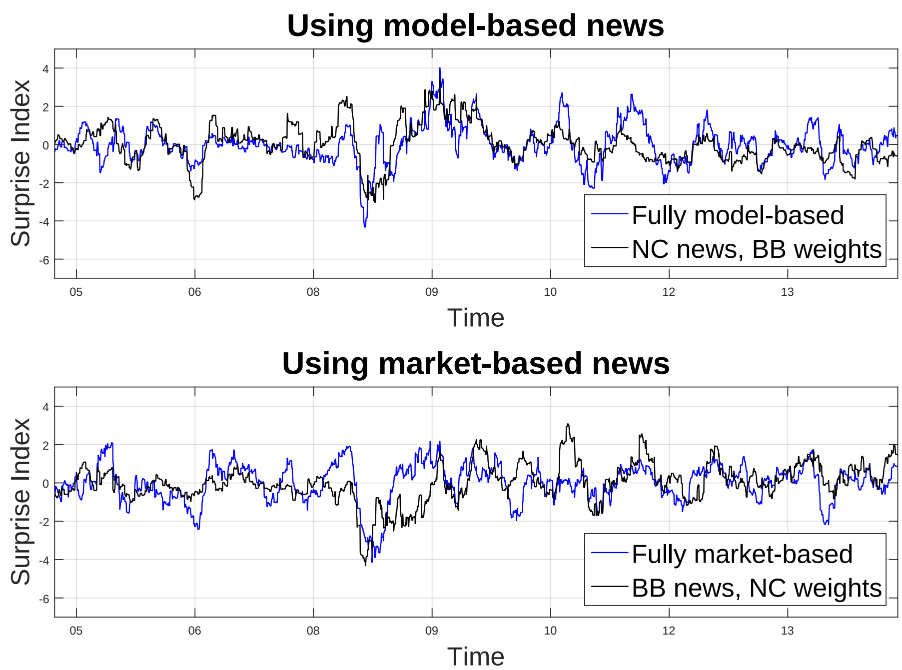


Figure A.3.1: The charts report the indexes constructed using combinations of model-based (NC) and market-based (BB) news and weights (model with 13 variables).

Chapter 4

Does real-time macroeconomic information help to predict interest rates?

We analyse the predictive ability of real-time macroeconomic information for the yield curve of interest rates. We specify a mixed-frequency macro-yields model in real-time that incorporates interest rate surveys and treats macroeconomic factors as unobservable components. Results indicate that real-time macroeconomic information is helpful to predict interest rates, and that data revisions drive a superior predictive ability of revised macro data over real-time macro data. We also find that interest rate surveys can have significant predictive power over and above real-time macro variables.

JEL Classification: C32, C38, C53, E43, E44, G12.

Keywords: Government Bonds; Real-Time Macroeconomics; Forecasting; Survey Data; Factor Models.

1 Introduction

Macroeconomic variables may incorporate important information for forecasting the evolution of the yield curve. This is due to both the behaviour of policy makers, who operate on interest rates to stimulate aggregate demand and control inflation, and market agents, who closely monitor macroeconomic data and react to macroeconomic news (Beechey & Wright 2009, Altavilla, Giannone & Modugno 2017). Indeed, following the seminal work by Ang & Piazzesi (2003), there is a consensus in the literature that macroeconomic indicators are successful at predicting interest rates and excess bond returns.[1] However, Ghysels et al. (2017) find limited evidence of predictive ability of real-time macroeconomic variables for excess bond returns: they argue that the result of the previous literature was an artefact coming from the use of revised data, instead of real-time macroeconomic data.[2]

In this work, we assess the relevance of real-time macroeconomic information to predict the future path of the yield curve of interest rates. Our contribution is to make interest rate predictions based on the information set available to agents at each point in time by taking into account all the characteristics of the real-time macroeconomic data flow.[3] First, most macroeconomic data is released in a non-synchronous way and with different publication lags; therefore the available information at each point in time can be described by a dataset that has a ragged edge, and it is not balanced. Second, macroeconomic data is very often subsequently revised: the revisions might be substantial and affect the estimation and the forecast computed using different vintages of the data. Third, in real-time forecasting, soft information provided by surveys can have an important role as it is timely, not subject to revi-

[1]See among others Mönch (2008), Ludvigson & Ng (2009), Favero et al. (2012) and Coroneo et al. (2016).

[2]A common denominator of this literature, in fact, is the use of revised macroeconomic data to predict interest rates, which involves using an information set that is different from the one available to market participants when the predictions were made.

[3]Adequately specifying the information set available to agents in real-time is particularly important when evaluating models in macroeconomics and finance, especially when the objective is to forecast asset prices using external information, since according to the efficient market hypothesis asset prices should already incorporate all the available information about their future evolution, see Orphanides (2001), Orphanides & Van Norden (2002) and Croushore & Stark (2003).

sions and can readily incorporate any information available to survey participants, such as information about the current state of the economy or forward-looking information contained in monetary policy announcements. However, one drawback of using survey expectations is that they are released only infrequently, most often on a quarterly basis.

In order to exploit the informational content of real-time macro data for interest rate predictions, we specify a mixed-frequency macro-yields model in real-time that incorporates interest rate surveys and treats macroeconomic factors as unobservable components, which we extract simultaneously with the traditional yield curve factors. Similarly to Coroneo et al. (2016), we identify the factors driving the yield curve by constraining the loadings to follow the smooth pattern proposed by Nelson & Siegel (1987). More specifically, our empirical model is a mixed-frequency dynamic factor model for Treasury zero-coupon yields, a representative set of real-time macroeconomic variables and interest rate surveys with restrictions on the factor loadings.

Our model can be estimated by maximum likelihood – see Doz et al. (2012*b*) – using an Expectation-Maximization (EM) algorithm adapted to the presence of restrictions on the factor loadings and to missing data. Using U.S. data from 1972 to 2016, we find that real-time macroeconomic information is helpful to predict interest rates, especially short maturities at mid and long horizons, and that data revisions drive an increase in the predictive power of revised macro information with respect to real-time macro information. Moreover, during a period when a forward guidance policy is implemented, we find that incorporating interest rate surveys in the model significantly improves its predictive ability.

Our finding that data revisions drive the increased predictive ability of revised macro data with respect to real-time macro data is in line with Ghysels et al. (2017). However, while they find that real-time macro information has only a marginal (and often statistically non significant) role in predicting excess bond returns, our results show that real-time macroeconomic information is helpful to predict interest rates, as its predictive power is similar to that of revised macro data. The crucial difference between our approach and the one in Ghysels et al. (2017) lies in how the real-time dataset is specified: we use the latest information available to market participants at the time in which forecasts are made (that includes both new releases of data points and revisions of already observed data), Ghysels et al. (2017) instead use first releases of data. In general, when the objective is to forecast macroeconomic variables, first releases provide accurate predictions (Koenig et al. 2003). However, for predicting financial variables it is important to use all the latest available information, as financial operators care about the final revised value of a macroeconomic series (Gilbert 2011). Indeed, our results indicate that the latest information available on real-time macro variables has a stronger predictive ability than their first releases, which is in line with the intuition that revisions enhance the quality of macroeconomic information.

Lastly, we find that incorporating interest rate surveys from the Surveys of Professional Forecasters can improve the predictive ability of models that use only information embedded in the yield curve and in macroeconomic variables. Surveys, in fact, incorporate soft information about the future path of interest rates – that comes from policy announcements, for example – that cannot be taken into account by standard macroeconomic variables. With this in mind, we test the predictive ability of the model by incorporating surveys in a period in which the Federal Reserve implemented a forward guidance policy. The resulting improvement in predictive ability is statistically significant. This intuitively appealing result is in line with Altavilla, Giacomini & Ragusa (2017), who use the selected survey forecast value as their forecast for the specific horizon and maturity. However, our results show that in some periods our model produces more accurate forecasts than the surveys forecasts. Therefore, we incorporate the surveys into the model itself. In this way, we combine in a single framework the "soft" information embedded in the surveys with the information carried by interest rates and by the real-time macroeconomic data, fully exploiting all the relevant available information in forecasting the whole yield curve.

2 Model

We model the joint behavior of monthly government bond yields, real-time macroeconomic indicators, and quarterly interest rate surveys using a mixed-frequency dynamic factor model. Bond yields at different maturities are driven by the traditional level, slope and curvature factors, while real-time macroeconomic variables load on the yield curve factors as well as on some additional macro factors that capture the information in macroeconomic variables over and above the yield curve factors. Finally, interest rate surveys load on quarterly averages of the monthly yields and macro factors. In what follows, we describe each point in detail.

1 Yields

We model the cross-section of bond yields using the dynamic Nelson-Siegel framework of Diebold & Li (2006). Denoting by y_t the $N_y \times 1$ vector of yields with N_y different maturities at time t, we have:

$$y_t \;=\; a_y + \;\Gamma_{yy}\; F_t^y + v_t^y, \tag{4.1}$$

where F_t^y is a 3×1 vector containing the latent yield-curve factors at time t, Γ_{yy} is a $N_y \times 3$ matrix of factor loadings, and v_t^y is an $N_y \times 1$ vector of idiosyncratic components. The yield curve factors F_t^y are identified by constraining the factor loadings to follow the smooth pattern proposed by Nelson & Siegel (1987)

$$a_y = 0; \quad \Gamma_{yy}^{(\tau)} = \left[1 \;\; \frac{1-e^{-\lambda\tau}}{\lambda\tau} \;\; \frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}\right] \equiv \Gamma_{NS}^{(\tau)}, \tag{4.2}$$

where $\Gamma_{yy}^{(\tau)}$ is the row of the matrix of factor loadings corresponding to the yield with maturity τ months and λ is a decay parameter of the factor loadings. Diebold & Li (2006) show that this functional form of the factor loadings implies that the three yield curve factors can be interpreted as the level, slope, and curvature of the yield curve. The specific shape of the loadings depends on the decay parameter λ, which we calibrate to the value that maximizes the loading on the curvature factor for the yields with maturity 30 months, as in Diebold & Li (2006). Due to its flexibility and parsimony, the Nelson & Siegel (1987) model accurately fits the yield curve and performs well in out-of-sample forecasting exercises, see Diebold & Li (2006) and Coroneo et al. (2011).

2 Real-time macro variables

We assume that real-time macroeconomic variables are potentially driven by two sources of co-movement: the yield curve factors F_t^y and some macro specific factors F_t^x. Denoting by x_t the $N_x \times 1$ vector of real-time macroeconomic variables at time t, we have

$$x_t \;=\; a_x + \Gamma_{xy}\, F_t^y + \Gamma_{xx}\, F_t^x + v_t^x, \tag{4.3}$$

where F_t^x is an $r \times 1$ vector of macroeconomic latent factors, Γ_{xy} is a $N_x \times 3$ matrix of factor loadings of the real-time macro variables on the yield curve factors, Γ_{xx} is a $N_x \times r$ matrix of factor loadings of the real-time macro variables on the macro factors, and v_t^x is an $N_x \times 1$ vector of idiosyncratic components.

To accommodate for the features of the real-time macroeconomic information set, we allow x_t to contain missing values due to publication lags. As for data revisions, these can be easily accommodated in an out-of-sample exercise by using the latest vintage of data available at the date in which the forecasts are made.

Allowing Γ_{xy} to be different from zero is crucial to ensure that the macroeconomic factors F_t^x capture only those source of co-movement in the macroeconomic variables that are not already spanned by the yield curve factors. Also, assuming that macroeconomic factors do not provide any information about the contemporaneous shape of the yield curve ($\Gamma_{yx} = 0$ in (4.1)) restricts the macroeconomic factors F_t^x to be unspanned by the cross-section of yields. This restriction is expected to be immaterial since the yield factors F_t^y are notoriously effective at fitting the entire yield curve. Coroneo et al. (2016) perform a likelihood ratio test for $\Gamma_{yx} = 0$ and do not reject the restriction. They also show that imposing a block-diagonal structure of the factor loadings ($\Gamma_{xy} = 0$ and $\Gamma_{yx} = 0$) implies a duplication of factors and, as a consequence of the loss of parsimony of the model, a deterioration of the forecasting performance. Accordingly, in the remainder of the chapter, we will maintain the restriction $\Gamma_{yx} = 0$ and leave Γ_{xy} unrestricted.

3 Interest rate surveys

The information set that forecasters use in real-time to form their expectations about future interest rates includes not only current and past interest rates and real-time macroeconomic information, but also interest rate surveys. However, they are usually available at a lower frequency than interest rates, most often on a quarterly basis.

Surveys might be good predictors for the yield curve, because they can embed "soft" and forward-looking information which is difficult to incorporate in econometric models. For example, they can take into account policy announcements, which are of fundamental importance in periods in which forward guidance is used by central banks, or they can consider the existence of possible non-linearities, for example the presence of a zero lower bound for interest rates.

A successful attempt to incorporate information from surveys in econometric models for forecasting the yield curve is in Altavilla, Giacomini & Ragusa (2017). They anchor the model forecasts to interest rate surveys and find that using survey data on the 3-month Treasury Bill can significantly improve the forecasting performance of the Dynamic Nelson-Siegel model. Accordingly, we exploit the informational content of the Survey of Professional Forecasters (SPF) on the 3-month Treasury Bill. However, while Altavilla, Giacomini & Ragusa (2017) use the selected survey forecast value as their forecast for the specific horizon and maturity, in our case we incorporate survey forecasts into our model such that all forecasts take into account all the available information (yields, real-time macro variables and survey expectations).

Forecasts from the SPF are released the middle of the quarter for the current quarter and the following four quarters. Given that the values reported are quarterly averages, we can denote the SPF forecast for the quarterly yield at time t made at time $t-h$ as $E^s_{t-h}(y^q_{t,\tau})$. This forecast is related to the unobservable monthly forecasts as follows

$$E^s_{t-h}(y^q_{t,\tau}) = \frac{1}{3}\left[E^s_{t-h}(y_{t,\tau}) + E^s_{t-h}(y_{t-1,\tau}) + E^s_{t-h}(y_{t-2,\tau})\right], \; t = 3, 6, 9, \dots \tag{4.4}$$

We assume that the unobservable monthly forecast is related to the monthly factors as follows

$$E^s_{t-h}(y_{t,\tau}) = a_s + \Gamma_{h,\tau} F_t + v_{t,h,\tau}$$

where $F_t = [F^y_t, F^x_t]$. Substituting in (4.4) we get

$$E^s_{t-h}(y^q_{t,\tau}) = a_s + \Gamma_{h,\tau}\left(\frac{1}{3}F_t + \frac{1}{3}F_{t-1} + \frac{1}{3}F_{t-2}\right) + v^q_{t,h,\tau} = a_s + \Gamma_{h,\tau} F^q_t + v^q_{t,h,\tau}, \; t = 3, 6, 9, \dots \tag{4.5}$$

where F_t^q are the quarterly factors measured as quarterly averages of the monthly factors F_t, F_{t-1} and F_{t-2}, and $v_{t,h,\tau}^q$ follows an AR(1) to allow for persistent divergences between SPF and model based forecasts.

We can write the quarterly factors at a monthly frequency, such that at the end of the quarter they represent the quarterly average, as follows

$$F_t^q = \begin{cases} F_t, & t = 1, 4, 7, 10, \ldots \\ \frac{1}{2}F_{t-1}^q + \frac{1}{2}F_t, & t = 2, 5, 8, 11, \ldots \\ \frac{2}{3}F_{t-1}^q + \frac{1}{3}F_t, & \text{otherwise.} \end{cases}$$

This can be represented as

$$F_t^q - w_t F_t = \iota_t F_{t-1}^q \tag{4.6}$$

where w_t is equal to $1, 1/2, 1/3$ respectively the first, second and third month of the quarter, and ι_t is equal to $0, 1/2, 2/3$ respectively the first, second and third month of the quarter.

4 Joint model

The yield curve and the macroeconomic factors are extracted by estimating (4.1), (4.3) and (4.5) simultaneously

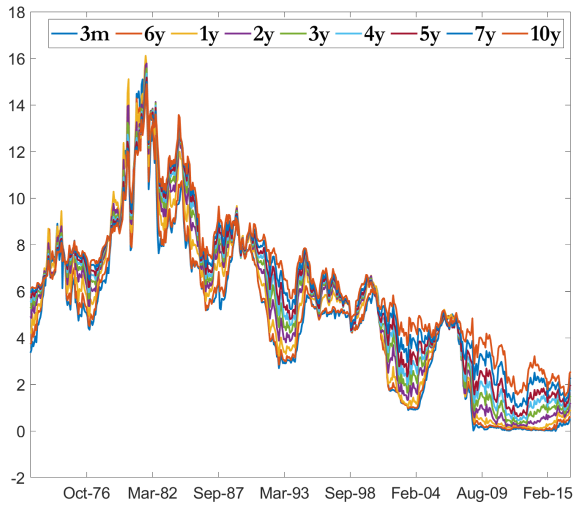
$$\begin{pmatrix} y_t \\ x_t \\ E^s(y_t^q) \end{pmatrix} = \begin{pmatrix} 0 \\ a_x \\ a_s \end{pmatrix} + \begin{bmatrix} \Gamma_{yy} & \Gamma_{yx} & 0 \\ \Gamma_{xy} & \Gamma_{xx} & 0 \\ 0 & 0 & \Gamma_q \end{bmatrix} \begin{pmatrix} F_t^y \\ F_t^x \\ F_t^q \end{pmatrix} + \begin{pmatrix} v_t^y \\ v_t^x \\ v_t^q \end{pmatrix}, \; \Gamma_{yy} = \Gamma_{NS}, \; \Gamma_{yx} = 0, \tag{4.7}$$

where $F_t^q = [F_t^{yq}, F_t^{xq}]$. The joint dynamics of the yield curve and the macroeconomic factors follow

$$\begin{pmatrix} F_t \\ F_t^q \end{pmatrix} = \begin{pmatrix} \mu \\ w_t \mu \end{pmatrix} + \begin{bmatrix} A & 0 \\ w_t A & \iota_t I_r \end{bmatrix} \begin{pmatrix} F_{t-1} \\ F_{t-1}^q \end{pmatrix} + \begin{pmatrix} u_t \\ w_t u_t \end{pmatrix}, u_t \sim N(0, Q), \tag{4.8}$$

where $F_t = [F_t^y, F_t^x]$. This is a VAR(1) with time-varying coefficients, where w_t is equal to $1, 1/2, 1/3$ respectively the first, second and third month of the quarter, and ι_t is equal to $0, 1/2, 2/3$ respectively the first, second and third month of the quarter, as in (4.6).

Figure 1: Interest rates data



The chart shows the interest rates data used in our analysis.

The idiosyncratic components collected in $v_t = [v_t^y \quad v_t^x \quad v_t^q]'$ are modelled to follow independent autoregressive processes:

$$v_t = Bv_{t-1} + \xi_t, \quad \xi_t \sim N(0, R) \tag{4.9}$$

where B and R are diagonal matrices, implying that the common factors fully account for the joint correlation of the observations. The residuals to the idiosyncratic components of the individual variables, ξ_t, and the innovations driving the common factors, u_t, are assumed to be normally distributed and mutually independent. This assumption implies that the common factors are not allowed to react to variable specific shocks.

3 Data

Our dataset for interest rates and macroeconomic variables consists of U.S. observations from January 1972 to December 2016. For interest rates, we use end-of-month zero-coupon yields on 3-month and 6-month Treasury Bills from the FRED dataset, and on 1, 2, 3, 4, 5, 7 and 10-year bonds from the Federal Reserve Board dataset. In Figure 1 we plot the time series of interest rates in our sample. The figure shows a strong comovement among interest rates, and that, in the last period, short term interest rates are close to the zero lower bound.

Series N.	Mnemonic	Description	Transf.	Delay (days)
1	AHE	Average Hourly Earnings: Total Private	1	4
2	CPI	Consumer Price Index: All Items	1	15
3	INC	Real Disposable Personal Income	1	28
4	FFR	Effective Federal Funds Rate	0	0
5	HSal	New One Family Houses Sold	1	24
6	IP	Industrial Production Index	1	16
7	M1	M1 Money Stock	1	3
8	Manf	PMI Composite Index (NAPM)	0	1
9	Paym	All Employees: Total nonfarm	1	4
10	PCE	Personal Consumption Expenditures	1	28
11	PPIc	Producer Price Index: Crude Materials	1	16
12	PPIf	Producer Price Index: Finished Goods	1	16
13	CU	Capacity Utilization: Total Industry	0	16
14	Unem	Civilian Unemployment Rate	0	14
15	CC	Conf. Board Consumer Confidence	0	-3
16	GBA	Philadelphia Fed Outlook survey	0	-15

Note: real-time macroeconomic data descriptions, transformations and publication delays (number of days from the end of the reference month). Transformation codes: 0 = no transformation, 1 = annual growth rate. Source: Archival Federal Reserve Economic Database (ALFRED).

Table 1: Real-time macroeconomic data

As for macro variables, we use a monthly real-time data set using the vintages available in the Archival Federal Reserve Economic Database (ALFRED) of the Federal Reserve Bank of St. Louis and the accurate publication pattern. Macroeconomic data and the publication delay of the variables are described in Table 1. We use 16 macroeconomic variables, including real activity indicators, inflation measures, surveys, one money aggregate and the Federal Funds rate.[4] We use annual growth rates for all variables, except for capacity utilization, the federal funds rate, the unemployment and the surveys, that we keep in levels. With the exception of the Conference Board Consumer Confidence survey and the GBA Philadelphia Fed Outlook survey, this is the same macro data set considered in Coroneo et al. (2016). We add these two surveys because of their timeliness and therefore the possibility to include early information in the forecasts: they are released before the start of the reference period (3 and 15 days before), so being amongst the first macroeconomic signals about economic activity taken into account by a forecaster. All the other macroeconomic indicators, with the exception of the Federal Funds rate, are released only after the end of the reference period, which means that in real-time their value for the current month is not available when forming expectations about future interest rates.

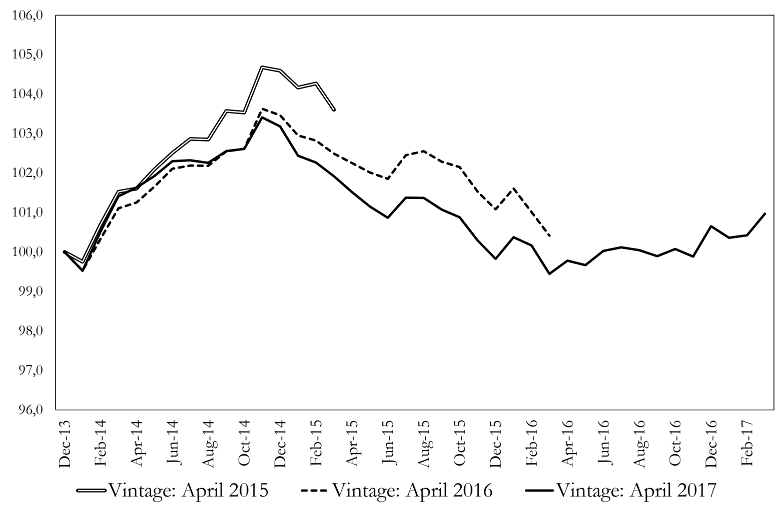
To illustrate the relevance of revisions in macroeconomic series, in Figure 2 we look at an example. The chart refers to the data for US Industrial Production as released in three different vintages, in April 2015, 2016 and 2017. As shown in the chart, the series is subject to substantial revisions: the information in real-time can be substantially different from the one that we can get using revised data. It is, therefore, important to use the information available in real-time when evaluating the forecasting performance.[5]

In Table 2, we give an example of the information set relative to Industrial Production in different points in time, in what is called a "revision triangle". In the top panel, the columns represent the publication date of a vintage of data, and correspond to the information set that a forecaster has until the following release. The rows represent the reference period. If a forecaster needs the data relative to

[4]We use a medium-size data set as it has been proven that such dimension provides the best results in forecasting macroeconomic variables using dynamic factor models (Boivin & Ng 2006, Banbura et al. 2013*a*, Banbura & Modugno 2014).

[5]We recall that, however, if the revisions are weakly cross-correlated, factor extraction is robust to data revisions (Giannone et al. 2008).

Figure 2: Example: revisions in Industrial Production



The chart shows an example of data revisions in macroeconomic series, showing data for US Industrial Production as released in April 2015, April 2016, April 2017. Data are normalized (avoiding rebasing issues) constructing indexes, putting 100=December 2013. Source: authors' calculations on ALFRED data.

April, she must wait until the 15th May, date in which the April data gets released. However, that data point, the "first release" (104.1), is subject to revisions: on the 15th June, the data is revised to 104.0; then, after other revisions, she reads the final revised data (last column), 102.9. The series of "Revised data" for Industrial Production, therefore, corresponds to the last column. "First Releases" corresponds to the first available data for each reference period (the bold diagonal). A series in real-time corresponds to any of the first four columns of the table. Keeping this revision process in mind, we consider the following definitions of our macro dataset:

- Revised data: we consider the data as available on 31 March 2017, incorporating all data revisions, in a balanced dataset.

- Pseudo Real-Time: we still consider the revised data as available on 31 March

Table 2: Industrial production - revision triangle and construction of the dataset

	15-Apr-16	15-May-16	15-Jun-16	15-Jul-16	...	31-Mar-17
Mar-16	**103.4**	103.5	103.4	103.4	...	**102.5**
Apr-16		**104.1**	104.0	103.8	...	**102.9**
May-16			**103.6**	103.5	...	**102.8**
Jun-16				**104.1**	...	**103.1**

		Revised	*Pseudo RT*	*Real-Time*	*First release*	
Mar-16		102.5	102.5	103.4	103.4	
Apr-16		102.9	102.9	104.0	104.1	
May-16		102.8	102.8	103.6	103.6	
Jun-16		103.1	-	-	-	

The top panel reports five vintages of data relative to Industrial Production. The names of the columns represent the release dates of the vintages, the rows represent the reference period of each data point. The bottom panel reports the different possibilities in constructing the macro series for a forecast conducted on the 30 of June 2016, following the definitions reported in the main text.

2017, but using the correct calendar of macroeconomic releases and publication lags, in a "ragged edge" dataset with missing data at the end.

- Real-Time: this is the proper real-time dataset that uses both real-time vintages and the correct publication lag structure, as such it takes into account the exact information set at the vintage date (ragged edge dataset). The last value of a series is the first release of that data point, while the previous data points are reported as revised on that specific vintage date.

- First Releases: we consider only the first release for each data point, taking into account the correct publication lag structure (ragged edge dataset).

The bottom panel of Table 2 reports an example of these definitions for the case of a forecast made on the 30th of June 2016. The table shows that using the Revised dataset, we have one extra data point (Jun-16) that in reality was not available to forecasters at the end of June 2016; taking this point away, we have the Pseudo Real-

Time dataset. Both these datasets use finally revised values that can be different from the data available at the end of June 2016. The Real-Time dataset has values for the Industrial Production that are as released on the 15th of June 2016. The last value of this series is the first release for May 2016, while the previous data points are reported as revised on the 15th of June 2016. Finally, the First Release data collects all the first releases: the data point for March 2016 (released the 15th of April 2016), the data point for April 2016 (released the 15th of May 2016) and the data point for May 2016 (released on the 15th of June 2016).

Surveys of Professional Forecasters data on the 3-month Treasury Bill are provided by the Federal Reserve Bank of Philadelphia at quarterly frequency. Data are quarterly averages of the daily levels of interest rates, available since 1981:Q3, and we use the median forecast of the 3-month Treasury Bill collected for three and four quarters ahead.[6]. The surveys were conducted by the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER) until 1990:Q2, and then by the Philadelphia Fed. The deadlines for the answers are known since 1990:Q3 and are in the middle of the second month of the quarter. Since the deadlines for the respondents define their information set, we fix the release dates in correspondence to those deadlines on the 15th of the second month of the quarter.

4 Estimation and preliminary results

The mixed-frequency real-time macro-yields model in equations (4.7)-(4.9) can be cast in a state-space form by augmenting the state variables to include the intercept and the idiosyncratic components, for details see Appendix A.4.1. Following Doz et al. (2012*b*), we estimate the model by quasi-maximum likelihood using an Expectation-Maximization (EM) algorithm initialized by Principal Components. The complication of having a ragged edge data set, which involves missing data also at the end of the sample, can be solved by adapting the EM algorithm to the presence of missing data, as in Banbura & Modugno (2014). Also, the factor loading restrictions that identify the yield curve factors can be imposed by performing a

[6]The horizon up to one year is the same as in Kim & Orphanides (2012).

constrained maximization in the EM algorithm, for more details see Appendix A.4.2.

For comparison, we also estimate an only-yields model, which uses only the information contained in yields. This is a restricted version of the macro-yields model in Equations (4.7)-(4.9) with $\Gamma_{xy} = 0$, $A_{yx} = 0$ and $Q_{yx} = 0$, and can hence be estimated using the same procedure.

To select the number of factors, we use the information criterion (IC) of Coroneo et al. (2016), which is a modification of the Bai & Ng (2002) criterion to account for the fact that the estimation is performed by quasi-maximum likelihood. We report in Table 3 the IC and the average variance of the idiosyncratic components when different numbers of factors are estimated. Results refer to both the subsample up to the Great Recession (from 1972 to 2008) and to the full sample (from 1972 to 2016). In the sample up to 2008, we find that the IC is minimized for the model with 5 factors, as in Coroneo et al. (2016). In the full sample, however, the information criterion does not deliver clear-cut results as the IC is minimised in correspondence of both 4 and 5 factors. This is due to the fact that the decrease in the variance of the idiosyncratic component achieved by adding the fifth factor is lower in the full sample than in the sample up to 2008, indicating a more marginal role of the fifth factor in the last part of the sample. Therefore, after 2008, we select the more parsimonious model, with four factors.

5 Out-of-sample forecast

We design a forecasting exercise in a truly real-time out-of-sample fashion. We perform a recursive estimation using data starting in January 1972 and use the out-of-sample evaluation period from January 1995 to December 2016. We reconstruct the information set available to forecasters at each point in time in which the forecast is computed, that is at the end of each month of the out-of-sample period, using the information available at that time. This entails using the real-time vintages for all the variables in the dataset, and also reconstructing the exact calendar of the releases. Since the macroeconomic data releases are not synchronous, we have to deal with the ragged edge of the dataset: as stated above, the estimation performed within an Expectation-Maximization algorithm conveniently helps us in this respect.

Table 3: Model selection

	1972-2008		1972-2016	
N. of factors	**IC**	**V**	**IC**	**V**
3	-0.05	0.43	-0.06	0.43
4	-0.16	0.30	-0.15	0.30
5	-0.22	0.21	-0.15	0.23
6	-0.19	0.17	-0.10	0.19
7	-0.07	0.15	0.01	0.16
8	0.06	0.13	0.09	0.13

Note: the table reports the IC criterion relative to models with different numbers of factors, following the modified version of the Bai & Ng (2002) criterion described in Coroneo et al. (2016). Columns IC report the information criteria, columns V report the average variance of the idiosyncratic components.

Being aware of the presence of the zero lower bound for interest rates, a serious issue since 2008, we impose non-negativity of the predicted interest rates as follows

$$E_t(y_{t+h}^{(\tau)}) \equiv \hat{y}_{t+h|t} = \max(\hat{\Gamma}_{|t}^{y*} \hat{F}_{t+h|t}^{*}, 0)$$

where $\hat{\Gamma}_{|t}^{y*}$ contains the factor loadings for yields and is estimated using information up to time t and $\hat{F}_{t+h|t}^{*} \equiv E_t(F_{t+h}^{*})$ is the out-of-sample iterative forecast of the factors.[7] We take as benchmark the forecast at horizon h for the maturity τ produced by a random walk at time t

$$E_t(y_{t+h}^{(\tau)}) \equiv \hat{y}_{t+h|t}^{(\tau)} = y_t^{(\tau)}.$$

[7]See Appendix A.4.2 for the definitions of Γ^* and F_t^*.

6 Results

Our empirical results are organised into two parts. First, we assess the predictive content of real-time macroeconomic information for interest rates by comparing the out-of-sample performance of a macro-yield model in real-time with one that uses revised macro data. We then add the interest rate surveys into the model, and analyse their role over and above real-time macroeconomic information.

1 Real-time macro data: is it useful?

In order to assess the role of the real-time macroeconomic data flow for interest rate predictions, in this section, we report the out-of-sample evaluation of the macro-yields model using real-time data.

In Table 4, we report the MSFE (relative to the random walk) of the only-yields model, the macro-yields model using revised macro data and the macro-yields model using real-time macro data. We test for the significance of their outperformance with respect to the random walk using the Diebold & Mariano (1995) test statistic with fixed-b asymptotics to avoid size distortions due to small sample size and autocorrelation in the loss differentials, see Coroneo & Iacone (2020). Results indicate that macroeconomic data has a strong predictive ability for interest rates especially at long forecasting horizons and short-mid maturities, while the only-yields model never outperforms the random walk. The forecasting ability is stronger using revised data, but robust to the use of real-time macro data: the real-time macro-yields model forecasts significantly better than the random walk at short maturities for mid-long forecasting horizons.

In order to understand the drivers of the difference in the forecasting performance between revised and real-time macroeconomic information, in Figure 3 we plot the Mean Squared Forecast Error of the macro-yields model using the four different definitions of the macroeconomic dataset described in Section 3: the revised, the pseudo real-time, the real-time and the first releases datasets. Results indicate that the macro-yields model consistently outperforms the random walk at short maturities for all horizons. The real-time macro-yields model is slightly worse than the macro-yields using revised data and pseudo real-time data, but it still outperforms the

Table 4: Relative MSFE, Evaluation: 1995-2016

Only-yields model

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	1.02	1.04	1.02	1.05	1.05	1.04	1.04	1.04	1.02
3	1.06	1.10	1.07	1.12	1.12	1.11	1.10	1.10	1.05
6	1.06	1.13	1.13	1.21	1.21	1.20	1.19	1.18	1.12
12	1.05	1.10	1.12	1.28	1.35	1.38	1.38	1.37	1.23
24	1.13	1.15	1.13	1.33	1.51	1.64	1.75	1.91	1.80

Macro-yields model

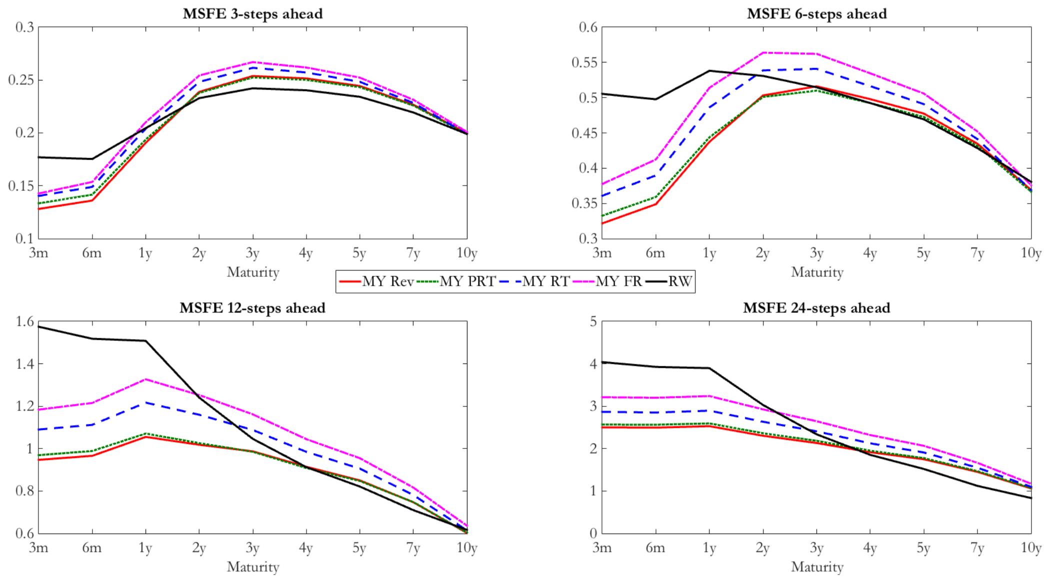
	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	0.84	0.89	0.98	1.03	1.04	1.04	1.03	1.03	1.02
3	0.72*	0.78*	0.93	1.03	1.05	1.05	1.04	1.03	1.00
6	0.64**	0.70*	0.81*	0.95	1.00	1.01	1.02	1.01	0.97
12	0.60**	0.64**	0.70**	0.82*	0.94	1.00	1.04	1.05	0.98
24	0.62**	0.64**	0.65**	0.76*	0.91	1.03	1.15	1.29	1.27

Real-time macro-yields model

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	0.90	0.93	0.98	1.06	1.06	1.05	1.04	1.03	1.02
3	0.79	0.85	1.00	1.07	1.08	1.07	1.06	1.04	1.00
6	0.71**	0.78*	0.90	0.95	1.05	1.05	1.05	1.03	0.97
12	0.69**	0.73*	0.81*	0.93	1.04	1.08	1.10	1.10	1.00
24	0.71*	0.73*	0.74*	0.87	1.03	1.15	1.26	1.38	1.32

Note: The table reports the relative Mean Squared Forecast Error relative to the random walk of the only-yields model (top panel), the macro-yields model (middle panel) and the Real-time macro-yields model (bottom panel), for the evaluation period 1995-2016. A number smaller than one indicates that the model performs better than the random walk. (*) and (**) indicate one-side significance at the 10% and 5%, respectively, using the Diebold & Mariano (1995) test statistic with fixed-b asymptotics, as in Coroneo & Iacone (2020).

Figure 3: Real-time macroeconomic information



Mean Squared Forecast Error for the macro-yields model with revised data (MY Rev), the macro-yields model with pseudo real-time data (MY PRT), the macro-yields model with truly real-time data (MY RT), the macro-yields model with first releases (MY FR), and the random walk. Evaluation period 1995-2016.

random walk at short maturities for all horizons: this indicates that macroeconomic information is useful in predicting interest rates, even when using real-time data. Taking into account only the publication lags plays a lesser role, since the model in pseudo real-time has a forecasting performance very similar to the one with revised data. The model that uses the first releases, instead, performs worse than the others: this is consistent with the intuition that revisions improve the quality of macroeconomic data and, as a consequence, the signal they convey about the future path of interest rates. Therefore, we can conclude that the main drivers of the difference in forecasting performance between the model that uses revised macro data and the one that uses real-time macro data are the data revisions.

Our results are different from the general message of Ghysels et al. (2017)[8]. In addition to the finding that a "real-time" dataset is significantly less powerful in such a forecasting exercise (our results are milder in this respect), they also find that it also performs worse than a dataset with first releases. Their definition of "real-time" differs from ours: their dataset corresponds to our definition of "first releases", lagged by one period (for macro variables with a "standard" publication lag, like Industrial Production) to take into account the publication lags; instead, we use the latest information available at the time the forecast is computed, including the revisions occurred up to that point in time, and treat publication lags as missing observations. In this way, the information set closely mimics the data available to the forecaster in real-time, maintaining the contemporaneous relationships between macro variables and interest rates. The filtering techniques widely used in the nowcasting literature (for details see Banbura et al. 2013*a*) conveniently help us in order to efficiently incorporate missing variables and properly treat a ragged edge dataset.

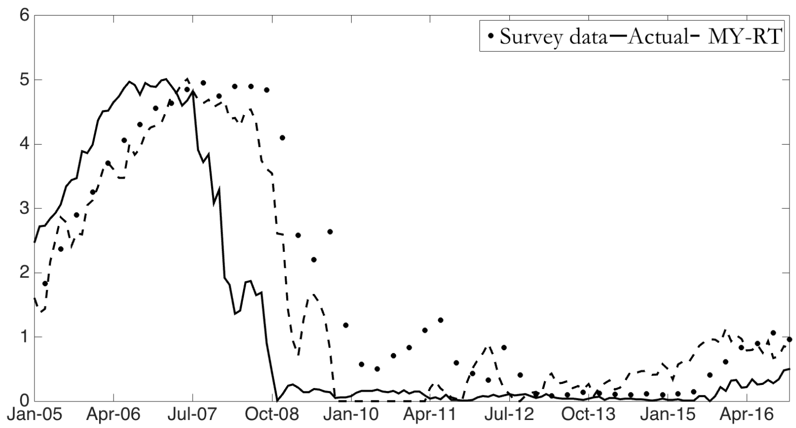
2 Interest rate surveys: do they help?

We now add the Surveys of Professional Forecasters data on the 3-month Treasury Bill to our real-time dataset, in order to evaluate if they contain additional information to predict the yield curve. We recall that we use the median forecast of the 3-month Treasury Bill collected for three and four quarters ahead. In fact, we assume that at this horizon soft information about monetary policy can play a strong role, especially during periods in which the FOMC uses forward guidance.

As a preliminary evidence of the importance of including interest rate surveys in our macro-yield model, in Figure 4, we report the 12-month ahead forecast for the 3-month interest rate obtained from the macro-yield model in real-time, along with the four-quarters ahead survey for the quarterly average of the 3-month Treasury Bill, and the realised value. The figure shows how the macro-yield model is able to provide predictions that are closer to the realised value than the survey forecasts from 2007Q3 up to 2012Q2. After this date, the surveys consistently predict very low values for the 3-month rate, and these predictions are correct. Only at the

[8]Note that their analysis refers to excess returns, and is based on a different sample.

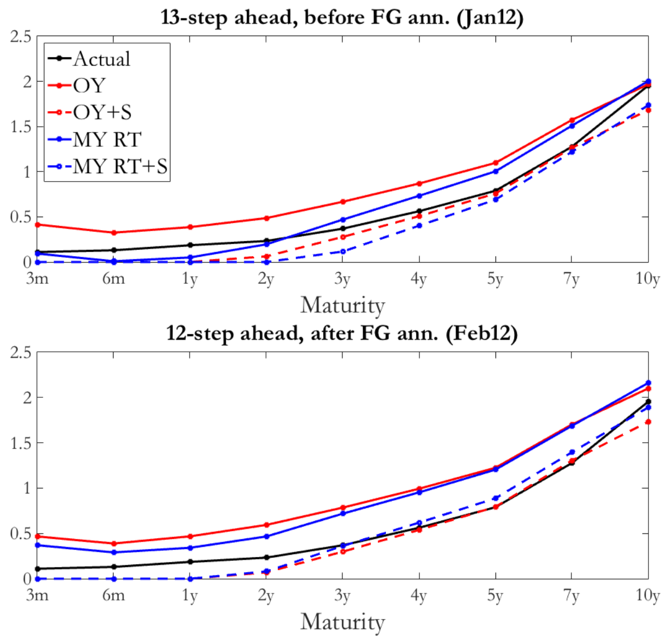
Figure 4: Forecasts: macro-yield model in real-time vs. interest rate surveys



The charts report the 12-month ahead forecast for the 3-month interest rate obtained from the macro-yield model in real-time (MY-RT, dashed line), the four-quarters ahead survey for the quarterly average of the 3-month Treasury Bill (Survey Data), and the realised value (Actual, solid line).

very end of the sample, the macro-yield model in real-time provides more accurate predictions than the surveys again. This is due to the fact that on August 9, 2011 the FOMC announced that it would likely keep the federal funds rate at exceptionally low levels "at least through mid-2013". In the figure, we can see the effect of the announcement on the decline of the survey forecast for 2012Q3, which was formed one year ahead, i.e. just after the forward guidance announcement. The figure also shows that forward guidance announcements have been effective at stabilizing expectations up to mid-2014 when the one-year ahead predictions for mid-2015 indicated a rise in interest rates. On the other hand, the macro-yield model in real-time could not incorporate this type of announcement, and for all this period predicted low interest rates but higher than expected from the survey. Notice also that the time varying relative importance of model-based and survey-based forecasts signals the advantage of efficiently combining the different sources of information.

Figure 5: Example: forecasts made before and after a FG announcement



The charts report the forecasts relative to the yield curve in February 2013, made in January 2012 (top panel) and in February 2012 (bottom panel), produced by the only-yields model (OY), the only-yields model plus surveys (OY+S), the real-time macro-yields model (MY) and the real-time macro-yields model plus surveys (MY+S), along with the realized yield curve (Actual) in February 2013.

In Figure 5 we give an intuitive example of the mechanism for which the use of surveys helps to improve the forecasts of the model. In the top panel, we report the 13-month ahead forecasts from the only-yields and the real-time macro-yields model (both with and without the interest rate surveys) made in January 2012, along with the actual realization of the yield curve in February 2013. In the bottom panel, we report the forecasts for February 2013 made one month later, i.e. in February 2012. In between, there have been some macroeconomic releases and revisions, which induced the revisions of the forecasts made using the macro-yields model, but more importantly, there has been an FOMC release with a "forward guidance type" announcement on the 25th of January 2012.[9] In February, the macroeconomic news releases (and the revisions) brought up the forecasts produced by the macro-yields model (solid blue line), but the forecasts obtained using the information in the surveys are lower and closer to the realised values. Notice how, despite including information only on survey forecasts for the 3-month Treasury Bill, the forecasts for all interest rates incorporate this information and, as a consequence, are much lower than in the models that do not use interest rate survey forecasts.

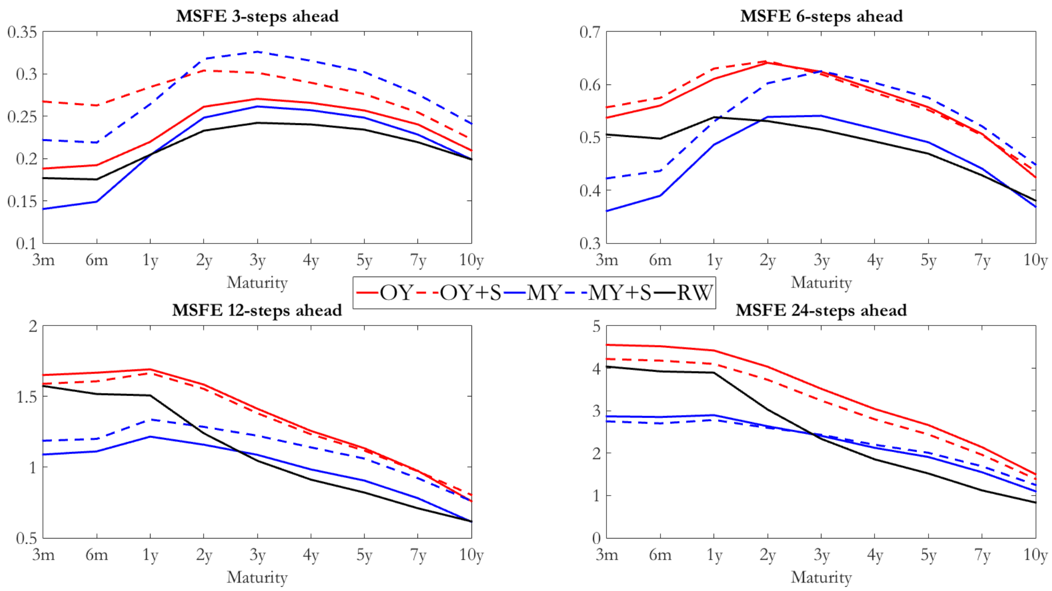
To assess whether interest rate surveys indeed help in predicting interest rates, in Figure 6 we report MSFEs for the macro-yields model in real-time and the only-yields model, both with and without surveys. Results show that in general surveys worsen the results almost on all occasions, and when they bring useful information the impact is marginal (as in the case of the 24-month forecasting horizon). This indicates that, overall, all the relevant information to predict interest rates in real-time can be extracted only from yields and macroeconomic variables. However, as stated above, we expect that there are circumstances in which soft information from surveys can bring additional value to the model, as in the case of forward guidance announcements.

To this aim, we test the relevance of the 3 and 4 quarters ahead survey forecasts for the 3-month Treasury Bill rate from the Survey of Professional Forecasters in a period in which the Federal Reserve adopted an "Odyssean" forward guidance, i.e. since when in FOMC statements we can find an explicit reference to future dates.[10]. In Table 5, we report relative Mean Squared Forecast Error of the only-yields model with surveys relative to the only-yields model (top panel) and of the real-time macro-yields model with surveys relative to the real-time macro-yields (bottom panel), for the evaluation period going from August 2011 to June 2015. Results indicate that the use of Survey of Professional Forecasters, in a mixed-frequency model, improves the

[9] The statement reads as follows "(...) the Committee decided today to keep the target range for the federal funds rate at 0 to 1/4 percent and currently anticipates that economic conditions–including low rates of resource utilization and a subdued outlook for inflation over the medium run–are likely to warrant exceptionally low levels for the federal funds rate at least through late 2014." Source: https://www.federalreserve.gov/newsevents/pressreleases/monetary20120125a.htm.

[10] On this topic, see Campbell et al. (2012).

Figure 6: Information from surveys



Mean Squared Forecast Error for the only-yields model without (OY) and with surveys (OY+S), of the macro-yields model without (MY) and with surveys (MY+S), and the random walk (RW). Evaluation period: 1995-2016.

predictive power of both the only-yields model and the real-time macro-yields model. In particular, the improvement is statistically significant for long horizons and short maturities, which are the cases in which a forward guidance announcement is hoped to be effective. Note that the results show that adding the Surveys of Professional Forecasters is more beneficial to the only-yields model than to the macro-yields one, as surveys may carry some information about the state of the economy that is already embedded in "standard" real-time macroeconomic variables.

Table 5: The usefulness of SPF (RMSFE, August 2011 to June 2015)

(OnlyYields with SPF) vs OnlyYields

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	1.13	1.41	1.89	1.32	1.1	1.06	1.04	1.03	1.05
3	0.48*	0.72	0.87	1.04	0.98	0.99	1.00	0.98	1.05
6	0.11**	0.3**	0.52	0.73	0.92	1.04	1.08	1.03	1.15
12	0.05**	0.17**	0.45*	0.62	0.91	1.04	1.08	1.07	1.19
24	0.25**	0.19**	0.23**	0.51**	0.81	1.00	1.07	1.05	1.18

(RT MacroYields with SPF) vs RT MacroYields

	3m	6m	1y	2y	3y	4y	5y	7y	10y
1	1.23	2.41	2.13	1.23	1.06	1.02	1.01	1.00	1.00
3	0.74**	1.14	1.25	1.21	1.03	1.04	1.02	1.00	1.03
6	0.49**	0.61*	0.68	0.99	1.00	1.10	1.09	1.04	1.08
12	0.34**	0.33**	0.44*	0.65	0.75	0.83	0.86	0.88	0.94
24	0.87	0.87	0.87	0.91	0.93	0.95	0.96	0.94	0.98

Note: The table reports the relative Mean Squared Forecast Error of the only-yields model with SPF relative to the only-yields model (top panel) and of the macro-yields model with SPF relative to the macro-yields (bottom panel), for the evaluation period Aug2011-Jun2015. A number smaller than one indicates that the model with SPF performs better. (*) and (**) indicate one-side significance at 10% and 5%, respectively, Diebold and Mariano (1995) test statistic with fixed-b asymptotics, as in Coroneo and Iacone (2018).

7 Conclusions

In this chapter, we assess the predictive ability of real-time macroeconomic information and interest rates surveys for the yield curve of interest rates. We propose a mixed-frequency dynamic factor model with restrictions on the factor loadings which includes Treasury yields, a set of real-time macroeconomic variables and interest rate survey expectations. Through the lens of a real-time out-of-sample exercise, we document the following findings.

First, we show the importance of macroeconomic information in predicting interest rates in a fully real-time out-of-sample exercise in which, in order to reconstruct the information set available to market participants at each point in time, we use the real-time vintages and the exact calendar of data releases.

Second, we document that survey expectations can play an important role in improving interest rate forecasts at long horizons for short maturities. An interpretation of this finding is that surveys incorporate soft information which might be neglected in "standard" data: for example, they can consider forward-looking information coming from policy announcements (e.g. forward guidance). In fact, we prove that properly adding surveys to our model in a forward guidance period significantly enhances its predictive power, especially for short maturities.

In future research, we plan to extend our empirical specification to explicitly incorporate long-run trends, to account for the recent decline in interest rates. The macro-yields model presented in this work cannot identify trends as it is estimated on real-time macroeconomic variables transformed to achieve stationarity; however, our model can be easily extended to deal with trends along the lines of Del Negro et al. (2017).

A. 4 Appendix - Estimation procedure

A.4.1 State-space representation

The mixed-frequency macro-yields model with real-time macro information in equations (4.7)-(4.9) can be cast in a state-space form by augmenting the state variables to include the intercept and the idiosyncratic components. In particular, the measurement equation can be written as

$$\begin{pmatrix} y_t \\ x_t \\ E^s(y_t^q) \end{pmatrix} = \begin{bmatrix} \Gamma_{yy}^{NS} & 0 & 0 & 0 & I_n & 0 & 0 \\ \Gamma_{xy} & \Gamma_{yy} & 0 & a_x & 0 & I_m & 0 \\ 0 & 0 & \Gamma_q & a_s & 0 & 0 & I_s \end{bmatrix} \begin{pmatrix} F_t^y \\ F_t^x \\ F_t^q \\ c_t \\ v_t^y \\ v_t^x \\ v_t^s \end{pmatrix} + \begin{pmatrix} \eta_t^y \\ \eta_t^x \\ \eta_t^s \end{pmatrix} \tag{4.10}$$

where $(\eta_t^y, \eta_t^x, \eta_t^s)' \sim N(0, \epsilon I_{n+m+s})$ with ε a very small fixed coefficient. Γ_{yy}^{NS} is the matrix whose rows correspond to the smooth patterns proposed by Nelson & Siegel (1987) and shown in equation (4.2). Also notice that, since we are using real-time macro data, x_t contains missing values.

If we denote by $F_t = [F_t^y, F_t^x]$ and $v_t = [v_t^y, v_t^x]$, then we can write the state equation as

$$\begin{pmatrix} F_t \\ F_t^q \\ c_t \\ v_t \\ v_t^s \end{pmatrix} = \begin{bmatrix} A & 0 & \mu & 0 & 0 \\ w_t A & \iota_t I_r & w_t \mu & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & B & 0 \\ 0 & 0 & 0 & 0 & B_s \end{bmatrix} \begin{pmatrix} F_{t-1} \\ F_{t-1}^q \\ c_{t-1} \\ v_{t-1} \\ v_{t-1}^s \end{pmatrix} + \begin{pmatrix} u_t \\ u_t^s \\ \nu_t \\ \xi_t \\ \xi_t^s \end{pmatrix} \tag{4.11}$$

with $(u_t, u_t^s, \nu_t, \xi_t, \xi_t^s)' \sim N\left(0, blkdiag(Q, w_t' Q w_t, \epsilon, R, R_s)\right)$ and where the coefficients w_t and ι_t are known (w_t is equal to $1, 1/2, 1/3$ and ι_t is equal to $0, 1/2, 2/3$ respectively the first, second and third month of the quarter). In this state-space form, c_t an additional state variable restricted to one at every time t.

A.4.2 Estimation

The state-space model in (4.10)-(4.11) can be written compactly as

$$\begin{aligned} z_t &= \Gamma^* F_t^* + v_t^*, \quad v_t^* \sim N(0, R^*) \\ F_t^* &= A_t^* F_{t-1}^* + u_t^*, \quad u_t^* \sim N(0, Q_t^*) \end{aligned}$$

where $z_t = \begin{bmatrix} y_t \\ x_t \\ E^s(y_t^q) \end{bmatrix}$, $F_t^* = \begin{bmatrix} F_t \\ F_t^q \\ c_t \\ v_t \\ v_t^s \end{bmatrix}$, $v_t^* = \begin{bmatrix} \eta_t^y \\ \eta_t^x \\ \eta_t^s \end{bmatrix}$ and $u_t^* = \begin{bmatrix} u_t \\ u_t^s \\ \epsilon_t \\ \xi_t \\ \xi_t^s \end{bmatrix}$.

The restrictions on the factor loadings Γ^* and on the transition matrix A_t^* can be written as

$$H_1 \ \text{vec}(\Gamma^*) = q_1, \qquad H_2 \ \text{vec}(A_t^*) = q_{2t},$$

where H_1 and H_2 are selection matrices, and q_1 and q_{2t} contain the restrictions.

We assume that $F_1^* \sim N(\pi_1, V_1)$, and define $z = [z_1, \ldots, z_T]$ and $F^* = [F_1^*, \ldots, F_T^*]$. Then denoting the parameters by $\theta_t = \{\Gamma^*, A_t^*, Q_t^*, \pi_1, V_1\}$, we can write the joint loglikelihood of z_t and F_t, for $t = 1, \ldots, T$, as

$$\begin{aligned} L(z, F^*; \theta) = & -\sum_{t=1}^{T} \left(\frac{1}{2} \left[z_t - \Gamma^* F_t^* \right]' (R^*)^{-1} \left[z_t - \Gamma^* F_t^* \right] \right) + \\ & -\frac{T}{2} \log |R^*| - \sum_{t=2}^{T} \left(\frac{1}{2} [F_t^* - A_t^* F_{t-1}^*]' (Q_t^*)^{-1} [F_t^* - A_t^* F_{t-1}^*] \right) + \\ & -\frac{T-1}{2} \log |Q_t^*| + \frac{1}{2} [F_1^* - \pi_1]' V_1^{-1} [F_1^* - \pi_1] + \\ & -\frac{1}{2} \log |V_1| - \frac{T(p+k)}{2} \log 2\pi + \lambda_1' \left(H_1 \, \text{vec}(\Gamma^*) - q_1 \right) + \lambda_2' \left(H_2 \, \text{vec}(A_t^*) - q_2 \right) \end{aligned}$$

where λ_1 contains the lagrangian multipliers associate with the constraints on the factor loadings Γ^* and λ_2 contains the lagrangian multipliers associated with the constraints on the transition matrix A_t^*.

The computation of the Maximum Likelihood estimates is performed using the EM algorithm. Broadly speaking, the algorithm consists in a sequence of simple steps, each of which uses the time-varying parameter Kalman smoother to extract the common factors for a given set of parameters and closed form solutions to estimate the parameters given the factors. In practice, we use the restricted version of the EM algorithm, the Expectation Restricted Maximization, since we need to impose the smooth pattern on the factor loadings of the yields on the Nelson-Siegel factors. The ERM algorithm alternates Kalman filter extraction of the factors to the restricted maximization of the likelihood. At the j-th iteration the ERM algorithm performs two steps:

1. In the Expectation-step, we compute the expected log-likelihood conditional on the data and the estimates from the previous iteration, i.e.

$$\mathcal{L}(\theta) = E[L(z, F^*; \theta^{(j-1)})|z]$$

   which depends on three expectations

$$\begin{aligned} \hat{F}_t^* &\equiv E[F_t^*; \theta^{(j-1)}|z] \\ P_t &\equiv E[F_t^*(F_t^*)'; \theta^{(j-1)}|z] \\ P_{t,t-1} &\equiv E[F_t^*(F_{t-1}^*)'; \theta^{(j-1)}|z] \end{aligned}$$

   Given that our observables contain missing values, these expectations can be computed, for given parameters of the model, using the time-varying parameters Kalman smoother. This entails pre-multiplying the measurement equation by a selection matrix S_t of dimension $(n - \#missing) \times n$, as follows

$$S_t z_t = S_t \Gamma^* F_t^* + S_t v_t^*, \quad S_t v_t^* \sim N(0, S_t R^* S_t)$$

   and apply the Kalman filter to a time-varying measurement equation with parameters $S_t\Gamma^*$ and $S_t R^* S_t$, and observables $S_t z_t$.

2. In the Restricted Maximization-step, we update the parameters maximizing the expected the expected lagrangian with missing values with respect to θ:

$$\theta^{(j)} = \arg\max_{\theta} \mathcal{L}(\theta)$$

This can be implemented taking the corresponding partial derivative of the expected log likelihood, setting to zero, and solving. In particular, the measurement equation parameters are estimated by using a selection matrix W_t with diagonal element equal to 1 if non-missing, and 0 otherwise, so that only the available data are used in the calculations.

Following Coroneo et al. (2016), we initialize the yield curve factors with the Nelson-Siegel factors using the two-steps ordinary least squares (OLS) procedure introduced by Diebold & Li (2006). We then project the balanced panel of macroeconomic variables on the Nelson-Siegel factors and use the principal components of the residuals of this regression to initialize the unspanned macroeconomic factors. The quarterly factors are then computed by time aggregating the monthly yield curve and macro factors. All the parameters are initialized with the OLS estimates obtained using the initial guesses of yields and macro factors described above. The initial values for the factor loadings of surveys are obtained by projecting the linearly interpolated quarterly surveys on the quarterly factors observed at a monthly frequency.

Chapter 5

Financial and Fiscal Interaction in the Euro Area Crisis: This Time was Different

This work highlights the anomalous characteristics of the Euro Area 'twin crises' by contrasting the aggregate macroeconomic dynamics in the period 2009-2013 with the business cycle fluctuations of the previous decades. We report three novel stylised facts. First, the contraction in output was marked by an anomalous downfall in private investment and an increase in households' savings, while consumption and unemployment followed their historical relation with GDP. Second, households' and financial corporations' debts, and house prices deviated from their pre-crisis trends, while non-financial corporations' debt followed historical regularities. Third, the jumps in the public deficit-GDP and debt-GDP ratios in 2008-2009 were unprecedented and so was the fiscal consolidation that followed. Our analysis points to the financial nature of the crisis as a likely explanation for these facts.

JEL Classification: C11, C32, C54, E52, E62, F45.

Keywords: Euro Area, government debt, financial crises, business cycles.[1]

[1]This study was supported by the DG ECFIN's 2014-2015 Fellowship Initiative 'Growth, integration and structural convergence revisited'. We are grateful to Luca Benati (editor) and two

1 Introduction

This work analyses the anomalous characteristics in the responses of a rich set of fiscal, financial and macroeconomic variables to the macroeconomic shocks that generated the 2008 and 2012 prolonged recessions, as compared to the business cycle regularities of the previous decades. In particular, we focus and provide novel results on the anomalous debt-deficit dynamics that characterised the aftermath of the financial crisis. Our approach is to model the Euro Area as a single economy and the twin crises – the 2008 financial crisis and the 2012 sovereign debt crisis – as a potentially unique event. This to account for the highly integrated economic and financial features of the Euro Area, and for the possibly common chain of events linking the two recessions.

Our analysis contributes to the literature on the special nature of financial crises as opposed to regular recessions. Much of the existing empirical literature in this area has investigated the path of a handful of macroeconomic variables by using a single regression approach, in which financial crises are identified by using a narrative dummy or a quantitative index (e.g., among others, Reinhart et al. 2012, Jordà et al. 2013*b*, and Romer & Romer 2017). A stylised fact emerging from this strand of research is that recessions that are associated to financial crises tend to be deeper, longer, and characterised by prolonged cycles of deleveraging which weigh on the economy.

Differently from this approach, we focus on the fallout of a single financial crisis but provide a landscape view over the economy by adopting a rich multivariate Vector Autoregression (VAR) model with real, nominal and financial variables to capture the interdependence of business and financial cycles.[2] Our Euro Area-wide VAR model

anonymous referees for insightful suggestions that greatly improved this work. We thank Joan Paredes for providing us with a timely updated (time and again!) version of the quarterly fiscal database for the Euro Area (Paredes et al. 2009), and disaggregated fiscal data for Germany. We also thank Jacopo Cimadomo, Giovanni Callegari and Ingrid Toming for helping interpreting the data and insightful comments. Finally, we are grateful to Marta Bańbura, Domenico Giannone, Michele Lenza, Bartosz Mackowiak for insightful comments and discussions. The views expressed in this work are those of the authors and do not necessarily reflect those of Confindustria.

[2]We adopt a Large Vector Autoregression (VAR) model with Bayesian priors that can incorpo-

makes use of historical quarterly time series data from 1983 to 2013 to jointly model the dynamic interaction of (i) macro aggregates – real GDP, consumption, private investment, unemployment; (ii) inflation, long- and short-term interest rates; (iii) several fiscal indicators – spending, taxes, transfers, public investment and interest payments; (iv) different spreads; (v) credit aggregates; (vi) house prices.[3] Including in our model a rich set of fiscal aggregates and rates capturing the monetary policy stance is potentially of great importance in examining the policy mix historically adopted in the Euro Area before and after the crisis. In fact, as firstly shown by Leeper (1991), it is important to model the joint behaviour of the monetary and fiscal authorities in explaining macroeconomic outcomes (see Leeper & Leith 2016, for a review of the extensive research on the issue). Moreover, expanding the econometric information to incorporate both flow and stock variables such as household, financial and non-financial corporation households', financial and non-financial corporations' leverage helps identify the potential role of balance sheet adjustments. Similarly to us, Brunnermeier et al. (2017) propose a multivariate VAR approach to distinguish the several channels of interaction between financial variables and the macroeconomy and to control for the response of policy variables.

In joint modelling the evolution of financial and macro variables and the underlying cycles, we have to deal with a number of issues. First, trends and low frequency components are difficult to capture empirically, due to the inherent low number of observations (see Sims 2000). More specifically, the limited lag order of VAR models may fail to correctly capture the financial cycles, that are thought to have much lower frequency than (and associate weakly with) the traditional business cycle (see, e.g. Borio 2014). We try to address these issues by enriching our econometric information set and by adopting macroeconomic priors providing credibility to the idea of independent stochastic trend components. Also, we explicitly analyse and assess the

rates a rich set of variables capturing monetary, fiscal, financial and real economic conditions, by efficiently coping with the dimensionality problem (De Mol et al. 2008, Bańbura et al. 2010). In our empirical specification, we adopt two sets of standard macroeconomic priors: Minnesota priors (Litterman 1980, 1986) and sum-of-coefficients priors (Doan et al. 1984). The strength of these priors is optimally set using the hierarchical approach proposed by Giannone et al. (2015).

[3]The fiscal variables come from an updated version of a unique quarterly database for the Euro Area, described in Paredes et al. (2009).

plausibility the implicit trends retrieved by our model. Second, VAR-based estimates allow to take into account general equilibrium effects but do not accommodate for non-linearities, which are implicit, for example, in the debt accumulation equation (see, for example, Favero & Giavazzi 2007 for a discussion on this point). To handle this issue we follow Favero & Giavazzi (2007) and adopt a VARX framework, where public debt can affect all variables but its dynamics is reconstructed externally as a cumulated sum of the deficit implied by the evolution of fiscal aggregates inside the model. This approach, beyond providing robustness to our analysis, also allows to highlight how the measure of public debt resulting from the cumulative sum of public deficit can differ from the actual public debt, due to stock-flow adjustments. In fact, the latter can be large in periods of financial distress given the size of financial transfers which are accounted for as debt but did not originate from fiscal deficits (for a discussion of the significance of this measure, see Alt & Lassen 2006).

Our model provides three sets of empirical results. First, we perform a model-based counterfactual exercise by estimating the model for the period 1983-2007 (pre-crisis sample) and computing forecasts for 2008-2013, based on the pre-crisis parameters and conditional on the realised (observed) paths of nominal GDP and inflation. In computing conditional forecasts, we adopt the methodology proposed in Giannone et al. (2010) and detailed in Bańbura et al. (2015). This exercise can be interpreted as a test for the statement 'this time is different'. In fact, conditional on the prolonged drop in output triggered by the 2008 crisis (and the related path of inflation), it allows to uncover the differences between the conditional and the realised paths of the other variables examined and highlights potential anomalous responses as compared to the historical pattern observed in recessions.[4] Results provide us with a unified assessment of previously reported stylised facts, across many variables and also with new insights on the financial-fiscal interaction during and after the crisis.

Second, using results from the first exercise, we then study how two measures of public debt – the cumulative sum of the deficit and the observed debt incorporating stock-flow adjustments – deviated from its predicted measure conditional on the

[4]A similar approach has been used in recent works by Giannone et al. (2014) and Colangelo et al. (2017) in studying the response of monetary policy to the crisis.

collapse in output. If the observed path of any variable is found to be significantly different from what observed in its 'stressed' scenario, we conclude that there is a departure from previous cyclical experiences. This exercise is at the core of our work, and highlights a novel set of results concerning the anomalous dynamics in fiscal variables, following the financial crisis.

Third, we study how the realised paths of the variables of interest deviated from the unconditional forecast and the implicit trends recovered by the model. This exercise provides a gauge on how much (or how little) correlation exists in the data between macro and financial variables. It also provides useful information on pre-crisis trends.

Our approach does not recover the nature of the shocks that caused the deep recessions, nor allows to infer causal relationships among the variables. Indeed, while our findings provide new evidence on what happens after financial crises, they only convey suggestive evidence of any causal impact of financial distress onto the economy. Also, importantly, the approach does not disentangle the complex causal relation between the exceptional fiscal and monetary policies undertaken and the macroeconomic performances observed. This limitation is common to the rest of the literature that has studied financial crises by adopting a treatment variable (and not exogenous events) defined in terms of anomalous credit conditions with respect to an historical norm.[5]

Our results confirm, as reported by extant literature, that households', financial corporations' debts and house prices are weakly associated to the economic cycle in the pre-crisis sample, possibly due to two decades of leveraging. In the post-crisis sample, they markedly deviated from their pre-crisis trends, as a consequence of the deleveraging. On the background of this deleveraging, our analysis provides three novel stylised facts. First, the contraction in output was marked by an anomalous deep and persistent downfall in private investment and an increase in households'

[5]It is important to stress that, given our approach, we cannot discriminate amongst competing explanations. In particular we cannot determine whether the uncovered anomalous features were due to the 'depth' of the drop in output (and hence the activation of non-linearities and hysteresis effects), to the financial nature of the crisis, or to a sudden permanent change in the underlying trends.

savings beyond historical regularities; conversely, consumption and unemployment followed their historical relation with GDP. Interestingly, the contraction in private investment was at least initially counterbalanced by an increase in public investment – this marking a difference in the aggregate behaviour of private and public investment. Second, house prices contracted, and households' and financial corporations' debt adjusted more than in previous business cycle recessions, while deviating from their pre-crisis trends; non-financial corporations debt instead followed historical regularities. Finally, and importantly, the jumps in the fiscal deficit-GDP and debt-GDP ratios in 2008-2009 were unprecedented and so was the fiscal consolidation that followed. Notably, the 'anomaly' in public deficit is in large part explained by extraordinary measures in support of the financial sector, which show up in the stock-flow adjustments and reveals a key interaction between the fiscal and the financial sectors. Our analysis points to the financial nature of the crisis as a likely explanation for these facts.

Related Literature. This work is related to the recent literature investigating the behaviour of the economy in the aftermath of deep recessions and financial crises. A narrative approach in dating crises is commonly used in the literature, as for example in the influential book of Reinhart & Rogoff (2009*b*) and in a series of articles (e.g. Reinhart & Rogoff 2009*a*, 2014). This approach has been pioneered by Caprio & Klingebiel (1996), and then extended by a number of important works, as for example Bordo et al. (2001), Cerra & Saxena (2008), Claessens et al. (2009, 2010), Gourinchas & Obstfeld (2012), Schularick & Taylor (2012), Jordà et al. (2013*b*), Laeven & Valencia (2014), and Bordo & Haubrich (2017). Most of these studies adopt a single regression approach to investigate the path of a handful of macroeconomic variables following a crisis, identified by using a narrative dummy or a quantitative index. A common finding in this literature is that recessions accompanied by financial crises tend to be more severe, while recoveries are particularly slow compared to deep recessions. Hoggarth et al. (2002), and Laeven & Valencia (2013) compare the path of output following crises with projections of pre-crisis trends. These studies find that output often falls far below the pre-crisis path, but that there is substantial dispersion across episodes.

Slightly different results are reported by Bordo & Haubrich (2017), who find that the slow recovery pattern in the US is true only in the 1930s, the early 1990s and after the 2008 financial crisis. Romer & Romer (2017) refine the narrative approach employing OECD accounts of financial crises to classify financial distress on a relatively fine scale. They find that the average decline in output following a financial crisis is statistically significant and persistent, but only moderate in size, with effects that are highly variable across major episodes.

In focussing on a rich set of fiscal variables we also connect to the literature which studies the impact of prolonged periods of exceptionally high public debt onto economic growth. Reinhart et al. (2012), basing their analysis on a cross-section of countries, have suggested that high public debt overhang has a negative effect on growth. Jordá et al. (2013*a*), focussing on a cross-section of recessions for different countries, show that this negative effect is only at work when recessions are associated to financial crises. Furthermore, by incorporating some measure of interest rates spread we relate to Krishnamurthy & Muir (2017), who investigate credit spreads as a possible indicator of financial disturbances, and finds a substantial correlation between this statistical measure of financial distress and common crisis chronologies.

Finally, this work may provide relevant insights to the debate about the post crisis slump in the Euro Area and the ongoing discussion on the reform of the economic governance of the European Monetary Union (EMU).[6] The policy debate has emphasised, for example, that the fiscal framework of the Euro Area induces procyclicality of fiscal policy in response to large macro-shocks. When monetary policy is constrained at the zero-lower bound this implies an inadequate policy mix and depresses aggregate demand excessively (see, for example, Corsetti et al. 2019). In the light of this debate, our results lend support to proposals for reform of the Euro Area governance that would allow a slower fiscal consolidation in case of large negative shocks, by distinguishing between the cyclical component of the government fiscal balance, and the part that is explained by policy stabilisation interventions (see Corsetti 2015*a*,*b*).

[6] The European Economic Review has devoted a special issue to the debate on the persistent post-crisis slump and on the resulting fiscal and monetary policy challenges (see *European Economic Review* 2016).

2 Fiscal and Financial Facts

In this section we report some background facts providing suggestive evidence on the financial nature of the crisis. First, we document the anomalous pattern of term and sovereign spreads in the Euro Area, and show that they suggest the activation of different types of financial stress at different points of the crisis. Second, we provide evidence of the fact that the anomalous accumulation of public debt during the last crisis in the Euro Area as a whole is related to the crisis in the financial sector of the core countries of the area. While this observation cannot fully determine the fiscal or financial nature of the crisis, it provides some interesting facts about the sources of deterioration of the fiscal position of the Euro Area.

Let us first turn to some potential indicators of financial frictions. We select two variables as proxies: the spread between the ten-year interest rate on government bonds and the three month Euribor (term spread) and the spread between the ten year interest rates on Italian debt and German debt (sovereign spread). We use the sovereign spread as an indicator of risk associated with the risk of disintegration of the EMU, the so-called 'redenomination' risk. To this aim we consider Italy rather than a country that lost access to the market during the crisis like Greece, Portugal or Ireland. Figure 1 plots these variables.

The left-hand chart includes the entire sample and is dominated by the decline of the sovereign spread in preparation of the euro, while it does not show a cyclical behaviour. Conversely, the term spread has a typical anti-cyclical dynamics, raising in recessions and then normalising with a lag. The chart on the right is a zoom of the recent years, with shaded areas indicating CEPR dated recessions. A simple message is apparent: the dominant friction in the 2008-09 recession was the steepening of the term spread affecting all countries, while in the second was the cross-country spread revealing periphery countries stress. In other words, the Euro Area economy in the period 2008-2013 was subject to two different sources of risks: term risk and sovereign risk. The former characterises the first recession, the latter, the second.

Let us now report some key facts about fiscal deficit of the Euro Area as a whole. Figure 2 focuses on the three recessions in our sample with starting dates in 1980, 1991, and 2008. In the left panel it reports public debt to GDP ratios and in the

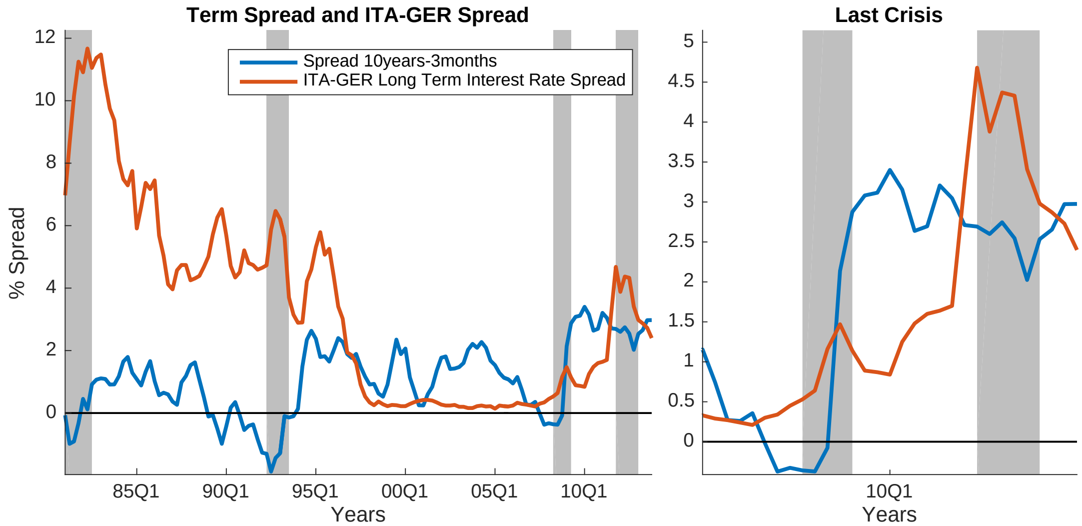


Figure 1: **Italy-Germany long term sovereign interest rates spread and term spread defined as 10 years - 3 months.**

right one the deficit to GDP ratio. For each episode the debt and deficit variables are set equal to 100 at the beginning of the recession. The horizontal axis indicates quarters after that date.

Following each recession, the deficit to GDP ratio increases due to the decline of GDP (the denominator), the decline in tax income and the effect of fiscal stabilisers on public expenditure. The 2008 recession, however, is of a different order of magnitude: due to the dramatic decline of GDP, the deficit to GDP ratio spikes up and continues to do so until early 2009, when a massive fiscal consolidation takes place. The latter, also unprecedented, implied a halving of the deficit in about four years, but failed to stabilise public debt which continued to increase albeit at a declining rate.

The question of whether fiscal consolidation was excessive, thereby contributing to slow down the recovery due to a large multiplier in a context of distressed financial markets, or whether it was not aggressive enough, has generated a large debate.[7]

[7]Our analysis is silent on this important question.

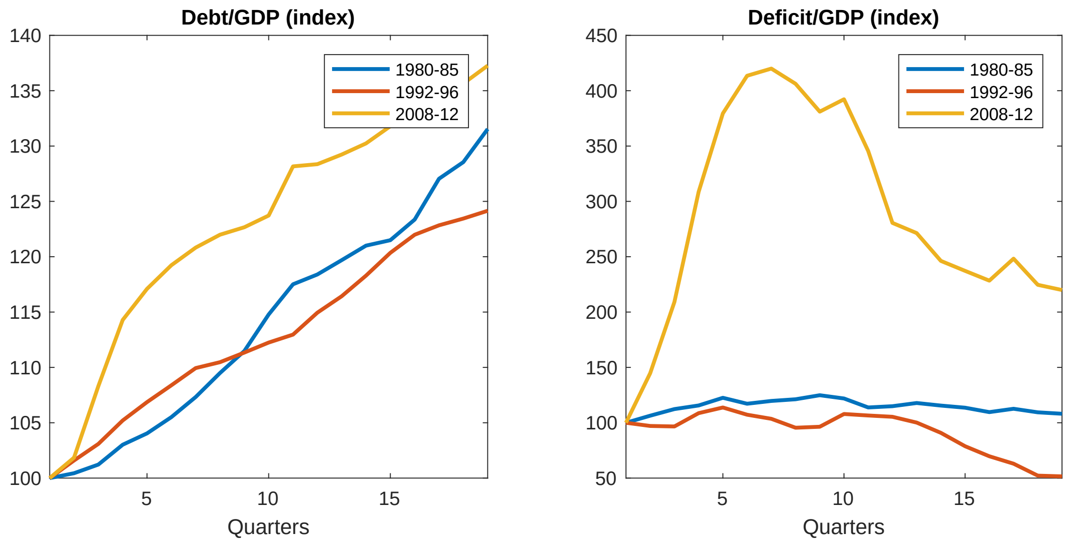


Figure 2: **Euro Area government debt/GDP and deficit/GDP.** Indices based at 100 in the quarters in which each recession starts.

Less attention has been devoted to the anomalous debt-deficit dynamics related to the interaction between financial distress and public expenditure. To appreciate this point it is interesting to look at the historical relation between public debt and the rate of change (quarterly differences) of public deficit. The relation between debt and deficit can be expressed as:

$$D_t - D_{t-1} = pd_t + adj_t, \tag{5.1}$$

where D is the stock of the public sector gross debt and pd is the public deficit. The residual, the so-called stock-flow adjustment, is explained by valuation effects, financial transactions which are not reflected in the deficit, and errors and omissions.

Typically the residual is small, but occasionally it can be big. The literature has documented that creative accounting can inflate the residual near election time or when the economy enters a slump (Reischmann 2016). In Europe, there is also evidence of a persistent positive residual in the nineties when EU rules kicked in (see Alt et al. 2014 for evidence on this point). However, data from 2010 and 2012 are striking and point to very special circumstances. Figure 3 describes the first difference

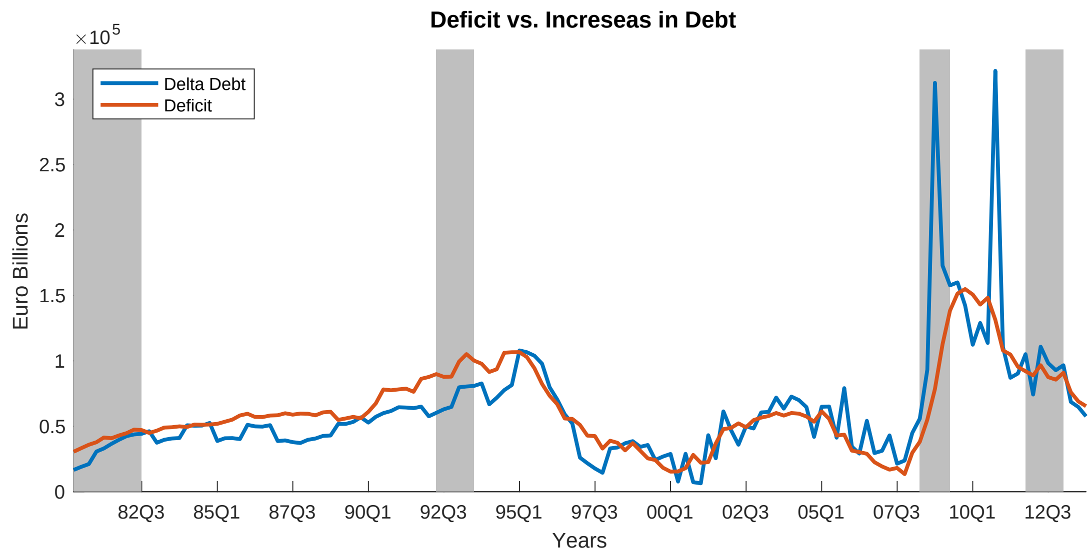


Figure 3: **Euro Area government deficit and first differences of government debt.**

in public debt and the public deficit. Typically the two series are very similar, indicating a small residual. In the nineties the residual was positive, confirming results of the earlier literature but, in 2009 and 2011, there are two large peaks in the debt series which are unprecedented.

Eurostat data for the period 2008-2011 in Table 1 shows that these peaks are almost entirely explained by financial transactions which did not originate from the deficit but are accounted for in the public debt. These are related to special measures adopted in the crisis to support the financial sector, mainly acquisition of financial assets by the government (see Appendix B.5.1 for further details). Several countries in the Euro Area had stock-flow adjustments which exceeded 2% of GDP. The large positive figure in Germany in 2008 reflects the purchases of securities by two special purpose vehicles in the context of operations related to the financial crisis, while in 2010 it reflects the transfer of assets of two public defeasance structures classified in the government sector[8]. The 2009 figure for Ireland reflects capital injection in

[8]The ESA2010 Eurostat Manual on Government Deficit and Debt, in sub-section IV.5.2.1 defines

Country	2008	2009	2010	2011	Average	Sum	Sum (% of 2011 EA GDP)
Euro Area	3.2	0.8	1.5	0.6	1.6	6.2	6.2
BE	6.7	-0.5	0.2	2.1	2.1	8.5	0.3
DE	2.7	1.8	7.5	0.3	3.1	12.3	3.2
IE	10.7	1.6	-5.6	2.4	2.3	9.1	0.2
ES	0.5	1.0	-2.1	-0.8	-0.3	-1.4	-0.2
FI	4.3	4.5	4.2	2.5	3.9	15.5	0.3
FR	2.2	1.7	-1.8	0.9	0.8	3	0.6
IT	1.5	1	0.8	-0.4	0.7	2.9	0.5
NL	15.4	-5.5	-1.1	-0.8	2	8	0.5
PT	0.7	-0.1	2.5	9.2	3.1	12.3	0.2

Table 1: **Stock-flow adjustments in 2008-2011.** Percent of GDP. Source: Eurostat (2012).

the form of preference shares. Similar measures are in evidence for other countries (see Eurostat 2012 for details). Aggregate figures are heavily influenced by Germany, which is the largest country in the Union and also the country that showed the largest debt increase due to extraordinary financial expenses as well as the most drastic fiscal consolidation.

Clearly the increase in debt due to these measures represents a cost in terms of future taxes. Since the Stability and Growth Pact rules are set for public debt as well as public deficit, the very large fiscal consolidation since 2009 is likely to have been motivated by the increase in debt caused by these special measures.

the defeasance structures (the so-called 'bad banks') as 'an institutional unit, which has substantial problematic assets, whose principal activity is the resolution of these assets generally over an extended period and not the provision of financial intermediation services. (...) When there is evidence that government is assuming all or the majority of the risks and rewards associated with the activities of a government-controlled defeasance structure, as described above, this structure is classified in the general government sector.'

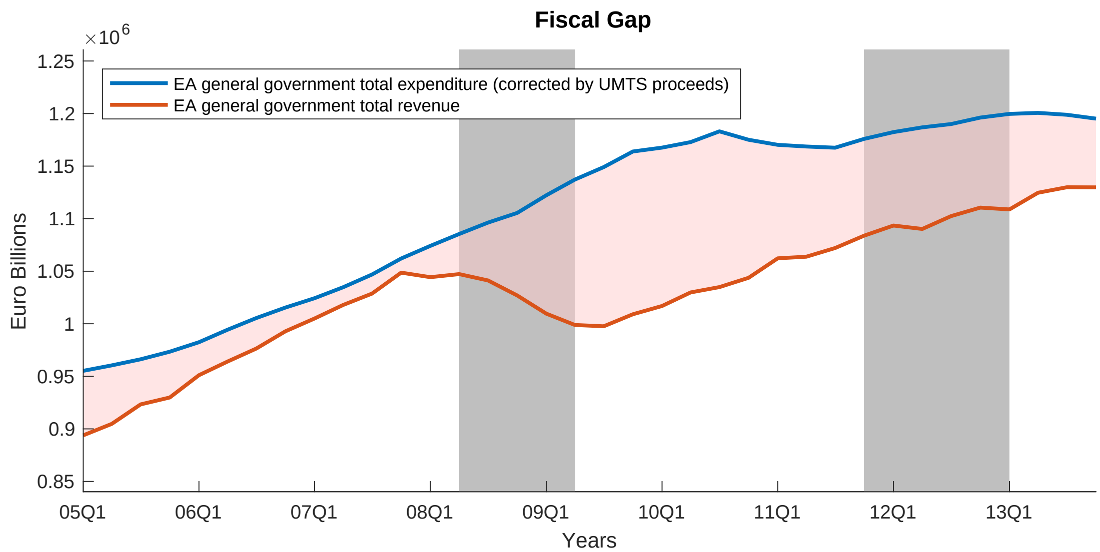


Figure 4: **Euro Area government total expenditures and revenues.**

Turning now to the analysis of the deficit, Figure 4 shows the dynamics of government expenditures and revenues. While public debt was increasing due to measures in support of the financial sector, fiscal consolidation since 2010 was taking place mostly by a flattening of government expenditures. Figure 5 reports the growth of different public expenditures items as percentage of the rate of growth of total expenditures. It shows that the decline in the growth rate of government expenditures is associated to a decline in the contribution of social payments, government consumption and public investment. Notice also two spikes in the contribution of what is defined as a residual, which is explained by ad hoc capital transfers (that appear directly in the deficit) related to support of the financial sector.

Let us summarise the descriptive features we have illustrated.

1. In 2008, in relation to the collapse of GDP, both the public debt-GDP and public deficit-GDP ratios experienced a sudden deterioration which is much larger than anything experienced in the recessions included in our sample.

2. The dynamics of public debt is partly explained by measures in support of the

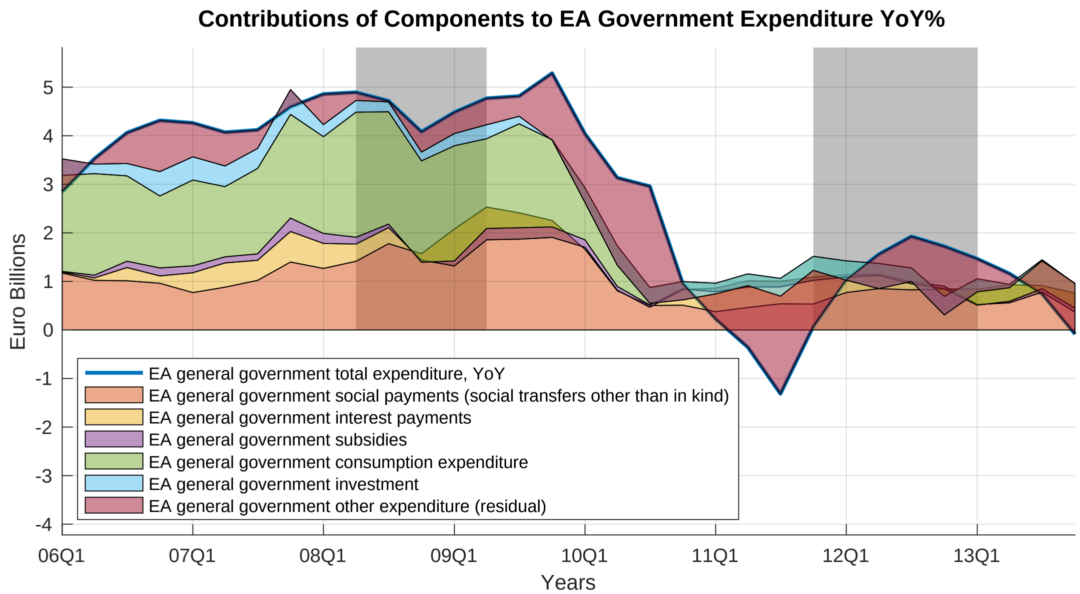


Figure 5: **Contributions to the year on year growth rate of Euro Area government expenditures.**

financial system that were not accounted for as deficit.

3. Since 2009, we have seen a major fiscal adjustment with the deficit-GDP ratio declining more than in any other expansions.

4. The fiscal adjustment was mostly achieved by a flattening of government expenditures.

5. The latter was achieved by a decrease in the contribution of social payments, government consumption and public investment in favour of an increase to expenses in favour of the financial sector (capital transfers).

In the next sections we analyse these facts through the lens of an econometric model.

3 A Macro-Finance VAR for the Euro Area

In order to capture the complex interactions shaping the aggregate Euro Area economy we adopt a large VAR including a rich set of macroeconomic and financial indicators. In particular we consider 22 time series for the Euro Area aggregate, including fiscal and monetary policy variables, real output and its components, unemployment, prices, assets and several credit and financial variables for the sample 1981Q1-2008Q1. Importantly, we incorporate both standard macroeconomic flow variables and detailed fiscal indicators, but also stocks such as debt in different sectors. Table 2 lists the variables used in the model. Variables enter the model in log-levels, except for variables expressed in rates or with negative levels. When in levels (or log-levels), they are deflated by using the GDP deflator. This choice has the advantage of avoiding problems related to arbitrary choices of data transformations which can distort results.[9]

In incorporating this rich dataset in our VAR we have to deal with four major challenges. First, while VARs are usually specified for flow variables and rates – e.g. output and its components or policy rates –, we need to model the joint evolution of stock and flow variables. In doing this the potentially non-linear relationship between stocks and flows may distort VAR estimates. This is of particular concern, for example, for the deficit and the debt accumulation equation. Second, a model capturing the joint dynamics of many macro and financial variables has necessarily a large cross-sectional dimension and an expansive set of parameters to be estimated with non-standard techniques. Third, VARs tend to extract 'implicit' deterministic components (trends) from the initial conditions of the data, that are taken as given. In doing so they may overfit the data, and explain too much of their variation by these deterministic components. Finally, in our VAR this problems are compounded by the empirical issue that financial stock variables – often thought of as driven by long cycles – tend to have low correlation with real variables at business cycle frequency, and may not be well captured by a VAR with limited lags.

[9]The fiscal variables come from an updated version of a unique quarterly database for the Euro Area, described in (Paredes et al. 2009). A more detailed description including sources and data treatment is provided in the Appendix.

To deal with the possible non-linear equation of debt accumulation, we adopt an approach similar to the one suggested by Favero & Giavazzi (2007) and consider a VARX, that is a VAR with public debt treated as an exogenous variable. Differently from Favero & Giavazzi (2007), we introduce fiscal budget components independently in the VAR and reconstruct the public debt as the cumulative sum of the fiscal deficit. The variables listed in Table 2, with the exception of the public debt and the public deficit, are collected in a vector of endogenous variables Y_t, while we specify separate equations for D_t – the stock of the Euro Area consolidated public debt (without the stock-flow adjustment) –, and for the public deficit pd_t. Our VARX model has the form:

$$Y_t = c + A(L)Y_{t-1} + b(L)D_t + u_t \tag{5.2}$$

$$D_t = D_0 + \sum_{j=0}^{t} pd_j \tag{5.3}$$

$$pd_t = G_t + TR_t + IP_t - T_t \tag{5.4}$$

where u_t is a normally distributed multivariate white noise with covariance matrix Σ and $A(L)$ is a matrix polynomial of order $p = 4$ in the lag operator L. The fiscal deficit, pd_t, is constructed as the sum of the relevant fiscal variables – i.e. public expenditure G, fiscal transfers TR, interest payments IP, and tax receipts T – that are individually present in the vector of endogenous variables Y_t. In this form the debt accumulation equation is a linear function of its components.

We deal with the challenge of incorporating in an efficient manner a large set of variables by adopting Bayesian VAR techniques, that offer a convenient way to deal with large datasets. In fact, BVARs can efficiently deal with the problem of over-parametrisation through the use of prior information about the model coefficients. The key idea is to use informative priors that shrink the unrestricted model towards a parsimonious stylised benchmark model, thereby – in frequentist language – reducing parameter uncertainty, while introducing minimal bias.

More specifically, our BVAR is estimated adopting two sets of standard macroeconomic priors: Minnesota priors (Litterman 1980, 1986) and sum-of-coefficients priors (Doan et al. 1984). While these priors are not motivated by economic theory, they capture commonly held beliefs about how economic time series behave. In fact, Minnesota and sum-of-coefficients are widely applied standard priors in macroeconometric research, that are proven to improve forecasting performances of VAR models.

Minnesota priors can be casted in the form of Normal-Inverse Wishart (NIW) conjugate priors, that assume a multivariate normal distribution for the regression coefficients and an Inverse Wishart specification for the covariance matrix of the error term Σ. Conditional on a draw for Σ, the Minnesota prior assumes the coefficients $A_1, \dots, A_p$ to be a priori independent and normally distributed, with the following moments

$$\mathbb{E}\left[(A_\ell)_{ij}|\Sigma\right] = \begin{cases} \delta_i & i = j,\ \ell = 1 \\ 0 & \text{otherwise} \end{cases} \qquad \mathbb{V}ar\left[(A_\ell)_{ij}|\Sigma\right] = \begin{cases} \frac{\lambda}{\ell} & \text{for } i = j, \forall \ell \\ \frac{\lambda}{\ell}\frac{\Sigma_{ij}}{\sigma_j^2} & \text{for } i \neq j, \forall \ell. \end{cases} \tag{5.5}$$

In Eq. (5.5), $(A_\ell)_{ij}$ denotes the coefficient of variable j in equation i at lag ℓ. δ_i is either 0 or 1 – for stationary series, or variables that have been transformed to achieve stationarity, we centre the distribution around zero. The factor Σ_{ij}/σ_j^2 accounts for the different scales of variables i and j. The hyperparameters σ_i are fixed using sample information, as the standard deviations of the residuals of univariate regressions of each variable onto its own lags. Importantly, λ is a hyperparameter that controls the overall tightness of the random walk prior. If $\lambda = 0$ the prior information dominates, and the VAR reduces to a vector of univariate models. Conversely, as $\lambda \to \infty$ the prior becomes less informative, and the posterior mostly mirrors sample information. Minnesota priors can be implemented using dummy observations. Priors on A coefficients are implemented by the following pseudo-observations

$$y_d^{(1)} = \left[\begin{array}{c} diag([\delta_1\sigma_1, \dots, \delta_n\sigma_n])/\lambda \\ 0_{n(p-1)\times n} \end{array}\right], \tag{5.6}$$

$$x_d^{(1)} = \left[\begin{array}{cc} J_p \otimes diag([\sigma_1, \dots, \sigma_n])/\lambda & 0_{np\times 1} \end{array}\right]. \tag{5.7}$$

A second set of priors, the sum-of-coefficients (or 'no-cointegration') priors (Doan et al. 1984), can be relevant in dealing with the challenge of the relatively weak joint dynamics connecting private debt and real variables, while reducing concerns about the overfitting of VARs estimated conditional on initial observations. (See the original discussion on this issue in Sims 1996, 2000, 2005*a*,*b*. A recent contribution to this debate is in Giannone et al. 2016.) In fact, these priors provide more weight to the hypothesis that macro and financial variables can be approximated by independent random walks with drifts.[10] This stylised description is helpful in modelling the joint dynamics of macroeconomic and financial variables, combining stock and flow indicators, and possibly exhibiting heterogenous trend components.

Specifically, the sum-of-coefficients prior captures the belief that when the average lagged values of a variable $y_{i,t}$ is at some level y_i, that same value y_i is likely to be a good forecast of $y_{i,t}$. It also implies that knowing the average of lagged values of variable j does not help in predicting a variable $i \neq j$. This prior is implemented using n artificial observations, one for each variable in y_t

$$\underset{[n\times n]}{y_d^{(2)}} = diag\left(\left[\frac{\bar{y}_{0,1}}{\tau}, \ldots, \frac{\bar{y}_{0,n}}{\tau}\right]\right), \qquad \underset{[n\times(np+1)]}{x_d^{(2)}} = [y_d^{(2)}, \ldots, y_d^{(2)}, 0], \tag{5.8}$$

where $\bar{y}_{0,i},\ i = 1, \ldots, n$ are the average of the first four initial values of each variable. The prior implied by these dummy observations is centred at 1 for the sum of coefficients on own lags for each variable, and at 0 for the sum of coefficients on other variables' lags. It also introduces correlation among the coefficients of each variable in each equation. In fact, it is easy to show that equation by equation this prior implies the stochastic constraint

$$\left(1 - (A_1)_{jj} - \ldots - (A_p)_{jj}\right)\bar{y}_{0,j} = \tau u_t^d \qquad \forall j\ , \tag{5.9}$$

where $(A_\ell)_{jj}$ denotes the coefficient of variable j in equation j at lag ℓ. The hyperparameter τ controls the variance of these prior beliefs. As $\tau \to \infty$ the prior becomes uninformative, while for $\tau \to 0$ the model implies that each variable is an independent unit-root process and there is no cointegration relationship.

In order to assign less probability to versions of the model in which deterministic transient components are more important than the stochastic component in explaining the series variance, we combine sum-of-coefficients dummy observations

[10] While results for a BVARs with only Minnesota priors are qualitatively unchanged, sum-of-coefficients priors are helpful in reducing estimation uncertainty on the long end of the conditional forecast.

with dummy observations that favour the VAR intercept to be equal to zero ($c = 0$), as suggested by Sims & Zha (1998). A fairly loose prior for the intercept of this type can be implemented with the following dummy observations:

$$y_d^{(3)} = \left[\begin{array}{c} 0_{1\times n} \end{array} \right],$$
$$x_d^{(3)} = \left[\begin{array}{cc} 0_{1\times np} & \epsilon \end{array} \right],$$

where ϵ is an hyperparameter set to a very small number.[11]

The setting of the priors depends importantly on the hyperparameters λ and τ, which reflect the informativeness of the prior distributions for the model coefficients. In setting the value of these hyperparameters, regulating the strength of prior beliefs, we follow the approach proposed by Giannone et al. (2015). This involves treating the hyperparameters as additional parameters, in the spirit of hierarchical modelling.

Conditional forecasts are obtained from a Bayesian Vector Autoregression estimated on the pre-crisis sample, by employing the Kalman filtering techniques used first in Giannone et al. (2010) and detailed in Bańbura et al. (2015). The procedure exploits the fact that Vector Autoregressive models can be cast in a state-space form. Hence, the conditional forecasts can be computed using Kalman filtering techniques and the counterfactual simulations can be drawn using the simulation smoother of Carter & Kohn (1994). As discussed in Bańbura et al. (2015), since the Kalman filter works recursively, this algorithm reduces the computational burden significantly for longer forecast horizons, and is particularly well suited for empirical approaches where large data sets are being handled.

4 This Time Was Different

In this section we present three sets of empirical results: (i) we compare the actual path of macroeconomic and financial variables with their model-based forecast conditional on the pre-crisis sample and the realised path for output and inflation during the crisis; (ii) we zoom into the conditional predicted outcome for public debt and deficit and assess the role of stock-flow adjustment and measures of support to

[11] We set ϵ to have a fairly loose prior variance equal to 10^6.

financial institutions; (iii) we compare conditional and unconditional forecasts and make inference about pre- and post-crisis trends.

1 What if the 2008 crisis had been just a 'normal' recession?

The question we want to ask is whether the observed behaviour of the variables since 2008 could have been expected given their historical correlation with the macroeconomy and the observed path of GDP and inflation. To provide an answer to this question, we compute model-based expectations for all macroeconomic and financial variables, conditional on the actual path of output and prices in 2008Q2–2013Q4, and using parameters estimated on the sample 1981Q1–2008Q1.[12] A significant difference between the observed path and the median of the simulated path (conditional expectation) would suggest that the exceptional decline of GDP alone cannot explain what we have observed, given the realised inflation and the historical pattern of business cycle recessions.

Figure 6 reports the realised paths of all the variables included in the model, the median of the conditional forecasts as well as 68% (darker blue) and 90% (lighter blue) coverage intervals to provide a measure of uncertainty. A number of features are apparent.

First, while consumption and unemployment followed their historical relation with GDP, the contraction in output was marked by an anomalous protracted downfall in private investment and an increase in households' savings. In fact, while the high persistence of unemployment in Europe is in line with past regularities (albeit in the upper tail of the forecast outcomes),[13] the 'hysteresis' pattern in investment (see Dixit

[12] To obtain conditional forecasts we first estimate the VAR model parameters' posterior distributions for the period 1981Q1–2008Q1. Then, we compute for all variables the conditional expectations for 2008Q2–2013Q4. For any given draw of the model's parameters from their posterior density, the draws from the counterfactual exercise are computed as conditional forecasts in which the conditioning information is given by: (1) the pre-crisis history of all variables in the model; (2) their estimated parameters capturing historical correlations; (3) the observed paths of GDP and inflation for 2008Q2–2013Q4. We report the median as well as 68% and 90% coverage intervals.

[13] Blanchard & Summers (1986) and more recently Galí (2015) observed that 'hysteresis' in labour market (i.e. high persistence of unemployment) in Europe may be due to the nature of its

1992) – to which the model assigns probability close to zero – is markedly anomalous. Interestingly, this is not explained by large movements in labour productivity, that behaved in line with past regularities. The increase in households' savings reflects the sharp deleveraging in households' debt, that is visible in the path of households' debt after the crisis.

Second, also fiscal aggregates show an anomalous behaviour. It is useful, however, to distinguish between the first recession, in the period 2008Q1-2009Q3, from the subsequent adjustment. The first recession was characterised by an unusual decline in government revenues, which fell below the distribution of the forecast paths conditional on the large observed decline of GDP; and by an increase in government expenditures, in particular public investment and social payments, in the upper tail of the predicted outcomes. The fact that tax revenues declined more than what could have been expected given the behaviour of output and prices could suggest the activations of non-linearities due to the progressive nature of the tax system. However, the adjustment since late 2009 produced a sudden normalisation for tax revenues, government expenditures and social payments.

Third, during the first recession there was an anomalously large current account deficit, possibly explained by the collapse of world trade which, in 2008, was larger than the one of GDP. The adjustment since late 2009 involved a sharp reversal, with the current account returning to the historical counterfactual path and then overshooting to an unusually large surplus. This may also relate to the unusual decline in investment and sharp fiscal adjustment experienced by the Euro Area.

Fourth, while household savings were quite stable, households' and financial corporations' debts and house prices deviated from the predicted paths.[14] This shows a strong deleveraging of the European economy after the crisis. Also, the long-term interest rate stayed for the first part of the crisis at an unusually high level, possibly calling into action the unconventional monetary policy measures enacted by the ECB

wage setting mechanisms and their impact on the sensitivity of wages to unemployment.

[14]To control for potential outliers in the house markets of some smaller countries, as for example Ireland, in a robustness exercise we replace the Euro Area index with a weighted average of the house price indices in the five largest countries. Our results are robust to this test and are reported in Appendix C5.3.

in the rest of the sample.

Finally, other features of the results deserve some comments. In correspondence to the debt crisis of 2011, we have an unusual steep increase in the Italian-German spread debt which persist till the end of the forecast period. Conversely, the interest rate term spread 10 year - 3 months on government bonds moves steeply to the upper tail of the distribution of the forecast during the 2008-2009 recession. Indeed results quantify the observations of Section 2 by showing that while an unusually high term spread was a feature of the first recession, an unusually high core-periphery sovereign spread was a feature of the second. In other words, the model correctly identifies different financial frictions in the two recessions.

2 The debt-deficit dynamics

Against the background described in the previous section, we now focus on to the public debt and fiscal deficit to analyse the effects of the fiscal-financial interaction. As described earlier, we construct the deficit from the disaggregated data on revenues and expenditures while we construct public debt as the cumulative sum of the deficit. Figure 7a shows the observed and counterfactual paths for the two variables expressed as ratios with respect to GDP. In addition, we report data on public debt without stock-flow adjustments.

The left panel, showing actual and counterfactual paths for the deficit-to-GDP ratio, reflects the features noticed on Figure 6. A sharp fiscal consolidation from 2009Q3, started more than a year earlier than what predicted by the counterfactual path, brought down the large gap in 2008-2009 between the counterfactual path of the deficit ratio and the actual ratio. By 2011, the realised deficit is back inside the predicted conditional distribution of forecasts. This quantifies in statistical term what observed in the previous section by comparing data across recessions: the fiscal consolidation of 2009-2010 was sudden and of an unprecedented size.

The right panel shows the dynamics of public debt. It reports both the actual level of debt-to-GDP ratio (red line) and the non-stock-flow adjusted ratio (green line). The adjusted debt ratio, that includes measure of support to the financial sector, jumps up immediately above the counterfactual and stays about 10% higher than the non-adjusted line until 2012, when it jumps up again as the effect of an other wave of special measures in support of the financial sector (see Table 1 in Section 2). The non-adjusted path, which we compute as the sum of the deficit, is at the end of the sample just outside the upper limit of the 90% predicted distribution. The big anomaly of the stock-flow adjusted debt dynamics seems therefore largely explained by the special measures in support of the financial sector.

We further explore these results, by performing a robustness exercise and excluding Germany from the Euro Area aggregate. This to the aim of assessing whether the results reported are due to a common pattern across the Euro Area or are determined by it largest member only. Results in Figure 7b show that the anomalous debt-deficit dynamics is by large a common feature of the Euro Area crisis, albeit Germany provided a major share of the stock-flow adjustments that increased the stock of the debt during the crisis. Finally, Figure 7c extend the exercise to 2017 to show that the unprecedented effort in bringing the Euro Area deficit down managed to stabilise both deficit and the stock of debt, by lowering their values to the rage of the values forecastable given past business cycles regularities.[15]

To gain further insight about the joint path of public debt and deficit, let us consider the observed and counterfactual scatter-plot illustrated in Figure 8. Let us keep in mind that the latter is computed taking into account all general equilibrium relationships implicit in the VAR model. The figure shows that the relationship between deficit and debt is highly non-linear and that, during the fiscal contraction, the increase in debt associated with a given decline in deficit has been larger than expected. The yellow dots, representing the deficit-debt counterfactual scatter plot where the debt is not adjusted, show an inverse U-shape: up to 2009 we have an increase in debt corresponding to an increase in deficit while, after 2009, as the deficit contracts (still remaining positive), debt increases. The data, both when the debt is adjusted (red dots) and when is not (green dots), follow the same pattern but the curves are shifted up and to the right. The red dots in particular are outside the 90% confidence intervals.

[15] The full set of results provided by these two robustness exercises are reported in Appendix C5.3.

3 Unconditional forecast and trends

Figure 9 presents conditional and unconditional median forecasts against the realised paths of the variables since 2008. This exercise is meant to assess two aspects of our analysis. First, the unconditional forecasts, based on the pre-crisis estimated parameters, provide on the medium run a gauge on the pre-crisis trends that the model would extrapolate from the data. Second, the difference between the conditional and unconditional forecast provides an indirect measure of the strength or weakness of the coupling of each single variable with GDP and inflation.

It is worth observing that the difference between the realised paths for GDP and HCPI and their unconditional forecasts can be thought of as the deviation by which the conditional forecasts are informed. Conditional on the pre-crisis data, the model would implicitly read them as due to a given sequence of shocks and use this information to produce the conditional forecasts shown in Figure 6. By doing so the model should be able to capture the cyclical dynamics of those variables that are correlated with GDP and inflation (and that were not subject to structural change).

Figure 9 shows that several variables were co-moving with GDP and inflation in the pre-crisis period – the gap between the conditional and the unconditional projections is a measure of this. However, this is notably not the case for public, households', and financial corporations' debts. This can be read as an indication of the fact that due to two (pre-crisis) decades of leveraging, these variables have experienced movements unrelated to GDP and in general to the economic cycle. This observation matches with some of the stylised facts on financial cycles reported in the literature (see, for example, Borio 2014).

Another feature that is in evidence in Figure 9 is the marked and very persistent deviation of the path of many variables from the pre-crisis trends. The gap that opened up during the crisis with respect to pre-crisis trends – among others for output, consumption, investment, private and public debts, and house prices – does not seem to close down in the final part of the sample. This begs the question whether the observed deviations are due to a very unusual and persistent cyclical event due to hysteresis effects, or they are better thought of as due to structural changes in the trend growth.

5 Conclusions and discussion

The analysis summarised in this section employs a large VAR incorporating a rich set of macroeconomic, fiscal and financial variables. Our model extracts information on the multivariate dynamics of economic indicators from the 1981-2008 sample, and produces forecasts (i) unconditional and (ii) conditional to the realised paths of output and prices. While the first can be thought of as a measure of the model-implied trends on the medium horizon, the latter provide an indication of how the behaviour of the economy since 2008 deviated from historical business cycle regularities.

Our analysis provides a bird's-eye view of the effect of the financial crisis in the Euro Area, and a few novel stylised facts. First, most of the variables deviated strongly and persistently from pre-crisis trends, among others output, consumption, private investment, private and public debts, and house prices. The deviations from pre-crisis trends do not seem to close down in the final part of the sample. While for some of the variables the deviation is explained by business cycle regularities and the deep contraction in production, for others the deviation was anomalous even given the large drop in output. This is notably the case for the protracted contraction in private investment. Second, households' and financial corporations' debts seem to be weakly associated to the economic cycle in the pre-crisis sample, possibly due to two decades of leveraging. Moreover, during the crisis, households' and financial corporations' debts and house prices markedly deviated from their pre-crisis trends. Finally, the jumps in the fiscal deficit-GDP and debt-GDP ratios in 2008-2009 were unprecedented and so was the fiscal consolidation that followed. Importantly, this anomaly in public debt is in large part explained by extraordinary measures in support of the financial sector, which show up in the stock-flow adjustments and reveals a key interaction between the fiscal and financial sectors.

Our approach does not recover the nature of the shocks that caused the deep recession, nor allows to make causal statements. This limitations are largely common to the literature that has studied financial crises. However, our methodology provides a useful descriptive account of the adjustment since the crisis, by distinguishing what can be explained by its cyclical component and what are its specific characteristics as compared to historical regularities.

The stylised facts recovered by our analysis point to the financial stress and the associated sharp fiscal consolidation and as potential explanatory factors of the observed anomalies. However, it is important to remark that, given our approach, we cannot discriminate amongst potential competing explanations. In particular we cannot determine whether the uncovered anomalous features were due to the 'depth' of the drop in output (and hence the activation of non-linearities and hysteresis effects), to a sudden permanent change in the underlying trends, or to the financial nature of the crisis.

On balance, our results on fiscal debt-deficit dynamics support the observation that, in the Great Recession, the financial-fiscal interaction determined a deterioration of the budget and an increase in the stock of debt, beyond business cycle regularities. As recovery began, countries reacted to the unprecedented accumulation of the stock of debt by a severe fiscal consolidation which is likely to have negatively affected the recovery path. These observations lend support to proposals for reform of the Euro Area governance that would allow a slower fiscal consolidation in case of large negative shocks and would distinguish between that part of the government fiscal balance depending on the business cycle and that part that is explained by the reaction to the increase in the stock of debt (see, for example, Corsetti 2015*a*,*b*.)

A.5 Appendix - Data

A.5.1 Euro Area Data

Variable	Source	Name	ID / Details
GDP	Euro Area Wide Model	GDP	YER
Consumption	Euro Area Wide Model	Private Consumption	PCR
Private Investment	Authors' calculations		
Public Investment	Euro Area Fiscal Database	EA general government investment	GIN, deflated by GDP deflator (ID: YED of EAWM
Unemployment	Euro Area Wide Model	Unemployment rate (as a percentage of labour force)	URX
Gov Deficit	Euro Area Fiscal Database	EA general government deficit (computed = TOE-TOR)	DEF, deflated by GDP deflator
Gov Debt	Euro Area Fiscal Database	EA general government debt	MAL, deflated by GDP deflator
Gov Spending	Euro Area Fiscal Database	EA general government total expenditure (corrected by UMTS proceeds), excluding Social Payments and Interest Payments	TOE, deflated by GDP deflator
Gov Revenues	Euro Area Fiscal Database	EA general government total revenue	TOR, deflated by GDP deflator
Social Payments	Euro Area Fiscal Database	EA general government social payments (social transfers other than in kind, D62)	THN, deflated by GDP deflator
Interest Payments	Euro Area Fiscal Database	EA general government interest payments	INP, deflated by GDP deflator
HH Savings	Euro Area Wide Model	Household savings rate	SAX
HH Debt	BIS and authors' calculations	Debt of Households	Calculations on Q:XM:H:A:M:XDC:A

Table A.5.1: Variables included in the VAR model [1/2]. Euro area data are relative to a fixed composition with 19 members.

Variable	Source	Name	ID / Details
NFC Debt	BIS and authors' calculations	Debt of Non-Financial Corporations	Calculations on Q:XM:N:A:M:XDC:A
FC Debt	IMF, ECB and authors' calculations	Debt of Financial Corporations	See details below
CA/GDP	Euro Area Wide Model	Current Account Balance/GDP	CAN, YEN
House Prices	ECB	Residential property prices, New and existing dwellings	RPP.Q.I7.N.TD.00.3.00
Long Term IR	Euro Area Wide Model	10-year Interest Rate	LTN
Short Term IR	Euro Area Wide Model	3-month Interest Rate	STN
HCPI	Euro Area Wide Model	Overall HICP (Non-seasonally adjusted)	HICP
ITA-GER i.r. spread	Eurostat	ITA-GER spread	Spread between Italian and German Maastricht criterion bond yields, around 10-year residual maturity
Productivity	EAWM, Eurostat and authors' calculations	Real GDP/Hours	GDP: YER of EAWM; Hours: Thousand hours worked from Eurostat, namq10a10e

Table A.5.2: Variables included in the VAR model [2/2]. Euro area data are relative to a fixed composition with 19 members.

A.5.2 Data Details

For "Euro Area Wide Model" we mean the 18th update of the database described in Fagan et al. (2005). All the non seasonally adjusted series have been seasonally adjusted using the TRAMO-SEATS procedure. Additional details:

- **Private Investment** - Difference between real Gross Fixed Capital Formation (Source: Euro Area Wide Model, ID: ITR) and Public Investment.

- **HH Debt** - Source: BIS data, Long series on total credit and domestic bank credit to the private non-financial sector, Households and NPISHs. Data for the Euro Area are available since 1999. To reconstruct data prior to 1999, we used the quarterly growth rates of the sum of the correspondent data for Belgium, Finland, France, Germany, Italy, Spain and Portugal.

- **NFC Debt** - Source: BIS data, Long series on total credit and domestic bank credit to the private non-financial sector, Non-financial corporations. Data for the Euro Area are available since 1999. To reconstruct data prior to 1999, we used the quarterly growth rates of the sum of the correspondent data for Belgium, Finland, France, Germany, Italy, Spain and Portugal.

- **FC Debt** - ECB Data for the Euro Area (ID BSI.M.U2.N.A.L40.A.1.Z5.0000.Z01.E) is available since 1997 Q3. To reconstruct data prior to 1997 Q3, we used the quarterly growth rates of the sum of the IMF data of Debt securities for Other Depository Corporations in Austria, France, Germany, Italy, Netherlands, Portugal, Spain.

- **Productivity** We measure it using the ratio between Real GDP and Total Hours Worked. Since the Eurostat data on hours is available since 1995 Q1, we reconstruct data prior to 1995 using the growth rate of the series "Hours worked in the Eurozone" used in Benati (2007). We then compute the index 1995=100.

B.5 Appendix - Financial interventions

B.5.1 Public Interventions in Support of the Financial Sector During the Crisis

We can distinguish between two types of public interventions for the financial sectors: those that affect both debt and deficit and those that affect debt only. According to the budget rules a capital injection can be considered as a capital transfer (increasing the government deficit, see the "residual" component in Figure 5) or as an acquisition of equity (a financial transaction, which does not impact on the government deficit; we have shown some figures relative to the period 2008-2011 in the Table 1 in the text).

Between 2008 and 2013 in the European Union there have been recapitalisation measures for 448.16 billions of euros accounting for 3.43% of GDP, and asset relief interventions for 188.24 billions accounting for 1.44% of GDP. Overall these measures accounted for 5.06% of GDP. This however is a small fraction of what was approved. We provide a list of approved measures by categories below.

Guarantees on liabilities (bulk of the intervention):

- The EC authorised a total aid of EUR 3 892.6 billion (29.8% of EU GDP in 2013) for guarantees on liabilities.
- The outstanding amount peaked in 2009 at EUR 835.8 billion (6.39% of EU 2013 GDP), and has decreased since.
- In 2013, outstanding guarantees amounted to EUR 352.3 billion (2.7% of EU 2013 GDP). However only EUR 3.13 billion of the total guarantees provided have been called.

Recapitalisation

The EC authorised aid for EUR 821.1 billion (6.3% of EU 2013 GDP) in the last six years. In 2008-2013, EUR 448 billion (3.4% of EU 2013 GDP) granted in recapitalisation measures. This was mostly for the UK, Germany, Ireland and Spain.

Direct Short Term Liquidity Support

The EC approved EUR 379.9 billion (2.9% of EU 2013 GDP) for liquidity measures. However, Member States have practically used only a very small amount. Spain and the Netherlands account for more than a half of the outstanding amounts in the peak year 2009.

Asset Relief Measures

In 2008-2013, Member States provided asset relief measures reaching EUR 188.2 billion (1.4% of EU 2013 GDP) while the total aid approved was EUR 669.1 billion (5.1% of EU 2013 GDP).

C.5 Appendix - Robustness

In this section we present the results of some robustness checks conducted on our analysis.

C5.1 Results up to 2017

In Figure C.5.1 we show the conditional forecast exercise performed up to 2017 Q4, showing the results for all the variables.

The results highlight three interesting facts: (i) the normalisation of the long term interest rates, as compared to past regularities, and hence the success of the ECB unconventional monetary policy measures; (ii) the protracted reduction of governments' deficits and hence the stabilisation of the stock of debt; (iii) the post-crisis adjustments in HH debt, FC debt and house prices, that appear as changes in the trends.

C5.2 Results relative to the Euro Area without Germany

We report here the results of a robustness exercise performed excluding Germany from the Euro Area aggregate. In Tables 5-6 we report the details on the data relative to Germany. For National Account variables and other indicators expressed in monetary terms, we have subtracted Germany data from the Euro Area aggregate. For unemployment, interest rates and price indexes, we have subtracted the value for Germany weighted by GDP (constant 1995 PPP prices for the Euro Area), then we have rescaled the indicators multiplying them by GDP_{EA}/GDP_{EA-Ger}. In Figure C.5.2 we report the results of the conditional forecast for all the variables. The main results are robust, especially looking at the anomalous behaviour of private investment, government deficit, government debt and house prices. Also, the adjustments in households' debt and financial corporations' debt is well evident and in line with the results relative to the Euro Area as a whole.

Variable	Source	Name	ID / Details
GDP	OECD	GDP	VOBARSA: National currency, volume estimates. Deflated using CPI index (OECD), rebased to 1995.
Consumption	OECD	Private final consumption expenditure	VOBARSA: National currency, volume estimates. Deflated using CPI index (OECD), rebased to 1995.
Investment	OECD	Gross fixed capital formation	VOBARSA: National currency, volume estimates. Deflated using CPI index (OECD), rebased to 1995.
Unemployment	OECD	Unemployment rate	
Gov Deficit	EA Fiscal Database and authors' calculations	General government deficit (computed = TOE-TOR)	DEF, deflated by GDP deflator.
Gov Debt	EA Fiscal Database and authors' calculations	General government debt	MAL, deflated by GDP deflator
Gov Spending	EA Fiscal Database and authors' calculations	General government total expenditure (corrected by UMTS proceeds), excluding Social Payments and Interest Payments	TOE, deflated by GDP deflator
Gov Revenues	EA Fiscal Database and authors' calculations	General government total revenue	TOR, deflated by GDP deflator
Social Payments	EA Fiscal Database and authors' calculations	General government social payments (social transfers other than in kind, D62)	THN, deflated by GDP deflator
Interest Payments	EA Fiscal Database and authors' calculations	General government interest payments	INP, deflated by GDP deflator
HH Savings	Datastream, Bundesbank	Household savings rate	BDPERSAVE; Pan BD Q0191.
HH Debt	BIS	Debt of Households	Q:DE:H:A:M:XDC:A

Table C.5.1: Variables relative to Germany used to construct the aggregate EA-Germany [1/2].

Variable	Source	Name	ID / Details
NFC Debt	BIS	Debt of Non-Financial Corporations	Q:DE:N:A:M:XDC:A
FC Debt	ECB, Bundesbank and authors' calculations	Debt of Financial Corporations	ECB: BSI.Q.DE.N.A.L40.A.1.Z5.0000.Z01.E; Bundesbank: BBK01.OU0370
CA/GDP	OECD	Current Account Balance/GDP	VOBARSA: National currency, volume estimates. Deflated using CPI index (OECD), rebased to 1995.
House Prices	BIS	Nominal house price index, SA	Long-term series on nominal residential property prices
Long Term IR	Eurostat	10-year Interest Rate	EMU convergence criterion series, irt-lt-mcby-q
Short Term IR	Datastream	3-month Interest Rate	BD EU-MARK 3M DEPOSIT (FT/TR) - MIDDLE RATE, ECWGM3M
CPI	OECD	CPI	
ITA-GER i.r. spread	Eurostat	ITA-GER spread	Spread between Italian and German Maastricht criterion bond yields, around 10-year residual maturity
Productivity	Destatis and authors' calculations	Real GDP/Hours	Datastream: BDIAGPHCE and BDGNPEMHE

Table C.5.2: Variables relative to Germany used to construct the aggregate EA-Germany [2/2].

All the non seasonally adjusted series have been seasonally adjusted using the TRAMO-SEATS procedure. Additional details on the data:

- **Fiscal data** - Quarterly data are available since 1991 Q1. To reconstruct data prior to 1991, we have interpolated the corresponding annual data using the Chow et al. (1971) procedure.

- **HH Debt** - BIS data: Long series on total credit and domestic bank credit to the private non-financial sector, Households and NPISHs.

- **NFC Debt** - BIS data: Long series on total credit and domestic bank credit to the private non-financial sector, Non-financial corporations.

- **FC Debt** - ECB Data are available since 1997 Q3. Prior to 1997 Q3 we have reconstructed the series using the growth rate of the Bundesbank series "Principal assets and liabilities of banks (MFIs) in Germany by category of banks / Bearer debt securities outstanding / All categories of banks" (real, 1995 prices).

- **Productivity** We measure it using the ratio between Real GDP and Total Hours Worked. Since data on GDP/Hours is available since 1995 Q1, we reconstruct data prior to 1995 using the growth rate of the GDP per man/hour. We then computed the index 1995=100.

C5.3 Results replacing the house price index

We performed another robustness exercise replacing the existing index with a weighted average (weighted by constant GDP at market prices, PPP, for 1995) of the house price index in Germany, France, Italy, Spain and Netherlands (Source: BIS, Long-term series on nominal residential property prices, seasonally adjusted using TRAMO-SEATS). Results are not significantly affected, as shown in Figure C.5.3.

Variable	Description	Source
GDP	Real GDP	Euro Area Wide Model
Consumption	Personal consumption	Euro Area Wide Model
Private Investment	Gross investment	Authors' calculations
Public Investment	General government investment	Euro Area Fiscal Database
Unemployment	Unemployment rate	Euro Area Wide Model
Gov Deficit	General government deficit	Euro Area Fiscal Database
Gov Debt	General government debt	Euro Area Fiscal Database
Gov Spending	General government total expenditure, excluding Social Payments and Interest Payments	Euro Area Fiscal Database
Gov Revenues	General government total revenue	Euro Area Fiscal Database
Social Payments	General government social payments	Euro Area Fiscal Database
Interest Payments	General government interest payments	Euro Area Fiscal Database
HH Savings	Household saving rate	Euro Area Wide Model
HH Debt	Households debt	Authors' Calculations
NFC Debt	Non-financial corporations debt	Authors' Calculations
FC Debt	Debt securities of MFI excl. ESCB	Authors' Calculations
CA/GDP	Current account / GDP	Euro Area Wide Model
House Prices	House prices	ECB
Long Term IR	Long term interest rate	Euro Area Wide Model
Short Term IR	Short term interest rate	Euro Area Wide Model
HCPI	Harmonized consumer price index	Euro Area Wide Model
ITA-GER i.r. spread	Spread Italian-German 10-year bond yields	Eurostat
Productivity	Real GDP / Hours	Authors' Calculations

Table 2: **List of Variables.** See Appendix **??** for the details.

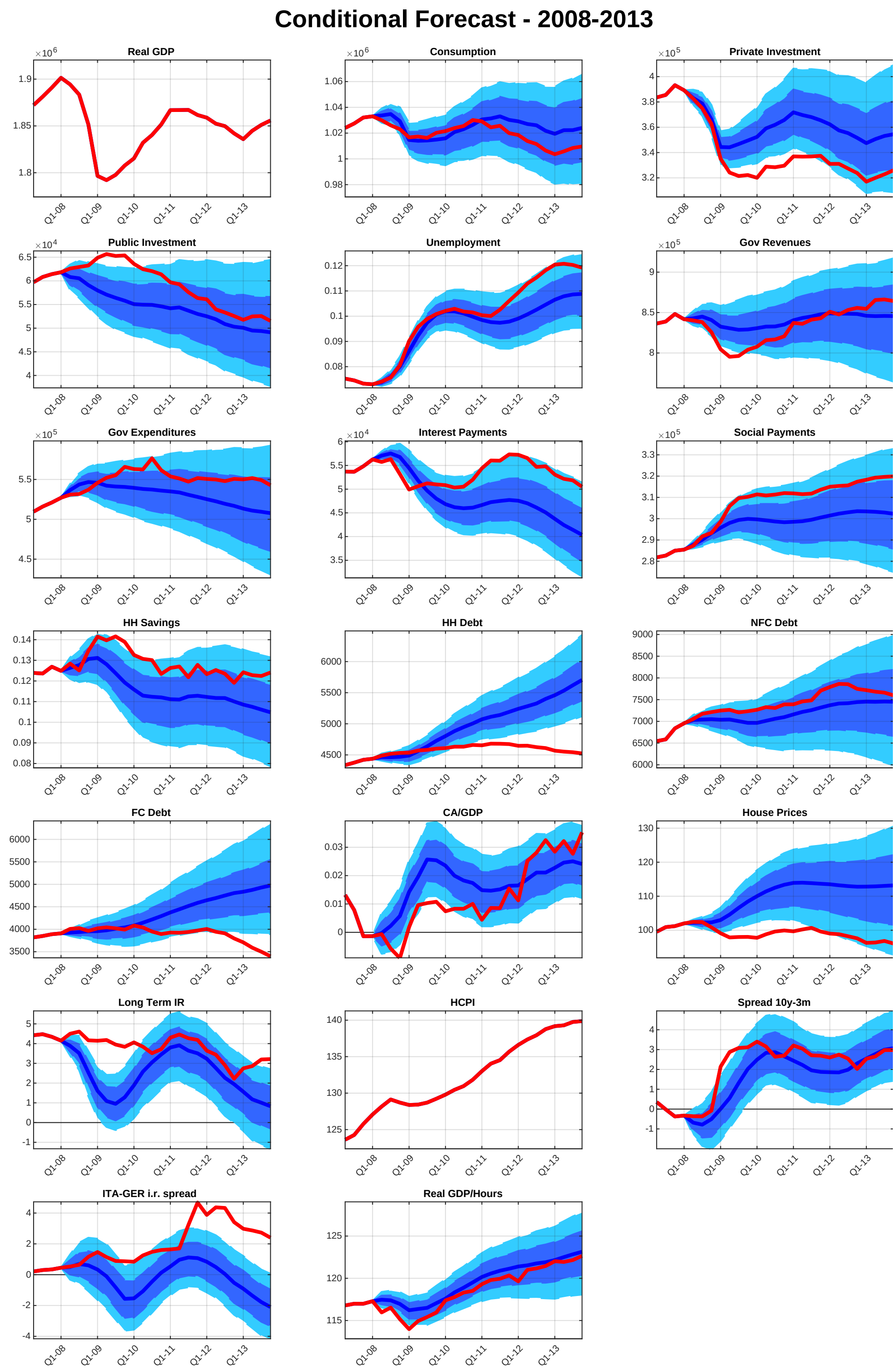
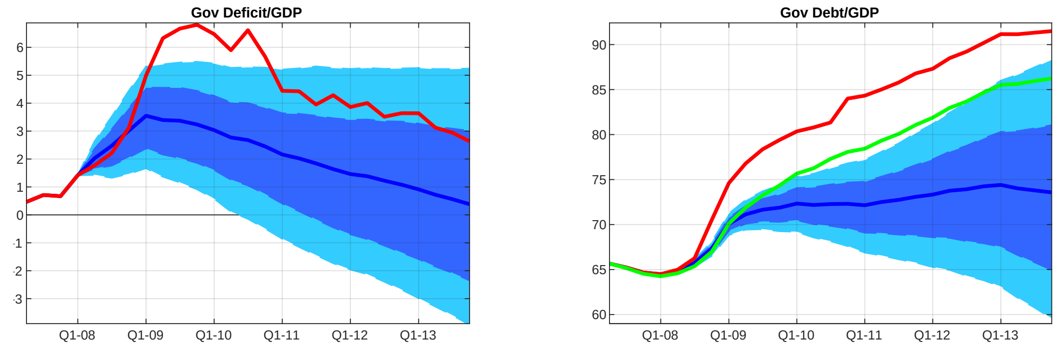
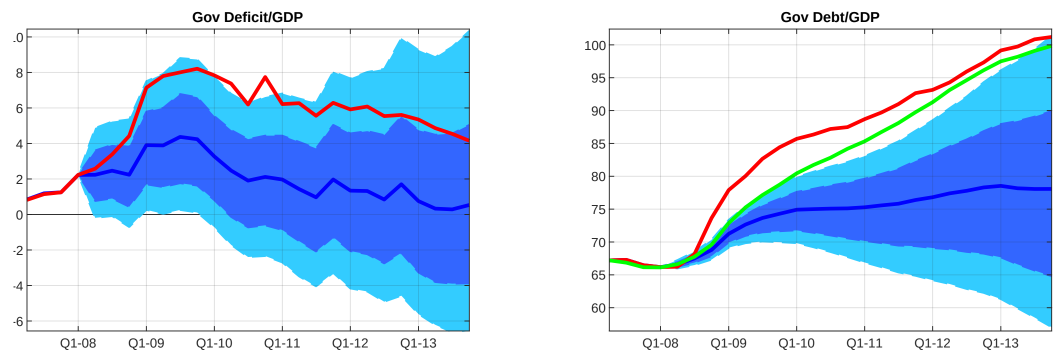


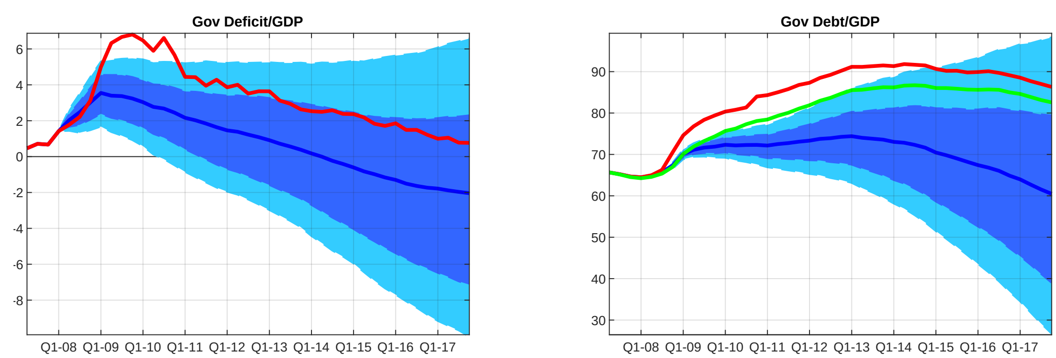
Figure 6: **Conditional forecast.** The figure shows the realised data (red) and the counterfactual path of the variables. The blue lines are the medians of the forecasts conditional on the path of GDP, plotted with 68% (dark blue) and 90% (light blue) coverage intervals. House Prices and HICP are indices, interest rates and spreads are expressed in yearly rates, HH Savings is the Eurostat saving ratio; all the other variables are in Millions of Euros in real terms, with 1995 as reference year.



(a) **Conditional forecast, public debt and public deficit ratios, 2008-2013.**



(b) **Conditional forecast, Euro Area without Germany, 2008-2013.**



(c) **Conditional forecast, public debt and public deficit ratios, 2008-2017.**

Figure 7: The figures show the realised data (red), the data minus stock-flow adjustment (green) and the counterfactual path (blue). The blue lines are the medians of the forecasts conditional on the path of GDP and inflation, plotted with 68% (dark blue) and 90% (light blue) coverage intervals.

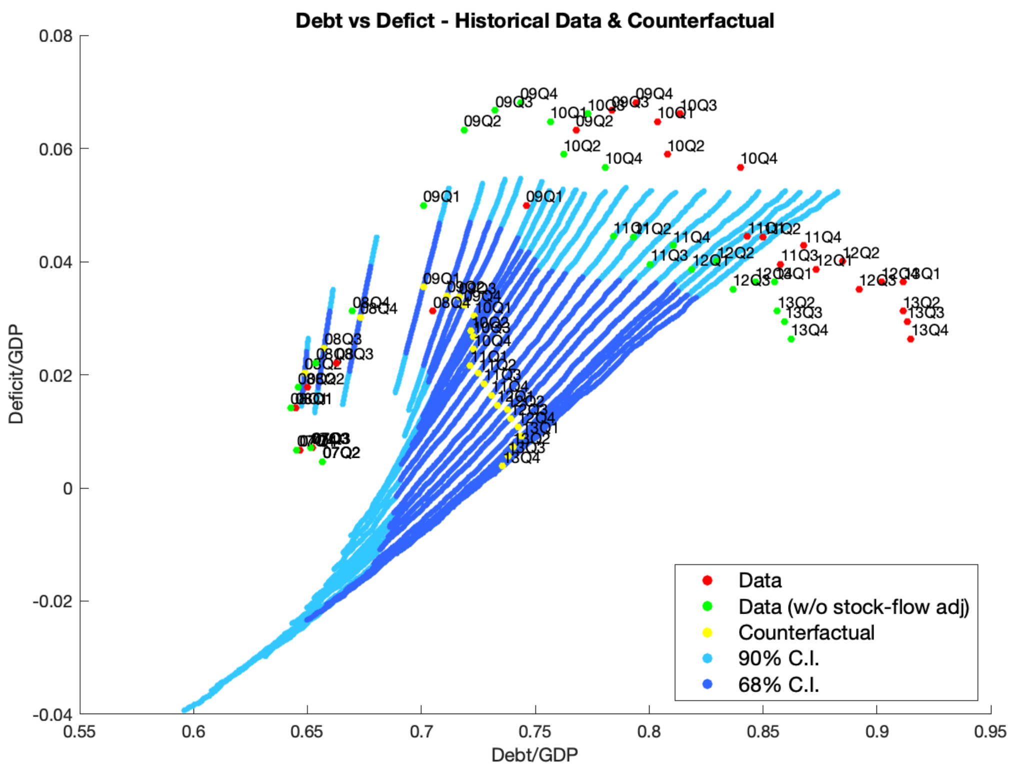


Figure 8: **Scatter plot: Debt and deficit counterfactual.**

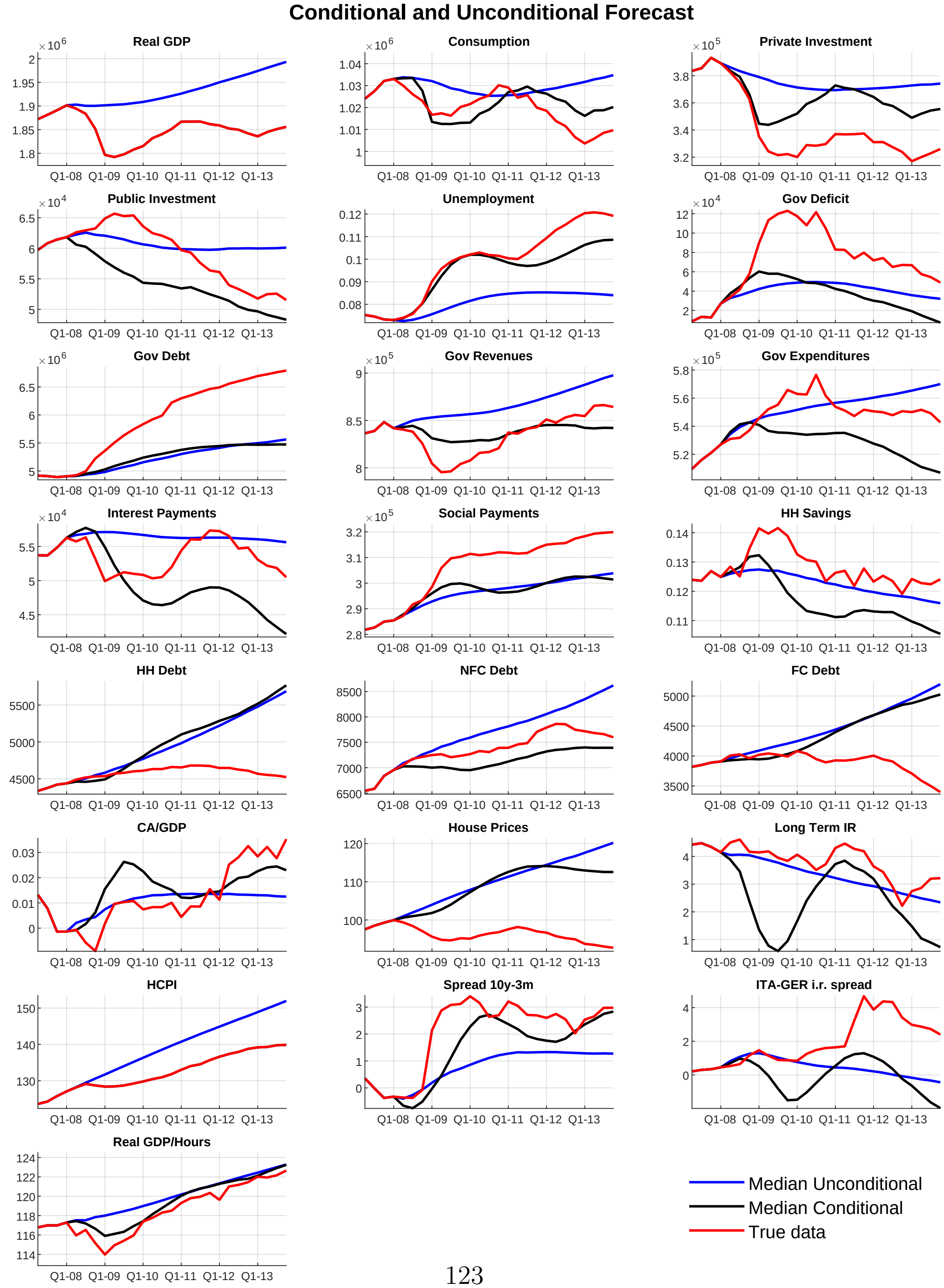


Figure 9: **Conditional and unconditional forecast.** The figure shows the realised data (red), the median of the forecast conditioned on GDP and HICP paths (black) and the median of the unconditional forecast (blue). House Prices and HICP are indices, interest rates and spreads are expressed in yearly rates, HH Savings is the Eurostat saving ratio; all the other variables are in Millions of Euros in real terms with 1995 as reference year.

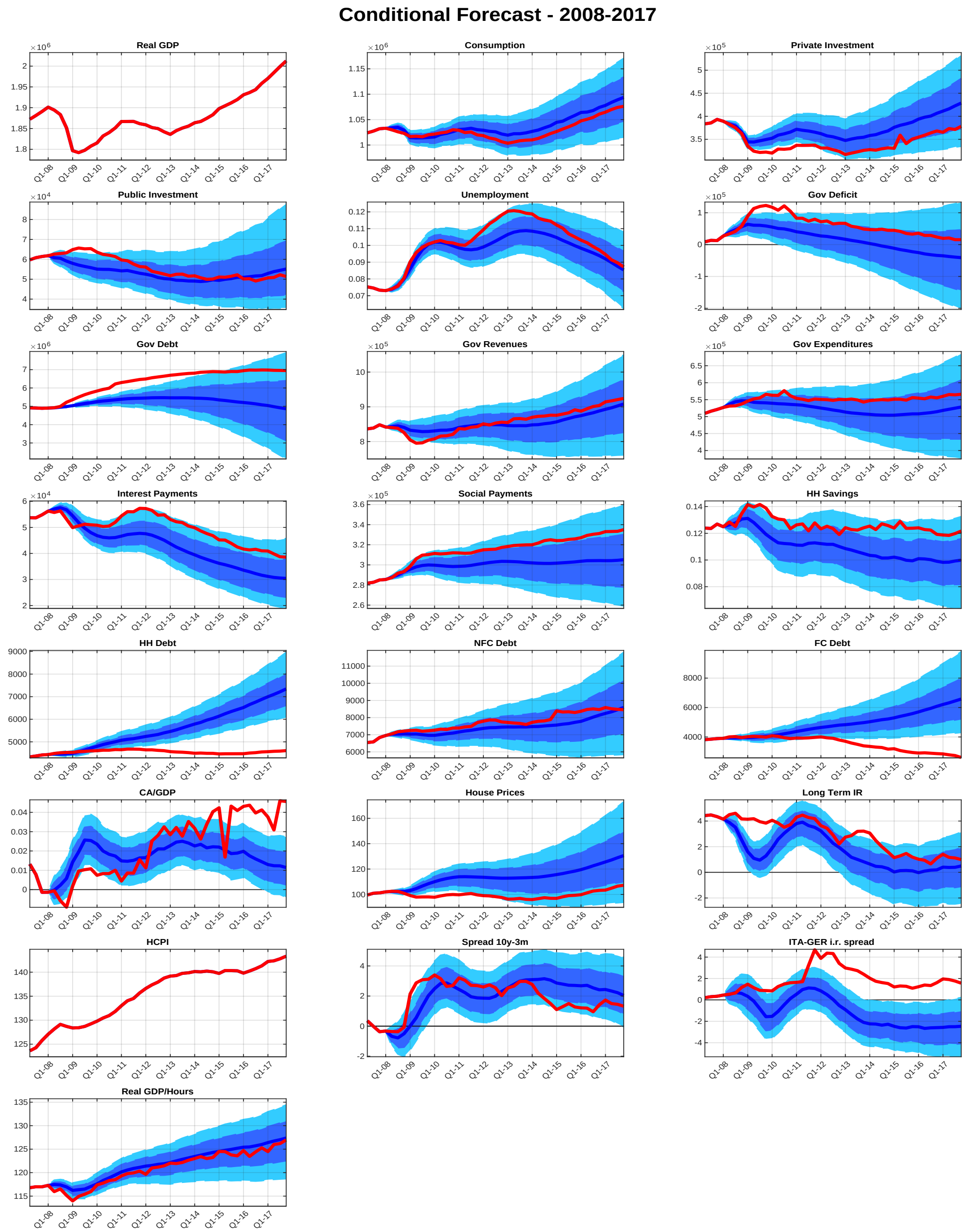


Figure C.5.1: **Conditional forecast.** The figure shows the realised data (red) and the counterfactual path of the variables. The blue lines are the medians of the forecasts conditional on the path of GDP, plotted with 68% (dark blue) and 90% (light blue) coverage intervals. House Prices and HICP are indices, interest rates and spreads are expressed in yearly rates, HH Savings is the Eurostat saving ratio; all the other variables are in Millions of Euros in real terms, with 1995 as reference year.

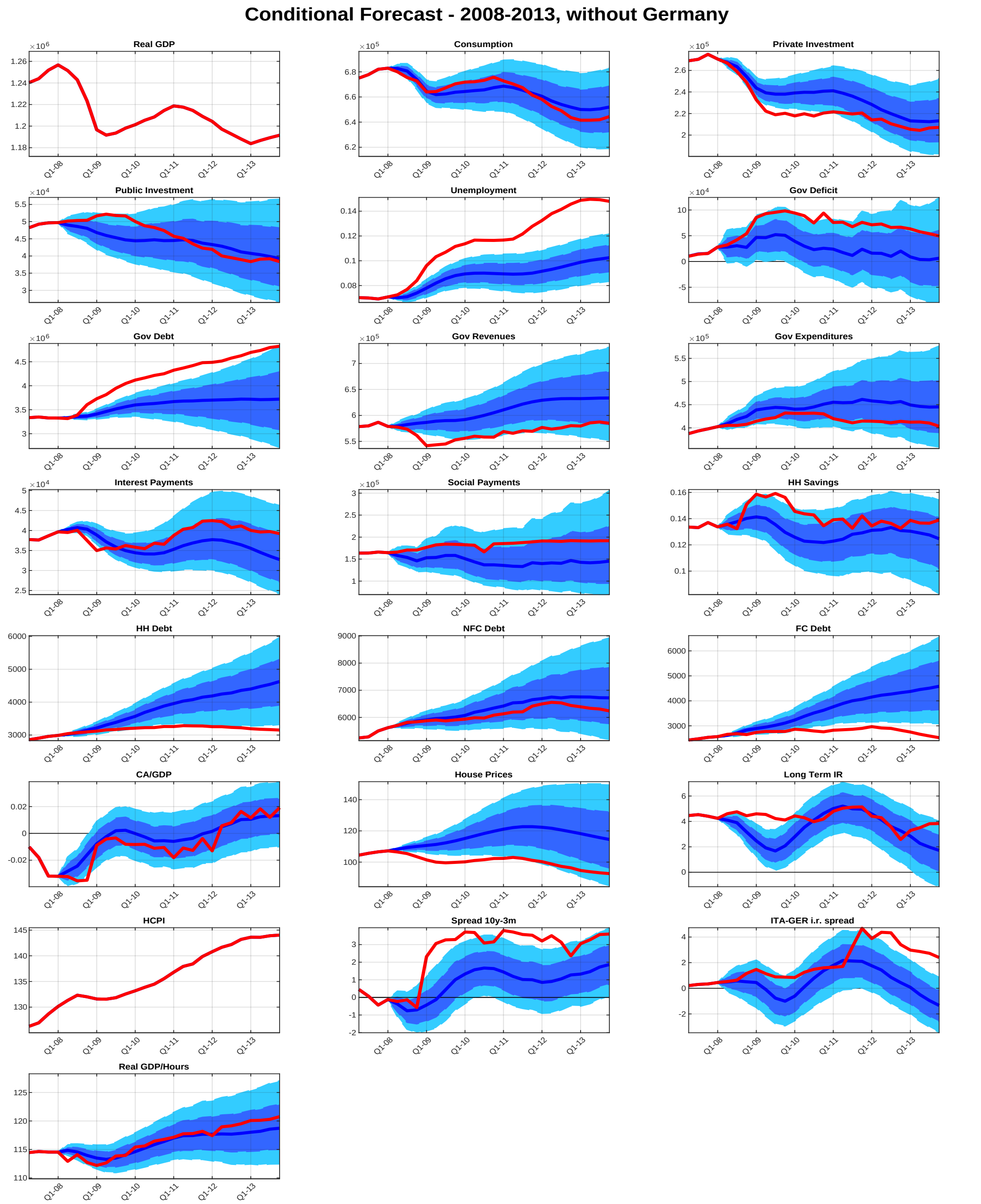


Figure C.5.2: **Conditional forecast - Euro Area without Germany.** The figure shows the realised data (red) and the counterfactual path of the variables, performing the exercise on a dataset of Euro Area excluding Germany. The blue lines are the medians of the forecasts conditional on the path of GDP, plotted with 68% (dark blue) and 90% (light blue) coverage intervals. House Prices and HICP are indices, interest rates and spreads are expressed in yearly rates, HH Savings is the Eurostat saving ratio; all the other variables are in Millions of Euros in real terms, with 1995 as reference year.

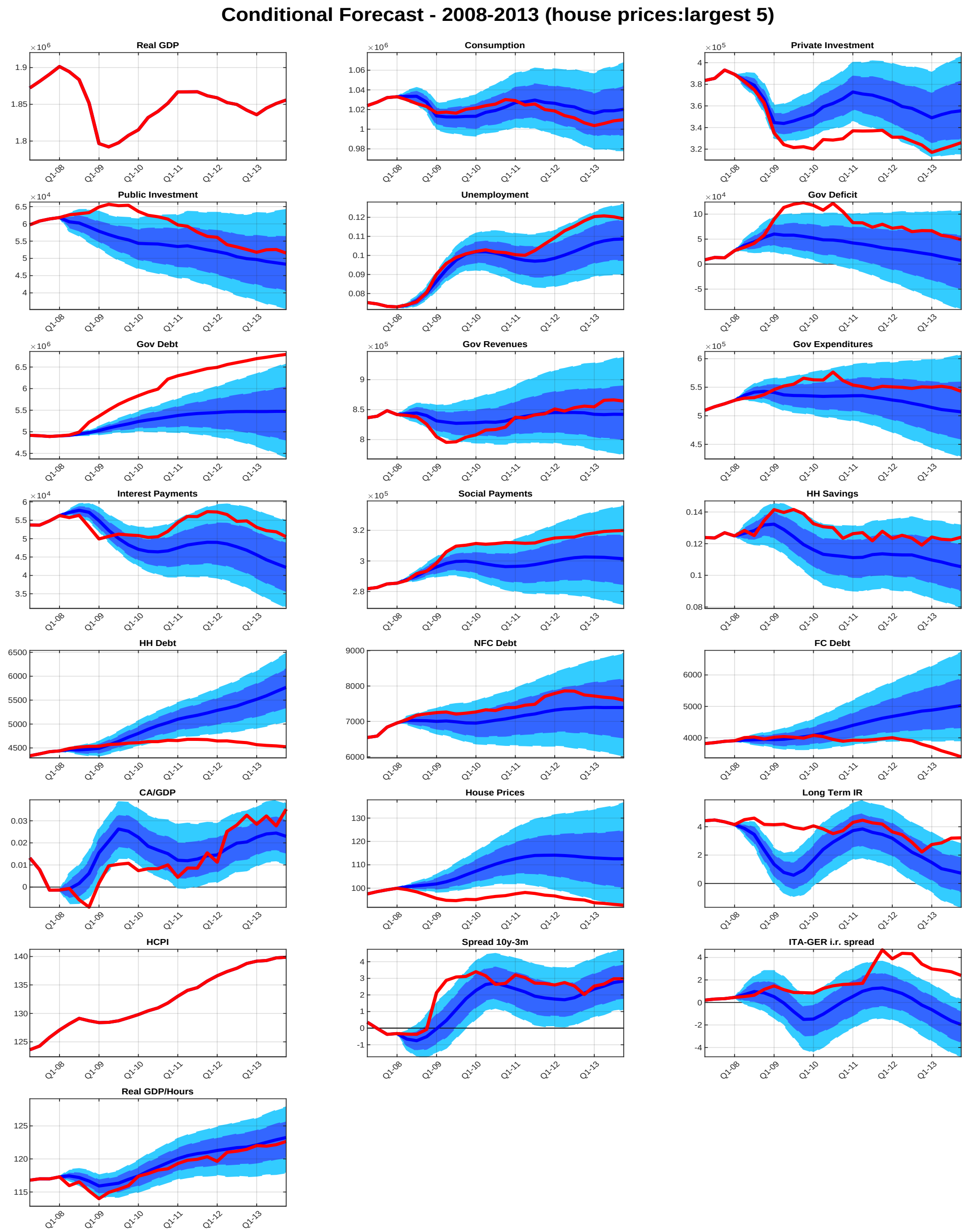


Figure C.5.3: **Conditional forecast - replacing the house price index.** The figure shows the realised data (red) and the counterfactual path of the variables, performing the exercise replacing the Euro Area house price index with a weighted average of the house prices indices relative to the five largest countries. The blue lines are the medians of the forecasts conditional on the path of GDP, plotted with 68% (dark blue) and 90% (light blue) coverage intervals. House Prices and HICP are indices, interest rates and spreads are expressed in yearly rates, HH Savings is the Eurostat saving ratio; all the other variables are in Millions of Euros in real terms, with 1995 as reference year.

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