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On measuring uncertainty and its impact on investment: cross-country evidence from the euro area

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Non-technical summary

Research Question

In view of the sluggish recovery of euro area investment in the course of the financial and sovereign debt crisis, the role of aggregate uncertainty as an impediment to growth has been a topic of heightened interest. While theory points to a number of channels through which an adverse impact of uncertainty on investment can be rationalized, empirical research suffers from the lack of an objective measure of uncertainty, complicating a sound evaluation of uncertainty and its effect on investment. Hence, it is hardly surprising that the literature comes up with a range of uncertainty proxies which, from a conceptual point of view, vary in some cases substantially.

Contribution

Focussing on the four largest euro-area countries, this paper investigates the role of uncertainty for investment dynamics. By doing so, we compare five prominent uncertainty proxies put forward in the recent literature: the (implied) stock market volatility, a survey-derived measure of expectations dispersion, a newspaper-based indicator of policy uncertainty, and two indicators taking up the concept of (econometric) unpredictability. The analysis of the different uncertainty proxies is conducted on the grounds of both descriptive and VAR model-based evidence.

Results

Although all uncertainty measures show countercyclical behaviour, we find uncertainty as measured by the conditional volatility of the unforecastable components of a broad set of time series to exhibit noticeable robust effects across different model specifications and countries. This is remarkable as the indicator is closely related to the typical notion of uncertainty by approximating the purely unforecastable component of future values of macroeconomic indicators given the information set available to an economic decision maker. Based on this type of uncertainty proxy, we document pronounced negative investment responses to uncertainty shocks. Moreover, we find that uncertainty can account for a relevant portion of the decrease in gross fixed capital formation in machinery and equipment in the course of the Great Recession.

Nichttechnische Zusammenfassung

Fragestellung

Mit Blick auf die im Zuge der Finanz- und Staatsschuldenkrise nur zögerliche Erholung der Investitionen im Euro-Raum, ist die Rolle von Unsicherheit als ein mögliches Wachstumshemmnis verstärkt in den Fokus gerückt. Während aus theoretischer Sicht zahlreiche Wirkungskanäle bestehen, die einen negativen Einfluss von Unsicherheit auf die Investitionstätigkeit erklären können, ist die empirische Wirtschaftsforschung mit der Absenz eines objektiven Unsicherheitsmaßes konfrontiert, die eine Untersuchung der Effekte von Unsicherheit auf Investitionen erschwert. Vor diesem Hintergrund ist es verständlich, dass im Rahmen empirischer Analysen zahlreiche Unsicherheitsindikatoren verwendet werden, welche sich aus konzeptioneller Sicht zum Teil erheblich unterscheiden.

Beitrag

Das vorliegende Diskussionspapier untersucht den Einfluss von Unsicherheit auf die Investitionsdynamik in den vier größten Volkswirtschaften des Euro-Raums. In diesem Zusammenhang werden fünf - in der Literatur häufig verwendete - Unsicherheitsmaße miteinander verglichen. Diese umfassen neben der anhand der realisierten sowie auf Basis von Aktienoptionen abgeleiteten impliziten Volatilität von Aktienindizes, die auf Konjunkturumfragen basierende Streuung von Produktionserwartungen, ein aus der Auswertung von Zeitungsartikeln abgeleitetes Maß für politische Unsicherheit sowie zwei Indikatoren, welche auf den Prognosefehlern ökonometrischer Modelle beruhen. Neben einer deskriptiven Analyse erfolgt eine Betrachtung der Unsicherheitsmaße mittels struktureller Vektorautoregressionsmodelle.

Ergebnisse

Obgleich alle der betrachteten Unsicherheitsmaße einen antizyklischen Verlauf aufweisen, indizieren die Analyseergebnisse insbesondere für das Unsicherheitsmaß, welches auf der bedingten Volatilität der nicht prognostizierbaren Komponente wichtiger makroökonomischer Indikatoren beruht, einen hohen Grad an Robustheit über verschiedene Modellspezifikationen und Länder hinweg. Dieses Resultat ist insofern bemerkenswert, als dass das angeführte Maß eng mit dem theoretischen Konzept von Unsicherheit verbunden ist, welches Unsicherheit als die bei gegebener Informationsmenge völlig unvorhersehbare Komponente zukünftiger Realisationen makroökonomischer Indikatoren definiert. Unter Verwendung dieses Unsicherheitsindikators lassen sich ausgeprägte negative Effekte von Unsicherheit auf die Investitionstätigkeit nachweisen. Darüber hinaus wird ersichtlich, dass Unsicherheit einen relevanten Anteil des Rückgangs der Ausrüstungsinvestitionen im Verlauf der Finanzkrise erklären kann.

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On measuring uncertainty and its impact on investment: cross-country evidence from the euro area*

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Abstract

Investment fell sharply in the euro area after the financial crisis and has not yet returned to pre-crisis levels in many core economies. Focusing on the four largest euro-area countries, this paper investigates the role of uncertainty for investment dynamics. By doing so, we compare five prominent uncertainty proxies put forward in the recent literature: the (implied) stock market volatility, a survey-derived measure of expectations dispersion, a newspaper-based indicator of policy uncertainty, and two indicators taking up the concept of (econometric) unpredictability. Although all uncertainty measures show countercyclical behavior, we find uncertainty as measured by the conditional volatility of the unforecastable components of a broad set of time series to exhibit noticeable robust effects across different model specifications and countries. Based on this type of uncertainty proxy, we document pronounced negative investment responses to uncertainty shocks. We further show that these effects can explain a relevant portion of the decrease in investment in the course of the Great Recession.

Keywords: Uncertainty, Investment, Euro Area

JEL classification: C53, D81, E22, E32.

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1 Introduction

Investment fell sharply in the euro area after the financial crisis and has not yet returned to pre-crisis levels in many of the region's core economies. While the downturn in investment after 2008 was broadly in line with past experiences of financial crises, the outbreak of the European sovereign debt crisis further depressed investment activity, impeding a "typical" recovery (see European Commission, 2015). Several factors have been associated with the observed sluggish recovery of investment, including weak demand, low profitability growth, bank and corporate deleveraging, and a high degree of economic uncertainty. In this paper we analyze the role of increased macroeconomic uncertainty for investment activity in four major euro-area economies.

The potentially adverse effects of uncertainty on the processes underlying investment decisions have been studied in a large body of theoretical work.[1] For example, Bernanke (1983), Pindyck (1991), and Bloom (2009) lay out the negative impact of uncertainty on investment using a framework of irreversible investment, where there exists a "real-option value" to waiting to invest until uncertainty is resolved. Nakamura (2002) shows that, under the assumption of a decreasing-returns-to-scale technology, uncertainty reduces investment activity if the lifetime of capital is shorter than the firm's planning horizon, even without irreversibility of investment. Saltari and Ticchi (2007) and Femminis (2012) outline that the presence of risk-aversion, although not sufficient by itself, can explain a negative effect of uncertainty on investment activity. Arellano, Bai, and Kehoe (2012), Christiano, Motto, and Rostagno (2014), Gilchrist, Sim, and Zakrajšek (2014), and Dorofeenko, Lee, Salyer, and Strobel (2016) emphasize the role of financial distortions through which uncertainty negatively affects investment. Focusing on the role of agency conflicts stemming from the design of managerial compensation, Glover and Levine (2015) provide a further theoretical explanation for a negative relationship between uncertainty and investment activity.

An empirical validation of the adverse effects of uncertainty appears challenging, however, in the absence of an objective measure of uncertainty. Hence, a range of uncertainty proxies have been proposed in recent empirical studies, which focus on the impact of uncertainty on macroeconomic dynamics.

In this paper we perform both a descriptive and a structural vector autoregressive (SVAR) analysis to compare five prominent uncertainty measures recently put forward in the literature: the realized or implied volatility of stock market returns (*SVOL*) in accordance with Bloom (2009), cross-sectional dispersion in firms' subjective expectations (*EDISP*) using business climate survey data following Bachmann, Elstner, and Sims (2013), economic policy uncertainty derived from newspaper article counts as proposed by Baker, Bloom, and Davis (2016), and indicators of macroeconomic uncertainty (*MU1*, *MU2*) that are based on the unpredictable components of a broad set of economic variables as in Jurado, Ludvigson, and Ng (2015) and Rossi and Sekhposyan (2015). Although these measures differ, in some cases substantially, from a conceptual point of view, they are frequently used in the literature to gauge the macroeconomic effects of uncertainty.

In our analysis of the dynamic impact of the five uncertainty measures on investment activity, we focus on the four largest euro-area economies: Germany, France, Italy, and

[1] Note that the relationship between uncertainty and investment is theoretically ambiguous in general (see, e.g., Carruth, Dickerson, and Henley, 2000, for an overview).

Spain. Investment activity is captured by the main industrial groupings (MIG) classification "capital goods" of industrial production, which allows us to conduct the analysis on a monthly basis. Our investigation is complemented by using quarterly gross fixed capital formation in machinery and equipment as a measure of investment. Starting with a bivariate model in accordance with Bachmann et al. (2013) and Scotti (2016), we extend our empirical investigation using higher-dimensional SVARs as in Bloom (2009) and Jurado et al. (2015).

The main results of the analysis are as follows. First, all uncertainty measures show countercyclical behavior with respect to investment activity. However, the frequency of uncertainty episodes detected and the raw correlation between the uncertainty proxies under investigation vary markedly, reflecting the conceptual differences of the respective indicators. Second, the results obtained from the VAR analysis reveal that uncertainty as captured by the conditional volatility of the unforecastable components of a broad set of macroeconomic time series (*MU1*) generates remarkably robust investment dynamics across model specifications and countries. This is even more noteworthy as this indicator is closely related to the typical definition of uncertainty by approximating the purely unforecastable component of future values of macroeconomic indicators given the information set available to an economic decision maker (see Jurado et al., 2015). Third, resorting to quarterly gross fixed capital formation in machinery and equipment, we show that periods of low or negative investment growth in Germany, France, Italy, and Spain can be explained in part by increased uncertainty. In particular, we find heightened uncertainty to account for a considerable share of the drop in investment activity across all four euro-area countries during the Great Recession in 2008/09.

Our paper thus makes two important contributions. First, we conduct an extensive comparison of five widely used uncertainty proxies employing a standard macroeconometric framework. To this end, we construct some of these measures – which to the best of our knowledge so far exist for the US only – for four major euro-area countries.[2] Second, the paper provides insights into the impact of uncertainty on investment activity in Germany, France, Italy, and Spain.

The remainder of the paper is organized as follows. Section 2 begins by describing the distinct uncertainty concepts and then provides a descriptive analysis of the five uncertainty measures under investigation, while Section 3 outlines the econometric framework applied. In Section 4 we present the results of the SVAR analysis, whereas Section 5 discusses the results obtained from both the descriptive and the model-based analysis and relates them to findings in the recent theoretical and empirical literature. Section 6 concludes and outlines directions of future research. A detailed description of the data we use and some additional estimation results are provided in a supplementary appendix.

2 Measuring Uncertainty

Subsequently, we first give a brief outline of the methodological approaches underlying the five uncertainty proxies under consideration before carrying out a descriptive analysis of the respective indicators. In this context it should be pointed out that the uncertainty measures differ in part substantially from a conceptual perspective. First, the particular

[2] This holds specifically with respect to the uncertainty indicators *MU1* and *MU2*.

data inputs of the uncertainty indicators vary considerably, leading to broad-based measures as well as proxies that rely entirely on financial market data, survey data, or data from newspaper article counts. Second, it could be argued that specific indicators are more closely related to the concept of risk, while other measures rather relate to ambiguity or Knightian uncertainty (see Knight, 1921).[3] However, since all indicators considered are frequently applied in studies that intend to assess the macroeconomic effects of uncertainty, we deliberately refrain from any attempt to disentangle risk and (Knightian) uncertainty in the current paper and hence refer to a broader definition of uncertainty that blends both components.[4]

2.1 Uncertainty Indicators

Since uncertainty is inherently unobservable, its measurement becomes a challenging task. Indeed, a wide range of empirical studies propose alternative proxies for uncertainty. In this paper, we compare five prominent measures of uncertainty which have recently been put forward in the literature. These uncertainty proxies are based on the (implied) volatility of stock market returns (*SVOL*), the frequency of newspaper articles related to economic policy uncertainty (*EPU*), the cross-sectional dispersion of production expectations in business surveys (*EDISP*), and the unpredictable components of a large set of macroeconomic indicators (*MU1* and *MU2*).

Since most of the aforementioned uncertainty proxies have been applied to US data only, one contribution of the current paper consists in the construction of some of these indicators for four major euro-area countries (Germany, France, Italy, Spain). This applies, in particular, to *MU1* and *MU2*. Subsequently, we present a brief description of each indicator.[5]

2.1.1 *SVOL* – Stock Market Volatility

One of the most prominent uncertainty proxies in the literature was proposed by Bloom (2009) and captures the implied or realized volatility of stock market returns. In particular, Bloom (2009) uses a concatenated series of the volatility of actual daily returns for the S&P500 and the implied volatility as measured by the VXO index (based on the S&P100). We follow this approach and apply a series of implied volatility where available. For Germany, we thus use the VDAX, which measures the implied volatility of the DAX. For France, we concatenate the series of the actual volatility of the CAC40 and of the implied volatility measured by the VCAC, which is available as of 2000.[6] For Italy

[3] Bekaert, Hoerova, and Duca (2013) decompose an index of implied stock market volatility into two components: one that refers to expected stock market volatility and another that reflects risk aversion and possibly also Knightian uncertainty.

[4] In this respect, we follow the approach of Bloom (2014). For an explicit decomposition of uncertainty into ambiguity and risk, see Rossi, Sekhposyan, and Soupre (2016).

[5] The heightened interest in uncertainty in the course of the Great Recession prompted the development of numerous uncertainty measures (see, e.g., Bloom, 2014; Gilchrist et al., 2014; Scotti, 2016). Since an exhaustive analysis of these proxies is beyond the scope of this work, we instead focus our attention on the five uncertainty indicators listed above on grounds of data availability and their prominent role in the recent literature.

[6] The VDAX (new) and the VCAC were taken from Thomson Reuters Datastream. Both indicators are designed to measure the 30-day expected volatility of the underlying stock price indexes.

and Spain, we compute the index based on the volatility of actual returns for the FTSE MIB Storico and IGBM, respectively.[7] As noted by Bloom (2009), indicators of implied volatility of share returns are a canonical measure of uncertainty in the financial market.

2.1.2 *EPU* – Economic Policy Uncertainty

Baker et al. (2016) develop an indicator for economic policy uncertainty. The indicator is based on frequency counts of newspaper articles containing the words uncertainty or uncertain, economic or economy, and one or more policy-related terms. In each of the four euro-area economies, two newspapers are taken into account in setting up the index. Although the policy uncertainty indicator is available for each country under investigation, the length of the time series differs across countries. For France the *EPU* series begins in 1987, for Germany in 1993, for Italy in 1997, and for Spain in 2001.[8]

2.1.3 *EDISP* – Expectation Dispersion

Bachmann et al. (2013) propose an uncertainty measure based on the disagreement in production expectations revealed in business surveys. In the process, we compute country-specific uncertainty proxies using the business and consumer surveys managed by the Directorate General for Economic and Financial Affairs of the European Commission.[9] Specifically, we follow Bachmann et al. (2013) and exploit the dispersion of responses to the forward-looking survey question:

> *How do you expect your production to develop over the next three months? It will*
>
> - *increase,*
> - *remain unchanged,*
> - *decrease.*

Let $Frac_t^+$ denote the weighted fraction of firms in the cross section with "increase" responses at time t and $Frac_t^-$ the weighted fraction of firms with "decrease" responses. *EDISP* is then computed as

$$EDISP = \sqrt{Frac_t^+ + Frac_t^- - (Frac_t^+ - Frac_t^-)^2}. \tag{1}$$

Due to their reliance on firm-level information, indicators of this class become frequently associated with idiosyncratic (micro) uncertainty (see, e.g., Bloom, 2014).

2.1.4 *MU1* – Macroeconomic Uncertainty I

In a recent paper, Jurado et al. (2015) – hereinafter referred to as JLN – point out that conditions under which uncertainty proxies based on the volatility or dispersion of economic variables are "(...) tightly linked to the typical theoretical notion of uncertainty

[7] The returns are based on price indexes. The correlation between the implied volatility measures (VDAX, VCAC) and the actual volatility of the stock price returns in Germany and France (DAX and CAC40) amounts to 0.9 in each country.

[8] The indicators are obtained from `http://www.policyuncertainty.com`.

[9] The data are available on the DG ECFIN's website (see `http://ec.europa.eu/economy_finance/index_en.htm`.)

may be quite special" (JLN, p. 1178). For instance, it is unclear to what extent this variability is actually expected by market participants.[10] They further criticize the fact that existing uncertainty proxies are usually based on a fairly limited information set, e.g., a single economic indicator, which appears to be ambitious since the indicators are often used to measure aggregate macroeconomic uncertainty. Hence, JLN propose an uncertainty measure that addresses these issues. The indicator is based on the notion that what matters for economic agents is not whether certain economic indicators have become more or less stable, but rather whether the economy as a whole has become more or less predictable; i.e., less or more uncertain.

More precisely, the uncertainty measure proposed by JLN relies on the unforecastable components of a broad set of economic variables. To this end, JLN employ data on a large set of economic indicators and compute macroeconomic uncertainty at time t by aggregating the conditional volatility of the purely unpredictable component of the h-step-ahead realization of each underlying macroeconomic time series $y_{jt} \in Y = (y_{1t}, \ldots, y_{Nt})$:

$$\mathcal{U}^y_{jt}(h) = \sqrt{\mathrm{E}[(V^y_{jt+h})^2|I_t]}, \tag{2}$$

where $V^y_{jt+h} \equiv y_{jt+h} - \mathrm{E}[y_{jt+h}|I_t]$ denotes the h-step-ahead forecast error and $\mathrm{E}[\cdot|I_t]$ the expectations taken conditional on information I_t available to economic agents at time t. Letting w_j represent aggregation weights, macroeconomic uncertainty is formed as

$$\mathcal{U}^y_t(h) \equiv \operatorname*{plim}_{N_y \to \infty} \sum_{j=1}^{N} w_j \mathcal{U}^y_{jt}(h). \tag{3}$$

To obtain estimates of macroeconomic uncertainty, JLN perform the following three steps. First, they form factors from a large set of economic and financial indicators which are supposed to adequately represent the information set I_t. These factors are used to approximate the forecastable component $\mathrm{E}[y_{jt+h}|I_t]$ by means of a diffusion index model. The corresponding forecast error V^y_{jt+h} is then computed based on $\mathrm{E}[y_{jt+h}|I_t]$. Second, JLN estimate the conditional volatility of this error, $\mathrm{E}[(V^y_{jt+h})^2|I_t]$, by employing a parametric stochastic volatility model for the one-step-ahead prediction errors of both y_{jt} and the factors (or functions thereof). With these estimates at hand, values of $\mathrm{E}[(V^y_{jt+h})^2|I_t]$ for $h > 1$ are computed recursively. The final step involves aggregating the individual uncertainty measures $\mathcal{U}^y_{jt}(h)$ to form $\mathcal{U}^y_t(h)$ by computing a weighted average across all macroeconomic series, using equal weights w_j in the baseline case.

We adopt the strategy proposed by JLN and compute indicators of time-varying macroeconomic uncertainty, *MU1*, for Germany, France, Italy, and Spain. To this end, for each of these countries we build large data sets comprising between 137 and 143 macroeconomic and financial time series. When constructing the data sets, we aimed at covering nine broad fields of macroeconomic time series data, in line with the US data used by JLN.[11] Detailed variable lists for each country are presented in the supplementary

[10] More specifically, dispersion in production expectations may mirror diverging but certain expectations. Furthermore, a rise in stock market volatility may be related to changes in risk aversion or market sentiment which are independent of changes in economic fundamentals.

[11] The macroeconomic categories are (i) real output and income, (ii) employment and compensation, (iii) housing, (iv) consumption, orders, and inventory, (v) money and credit, (vi) bond and exchange

appendix.

2.1.5 *MU2* – Macroeconomic Uncertainty II

Picking up on the issue of unpredictability, Rossi and Sekhposyan (2015) recently developed an alternative uncertainty indicator. However, in contrast to JLN, their index is based on a single series only, and, more importantly, on an ex post comparison of the ex ante forecast using the unconditional likelihood of the observed outcome. In line with JLN, the first step in computing this indicator relies on extracting the unforecastable component from a macroeconomic series. The proposed index is obtained in a second step by evaluating the cumulative density of forecast errors at the actual realized forecast error V^y_{jt+h}. By construction, the resulting indicator, which we denote $\mathcal{U}^y_{jt}(h)$, is defined on the interval $[0, 1]$, with values close to one indicating outcomes that are higher than expected (upside uncertainty), while values close to zero imply negative surprises (downside uncertainty). The final index is computed as $\mathcal{U}^{y*}_{jt}(h) = 0.5 + |\mathcal{U}^y_{jt}(h) - 0.5|$.[12]

In their application, Rossi and Sekhposyan (2015) focus on a single macroeconomic series (usually GDP) to compute the uncertainty index which we, however, consider as ill-suited in the current setup. While GDP may be an obvious candidate for a variable that provides information on the state of the business cycle on a quarterly basis, the choice of a single series containing a similar degree of information on higher-frequency data is less clear. Since we are working with monthly data, we thus construct *MU2* based on a larger set of economic indicators. Following the approach of JLN, we compute V^y_{jt+h} for a broad set of macroeconomic indicators using a diffusion index model.[13] Hence, for every country we obtain a large set of indicators of macroeconomic uncertainty. We aggregate the information contained in these probabilities by taking the arithmetic mean across all series. While this type of aggregation precludes interpreting the resulting indicator in terms of probabilities, it does preserve the property of each individual indicator that large forecast errors signal a rise in uncertainty; i.e. high values of *MU2* indicate difficulties in predicting macroeconomic data outcomes.[14]

rates, (vii) price indexes, (viii) stock market indexes, and (ix) international trade. In contrast to JLN, the last category is included to account for the relatively high degree of trade openness in the four euro-area countries. We follow JLN and construct a financial data set based on data obtained from Kenneth French's website at Dartmouth College. In extracting the unpredictable component of the various macroeconomic indicators, we follow the approach of JLN. We select 8 (Germany), 7 (France), 9 (Italy), and 5 (Spain) factors, with the first three factors explaining about 36% (Germany), 41% (France), 32% (Italy), and 31% (Spain) of the total variation in the underlying data sets, respectively.

[12] The appendix contains estimation results where *MU2* is based on downside uncertainty only. In line with findings of Rossi and Sekhposyan (2015), the negative impact of uncertainty shocks on macroeconomic outcomes tends to be higher when considering the measure based on downside uncertainty rather than the overall uncertainty measure. This finding appears also to be consistent with the results of Buchholz, Tonzer, and Berner (2016) derived from survey data of German manufacturing firms, who detect asymmetric responses of investment activity to firm-specific uncertainty.

[13] We exactly follow the initial step proposed by JLN to extract the unforecastable components from a wide range of economic indicators.

[14] The appendix presents results where *MU2* is based on single macroeconomic series. Using such a measure to proxy for uncertainty generally does not lead to significant responses of investment activity to uncertainty shocks.

2.2 Descriptive Evidence

There is broad indication in the empirical literature that uncertainty is countercyclical (see Baker and Bloom, 2013, for an overview). Moreover, several studies report a strong comovement of various uncertainty proxies (see, e.g., Born, Breuer, and Elstner, 2016). While these findings are essentially based on US data, we subsequently present corresponding evidence from the four largest euro-area economies. In Figures 1 to 4 we plot the computed uncertainty indicators for the four euro-area countries under investigation, while Table 1 displays selected summary statistics. Subsequently, both *MU1* and *MU2* are based on a 3-step-ahead forecast in order to be consistent with *EDISP*, which relies on three-months-ahead production expectations.[15]

The figures reveal that, with the exception of *EPU*, all uncertainty measures reached their maximum (peak) during the global financial crisis in 2008/09 in the four euro-area countries. *EPU* climaxed during 2011/12 in Germany and France, while it peaked in 1998 in Italy and in 2003 in Spain. It is noteworthy that, with the exception of *EPU* in the case of Spain, in all countries quarterly GDP growth is negative around the time when the indicators peaked. This type of countercyclical behavior is also suggested by the negative correlations between industrial production of capital goods (IPC) and the various uncertainty measures. However, this correlation is only consistently statistically significant for *MU1*, *MU2*, and *SVOL* in all four countries. While *EDISP* displays a statistically significant negative correlation in three out of four countries, this holds for *EPU* in Germany only.[16] Hence, we can broadly confirm a countercyclical behavior of uncertainty, although the degree of correlation varies notably across some indicators.

Turning to the cross-correlation among the indicators, we observe *MU1* to be generally highly positively correlated with *SVOL* and *MU2* across all countries, while the correlation with *EDISP* turns out to be more modest. These findings are broadly in line with evidence from the US (see, e.g., Born et al., 2016; Caldara, Fuentes-Albero, Gilchrist, and Zakrajŝek, 016b), although the correlation between *MU1* and *MU2* reported by Rossi and Sekhposyan (2015) is comparatively weaker.[17] Somehow in contrast to findings for the US, the link between *MU1* and *EPU* appears to be relatively weak or even absent in the euro-area economies. Moreover, *EPU* stands out as it represents the only indicator showing a (significant) negative comovement with other uncertainty measures. However, the correlation between *EPU* and *SVOL* turns out to be significantly positive across all four euro-area countries, although the link between these two uncertainty proxies generally tends to be weaker for the euro area compared to evidence from the US (see, e.g., Caldara, Fuentes-Albero, Gilchrist, and Zakrajŝek, 016a). Aside from the negative correlation with *EPU* observed in some cases, *EDISP* and *MU2* show a significant positive relationship with the other indicators across all countries, while the correlation between both indicators is partly insignificant.

As regards the persistence of the various proxies, we find – in line with results from JLN obtained for the US – *MU1* to be markedly more persistent than the other uncertainty

[15] The uncertainty indicators *MU1* and *MU2* are available from the authors upon request.

[16] In each country the correlations are based on a common sample length which is determined by the uncertainty indicator with the shortest time horizon. For Germany and France this implies that the sample begins in 1996:6, while for Italy and Spain in starts 1997:1 and in 2001:1, respectively.

[17] Note, however, that we deviate from the original specification proposed by Rossi and Sekhposyan (2015) since *MU2* is based on a large set of monthly economic indicators (see Section 2.1.5).

measures, as indicated by the half-life estimates. Moreover, we find that *MU1* signals uncertainty episodes less frequently compared to the other indicators.[18]

3 Empirical Setup

We investigate the role of uncertainty shocks for macroeconomic outcomes in a structural vector autoregression (VAR) framework using monthly data. Before presenting the estimation approach, we first describe the specifications of the different VAR models employed.

3.1 Model Specification and Identification

We compare the dynamic responses of investment to uncertainty shocks across three different VAR setups. Following the common practice in the empirical literature on the macroeconomic effects of uncertainty, we identify the structural shocks using a recursive ordering (Cholesky decomposition). As a starting point, we adopt the approach of Bachmann et al. (2013) and Scotti (2016) and estimate a bivariate VAR model, placing uncertainty first in the ordering (VAR-1). We then proceed by estimating two higher-dimensional SVAR models (VAR-2 and VAR-3), which differ in terms of variable ordering as proposed, e.g., by JLN. By estimating these alternative VAR setups, we can assess whether the uncertainty measures exhibit robust effects across different model specifications, both within a particular country but also across countries.

The higher-dimensional VARs (VAR-2 and VAR-3) contain seven variables: one of the five uncertainty measures introduced above, a stock market price index which covers a large set of publicly traded companies[19], a shadow short rate (SSR) serving as a proxy for the stance of monetary policy[20], the harmonized unemployment rate, the harmonized index of consumer prices (HICP), and two variables of industrial production. More precisely, we include industrial production of the main industrial grouping "capital goods" (IPC), which is our proxy of investment activity due to its availability at a monthly frequency,[21] and industrial production of non-capital goods (IPNC), which aims to control for general

[18] Following Bloom (2009), we count uncertainty episodes by the number of times a respective indicator exceeds 1.65 standard deviations from its mean.

[19] Specifically, we use the CDAX for Germany, the SBF 250 for France, the Morgan Stanley Capital International (MSCI) Index (without dividends, local currency-based), which aims at measuring the equity market performance, for Italy, and the Madrid Stock Exchange General Index (IGBM) for Spain. All indexes are price indexes.

[20] Following Krippner (2013), the shadow short rate (SSR) seeks to measure the accommodation in monetary policy when the short rate is at the zero lower bound (ZLB). As outlined, e.g., in Krippner (2014), the SSR essentially corresponds to the policy interest rate in non-ZLB monetary policy environments, while it is free to take on negative values in ZLB environments. Note that we use country-specific short rates before 1999, a period where monetary policy was not constrained by the zero lower bound. We obtain the shadow short rate from Leo Krippner's website at the Reserve Bank of New Zealand `http://www.rbnz.govt.nz/research_and_publications/research_programme/additional_research/comparison-of-international-monetary-policy-measures.html`.

[21] Admittedly, this investment proxy is prone to some caveats, for instance, it only measures domestic production of capital goods and hence does not take into account imports and exports. Against this background, we subsequently also assess the role of uncertainty for aggregate investment activity as measured by gross fixed capital formation in machinery and equipment.

economic activity.[22] The VAR models are generally estimated over the 1996:7–2015:12 period, except for specifications including *EPU*, which start in 1997:1 for Italy and 2001:1 for Spain. We choose the following ordering of variables in the two higher-dimensional VAR setups:

$$\underline{\text{VAR-2}} \qquad\qquad \underline{\text{VAR-3}}$$

$$\begin{pmatrix} \ln(\text{Stock Market Index}) \\ \textit{Uncertainty} \\ \text{SSR} \\ \ln(\text{HICP}) \\ \text{Unemployment} \\ \ln(\text{IPC}) \\ \ln(\text{IPNC}) \end{pmatrix} \qquad \begin{pmatrix} \ln(\text{IPNC}) \\ \ln(\text{IPC}) \\ \text{Unemployment} \\ \ln(\text{HICP}) \\ \text{SSR} \\ \ln(\text{Stock Market Index}) \\ \textit{Uncertainty} \end{pmatrix}$$

The ordering of VAR-2 implies that all variables except "Stock Market Index" respond contemporaneously to an uncertainty shock.[23] By placing "*Uncertainty*" at the end in VAR-3, this choice of ordering represents a more conservative setup which precludes a contemporaneous response of the remaining variables to an uncertainty shock.[24]

3.2 Estimation Approach

We estimate the models as pth-order VAR in (log) levels including both a constant term and a linear time trend:

$$\begin{aligned} y_t &= c + \gamma t + B_1 y_{t-1} + \ldots B_p y_{t-p} + u_t && (4) \\ u_t &\sim N(0, \Sigma), && (5) \end{aligned}$$

where y_t denotes a $q \times 1$ vector of endogenous variables, u_t a $q \times 1$ vector of errors, and $c, \gamma, B_1 \ldots, B_p$, and Σ represent matrices of suitable dimensions containing the unknown parameters of the model, including the constants (c), time trends (γ), coefficients of lagged endogenous variables ($B_1 \ldots, B_p$), and the covariance matrix (Σ).

[22] We compute IPNC based on weights for the main industrial grouping (MIG) components of industrial production published by Eurostat. By adding both IPC and IPNC simultaneously to the VAR framework, we can also investigate whether the production of capital goods responds more strongly to uncertainty shocks compared to other segments of the manufacturing sector (see the supplementary appendix for details).

[23] Note that the variable selection and ordering of VAR-2 are inspired by Bloom (2009). In comparison to our VAR, Bloom (2009) additionally controls for monthly wages and hours worked; since neither variable is consistently available on a monthly basis for the four euro-area countries, we had to exclude them. Due to issues of data availability, we also depart from Bloom (2009) by using monthly unemployment instead of monthly employment. Moreover, since we are mainly interested in investment activity, we include two measures of industrial production, i.e. capital goods and other manufacturing goods, instead of using an overall measure of manufacturing production as in Bloom (2009).

[24] This variable ordering is in line with the first VAR estimated by JLN ("VAR-11"), which is inspired by Christiano et al. (2005). Note that the VAR estimated by JLN differs from the original Bloom (2009) VAR not only in terms of variable ordering, but also by containing three additional variables. One of these variables being real orders, in the appendix we present a robustness check where we add a survey indicator on orders to the VAR.

Since the VAR model is estimated with monthly data, we follow the common practice in the literature and include twelve lags. To overcome the ensuing problem of "overfitting", we employ Bayesian estimation techniques.[25] Specifically, we use an independent Normal inverse Wishart prior, assuming that $\beta \equiv vec(c, \gamma, B_1 \ldots, B_p)$ is normally distributed and that Σ has an inverse Wishart distribution with scale S and ν degrees of freedom:

$$\beta \sim N(b, H) \tag{6}$$
$$\Sigma \sim IW(S, \nu). \tag{7}$$

The prior for β is of the Minnesota-type. Specifically, let i refer to the dependent variable in the ith equation, j to the independent variable in that equation, and l to the lag number. We then assume that the prior distribution for β is defined such that $E[(B_l)_{ij}] = 1$ for $i = j$ and $l = 1$ and 0 otherwise, while all other elements in b are set to zero. The diagonal elements of the diagonal matrix H are defined as $\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2$ if $i = j$, $\left(\frac{\sigma_i \lambda_1 \lambda_2}{l^{\lambda_3} \sigma_j}\right)^2$ if $i \neq j$, and $(\sigma_i \lambda_4)^2$ for the constant and the time trend. The prior parameters σ are specified using ordinary least squares (OLS) estimates of univariate AR(1) models. More specifically, σ_i and σ_j denote the standard deviations of error terms from the OLS regressions. The hyperparameters λ_1 to λ_4 are set in accordance with standard values commonly used in the literature.[26] Turning to the inverse Wishart distribution, the degrees of freedom ν amount to $T+q+1$, with T denoting the sample length. The scale parameter S is a $q \times q$ diagonal matrix with diagonal elements σ_i^2. A Gibbs sampling approach is employed to generate draws of β and Σ from their respective marginal posterior distribution. Specifically, we simulate 10,000 draws and discard the first 90% as a burn-in.[27]

4 Results

To obtain an initial insight into the dynamic relationship between uncertainty and investment, we use a bivariate model (VAR-1) and investigate the impulse responses of IPC to innovations in the five uncertainty measures. Although we find a negative reaction of IPC to innovations in each of the uncertainty measures across all countries, the estimated impulse response functions (IRFs) differ to some extent markedly in terms of magnitude and statistical significance both within and across countries (see Figure 5). For example, no considerable effects are found in France if uncertainty is measured by *EPU* or *EDISP*, while strong negative reactions of investment are observed for *MU1*. Moreover, only the IRFs related to *SVOL*, *MU1*, and *MU2* exhibit significant effects consistently across all countries, as indicated by the 90% highest posterior density intervals.

To widen the scope of the analysis, we extend the model dimension by employing

[25] Note that the length of the available data series is much shorter for the four euro-area economies compared to the US.

[26] Specifically, we set hyperparameters $\lambda_1 = 0.2$, $\lambda_2 = 0.5$, $\lambda_3 = 1$, and $\lambda_4 = 100$.

[27] Note that we discard explosive draws during the sampling algorithm. The main results are robust to not discarding these draws; results are available from the authors upon request. To monitor convergence, we adopt the approach outlined in Gelman and Rubin (1992) and Brooks and Gelman (1998) and compare two parallel sequences of draws. Only the retained draws from the first chain are used for inference. We find 10,000 draws to be sufficient for convergence. The respective convergence plots are shown in the appendix.

the larger SVAR specification VAR-2 outlined in Section 3. In line with results from the bivariate model, the impulse responses with respect to *SVOL*, *MU1*, and *MU2* show significant negative reactions of investment activity to uncertainty shocks across all countries (see Figure 6). However, for Germany, Spain, and Italy the dynamic responses of investment activity to disturbances in *SVOL* are comparatively small shortly after the shock and insignificant thereafter. This holds in part also for *MU2*. Notably, no significant responses are prevalent when uncertainty is measured by *EPU*. Finally, in line with the results from the bivariate framework, we generally find no significant occurrence of rebound effects of investment in response to uncertainty shocks under the larger SVAR model.

In order to assess whether the VAR-2 results rely on a specific ordering of variables, we contrast our findings with those obtained from an SVAR model with the measure of uncertainty placed last (see Section 3). Figure 7 depicts the IRFs obtained from the estimated SVAR specification VAR-3. Overall, the impulse responses of IPC to the uncertainty shocks are quite similar to those obtained under VAR-2. However, since the IRFs turn out to be generally more muted under specification VAR-3, only *MU1* and *MU2* show a significant negative relationship between uncertainty and investment consistently across all countries. Specifically, the outcomes for *MU1* turn out to be broadly unaffected by the specific ordering of variables in the VAR setup, still accounting for a maximum decline in the level of IPC of around 3/4 percent, which occurs approximately after one year, in each of the countries under consideration.

To shed further light on the dynamics, we examine the relative importance of the five structural shocks for fluctuations in investment. Table 2 summarizes the forecast error variance decomposition at various forecast horizons for all model specifications. Beginning with the bivariate model, we find the five uncertainty proxies to explain – to some extent – a very large fraction of the forecast error variance over the different forecast horizons. For example, at a three-year horizon, *MU1* turns out to be the dominant source of investment fluctuations in France and Spain. However, when allowing for a richer set of variables (VAR-2, VAR-3), the contribution drops substantially in some cases. Nevertheless, we find that *MU1* still plays an important role in explaining the volatility of investment in the higher-dimensional frameworks over the different forecast horizons. Under specification VAR-3, for example, *MU1* shocks explain between 14 percent (Italy) and 32 percent (France) of the forecast error variance in IPC over a three-year horizon.

5 Discussion

5.1 Conceptual Aspects of Uncertainty Measures

Concerning the financial and sovereign debt crisis, uncertainty has been repeatedly suspected as a key impediment to growth in the euro area. Specifically, with respect to the sluggish recovery of investment activity, the role of aggregate uncertainty has been a topic of heightened interest. While, as outlined in Section 1, theory points to a number of channels through which an adverse impact of uncertainty on investment can be rationalized, empirical research suffers from the lack of an objective measure of uncertainty, complicating a sound evaluation of uncertainty and its effect on investment. Hence, it is hardly surprising that the literature comes up with a range of uncertainty proxies which, from a conceptual point of view, vary in some cases substantially.

In the foregoing analysis, we focused on five uncertainty measures recently put forward in the literature which rely on the (implied) volatility of stock market returns (*SVOL*), on newspaper coverage frequency of articles related to economic policy uncertainty (*EPU*), on the cross-sectional dispersion of production expectations in business surveys (*EDISP*), and on the unpredictable components of a large set of macroeconomic indicators (*MU1* and *MU2*).

Although all uncertainty measures under investigation exhibit a countercyclical nature, the observed comovement between uncertainty and investment activity varies, sometimes markedly, along the indicators from an intra-country perspective as revealed by the descriptive analysis in Section (2.2). Moreover, from Figures 1 to 4 it becomes evident that the various uncertainty measures deviate, to some extent considerably, in detecting episodes of high uncertainty. Specifically, *MU1* turns out to identify uncertainty episodes less frequently in comparison to the other measures.

It is not least this aspect which leads Jurado et al. (2015) to call into question whether swings in specific proxies, which, for instance, primarily capture financial volatility, idiosyncratic (micro) uncertainty, or policy uncertainty, are suited to indicate movements in common (macroeconomic) uncertainty.

While this also holds to a degree for the original specification of the uncertainty measure proposed by Rossi and Sekhposyan (2015), which is based on indicator-specific uncertainty through the perspective of professional forecasters, *MU2* and *MU1* differ substantially from the three other uncertainty indicators by explicitly considering the aspect of predictability.[28] As emphasized by Jurado et al. (2015) and Rossi and Sekhposyan (2015), it is decisive to remove the forecastable component of the data when estimating uncertainty in order to prevent a mixing of predictable variability with a virtually unpredictable phenomenon.

However, while *MU1* and *MU2* both follow this conceptual approach, they are distinctly different from a methodological perspective. While *MU2* relies on an ex post evaluation of an ex ante forecast using the historical forecast error distribution of a specific variable, *MU1* is derived from the conditional volatility of the purely unpredictable component of the future value of a time series. As pointed out by Jurado et al. (2015, p. 1177), the concept of *MU1* thereby closely resembles the typical definition of uncertainty "as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents" (see also Scotti, 2016). In this respect it appears remarkable that we find *MU1*, in particular, to exhibit robust effects of uncertainty on investment activity across different model specifications and countries in our empirical analysis.

5.2 Uncertainty Shocks and Gross Fixed Capital Formation

Ultimately, we are interested in the role of uncertainty shocks for investment activity as measured by gross fixed capital formation (GFCF) in machinery and equipment (M&E). However, the difficulty we face is that this variable is available only at a quarterly frequency. Simply estimating the VARs on quarterly data raises concerns regarding the identification strategy; for instance, while it may be plausible to assume that uncertainty

[28] Note that we deliberately deviate from the original specification of *MU2* and compute the indicator using the unforecastable components of a broad set of economic variables.

does not contemporaneously react to output shocks in the case of monthly data, this assumption appears quite strong when working with quarterly data. We thus resort to the two-step approach proposed by Kilian (2009).[29]

The first step involves aggregating the estimated monthly structural shocks obtained from the SVAR model to a quarterly frequency by computing their quarterly means. In the second step, we estimate the distributed lag model:

$$\Delta y_t = c + \sum_{i=0}^{8} \phi_i \tilde{\epsilon}_{t-i} + u_t, \tag{8}$$

where t now refers to a quarter, Δy_t indicates the quarterly growth rate of GFCF in M&E, $\tilde{\epsilon}_t$ denotes the structural shocks aggregated to a quarterly frequency, and u_t is an error term.[30] Note that we allow for contemporaneous effects of uncertainty shocks on GFCF in M&E, which implies the identifying assumption that uncertainty shocks are predetermined with respect to Δy_t.

In this setup, the impulse responses are derived from the coefficient vector ϕ. Moreover, the historical contribution of uncertainty shocks to GFCF in M&E at a given point in time is obtained by computing the predicted value of GFCF in M&E from $\sum_{i=0}^{8} \phi_i \tilde{\epsilon}_{t-i}$. We integrate this two-step approach into our Gibbs sampling algorithm. Hence, for every accepted draw, we run regression (8) to derive median responses and median contributions. The analysis in this sub-section is based on *MU1* due to its robust empirical performance and its conceptual proximity to the typical definition of uncertainty. Specifically, we obtain the structural shocks $\tilde{\epsilon}_t$ from the VAR-2 specification with *MU1* as uncertainty indicator.[31]

The IRFs suggest that uncertainty shocks also matter for investment activity as measured by GFCF in M&E, while the estimated confidence bands are quite wide indeed (see Figure A.1).[32] In Germany and Italy, in particular the effects are usually statistically significant for the 68% error bands only and for a relatively short period from two to four quarters. Nevertheless, the median impact magnitudes are quite pronounced, reaching a maximum of close to 2% in Germany and 1.5% in Italy. In France and, especially, in Spain, the responses of GFCF in M&E to uncertainty shocks are also sizeable, with maximum values of close to 2% and 4% and higher levels of statistical significance. Moreover, the effects last longer in these two countries; when considering the 68% error bands, they persist for about seven quarters.

To further elucidate the country-specific role of uncertainty, the respective historical contribution of uncertainty shocks to investment growth (GFCF in M&E) is depicted

[29] This approach has recently been applied in the context of uncertainty shocks by Born et al. (2016) and Born and Pfeifer (2016).

[30] The use of specification (8) may be motivated based on the final form representation of a dynamic simultaneous equation model (SEM). The final form is obtained by inverting the reduced form of the underlying fully specified dynamic SEM, expressing the data as a moving average in the exogenous variables (see, e.g., Lütkepohl, 2005).

[31] The appendix presents corresponding results with shocks from VAR-3. Moreover, the appendix presents an analysis of GDP responses to uncertainty shocks.

[32] Relatively wide error bands appear not to be euro-area specific, but rather related to the two-step approach, since they are also apparent in the response of US GDP to uncertainty shocks (see Born et al., 2016; Born and Pfeifer, 2016).

in Figures A.2 to A.5.[33] Note that we present the contribution to year-on-year growth rates, which depict a smoother development compared to quarterly growth rates. A first observation is that, during the Great Recession in 2008/09, increased uncertainty accounted for a substantial part of the drop in investment activity across all four euro-area countries. The effects were particularly pronounced in Germany, France, and Spain, where uncertainty shocks were responsible for around 30% of the downturn in investment activity in 2009. The contribution was also relevant in Italy, amounting to almost 15% of the total drop in investment activity. Moreover, the figures reveal a role for uncertainty in hampering investments during the sovereign debt crisis. Interestingly, this effect is also visible in Germany and France, even though these two countries were not directly affected by this crisis.[34] Overall, the negative impact of uncertainty was smaller during this crisis compared to 2009, ranging from minus one percentage point in Germany to minus one and a half percentage points in France and minus two and a half percentage points in Spain in 2011. In Italy, this effect occurred somewhat later, contributing minus two percentage points to investment growth in 2012.

5.3 Potential Transmission Channels

Although our previous findings confirm the results of Bloom (2009) by suggesting strong negative effects of uncertainty shocks on investment, they differ in so far as we do not detect any sizable rebound effects, which are commonly interpreted as an indication of "wait-and-see" behavior.[35] As pointed out by Bachmann and Bayer (2013) and Born and Pfeifer (2014), pronounced "wait-and-see" dynamics turn out to be primarily a partial equilibrium phenomenon, which becomes considerably dampened in a general equilibrium framework of irreversible investment.[36] However, findings of relatively small aggregate effects of uncertainty shocks in general equilibrium models with nonconvex capital adjustment frictions (see, e.g., Bachmann and Bayer, 2013; Gilchrist et al., 2014) point to the relevance of other potential propagation mechanisms in order to explain our observed investment dynamics. In this respect, a growing strand of theoretical literature stresses the link between uncertainty and financial frictions as another propagation mechanism through which uncertainty may hamper aggregate activity (see, e.g., Arellano et al., 2012;

[33] The appendix presents corresponding historical decompositions based on specification VAR-3 which confirm the main findings presented above.

[34] In the supplementary appendix, we present cross-country correlations between the monthly uncertainty shocks related to *MU1* obtained from VAR-2. The correlation coefficients are quite high indeed, ranging from 0.7 to 0.8. This may point to spillovers from uncertainty shocks across the four euro-area economies or, more generally, a global component in uncertainty shocks. Furthermore, a certain degree of co-movement may also be related to the fact that the financial variable data set does not contain country-specific variables. See the appendix for more details about the data.

[35] In a standard irreversible investment framework, investment opportunities are considered as real options, while uncertainty increases the value of the option to wait and invest later (frequently referred to as a "wait-and-see" strategy). Therefore, after uncertainty has subsided, investment activity surges, resulting in an overshooting phenomenon (see, e.g., Bloom, 2009).

[36] In this respect, it is notable that JLN do not find evidence for "wait-and-see" dynamics in the US either. Moreover, they point out that previous empirical findings of significant overshooting behavior in the US may be related to the choice of data alignment.

Christiano et al., 2014).[37]

In a recent study, Gilchrist et al. (2014) incorporate both of the aforementioned channels into a dynamic general equilibrium model with heterogeneous firms. The model features partial irreversibility and fixed adjustment costs in investment activity as well as financial frictions. The authors emphasize that in their analytical framework, partial irreversibility of investment is of relevance for both transmission channels. In a simulation-based analysis, the authors find that financial frictions account for more than three quarters of the total effect of uncertainty shocks on investment activity. Gilchrist et al. (2014) corroborate the finding of an important role for financial frictions by estimates based on both micro and macro data. In an SVAR analysis for the US, Caldara et al. (016a) also present results suggesting a close relationship between economic uncertainty and changes in financial market conditions. Specifically, the authors detect an important role for uncertainty (as measured by *MU1*) during the Great Recession, even when explicitly distinguishing between financial and uncertainty shocks employing a penalty function approach. Thereby, Caldara et al. (016a) find that these two types of shocks can fully explain the drop in output during the financial crisis in the US, with uncertainty accounting for between one and two thirds of that drop, depending on whether it is ordered second or first in the VAR.[38]

Although we do note that it is challenging to clearly distinguish between financial and uncertainty shocks using an identification strategy based on recursive ordering, our observation of a particularly strong adverse economic impact of uncertainty on real activity in periods of financial distress for euro-area economies is well in line with the aforementioned evidence for the US.[39]

Nevertheless, we note that our results do not generally contradict the notion that (partial) irreversibility plays a relevant role for the relationship between uncertainty and real activity. Rather, our findings emphasize the importance of other propagation mechanisms currently being discussed in the literature, which result in powerful effects on investment activity.

6 Conclusion

Investment activity dropped sharply after the financial crisis and has not yet returned to its pre-crisis levels in many euro-area economies. In this paper, we investigate the role of aggregate economic uncertainty for investment dynamics in the euro area. Our focus is on the four largest euro-area countries: Germany, France, Italy, and Spain. In the course of our analysis, we additionally compare five prominent uncertainty measures put forward in the recent literature, which are based on the (implied) volatility of stock

[37] Note that, consistent with recent theoretical models (see, e.g., Christiano et al., 2014; Gilchrist et al., 2014), we find that investment (IPC) responds relatively more strongly to uncertainty shocks than non-capital related output components (IPNC). The respective impulse response functions are presented in the supplementary appendix.

[38] Note that the penalty function approach applied by Caldara et al. (016a) still requires an ordering assumption between uncertainty and financial shocks. Further note that the results of Caldara et al. (016a) are also consistent with the findings of Stock and Watson (2012).

[39] See also Born et al. (2016), who find that uncertainty (as measured by *MU1*) accounted for 20% of the drop in US GDP during the height of the Great Recession, using a standard SVAR framework in accordance with our approach.

market returns (*SVOL*), the frequency of newspaper articles related to economic policy uncertainty (*EPU*), the cross-sectional dispersion of production expectations in business surveys (*EDISP*), and the unpredictable components of a large set of macroeconomic indicators (*MU1* and *MU2*). The five uncertainty proxies are analyzed using both descriptive and VAR model-based evidence. While all uncertainty measures under investigation display countercyclical behavior, we only find *MU1*, which measures time-varying macroeconomic uncertainty, to exhibit robust dynamics across different model specifications and countries. This is remarkable as the indicator is closely related to the typical notion of uncertainty by approximating the purely unforecastable component of future values of macroeconomic indicators given the information set available to an economic decision maker. Based on this type of uncertainty proxy, we document pronounced negative investment responses to uncertainty shocks. Moreover, we find that uncertainty can account for a relevant portion of the decrease in gross fixed capital formation in machinery and equipment in the course of the Great Recession.

A particular relevant question in this regard is whether macroeconomic uncertainty as measured by *MU1* indeed is an exogenous source of business cycle fluctuations or an endogenous response to them. A recent study by Ludvigson, Ma, and Ng (2015), suggesting that it is financial rather than macroeconomic uncertainty that causes US business cycle movements, opens an important avenue for future research.

	SVOL	*EPU*	*EDISP*	*MU1*	*MU2*
			Germany		
Half life	5.758	1.490	3.406	18.663	1.228
Corr w/ Δ ln(*IPC*)	-0.207***	-0.139**	-0.131**	-0.193***	-0.120*
Corr w/ *SVOL*	1.000				
Corr w/ *EPU*	0.361***	1.000			
Corr w/ *EDISP*	0.189***	0.330***	1.000		
Corr w/ *MU1*	0.601***	0.179***	0.348***	1.000	
Corr w/ *MU2*	0.378***	0.037	0.122*	0.621***	1.000
			France		
Half life	4.399	3.037	1.501	20.705	1.801
Corr w/ Δ ln(*IPC*)	-0.144**	-0.057	-0.065	-0.193***	-0.128*
Corr w/ *SVOL*	1.000				
Corr w/ *EPU*	0.200***	1.000			
Corr w/ *EDISP*	0.177***	0.252***	1.000		
Corr w/ *MU1*	0.652***	0.045	0.225***	1.000	
Corr w/ *MU2*	0.350***	-0.157**	0.061	0.680***	1.000
			Italy		
Half life	1.300	1.393	2.621	36.873	1.129
Corr w/ Δ ln(*IPC*)	-0.111*	-0.019	-0.137**	-0.161**	-0.148**
Corr w/ *SVOL*	1.000				
Corr w/ *EPU*	0.348***	1.000			
Corr w/ *EDISP*	0.174***	-0.013	1.000		
Corr w/ *MU1*	0.543***	0.112*	0.342***	1.000	
Corr w/ *MU2*	0.301***	-0.018	0.201***	0.621***	1.000
			Spain		
Half life	1.589	1.601	0.943	20.118	0.800
Corr w/ Δ ln(*IPC*)	-0.202***	-0.100	-0.126*	-0.287***	-0.151**
Corr w/ *SVOL*	1.000				
Corr w/ *EPU*	0.411***	1.000			
Corr w/ *EDISP*	0.171**	0.016	1.000		
Corr w/ *MU1*	0.704***	0.249***	0.381***	1.000	
Corr w/ *MU2*	0.348***	0.043	0.236***	0.588***	1.000

Table 1: Summary Statistics

Notes: This table lays out basic summary statistics for the uncertainty measures under investigation (*SVOL*, *EPU*, *EDISP*, *MU1*, *MU2*). *Corr* denotes the correlation coefficient, where *** indicates 1%, ** 5%, and * 10% significance levels, respectively. *Half life* is computed on the basis of univariate AR(1) models. Data are monthly and span the period 1996:6–2015:12. Exceptions are Italy and Spain where the *EPU* series starts later (in 1997:1 in Italy and in 2001:1 in Spain.

		VAR-1				VAR-2				VAR-3			
		DE	ES	FR	IT	DE	ES	FR	IT	DE	ES	FR	IT
SVOL	h = 1	0.01	0.01	0.02	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00
	h = 12	0.35	0.26	0.29	0.16	0.06	0.04	0.15	0.03	0.05	0.01	0.07	0.01
	h = 36	0.46	0.37	0.45	0.22	0.08	0.03	0.15	0.03	0.05	0.01	0.08	0.01
	h = 60	0.46	0.37	0.46	0.22	0.08	0.02	0.13	0.03	0.05	0.01	0.07	0.01
EPU	h = 1	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	h = 12	0.13	0.09	0.04	0.08	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	h = 36	0.16	0.14	0.06	0.12	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.01
	h = 60	0.16	0.14	0.07	0.12	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.01
EDISP	h = 1	0.03	0.01	0.00	0.02	0.03	0.00	0.00	0.02	0.00	0.00	0.00	0.00
	h = 12	0.25	0.08	0.02	0.22	0.13	0.02	0.01	0.10	0.07	0.01	0.01	0.06
	h = 36	0.33	0.10	0.03	0.25	0.10	0.06	0.01	0.11	0.06	0.02	0.01	0.07
	h = 60	0.33	0.10	0.04	0.26	0.09	0.06	0.01	0.11	0.06	0.02	0.01	0.07
MU1	h = 1	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	h = 12	0.20	0.44	0.34	0.14	0.30	0.27	0.34	0.12	0.28	0.21	0.32	0.09
	h = 36	0.37	0.74	0.64	0.34	0.29	0.24	0.35	0.16	0.26	0.18	0.32	0.14
	h = 60	0.36	0.75	0.64	0.34	0.27	0.17	0.29	0.14	0.24	0.14	0.27	0.13
MU2	h = 1	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00
	h = 12	0.04	0.12	0.17	0.08	0.07	0.04	0.12	0.07	0.05	0.02	0.09	0.05
	h = 36	0.08	0.20	0.32	0.14	0.07	0.05	0.12	0.08	0.05	0.03	0.09	0.05
	h = 60	0.08	0.20	0.33	0.15	0.07	0.04	0.10	0.07	0.05	0.02	0.08	0.05

Table 2: Summary FEVD

Notes: This table summarizes the median contribution of the respective uncertainty shocks (*SVOL*, *EPU*, *EDISP*, *MU1*, *MU2*) to the forecast error variance of investment at different forecast horizons (h) for Germany (DE), Spain (ES), France (FR), and Italy (IT). The left block shows the forecast error variance decompositions (FEVD) obtained from bivariate VARs (VAR-1), while the middle and the right block depict the FEVDs from higher-dimensional VAR models (VAR-2 and VAR-3). All models are estimated on monthly data and span the period 1996:7–2015:12 except for *EPU* which starts in 1997:1 for Italy and in 2001:1 for Spain. Investment is measured by industrial production of capital goods (IPC).

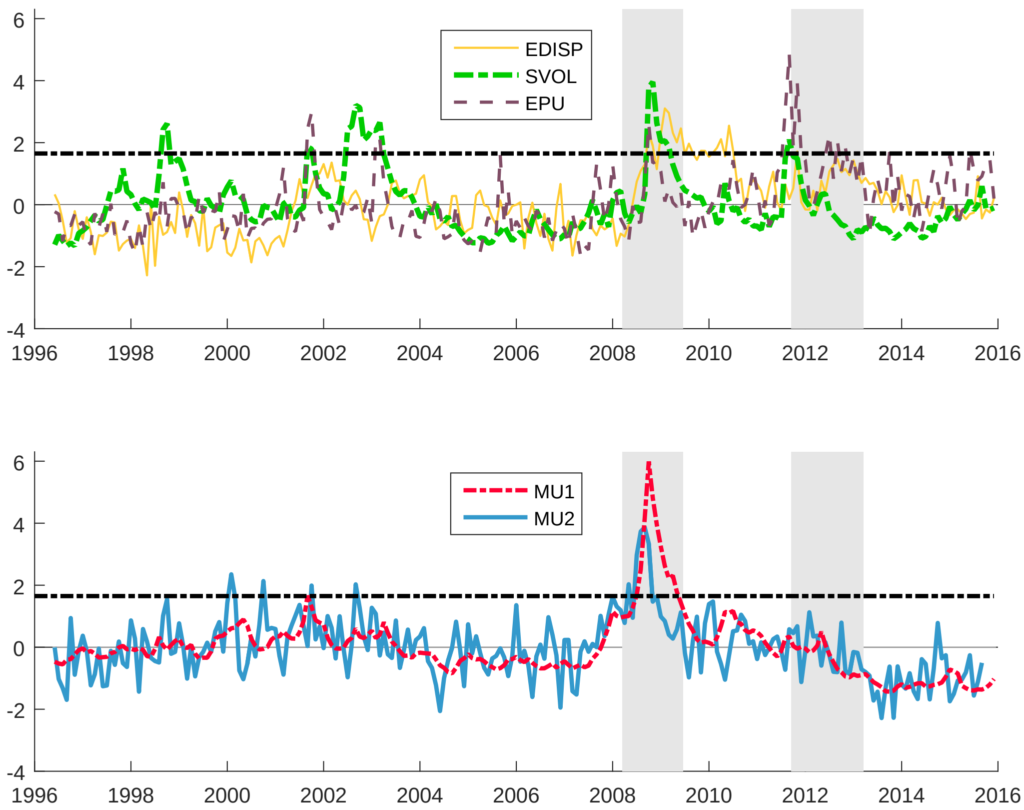

Figure 1: Uncertainty indicators for Germany

Notes: Each series has been demeaned and standardized by its standard deviation. The dashed horizontal lines indicate 1.65 standard deviations above the mean of each series. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles. Data are monthly and span the period 1996:6–2015:12 .

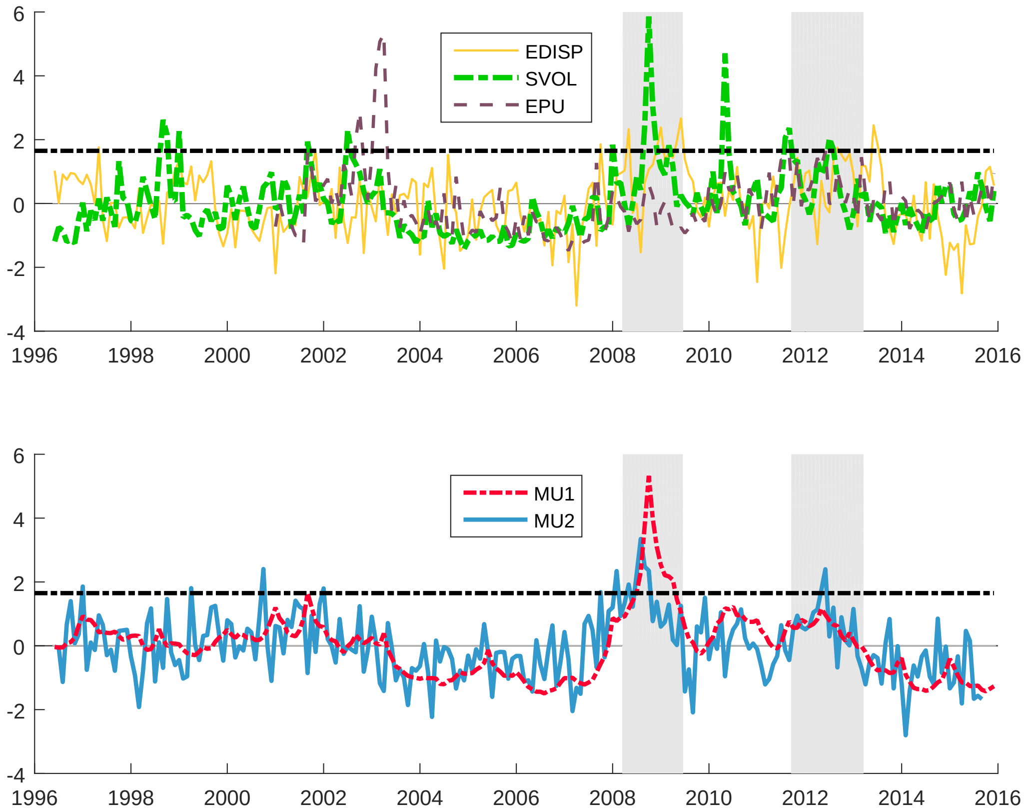

Figure 2: Uncertainty indicators for Spain

Notes: Each series has been demeaned and standardized by its standard deviation. The dashed horizontal lines indicate 1.65 standard deviations above the mean of each series. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles. Data are monthly and span the period 1996:6–2015:12 except for *EPU*, which starts in 2001:1.

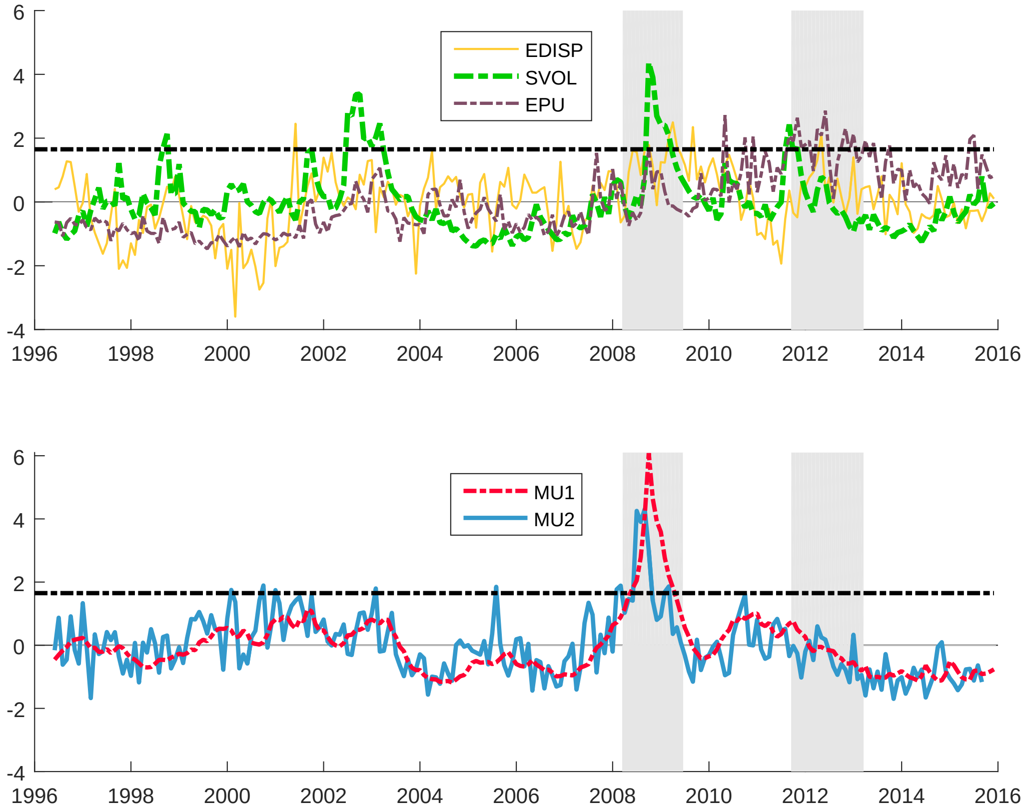

Figure 3: Uncertainty indicators for France

Notes: Each series has been demeaned and standardized by its standard deviation. The dashed horizontal lines indicate 1.65 standard deviations above the mean of each series. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles. Data are monthly and span the period 1996:6–2015:12.

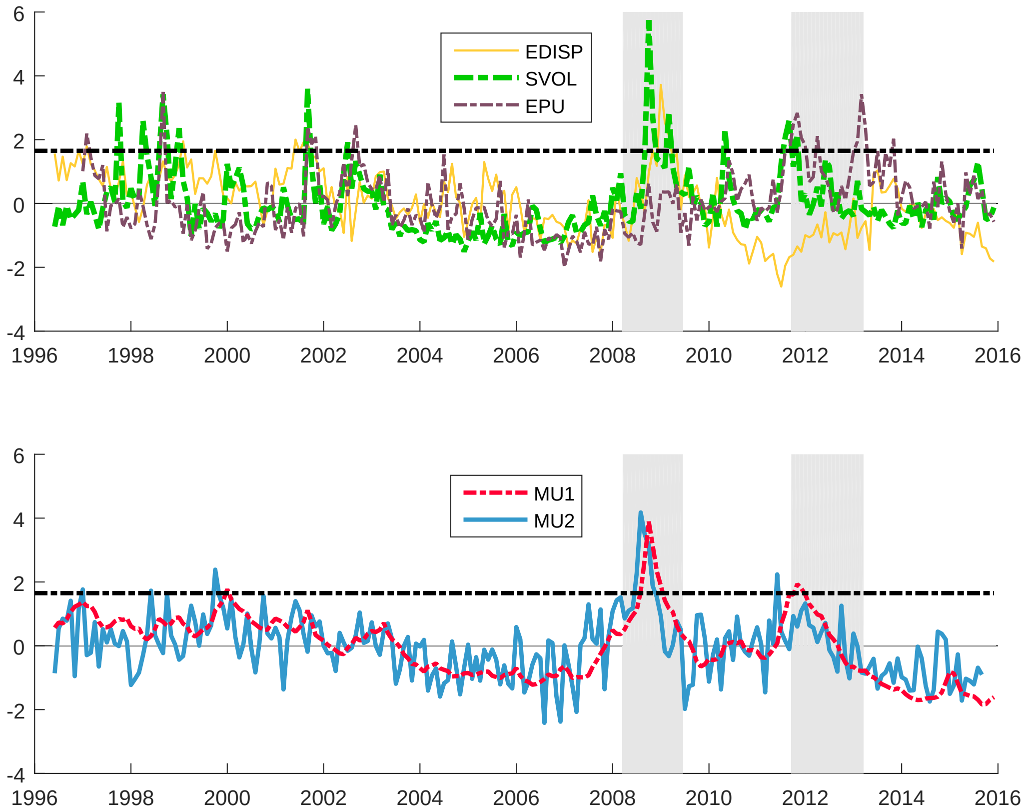

Figure 4: Uncertainty indicators for Italy

Notes: Each series has been demeaned and standardized by its standard deviation. The dashed horizontal lines indicate 1.65 standard deviations above the mean of each series. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles. Data are monthly and span the period 1996:6–2015:12 except for *EPU*, which starts in 1997:1.

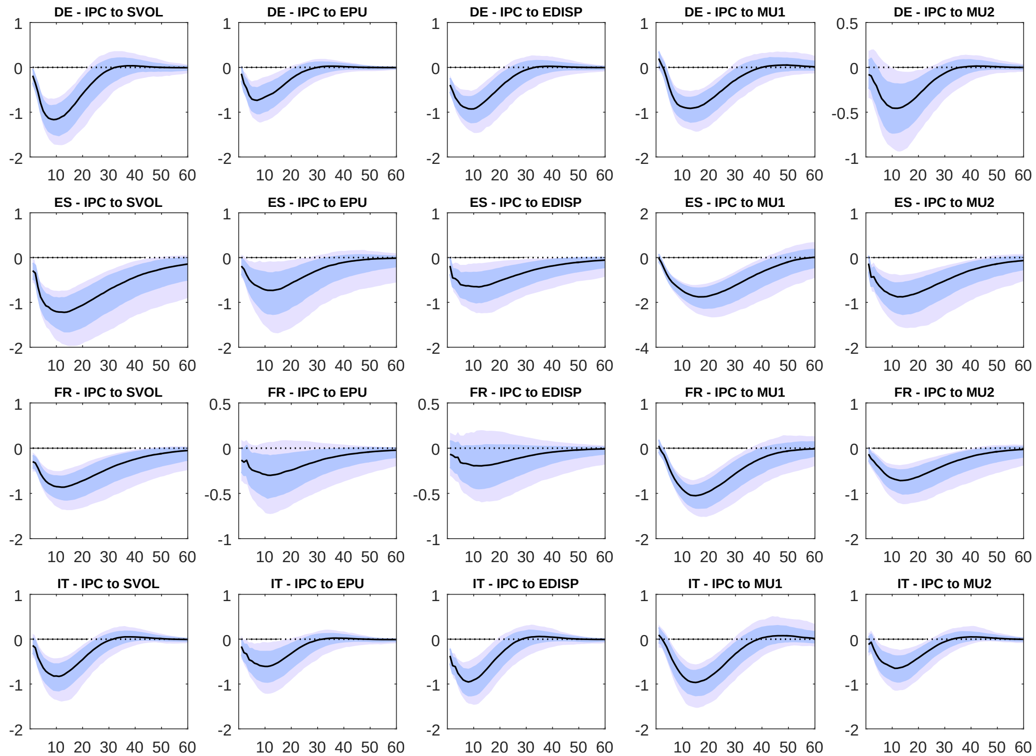

Figure 5: IRFs of Investment (IPC) – Bivariate SVARs (VAR-1), Monthly Data

Notes: Impulse responses (IRFs) of investment, as measured by industrial production of capital goods (IPC), to uncertainty shocks obtained from a bivariate VAR model estimated on monthly data spanning the period 1996:7–2015:12, except for *EPU*, which starts in 1997:1 for Italy and in 2001:1 for Spain. Each row shows the IRFs (in percent) across the five uncertainty proxies (*SVOL*, *EPU*, *EDISP*, *MU1*, *MU2*) for the respective country (Germany (DE), Spain (ES), France (FR), Italy (IT)). Solid lines depict median responses to a shock of one standard deviation. Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

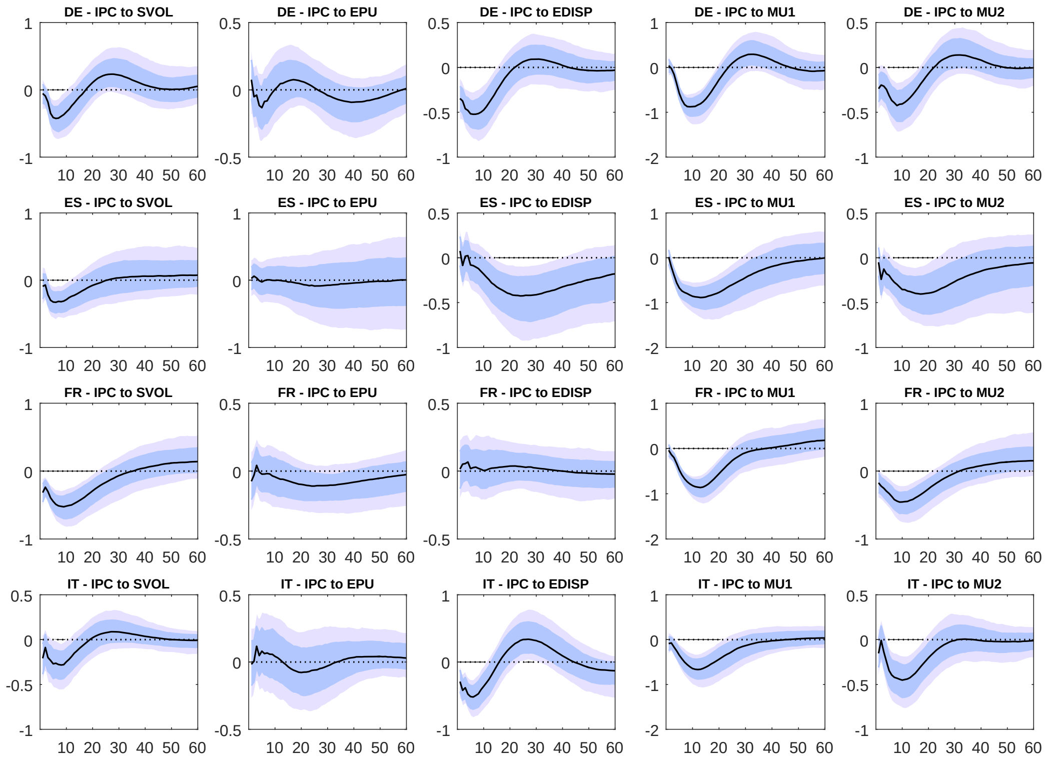

Figure 6: IRFs of Investment (IPC) – Higher-dimensional SVARs (VAR-2), Monthly Data

Notes: Impulse responses (IRFs) of investment, as measured by industrial production of capital goods (IPC), to uncertainty shocks obtained from the SVAR model VAR-2 estimated on monthly data spanning the period 1996:7–2015:12, except for *EPU*, which starts in 1997:1 for Italy and in 2001:1 for Spain. Each row shows the IRFs (in percent) across the five uncertainty proxies (*SVOL*, *EPU*, *EDISP*, *MU1*, *MU2*) for the respective country (Germany (DE), Spain (ES), France (FR), Italy (IT)). Solid lines depict median responses to a shock of one standard deviation. Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

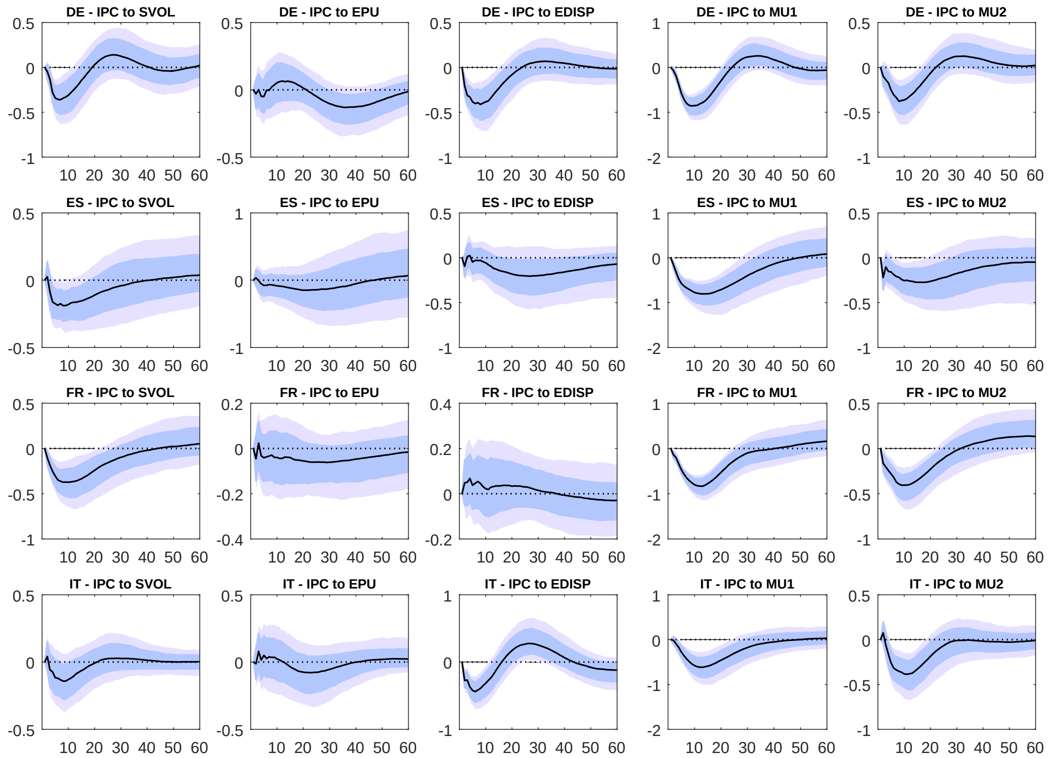

Figure 7: IRFs of investment (IPC) – Higher-dimensional SVARs (VAR-3), Monthly Data

Notes: Impulse responses (IRFs) of investment, as measured by industrial production of capital goods (IPC), to uncertainty shocks obtained from the SVAR model VAR-3 estimated on monthly data spanning the period 1996:7–2015:12, except for *EPU*, which starts in 1997:1 for Italy and in 2001:1 for Spain. Each row shows the IRFs (in percent) across the five uncertainty proxies (*SVOL*, *EPU*, *EDISP*, *MU1*, *MU2*) for the respective country (Germany (DE), Spain (ES), France (FR), Italy (IT)). Solid lines depict median responses to a shock of one standard deviation. Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

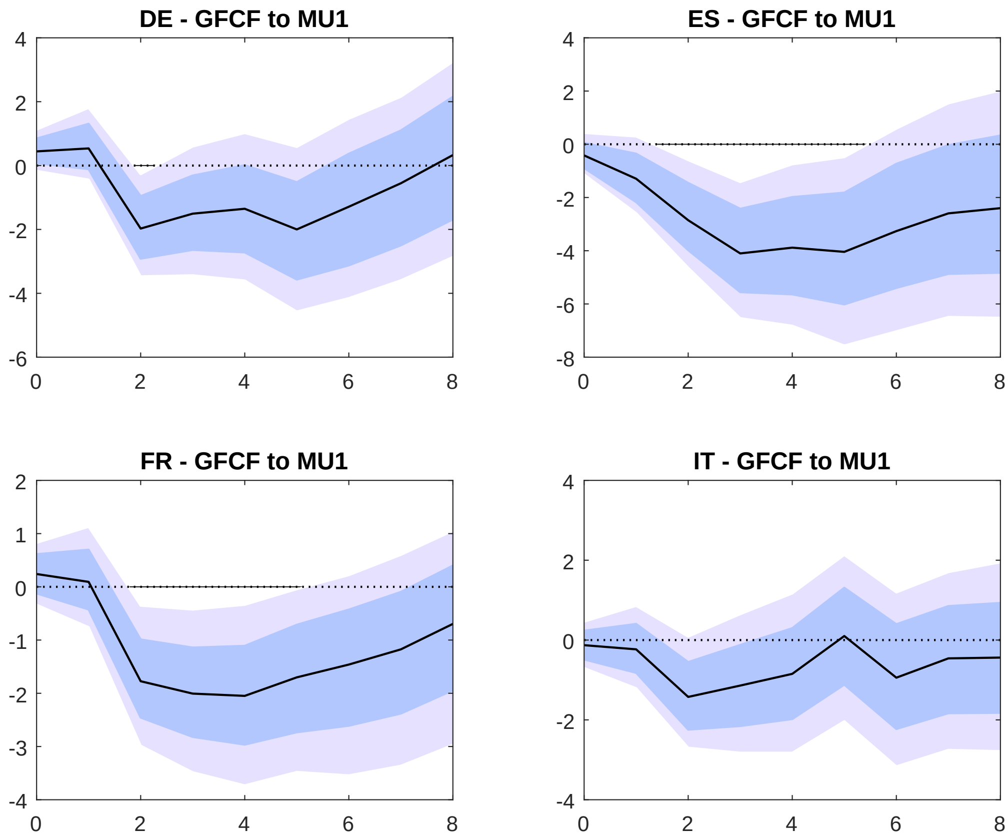

Figure 8: IRFs of investment (GFCF in M&E), Quarterly Data

Notes: Impulse responses (IRFs) of investment (in percent), as measured by gross fixed capital formation (GFCF) in machinery and equipment (M&E), for Germany (DE), Spain (ES), France (FR), and Italy (IT). IRFs are derived from model (8) (two-step approach) and transformed to present level responses. Quarterly structural uncertainty shocks are obtained from SVAR model VAR-2, estimated on monthly data spanning the period 1996:7–2015:12. Solid lines depict median responses to an uncertainty shock (*MU1*). Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

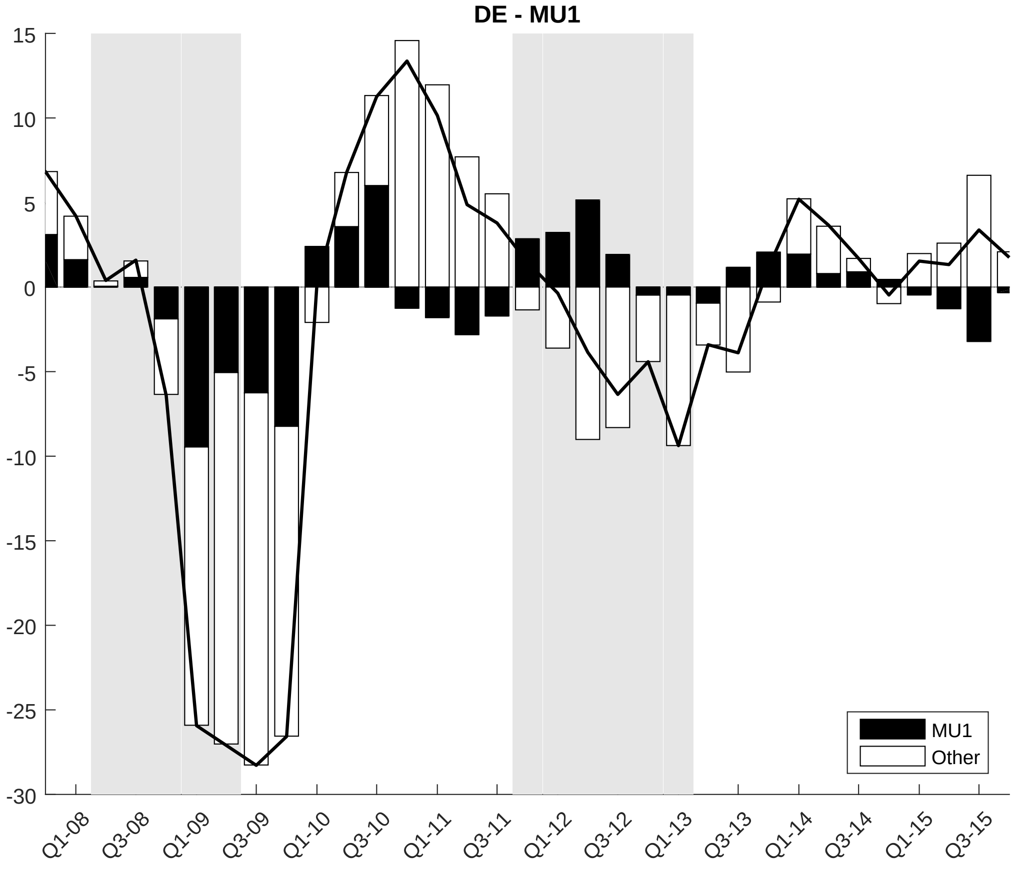

Figure 9: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – Germany (DE)

Notes: Cumulative effects of uncertainty shocks on investment derived from model (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-2, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to the (demeaned) year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

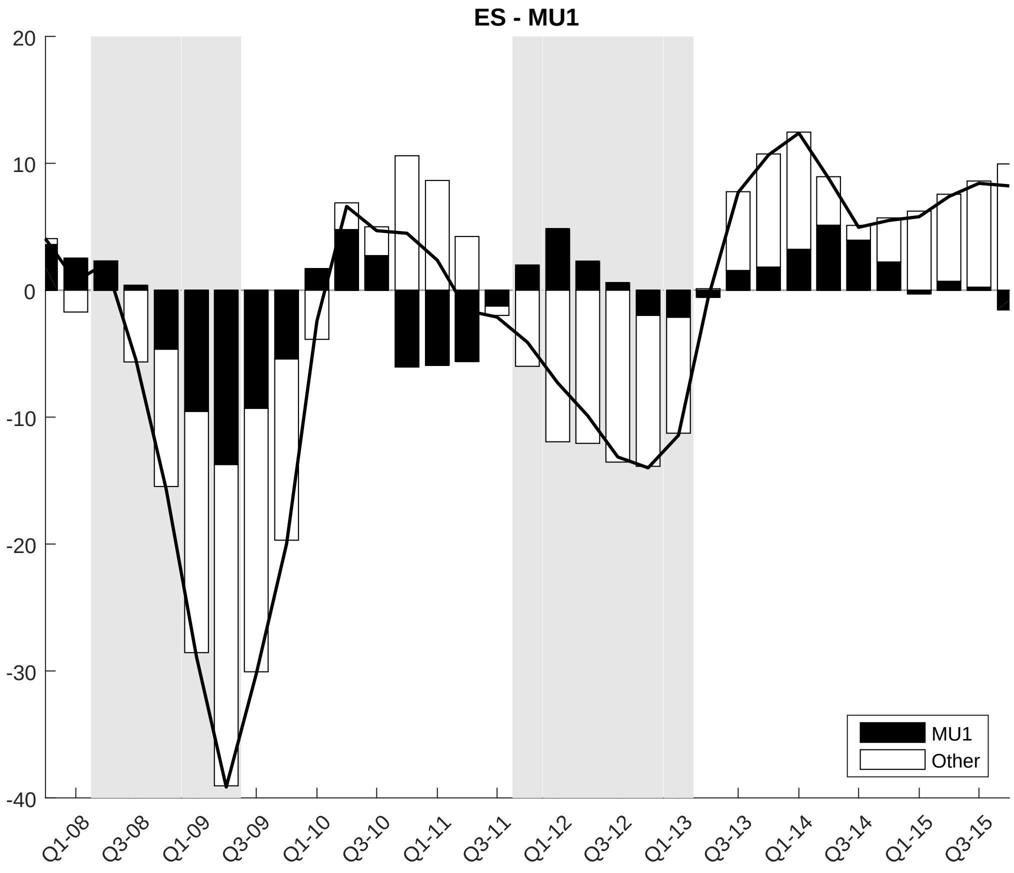

Figure 10: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – Spain (ES)

Notes: Cumulative effects of uncertainty shocks on investment derived from model (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-2, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to the (demeaned) year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

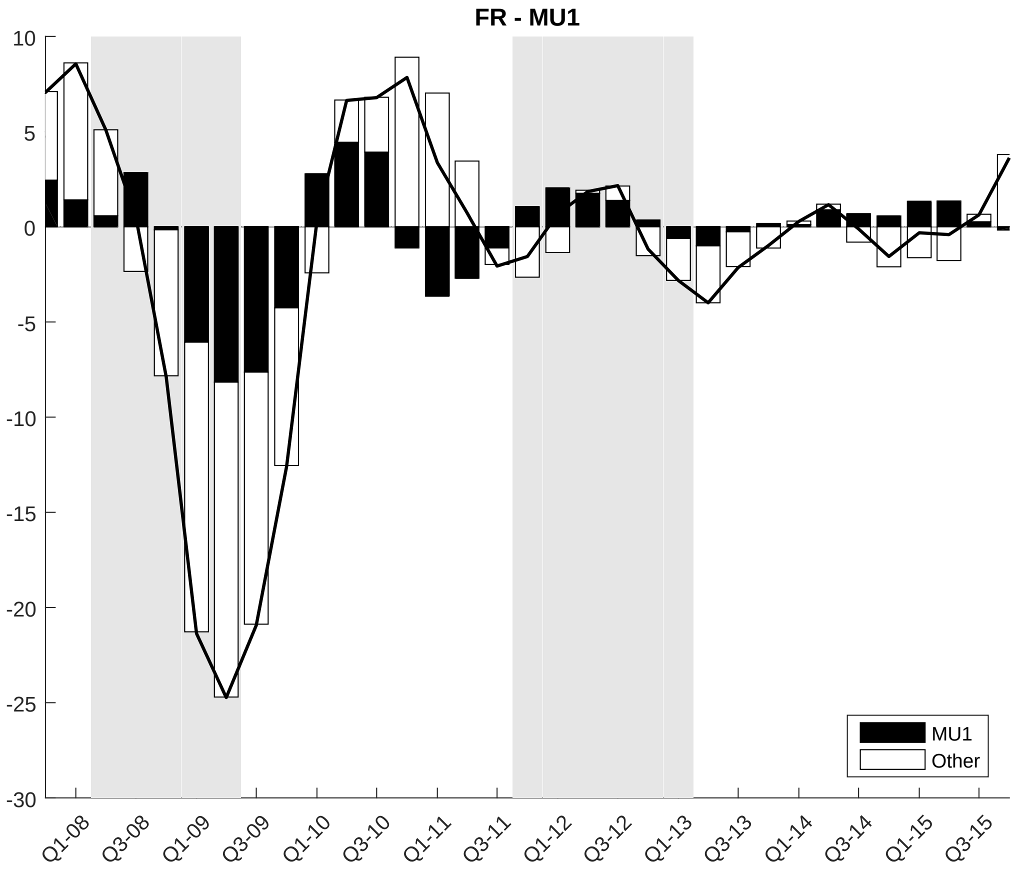

Figure 11: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – France (FR)

Notes: Cumulative effects of uncertainty shocks on investment derived from model (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-2, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to (demeaned) the year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

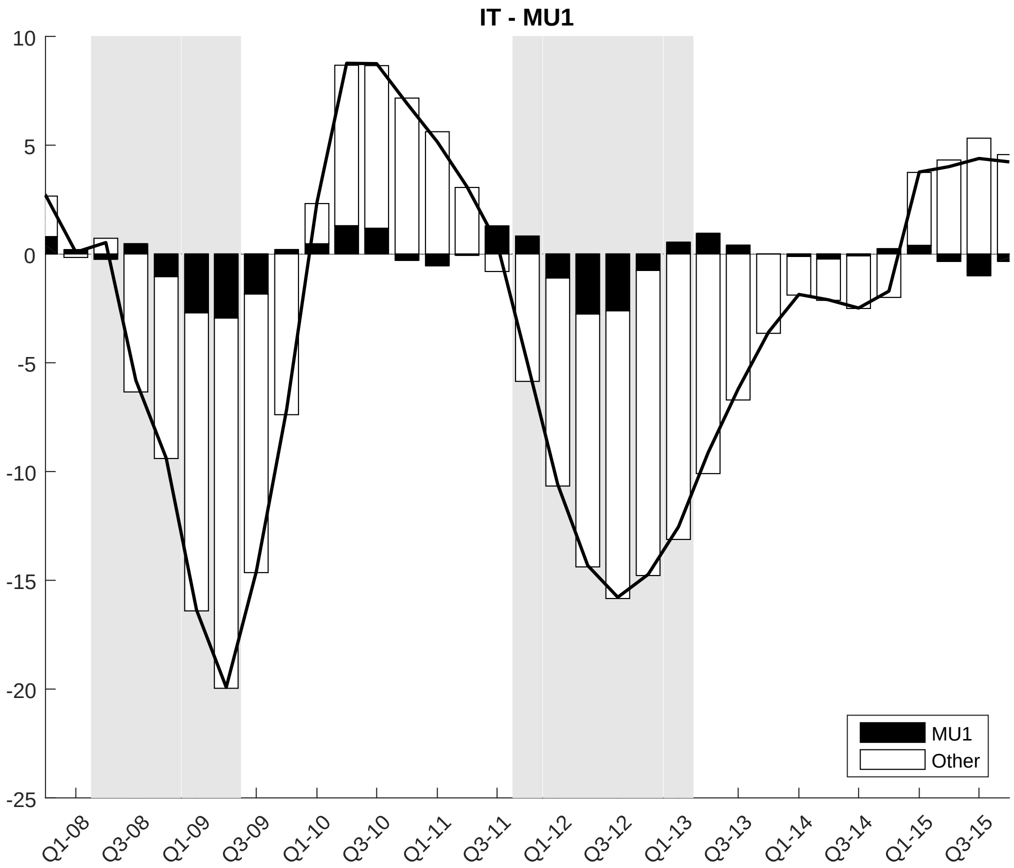

Figure 12: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – Italy (IT)

Notes: Cumulative effects of uncertainty shocks on investment derived from model (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-2, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to the (demeaned) year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

A Appendix

The appendix contains supplementary material, including a presentation of the data sets used to compute *MU1* and *MU2*, along with the data employed to estimate the SVAR models (Section A.1) and some additional results not included in the main body of the paper (Section A.2).

A.1 Data

This section presents macro and financial data sets used to compute the uncertainty indicators *MU1* and *MU2* as well as the data used in the VAR analysis.

A.1.1 Macro and financial data sets

In line with the macro data set for the US used by Jurado, Ludvigson, and Ng (2015) – henceforth JLN – we build four large macro data sets: one each for Germany, France, Italy, and Spain. Each data set is designed to cover broad categories of macroeconomic time series data:

1. real output and income (OAI)
2. employment and compensation (LAB)
3. housing (HOU)
4. consumption, orders, and inventory (COI)
5. money and credit (MAC)
6. bond and exchange rates (BER)
7. price indices (PRI)
8. stock market indices (STM)
9. international trade (TRD)

While some of these categories are rather standard and thus quite similar across the four countries (e.g., OAI and PRI), for other categories the range of data availability turns out to be more heterogeneous, particularly for LAB. Generally, we tried to cover the most important aspects of each category for every country. We ended up with 113, 114, 108, and 110 time series for Germany, France, Italy, and Spain, respectively. All data sets contain monthly time series for the period 1996:01–2015:12. Where available, we downloaded seasonally adjusted data; otherwise, we have seasonally adjusted the data using an X-12-ARIMA filter.

Depending on the time series properties, we transform each macro series before using it to compute *MU1* and *MU2*. Specifically, we check each series for unit roots using a Dickey-Fuller test. In case of non-stationarity, we perform a suitable transformation. Let x_t^a denote the actual series and x_t the series after transformation; the alternative transformations are then given by:

1. lv: $x_t = x_t^a$
2. Δlv: $x_t = x_t^a - x_{t-1}^a$
3. $\Delta^2 lv$: $x_t = \Delta^2 x_t^a$
4. Δln: $x_t = ln(x_t^a) - ln(x_{t-1}^a)$
5. $\Delta^2 ln$: $x_t = \Delta^2 ln(x_t^a)$

Tables A1 to A4 depict the macro series for the four countries including information on data sources, seasonal adjustment, and data transformation.

Moreover, we follow JLN and supplement the macro data with financial time series obtained from Kenneth French's website at Dartmouth College.[40] Since no timely country-specific series are available for European countries, we use the aggregated series for Europe for each country. Specifically, we include Fama and French risk factors for Europe, 25 portfolios formed on size and book-to-market (5x5) for Europe, and the series termed R15-R11, which is a spread computed from these portfolios.[41,42] This gives us a total of 29 time series in the financial data set, as listed in Table A5. Note that in contrast to JLN, we do not annualize the returns and spreads. Moreover, our macro data were not annualized either.

For each country, large data sets comprising these 29 financial time series and the respective macro time series are used to estimate country-specific forecasting factors. However, it is important to stress that the financial data are only used to improve the predictive content of the forecasting factors and are not part of the data used to estimate macroeconomic uncertainty. We follow JLN in this point, since we do not wish to over-represent financial time series in the uncertainty estimate. This matters because the macroeconomic data sets already contain several financial indicators.

A.1.2 VAR data

Most of the data used in the VAR analysis are standard macroeconomic time series obtained from Eurostat. This holds for the harmonized unemployment rate, the harmonized index of consumer prices (HICP) and for the following measures of investment activity: industrial production of capital goods (IPC) and gross fixed capital formation in machinery and equipment (GFCF M&E). We compute the series for industrial production of non-capital goods (IPNC) using data from Eurostat on real growth rates and nominal shares of the main industrial grouping (MIG) components of industrial production. Moreover, we obtain the data on stock market indexes from Haver Analytics[43] and, as

[40] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/; the data set was downloaded in May 2016.

[41] The European factors and portfolios include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[42] R15-R11 is the spread between the small, high book-to-market and small, low book-to-market portfolios.

[43] We use the CDAX for Germany, the SBF 250 for France, the Morgan Stanley Capital International (MSCI) Index (without dividends, local currency-based), which aims at measuring the equity market performance, for Italy, and the Madrid Stock Exchange General Index (IGBM) for Spain. All series are price indexes.

outlined in the main text, the shadow short rate (SSR) is from Leo Krippner's website at the Reserve Bank of New Zealand. We concatenate this series with country-specific short rates before 1999.[44]

A.2 Additional Results

In this section we show some additional results not included in the main body of the paper. First, we present results from the two-step approach based on VAR-3. Figure A.1 contains the IRFs, while Figures A.2 to A.5 depict the corresponding historical contributions. Although the results tend to be somewhat more muted, the conclusion derived from the figures in the main text remains unaffected.

Second, we present impulse responses obtained from a second-stage model estimated with GFCF in levels while adding a linear trend to the right hand side of the equation:

$$y_t = c + \gamma t + \sum_{i=0}^{8} \phi_i \tilde{\epsilon}_{t-i} + u_t. \tag{9}$$

Figures A.6 and A.7 present the results for uncertainty shocks related to *MU1* obtained from VAR-2 and VAR-3, respectively. The results do not alter substantially.

Third, we add a measure for orders to the VAR-3 which is, e.g., in line with the larger VAR framework estimated by JLN. Unfortunately, time series data on real orders is not consistently available across the four euro-area countries. Specifically, for Spain data are available only from 2002 onwards, while France no longer publishes a series on real orders (France published the series for the period 1998-2012). Hence, we can only use a survey-based measure to check the sensitivity of our results with respect to including a forward looking variable such as orders to our VAR setup if we want to ensure comparable sample lengths across countries. We thus use the survey indicator on current book orders reported by the European Commission. We estimate a model with variables ordered as in VAR-3, while we include the measure for orders between the price index and the short rate. The IRFs (Figures A.8 and A.9) for both monthly IPC and quarterly GFCF are hardly affected by the addition of this variable to the VAR model.

Fourth, in Figure A.10 we show impulse response functions for both IPC and IPNC to uncertainty shocks where uncertainty is measured by *MU1*. The figures indicate that investment (IPC) responds relatively more strongly to uncertainty shocks than non-capital related output components (IPNC).

Moreover, we presents results for the response of aggregated activity (i.e. GDP) to uncertainty shocks. To this end, we first estimate a monthly VAR. Specifically, we estimate a model similar to VAR-2, while we replace the two variables IPC and IPNC with the aggregate measure of industrial production (IP). We focus our attention to the uncertainty indicator *MU1*. As expected, the results from the monthly VAR are in line with those for IPC and IPNC; i.e. in all countries we find significant negative responses of industrial production to uncertainty shocks (Figure A.11). Using these structural uncertainty shocks in our two-step procedure, we also find negative responses of GDP to uncertainty shocks,

[44] http://www.rbnz.govt.nz/research_and_publications/research_programme/additional_research/comparison-of-international-monetary-policy-measures.html; the data set was downloaded in May 2016.

even though the effects are more muted compared to the responses of GFCF. This is in line with findings from before (Figure A.10), suggesting that investment activity responds more strongly to uncertainty shocks than non-investment related activity.

Next, Figure A.13 contains estimation results for various ways of computing *MU2*. The first row presents results based on our default measure presented in the main text. Results in the second row are based on *MU2* measuring downside uncertainty only. In line with results from Rossi and Sekhposyan (2015), we also find that the responses to uncertainty shocks tend to be stronger when using this indicator compared to row 1. The last two rows of Figures A.13 are based on an uncertainty measure derived from a single series only, namely industrial production of capital goods (row 3) and total manufacturing production (row 4). In each case, the responses to uncertainty shocks are mostly insignificant. This suggests that our proposed extension of computing this uncertainty proxy from a large number of series is indeed of relevance.

Furthermore, following the approach outlined in Gelman and Rubin (1992) and Brooks and Gelman (1998), we present the convergence statistic in Figures A.14 to A.16. The statistics are computed for each parameter (coefficient and covariance matrix) based on two parallel Markov chains of length 10,000. The first 9,000 draws of each chain were used as a burn-in. Note that the chains are initialized with starting values for the coefficient vector which are drawn from an overdispersed distribution (i.e. N(0,100)). Values close to 1 indicate that convergence is reached for the respective parameter. The Figures thus suggest that 10,000 draws are indeed sufficient for convergence in our VAR exercise.

Finally, Table A.6 presents cross-country correlations between uncertainty shocks mentioned in the main body of the paper.

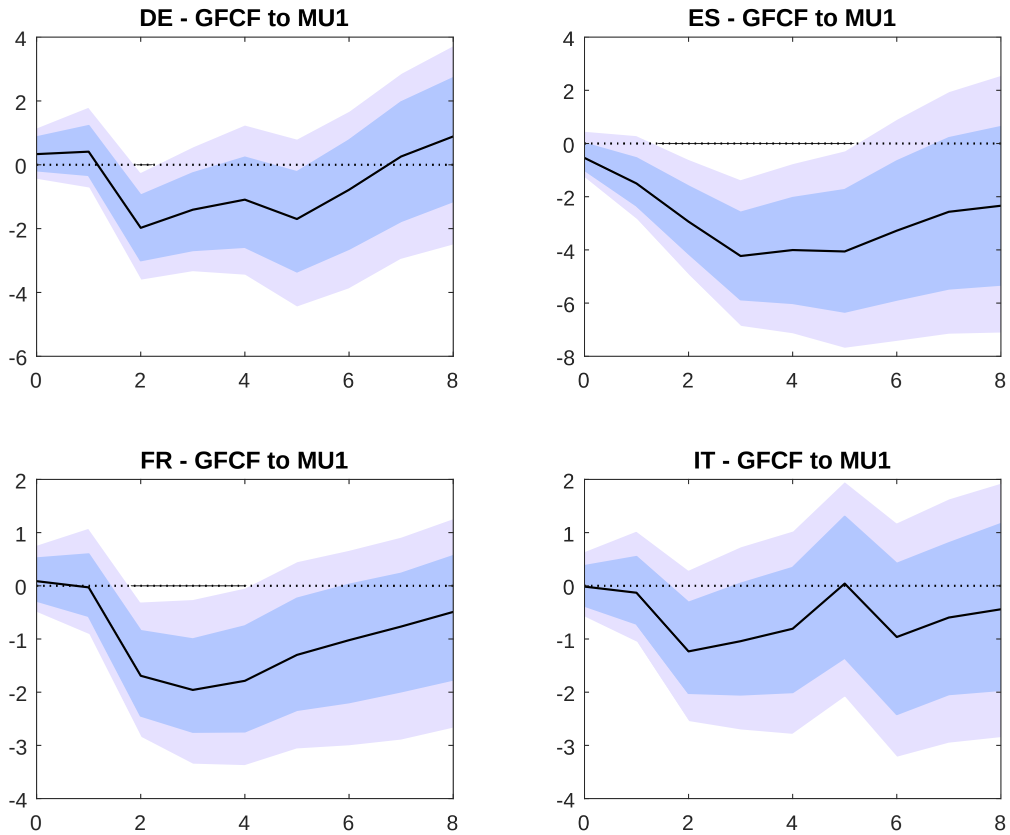

Figure A.1: IRFs of investment (GFCF in M&E), Quarterly Data, (VAR-3)

Notes: Impulse responses (IRFs) of investment (in percent) as measured by gross fixed capital formation (GFCF) in machinery and equipment (M&E) for Germany (DE), Spain (ES), France (FR), and Italy (IT). IRFs are derived from equation (8) (two-step approach) and transformed to present level responses. Quarterly structural uncertainty shocks are obtained from SVAR model VAR-3, estimated on monthly data spanning the period 1996:6–2015:12. Solid lines depict median responses to an uncertainty shock (*MU1*). Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

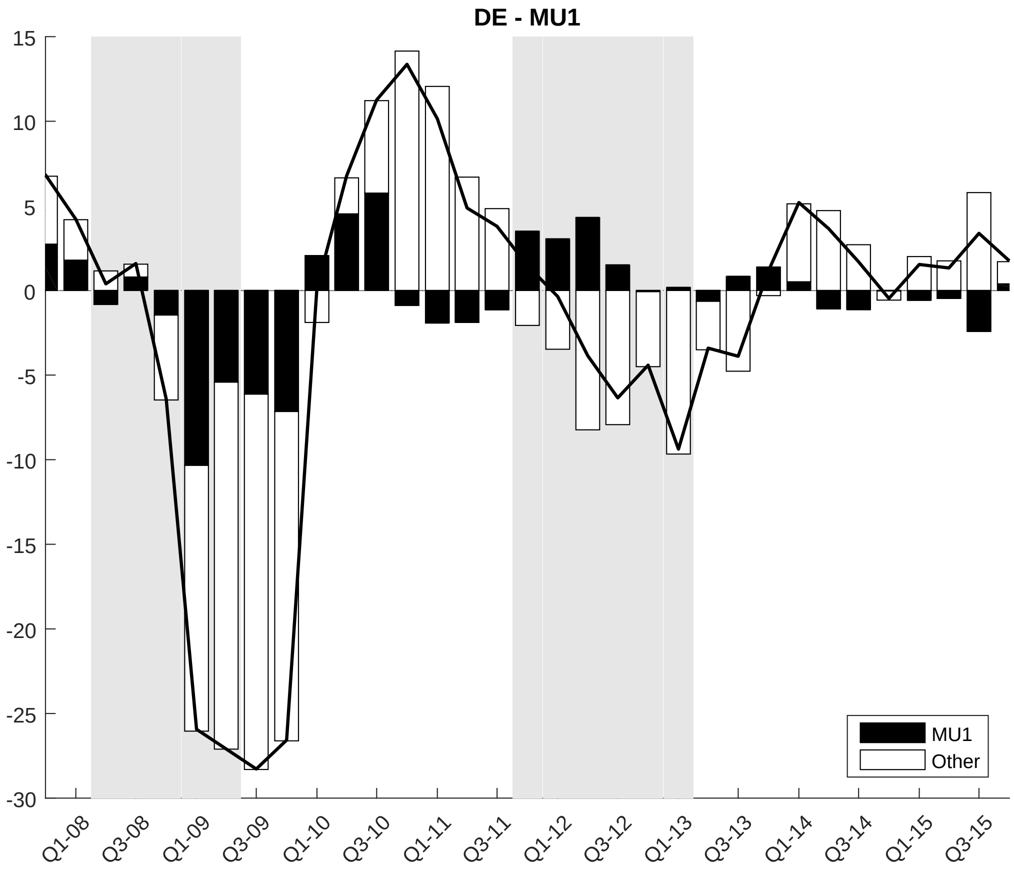

Figure A.2: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – Germany (DE), (VAR-3)

Notes: Cumulative effects of uncertainty shocks on investment derived from equation (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-3, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to the (demeaned) year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

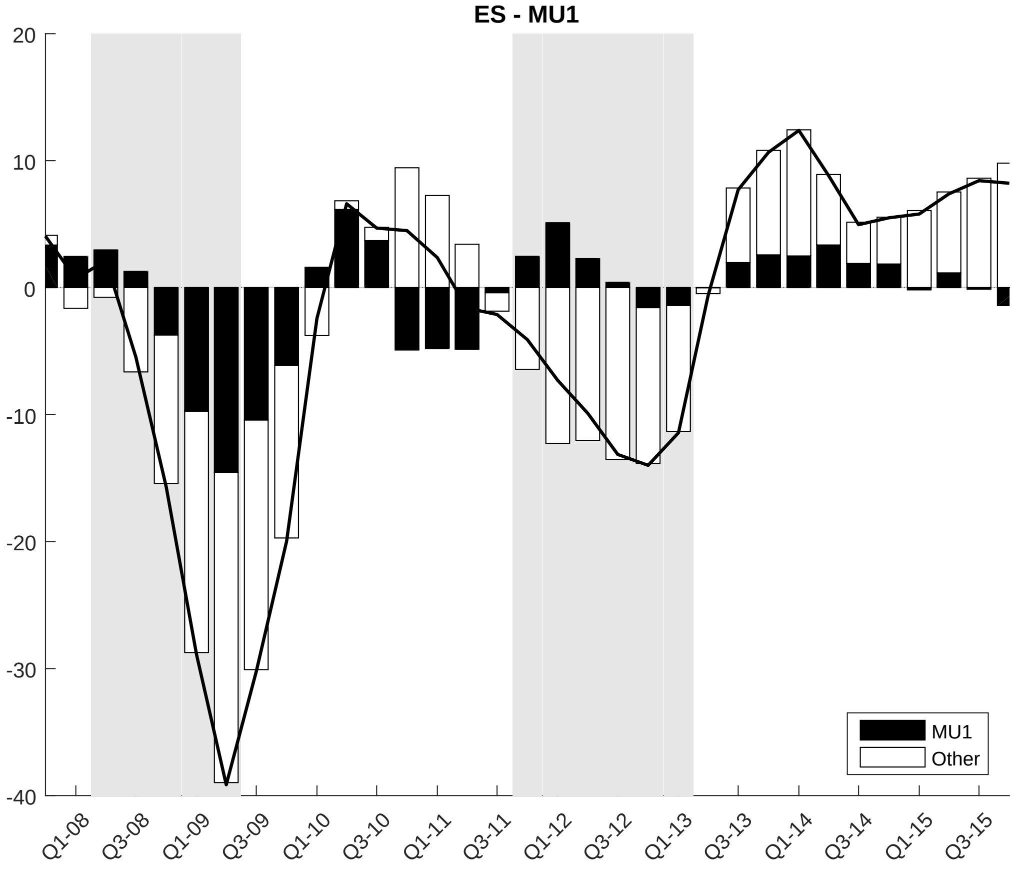

Figure A.3: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – Spain (ES), (VAR-3)

Notes: Cumulative effects of uncertainty shocks on investment derived from equation (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-3, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to the (demeaned) year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

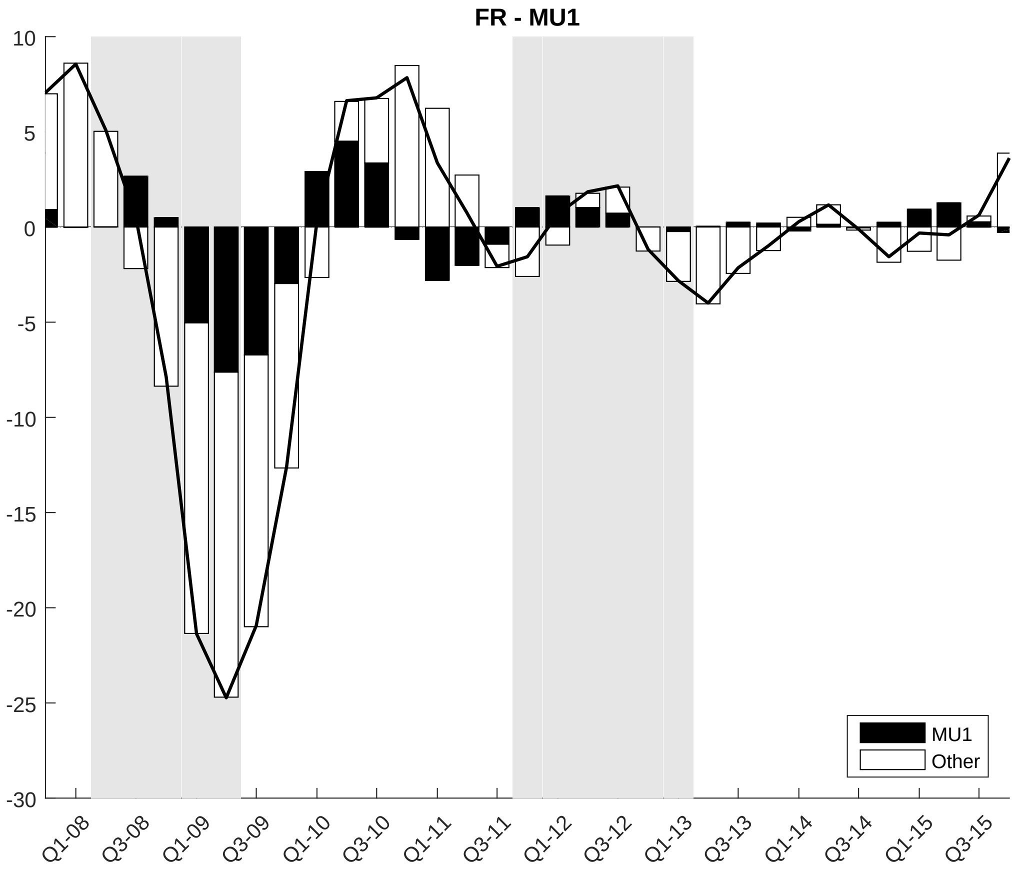

Figure A.4: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – France (FR), (VAR-3)

Notes: Cumulative effects of uncertainty shocks on investment derived from equation (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-3, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to the (demeaned) year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

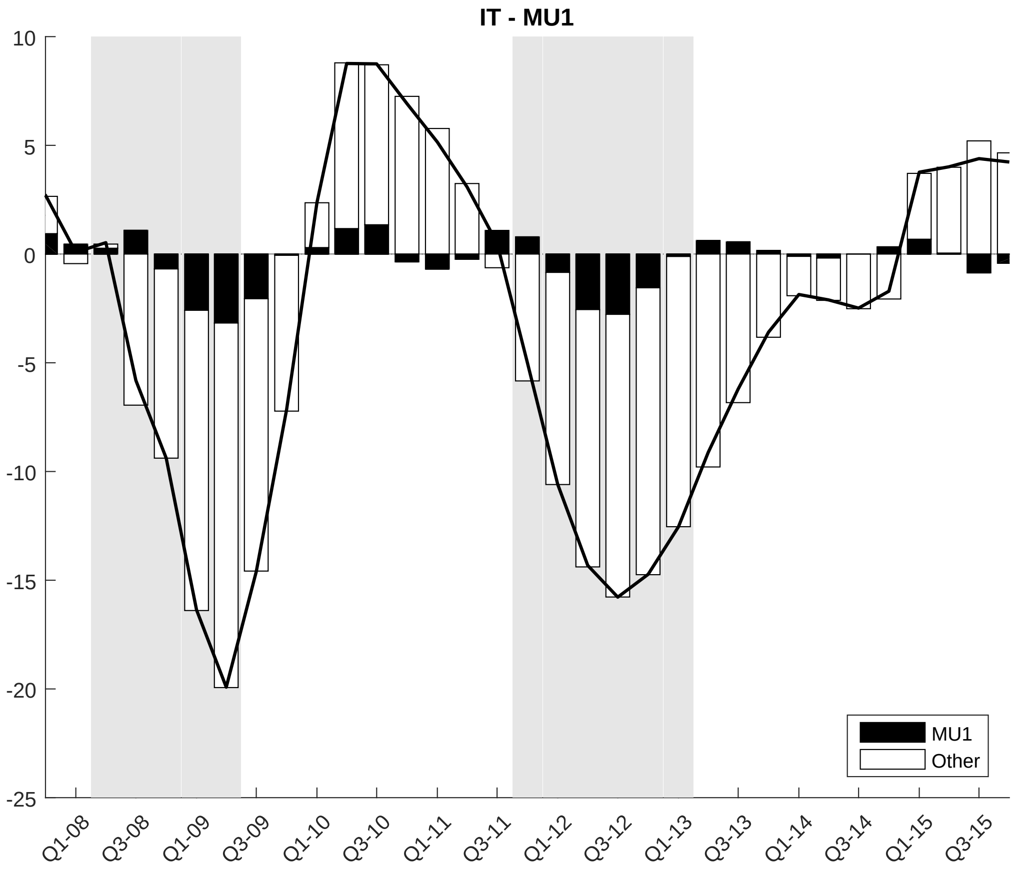

Figure A.5: Cumulative Effects of (*MU1*) Shocks on Investment (GFCF) – Italy (IT), (VAR-3)

Notes: Cumulative effects of uncertainty shocks on investment derived from equation (8) (two-step approach). Quarterly structural uncertainty shocks are obtained from SVAR model VAR-3, estimated on monthly data spanning the period 1996:7–2015:12. The dark colored bars show the median contribution of uncertainty shocks (*MU1*), while the light colored bars summarize the median contributions of the remaining shocks to the (demeaned) year-on-year growth rate of gross fixed capital formation in machinery and equipment (solid line). The shock contribution is expressed in percentage points. Shaded vertical bars correspond to CEPR recession periods for euro-area business cycles.

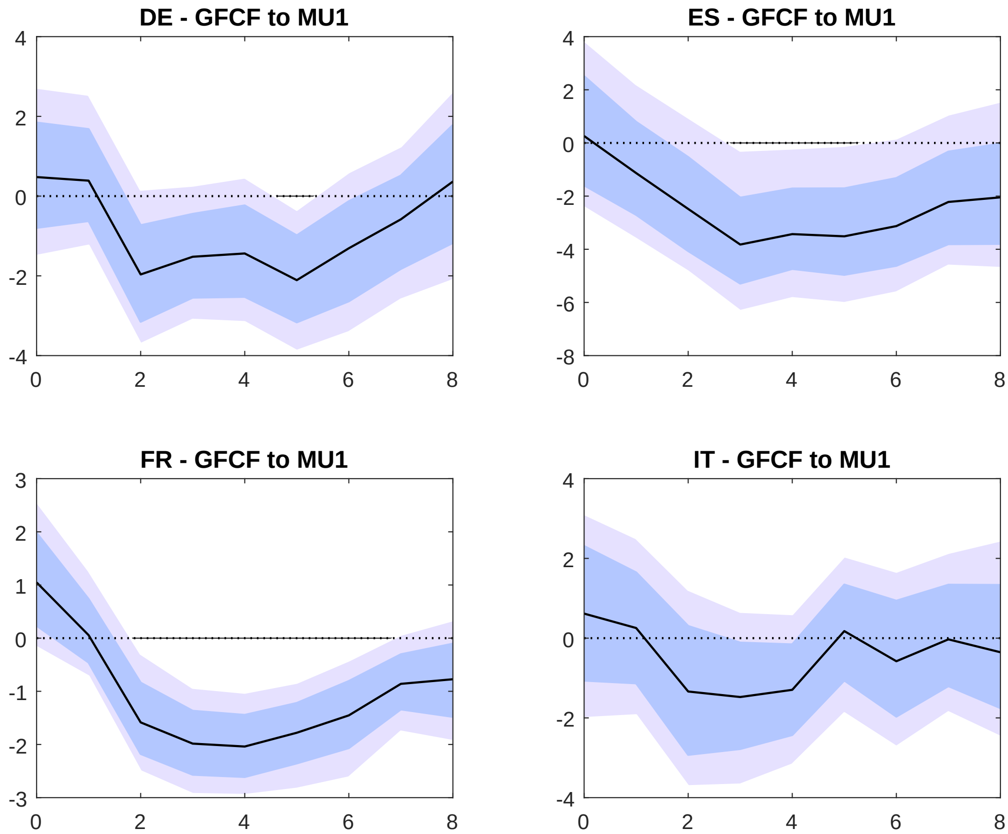

Figure A.6: IRFs of investment (GFCF in M&E), Quarterly Data, Alternative Second-stage Model (VAR-2)

Notes: Impulse responses (IRFs) of investment (in percent) as measured by gross fixed capital formation (GFCF) in machinery and equipment (M&E) for Germany (DE), Spain (ES), France (FR), and Italy (IT). IRFs are derived from the two-step approach, whereas the second-stage model is estimated with GFCF in levels and a linear trend added to the right hand side of the regression equation. Quarterly structural uncertainty shocks are obtained from SVAR model VAR-2, estimated on monthly data spanning the period 1996:7–2015:12. Solid lines depict median responses to an uncertainty shock (*MU1*). Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

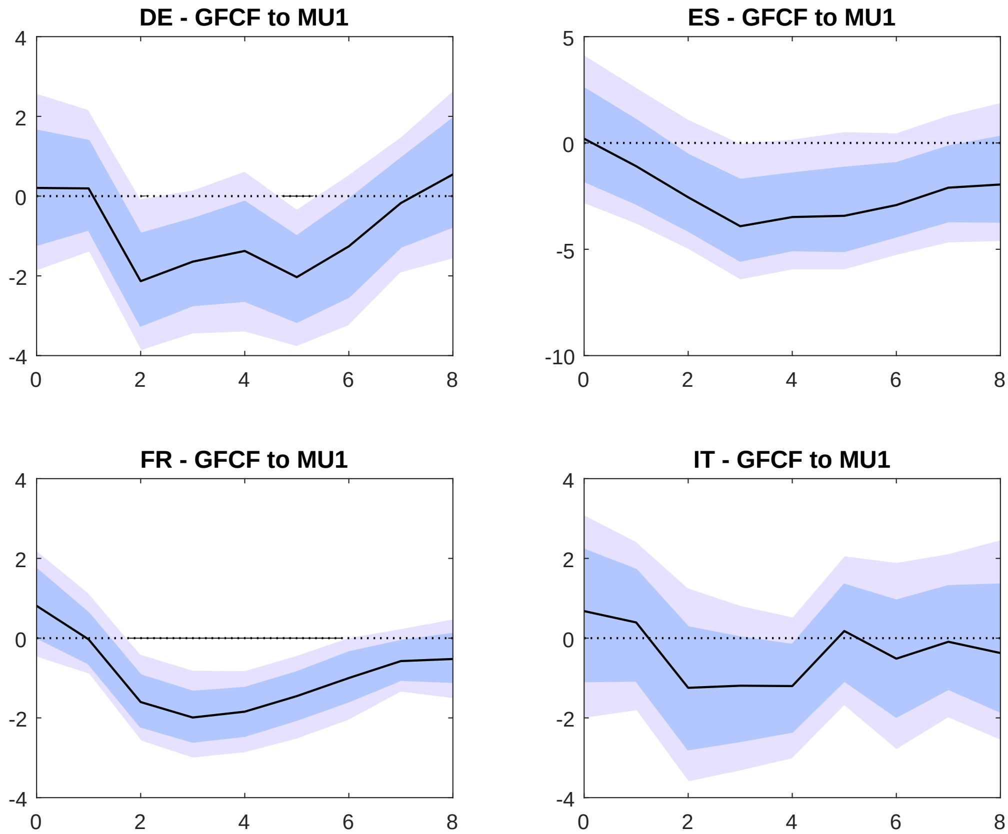

Figure A.7: IRFs of investment (GFCF in M&E), Quarterly Data, Alternative Second-stage Model (VAR-3)

Notes: Impulse responses (IRFs) of investment (in percent) as measured by gross fixed capital formation (GFCF) in machinery and equipment (M&E) for Germany (DE), Spain (ES), France (FR), and Italy (IT). IRFs are derived from the two-step approach, whereas the second-stage model is estimated with GFCF in levels and a linear trend added to the right hand side of the regression equation. Quarterly structural uncertainty shocks are obtained from SVAR model VAR-3, estimated on monthly data spanning the period 1996:7–2015:12. Solid lines depict median responses to an uncertainty shock (*MU1*). Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

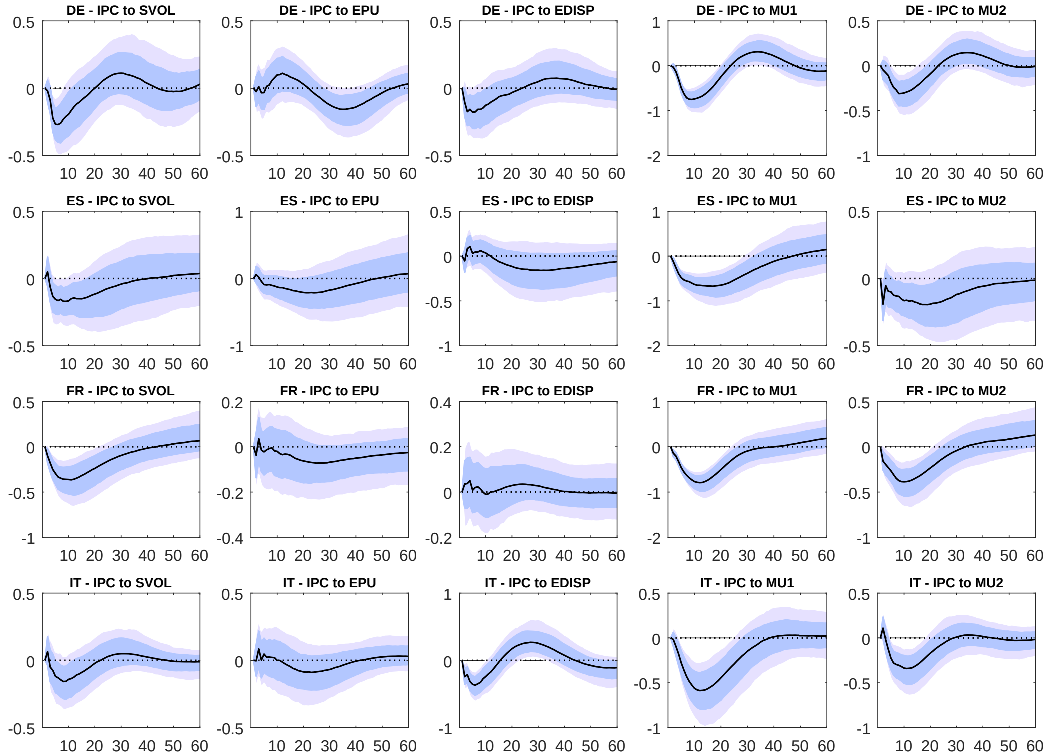

Figure A.8: IRFs of investment (IPC) – Higher-dimensional SVARs (VAR-3), Monthly Data, (VAR-3 with orders)

Notes: Impulse responses (IRFs) of investment, as measured by industrial production of capital goods (IPC), to uncertainty shocks obtained from the SVAR model VAR-3, supplemented by a survey indicator on current book orders, estimated on monthly data spanning the period 1996:7–2015:12, except for *EPU*, which starts in 1997:1 for Italy and in 2001:1 for Spain. Each row shows the IRFs (in percent) across the five uncertainty proxies (*SVOL*, *EPU*, *EDISP*, *MU1*, *MU2*) for the respective country (Germany (DE), Spain (ES), France (FR), Italy (IT)). Solid lines depict median responses to a shock of one standard deviation. Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

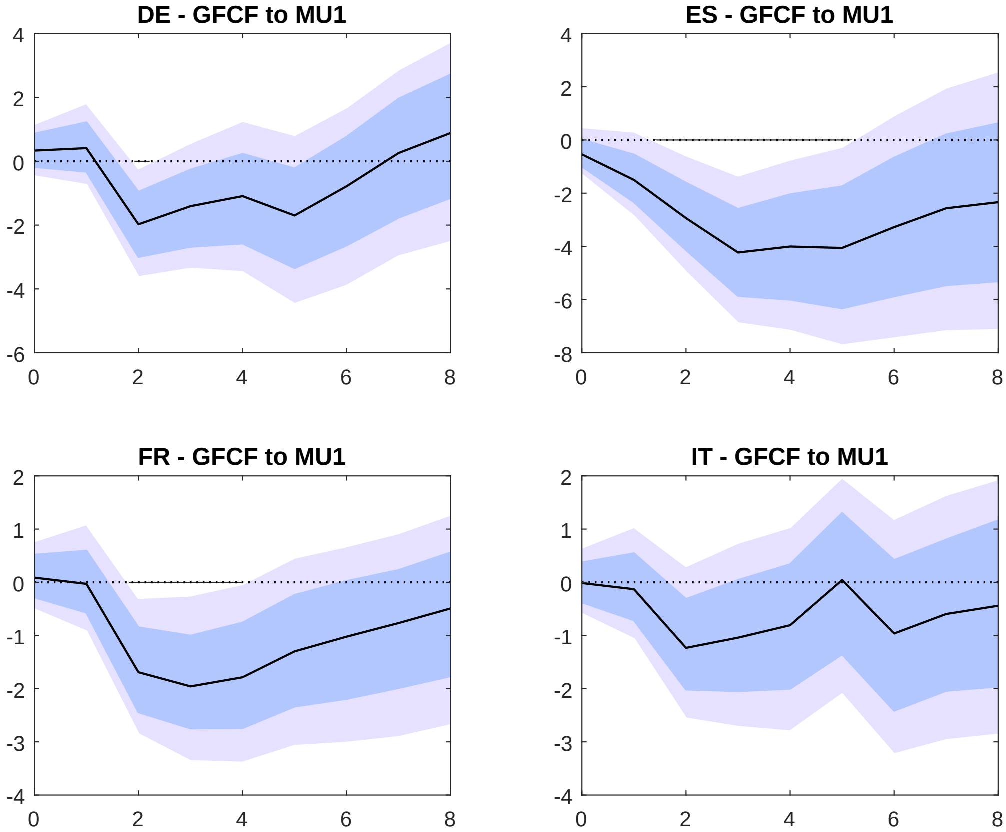

Figure A.9: IRFs of investment (GFCF in M&E), Quarterly Data, (VAR-3 with orders)

Notes: Impulse responses (IRFs) of investment (in percent) as measured by gross fixed capital formation (GFCF) in machinery and equipment (M&E) for Germany (DE), Spain (ES), France (FR), and Italy (IT). IRFs are derived from equation (8) (two-step approach) and transformed to present level responses. Quarterly structural uncertainty shocks are obtained from SVAR model VAR-3, supplemented by a survey indicator on current book orders, estimated on monthly data spanning the period 1996:7–2015:12. Solid lines depict median responses to an uncertainty shock (*MU1*). Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

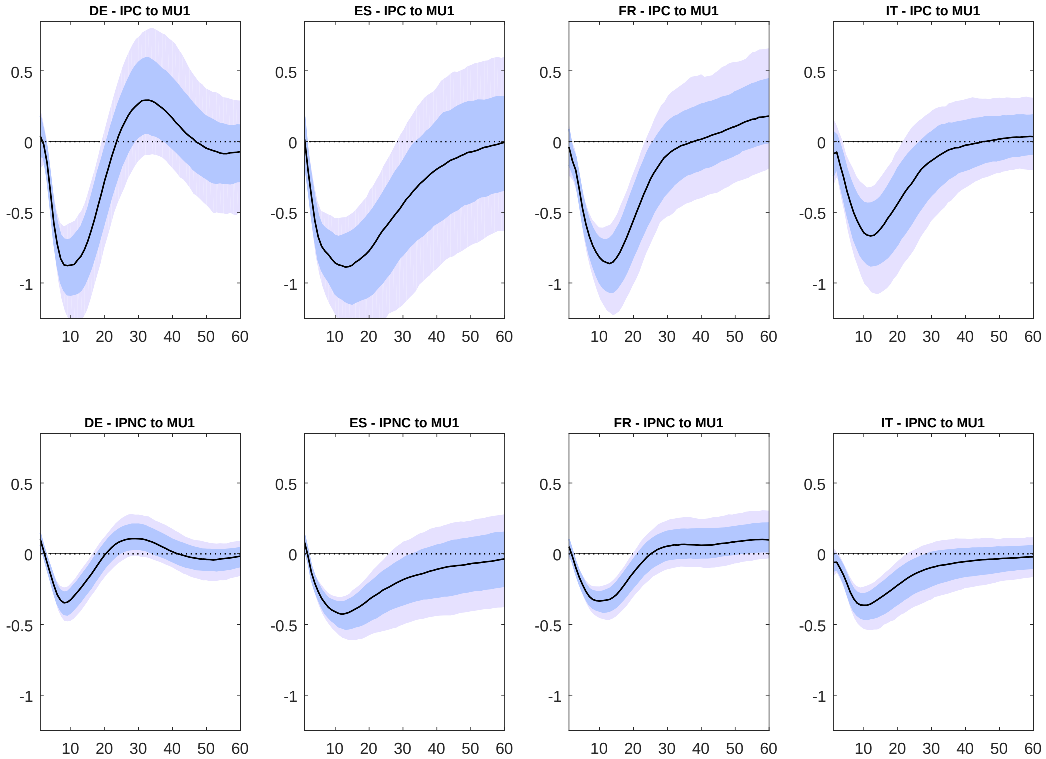

Figure A.10: IRFs of IPC and IPNC – Higher-dimensional SVARs (VAR-2), Monthly Data

Notes: Impulse responses (IRFs) of investment (in percent), as measured by industrial production of capital goods (IPC) and general economic activity, captured by non-industrial production of non-capital goods (IPNC), to uncertainty shocks for Germany (DE), Spain (ES), France (FR), and Italy (IT). IRFs are obtained from the SVAR model VAR-2, estimated on monthly data spanning the period 1996:7–2015:12. Solid lines depict median responses to an *MU1* shock of one standard deviation. Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

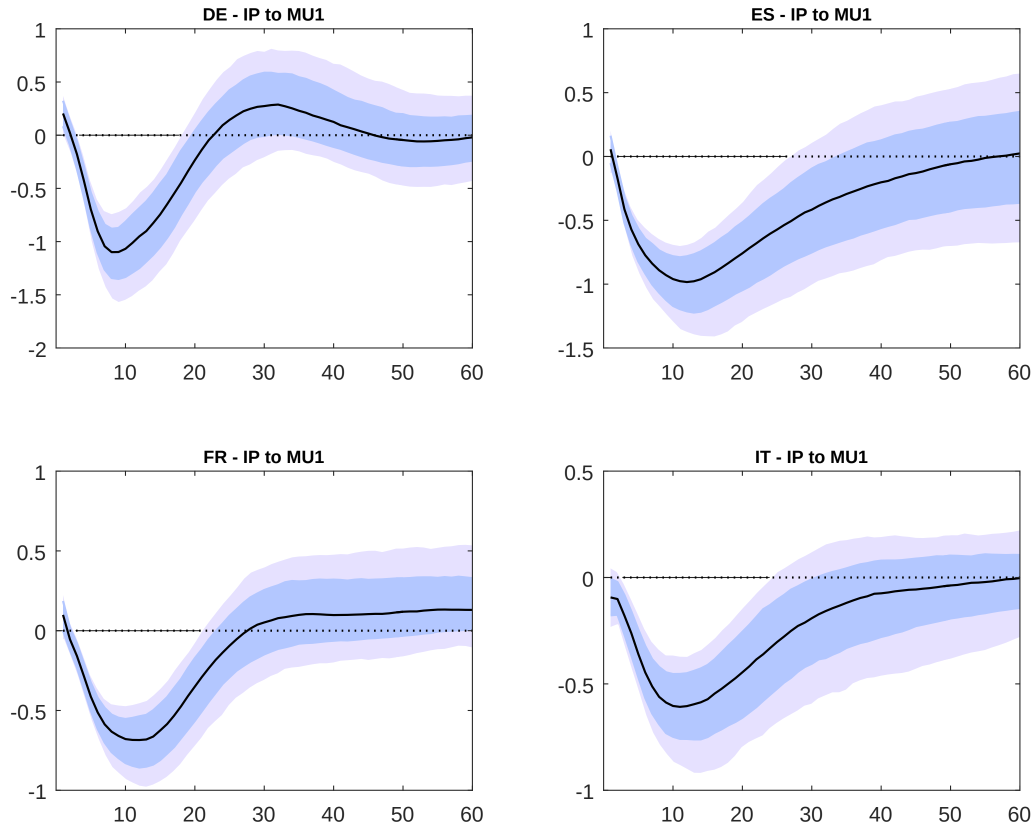

Figure A.11: IRFs of Industrial Production (IP) – Higher-dimensional SVARs (VAR-2 with IP), Monthly Data

Notes: Impulse responses (IRFs) of industrial production (IP, in percent) to uncertainty shocks obtained from the SVAR model VAR-2, where IPC and NIPC are replaced by IP, estimated on monthly data spanning the period 1996:7–2015:12, for the respective country (Germany (DE), Spain (ES), France (FR), Italy (IT)). Solid lines depict median responses to a shock of one standard deviation. Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

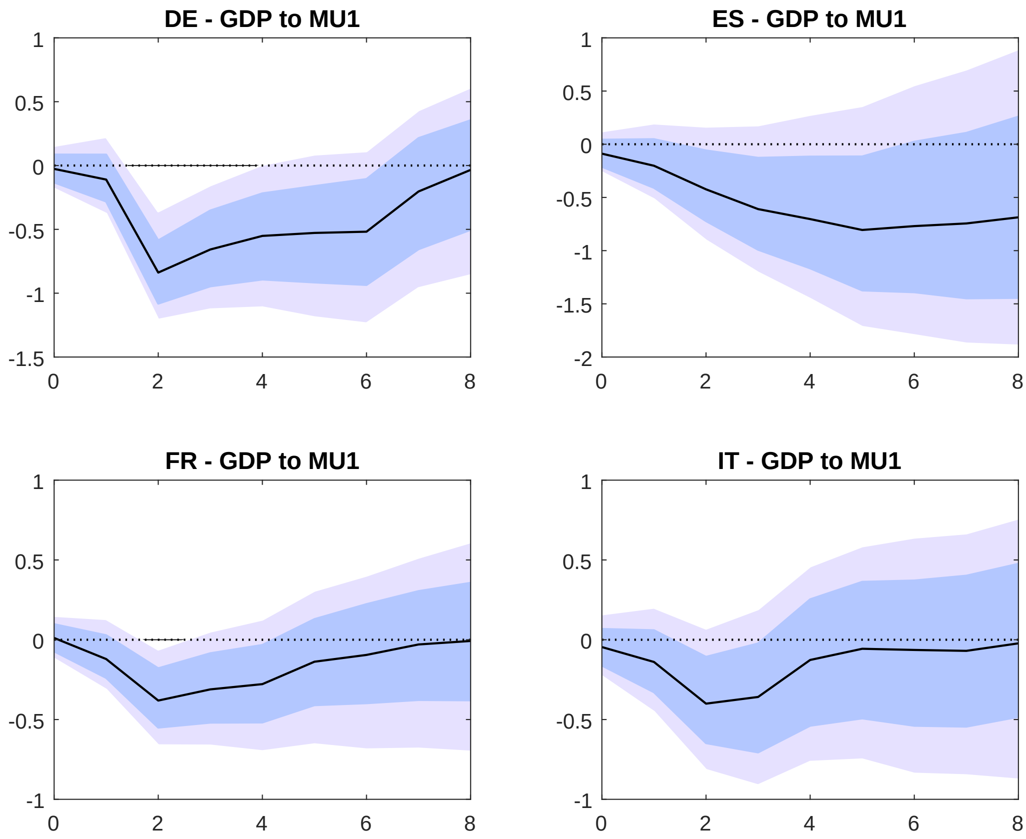

Figure A.12: IRFs of GDP, Quarterly Data, (VAR-2 with IP)

Notes: Impulse responses (IRFs) of GDP to uncertainty shocks for Germany (DE), Spain (ES), France (FR), and Italy (IT). IRFs are derived from equation (8) (two-step approach) and transformed to present level responses. Quarterly structural uncertainty shocks are obtained from SVAR model VAR-2 with IP, estimated on monthly data spanning the period 1996:7–2015:12. Solid lines depict median responses to an uncertainty shock (*MU1*). Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

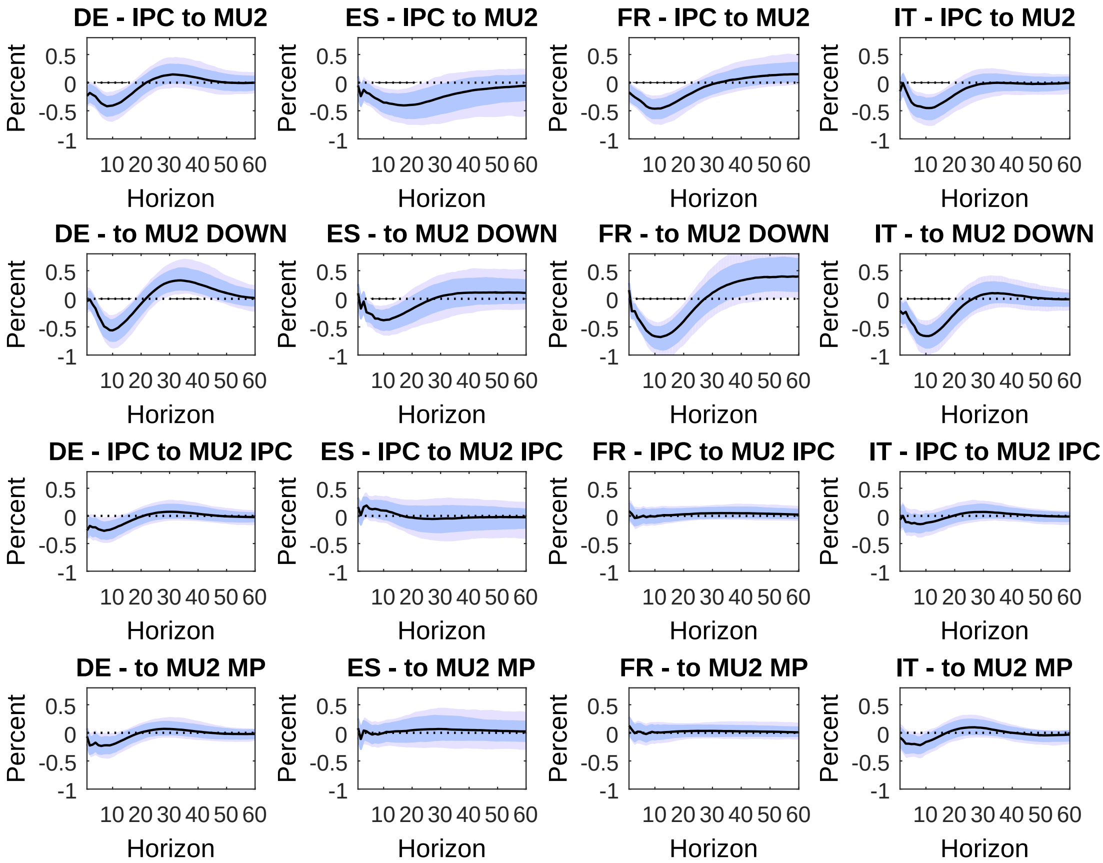

Figure A.13: IRFs of Investment (IPC) – Higher-dimensional SVARs (VAR-2), Monthly Data – Various Measures of MU2

Notes: Impulse responses (IRFs) of investment, as measured by industrial production of capital goods (IPC) to uncertainty shocks obtained from the SVAR model VAR-2, estimated on monthly data spanning the period 1996:6–2015:9. Each column shows the IRFs (in percent) across the four versions of the uncertainty proxies MU2 for the respective country (Germany (DE), Spain (ES), France (FR), Italy (IT)). While MU2 refers to the indicator used in the main text, MU2 DOWN refers to downside uncertainty and MU2 IPC and MU2 MP are based on a single macroeconomic series, namely industrial production and total manufacturing production, respectively. Solid lines depict median responses to a shock of one standard deviation. Dark and light shaded areas indicate the 68% and 90% posterior probability regions, respectively.

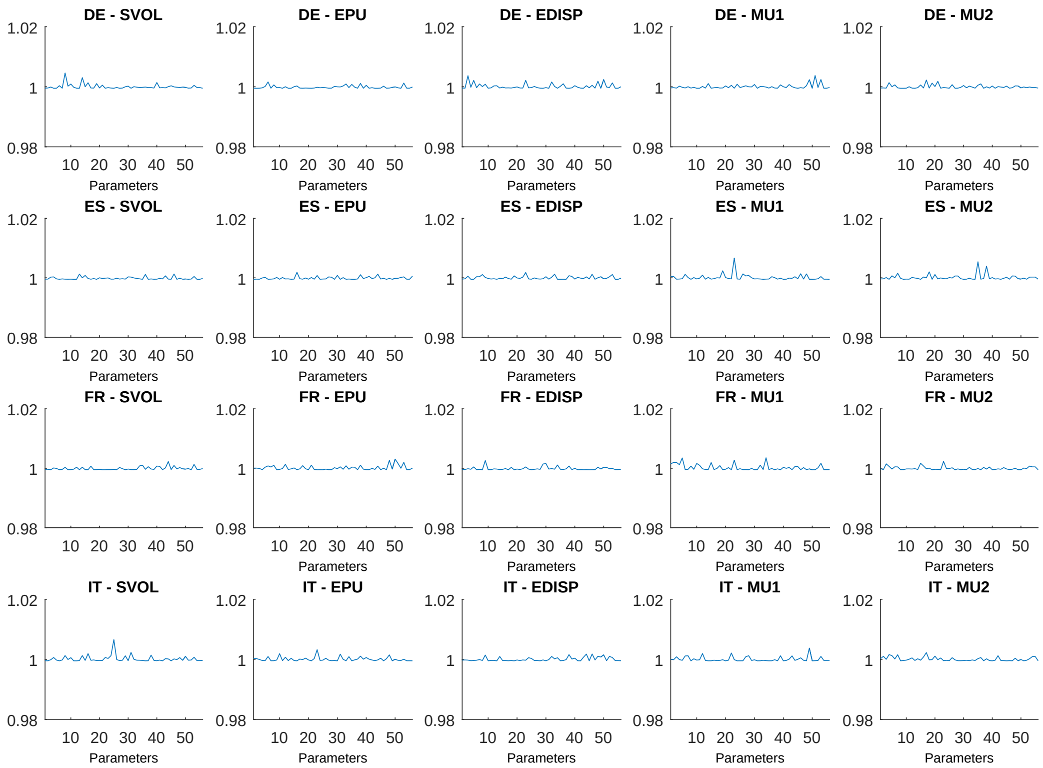

Figure A.14: Convergence Check – Bivariate SVARs (VAR-1)

Notes: Convergence statistics computed following Gelman and Rubin (1992) by estimating two parallel Markov chains. Values close to 1 indicate that convergence is reached.

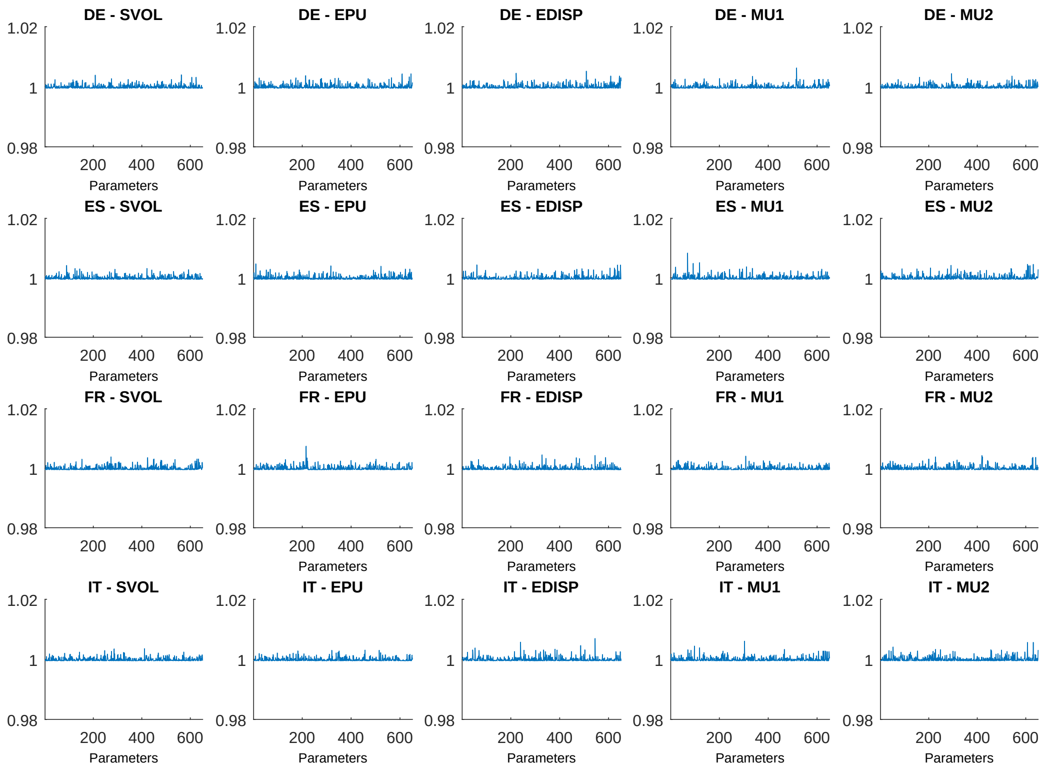

Figure A.15: Convergence Check – Higher-dimensional SVARs (VAR-2)

Notes: Convergence statistics computed following Gelman and Rubin (1992) by estimating two parallel Markov chains. Values close to 1 indicate that convergence is reached.

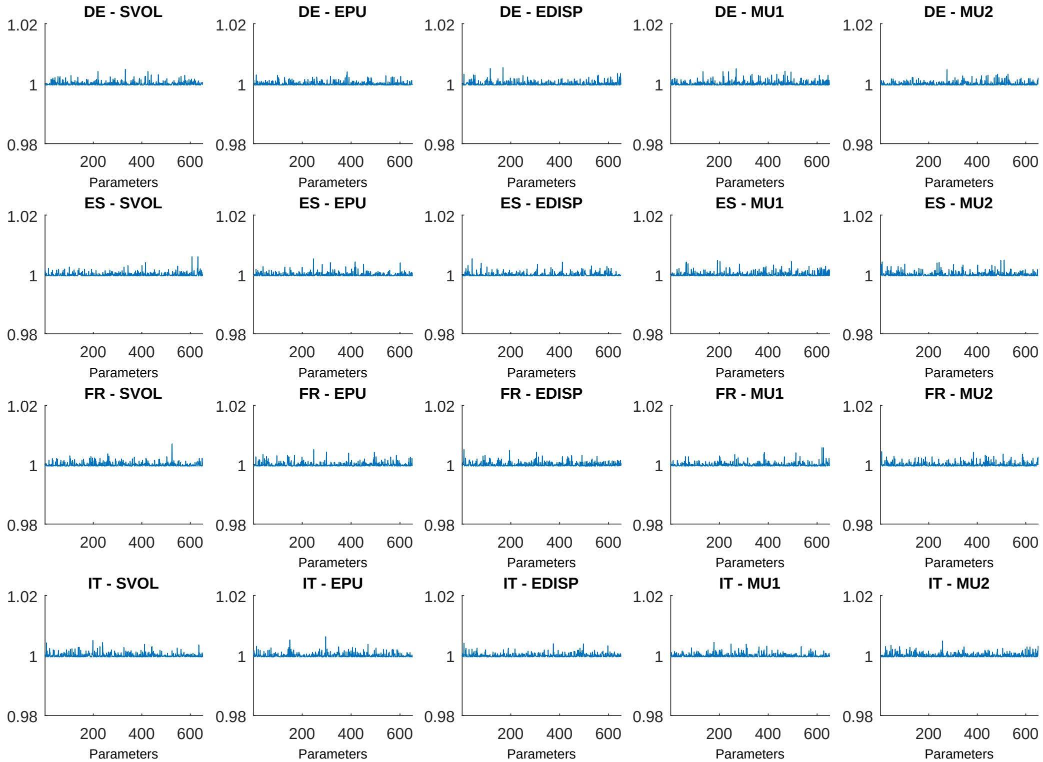

Figure A.16: Convergence Check – Higher-dimensional SVARs (VAR-3)

Notes: Convergence statistics computed following Gelman and Rubin (1992) by estimating two parallel Markov chains. Values close to 1 indicate that convergence is reached.

Variable	Description	Trans- formation	Seasonal adjustment*	Series code / mnemonic	Source
OAI_DE_1	IP MIG intermediate goods	Δln	sa	sts_inpr_m_MIG_ING_PROD_I10_DE	Eurostat
OAI_DE_2	IP MIG energy	Δln	sa	sts_inpr_m_MIG_NRG_X_D_E_PROD_I10_DE	Eurostat
OAI_DE_3	IP MIG capital goods	Δln	sa	sts_inpr_m_MIG_CAG_PROD_I10_DE	Eurostat
OAI_DE_4	IP MIG consumer goods, durable	Δln	sa	sts_inpr_m_MIG_DCOG_PROD_I10_DE	Eurostat
OAI_DE_5	IP MIG consumer goods, non-durable	Δln	sa	sts_inpr_m_MIG_NDCOG_PROD_I10_DE	Eurostat
OAI_DE_6	IP mining and quarrying	Δln	sa	sts_inpr_m_B_PROD_I10_DE	Eurostat
OAI_DE_7	IP manufacturing	Δln	sa	sts_inpr_m_MIG_C_PROD_I10_DE	Eurostat
OAI_DE_8	IP energy supply	lv	sa	sts_inpr_m_MIG_D_PROD_I10_DE	Eurostat
OAI_DE_9	BCS economic sentiment	lv	sa	E134ES@EUSRVYS	HAVER
OAI_DE_10	BCS industry, production in recent months	lv	sa	E134IPT@EUSRVYS	HAVER
OAI_DE_11	BCS retail, present business situation	Δlv	sa	E134RB@EUSRVYS	HAVER
OAI_DE_12	BCS services, present business situation	Δlv	sa	E134SB@EUSRVYS	HAVER
OAI_DE_13	BCS construction, activity in recent months	Δlv	sa	E134TR@EUSRVYS	HAVER
OAI_DE_14	BCS consumer, economic situation last 12 months	lv	sa	E134CGL@EUSRVYS	HAVER
LAB_DE_1	Unemployment rate, total	Δln	sa	une_rt_m_TOTAL_PC_ACT_T_DE	Eurostat
LAB_DE_2	Unemployment rate, under 25	Δln	sa	une_rt_m_Y_LT25_PC_ACT_T_DE	Eurostat
LAB_DE_3	BCS industry, employment expectations	lv	sa	E134IE@EUSRVYS	HAVER
LAB_DE_4	BCS consumer, unemployment expectations	lv	sa	E134CU@EUSRVYS	HAVER
LAB_DE_5	BCS retail, employment expectations	Δlv	sa	E134RE@EUSRVYS	HAVER
LAB_DE_7	BCS construction, employment expectations	Δlv	sa	E134TE@EUSRVYS	HAVER
LAB_DE_8	Employed persons	Δln	sa	DESELE@GERMANY	HAVER
LAB_DE_9	Wages per hour, industry	Δln	sa	DESECWPH@GERMANY	HAVER
LAB_DE_11	Negotiated hourly earnings	Δln	nsa	DENEAH@GERMANY	HAVER
LAB_DE_13	Notified vacancies	Δln	sa	HIST/MONT/DEUQLTTVBVA.M	DataInsight
LAB_DE_14	Wholesale, employment index	Δln	nsa	HIST/MONT/DEU4521110144.M	DataInsight
LAB_DE_15	Retail, employment index	Δln	nsa	HIST/MONT/DEU4521230027.M	DataInsight
LAB_DE_16	Hotel and restaurants, employment index	Δln	nsa	HIST/MONT/DEU452130010094.M	DataInsight
LAB_DE_17	Construction, employment index	lv	nsa	HIST/MONT/DEUUUMB01.M	DataInsight
HOU_DE_1	Housing permits, estimated value, total	Δln	nsa	DENHPTV@GERMANY	HAVER
HOU_DE_2	Housing permits, estimated value, residential	Δln	nsa	DENHPR@GERMANY	HAVER
HOU_DE_3	Housing permits, estimated value, non-residential	lv	nsa	DENHPNRT@GERMANY	HAVER
HOU_DE_4	Civil engineering, trend of activity in recent months	lv	sa	E134TUR@EUSRVYS	HAVER
HOU_DE_5	Civil engineering, volume of order books	Δlv	sa	E134TUO@EUSRVYS	HAVER
HOU_DE_6	Housing permits, total	Δln	nsa	DENHPTN@GERMANY	HAVER
HOU_DE_7	Housing permits, residential	Δln	nsa	DENHPNH@GERMANY	HAVER
HOU_DE_8	Housing permits, non-residential	lv	nsa	DENHPNN@GERMANY	HAVER
HOU_DE_9	EC construction survey, evolution of current order books	Δlv	sa	HIST/MONT/DEURCOCNA.M	DataInsight
HOU_DE_10	EC construction survey, building activity development in recent months	Δlv	sa	HIST/MONT/DEURCCNTA.M	DataInsight
HOU_DE_11	EC construction survey, construction confidence indicator	Δlv	sa	HIST/MONT/DEURCCNCA.M	DataInsight

COI_DE_1	BCS consumer goods, order-book levels	Δlv	sa	INDU.DE.CONS.2.BS.M	BCS
COI_DE_2	BCS capital goods, order-book levels	lv	sa	INDU.DE.INVE.2.BS.M	BCS
COI_DE_3	BCS intermediate goods, order-book levels	lv	sa	INDU.DE.INTM.2.BS.M	BCS
COI_DE_4	BCS consumer goods durable, order-book levels	Δlv	sa	INDU.DE.CDUR.2.BS.M	BCS
COI_DE_5	BCS consumer goods non-durable, order-book levels	Δlv	sa	INDU.DE.CNDU.2.BS.M	BCS
COI_DE_6	BCS food and beverages, order-book levels	lv	sa	INDU.DE.FOBE.2.BS.M	BCS
COI_DE_7	BCS consumer goods, stocks of finished products	Δlv	sa	INDU.DE.CONS.4.BS.M	BCS
COI_DE_8	BCS capital goods, stocks of finished products	lv	sa	INDU.DE.INVE.4.BS.M	BCS
COI_DE_9	BCS intermediate goods, stocks of finished products	lv	sa	INDU.DE.INTM.4.BS.M	BCS
COI_DE_10	BCS consumer goods durable, stocks of finished products	lv	sa	INDU.DE.CDUR.4.BS.M	BCS
COI_DE_11	BCS consumer goods non-durable, stocks of finished products	lv	sa	INDU.DE.CNDU.4.BS.M	BCS
COI_DE_12	BCS food and beverages, stocks of finished products	lv	sa	INDU.DE.FOBE.4.BS.M	BCS
COI_DE_13	BCS retail, volume of stock currently hold	lv	sa	RETA.DE.TOT.2.BS.M	BCS
COI_DE_14	BCS retail, order expectations	Δlv	sa	RETA.DE.TOT.3.BS.M	BCS
COI_DE_15	BCS consumer, major purchases at present	Δlv	sa	E134CM@EUSRVYS	HAVER
COI_DE_16	BCS consumer, confidence indicator	lv	sa	E134C@EUSRVYS	HAVER
COI_DE_17	Retail, turnover index	Δln	sa	sts_trtu_m_G47_X_G473_TOVV_I10_DE	Eurostat
COI_DE_18	Car registrations	lv	sa	STS:M:DE:Y:CREG:PC0000:3:ABS	ECB
MaC_DE_1	Money supply M3	Δln	nsa	HIST/MONT/M134EVMM3.M	DataInsight
MaC_DE_2	Money supply M2	Δln	nsa	HIST/MONT/M134EVMM2.M	DataInsight
MaC_DE_3	Money supply M1	Δln	nsa	HIST/MONT/M134EVMM1.M	DataInsight
MaC_DE_4	Credit to non-financial private sector	lv	nsa	BIS:M:COFA:DE:L1	BIS
BER_DE_1	NEER - IMF all members	Δln	nsa	C134EINC@IFS	HAVER
BER_DE_2	REER - IMF all members CPI	Δln	nsa	C134EIRC@IFS	HAVER
BER_DE_3	NEER - IMF advanced economies	Δln	nsa	C134EINU@IFS	HAVER
BER_DE_4	REER - IMF advanced economies ULC	Δln	nsa	C134EIRU@IFS	HAVER
BER_DE_5	EONIA - euro area overnight deposits	Δlv	sa	I023ONIA@EUDATA	HAVER
BER_DE_7	Bond yield, 3-year	Δlv	sa	DENT3@GERMANY	HAVER
BER_DE_8	Bond yield, 5-year	Δlv	sa	DENT5@GERMANY	HAVER
BER_DE_9	Bond yield, 10-year	Δlv	sa	DENTA@GERMANY	HAVER
BER_DE_10	Money market rate, 1-month	Δlv	sa	HIST/MONT/M134RIIFB1.M	DataInsight
BER_DE_11	Treasury bill yield, 12-month	Δlv	sa	HIST/MONT/DEURIBT12.M”	DataInsight
BER_DE_12	Treasury bill yield, 6-month	Δlv	sa	HIST/MONT/DEURIBT6.M”	DataInsight
BER_DE_13	Treasury bill yield, 3-month	Δlv	sa	HIST/MONT/DEURIBT3.M”	DataInsight
BER_DE_14	Money market rate, 3-month	Δlv	sa	HIST/MONT/M134RIIFB3.M	DataInsight
BER_DE_15	Spread bond yield 3-year - EONIA	lv	sa		
BER_DE_16	Spread bond yield 5-year - EONIA	lv	sa		
BER_DE_17	Spread bond yield 10-year - EONIA	lv	sa		
BER_DE_18	Spread treasury bill yield 12-month - EONIA	lv	sa		
BER_DE_19	Spread treasury bill yield 6-month - EONIA	lv	sa		
BER_DE_20	Spread treasury bill yield 3-month - EONIA	lv	sa		

PRI_DE_1	PPI manufacturing, domestic	Δln	nsa	sts_inppd_m_C_PRIN_I10_DE	Eurostat
PRI_DE_2	PPI MIG energy, domestic	Δln	nsa	sts_inppd_m_NRG_PRIN_I10_DE	Eurostat
PRI_DE_3	PPI mining and quarrying, domestic	Δln	nsa	sts_inppd_m_B_PRIN_I10_DE	Eurostat
PRI_DE_4	PPI MIG capital goods, domestic	Δln	nsa	sts_inppd_m_CAG_PRIN_I10_DE	Eurostat
PRI_DE_5	PPI MIG intermediate goods, domestic	Δln	nsa	sts_inppd_m_ING_PRIN_I10_DE	Eurostat
PRI_DE_6	PPI manufacturing, non-domestic	Δln	nsa	sts_inppnd_m_C_PRIN_I10_DE	Eurostat
PRI_DE_7	PPI MIG durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_DE	Eurostat
PRI_DE_8	PPI MIG non-durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_DE	Eurostat
PRI_DE_9	HICP total	Δln	nsa	prc_hicp_midx_CP00_DE	Eurostat
PRI_DE_10	HICP clothing and footwear	Δln	nsa	prc_hicp_midx_CP03_DE	Eurostat
PRI_DE_11	HICP health	Δln	nsa	prc_hicp_midx_CP06_DE	Eurostat
PRI_DE_12	HICP transport	Δln	nsa	prc_hicp_midx_CP07_DE	Eurostat
PRI_DE_13	HICP goods	Δln	nsa	prc_hicp_midx_GD_DE	Eurostat
PRI_DE_14	HICP services	Δln	nsa	prc_hicp_midx_SERV_DE	Eurostat
PRI_DE_15	HICP excluding seasonal goods	Δln	nsa	prc_hicp_midx_TOT_XFOOD_S_DE	Eurostat
PRI_DE_16	HICP excluding housing and energy	Δln	nsa	prc_hicp_midx_TOT_XHOUS_DE	Eurostat
PRI_DE_17	HICP excluding education, health, social protection	Δln	nsa	prc_hicp_midx_TOT_X_EDUC_HLTH_SPR_DE	Eurostat
STM_DE_1	Stock market index, CDAX	Δln	nsa	DENFKCDX@GERMANY	HAVER
TRD_DE_1	Export values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_EXP_DE	Eurostat
TRD_DE_2	Export unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_EXP_DE	Eurostat
TRD_DE_3	Import values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_IMP_DE	Eurostat
TRD_DE_4	Import unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_IMP_DE	Eurostat
TRD_DE_5	CPB world production	Δln	sa	ipz_w1_qnmi_sp	CPB
TRD_DE_6	CPB world trade	Δln	sa	tgz_w1_qnmi_sn	CPB
TRD_DE_7	Oil price (Brent, USD per barrel)	Δln	nsa	OILBRNI	Datastream
TRD_DE_8	Purchasing manager index, US	lv	sa	NAPMC@USECON	HAVER
TRD_DE_9	OECD composite leading indicators for euro area	Δlv	nsa	C023LIOT@OECDMEI	HAVER
TRD_DE_10	Export values, intermediate goods	Δln	sa	DESIXIG@GERMANY	HAVER
TRD_DE_11	Export values, capital goods	Δln	sa	DESIXK@GERMANY	HAVER
TRD_DE_12	Export values, consumer goods	Δln	sa	DESIXC@GERMANY	HAVER
TRD_DE_13	Import values, intermediate goods	Δln	sa	DESIMIG@GERMANY	HAVER
TRD_DE_14	Import values, capital goods	Δln	sa	DESIMK@GERMANY	HAVER
TRD_DE_15	Import values, consumer goods	Δln	sa	DESIMC@GERMANY	HAVER

Table A.1: Macro Data, Germany

Notes: * nsa series are seasonally adjusted by us using X-12-ARIMA.

Variable	Description	Trans-formation	Seasonal adjustment*	Series code / mnemonic	Source
OAI_ES_1	IP MIG intermediate goods	Δln	sa	sts_inpr_m_MIG_ING_PROD_I10_ES	Eurostat
OAI_ES_2	IP MIG energy	Δln	sa	sts_inpr_m_MIG_NRG_X_D_E_PROD_I10_ES	Eurostat
OAI_ES_3	IP MIG capital goods	Δln	sa	sts_inpr_m_MIG_CAG_PROD_I10_ES	Eurostat
OAI_ES_4	IP MIG consumer goods, durable	Δln	sa	sts_inpr_m_MIG_DCOG_PROD_I10_ES	Eurostat
OAI_ES_5	IP MIG consumer goods, non-durable	Δln	sa	sts_inpr_m_MIG_NDCOG_PROD_I10_ES	Eurostat
OAI_ES_6	IP mining and quarrying	Δln	sa	sts_inpr_m_B_PROD_I10_ES	Eurostat
OAI_ES_7	IP manufacturing	Δln	sa	sts_inpr_m_MIG_C_PROD_I10_ES	Eurostat
OAI_ES_8	IP energy supply	Δln	sa	sts_inpr_m_MIG_D_PROD_I10_ES	Eurostat
OAI_ES_9	BCS economic sentiment	Δlv	sa	E184ES@EUSRVYS	HAVER
OAI_ES_10	BCS industry, production in recent months	Δlv	sa	E184IPT@EUSRVYS	HAVER
OAI_ES_11	BCS retail, present business situation	Δlv	sa	E184RB@EUSRVYS	HAVER
OAI_ES_13	BCS construction, activity in recent months	Δlv	sa	E184TR@EUSRVYS	HAVER
OAI_ES_14	BCS consumer, economic situation last 12 months	Δlv	sa	E184CGL@EUSRVYS	HAVER
LAB_ES_1	Unemployment rate, total	$\Delta^2 ln$	sa	une_rt_m_TOTAL_PC_ACT_T_ES	Eurostat
LAB_ES_2	Unemployment rate, under 25	Δln	sa	une_rt_m_Y_LT25_PC_ACT_T_ES	Eurostat
LAB_ES_3	BCS industry, employment expectations	Δlv	sa	E184IE@EUSRVYS	HAVER
LAB_ES_4	BCS consumer, unemployment expectations	Δlv	sa	E184CU@EUSRVYS	HAVER
LAB_ES_5	BCS retail, employment expectations	Δlv	sa	E184RE@EUSRVYS	HAVER
LAB_ES_7	BCS construction, employment expectations	Δlv	sa	E184TE@EUSRVYS	HAVER
LAB_ES_8	Notified vacancies	Δln	nsa	HIST/MONT/M184QLTTV.M	DataInsight
LAB_ES_9	Employment contracts, total	Δln	nsa	ESCT@SPAIN	HAVER
LAB_ES_10	Employment contracts, permanent	Δln	nsa	ESCPT@SPAIN	HAVER
LAB_ES_11	Employment contracts, fixed-term	Δln	nsa	ESCFT@SPAIN	HAVER
LAB_ES_12	Wage increases registered in collective bargaining	Δln	nsa	ESNEWGY@SPAIN	HAVER
LAB_ES_13	Large firms compensated employees - energy and water	lv	sa	ESNTRE@SPAIN	HAVER
LAB_ES_14	Large firms compensated employees - industry	Δlv	sa	ESNTRI@SPAIN	HAVER
LAB_ES_15	Large firms compensated employees - construction	Δlv	sa	ESNTRC@SPAIN	HAVER
LAB_ES_16	Large firms compensated employees - services	Δlv	sa	ESNTRS@SPAIN	HAVER
LAB_ES_17	Large firms average gross compensation - energy and water	lv	sa	ESNGCME@SPAIN	HAVER
LAB_ES_18	Large firms average gross compensation - industry	Δlv	sa	ESNGCMI@SPAIN	HAVER
LAB_ES_19	Large firms average gross compensation - construction	Δlv	sa	ESNGCMC@SPAIN	HAVER
LAB_ES_20	Large firms average gross compensation - services	Δlv	sa	ESNGCMS@SPAIN	HAVER
HOU_ES_1	Housing permits, total	Δln	nsa	ESNHP@SPAIN	HAVER
HOU_ES_2	Housing permits, residential	Δln	nsa	ESNHPR@SPAIN	HAVER
HOU_ES_3	Housing permits, non-residential	Δln	nsa	ESNHPN@SPAIN	HAVER
HOU_ES_4	Civil engineering, confidence indicator	Δlv	sa	E184TU@EUSRVYS	HAVER
HOU_ES_5	Civil engineering, trend of activity in recent months	lv	sa	E184TUR@EUSRVYS	HAVER
HOU_ES_6	Civil engineering, volume of order books	Δlv	sa	E184TUO@EUSRVYS	HAVER
HOU_ES_7	Specifal construction, confidence indicator	Δlv	sa	E184TS@EUSRVYS	HAVER
HOU_ES_8	Specifal construction, trend of activity in recent months	lv	sa	E184TSR@EUSRVYS	HAVER
HOU_ES_9	Specifal construction, volume of order books	Δlv	sa	E184TSO@EUSRVYS	HAVER
HOU_ES_10	EC construction survey, evolution of current order books	Δlv	sa	HIST/MONT/ESPRCOCNA.M" /¿	DataInsight
HOU_ES_11	EC construction survey, building activity development in recent months	Δlv	sa	HIST/MONT/ESPRCCNTA.M	DataInsight
HOU_ES_12	EC construction survey, construction confidence indicator	Δlv	sa	HIST/MONT/ESPRCCNCA.M	DataInsight

COI_ES_1	BCS consumer goods, order-book levels	Δlv	sa	INDU.ES.CONS.2.BS.M	BCS
COI_ES_2	BCS capital goods, order-book levels	Δlv	sa	INDU.ES.INVE.2.BS.M	BCS
COI_ES_3	BCS intermediate goods, order-book levels	Δlv	sa	INDU.ES.INTM.2.BS.M	BCS
COI_ES_5	BCS consumer goods non-durable, order-book levels	Δlv	sa	INDU.ES.CNDU.2.BS.M	BCS
COI_ES_7	BCS consumer goods, stocks of finished products	Δlv	sa	INDU.ES.CONS.4.BS.M	BCS
COI_ES_8	BCS capital goods, stocks of finished products	Δlv	sa	INDU.ES.INVE.4.BS.M	BCS
COI_ES_9	BCS intermediate goods, stocks of finished products	lv	sa	INDU.ES.INTM.4.BS.M	BCS
COI_ES_11	BCS consumer goods non-durable, stocks of finished products	Δlv	sa	INDU.ES.CNDU.4.BS.M	BCS
COI_ES_13	BCS retail, volume of stock currently hold	lv	sa	RETA.ES.TOT.2.BS.M	BCS
COI_ES_14	BCS retail, order expectations	Δlv	sa	RETA.ES.TOT.3.BS.M	BCS
COI_ES_15	BCS consumer, major purchases at present	Δlv	sa	E184CM@EUSRVYS	HAVER
COI_ES_16	BCS consumer, confidence indicator	Δlv	sa	E184C@EUSRVYS	HAVER
COI_ES_17	Retail, turnover index	Δln	sa	sts_trtu_m_G47_X_G473_TOVV_I10_ES	Eurostat
COI_ES_18	Car registrations	Δln	sa	STS:M:ES:Y:CREG:PC0000:3:ABS	ECB
MaC_ES_1	Money supply M3	Δln	nsa	HIST/MONT/M3@EURNS@SP.M" /¿	DataInsight
MaC_ES_2	Money supply M2	Δln	nsa	HIST/MONT/M2@EURNS@SP.M	DataInsight
MaC_ES_3	Money supply M1	Δln	nsa	HIST/MONT/M1@EURNS@SP.M	DataInsight
MaC_ES_4	Credit to households	$\Delta^2 ln$	nsa	BIS:M:CPVA:ES:04	BIS
MaC_ES_5	Credit to non-financial private sector	$\Delta^2 ln$	nsa	BIS:M:CPFA:ES:03	BIS
MaC_ES_6	Total assets	$\Delta^2 ln$	nsa	BIS:M:CNAA:ES:03	BIS
MaC_ES_7	Credit to residents	$\Delta^2 ln$	nsa	BIS:M:CPCA:ES:03	BIS
MaC_ES_8	Non-performing loans	$\Delta^2 ln$	nsa	BIS:M:CGMA:ES:03	BIS
BER_ES_1	NEER - IMF all members	Δln	nsa	C184EINC@IFS	HAVER
BER_ES_2	REER - IMF all members CPI	Δln	nsa	C184EIRC@IFS	HAVER
BER_ES_3	NEER - IMF advanced economies	Δln	nsa	C184EINU@IFS	HAVER
BER_ES_4	REER - IMF advanced economies ULC	Δln	nsa	C184EIRU@IFS	HAVER
BER_ES_5	EONIA - euro area overnight deposits	Δlv	sa	I023ONIA@EUDATA	HAVER
BER_ES_6	Bond yield, 3-year	lv	sa	ESNRGS3@SPAIN	HAVER
BER_ES_7	Bond yield, 10-year	lv	sa	ESNRGS10@SPAIN	HAVER
BER_ES_8	Money market rate, 3-month	Δlv	sa	HIST/MONT/RMIB3S@SP.M	DataInsight
BER_ES_9	Treasury bill yield, 12-month	lv	sa	HIST/MONT/ESPINTR0001.M	DataInsight
BER_ES_10	Spread bond yield 3-year - EONIA	Δlv	sa		
BER_ES_11	Spread bond yield 10-year - EONIA	Δlv	sa		
BER_ES_12	Spread treasury bill yield 12-month - EONIA	lv	sa		

PRI_ES_1	PPI manufacturing, domestic	Δln	nsa	sts_inppd_m_C_PRIN_I10_ES	Eurostat
PRI_ES_2	PPI MIG energy, domestic	Δln	nsa	sts_inppd_m_NRG_PRIN_I10_ES	Eurostat
PRI_ES_3	PPI mining and quarrying, domestic	Δln	nsa	sts_inppd_m_B_PRIN_I10_ES	Eurostat
PRI_ES_4	PPI MIG capital goods, domestic	Δln	nsa	sts_inppd_m_CAG_PRIN_I10_ES	Eurostat
PRI_ES_5	PPI MIG intermediate goods, domestic	Δln	nsa	sts_inppd_m_ING_PRIN_I10_ES	Eurostat
PRI_ES_7	PPI MIG durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_ES	Eurostat
PRI_ES_8	PPI MIG non-durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_ES	Eurostat
PRI_ES_9	HICP total	Δln	nsa	prc_hicp_midx_CP00_ES	Eurostat
PRI_ES_10	HICP clothing and footwear	Δln	nsa	prc_hicp_midx_CP03_ES	Eurostat
PRI_ES_11	HICP health	Δln	nsa	prc_hicp_midx_CP06_ES	Eurostat
PRI_ES_12	HICP transport	Δln	nsa	prc_hicp_midx_CP07_ES	Eurostat
PRI_ES_13	HICP goods	Δln	nsa	prc_hicp_midx_GD_ES	Eurostat
PRI_ES_14	HICP services	Δln	nsa	prc_hicp_midx_SERV_ES	Eurostat
PRI_ES_15	HICP excluding seasonal goods	Δln	nsa	prc_hicp_midx_TOT_XFOOD_S_ES	Eurostat
PRI_ES_16	HICP excluding housing and energy	Δln	nsa	prc_hicp_midx_TOT_XHOUS_ES	Eurostat
PRI_ES_17	HICP excluding education, health, social protection	Δln	nsa	prc_hicp_midx_TOT_X_EDUC_HLTH_SPR_ES	Eurostat
STM_ES_2	Stock market index, Madrid General Index	Δln	nsa	ESNFMGI@SPAIN	HAVER
TRD_ES_1	Export values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_EXP_ES	Eurostat
TRD_ES_2	Export unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_EXP_ES	Eurostat
TRD_ES_3	Import values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_IMP_ES	Eurostat
TRD_ES_4	Import unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_IMP_ES	Eurostat
TRD_ES_5	CPB world production	Δln	sa	ipz_w1_qnmi_sp	CPB
TRD_ES_6	CPB world trade	Δln	sa	tgz_w1_qnmi_sn	CPB
TRD_ES_7	Oil price (Brent, USD per barrel)	Δln	nsa	OILBRNI	Datastream
TRD_ES_8	Purchasing manager index, US	lv	sa	NAPMC@USECON	HAVER
TRD_ES_9	OECD composite leading indicators for euro area	Δlv	nsa	C023LIOT@OECDMEI	HAVER
TRD_ES_10	Export values, intermediate goods	Δln	sa	ESNICX@SPAIN	HAVER
TRD_ES_11	Export values, capital goods	Δln	sa	ESNIIX@SPAIN	HAVER
TRD_ES_12	Export values, consumer goods	Δln	sa	ESNIKX@SPAIN	HAVER
TRD_ES_13	Import values, intermediate goods	Δln	sa	ESNICM@SPAIN	HAVER
TRD_ES_14	Import values, capital goods	Δln	sa	ESNIIM@SPAIN	HAVER
TRD_ES_15	Import values, consumer goods	Δln	sa	ESNIKM@SPAIN	HAVER

Table A.2: Macro Data, Spain

Notes: * nsa series are seasonally adjusted by us using X-12-ARIMA.

Variable	Description	Trans-formation	Seasonal adjustment*	Series code / mnemonic	Source
OAI_FR_1	IP MIG intermediate goods	Δln	sa	sts_inpr_m_MIG_ING_PROD_I10_FR	Eurostat
OAI_FR_2	IP MIG energy	Δln	sa	sts_inpr_m_MIG_NRG_X_D_E_PROD_I10_FR	Eurostat
OAI_FR_3	IP MIG capital goods	Δln	sa	sts_inpr_m_MIG_CAG_PROD_I10_FR	Eurostat
OAI_FR_4	IP MIG consumer goods, durable	Δln	sa	sts_inpr_m_MIG_DCOG_PROD_I10_FR	Eurostat
OAI_FR_5	IP MIG consumer goods, non-durable	Δln	sa	sts_inpr_m_MIG_NDCOG_PROD_I10_FR	Eurostat
OAI_FR_6	IP mining and quarrying	Δln	sa	sts_inpr_m_B_PROD_I10_FR	Eurostat
OAI_FR_7	IP manufacturing	Δln	sa	sts_inpr_m_MIG_C_PROD_I10_FR	Eurostat
OAI_FR_8	IP energy supply	Δln	sa	sts_inpr_m_MIG_D_PROD_I10_FR	Eurostat
OAI_FR_9	BCS economic sentiment	lv	sa	E132ES@EUSRVYS	HAVER
OAI_FR_10	BCS industry, production in recent months	lv	sa	E132IPT@EUSRVYS	HAVER
OAI_FR_11	BCS retail, present business situation	lv	sa	E132RB@EUSRVYS	HAVER
OAI_FR_12	BCS services, present business situation	lv	sa	E132SB@EUSRVYS	HAVER
OAI_FR_13	BCS construction, activity in recent months	Δlv	sa	E132TR@EUSRVYS	HAVER
OAI_FR_14	BCS consumer, economic situation last 12 months	Δlv	sa	E132CGL@EUSRVYS	HAVER
OAI_FR_15	BdF business sentiment indicator, industry	lv	sa	FRSVFBSI@FRANCE	HAVER
OAI_FR_16	BdF business sentiment indicator, services	Δlv	sa	FRSVFBSS@FRANCE	HAVER
LAB_FR_1	Unemployment rate, total	Δln	sa	une_rt_m_TOTAL_PC_ACT_T_FR	Eurostat
LAB_FR_2	Unemployment rate, under 25	Δln	sa	une_rt_m_Y_LT25_PC_ACT_T_FR	Eurostat
LAB_FR_3	BdF employment expectations, industry total	lv	sa	FRSVFZG@FRANCE	HAVER
LAB_FR_4	BCS consumer, unemployment expectations	lv	sa	E132CU@EUSRVYS	HAVER
LAB_FR_5	BCS retail, employment expectations	Δlv	sa	E132RE@EUSRVYS	HAVER
LAB_FR_6	BCS services, employment expectations	lv	sa	E132SE@EUSRVYS	HAVER
LAB_FR_7	BCS construction, employment expectations	Δlv	sa	E132TE@EUSRVYS	HAVER
LAB_FR_8	BdF employment expectations, food/bev/tobacco	lv	sa	FRSVFCAG@FRANCE	HAVER
LAB_FR_9	BdF employment expectations, computer/elec/mach	lv	sa	FRSVFC3G@FRANCE	HAVER
LAB_FR_10	BdF employment expectations, transport eqpt	lv	sa	FRSVFCLG@FRANCE	HAVER
LAB_FR_11	BdF employment expectations, misc mfg	Δlv	sa	FRSVFC5G@FRANCE	HAVER
LAB_FR_12	BdF employment vs. last month, industry total	lv	sa	FRSVFZ8@FRANCE	HAVER
LAB_FR_14	BdF employment vs. last month, food/bev/tobacco	lv	sa	FRSVFCA8@FRANCE	HAVER
LAB_FR_15	BdF employment vs. last month, computer/elec/mach	lv	sa	FRSVFC38@FRANCE	HAVER
LAB_FR_16	BdF employment vs. last month, transport eqpt	lv	sa	FRSVFCL8@FRANCE	HAVER
LAB_FR_17	BdF employment vs. last month, misc mfg	lv	sa	FRSVFC58@FRANCE	HAVER
LAB_FR_18	Hourly labor costs, engineering industries	Δln	nsa	FRNEWCHM@FRANCE	HAVER
LAB_FR_19	Notified vacancies	Δln	sa	FRSEJ@FRANCE	HAVER
HOU_FR_7	Civil engineering, confidence indicator	Δlv	sa	E132TU@EUSRVYS	HAVER
HOU_FR_8	Civil engineering, trend of activity in recent months	Δlv	sa	E132TUR@EUSRVYS	HAVER
HOU_FR_9	Civil engineering, volume of order books	Δlv	sa	E132TUO@EUSRVYS	HAVER
HOU_FR_10	Specifal construction, confidence indicator	Δlv	sa	E132TS@EUSRVYS	HAVER
HOU_FR_11	Specifal construction, trend of activity in recent months	Δlv	sa	E132TSR@EUSRVYS	HAVER
HOU_FR_12	Specifal construction, volume of order books	Δlv	sa	E132TSO@EUSRVYS	HAVER
HOU_FR_13	EC construction survey, evolution of current order books	Δlv	sa	HIST/MONT/FRARCOCNA.M	DataInsight
HOU_FR_14	EC construction survey, building activity development in recent months	Δlv	sa	HIST/MONT/FRARCCNTA.M	DataInsight
HOU_FR_15	EC construction survey, construction confidence indicator	Δlv	sa	HIST/MONT/FRARCCNCA.M	DataInsight

COI_FR_1	BdF total orders vs. last month, total industry	lv	sa	FRSVFZ3@FRANCE	HAVER
COI_FR_2	BdF current order books, total industry	lv	sa	FRSVFZB@FRANCE	HAVER
COI_FR_3	BdF current finished goods inventories, total industry	lv	sa	FRSVFZ9@FRANCE	HAVER
COI_FR_4	BdF total orders vs. last month, food/bev/tobacco	lv	sa	FRSVFCA3@FRANCE	HAVER
COI_FR_5	BdF current order books, food/bev/tobacco	lv	sa	FRSVFCAB@FRANCE	HAVER
COI_FR_6	BdF current finished goods inventories, food/bev/tobacco	lv	sa	FRSVFCA9@FRANCE	HAVER
COI_FR_7	BdF total orders vs. last month, computer/elec/mach	lv	sa	FRSVFC34@FRANCE	HAVER
COI_FR_8	BdF current order books, computer/elec/mach	lv	sa	FRSVFC3B@FRANCE	HAVER
COI_FR_9	BdF current finished goods inventories, computer/elec/mach	lv	sa	FRSVFC39@FRANCE	HAVER
COI_FR_10	BdF total orders vs. last month, transport eqpt	lv	sa	FRSVFCL3@FRANCE	HAVER
COI_FR_11	BdF current order books, transport eqpt	lv	sa	FRSVFCLB@FRANCE	HAVER
COI_FR_12	BdF current finished goods inventories, transport eqpt	lv	sa	FRSVFCL9@FRANCE	HAVER
COI_FR_13	BdF total orders vs. last month, misc mfg	lv	sa	FRSVFC53@FRANCE	HAVER
COI_FR_14	BdF current order books, misc mfg	lv	sa	FRSVFC5B@FRANCE	HAVER
COI_FR_15	BdF current finished goods inventories, misc mfg	lv	sa	FRSVFC59@FRANCE	HAVER
COI_FR_16	BCS retail, volume of stock currently hold	lv	sa	RETA.FR.TOT.2.BS.M	BCS
COI_FR_17	BCS retail, order expectations	lv	sa	RETA.FR.TOT.3.BS.M	BCS
COI_FR_18	BCS consumer, major purchases at present	Δlv	sa	E132CM@EUSRVYS	HAVER
COI_FR_19	BCS consumer, confidence indicator	lv	sa	E132C@EUSRVYS	HAVER
COI_FR_21	Car registrations	lv	sa	STS:M:FR:Y:CREG:PC0000:3:ABS	ECB
MaC_FR_1	Money supply M2	Δln	nsa	HIST/MONT/FRAMON0002.M	DataInsight
MaC_FR_2	Money supply M1	Δln	nsa	HIST/MONT/FRAMON0001.M	DataInsight
MaC_FR_3	Money supply M3	Δln	nsa	HIST/MONT/FRAMON0003.M	DataInsight
MaC_FR_4	Credit to government	Δln	nsa	BIS:M:COUA:FR:03	BIS
MaC_FR_5	Credit to households	$\Delta^2 ln$	nsa	BIS:M:COVA:FR:04	BIS
MaC_FR_6	Credit to non-financial private sector	Δln	nsa	BIS:M:CO8A:FR:03	BIS
MaC_FR_7	Credit to households, consumer	lv	nsa	BIS:M:COXA:FR:04	BIS
MaC_FR_8	Credit to households, house purchase	$\Delta^2 ln$	nsa	BIS:M:COWA:FR:04	BIS
MaC_FR_9	Credit to residents	Δln	nsa	BIS:M:COCA:FR:03	BIS
BER_FR_1	NEER - IMF all members	Δln	nsa	C132EINC@IFS	HAVER
BER_FR_2	REER - IMF all members CPI	Δln	nsa	C132EIRC@IFS	HAVER
BER_FR_3	NEER - IMF advanced economies	Δln	nsa	C132EINU@IFS	HAVER
BER_FR_4	REER - IMF advanced economies ULC	Δln	nsa	C132EIRU@IFS	HAVER
BER_FR_5	EONIA - euro area overnight deposits	Δlv	sa	I023ONIA@EUDATA	HAVER
BER_FR_6	Money market rate, 3-month	Δlv	sa	C132FRIO@OECDMEI	HAVER
BER_FR_7	Treasury bill yield, 3-month	Δlv	sa	FRNRT3@FRANCE	HAVER
BER_FR_8	Treasury bill yield, 6-month	Δlv	sa	FRNRT6@FRANCE	HAVER
BER_FR_9	Treasury bill yield, 12-month	Δlv	sa	FRNRG1Y@FRANCE	HAVER
BER_FR_10	Bond yield, 5-year	Δlv	sa	FRNRG5Y@FRANCE	HAVER
BER_FR_11	Bond yield, 10-year	Δlv	sa	FRNRG10Y@FRANCE	HAVER
BER_FR_12	Spread treasury bill yield 3-month - EONIA	lv	sa		
BER_FR_13	Spread treasury bill yield 6-month - EONIA	lv	sa		
BER_FR_14	Spread treasury bill yield 12-month - EONIA	lv	sa		
BER_FR_15	Spread bond yield 5-year - EONIA	lv	sa		
BER_FR_16	Spread bond yield 10-year - EONIA	lv	sa		

PRI_FR_1	PPI manufacturing, domestic	Δln	nsa	sts_inppd_m_C_PRIN_I10_FR	Eurostat
PRI_FR_2	PPI MIG energy, domestic	Δln	nsa	sts_inppd_m_NRG_PRIN_I10_FR	Eurostat
PRI_FR_3	PPI mining and quarrying, domestic	Δln	nsa	sts_inppd_m_B_PRIN_I10_FR	Eurostat
PRI_FR_4	PPI MIG capital goods, domestic	Δln	nsa	sts_inppd_m_CAG_PRIN_I10_FR	Eurostat
PRI_FR_5	PPI MIG intermediate goods, domestic	Δln	nsa	sts_inppd_m_ING_PRIN_I10_FR	Eurostat
PRI_FR_7	PPI MIG durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_FR	Eurostat
PRI_FR_8	PPI MIG non-durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_FR	Eurostat
PRI_FR_9	HICP total	Δln	nsa	prc_hicp_midx_CP00_FR	Eurostat
PRI_FR_10	HICP clothing and footwear	Δln	nsa	prc_hicp_midx_CP03_FR	Eurostat
PRI_FR_11	HICP health	Δln	nsa	prc_hicp_midx_CP06_FR	Eurostat
PRI_FR_12	HICP transport	Δln	nsa	prc_hicp_midx_CP07_FR	Eurostat
PRI_FR_13	HICP goods	Δln	nsa	prc_hicp_midx_GD_FR	Eurostat
PRI_FR_14	HICP services	Δln	nsa	prc_hicp_midx_SERV_FR	Eurostat
PRI_FR_15	HICP excluding seasonal goods	Δln	nsa	prc_hicp_midx_TOT_XFOOD_S_FR	Eurostat
PRI_FR_16	HICP excluding housing and energy	Δln	nsa	prc_hicp_midx_TOT_XHOUS_FR	Eurostat
PRI_FR_17	HICP excluding education, health, social protection	Δln	nsa	prc_hicp_midx_TOT_X_EDUC_HLTH_SPR_FR	Eurostat
STM_FR_1	Stock market index, CAC all tradeable	Δln	nsa	FRNKSBFV@FRANCE	HAVER
TRD_FR_1	Export values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_EXP_DE	Eurostat
TRD_FR_2	Export unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_EXP_DE	Eurostat
TRD_FR_3	Import values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_IMP_DE	Eurostat
TRD_FR_4	Import unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_IMP_DE	Eurostat
TRD_FR_5	CPB world production	Δln	sa	ipz_w1_qnmi_sp	CPB
TRD_FR_6	CPB world trade	Δln	sa	tgz_w1_qnmi_sn	CPB
TRD_FR_7	Oil price (Brent, USD per barrel)	Δln	nsa	OILBRNI	Datastream
TRD_FR_8	Purchasing manager index, US	lv	sa	NAPMC@USECON	HAVER
TRD_FR_9	OECD composite leading indicators for euro area	Δlv	nsa	C023LIOT@OECDMEI	HAVER

Table A.3: Macro Data, France

Notes: * nsa series are seasonally adjusted by us using X-12-ARIMA.

Variable	Description	Trans-formation	Seasonal adjustment*	Series code / mnemonic	Source
OAI_IT_1	IP MIG intermediate goods	Δln	sa	sts_inpr_m_MIG_ING_PROD_I10_IT	Eurostat
OAI_IT_2	IP MIG energy	Δln	sa	sts_inpr_m_MIG_NRG_X_D_E_PROD_I10_IT	Eurostat
OAI_IT_3	IP MIG capital goods	Δln	sa	sts_inpr_m_MIG_CAG_PROD_I10_IT	Eurostat
OAI_IT_4	IP MIG consumer goods, durable	Δln	sa	sts_inpr_m_MIG_DCOG_PROD_I10_IT	Eurostat
OAI_IT_5	IP MIG consumer goods, non-durable	Δln	sa	sts_inpr_m_MIG_NDCOG_PROD_I10_IT	Eurostat
OAI_IT_6	IP mining and quarrying	Δln	sa	sts_inpr_m_B_PROD_I10_IT	Eurostat
OAI_IT_7	IP manufacturing	Δln	sa	sts_inpr_m_MIG_C_PROD_I10_IT	Eurostat
OAI_IT_8	IP energy supply	Δln	sa	sts_inpr_m_MIG_D_PROD_I10_IT	Eurostat
OAI_IT_9	BCS economic sentiment	lv	sa	E136ES@EUSRVYS	HAVER
OAI_IT_10	BCS industry, production in recent months	lv	sa	E136IPT@EUSRVYS	HAVER
OAI_IT_11	BCS retail, present business situation	lv	sa	E136RB@EUSRVYS	HAVER
OAI_IT_13	BCS construction, activity in recent months	Δlv	sa	E136TR@EUSRVYS	HAVER
OAI_IT_14	BCS consumer, economic situation last 12 months	Δlv	sa	E136CGL@EUSRVYS	HAVER
LAB_IT_1	Unemployment rate, total	Δln	sa	une_rt_m_TOTAL_PC_ACT_T_IT	Eurostat
LAB_IT_2	Unemployment rate, under 25	Δln	sa	une_rt_m_Y_LT25_PC_ACT_T_IT	Eurostat
LAB_IT_3	BCS industry, employment expectations	lv	sa	E136IE@EUSRVYS	HAVER
LAB_IT_4	BCS consumer, unemployment expectations	Δlv	sa	E136CU@EUSRVYS	HAVER
LAB_IT_5	BCS retail, employment expectations	lv	sa	E136RE@EUSRVYS	HAVER
LAB_IT_7	BCS construction, employment expectations	Δlv	sa	E136TE@EUSRVYS	HAVER
LAB_IT_9	Large firms employment, industry	Δln	sa	ITSEXY@ITALY	HAVER
LAB_IT_10	Large firms employment, services	Δln	sa	ITSEXGNZ@ITALY	HAVER
LAB_IT_11	Large firms employment, wholesale and retail	Δln	nsa	ITNEXG@ITALY	HAVER
LAB_IT_12	Large firms employment, accommodation and food services	Δln	nsa	ITNEXI@ITALY	HAVER
LAB_IT_13	Large firms employment, financial and insurance	Δln	nsa	ITNEXK@ITALY	HAVER
LAB_IT_14	Contractual wages per employee, total	Δln	nsa	ITNER@ITALY	HAVER
LAB_IT_15	Contractual wages per employee, industry	Δln	nsa	ITNERY@ITALY	HAVER
LAB_IT_19	Hours worked, industry incl construction	Δln	sa	ITSLHY@ITALY	HAVER
LAB_IT_20	Hours worked, services	Δln	sa	ITSLHGNZ@ITALY	HAVER
HOU_IT_1	Civil engineering, confidence indicator	Δlv	sa	E136TU@EUSRVYS	HAVER
HOU_IT_2	Civil engineering, trend of activity in recent months	Δlv	sa	E136TUR@EUSRVYS	HAVER
HOU_IT_3	Civil engineering, volume of order books	lv	sa	E136TUO@EUSRVYS	HAVER
HOU_IT_4	Specifal construction, confidence indicator	Δlv	sa	E136TS@EUSRVYS	HAVER
HOU_IT_5	Specifal construction, trend of activity in recent months	lv	sa	E136TSR@EUSRVYS	HAVER
HOU_IT_6	Specifal construction, volume of order books	Δlv	sa	E136TSO@EUSRVYS	HAVER
HOU_IT_7	EC construction survey, evolution of current order books	Δlv	sa	HIST/MONT/ITARCOCNA.M	DataInsight
HOU_IT_8	EC construction survey, building activity development in recent months	Δlv	sa	HIST/MONT/ITARCCNTA.M	DataInsight
HOU_IT_9	EC construction survey, construction confidence indicator	Δlv	sa	HIST/MONT/ITARCCNCA.M	DataInsight

COI_IT_1	BCS consumer goods, order-book levels	lv	sa	INDU.IT.CONS.2.BS.M	BCS
COI_IT_2	BCS capital goods, order-book levels	lv	sa	INDU.IT.INVE.2.BS.M	BCS
COI_IT_3	BCS intermediate goods, order-book levels	lv	sa	INDU.IT.INTM.2.BS.M	BCS
COI_IT_4	BCS consumer goods durable, order-book levels	Δlv	sa	INDU.IT.CDUR.2.BS.M	BCS
COI_IT_5	BCS consumer goods non-durable, order-book levels	lv	sa	INDU.IT.CNDU.2.BS.M	BCS
COI_IT_6	BCS food and beverages, order-book levels	lv	sa	INDU.IT.FOBE.2.BS.M	BCS
COI_IT_7	BCS consumer goods, stocks of finished products	lv	sa	INDU.IT.CONS.4.BS.M	BCS
COI_IT_8	BCS capital goods, stocks of finished products	lv	sa	INDU.IT.INVE.4.BS.M	BCS
COI_IT_9	BCS intermediate goods, stocks of finished products	Δlv	sa	INDU.IT.INTM.4.BS.M	BCS
COI_IT_10	BCS consumer goods durable, stocks of finished products	Δlv	sa	INDU.IT.CDUR.4.BS.M	BCS
COI_IT_11	BCS consumer goods non-durable, stocks of finished products	lv	sa	INDU.IT.CNDU.4.BS.M	BCS
COI_IT_12	BCS food and beverages, stocks of finished products	lv	sa	INDU.IT.FOBE.4.BS.M	BCS
COI_IT_13	BCS retail, volume of stock currently hold	Δlv	sa	RETA.IT.TOT.2.BS.M	BCS
COI_IT_14	BCS retail, order expectations	Δlv	sa	RETA.IT.TOT.3.BS.M	BCS
COI_IT_15	BCS consumer, major purchases at present	Δlv	sa	E136CM@EUSRVYS	HAVER
COI_IT_16	BCS consumer, confidence indicator	Δlv	sa	E136C@EUSRVYS	HAVER
COI_IT_18	Car registrations	Δln	sa	STS:M:IT:Y:CREG:PC0000:3:ABS	ECB
MaC_IT_1	Money supply M3	Δln	nsa	HIST/MONT/ITAMON0013.M	DataInsight
MaC_IT_2	Money supply M2	Δln	nsa	HIST/MONT/ITAMON0012.M	DataInsight
MaC_IT_3	Money supply M1	Δln	nsa	HIST/MONT/ITAMON0011.M	DataInsight
MaC_IT_4	Non-performing loans	Δln	nsa	BIS:M:CGMA:IT:05	BIS
BER_IT_1	NEER - IMF all members	lv	nsa	C136EINC@IFS	HAVER
BER_IT_2	REER - IMF all members CPI	lv	nsa	C136EIRC@IFS	HAVER
BER_IT_3	NEER - IMF advanced economies	lv	nsa	C136EINU@IFS	HAVER
BER_IT_4	REER - IMF advanced economies ULC	Δln	nsa	C136EIRU@IFS	HAVER
BER_IT_5	EONIA - euro area overnight deposits	Δlv	sa	I023ONIA@EUDATA	HAVER
BER_IT_6	Money market rate, 3-months	Δlv	sa	C136FRIO@OECDMEI	HAVER
BER_IT_7	Bond yield, 3-year	lv	sa	ITNFRG3@ITALY	HAVER
BER_IT_8	Bond yield, 5-year	lv	sa	ITNFRG5@ITALY	HAVER
BER_IT_9	Bond yield, 10-year	lv	sa	ITNFRG10@ITALY	HAVER
BER_IT_10	Bond yield, 30-year	lv	sa	ITNFRG30@ITALY	HAVER
BER_IT_11	Treasury bill yield, 6-month	Δlv	sa	ITNFRT6@ITALY	HAVER
BER_IT_12	Treasury bill yield, 12-month	Δlv	sa	ITNFRT12@ITALY	HAVER
BER_IT_13	Spread bond yield 3-year - EONIA	Δlv	sa		
BER_IT_14	Spread bond yield 5-year - EONIA	Δlv	sa		
BER_IT_15	Spread bond yield 10-year - EONIA	Δlv	sa		
BER_IT_16	Spread bond yield 30-year - EONIA	Δlv	sa		
BER_IT_17	Spread treasury bill yield 6-month - EONIA	Δlv	sa		
BER_IT_18	Spread treasury bill yield 12-month - EONIA	Δlv	sa		

PRI_IT_1	PPI manufacturing, domestic	Δln	nsa	sts_inppd_m_C_PRIN_I10_IT	Eurostat
PRI_IT_2	PPI MIG energy, domestic	Δln	nsa	sts_inppd_m_NRG_PRIN_I10_IT	Eurostat
PRI_IT_3	PPI mining and quarrying, domestic	Δln	nsa	sts_inppd_m_B_PRIN_I10_IT	Eurostat
PRI_IT_4	PPI MIG capital goods, domestic	Δln	nsa	sts_inppd_m_CAG_PRIN_I10_IT	Eurostat
PRI_IT_5	PPI MIG intermediate goods, domestic	Δln	nsa	sts_inppd_m_ING_PRIN_I10_IT	Eurostat
PRI_IT_7	PPI MIG durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_IT	Eurostat
PRI_IT_8	PPI MIG non-durable consumer goods, domestic	Δln	nsa	sts_inppd_m_PRIN_I10_IT	Eurostat
PRI_IT_9	HICP total	Δln	nsa	prc_hicp_midx_CP00_IT	Eurostat
PRI_IT_10	HICP clothing and footwear	Δln	nsa	prc_hicp_midx_CP03_IT	Eurostat
PRI_IT_11	HICP health	Δln	nsa	prc_hicp_midx_CP06_IT	Eurostat
PRI_IT_12	HICP transport	Δln	nsa	prc_hicp_midx_CP07_IT	Eurostat
PRI_IT_13	HICP goods	Δln	nsa	prc_hicp_midx_GD_IT	Eurostat
PRI_IT_14	HICP services	lv	nsa	prc_hicp_midx_SERV_IT	Eurostat
PRI_IT_15	HICP excluding seasonal goods	Δln	nsa	prc_hicp_midx_TOT_XFOOD_S_IT	Eurostat
PRI_IT_16	HICP excluding housing and energy	Δln	nsa	prc_hicp_midx_TOT_XHOUS_IT	Eurostat
PRI_IT_17	HICP excluding education, health, social protection	Δln	nsa	prc_hicp_midx_TOT_X_EDUC_HLTH_SPR_IT	Eurostat
STM_IT_1	Stock market index, MSCI	Δln	nsa	ITNFKML@ITALY	HAVER
TRD_IT_1	Export values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_EXP_IT	Eurostat
TRD_IT_2	Export unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_EXP_IT	Eurostat
TRD_IT_3	Import values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_TRD_VAL_IMP_IT	Eurostat
TRD_IT_4	Import unit values, total	Δln	nsa	ext_st_25msbec_TOT_WORLD_IVU_IMP_IT	Eurostat
TRD_IT_5	CPB world production	Δln	sa	ipz_w1_qnmi_sp	CPB
TRD_IT_6	CPB world trade	Δln	sa	tgz_w1_qnmi_sn	CPB
TRD_IT_7	Oil price (Brent, USD per barrel)	Δln	nsa	OILBRNI	Datastream
TRD_IT_8	Purchasing manager index, US	lv	sa	NAPMC@USECON	HAVER
TRD_IT_9	OECD composite leading indicators for euro area	Δlv	nsa	C023LIOT@OECDMEI	HAVER
TRD_IT_10	Export values, intermediate goods	Δln	sa	ITNIXGC@ITALY	HAVER
TRD_IT_11	Export values, capital goods	Δln	sa	ITNIXV@ITALY	HAVER
TRD_IT_12	Export values, consumer goods	Δln	sa	ITNIXI@ITALY	HAVER
TRD_IT_13	Import values, intermediate goods	Δln	sa	ITNIMGC@ITALY	HAVER
TRD_IT_14	Import values, capital goods	Δln	sa	ITNIMV@ITALY	HAVER
TRD_IT_15	Import values, consumer goods	Δln	sa	ITNIMI@ITALY	HAVER

Table A.4: Macro Data, Italy

Notes: * nsa series are seasonally adjusted by us using X-12-ARIMA.

FiD_EA_1	Fama and French risk factor for Europe: Mkt-RF	*lv*
FiD_EA_2	Fama and French risk factor for Europe: SMB	*lv*
FiD_EA_3	Fama and French risk factor for Europe: HML	*lv*
FiD_EA_4	R15-R11	*lv*
FiD_EA_5	P5x5_1_Low	*lv*
FiD_EA_6	P5x5_1_2	*lv*
FiD_EA_7	P5x5_1_3	*lv*
FiD_EA_8	P5x5_1_4	*lv*
FiD_EA_9	P5x5_1_High	*lv*
FiD_EA_10	P5x5_2_Low	*lv*
FiD_EA_11	P5x5_2_2	*lv*
FiD_EA_12	P5x5_2_3	*lv*
FiD_EA_13	P5x5_2_4	*lv*
FiD_EA_14	P5x5_2_High	*lv*
FiD_EA_15	P5x5_3_Low	*lv*
FiD_EA_16	P5x5_3_2	*lv*
FiD_EA_17	P5x5_3_3	*lv*
FiD_EA_18	P5x5_3_4	*lv*
FiD_EA_19	P5x5_3_High	*lv*
FiD_EA_20	P5x5_4_Low	*lv*
FiD_EA_21	P5x5_4_2	*lv*
FiD_EA_22	P5x5_4_3	*lv*
FiD_EA_23	P5x5_4_4	*lv*
FiD_EA_24	P5x5_4_High	*lv*
FiD_EA_25	P5x5_5_Low	*lv*
FiD_EA_26	P5x5_5_2	*lv*
FiD_EA_27	P5x5_5_3	*lv*
FiD_EA_28	P5x5_5_4	*lv*
FiD_EA_29	P5x5_5_High	*lv*

Table A.5: Financial Data, Europe

Table A.6: Correlation between Monthly Uncertainty Shocks

	DE	ES	FR	IT
DE	1.00			
ES	0.81	1.00		
FR	0.73	0.70	1.00	
IT	0.73	0.74	0.68	1.00

Notes: Monthly shocks are obtained from VAR-2 with *MU1* as uncertainty indicator.

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