The Time-varying Impact of Uncertainty Shocks on the Comovement of Regional Housing Prices of the United Kingdom

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Oguzhan Cepni[a], Hardik A. Marfatia[b], and Rangan Gupta[c]

Abstract

The housing markets in districts across the United Kingdom (UK) co-move over time. We use the dynamic factor model to decompose the co-movement in house prices of the smallest possible geographical unit into national, regional, and idiosyncratic factors. Using the Bayesian time-varying parameter VAR (TVP-VAR) model, we study the dynamic impact of uncertainty shocks on the synchronization in housing markets. We find that the estimated national factor accurately tracks the overall housing market cycles in the UK and explains nearly all the variations in East, SouthEast, and SouthWest districts. Furthermore, the results from TVP-VAR indicate that the estimated response of the national factor to uncertainty shocks is negative. However, the magnitude of the effect is more pronounced and persists longer in the case of housing price uncertainty shocks compared to overall economic uncertainty. Overall, our results suggest that uncertainty about house prices is a primary driver of the national factor.

*Keywords:*Uncertainty Shocks, Macroeconomic Shocks, Housing Prices, Regional Markets, the United Kingdom.

JEL Classification: C32, D8, E30, E40, R31.

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1. Introduction

The turmoil of the global financial crisis (GFC), resulting in heightened volatility and uncertainty, had its roots in the subprime mortgage crisis in the housing market of the United States (US), as outlined by Leamer (2007, 2015), before affecting the world economy (Hirata et al., 2013). Given this, several studies perform structural vector autoregressive (VAR) model-based analysis to highlight the effect of uncertainty shocks on international and US state-level house price movements (Antonakakis et al., 2015, 2016; El Montasser et al., 2016; Su et al., 2016; André et al., 2017; Christou et al., 2017, 2019; Aye, 2018; Chow et al., 2018; Christidou and Fountas, 2018; Aye et al., 2019; Choudhry, 2020; Huang et al., 2020; Nguyen Thanh et al., 2020; Strobel et al., 2020; Balcilar et al., 2021; Gupta et al., 2021; Bouri et al., forthcoming; van Eyden et al., forthcoming). There is also evidence in the literature of in- and out-of-sample predictability for house prices emanating from uncertainty.

The papers mentioned above outline multiple channels through which uncertainty can affect the housing market. First, increased uncertainty in housing demand or the cost of financing can cause developers to postpone new construction. This reduces supply due to the irreversible nature of housing investment decisions and in-elasticity due to geographical constraints. Second, increased uncertainty about future employment, income, and wealth might cause households to postpone the home-buying decision and instead increase precautionary savings. Third, when uncertainty about employment and income raises the probability of default on mortgages, lenders might reduce or deny mortgages to riskier borrowers. Taken together, these decisions in response to uncertainty can cause a decline in demand and prices in the housing markets unless demand for other assets is more sensitive to uncertainty. Fourth, the user cost of housing is equal to the sum of the depreciation rate of the dwelling, the maintenance and repair costs as a fraction of the current value, the marginal income tax rate, the nominal interest rate, the property tax rate, and the expected nominal housing price inflation rate. The last component is likely influenced by uncertainty surrounding any determinants of housing price, including income, interest and tax rates, and housing market regulations, among others. Therefore, one expects an empirical link between uncertainty and housing prices and/or returns. The existing literature suggests this effect is negative, with uncertainty being characterized as an adverse demand shock.

Against this backdrop, we aim to add to this burgeoning literature by analyzing the co-movement of housing markets across the United Kingdom (UK), and investigate the ability of housing market-related uncertainty shocks in explaining synchronous movements in regional housing markets, after controlling for standard macroeconomic shocks, using a Bayesian time-varying parameter VAR (TVP-VAR) model over the quarterly period of 1996:Q2 to 2019Q2. Using the same set-up, we also analyze the role of aggregate macroeconomic uncertainty shock on its own over 1998:Q1 to 2020:Q3, and in addition compare its effect to that of the sector-specific uncertainty, i.e., housing, in explaining the regional housing price co-movement over the common sample of 1998:Q1 to 2019:Q2. The decision to choose the UK is primarily driven by the availability of recent data on housing market uncertainty, as developed by Yusupova et al., (2020), in the public domain. Besides, our sample period, which includes not only several business cycles, the GFC, and the European sovereign debt crises, but also the recently concluded Brexit process, warrants studying the time-varying role of uncertainty shocks on the evolution of house price movements of the UK. This is an interesting case study since the Brexit process likely affects the UK housing market by reducing foreign investment and deferred buying, thus leading to heightened uncertainty in both the housing market and the overall economy.

At this stage, it is essential to highlight why we need to focus on the co-movement of regional housing prices and how we go ahead econometrically in capturing this synchronicity. Firstly, there is widespread acceptance that the housing market of the UK is segmented (see, for example, Montagnolia and Nagayasu (2015), Tsai (2015), Antonakakis et al., (2018), Zhang et al., (2021)), and thus its response to aggregate macroeconomic shocks should not be analyzed as a single homogeneous market based on the aggregate house price (Gupta et al., forthcoming). In light of this, secondly, we study the nature of synchronization in housing prices of the smallest geographic area (the highest level of disaggregation possible) for which the data are available, that is, Nomenclature of Territorial Units for Statistics (NUTS) level 3 counties/districts/groups of unitary authorities (districts, for short, henceforth). To this end, we follow the works of Del Negro and Otrok (2007), Fairchild et al., (2015), Gupta et al., (2021), Marfatia (2021), Sheng et al., (2021), and Luo and Ma (forthcoming) related to the state-level housing market of the US and across the Organisation for Economic Co-operation and Development (OECD) countries. We use a Bayesian dynamic factor model (DFM) to decompose the movement in the real house prices of all NUTS-3 level districts in the UK into a national factor, which captures the fluctuations that are common across all the districts, NUTS-1 level 10 regional factors, capturing regional forces, and 144 districts-specific factors, which are unique to each district.

This modeling strategy allows us to study the nature of synchronization over time and the relative importance of each latent factor in influencing the housing price dynamics in each district. Once we distinguish the national factor from local factors in the housing market, we can then use the TVP-VAR model to analyze the impact of aggregate macroeconomic and uncertainty shocks on the common factor to obtain reliable inferences. This is because the movement in the local factors is likely to be attributable to circumstances that are specific to each geographic market. Given the well-established historical role of housing price as a leading indicator for the UK (Plakandaras et al., 2020), our analysis is of tremendous significance since understanding the relative importance of macroeconomic and uncertainty shocks that drives the housing market comovement is a pertinent question for a policymaker aiming to avoid future catastrophic effects observed under the GFC.

We find that the national factor that we model as unobserved aptly captures the aggregate movements in the UK house prices. This is one measure of the accuracy of our modeling approach. Our results also suggest a very well-integrated housing market in the UK. The national-level forces, for example, monetary policy and economic growth, explain 80% or more variation in house prices in several districts across the UK. In fact, the national factor explains nearly all the house prices variation in the districts in East, SouthEast, and SouthWest regions. This contrasts with the housing prices in the districts in NorthEast, NorthWest, Yorkshire and Humber, and Wales regions, where regional forces play a sizable role (25% to 55%). District-specific factors explain over 30% of variations only in these 3 out of 143 districts - Shropshire, Breckland and South Norfolk, and Wandsworth.

The results from TVP-VAR show that the estimated response of the national factor to uncertainty shocks is negative. However, the magnitude of the effect is more pronounced in the presence of housing price uncertainty shocks. On the other hand, the national factor responds more quickly to economic policy uncertainty shock, but the subsequent decrease in the national factor is not long-lasting and dies out within ten quarters. When we include two types of uncertainty in the TVP-VAR model at the same time, the response of the national factor to economic policy uncertainty shock becomes statistically insignificant. In contrast, the negative impact of house price uncertainty shock on housing returns is still statistically significant. This result suggests that uncertainty about house prices is the primary driver of the national factor.

To the best of our knowledge, this is the first paper to provide a time-varying analysis of the housing market and overall macroeconomic uncertainties in the UK on co-movements of house prices. In this regard, the only related work is that of Nguyen Thanh et al., (2020), whereby the authors (developed and) used a real estate-based uncertainty index for the US to highlight its stronger negative impact, compared to macroeconomic uncertainty, on the aggregate housing market in a (constant-parameter) VAR-setting over the period of 1970 to 2017.[1] The rest of the paper is organized as follows: Section 2 describes the data, while Section 3 is devoted to the TVP-VAR and DFM methodologies; Section 4 presents the empirical results, and Section 5 concludes.

[1] However, this real-estate uncertainty index data runs till 2017, and is no longer updated.

2. Data

One major obstacle in constructing accurate house price indices is the high degree of heterogeneity of real estate properties. To account for price differences in homes with varying characteristics, the Housing Observatory Price Indices (HOPIs) are based on the popular repeat-sales methodology. Repeat sales methodologies control for property characteristics by assessing how valuations of the same property change over time and are recognised as one of the most reliable means of measuring house price inflation. The construction of HOPIs employs data from the HM Land Registry Price Paid database, which covers all property sales in England and Wales that are sold for value and are lodged with the HM Land Registry for registration. The data for the 144 districts under NUTS-3 is available for download from the website of the United Kingdom Housing Observatory.[2] To transform the data into real values, each series is deflated with consumer price index (CPI), derived from the Main Economic Indicators (MEI) database of the OECD, which is also the source of the real Gross Domestic Product (GDP) data. Note that, while analyzing the impact of uncertainty shocks (the details of which we describe below) on the national real house price growth factor, we control for quarter-on-quarter real GDP growth and CPI-based inflation, in addition to a uniform measure of both conventional and unconventional monetary policy decisions. To measure the stance of monetary policies, we consider the shadow short rate (SSR) developed by Wu and Xia (2016; SSRWX),[3] given that our period of analysis involves the zero lower bound (ZLB) scenario in the wake of the Great Recession and the global financial crisis.[4]

We now turn to the descriptions of the housing market-related and aggregate macroeconomic uncertainties.[5] We gather the quarterly housing price uncertainty (HPU) index from the United Kingdom Housing

[2]See: https://uk.housing-observatory.com/dashboard.html.

[3]The data is available for download from the website of Professor Jing Cynthia Wu at: https://sites.google.com/view/jingcynthiawu/shadow-rates?authuser=0.

[4]The SSR is based on models of the term-structure, which essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves, resulting in a hypothetical "shadow yield curve" that would exist if the physical currency were not available. The process allows one to answer the question: "what policy rate would generate the observed yield curve if the policy rate could be taken negative?" The "shadow policy rate" generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero. The main advantage of the SSRWX is that it is not constrained by the ZLB and thus allows us to combine the data from the ZLB period with that of the non-ZLB era, and use it as the common metric of monetary policy stance across the conventional and unconventional monetary policy episodes.

[5]Uncertainty is latent by nature and hence, measuring it is a challenge. Besides alternative metrics of uncertainty associated with financial markets (such as the implied-volatility indices (popularly called the VIX), realized volatility, idiosyncratic volatility of equity returns, corporate spreads), there are primarily three broad approaches to quantify uncertainty (Gupta et al., 2018). First, a news-based measure where the idea is to perform searches of major newspapers for terms related to uncertainty, and then to use the results to construct uncertainty indices. Second, derive uncertainty from stochastic-volatility estimates of various types of small and large-scale structural models related to macroeconomics and finance. And third, use the dispersion or disagreement among professional forecasters to measure uncertainty. In this paper, we use the news-based measure. This measure has the merit of not requiring any complicated estimation of a large-scale model to generate it in the first place, and hence, is not model-specific. In addition, the data is available publicly for download.

Observatory as well, just like the HOPIs.[6] The HPU index is constructed by Yusupova et al., (2020) using the methodology suggested by Baker et al., (2016). The HPU is an index of search results from five large newspapers in the UK: The Guardian, The Independent, The Times, Financial Times and Daily Mail. In particular, the authors use LexisNexis digital archives of these newspapers to obtain a quarterly count of articles that contain the following three terms: 'uncertainty' or 'uncertain'; 'housing' or 'house prices' or 'real estate'; and one of the following: 'policy', 'regulation', 'Bank of England', 'mortgage', 'interest rate', 'stamp-duty', 'tax', 'bubble' or 'buy-to-let' (including variants like 'uncertainties', 'housing market' or 'regulatory'). To meet the search criteria, an article must contain terms in all three categories. The resulting search counts are then scaled by the total number of articles in the given newspaper and in the given quarter. Finally, to obtain the HPU index, Yusupova et al., (2020) average across the five newspapers by quarter and normalise the index to a mean of 100. As far as the overall uncertainty index of the UK is concerned, we utilize the economic policy uncertainty (EPU) index of Baker et al., (2016). This measure is based on the number of news articles containing the terms uncertain or 'uncertainty', 'economic' or 'economy', as well as policy-relevant terms: 'policy', 'tax', 'spending', 'regulation', 'Bank of England', 'budget', and 'deficit'.[7]

Based on data availability, our analysis involving the HPU runs from 1996:Q2 to 2019:Q2, while that of EPU from 1998:Q1 to 2020:Q3, and for both HPU and EPU over 1998:Q1 to 2019:Q2, with the start and end dates are driven primarily by the real housing price growth factor and the uncertainty indexes. The national factor is stationary by design, while we work with GDP growth and inflation to ensure stationarity, but the SSRs and natural logarithms of HPU and EPU are found to have no unit root issues, and are thus used in levels.

3. Methodologies

*3.1. **Dynamic factor model***

The movement of house prices and its relationship with macroeconomic developments is central to the understanding of housing markets. It is well-established that house prices in different geographical segments within a country/region move together. However, how the comovement relates to a wide array of macroeconomic and financial forces (besides just monetary policy for instance, as in Del Negro and Otrok (2007)) has gained attention only recently (Gupta et al., 2021, forthcoming; Marfatia, 2021; Sheng et al., 2021). One hurdle to this end is the unobserved nature of forces that drive comovement in house prices.

[6]See: https://uk.housing-observatory.com/dashboard.html.

[7]The data is downloadable from: http://policyuncertainty.com/uk_monthly.html.

While we observe that house prices move together, the exact reasons for its comovement are latent. Thus, we employ a dynamic factor model which, prima facie, assumes that the exact forces behind the synchronous pattern in the housing market are unobserved.

More particularly, we decompose NUTS-3 level real house prices growth into national, regional, and unit-specific factors. The national factor captures shocks, such as monetary policy shocks, that affect the housing markets across the country, of course, with varying degree. In addition to the national level factor, the house prices in North West UK, for example, has significantly risen post-2009, compared to South West UK. Thus, regional level dynamics play an important role in driving house prices in a particular geographic segment. And finally, district-specific factor unique to each district. Thus, the real house price growth rate ($h_{i,t}$) for each i unit at NUTS-3 ($i = 1, ..., N$) is decomposed into three latent factors.

$$h_{i,t} = \beta_i^n f_t^n + \beta_i^r f_t^r + \epsilon_{i,t} \tag{1}$$

In the above equation, the subscript i represents each of the N unit at NUTS-3 level. The degree to which the national and regional level factors affect house price is captured by factor loadings, β_i^n and β_i^r, respectively. The housing market factors that are unique to NUTS-3 level units are captured by the idiosyncratic component, $\epsilon_{i,t}$. Our intrests particularly is in the national level factor, f_t^n, as it measures the role of common factor that affects all the markets,

To model the latent factors, f_t^n, f_t^r, and $\epsilon_{i,t}$, we follow the standard assumption in the literature of an autoregressive (AR) process. Thus,

$$f_t^n = \phi_1^n f_{t-1}^n + ... + \phi_p^n f_{t-p}^n + \upsilon_t^n, \qquad \upsilon_t^n \sim i.i.d.N(0, \sigma_n^2), \tag{2}$$

$$f_t^r = \phi_1^r f_{t-1}^r + ... + \phi_p^r f_{t-p}^r + \upsilon_t^r, \qquad \upsilon_t^r \sim i.i.d.N(0, \sigma_r^2), \tag{3}$$

$$\epsilon_{i,t} = \phi_{i,1}\epsilon_{i,t-1} + ... + \phi_{i,q}\epsilon_{i,t-q} + \upsilon_{i,t}, \qquad \upsilon_{i,t} \sim i.i.d.N(0, \sigma_i^2). \tag{4}$$

We need two additional restrictions for a meaningful identification of latent components and their loadings. First, we assume the shocks are orthogonal contemporaneously as well as at all leads and lags. Thus, $E(\upsilon_t^n, \upsilon_{t-s}^n) = E(\upsilon_t^r, \upsilon_{t-s}^r) = E(\upsilon_{i,t}, \upsilon_{i,t-s}) = 0$. Second, the sign and scale restriction. Here again, we follow the strategy established in the literature (Kose et al., 2003, 2008; Neely and Rapach, 2011).[8]

[8] In particular, for sign identification, the national factor for Camden and City of London is restricted to be positive, whereas the sign restriction on regional factor loadings is chosen arbitrarily. We achieve scale normalizations by following Sargent and Sims (1977), Stock and Watson (1989, 1993), and Del Negro and Otrok (2007) and restrict σ_n^2 and σ_r^2 to unity. The signs and scale normalization do not have any economic content and do not affect any economic inference (Neely and Rapach, 2011).

Naturally, given the latent nature of factors, the usual regression apparatus is not available for estimating the model. Thus, we use the Bayesian procedure developed by Otrok and Whiteman (1998). We the complete posterior distribution of all the parameters together with the latent factors from a series of conditional distributions use a Markov chain Monte Carlo (MCMC) procedure.[9] To study the role of the three latent factors in house price movements, we also estimate the fraction of variance due to the national (θ_i^n), regional (θ_i^r), and unit-specific (θ_i^s) factors in the overall variation as follows:

$$\theta_i^n = \frac{(\beta_i^n)^2 var(f_t^n)}{var(h_{i,t})}, \qquad \theta_i^r = \frac{(\beta_i^r)^2 var(f_t^r)}{var(h_{i,t})}, \qquad \theta_i^s = \frac{var(\epsilon_{i,t})}{var(h_{i,t})}. \tag{5}$$

The estimates of θ_i^n, θ_i^r, and θ_i^s show the proportion of variance in the national, regional, and unit-specific factors, respectively, relative to the overall variance in house price movements of each state.

*3.2. **Time varying Bayesian VAR model***

To examine the effects of housing sector specific and economy-wide uncertainty shocks on housing market, we adopt a time-varying Bayesian VAR model which allows for time variation in both the VAR coefficients and residual covariance matrix. In particular, we employ the following model:

$$y_t = A_{1,t}y_{t-1} + A_{2,t}y_{t-2} + \ldots + A_{p,t}y_{t-p} + \varepsilon_t \tag{6}$$

where ε_t denotes residuals with distribution $\mathcal{N}(0, \Sigma_t)$. y_t is vector of n endogenous variables, which includes the HPU (alternatively; EPU or both EPU and HPU), real GDP growth (GDP), and CPI-based inflation (CPI), national real housing returns common factor (f_t^n; Factor), and the shadow rate (SSRWX or SSRK). Note that, the ordering of the RGDP, CPI, Factor, and SSRs are in line with standard monetary VAR models, whereby all the variables respond with a lag to monetary policy shocks, i.e., when monetary policy is identified using standard Cholesky decomposition (see Caraiani et al., (2021) for a detailed discussion of this literature). In addition, when we add the two metrics of uncertainties, they are ordered first, since uncertainty is recognized as a leading indicator of macro economic variables (Bloom, 2009; Jurado et al., 2015; Christou et al., 2020), and the housing prices as well, following the only related work of Nguyen Thanh et al., (2020). Note that, when we use HPU and EPU together in the model, then the latter being a more general level of uncertainty is ordered first. With our focus being primarily the identification of the uncertainty shocks, we also look at a case of reverse ordering as robustness, whereby we have: SSRWX, Factor, CPI, RGDP, HPU and EPU.

[9]We use the standard priors, similar to Kose et al. (2003) and Del Negro and Otrok (2007). Idiosyncratic shocks follow an inverse-gamma distribution with parameters 6 and 0.001. The AR polynomial follows a normal distribution with tighter centering on zero. The factor loadings are standard normal.

The lag-length p is selected based on the Schwarz information criterion (SIC). $A_{i,t}$ is a time varying coefficient vector. We can formulate the model for each period in a more compact form:

$$y_t = \bar{X}_t \beta_t + \varepsilon_t \tag{7}$$

where $\bar{X}_t = I_n \otimes X_t$ where $\otimes$ represents the Kronecker product and I_n is n-dimensional identity matrix. If we denote $X_t = \begin{pmatrix} y'_{t-1} & y'_{t-2} & \cdots & y'_{t-p} \end{pmatrix}$ and $B'_t = \begin{pmatrix} A_{1,t} & A_{2,t} & \cdots & A_{p,t} \end{pmatrix}$ then the VAR coefficients $\beta_t = \mathrm{vec}\,(B_t)$ are assumed to follow driftless random walks:

$$\beta_t = \beta_{t-1} + \nu_t \quad , \quad \nu_t \sim N(0, \Omega) \tag{8}$$

Following Dieppe et al. (2018) and Cogley and Sargent (2005), we also assumed that Σ_t can be decomposed as:

$$\Sigma_t = F \Lambda_t F \tag{9}$$

where F is a n $\times$ n lower triangular matrix with ones its diagonal. Λ_t denotes the period-specific diagonal matrix with $\mathrm{diag}\,(\Lambda_t) = (\bar{s}_1 \exp(\lambda_{1,t}), \bar{s}_2 \exp(\lambda_{2,t}), \cdots, \bar{s}_n \exp(\lambda_{n,t}))$. While $\lambda_{1,t}, \lambda_{2,t}, \cdots, \lambda_{n,t}$ are dynamic processes yielding the model's heteroscedasticity, $\bar{s}_1, \bar{s}_2, \cdots, \bar{s}_n$ are known scaling terms. In particular, we suppose that the $\lambda_{i,t}$ terms follow autoregressive process:

$$\lambda_{i,t} = \gamma \lambda_{i,t-1} + v_{i,t}, \qquad v_{i,t} \sim \mathcal{N}(0, \phi_i) \tag{10}$$

where the shocks $v_{i,t}$ are i.i.d across periods $t = 1, \cdots, T$. Given the assumption that β, f^{-1} and λ are independent, Bayes Rules can be written as:

$$\pi\left(\beta, f^{-1}, \lambda, \phi \mid y\right) \propto f\left(y \mid \beta, f^{-1}, \lambda\right) \pi(\beta) \left(\prod_{i=2}^{n} \pi\left(f_i^{-1}\right)\right) \left(\prod_{i=1}^{n} \pi(\lambda_i \mid \phi_i)\right) \left(\prod_{i=1}^{n} \pi(\phi_i)\right) \tag{11}$$

where $\lambda_i = \{\lambda_{i,t} : t = 1, \cdots, T\}$. Then, the likelihood function for the data can be obtained as:

$$f\left(y \mid \beta, f^{-1}, \lambda\right) \propto \prod_{t=1}^{T} |F \Lambda_t F'|^{-1/2} \exp\left(-\frac{1}{2}\left(y_t - \bar{X}_t \beta\right)' (F \Lambda_t F')^{-1} \left(y_t - \bar{X}_t \beta\right)\right) \tag{12}$$

The priors for the parameters are set by closely following specification of Dieppe et al. (2018). We assume that the prior for the VAR coefficients β has a normal distribution with $\pi(\beta \mid \Omega) \sim N(0, \Omega)$ and is given by: $\pi(\beta \mid \Omega) = \pi(\beta_1 \mid \Omega) \prod_{t=2}^{T} \pi(\beta_t \mid \Omega, \beta_{t-1})$. Hence, conditional formulation can be formulated as:

$$\pi(\beta \mid \Omega) \propto |\Omega|^{-T/2} \exp\left(-\frac{1}{2}\left\{\beta_1'(\tau\Omega)^{-1}\beta_1 + \sum_{t=2}^{T} (\beta_t - \beta_{t-1}) \cdot \Omega^{-1} (\beta_t - \beta_{t-1})\right\}\right) \tag{13}$$

where Ω is a diagonal matrix with each term ω_i pursuing an inverse Gamma distribution with the following parameters:

$$\pi(\omega_i) \propto \omega_i^{-\frac{\chi_0}{2}-1} \exp\left(-\frac{\psi_0}{2\omega_i}\right) \tag{14}$$

We set hyper-parameter values at $\chi_0 = \psi_0 = 0.001$ to implement a loose prior. Similarly, the prior for each f_i^{-1} is assumed to be multivariate normal distribution with $f_i^{-1} \sim \mathcal{N}\left(f_{i0}^{-1}, \Upsilon_{i0}\right)$:

$$\pi\left(f_i^{-1}\right) \propto \exp\left[-\frac{1}{2}\left(f_i^{-1} - f_{i0}^{-1}\right)' \Upsilon_{i0}^{-1} \left(f_i^{-1} - f_{i0}^{-1}\right)\right] \quad i = 2, 3, \cdots, n \tag{15}$$

Furthermore, the conditional prior distribution of λ can be defined as $\pi(\lambda_i \mid \phi_i) = \pi(\lambda_{i,1} \mid \phi_i) \prod_{t=2}^{T} \pi(\lambda_{i,t} \mid \lambda_{i,t-1}, \phi_i)$ which gives:

$$\pi(\lambda_i \mid \phi_i) \propto \exp\left(-\frac{1}{2}\left\{\frac{\lambda_{i,1}^2}{\phi_i \omega} + \sum_{t=2}^{T} \frac{(\lambda_{i,t} - \gamma\lambda_{i,t-1})^2}{\phi_i}\right\}\right) \tag{16}$$

Finally, the prior for each heteroscedasticity variance parameter ϕ is inverse gamma with shape α_0 and δ_0 which yields:

$$\pi(\phi_i) \propto \phi_i^{-\alpha_0/2-1} \exp\left(\frac{-\delta_0/2}{\phi_i}\right) \tag{17}$$

Considering the all prior distributions, Bayes rule and the likelihood function, the joint posterior distribution is given by:

$$\begin{aligned}
& f\left(\beta, \Omega, f^{-1}, \lambda, \phi \mid y\right) \\
& \propto \prod_{t=1}^{T} \left|F\Lambda_t F'\right|^{-1/2} \exp\left(-\frac{1}{2}\left(y_t - \bar{X}_t\beta_t\right)' (F\Lambda_t F')^{-1} \left(y_t - \bar{X}_t\beta_t\right)\right) \\
& \times |\Omega_0| \exp\left(-\frac{1}{2} B'\Omega_0^{-1} B\right) \\
& \times \prod_{i=1}^{q} \omega_i^{-\frac{\chi_0}{2}-1} \exp\left(-\frac{\psi_0}{2\omega_i}\right) \\
& \times \prod_{i=1}^{n} \exp\left[-\frac{1}{2}\left(f_i^{-1} - f_{i0}^{-1}\right)' \Upsilon_{i0}^{-1} \left(f_i^{-1} - f_{i0}^{-1}\right)\right] \\
& \times |\Phi_0|^{-1/2} \exp\left[-\frac{1}{2} L_i' \Phi_0^{-1} L_i\right] \\
& \times \prod_{i=1}^{n} \phi_i^{-\alpha_0/2-1} \exp\left(\frac{-\delta_0/2}{\phi_i}\right)
\end{aligned} \tag{18}$$

Since the posterior does not admit analytical posteriors, we consider the Gibbs sampling algorithm with a total number of iterations of 2000 and a burn-in sample of 1000.[10]

[10] All estimations are obtained using the Dieppe et al. (2018) BEAR Matlab based toolbox.

4. Empirical Results

4.1. The national factor and its role in comovement

Figure 1 plots the aggregate national level factor. We find that this aggregate factor, common across all districts, closely captures the housing cycles in the UK. In the 1996-2002 period, the national factor overall rose steadily, with cyclical patterns lasting for about 2-3 years. This trend reversed in the 2002-2007 period, with a sharp dip during the global financial crisis and recovery in the following five years. Since then, the national factor has hovered at sub-zero levels. This overall pattern of common components accurately maps the housing cycles in the UK. Thus, the otherwise unobserved national factor of our model aptly captures the aggregate movements in the UK house prices.

– Please include Figure 1 and Table 1 about here. –

Table 1 presents the results of variance decomposition obtained from the DFM. We find that the national factor, like monetary policy, economic growth, explains a significant portion of the variation in house prices across all districts in the UK. National factor explains 80% or more variation in house prices in South Teesside in Northeast, Manchester in Northwest, Kingston, and Sheffield in Yorkshire and Humber, North Nottinghamshire in East Midlands, nearly half of West Midlands and London, nearly the whole of East, SouthEast, and SouthWest regions. In contrast, regional forces play a sizable role (25% to 55%) in the housing markets of NorthEast, NorthWest, Yorkshire, and Humber, and Wales regions. Some good examples of specific housing markets are Durham (47%), Hartlepool and Stockton (53%), West Cumbria (48%), Barnsley area (46%), Blackburn (55%), and Central Valley (47%). District-specific factors play a minor role in the UK, perhaps except the districts of Shropshire, Breckland and South Norfolk, and Wandsworth. The district-specific factor explains over 30% of variations in these districts. These results suggest that the housing market in the UK is well-integrated, nationally for the most part, and regionally in selected areas.

4.2. The effects of uncertainty shocks on the national factor

4.2.1. Time-invariant impulse responses

Figure 2 presents the estimated impulse responses due to the housing price uncertainty shocks to the four endogenous variables $y_t = [HPU, GDP, CPI, Factor, SSRWX]$ for the period of 1996:Q2-2019:Q2. We call this specification our baseline model. The initial reaction of the national factor to housing price uncertainty shock is negative, and the response becomes statistically significant after the third quarter. We find the response drops to its lowest value around six quarters and then returning to its initial level after fifteen quarters.

The negative reaction of the national factor to housing price uncertainty shock is intuitive. Heighten uncertainty places a hold on household demand, and firms delay building activity, both causing a clump in the housing market. Considering that the housing market is highly segmented and heterogeneous, a slow price adjustment might be caused by a variety of friction in the housing market. Our findings validate the theoretical predictions of Berkovec and Goodman (1996), who show that there is a sluggish price adjustment in response to an increase in demand shock since buyers and sellers have imperfect information about the underlying market conditions. Hence, an increase in uncertainty (a positive uncertainty shock) makes outcomes more uncertain and creates an information imbalance between buyers and sellers.

– Please include Figure 2 about here. –

Figure 2 also suggests that the reaction of GDP growth to house price uncertainty shocks is negative and statistically significant for about four quarters after the shock. This is intuitive. On the demand side, the increased uncertainty of house prices might cause households to postpone their home-buying decision. Whereas, on the supply side, increased uncertainty causes real estate firms to delay house building and investment activities, which contributes directly to GDP (Choudhry, 2020; Balcilar et al., 2021). Given that central banks closely monitor the developments in the housing market due to the risk that credit conditions tighten and mortgage spreads widen, one potential response of central banks to the uncertainty shocks is to cut interest rates. This explains the negative reaction of SSRWX in the plot.

In Figure 3, we present the impulse responses obtained from the baseline model by replacing HPU with EPU. While the estimated response of the national factor to economic policy uncertainty shock is negative, the magnitude of the effect is less pronounced than the housing price uncertainty shock. Moreover, the national factor responds more quickly to EPU shock, but the subsequent decrease in the national factor is not long-lasting and dies out within ten quarters. Considering that the effect of EPU is much broader, directly influencing economic decisions taken by households, firms and governments (see Bloom, 2009; Kang et al., 2014; Cepni et al., 2020), the central bank might adopt a more quick and stronger credit easing policies (for instance; decreasing policy rates, buying significant amounts of corporate bonds and expanding the funding for the lending scheme) to mitigate the effects of uncertainty that would weigh on the economic outlook. Accordingly, the negative reaction of SSRWX to EPU shocks is more pronounced than HPU shocks. Moreover, as shown in Figure 3, the response of GDP growth to EPU shock is negative, similar to the case of HPU shock.

– Please include Figure 3 about here. –

We extend our baseline specification by adding EPU to the model with the following ordering, $y_t = [EPU, HPU, GDP, CPI, Factor, SSRWX]$. We name this specification our extended model. Columns 1-2 of Figure 4 reveal that the response of the national factor to EPU shock becomes statistically insignificant, while the negative impact of HPU shock on housing returns is still statistically significant when the EPU is included in the model. This result suggests that uncertainty about house prices is the primary driver of the national factor. The reason might be that house price uncertainty shocks directly affects the housing market via both housing demand and real-options channels, thereby affecting the real options values of residential investment projects (Clapp et al., 2013). Similarly, an uncertainty shock to house prices makes mortgage debt and home-owning riskier, reducing housing prices because of the decrease in the housing market activity (Noh, 2020).

Overall, our results point out that using a housing sector-specific uncertainty measure is crucial for understanding the house price dynamics. This shows the importance of taking into account housing-specific information in the construction of uncertainty measures. Furthermore, our results validate the findings of Salisu et al. (2021), who show that using HPU for predicting housing returns results in better predictive performance than models with EPU.

– Please include Figure 4 about here. –

4.2.2. ***Time varying impact of uncertainty shocks on the UK housing market***

Figure 5 presents the median impulse responses to housing uncertainty shocks over 16 quarters over the 1996:Q2 - 2019:Q2 period. The x-axis of each sub-graph shows the periods, the y-axis is the horizon in quarters, and the z-axis denotes the period-specific impulse responses. We find the dynamic response of the model, i.e., the impulse response functions have changed over the considered period. After a house price uncertainty shock, the decline in the national factor is more persistent at the beginning of the sample, while the national factor recovers faster since 2015. Although housing price uncertainty intensified since the UK's decision to leave the EU (June 23, 2016), the Bank of England (BoE) quickly implemented the necessary actions to mitigate amplification of the uncertainty effect via the housing market by adopting a credit easing policy at its first monetary policy meeting after the Brexit. Accordingly, the house price uncertainty shocks become less persistent over time due to the easing financial conditions via unconventional monetary policies. Similarly, while the initial reaction of the national factor to one unit shock to house price uncertainty is negative and quickly reaches its lowest value in the fifth quarter, which is faster than the responses of previous quarters, it recovers more quickly to its initial level since 2016.

– Please include Figure 5 about here. –

Figure 6 shows the impulse responses to capture time-varying effects of economic policy uncertainty shocks on national factor and macroeconomic variables over the 1998:Q1 - 2020:Q3. The impulses responses to uncertainty shock exhibit time variation, especially during recession periods. The reaction of the national factor to EPU shocks is negative and more stable compared to the response of HPU shocks. On the other hand, Figure 7 presents the reactions of national factor using the extended model. Column 1 of Figure 7 shows the impulse responses to an EPU shock, while Column 2 represents the impulse response to a HPU shock.

Figure 7 provide several insights. First, the estimated responses of the national factor to uncertainty shocks are always negative, but the effect is more pronounced in the case of HPU shocks, especially during the global financial crisis and Brexit referendum. Second, the reaction of national factor to HPU shocks displays a more persistent response over the sample period than those of EPU shocks. Thus, households react more to housing sector-specific uncertainty, perhaps due to the irreversibility of housing investment decisions and an inelastic nature of housing supply following geographical constraints (see, for example, Saiz, A. (2010) and related studies). Further, an increase in overall economic policy uncertainty might cause higher demand for houses if the demand for other financial assets is more sensitive to the uncertainty (El-Montasser et al., 2016), thereby mitigating the negative effect of EPU shocks. Banks might also apply tighter credit scoring criteria in processing mortgage loan applications, especially among high loan to value borrowers due to elevated house price uncertainty, thereby reducing housing demand.

– Please include Figures 6 and 7 about here. –

4.3. ***Variance decomposition***

This section examines the changes in the historical and forecast error variance decompositions of the national factor due to the uncertainty shocks. Table 2 illustrates that the share of variance contributions to national factor. The first column shows different time horizons, while other columns show the fraction of the variance of forecast error of national factor due to the corresponding shock under different model specifications. The variance decomposition analysis shows that house price uncertainty shocks play a significant role in explaining the variance in the national factor. In the baseline model using house price uncertainty index, HPU shock accounts for a non-negligible part of the variability in the national factor, explaining the 10% variations in the forecast error variance.[11] In contrast, the EPU shock has lower importance for the variability of national factor where its share is relatively low (around 3%) both in the baseline and expanded

[11] On the contrary to the frequentist framework, forecast error variance decomposition components may not add up to 1 since the Bayesian approach is based on full distribution rather than a single point estimate.

models at a 16 quarters forecast horizon. Overall, the results of variance decomposition analysis confirm that HPU is relatively more important than the EPU in explaining the variation of national factor.

– Please include Table 2 about here. –

In Figure 8, we investigate how the contribution of each uncertainty shocks to the historical dynamics of the national factor changes over time. Precisely, we decompose the value of each variable into its different components for every period of the sample, each component being due to one structural shock of the model.[12] In doing so, we identify the historical contribution of each shock to the national factor. Note that the impact of a shock on a variable corresponds to the accumulated effects of current and past shocks when interpreting the historical decomposition. An examination of all the sub-graphs of Figure 8 highlights the central role of uncertainty shocks on the national factor, especially during financial stress periods. Interestingly, the HPU shocks explain a non-negligible fraction of the national factor between 2009 and 2010 and during the Eurozone sovereign debt crisis in 2012. On the contrary, the contribution of HPU shocks is positive at the beginning of the sample, which coincides with the house price boom period around the early 2000s.

– Please include Figure 8 about here. –

5. Robustness Check

Given that a range of unconventional monetary policies (such as large scale asset purchases, a maturity extension program, and forward guidance to manage expectations of a prolonged period of low policy rates) are pursued during the ZLB condition, one can argue the need to use a uniform and coherent measure of the monetary policy stance. Thus, we use the SSR, which measures the nominal interest rate that would prevail in the absence of its effective lower bound. As a matter of robustness analysis, we also use the SSR developed by Krippner (2013, 2015; SSRK), which are considered to be an improvement over those obtained by Wu and Xia (2016), as discussed in detail by Krippner (2020).[13] In this regard, we estimate the extended model by replacing SSWRK with SSRK. The results presented in Figure A1 of the appendix show that the estimated responses of national factor to house price uncertainty shocks are always negative and statistically significant. The other impulse responses are qualitatively similar to our main findings.

[12] The historical decompositions are obtained from the posterior median draw.

[13] The data is downloadable from: https://www.ljkmfa.com/test-test/united-states-shadow-short-rate-estimates/.

Furthermore, to ensure that the ordering we imposed in the extended model does not affect our results, we estimate the extended model using a reverse ordering of endogenous variables within the TVP-VAR model. Accordingly, this specific causal arrangement considers the variable EPU as the most endogenous in the system. We present the impulse response functions in Figure A2 of the appendix. Consistent with our baseline results, the response of the national factor to a shock to EPU is insignificant. The remaining results are also in line with our previous findings, indicating that our results are not sensitive to the ordering of the endogenous variables.

6. Conclusion

Using a dynamic factor model (DFM), we disentangle the co-movement in house prices in the smallest geographic units into unobserved factors - the national factor affecting all markets, the regional factor that drives house prices in districts within a particular region, and the unique district-specific factor. This information allows us to investigate how housing market-related uncertainty shocks affect synchronous movements in regional housing markets. We use the Bayesian time-varying parameter VAR (TVP-VAR) model to estimate the dynamic impact of aggregate macroeconomic and uncertainty shocks on the common factor.

Our results show the national factor accurately tracks the overall housing market cycles in the UK. Further, the national factor explains nearly all the variation in the districts in East, SouthEast, and SouthWest. We find a sizable role of regional factors in NorthEast, NorthWest, Yorkshire and Humber, and Wales housing markets. Furthermore, the Bayesian TVP-VAR model results show that the impulses responses to uncertainty shock exhibit time variation, especially during recession periods. In particular, the estimated responses of the national factor to uncertainty shocks are always negative, but the effect is more pronounced in the case of HPU shocks, especially during the global financial crisis and Brexit referendum.

The housing market acts as a key barometer of the economy. It is also an important amplifier of shocks to the broader economy, increasing the amplitude of the business and credit cycles. The global financial crisis has shown the impact and importance of the development of the housing market. Its overheating and the resulting downturn in the US were a catalyst for a financial crisis that spread from the US to the rest of the world through linkages in the global financial system. Thus, the deepening understanding of housing market dynamics could help, for example, central banks, to monitor the market and take a right and timely measures. For instance, the BoE can exert greater control on banks' mortgage underwriting standards on newly written mortgages and recommend appropriate interest rate tests to use in assessments of mortgage affordability. Hence, these measures might increase the resilience of banks and households to any subsequent fall in housing returns in the case of uncertainty shocks.

Considering that the regional effects of Brexit are less clear-cut than the overall housing market, it would be interesting to analyze the impact of uncertainty shock on regional housing factors. For instance, the provision of international financial services is concentrated in London, creating greater sensitivity to economic policy uncertainty. On the other hand, localized demand effects can have an aggregate housing market effect. Put differently, friction in one part of the housing market – such as London – can affect other regions as housing market chains are disrupted. Therefore, our analysis can uncover potential avenues for future research on the housing market.

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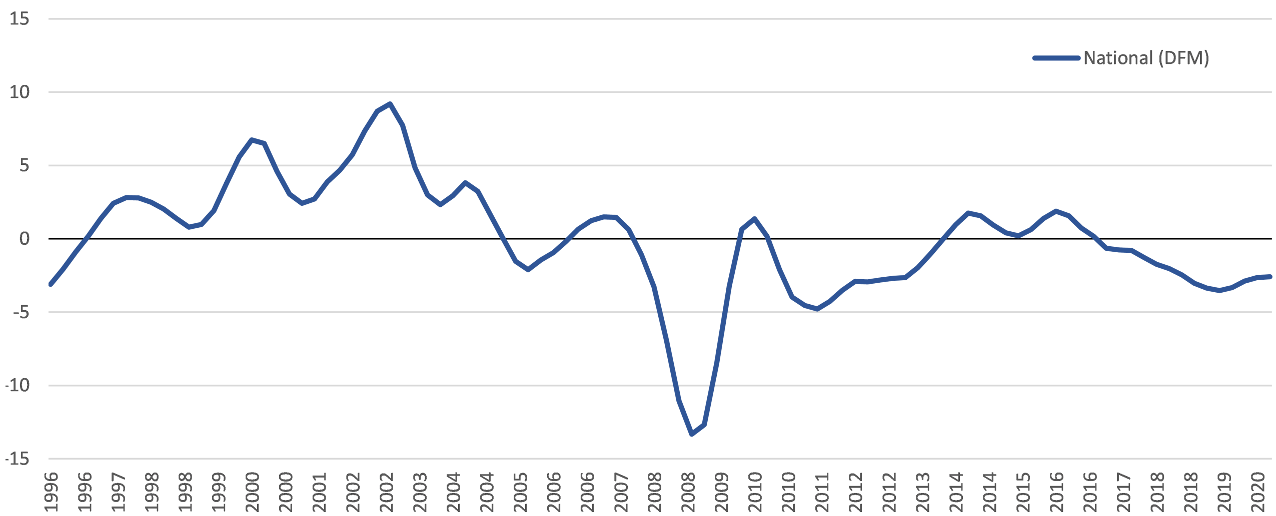
Table 1: Variance Decomposition

	Fact1	Fact2	Fact3		Fact1	Fact2	Fact3		Fact1	Fact2	Fact3
NorthEast				West Midlands				SouthEast			
Hartlepool and Stockton	0.40	0.53	0.07	Herefordshire	0.89	0.08	0.03	Berkshire	0.88	0.10	0.02
S Teesside	0.88	0.06	0.06	Worcestershire	0.93	0.05	0.02	Milton Keynes	0.93	0.05	0.02
Darlington	0.55	0.39	0.05	Warwickshire	0.95	0.02	0.02	Buckinghamshire	0.84	0.12	0.04
Durham	0.50	0.47	0.04	Telford & Wrekin	0.84	0.11	0.05	Oxfordshire	0.92	0.04	0.04
Numberland	0.61	0.35	0.04	Shropshire	0.36	0.27	0.37	Brighton & Hove	0.86	0.07	0.07
Tyneside	0.44	0.12	0.44	Stoke-on-Trent	0.95	0.00	0.05	E Sussex	0.98	0.00	0.02
Sunderland	0.69	0.28	0.03	Staffordshire	0.79	0.18	0.02	W Surrey	0.97	0.01	0.03
NorthWest				Birmingham	0.86	0.10	0.03	E Surrey	0.86	0.12	0.01
W Cumbria	0.43	0.48	0.09	Solihull	0.93	0.02	0.05	W Sussex (S W)	0.97	0.02	0.01
E Cumbria	0.59	0.37	0.05	Coventry	0.88	0.07	0.05	W Sussex (N E)	0.89	0.02	0.09
Manchester	0.91	0.01	0.08	Dudley	0.76	0.20	0.05	Portsmouth	0.98	0.00	0.02
Manchester SW	0.71	0.14	0.15	Sandwell	0.68	0.26	0.06	Sampton	0.97	0.00	0.03
Manchester SE	0.78	0.16	0.07	Walsall	0.73	0.20	0.07	Isle of Wight	0.96	0.00	0.04
Manchester NW	0.58	0.39	0.04	Wolverhampton	0.61	0.30	0.09	S Hampshire	0.82	0.10	0.08
Manchester NE	0.56	0.39	0.04	East				Central Hampshire	0.95	0.03	0.02
Blackburn	0.36	0.55	0.10	Peterborough	0.71	0.13	0.16	N. Hampshire	0.82	0.16	0.02
Blackpool	0.85	0.07	0.08	Cambridgeshire	0.97	0.00	0.03	Medway	0.76	0.17	0.08
Lancaster & Wyre	0.57	0.37	0.07	Suffolk	0.98	0.00	0.02	Kent Thames Gateway	0.95	0.00	0.05
Mid Lancashire	0.64	0.33	0.03	Norwich, E Norfolk	0.90	0.03	0.07	E Kent	0.96	0.01	0.03
E. Lancashire	0.43	0.47	0.11	N & W Norfolk	0.72	0.15	0.13	Mid Kent	0.95	0.00	0.05
Chorley and W Lancashire	0.58	0.39	0.03	Breckland and S Norfolk	0.43	0.24	0.33	W Kent	0.98	0.00	0.02
Warrington	0.52	0.42	0.06	Luton	0.82	0.10	0.08	SouthWest			
Cheshire E	0.87	0.10	0.03	Hertfordshire	0.91	0.05	0.05	Bristol	0.93	0.01	0.06
Cheshire W and Chester	0.81	0.16	0.03	Bedford	0.96	0.01	0.03	Bath, Somerset	0.98	0.00	0.02
E. Merseyside	0.67	0.27	0.05	Central Bedfordshire	0.72	0.12	0.15	Gloucestershire	0.62	0.22	0.16
Liverpool	0.71	0.12	0.17	Send-on-Sea	0.95	0.00	0.05	Swindon	0.86	0.07	0.08
Sefton	0.49	0.44	0.07	Thurrock	0.92	0.04	0.04	Wiltshire	0.95	0.02	0.03
Wirral	0.68	0.28	0.04	Essex Haven Gateway	0.98	0.00	0.02	Bournemouth & Poole	0.96	0.00	0.04
Yorkshire and Humber				W. Essex	0.94	0.02	0.04	Dorset	0.96	0.00	0.04
Kingston upon Hull	0.87	0.08	0.05	Heart of Essex	0.97	0.01	0.02	Somerset	0.94	0.04	0.02
E. Riding of Yorkshire	0.63	0.33	0.04	Essex Thames Gateway	0.94	0.00	0.06	Cornwall and Isles of Scilly	0.92	0.05	0.03
N. & NE Lincolnshire	0.53	0.42	0.05	London				Plymouth	0.89	0.05	0.06
York	0.74	0.19	0.07	Camden and City of London	0.61	0.34	0.05	Torbay	0.78	0.15	0.06
N Yorkshire	0.80	0.17	0.02	Wminster	0.93	0.01	0.06	Devon	0.77	0.09	0.14
Barnsley, Doncaster	0.51	0.46	0.02	Kensington, Chelsea	0.55	0.37	0.07	Wales			
Sheffield	0.90	0.01	0.08	Wandsworth	0.46	0.21	0.33	Isle of Anglesey	0.90	0.05	0.05
Bradford	0.54	0.39	0.06	Haringey and Islington	0.96	0.00	0.04	Gwynedd	0.65	0.30	0.06
Leeds	0.51	0.39	0.10	Lewisham and Swark	0.54	0.21	0.25	Conwy & Denbighshire	0.75	0.14	0.10
Calderdale & Kirklees	0.59	0.39	0.02	Lambeth	0.51	0.39	0.09	SW Wales	0.51	0.40	0.09
Wakefield	0.80	0.14	0.05	Bexley and Greenwich	0.88	0.06	0.05	Central Valleys	0.50	0.44	0.06
East Midlands				Barking, Dagenham	0.87	0.00	0.13	Gwent Valleys	0.90	0.06	0.04
Derby	0.80	0.18	0.03	Redbridge, Waltham Forest	0.89	0.06	0.04	Bridgend, Neath Port Talbot	0.47	0.46	0.07
E Derbyshire	0.68	0.30	0.02	Enfield	0.76	0.14	0.10	Swansea	0.75	0.23	0.02
S & W Derbyshire	0.80	0.19	0.01	Bromley	0.82	0.15	0.03	Monmouthshire, Newport	0.54	0.42	0.04
Nottingham	0.65	0.30	0.06	Croydon	0.84	0.11	0.05	Cardiff, Vale of Glamorgan	0.86	0.10	0.04
N. Nottinghamshire	0.85	0.10	0.05	Merton, Kingston	0.96	0.01	0.03	Flintshire , Wrexham	0.71	0.25	0.03
S. Nottinghamshire	0.57	0.32	0.11	Barnet	0.84	0.09	0.06	Powys	0.66	0.30	0.04
Leicester	0.90	0.09	0.01	Brent	0.82	0.14	0.04				
Leicestershire and Rutland	0.64	0.22	0.14	Ealing	0.34	0.42	0.24				
W. Namptonshire	0.78	0.14	0.08	Harrow, Hillingdon	0.75	0.18	0.08				
N. Namptonshire	0.97	0.00	0.03	Hounslow and Richmond	0.79	0.20	0.01				
Lincolnshire	0.84	0.16	0.01								

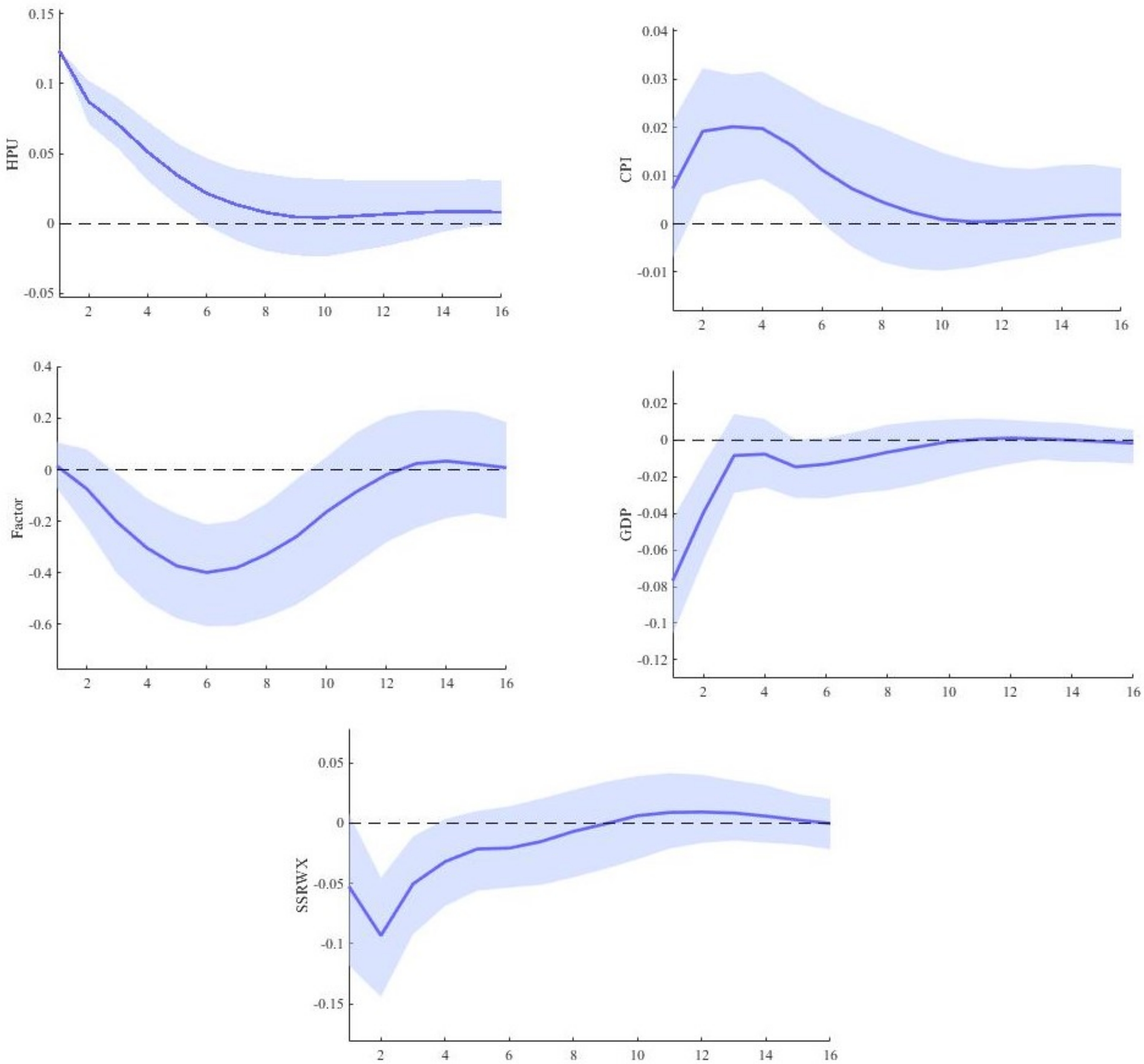
Note: This table reports the variance decomposition of real house price into the national (Fact1), regional (Fact2), and district-specific idiosyncratic factors (Fact3).

Figure 1: The UK National Factor



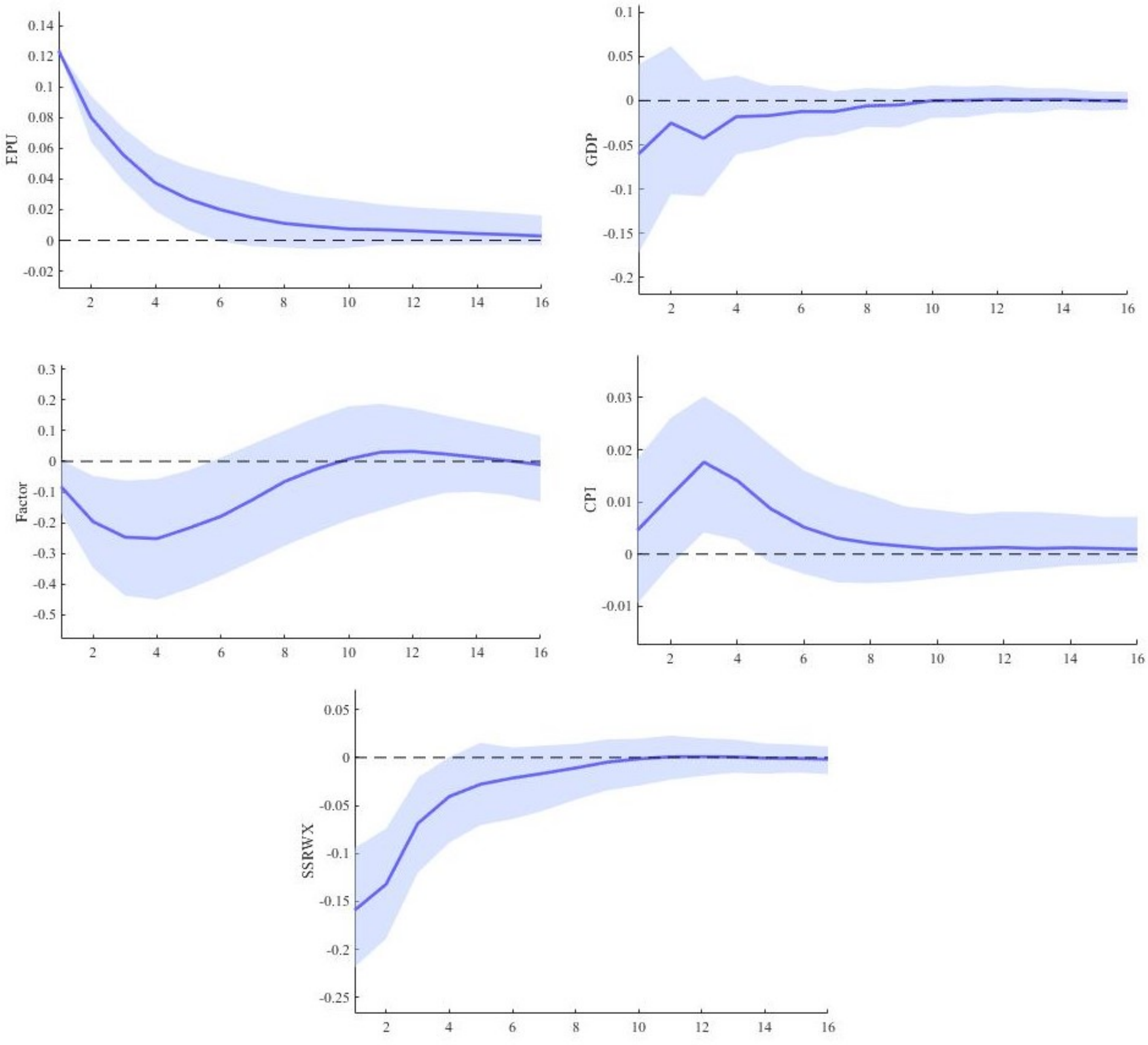
Note: The plot presents the aggregate national UK factor obtained from the dynamic factor model.

Figure 2: Impulse responses to house price uncertainty shock



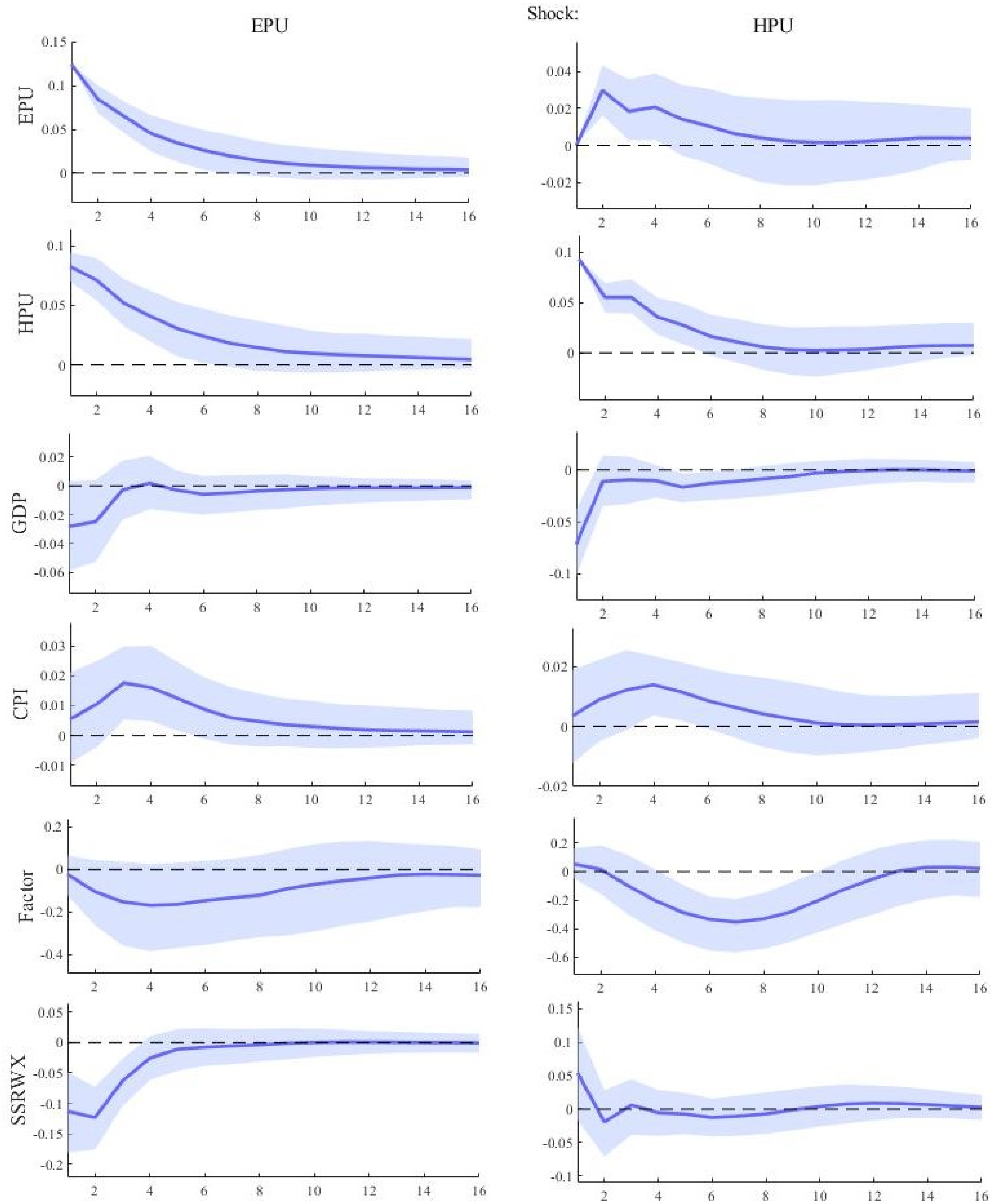
Notes: This figure shows the impulse responses to one unit shock to house price uncertainty index. The dashed lines are 68% probability bands.

Figure 3: Impulse responses to economic policy uncertainty shock



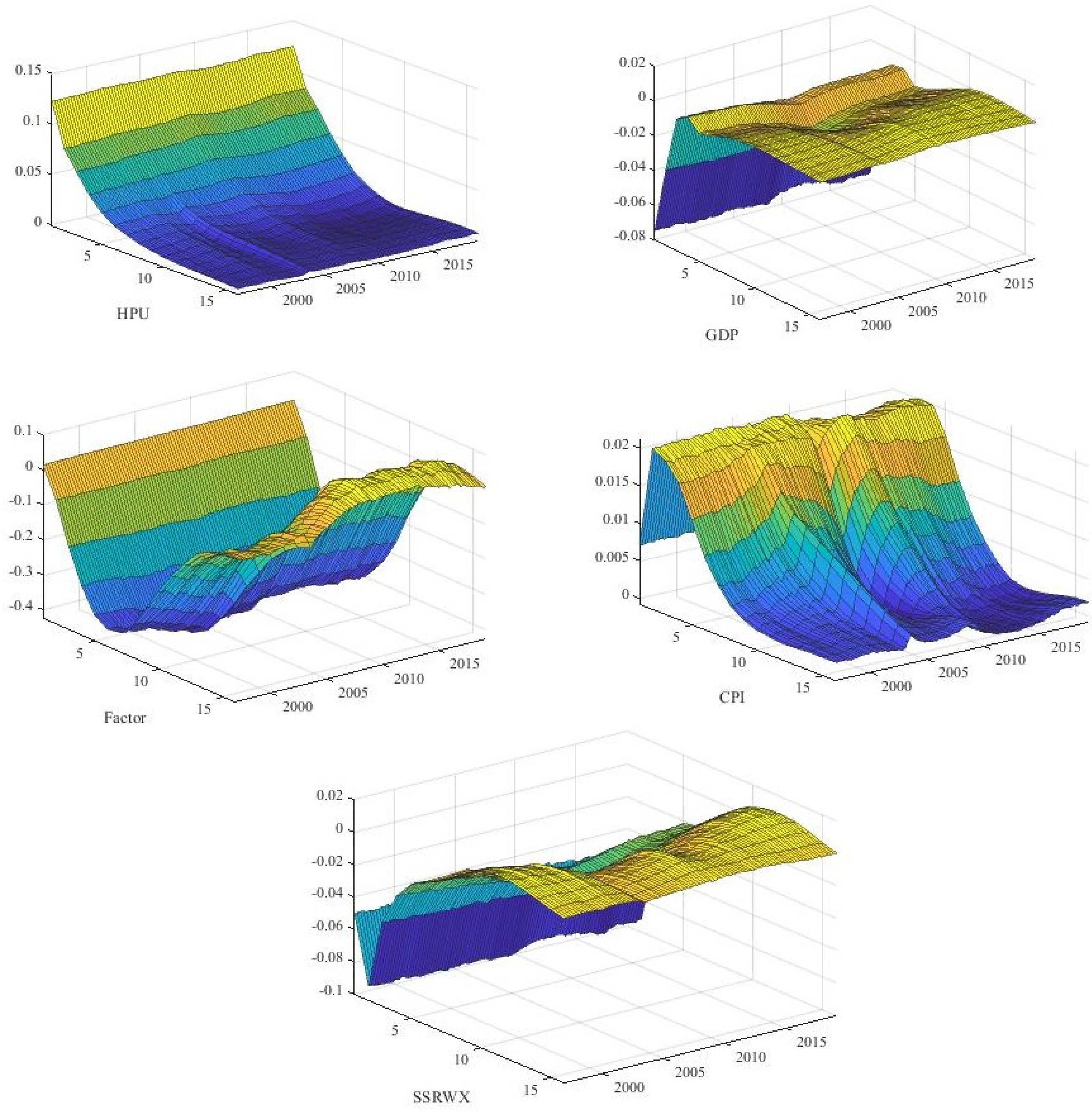
Notes: This figure shows the impulse responses to one unit shock to economic policy uncertainty index. The dashed lines are 68% probability bands.

Figure 4: Impulse responses to uncertainty shocks: HPU vs. EPU - Extended model



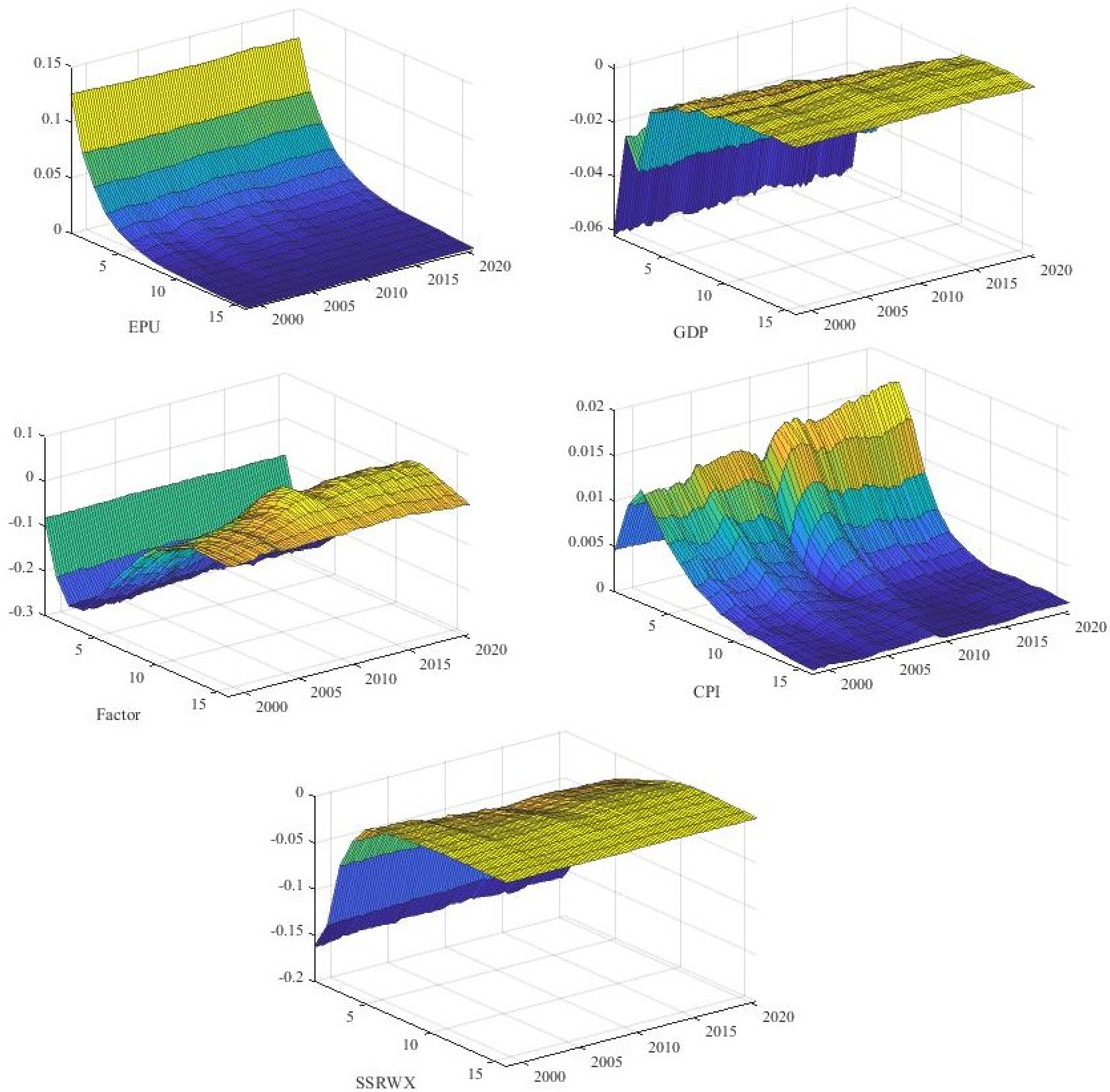
Notes: This figure shows the impulse responses to uncertainty shocks. The dashed lines are 68% probability bands.

Figure 5: Time varying impulse responses to house price uncertainty shock



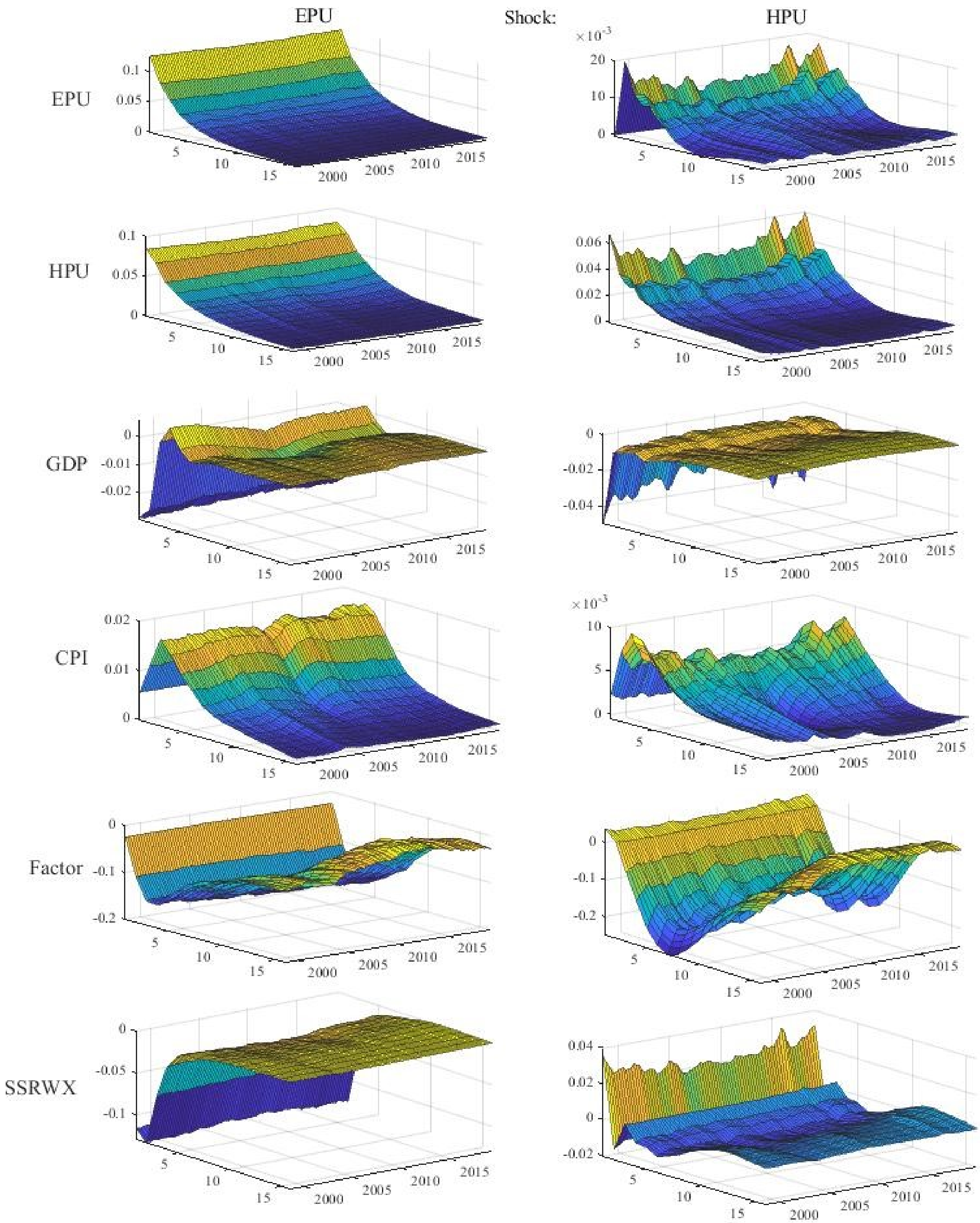
Notes: This figure shows the evolution of impulse responses to house price uncertainty shock variable along 16 quarters horizons and the time period from 1996:Q2 to 2019:Q2. The X-axis of each panel represents the time periods, the Y-axis is the horizon in quarters, while the Z-axis is the impulse responses.

Figure 6: Time varying impulse responses to economic policy uncertainty shock



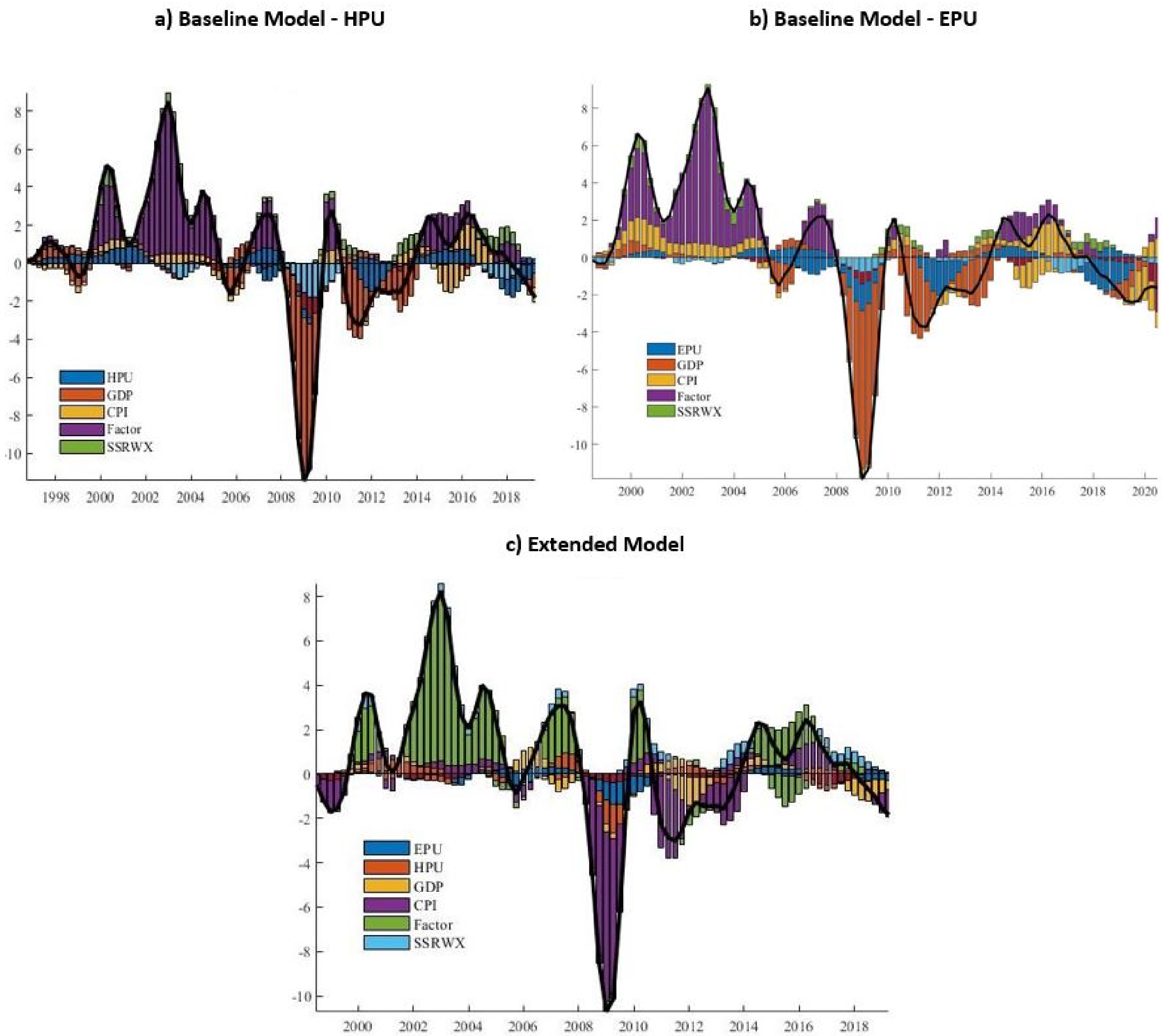
Notes: This figure shows the evolution of impulse responses to economic policy uncertainty shock variable along 16 quarters horizons and the time period from 1998:Q1 to 2020:Q3. The X-axis of each panel represents the time periods, the Y-axis is the horizon in quarters, while the Z-axis is the impulse responses.

Figure 7: Time varying impulse responses to uncertainty shocks: HPU vs. EPU - combined model



Notes: This figure shows the evolution of impulse responses to uncertainty shocks variable along 16 quarters horizons and the time period from 1998:Q1 to 2019:Q2. The X-axis of each panel represents the time periods, the Y-axis is the horizon in quarters, while the Z-axis is the impulse responses.

Figure 8: Historical decomposition of the national factor



Notes: The black solid line is the actual national factor. The coloured stacked bars represent the (median of the posterior) contribution of the identified structural shocks to national factor.

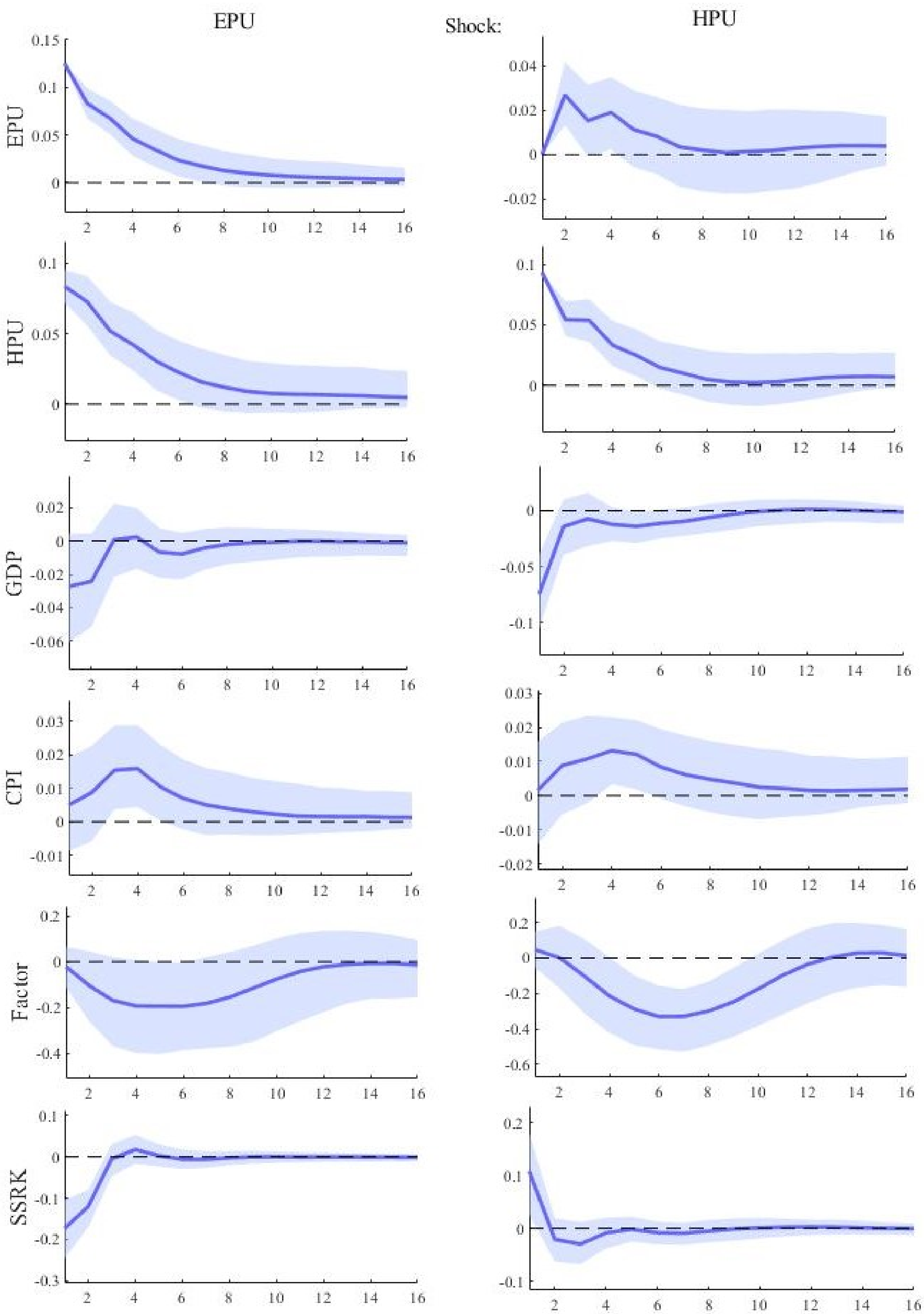
Table 2: Forecast error variance decomposition

	Baseline model with HPU					Baseline model with EPU					Extended model					
Horizon	HPU	GDP	CPI	Factor	SSRWX	EPU	GDP	CPI	Factor	SSRWX	EPU	HPU	GDP	CPI	Factor	SSRWX
1	0.009	0.008	0.017	0.945	0.000	0.016	0.028	0.047	0.872	0.000	0.010	0.014	0.014	0.014	0.909	0.000
2	0.012	0.026	0.025	0.905	0.001	0.024	0.068	0.057	0.811	0.002	0.013	0.012	0.034	0.019	0.876	0.002
3	0.019	0.039	0.046	0.851	0.003	0.027	0.072	0.082	0.770	0.004	0.015	0.015	0.044	0.036	0.837	0.004
4	0.033	0.043	0.070	0.795	0.009	0.028	0.066	0.109	0.738	0.007	0.018	0.022	0.044	0.058	0.792	0.008
5	0.053	0.042	0.091	0.739	0.021	0.029	0.066	0.132	0.702	0.015	0.020	0.032	0.044	0.078	0.749	0.017
6	0.072	0.043	0.107	0.689	0.035	0.030	0.067	0.147	0.669	0.025	0.023	0.045	0.042	0.090	0.705	0.027
7	0.090	0.043	0.113	0.652	0.049	0.032	0.072	0.156	0.647	0.034	0.027	0.060	0.043	0.096	0.670	0.037
8	0.102	0.043	0.111	0.635	0.055	0.033	0.074	0.156	0.633	0.043	0.031	0.070	0.044	0.095	0.651	0.044
9	0.106	0.042	0.108	0.633	0.058	0.034	0.075	0.153	0.627	0.047	0.033	0.074	0.045	0.092	0.647	0.046
10	0.106	0.043	0.104	0.635	0.058	0.034	0.076	0.150	0.628	0.047	0.034	0.076	0.044	0.091	0.644	0.047
11	0.105	0.043	0.104	0.634	0.058	0.034	0.077	0.149	0.628	0.048	0.035	0.077	0.044	0.089	0.642	0.047
12	0.107	0.043	0.105	0.631	0.058	0.035	0.076	0.152	0.626	0.048	0.036	0.077	0.043	0.090	0.638	0.047
13	0.106	0.043	0.105	0.627	0.059	0.034	0.075	0.153	0.626	0.049	0.036	0.078	0.043	0.093	0.637	0.049
14	0.106	0.043	0.106	0.625	0.061	0.034	0.076	0.154	0.621	0.050	0.036	0.079	0.043	0.093	0.634	0.049
15	0.107	0.043	0.106	0.625	0.062	0.034	0.078	0.155	0.619	0.051	0.036	0.080	0.044	0.092	0.632	0.050
16	0.108	0.044	0.106	0.623	0.063	0.034	0.078	0.155	0.617	0.051	0.037	0.080	0.044	0.093	0.629	0.050

Notes: This table reports the fraction of the variance of forecast error at 16-quarters horizon explained by the shocks to each of the variable. Entries are in percent.

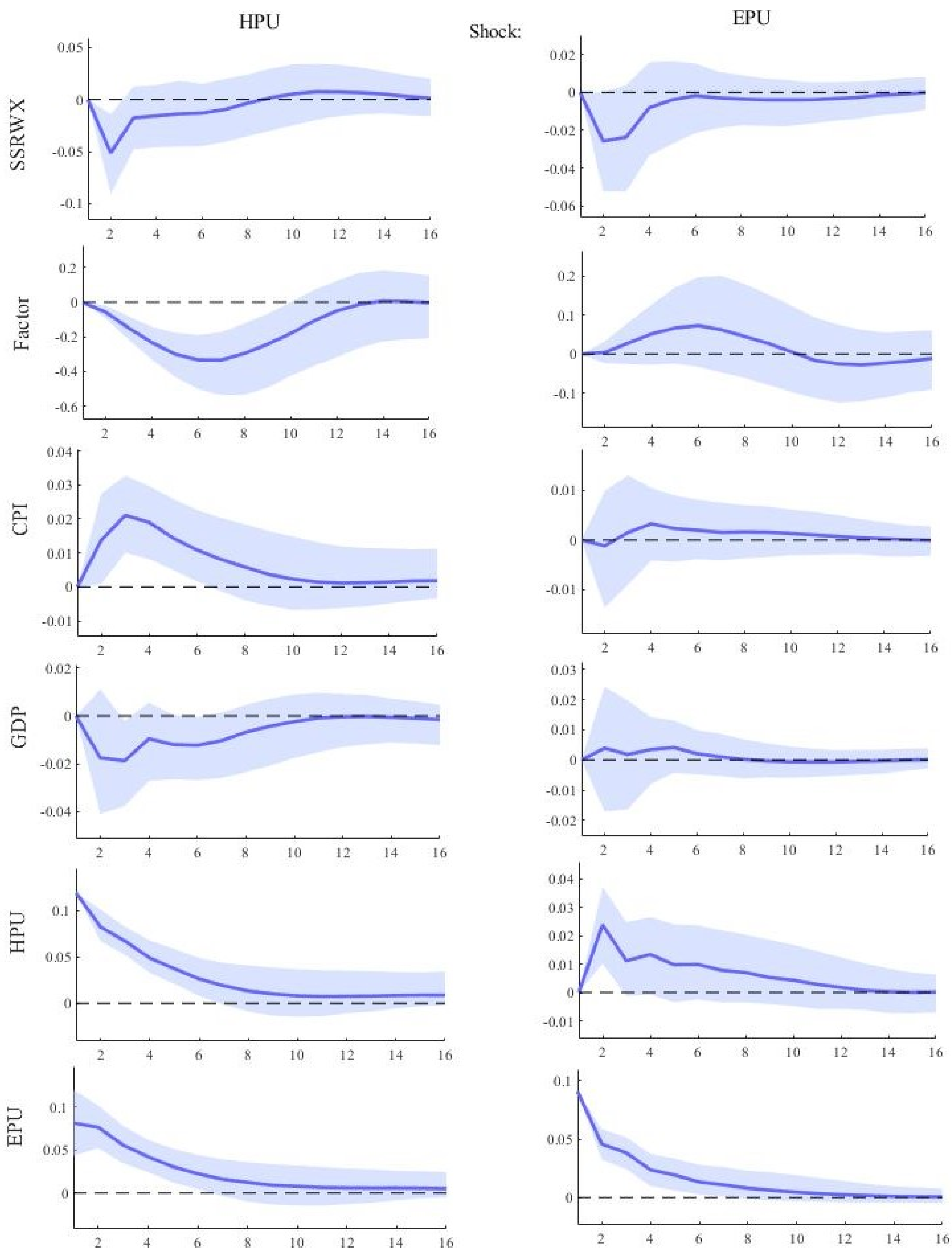
Appendix

Figure A1: An alternative measure of shadow policy rate - Robustness check



Notes: See notes to Figure 4.

Figure A2: Reverse ordering of variables - Robustness check



Notes: See notes to Figure 4.