Political Uncertainty in a Data-Rich Environment

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Abstract

We asses the general robustness of previous findings claiming that policy uncertainty exerts non-trivial influences on the US economy. Measuring the dynamic effects from a shock to policy uncertainty within a FAVAR model permits gauging the response of many more variables to policy uncertainty than is possible in a simple VAR model. Our results summarized by impulse responses are all corrected for small sample bias using a bootstrap-after-boostrap method. Our findings support the view of policy uncertainty exerting a *statistically* significant influence on the economy, which is however not always as *economically* significant for a number of variables as found in previous studies.

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Introduction

Ever since the publication of Thomas Hobbes' Leviathan (Hobbes, 1651) one view of the role of government prevailing to this day has been that of a supplier of a public good produced through a social contract between the governed and the government which promises relief from the brutish state of nature which would otherwise allegedly exist. In contrast, in a more contemporary contribution grounded in a multi-disciplinary approach employing elements of economics, history, sociology and psychoanalysis at times mirroring the approach taken by theorists of the Frankfurt School, Fromm (1941) illustrates with great clarity the tensions that can arise between positive freedom (the freedom to do something) and negative freedom (the freedom from something). Further, Fromm describes how conditions marked by political and economic uncertainty can emerge in which people may develop a sudden inclination towards seeking escape strategies from a type of perceived freedom which constitutes an unbearable burden by entering into new ties of bondage delivering a renewed sense of security, such as for instance that frequently promised by popular authoritarian political regimes.

Even from the point of view of our modern times characterised by the widespread existence and acceptance of legitimate liberal democracies (see Fukuyama 1989), these and other analyses may also suggest that the acute absence or at least temporary disturbance of sufficiently transparent, stable and forward-looking political and economic environments may lead to an insufficient supply of this public good of political certainty or predictability which many agents in the economy not only depend on for purposeful investment planning, but according to Fromm almost crave not only in their narrowly defined economic role they play as producers of goods and services and households formulating consumption plans, but as more broadly defined social agents more generally.

In our analysis we present here, by political certainty, or its inverse political uncertainty, we prefer to think of a condition which transcends the mere existence, acceptance, enforcement and execution - both actual and perceived - of the rule of law within sovereign states but also internationally, which is often taken to be to chief element underpinning a Hobbesian social contract conducive to the prevalence of social and economic stability. Instead, as we will describe further below, the measure of political uncertainty employed in our study aims at gauging elements of such uncertainty comprised of both fundamental (such as actual changes in important statutory tax regulations) as well as perceived (forecasters disagreement and Google News components) elements of such acute disturbances to political certainty, some of which may very well partially give rise to the sort of economic and social instability with resultant psychological consequences and commensurate political choices elaborated upon in Fromm (1941)[1].

In particular, our paper builds on previous work conducted by Bloom et al. (2012) (BBD henceforth) who employ a structural vector auto-regression approach in order to identify the dynamic effects resulting from such an acute disturbance to policy certainty measured via a novel index (see also Baker et al. 2012). Efforts of examining the effect of various sources of uncertainty impinging on the economy date back at least as far as Bernanke (1983) which has recently been re-examined again in in Gilchrist et al. (2010), Fernandez-Villaverde et al. (2011) and Bloom (2009). We expand on BBD's approach by identifying the same shock in a FAVAR modelling framework (see inter alia Stock and Watson 1999, Stock and Watson 2002, Forni et al. 2000, Forni et al. 2000, Bernanke and Boivin 2003, and Bernanke et al. 2005), using the identification scheme employed in Bernanke et al. (2005). The main purpose of our line of investigation is to assess the general robustness of BBD's finding that policy uncertainty exerts non-trivial influences on the dynamic evolution of the US economy[2]. This robustness check is carried out by advancing previous efforts along two dimensions.

First, our results summarized by impulse responses are all corrected for small sample bias using a bootstrap-after-bootstrap method developed in Kilian (1998). The bias-corrected results reported here constitute an important addition to existing findings, since a well-known body of literature has shown that impulse responses relying on asymptotic results tend to over-estimate and thus exaggerate estimated dynamic effects in small samples. By first replicating BBD's original results within a standard Cholesky-identified structural VAR (see Sims 1980, Sims 1992, Bernanke and Blinder 1992 and Bernanke and Mihov 1995) and correcting them for small-sample bias, depending on the

[1] Another insightful and related contribution to the literature is that of Buera et al. (2011) who construct a model employing learning in which free market systems are learnt by nations through interaction with their neighbours and in which a large economic shock which may well also be correlated with and amplified by policy uncertainty as measured by the political uncertainty index employed here can lead to reversals of state intervention.

[2] Recently, Bloom et al. have made their research findings focusing on the detrimental effects of policy uncertainty available via a dedicated website, which can be accessed at `http://www.policyuncertainty.com`. Interested readers will find the current version of their paper, the data and replication material ready at their convenience.

specification of the VAR model, we find that their measured effects on employment and industrial production are over-estimated and consequently exaggerated by only a small margin. This part of our robustness check therefore does not overturn the most salient conclusions drawn from BBD, at least in a qualitative sense.[3].

Secondly, identifying and measuring the dynamic effects originating from a shock to policy uncertainty within a FAVAR model permits an investigation into this partial effect using a far more comprehensive set of variables than that employed in Bloom et al's original study based on a VAR. By adopting a FAVAR model instead, we specifically address BBD's concerns raised over the possibility of policy uncertainty proxying partially for effects which may not be included in the small set of variables employed in their SVAR study. To estimate the effect in question as robustly as possible we include many variables which ought to help in capturing co-variates explaining, for instance, the effects of current and expected financial distress, output and employment intentions as well as expected inflation, co-variates which in themselves may also act as foreboding indicators for changing patterns in expected uncertainty. In sharp contrast to Bloom et al who infer their main results from a structural VAR employing only six variables measured at a monthly frequency, our monthly FAVAR incorporates a total of 61 variables.

Apart from the benefits derived from the shrinkage of a large set of variables into a small set of orthogonal factors via the method of principal components, the FAVAR modelling approach also makes allowance for measuring the response of many more variables to policy uncertainty than is possible in a simple structural VAR model. Overall, our findings support BBD's original conclusion that policy uncertainty exerts *statistically* significant influences on the economy, which depending on the variable's response examined, may however not always be as *economically* significant as previously established.

In particular, we find much more muted responses of employment, industrial production and investment from a shock to policy uncertainty, all of which are in the neighbourhood of or less than 0.25% in absolute magnitude. Responses of similar magnitude are obtained in the case of personal expenditure measures, where in particular changes in expenditure in durables but also

[3]Identification of structural shocks are typically non-unique and several methods of identifying them exist. A useful reference explaining such schemes in succinct style is Amisano and Giannini (1997)

non-durables are negative and statistically significant and larger than consumer expenditure on services, all of which occur in tandem with a higher savings ratio[4]. A sizable response in our dataset is that of the S&P500 U.S. stock market index, which is estimated to decline by as much as 1.5% on impact, but also tends to recover quickly thereafter.

In addition, our approach employing the FAVAR modelling methodology also uncovers a statistically significant but very moderate "flight-to-safety" effect affecting returns of US government bonds. Further, although measured deflationary pressures gauged from a number of downstream price indices are small in magnitude, upstream commodity prices are found to fall significantly following a shock to policy uncertainty. Therefore, the most plausible explanation for or interpretation of our results is that policy uncertainty tends to measurably repress indicators of consumption expenditure, raise the savings ratio, cause a sudden but short-lived negative wealth effect in asset markets which is followed by a temporary but marked drop of prices in commodity markets and comparatively small but significant responses of production, employment, and bond yields. Stronger responses of stock market and global commodity market prices are suggestive of links into the global economy magnifying the effects of unexpected shocks to policy uncertainty.

Our paper is structured into a total of 5 section. Following this introduction we will discuss the data employed in this study and in particular highlight the construction of the novel index measuring policy uncertainty. In the third section the estimation and identification method employed in our FAVAR modelling strategy is outlined, which broadly follows that of Stock and Watson (2005) and Bernanke et al. (2005). The penultimate section discusses the results and compares them to Bloom et al. (2012) while the remainder concludes.

[4]The usual caveat applies that estimated results are also somewhat sensitive to the methods chosen to de-trend the data

A data-rich environment

In this section we will briefly describe some of the characteristics of the data employed in this study. Due to the nature of our investigation, this discussion will focus primarily on a more in-depth explanation of the novel measure of policy uncertainty constructed and used in a structural VAR study by BBD. But before turning our attention to that index, we will first give brief mention to the large set of other time series covariates employed in our study, all of which have been obtained from the St. Louis Fed's FRED database and are all of monthly frequency[5]. In order to robustly assess the findings arrived at and conclusions drawn from BBD's original work, we employ the same set of variables they use in their study but use this only as a subset within a much broader set of variables belonging to a variety of categories. These additional time series co-variates can be broadly classified into data related to the labour market, currency exchange rates indices, measures of the money supply and its components, money market returns (based on government bond yields), the price level, commodity prices, forward-looking consumer sentiment and purchasing managers' surveys, measures of financial distress, the housing market, national accounts expenditure (and saving), national accounts income, economic real activity, and cost of private sector financing.

We collect all of the data in a $N \times 1$ vector X_t, where N can be very large (in our case X_t contains a total of 61 variables). As is customary when estimating the canonical FAVAR model as expounded in Bernanke et al., the extraction of the orthogonal factors in the first stage of our model estimation via principal components requires all of the data - wherever required - to be made covariance-stationary as well as distributed as a standard normal, since principal components analysis as a method is sensitive to and thus not invariant to scaling. This means that prior to estimation, all of the data contained in X_t has to be suitably transformed so as to be distributed as $X_t \sim \mathcal{N}(0, 1)$, which is accomplished through filtering any non-stationary series, and then de-meaning and normalizing by its standard deviation. The data appendix to this study summarizes properties of all of the time series employed and also provides information about any transformation carried out on each them prior to normalization and estimation.

[5]With the only exception of gross private domestic investment (Data Code: GPDI) and three measures of broad money velocity (Data Codes: MZMV, M2V, M1V), all of which are only available at quarterly frequency and had to be interpolated in order to be used in our monthly FAVAR.

The main purpose of our study is to robustly estimate the dynamic response of the US economy from a shock to policy uncertainty as measured by a novel index first introduced and discussed in BBD. Apart from computing all impulse responses in our study based on methods correcting small-sample bias, our chief contribution lies in extending BBD's original work by estimating a FAVAR model and identifying the responses from a structural shock to policy uncertainty. The estimated responses obtained from the FAVAR framework we take interest in are obtained from a model which may contain a very large number of variables in estimation without exhausting its degrees of freedom as is commonly found to be the case in the popular VAR approach, which is typically found to employ fewer than 10 variables in applications. The FAVAR estimation framework and its characteristic shrinkage of the variable space lends itself therefore ideally to the robust estimation of the responses in question, whenever misspecification due to omitted variable bias is suspected from a simple alternative VAR setup. Apart from that, factor models of the kind discussed here fit well into the popular DSGE paradigm (Giannoni and Boivin, 2005) and their orthogonality properties have also been exploited by employing them as instruments in estimation (see Kapetanios and Marcellino 2010 and Bai and Ng 2010). Since our main focus is on measuring how the US economy responds to a shock to the aforementioned novel index, a brief discussion of this index measuring policy uncertainty may be instructive.

[FIGURE 1 ABOUT HERE]

BBD's novel uncertainty index is constructed based on a weighted average of a total of three sub-components, each of which constitutes a distinct source of policy uncertainty. The first component is based on a month-by-month search of ten large U.S. newspapers (using data from Google) using a set of keywords which are chosen so as to reflect policy uncertainty as depicted in the news and thus potentially perceived by a wider public opinion. This constitutes arguably the most interesting component of the index and builds on an emerging body of literature which attempts to use Google news data for purposes such as for instance improving forecasts (see Askitas and Zimmermann 2009, D'Amuri and Marcucci 2010). The second component of the index is based on data determining the number of tax code expirations in each month[6].

[6]Actually, tax codes are typically set to expire in December of each year, so BBD employ a weighting scheme

Finally, the third component is made up of data obtained from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters which BBD employ in order to measure professional forecaster disagreement. This is done by choosing one-year ahead forecasts of the consumer price index (CPI), purchases of good and services by state and local governments, and purchases of goods and services by the federal government. The dispersion of such forecasts by individual forecasters entering the sample is taken as a proxy for disagreement in predictions of values in one year's time from each reference date. BBD's original study explores various different weighting schemes and how the subcomponents fare individually in explaining policy uncertainty by studying correlations with data from the real economy as well as with forward-looking survey data. For our purposes, we choose to work with their preferred benchmark index which they also select in deriving the key results of their paper.

Estimation & identification methodology

This section provides a discussion of the methods employed in estimating the dynamic responses of the US economy from a shock to policy uncertainty as well as of how such structural shocks can be identified (non-uniquely) in the first place. First, we replicated BBD's impulse responses, which are obtained from a conventional structural vector auto-regression based on a Cholesky decomposition of the variance-covariance matrix of the underlying estimated unrestricted VAR. To preserve succinctness in exposition, we choose not to provide an in-depth discussion here of how such structural VARs and their identified impulse responses are obtained in general. Suffice to say that in replicating the VAR results we have followed the authors' original benchmark specification, which employs a Cholesky-identified monthly vector auto-regression estimated using a constant and linear time-trend, and a lag order of six. The VAR is ordered with the policy uncertainty index first, then the log of the S&P500 index, the federal fund rate on third, and the log of employment and log of industrial production on fourth and fifth position, respectively. We did not however follow BBD exactly in their additional step to scale up the initial policy uncertainty shock on the first position of the impact diagonal matrix so as to obtain a standard impact shock equal to 112

with discounting to their data obtained from the Congressional Budget Office (CBO). We refer the interested reader to the original text in value. Instead, we follow the conventional path here and leave the impact matrix as a normal identity matrix[7].

Instead of computing confidence intervals based on asymptotic theory as in the original study of BBD, we employ Kilian's bootstrap-after-bootstrap procedure which corrects for small-sample bias and is based on the bootstrap procedure developed in Runkle (1987). All of the impulse responses computed in our study, including those obtained from the FAVAR model, are bias-corrected using this method. For comparison's sake we therefore also graph in dashed lines the original uncorrected impulse responses so that the severity of the bias is always made clear for each impulse response computed. We supplement each mean impulse response with bootstrapped confidence intervals based on 66% and 90% levels of reliability. This forms one aspect of our robustness check we employ in this study. The non-parametric bootstrap for the VAR is based on the usual vector of estimated residuals, while the FAVAR model employs the residuals obtained from the estimated VAR in the unobserved and observed factors, so in other words the factor innovations. Bootstrap estimates are based on 2000 replicated estimations each time using re-sampled data [8].

Indeed, the only reason for conducting such a replication exercise on this occasion is to augment and then compare it to an additional modification of the standard bootstrapped impulse responses and their confidence intervals so as to take account of small-sample bias and correct for it. Therefore, we will limit our discussion in this section first and foremost to an explication of the way we proceeded in estimating our more general FAVAR model (see Stock and Watson 2002, Bernanke et al. 2005) and how the response of the remaining variables can be estimated based on the identification of a structural shock to one variable in the system only. Specifically, the identification strategy we employ will be based on that used in Bernanke et al. (2005), who in their seminal contribution to the literature introduce and adopt the FAVAR modelling methodology to re-visit the issue of and estimate the dynamic response of the US economy from a shock to monetary policy [9].

[7] We do however provide exact replications of their results in our appendix.

[8] We estimate all of our models and their impulse responses based on our own code written in Python using the Numpy (Jones et al., 2001–a) and Scipy (Jones et al., 2001–b) libraries. To check that we have not made any obvious mistakes, wherever possible we have always made sure that our results are exactly identical to those obtained from the mature Python library Statsmodels which contains a VAR procedure. Of course, the same cross-check could not be carried out directly for the FAVAR model due the lack of publicly available Python libraries implementing this model. For the VAR, cross-checks have also been made against Gretl's output. Our code is available on request.

[9] Further, up-to-date surveys of the factor approach in time series modelling are discussed in Stock and Watson

The FAVAR modelling framework

First, we will turn to a discussion of the FAVAR modelling methodology after which we will briefly explain our estimation strategy. With regards to the FAVAR model setup, our notation closely follows that of Bernanke et al. (henceforth BBE) while our chosen estimation strategy is equivalent in spirit to that of Stock and Watson (2005). Following our notation first introduced in the section discussing the data employed in this study, we define a column vector X_t which is of size $N \times 1$ and which contains all of the data series incorporated into our analysis. Following BBE, we call this large-dimensional vector the vector containing all of the background of "informational" time series. The FAVAR approach, which can be viewed as a modelling framework combining the popular VAR modelling methodology with that of principal component analysis, can be best understood by referring to equation 1:

$$X_t' = \Lambda^f F_t' + \Lambda^y Y_t' + e_t' \tag{1}$$

This equation implies that all variables contained in X_t are explained by a linear combination of some vector of unobservable factors F_t which is assumed to be of dimension $K \times 1$ and a vector of observable factors Y_t, which is assumed to be of size $M \times 1$. The set of factors are taken to be pervasive in their ability to explain the evolution of all variables describing the current state of the economy, barring some residual e_t. Λ^f and Λ^y represent the so-called loading vectors which relate the factors back to the set of all observable variables contained within X_t. As we will discover shortly when discussing the estimation strategy, it may sometimes be convenient to collect both unobservable and observable factors into one vector of so-called common components, defined as $C_t\left(F_t, Y_t\right) \equiv C_t = \left(F_t', Y_t'\right)'$, which allows us to re-write equation 1 more succinctly as:

$$X_t' = \Lambda^c C_t' + e_t' \qquad \text{where} \qquad \Lambda^c = \left(\Lambda^f, \Lambda^y\right) \tag{2}$$

Employing the definition introduced in equation 2 is useful for motivating and highlighting the benefits we reap from employing the FAVAR modelling framework we chose to adopt in this study.

(2005), Bai and Ng (2008), Stock and Watson (2011b) and Stock and Watson (2011a)

An important advantage of the FAVAR model is that it manages to completely bypass the well-known problem of a rapid exhaustion of degrees of freedom constraining analysis in the popular VAR analysis first introduced by Sims (1980). It effectively does so by extracting a comparatively small-dimensional set of factors (or common components) from X_t using principal components analysis and then modelling the dynamic evolution of those common components by employing a standard VAR model:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t \tag{3}$$

More precisely, if X_t is $N \times 1$ while the set of common components C_t is of dimension $(K+M) \times 1$, we typically have that $N >> K+M$, so the number of "informational" time series is significantly greater than that of the estimated common components, in some applications by a multiple of 100. In the FAVAR modelling approach, a more abundant quantity of available time series turns into a virtue rather than into a constraint as is the case with standard VAR models where the exhaustion of degrees of freedom progresses at a quadratic rate the more series are being added to the analysis[10].

The estimation approach we adopt here closely adheres to the estimation methodology described in Stock and Watson (2005) and Bernanke et al. (2005) and is based on a two-step procedure. More specifically, the first step applies principal components directly to the set of "informational" series contained in X_t in order to extract the set of common components spanning the space of explanatory factors. The question of how many factors are to be extracted can either be settled by applying Bai and Ng's criterion approach (see Bai and Ng, 2002) or more informally by inspecting visually scree plots determining the optimal number of factors that way[11]. Before (or during) the second step, we need to disentangle the effect of policy uncertainty (which will become one of our principal factors) from the set of estimated common components obtained in the first step. How this is done exactly depends on the manner in which the structural shock we seek to study is

[10] Attempts to alleviate this problem somewhat by using prior information in Bayesian VARs have had some success (see Litterman, 1979), but even early applications of such BVARs employed no more than 10 variables in total. Using special priors, this constraint on the feasible number of variables used in BVARs has finally also been eliminated (Koop (2011)).

[11] Onatski (2006) develops a formal test for the number of factors based on the slope of the scree plot.

identified, and so we will defer a discussion of this to the next subsection.

But once we have a set of common components which no longer contain the effect from policy uncertainty (which we assume to be just as pervasive in its effect on the economy as all of the other factors), we can place both the set of factors purified of the effect of policy uncertainty and the index itself into a standard recursive VAR (with the policy uncertainty index ordered last) and also estimate the loadings with respect to all of the variables contained in X_t, which will provide us with sufficient information to generate impulse responses for those variables, which are just linear combinations of the underlying impulse responses from the lower-dimensional VAR in the factors. Estimation throughout is easily conducted using equation-by-equation OLS and so computational burden is kept at a minimum, in sharp contrast to the alternative Bayesian methods employing the Gibbs sampler discussed in Bernanke et al. (2005). This concludes the discussion of the formulation and estimation of our FAVAR specification, leaving identification to be discussed in the next subsection.

Estimation & Identification

Our estimation strategy follows closely that described in Stock and Watson (2005) which comprises a comparatively straightforward method of obtaining estimates of the factors and factor loadings relating the latter to the large set of "information" variables. Yet another avenue one could conceivably exploit in order to obtain said estimates is grounded in Bayesian estimation which is described in great detail in Bernanke et al. (2005). In fact, the aforementioned authors estimate their FAVAR models using both a two-step estimation procedure similar to the one we choose to adopt here as well as adopting the alternative Bayesian approach. In their analysis they reach the conclusion that neither of the two methods ought to be viewed as superior over the other based on prior reasoning, and estimates obtained from both methods yield nearly identical results.

In the two-step estimation procedure we employ here[12] the stationarized and standardized vector of "informational" variables is first subjected to principal components analysis based on

[12]Stock and Watson (2005) give mention to the possibility of extracting the principal components from *filtered* data which they denote $\tilde{X}_t$ and which are generated by a filtration employing each series own lagged values. In our model we do not pre-filter the data and leave all of the data's conditional distribution (and so also its degree of persistence) to be explained by the extracted factors only

a singular value decomposition of the data's correlation matrix. This yields the set of estimated factors which if chosen large enough should encompass or span the space of the model's theoretical common components we earlier denoted as $C_t = (F_t', Y_t')'$ under the null hypothesis that the model is explained by a factor structure.

In the first stage of our estimation procedure, following Bernanke et al. (2005), *all* of the factors are first treated as unobservable and are subsequently extracted from X_t to obtain $\hat{C}_t$, an estimate of the common components spanning the space of both the observable and unobservable factors. We then divide the set of "informational" data X_t into a total of three subsets, namely the scalar X_t^i containing the variable whose structural shock we wish to identify, the set of "slow-moving variables" such as labour market, current economic activity or prices data contained within X_t^s, as well as the subset of "fast-moving" data which holds all remaining series which are either forward-looking market surveys or financial markets data and are contained in X_t^f. The purpose of this division is two-fold. First, adopting a specific identification scheme we will discuss further below, akin to the Cholesky-decomposition method in standard structural VARs, allows us to impose some ordering on the factors which will help us in identifying the structural innovation of the policy uncertainty series. Second, this division of the data into "slow-moving" and "fast-moving" blocks will serve the purpose of aiding us in recovering $\hat{F}_t$ which is that part of $\hat{C}_t$ not covered by Y_t, i.e. the common components purified of the policy uncertainty index's effects.

In particular we will exploit the assumption that "slow-moving variables" are assumed not to respond contemporaneously to policy uncertainty shocks, while fast-moving series (typically financial markets and other forward-looking data) are allowed to react contemporaneously. This set of assumptions immediately opens up a way of recovering $\hat{F}_t$ from the estimated common components $\hat{C}_t = (F_t', Y_t')'$. This can be achieved by first running the following regression:

$$\hat{C}\left(F_t, Y_t\right) = b_{c^*}\hat{C}^*\left(F_t\right) + b_U U_t + e_t \tag{4}$$

where $\hat{C}^*\left(F_t\right)$ is an estimate of the common components spanned by the unobservable factors which can be estimated by applying principal components analysis to only the block of "slow-moving" variables. $\hat{F}_t$ can then easily be constructed by taking the difference:

$$\hat{F}_t = \hat{C}\left(F_t, Y_t\right) - b_U U_t \tag{5}$$

Using the above computed results we then proceed by constructing our factor VAR employing $\hat{F}_t$ and U_t ordered last, which exactly parallels the identification strategy chosen in Bernanke et al. (2005) who instead focus on identifying monetary policy shocks[13]. This concludes our discussion of the estimation and identification strategy we chose in this study. The next section contains the findings presented in shape of impulse response plots obtained from our estimated and identified FAVAR model.

[13] Kose et al. (2003) choose a different path of identifying structural shocks by instead placing restrictions on the factor loadings we defined here as Λ^f and Λ^y.

Results & Discussion

This section presents all of the impulse response graphs obtained from our estimated FAVAR model as well as the BBD's original responses estimated in their study upon which our work is based. In contrast to Bernanke et al. (2005), we do not report impulse responses in their untransformed form, but scale them by the standard error of the underlying variable and wherever natural logs were taken before estimation, multiply by 100 to turn all responses into percentage deviations. Also, in contrast to BBD, our impact shock matrix is defined as the usual identity matrix and so does not contain a scaled entry on one element of its diagonal[14]. All of the responses of our estimated FAVAR model reported below are - unless otherwise stated - based on the benchmark identification scheme described by the division of variables into slow- and fast-moving blocks which are detailed in the data appendix. This identification scheme is very similar in its way of identifying the structural shock in question as in other FAVAR applications, in that it tends to order financial markets and survey data first (fast block) and labour market data, prices and national accounts data after our variable whose response we wish to investigate[15].

However, to exactly mirror BBD's identification strategy, we would have to order policy uncertainty ahead of other variables, such as the S&P500 index (which they do and order 2nd), as well. In two alternative identification schemes we placed policy uncertainty ahead of only commodity prices, and in the second ahead of commodity prices and forward-looking survey data. What results is that in the first ordering many of the estimated effects remain in place but are more imprecisely estimated and so often turn outright or borderline statistically insignificant, with the only exception of the response of the stock market index and commodity prices, whose estimated responses remain robust to alternative orderings. The measured "flight-to-safety" effect of bond prices is also robust to alternative identification schemes. Therefore, it appears as if the estimated negative responses of the S&P500 stock market index, commodity as well as bond prices constitute findings which are robust across a number of identification strategies. We include the impulse responses obtained from the 2 alternative ordering schemes in our appendix for inspection.

[14] We do however report the corresponding exactly replicated impulse responses from BBD employing scaled shocks in our appendix to this study

[15] We deviate only marginally from this convention in ordering our money velocity measures into the slow-moving blocks, which we did in order to exercise prudence given that those measures have been interpolated.

The estimated responses shown here are based on a FAVAR model employing a total of 12 extracted factors (13 in total, once the uncertainty index is added to the modified set of the original set of 12 factors extracted in the first step of our estimation method). Compared against other applications of FAVAR studies this may appear to represent a comparatively large number of factors, but reflects a trade-off between including a sufficient number of factors to encompass the correct number of factors under the null that the model is represented by a factor structure and the spectre of non-invertibility, which occurred under more parsimonious alternative choices of numbers of factors ranging from 7-11. This problem could have been circumvented by choosing to de-trend the policy uncertainty index, which we however preferred not to entertain on theoretical grounds, or by choosing a significantly larger number of lags in the VAR specification employed in modeling the evolution of the factors. We could have therefore chosen more lags and fewer factors or fewer lags and more factors in order to obtain invertibility of the estimated matrix of VAR coefficients. We decided to choose the latter set-up so as to be conservative in our attempt of selecting a number of factors encompassing the true factor model, rather than to run the risk of underfitting on this aspect. The scree plots we include in our appendix illustrate our choice of numbers of factors to be very conservative and to provide ample of room to encompass the true number of factors. The lag length of the VAR in the factors is chosen so as to reflect that of BBD and is therefore set equal to 6. Since all of the series are in as far as required de-trended and de-meaned, the VAR in the factors neither contains a constant nor a time-trend in estimation.

[FIGURE 2 ABOUT HERE]

Figures 2 and 3 replicate the findings reported in BBD and show how the responses of industrial production and employment to a positive shock on the policy uncertainty variable are statistically significant, negative and also highly persistent. Our results presented here are however much smaller in magnitude than theirs as here we chose not to scale up the impact shock matrix on one of the entries along its diagonal. We also show, using the bootstrap-after-bootstrap procedure developed in Kilian (1998) that small-sample bias exists but remains of second-order relevance in the particular case of the two responses plotted in figures 2 and 3[16] So one of our first important

[16] Had we proceeded and estimated BBD's original model without the inclusion of a time trend, then the obtained impulse response bias would have increased significantly.

results is that the original results based on impulse response analysis obtained in BBD appear to be fairly robust to small-sample bias. Our next task will be to compare and contrast the responses obtained from the standard VAR model with those we estimate in our FAVAR model which employs a total of 61 variables as opposed to the small set of 6 variables used in BBD's original VAR study.

[FIGURE 3 ABOUT HERE]

Figure 4 illustrates how dynamic changes in employment are estimated in response to a shock to policy uncertainty. We find the response to be smaller in magnitude by a factor of approximately 2.5 when compared to the response obtained from the VAR model. Also, while the estimated response remains statistically significant based on the outer confidence band representing a 10% level of significance, given the muted response overall, the response's confidence intervals are generally closer to the zero baseline. Further, the impulse response remains most pronounced after approximately 1 1/2 years after the shock occurred, implying that the effects from policy uncertainty retain a degree of persistence also in the FAVAR modelling specification we adopt here. The estimated small-sample bias in our FAVAR model is considerably stronger and serves to diminish the effects from policy uncertainty substantially.

[FIGURE 4 ABOUT HERE]

Figure 5 describes the estimated response of the industrial production index from a shock to policy uncertainty based on our benchmark ordering scheme. What becomes immediately apparent is that the response is only approximately half as large in magnitude than that obtained from the VAR model and is also less persistent in the long-run, in spite of the depressed levels observed over the range of the first 15 to 20 months. This finding is perhaps also partially explained by the fact that the FAVAR model's estimated response of policy uncertainty on its own shock is not very persistent, once many other factors contained in the total set of 61 variables are factored in. So there is reason to believe that in BBD's original study, the policy index may correlate with many other variables which have not been included in the original VAR model due to rapid degrees-of-freedom exhaustion. As one would expect, the reduction in industrial production is more sudden and immediate than the rather more drawn-out fall in levels of employment plotted in the previous figure.

[FIGURE 5 ABOUT HERE]

Figure 6 shows how yields of a number of government debt instruments respond to a shock from policy uncertainty. While many of the responses are only marginally statistically significant for the first 4 or 5 months following the shock - we do however observe a response which may could viewed as a “flight-to-safety” choice by investors who faced with more and multi-faceted uncertainty prefer to allocate their wealth into allegedly safer government bonds. This view is further corroborated once we look at the more robust and pronounced response of the S&P500 stock market index, which exhibits a ‘risk-off’ response. It is also interesting to point out here that the response of short-term debt is more pronounced and also more sudden, while the minimum for higher-maturity notes is reached a couple of months after the shock. Also, the evolution of the yield on longer-term notes is more volatile in general (but less ample than that of short-term debt paper) than that of the two short-term bills. In the short-run, debt paper with a shorter maturity tends to overshoot paper with a longer maturity structure, which it continues also in the long-run when bond prices begin to recover again.

[FIGURE 6 ABOUT HERE]

Figure 7 documents the response of the S&P500 stock market index from a shock to policy uncertainty, based on all three identification schemes we consider in this paper. Irrespective of which identification is chosen, the direct and instantaneous impact of the policy uncertainty shock on this broad measure of the total value of the U.S. stock market is always statistically significant and ranges between negative 2.0 and 1.5%. All of the measured responses imply a gradual reversal of stock prices back to the baseline after approximately 1 1/2 years after the initial shock, with our benchmark case response remaining most depressed with a mean deviation of below 1.0% for 18 months after the shock. We take this as evidence of the general robustness of the negative effects of policy uncertainty on the stock markets which remain statistically significant in a variety of identification schemes we choose to employ here.

[FIGURE 7 ABOUT HERE]

Figure 8 illustrates pertinent responses of household expenditure measures drawn from personal consumption expenditure data. Immediately apparent are declines of just less than 1/6th a percent of consumption expenditure on both durable and non-durable consumption goods, while expenditure on service goods is only marginally depressed and but still statistically significant. The much-watched price index associated with overall personal consumption expenditure, while declining somewhat in its mean response, is barely statistically distinguishable from zero. At the same time however, as one would perhaps expect, the savings ratio increases by a marginally statistically significant magnitude of about 0.05 percentage points. The responses of all expenditure measures and saving are persistent and reach their minimum troughs after about one year following the shock to policy uncertainty.

[FIGURE 8 ABOUT HERE]

Finally, figure 9 documents the strong and statistically significant responses of prices in commodity markets observed following a shock to policy uncertainty. Given the results we have been surveying thus far, which included significant but muted responses on the production side of the economy and the labour market and close to equi-proportional responses seen on the expenditure side of the economy, the contraction of prices in global commodity markets may also be indicative of the presence of a strong global contagion effect associated with policy uncertainty as perceived domestically in the US economy[17]. Here, both oil and copper prices fall by about 3% then recover somewhat only to decline again to reach a second minimum trough after about a year following the shock to policy uncertainty. Although the disentanglement of "supply" and "demand" shocks are notoriously difficult to accomplish econometrically in economics, much of the evidence we have surveyed in this section points to the suspicion that shocks to policy uncertainty may have relatively strong effects on the demand side of the economy, which may also be further reinforced by negative wealth and balance sheet effects associated with sudden and pronounced declines in a broad stock market index such as the S&P500. The synchronous and similarly rapid declines in commodity market prices further point to the interlocking behaviour of global supply chains which

[17]Needless to say, some events such as the US' involvement in military conflicts in the Middle East may cause uncertainty elsewhere in the world directly in a geo-political sense and thus have to rely less on some contagion effect taking place across long distances, say, through a radical change in the US foreign policy stance, such as that occurring in the wake of the 9/11 attacks.

appear to be very susceptible to the changing behaviour of the US consumer in response to policy uncertainty as measured by BBD novel index.

[FIGURE 9 ABOUT HERE]

Conclusion

Our study's purpose was to build on previous work conducted by Bloom et al. (2012) and Baker et al. (2012) who construct and employ a novel measure of policy uncertainty. The robustness of the effect of policy uncertainty on the US economy is tested by extending BBD's original work along two key dimensions. Firstly, all of the impulse responses reported here are computed based on the bootstrap-after-bootstrap small sample bias correction method developed in Kilian (1998). We consider this an important additional robustness check, as impulse responses relying in asymptotic theory have been found to exaggerate the underlying responses they describe. We find that while for some responses and specific model specifications this may play a non-trivial role, in general the corrected responses do not by themselves overturn any of the qualitative conclusions reached in BBD. Secondly, and more importantly, we test the robustness of the role of policy uncertainty in driving the evolution of many important metrics of the state of the US economy by estimating its effect on said variables employing a FAVAR estimation framework, whose principal advantage is its ability to bypass the problem of rapid exhaustion of degrees of freedom in the canonical VAR modelling framework when the inclusion of a large number of variables is considered.

Besides the advantage of shrinkage, modelling policy uncertainty along with and its effect on 60 other variables measuring varying aspects of the state of the US economy in a FAVAR model also allows us to derive the impulse responses of each time series contained in the large set of variables considered in this study, permitting us to draw our conclusions based on a much broader evidence base. Our found results indicate to us that BBD's original findings that policy uncertainty exerts non-trivial influences on the US economy are generally valid, but the magnitude of the responses we measure here based on the FAVAR model are often found to be smaller, which implies that in BBD's original study the policy uncertainty index may correlate with other important variables omitted in their study but included in ours.

Further, our results imply significant but much more muted responses of the supply side of the economy and comparative responses of the demand side, which may be further propagated through global contagion effects we cannot however measure or confirm directly based on our model specification. The most pronounced responses appear to be felt in the stock market as well as global commodity markets, which all decline by magnitudes in the neighbourhood of several % points. Alternative orderings of the variables in our identified FAVAR may give rise to marginally different outcomes in some cases, but they do not overturn our most salient findings of policy uncertainty exerting non-trivial and statistically significant influences on many measures of the real side of the economy, on bond prices, as well as stock and global commodity markets.

We find weak but statistically significant evidence for a “flight-to-safety” effect following the declining economic conditions associated with a shock to policy uncertainty. The depressing effect on short-term yields on government bonds are generally found to be invariant to the consideration of alternative identification schemes. Much of the responses we estimate based on the FAVAR model, while not always statistically significant typically accord with a-priori expectations of the sign of the response arguably held by mainstream views. Fruitful directions for future research may be based on even more flexible frameworks such as that developed in Banerjee and Marcellino (2008) or Dufour and Stevanovic (2010), which augment the standard FAVAR model by also allowing for the modelling of co-integration between variables as well as moving average representations of shocks. Other avenues of potentially fruitful exploration may address the question to what extent the policy uncertainty index employed here may contribute to improving forecast accuracy of variables associated with the real side of the economy.

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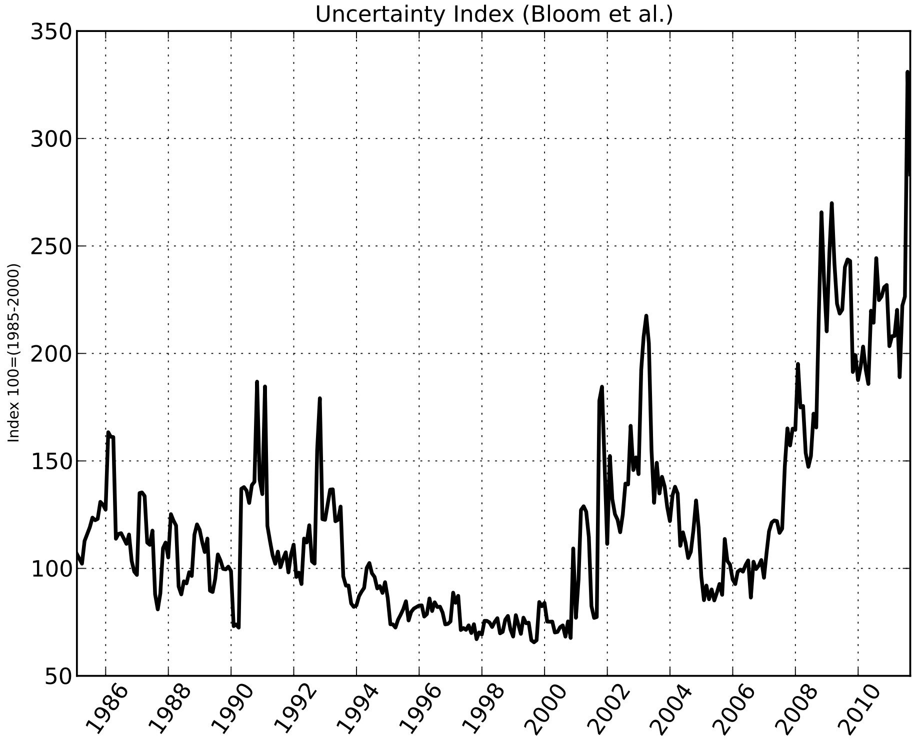


Figure 1: Index of Political Uncertainty. Source: Bloom et al. (2012)

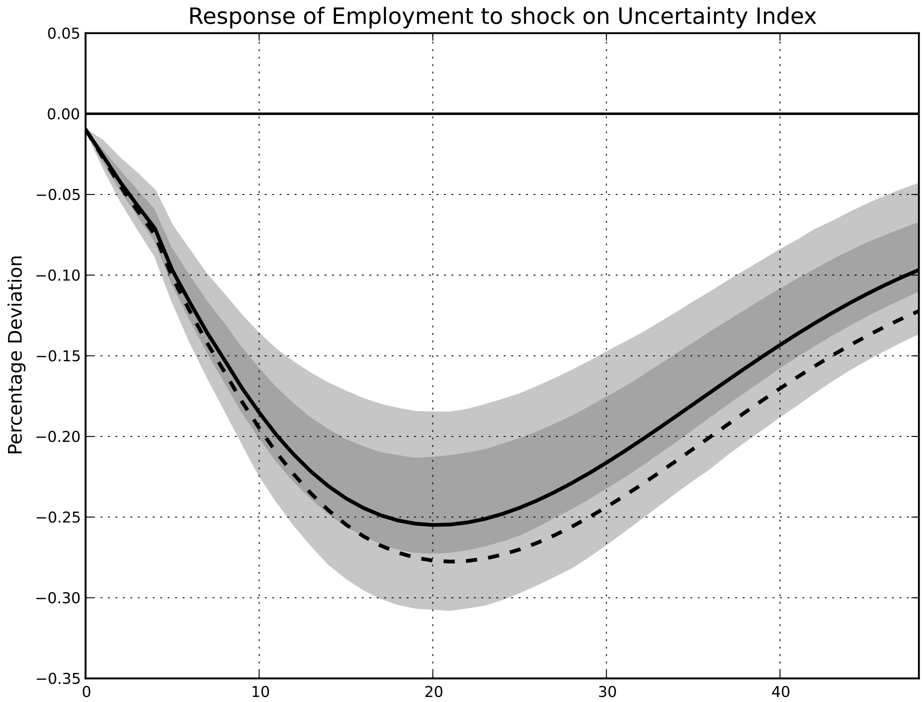


Figure 2: VAR Cholesky-identified impulse response of employment from shock to policy uncertainty. Replicated (unscaled) using data and methodology described in Bloom et al. (2012).

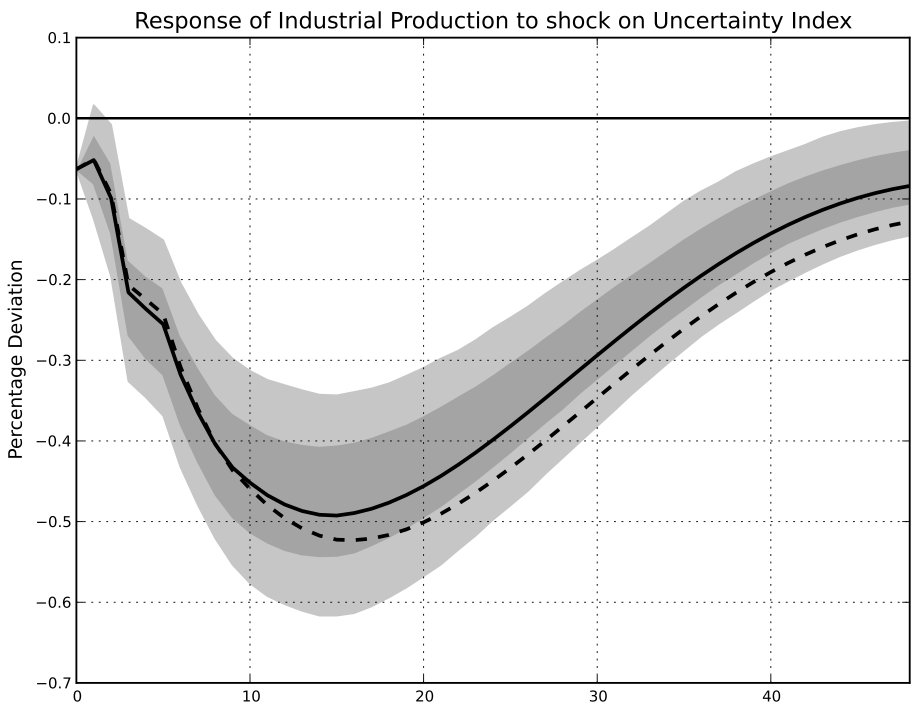


Figure 3: VAR Cholesky-identified impulse responses of industrial production from shock to policy uncertainty. Replicated (unscaled) using data and methodology described in Bloom et al. (2012).

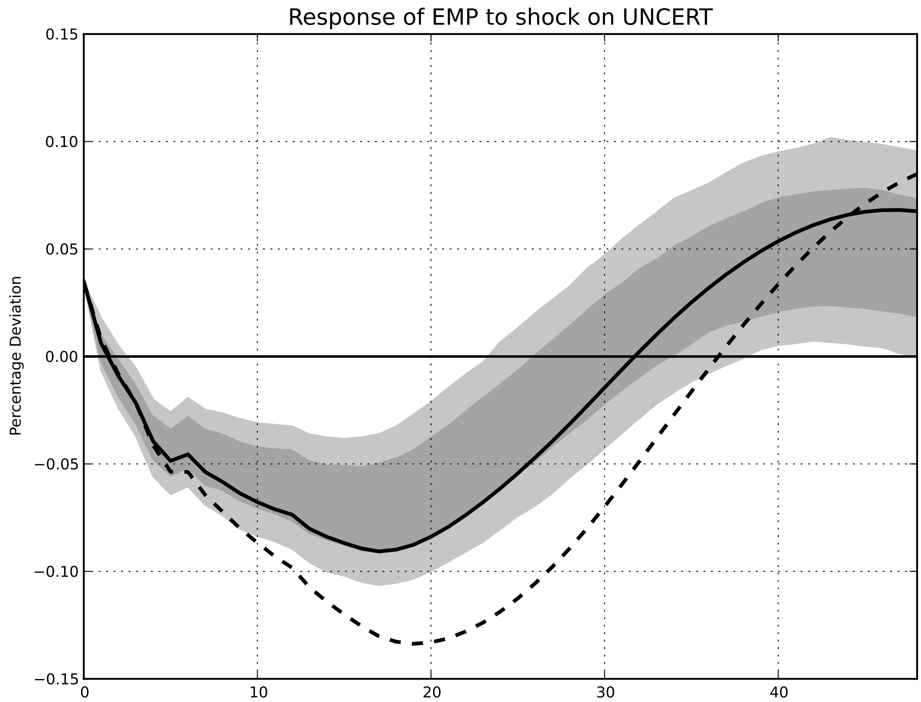


Figure 4: FAVAR identified impulse responses of employment from shock to policy uncertainty.

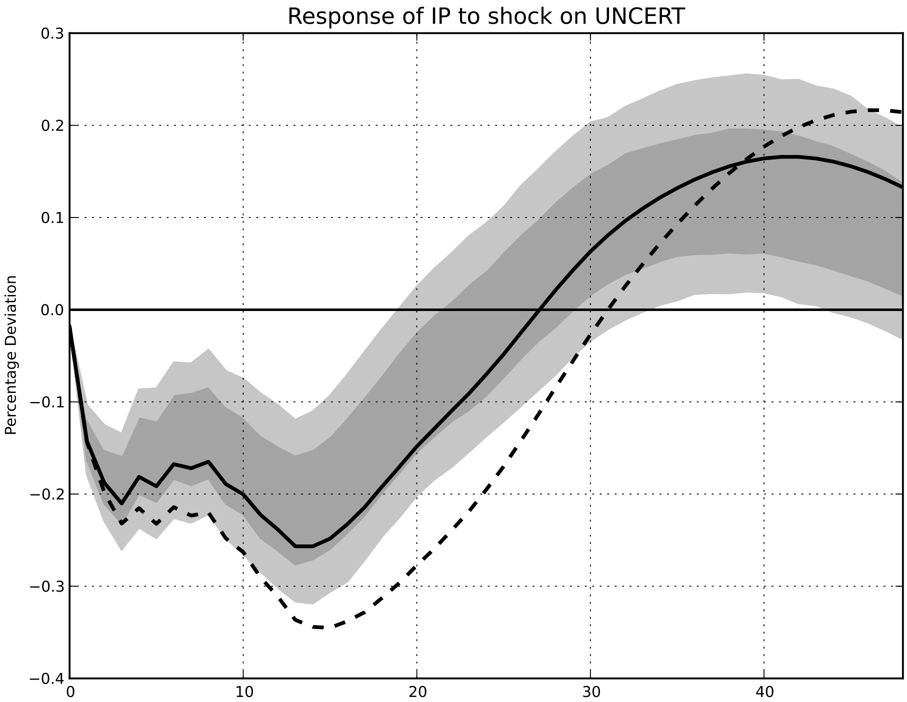


Figure 5: FAVAR identified impulse responses of industrial production from shock to policy uncertainty.

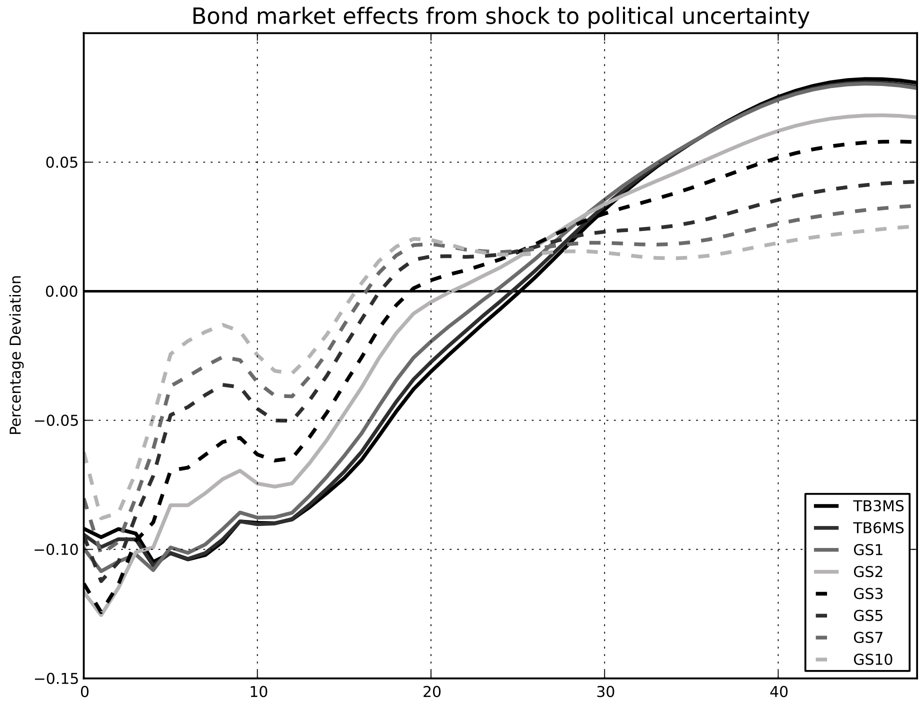


Figure 6: FAVAR identified impulse responses of yields on gov. bonds from shock to policy uncertainty.

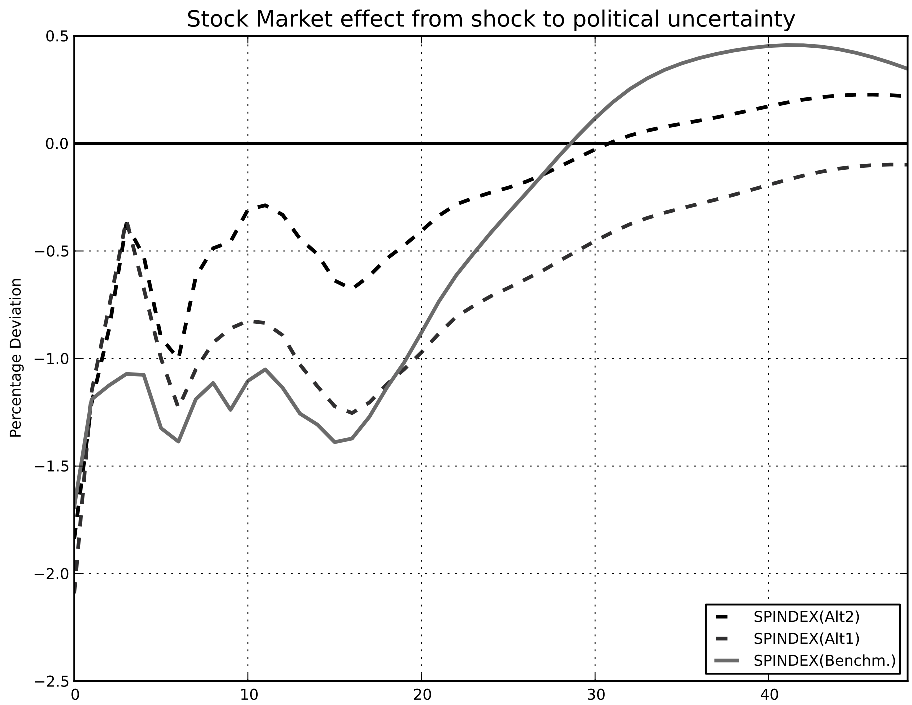


Figure 7: FAVAR identified impulse responses of measures of external finance capability from shock to policy uncertainty.

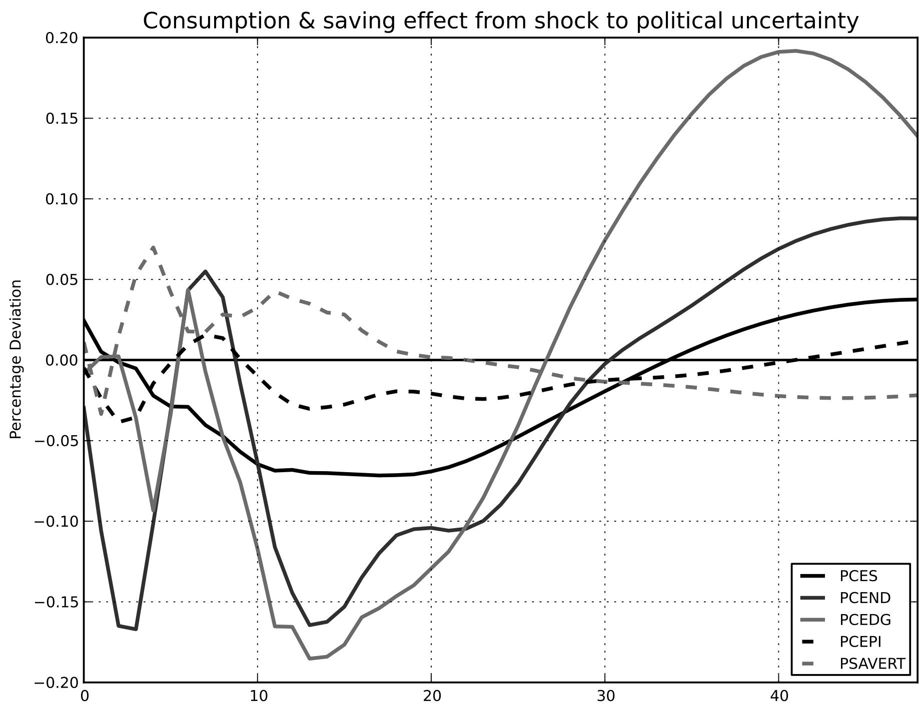


Figure 8: FAVAR identified impulse responses of consumption expenditure and saving from shock to policy uncertainty.

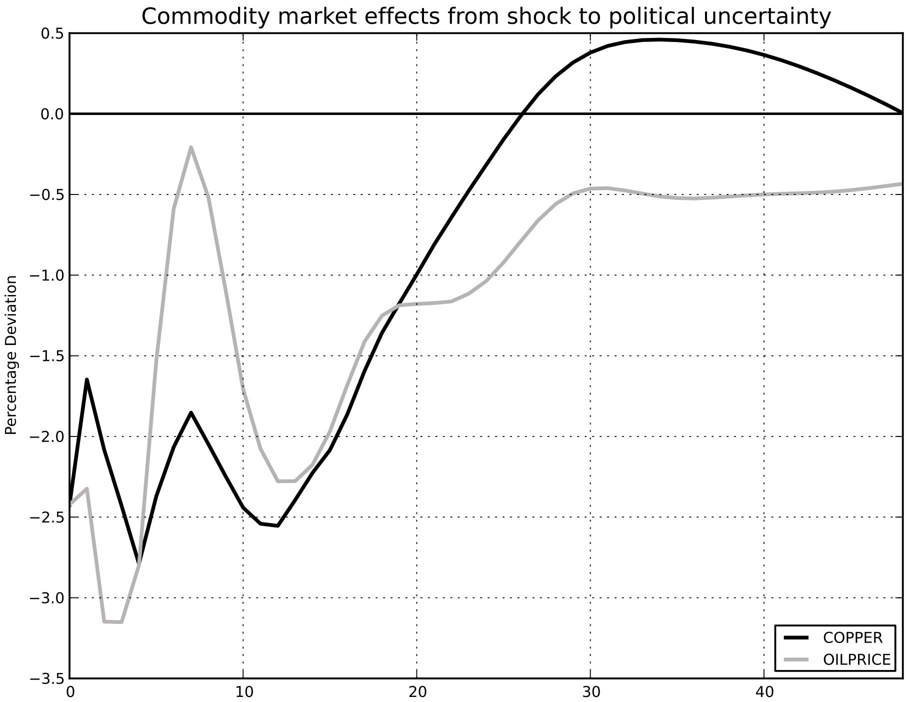


Figure 9: FAVAR identified impulse responses of Copper and Oil prices from shock to policy uncertainty.

Data Appendix

Table 1: Summary of all data used in FAVAR

No.	Description	Code	Source	Original Units	Identification schemes: Benchmark	Alt1	Alt2	TCode
1	Bloom et al.'s policy uncertainty index	UNCERT	Bloom et al.	Index	Identified	Identified	Identified	4
2	Standard and Poor's 500 US Stock Market Index	SPINDEX	Bloom et al.	Index	Fast	Slow	Slow	4
3	US Federal Funds Rate	FFR	Bloom et al.	Percent	Fast	Slow	Slow	1
4	US Total Civilian Employment	EMP	Bloom et al.	Total no. of persons in 1000s	Slow	Slow	Slow	7
5	US Industrial Production Index	IP	Bloom et al.	Index	Slow	Slow	Slow	7
6	Price of Copper in US dollars	COPPER	Bloom et al.	US dollars per tonne	Fast	Fast	Fast	4
7	2-Year Treasury Constant Maturity Rate	GS2	St. Louis Fed	Percent	Fast	Fast	Slow	1
8	10-Year Treasury Constant Maturity Rate	GS10	St. Louis Fed	Percent	Fast	Fast	Slow	1
9	Producer Price Index: Finished Goods	PPIFGS	St. Louis Fed	Index 1982=100	Slow	Slow	Slow	7
10	Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	St. Louis Fed	Index 1982-84=100	Slow	Slow	Slow	7
11	Consumer Price Index for All Urban Consumers: All Items Less Food and Energy	CPILFESL	St. Louis Fed	Index 1982-84=100	Slow	Slow	Slow	7
12	M2 Money Stock	M2SL	St. Louis Fed	Billions of Dollars	Fast	Fast	Slow	7
13	Chicago Fed National Activity Index	CFNAI	St. Louis Fed	Index	Fast	Fast	Slow	1
14	Industrial Production: Durable Consumer Goods	IPDCONGD	St. Louis Fed	Index 2007=100	Slow	Slow	Slow	7
15	Capacity Utilization: Total Industry	TCU	St. Louis Fed	Percent of Capacity	Slow	Slow	Slow	1
16	Capacity Utilization: Manufacturing (NAICS)	MCUMFN	St. Louis Fed	Percent of Capacity	Slow	Slow	Slow	1
17	Housing Starts: Total: New Privately Owned Housing Units Started	HOUST	St. Louis Fed	Thousands of Units	Slow	Slow	Slow	4
18	ISM Manufacturing: PMI Composite Index	NAPM	St. Louis Fed	Index	Fast	Fast	Slow	1
19	Leading Index for the United States	USSLIND	St. Louis Fed	Percent	Fast	Fast	Slow	1
20	4-Week Moving Average of Initial Claims	IC4WSA	St. Louis Fed	Number	Slow	Slow	Slow	4
21	Personal Saving Rate	PSAVERT	St. Louis Fed	Percent	Slow	Slow	Slow	1
22	MZM Money Stock	MZM	St. Louis Fed	Billions of Dollars	Fast	Fast	Slow	7
23	3-Month Treasury Bill: Secondary Market Rate	TB3MS	St. Louis Fed	Percent	Fast	Fast	Slow	1
24	6-Month Treasury Bill: Secondary Market Rate	TB6MS	St. Louis Fed	Percent	Fast	Fast	Slow	1
25	1-Year Treasury Constant Maturity Rate	GS1	St. Louis Fed	Percent	Fast	Fast	Slow	1
26	5-Year Treasury Constant Maturity Rate	GS5	St. Louis Fed	Percent	Fast	Fast	Slow	1
27	University of Michigan: Consumer Sentiment	UMCSENT	St. Louis Fed	Index 1st Quarter 1966=100	Fast	Fast	Slow	1
28	Employment Level - Part-Time for Economic Reasons	LNS12032195	St. Louis Fed	Thousands of Persons	Slow	Slow	Slow	7
29	Moody's Seasoned Aaa Corporate Bond Yield	AAA	St. Louis Fed	Percent	Fast	Fast	Slow	1
30	Civilian Employment-Population Ratio	EMRATIO	St. Louis Fed	Percent	Slow	Slow	Slow	7
31	Spot Oil Price: West Texas Intermediate	OILPRICE	St. Louis Fed	Dollars per Barrel	Fast	Fast	Fast	4
32	Real Disposable Personal Income	DSPIC96	St. Louis Fed	Billions of Chained 2005 Dollars	Slow	Slow	Slow	7
33	30-Year Conventional Mortgage Rate	MORTG	St. Louis Fed	Percent	Fast	Fast	Slow	1
34	Currency Component of M1	CURRENCY	St. Louis Fed	Billions of Dollars	Fast	Fast	Slow	7
35	Moody's Seasoned Baa Corporate Bond Yield	BAA	St. Louis Fed	Percent	Fast	Fast	Slow	1
36	Personal Consumption Expenditures	PCE	St. Louis Fed	Billions of Dollars	Slow	Slow	Slow	7
37	Total Consumer Credit Outstanding	TOTALSL	St. Louis Fed	Billions of Dollars	Fast	Fast	Slow	7
38	Gross Private Domestic Investment (interpolated from quarterly frequency)	GPDI	St. Louis Fed	Billions of Dollars	Slow	Slow	Slow	7
39	ISM Manufacturing: Inventories Index	NAPMII	St. Louis Fed	Index	Fast	Fast	Slow	1
40	ISM Manufacturing: New Orders Index	NAPMNOI	St. Louis Fed	Index	Fast	Fast	Slow	1
41	ISM Manufacturing: Employment Index	NAPMEI	St. Louis Fed	Index	Fast	Fast	Slow	1
42	ISM Manufacturing: Supplier Deliveries Index	NAPMSDI	St. Louis Fed	Index	Fast	Fast	Slow	1
43	ISM Manufacturing: Prices Index	NAPMPRI	St. Louis Fed	Index	Fast	Fast	Slow	1
44	ISM Manufacturing: Production Index	NAPMPI	St. Louis Fed	Index	Fast	Fast	Slow	1
45	Consumer Price Index for All Urban Consumers: Food	CPIUFDNS	St. Louis Fed	Index 1982-84=100	Slow	Slow	Slow	7
46	Consumer Price Index for All Urban Consumers: Commodities	CUSR0000SAC	St. Louis Fed	Index 1982-84=100	Slow	Slow	Slow	7
47	Consumer Price Index for All Urban Consumers: Energy services	CUSR0000SEHF	St. Louis Fed	Index 1982-84=100	Slow	Slow	Slow	7
48	Consumer Price Index for All Urban Consumers: Transportation services	CUSR0000SAS4	St. Louis Fed	Index 1982-84=100	Slow	Slow	Slow	7
49	Producer Price Index: Intermediate Materials: Supplies and Components	PPIITM	St. Louis Fed	Index 1982=100	Slow	Slow	Slow	7
50	7-Year Treasury Constant Maturity Rate	GS7	St. Louis Fed	Percent	Fast	Fast	Slow	1
51	3-Year Treasury Constant Maturity Rate	GS3	St. Louis Fed	Percent	Fast	Fast	Slow	1
52	Personal Consumption Expenditures: Chain-type Price Index	PCEPI	St. Louis Fed	Index 2005=100	Slow	Slow	Slow	7
53	Personal Consumption Expenditures: Chain-Type Price Index Less Food and Energy	PCEPILFE	St. Louis Fed	Index 2005=100	Slow	Slow	Slow	7
54	Personal Consumption Expenditures: Durable Goods	PCEDG	St. Louis Fed	Billions of Dollars	Slow	Slow	Slow	7
55	Personal Consumption Expenditures: Nondurable Goods	PCEND	St. Louis Fed	Billions of Dollars	Slow	Slow	Slow	7
56	Personal Consumption Expenditures: Services	PCES	St. Louis Fed	Billions of Dollars	Slow	Slow	Slow	7
57	Total Nonrevolving Credit Outstanding	NONREVSL	St. Louis Fed	Billions of Dollars	Fast	Fast	Slow	7
58	Trade Weighted U.S. Dollar Index: Major Currencies	TWEXMMTH	St. Louis Fed	Index March 1973=100	Fast	Fast	Slow	4
59	Velocity of MZM Money Stock (interpolated from quarterly frequency)	MZMV	St. Louis Fed	Ratio	Slow	Slow	Slow	4
60	Velocity of M2 Money Stock (interpolated from quarterly frequency)	M2V	St. Louis Fed	Ratio	Slow	Slow	Slow	4
61	Velocity of M1 Money Stock (interpolated from quarterly frequency)	M1V	St. Louis Fed	Ratio	Slow	Slow	Slow	4

Notes: Transformation codes are: 1=levels, 2=first seasonal difference, 3=second seasonal difference, 4=log level, 5=log first seasonal difference, 6=log second seasonal difference, 7=log hp-filtered monthly data. Alt1 shows the identification scheme used in the commodities ahead only set-up, while Alt2 also adds survey data ahead of policy uncertainty.

Replicated scaled IRFs from Bloom et al

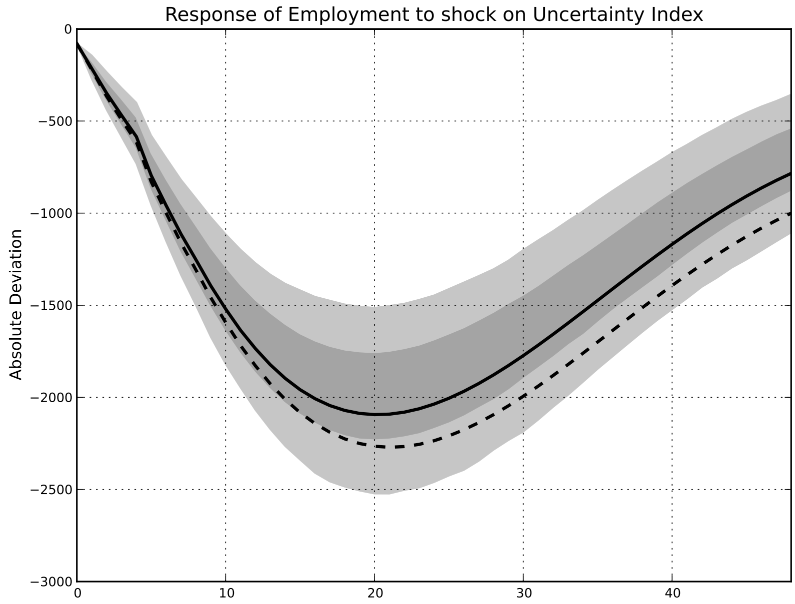


Figure 10: Replicated (scaled) impulse response from original SVAR study of Bloom et al. Units in 1000s of workers.

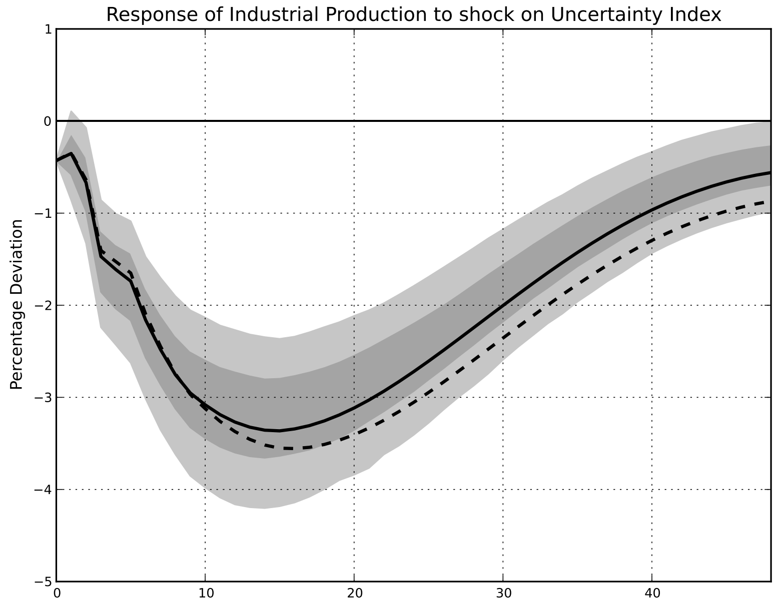


Figure 11: Replicated (scaled) impulse response from original SVAR study of Bloom et al.(2012). Units in percentages.

Table 2: Contribution of Policy Uncertainty Shock to Variance of Forecasts
Benchmark ordering

		Variance Decomposition at h						
No.	Variable	h=6	h=12	h=18	h=24	h=36	h=60	R^2
0	UNCERT	0.555	0.481	0.424	0.389	0.364	0.337	1.000
1	SPINDEX	0.101	0.115	0.134	0.126	0.095	0.071	0.967
2	FFR	0.194	0.219	0.207	0.174	0.138	0.171	0.976
3	EMP	0.107	0.194	0.261	0.255	0.184	0.199	0.954
4	IP	0.189	0.206	0.259	0.226	0.186	0.198	0.886
5	COPPER	0.166	0.180	0.196	0.180	0.160	0.147	0.962
6	GS2	0.229	0.209	0.184	0.155	0.133	0.159	0.994
7	GS10	0.146	0.114	0.097	0.091	0.081	0.085	0.992
8	PPIFGS	0.042	0.042	0.055	0.068	0.069	0.079	0.946
9	CPIAUCSL	0.026	0.027	0.039	0.052	0.064	0.073	0.977
10	CPILFESL	0.043	0.027	0.019	0.020	0.079	0.098	0.847
11	M2SL	0.203	0.254	0.253	0.223	0.249	0.235	0.833
12	CFNAI	0.120	0.074	0.055	0.067	0.125	0.128	0.812
13	IPDCONGD	0.078	0.075	0.107	0.088	0.097	0.118	0.867
14	TCU	0.087	0.107	0.129	0.096	0.131	0.183	0.978
15	MCUMFN	0.075	0.092	0.107	0.078	0.128	0.179	0.985
16	HOUST	0.070	0.058	0.043	0.035	0.049	0.067	0.843
17	NAPM	0.184	0.130	0.103	0.115	0.146	0.146	0.980
18	USSLIND	0.174	0.112	0.083	0.085	0.153	0.150	0.919
19	IC4WSA	0.148	0.162	0.158	0.116	0.128	0.149	0.935
20	PSAVERT	0.029	0.035	0.039	0.036	0.034	0.035	0.964
21	MZM	0.320	0.295	0.278	0.252	0.255	0.264	0.936
22	TB3MS	0.239	0.242	0.222	0.186	0.151	0.183	0.981
23	TB6MS	0.236	0.240	0.220	0.184	0.152	0.183	0.986
24	GS1	0.219	0.220	0.199	0.166	0.139	0.170	0.991
25	GS5	0.195	0.163	0.141	0.124	0.110	0.125	0.995
26	UMCSENT	0.106	0.099	0.070	0.065	0.094	0.102	0.919
27	LNS12032195	0.242	0.247	0.264	0.212	0.180	0.192	0.859
28	AAA	0.040	0.028	0.024	0.022	0.017	0.029	0.981
29	EMRATIO	0.085	0.187	0.254	0.243	0.179	0.198	0.916
30	OILPRICE	0.174	0.141	0.163	0.163	0.151	0.145	0.957
31	DSPIC96	0.016	0.021	0.057	0.100	0.093	0.111	0.804
32	MORTG	0.087	0.068	0.059	0.050	0.037	0.053	0.992
33	CURRENCY	0.040	0.045	0.108	0.142	0.144	0.147	0.894
34	BAA	0.009	0.006	0.006	0.007	0.022	0.029	0.976
35	PCE	0.035	0.065	0.154	0.175	0.150	0.169	0.960
36	TOTALSL	0.086	0.098	0.083	0.086	0.094	0.106	0.950
37	GPDI	0.170	0.219	0.268	0.225	0.181	0.194	0.929
38	NAPMII	0.178	0.133	0.116	0.090	0.127	0.128	0.763
39	NAPMNOI	0.188	0.127	0.103	0.125	0.142	0.147	0.905
40	NAPMEI	0.268	0.193	0.148	0.129	0.163	0.157	0.940
41	NAPMSDI	0.038	0.033	0.040	0.074	0.099	0.107	0.878
42	NAPMPRI	0.046	0.042	0.037	0.040	0.047	0.050	0.920
43	NAPMPI	0.196	0.135	0.108	0.126	0.145	0.148	0.941
44	CPIUFDNS	0.045	0.087	0.067	0.070	0.118	0.123	0.798
45	CUSR0000SAC	0.051	0.043	0.059	0.066	0.067	0.075	0.955
46	CUSR0000SEHF	0.003	0.007	0.031	0.055	0.061	0.067	0.903
47	CUSR0000SAS4	0.028	0.146	0.161	0.161	0.151	0.142	0.795
48	PPIITM	0.045	0.035	0.061	0.075	0.070	0.097	0.936
49	GS7	0.175	0.140	0.120	0.109	0.097	0.106	0.994
50	GS3	0.220	0.193	0.168	0.144	0.125	0.147	0.995
51	PCEPI	0.045	0.036	0.052	0.063	0.070	0.079	0.988
52	PCEPILFE	0.044	0.050	0.056	0.055	0.077	0.087	0.899
53	PCEDG	0.005	0.019	0.053	0.057	0.059	0.090	0.836
54	PCEND	0.071	0.056	0.094	0.105	0.098	0.116	0.936
55	PCES	0.032	0.136	0.228	0.270	0.236	0.236	0.914
56	NONREVSL	0.057	0.097	0.087	0.078	0.072	0.088	0.958
57	TWEXMMTH	0.015	0.011	0.009	0.008	0.007	0.009	0.954
58	MZMV	0.063	0.052	0.044	0.038	0.077	0.165	0.988
59	M2V	0.022	0.043	0.043	0.036	0.059	0.104	0.948
60	M1V	0.221	0.250	0.288	0.291	0.260	0.187	0.965

Notes: Right-hand side column shows R^2 from regression of variables on factors.

Table 3: Contribution of Policy Uncertainty Shock to Variance of Forecasts
Only commodities order first

		Variance Decomposition at h						
No.	Variable	h=6	h=12	h=18	h=24	h=36	h=60	R^2
0	UNCERT	0.652	0.568	0.504	0.453	0.381	0.320	1.000
1	SPINDEX	0.082	0.085	0.099	0.102	0.084	0.059	0.967
2	FFR	0.050	0.083	0.084	0.071	0.055	0.059	0.976
3	EMP	0.031	0.055	0.087	0.092	0.070	0.062	0.954
4	IP	0.061	0.063	0.093	0.080	0.063	0.061	0.886
5	COPPER	0.049	0.072	0.095	0.086	0.076	0.069	0.962
6	GS2	0.101	0.110	0.100	0.084	0.071	0.072	0.994
7	GS10	0.067	0.059	0.054	0.060	0.060	0.060	0.992
8	PPIFGS	0.023	0.039	0.041	0.040	0.037	0.037	0.946
9	CPIAUCSL	0.030	0.027	0.036	0.035	0.032	0.032	0.977
10	CPILFESL	0.031	0.050	0.041	0.033	0.035	0.035	0.847
11	M2SL	0.026	0.060	0.104	0.096	0.099	0.092	0.833
12	CFNAI	0.043	0.027	0.022	0.024	0.035	0.036	0.812
13	IPDCONGD	0.156	0.088	0.079	0.062	0.050	0.048	0.867
14	TCU	0.028	0.041	0.069	0.054	0.049	0.064	0.978
15	MCUMFN	0.024	0.036	0.058	0.044	0.044	0.062	0.985
16	HOUST	0.049	0.045	0.034	0.027	0.021	0.019	0.843
17	NAPM	0.044	0.033	0.029	0.038	0.044	0.041	0.980
18	USSLIND	0.034	0.022	0.021	0.021	0.038	0.040	0.919
19	IC4WSA	0.037	0.053	0.068	0.054	0.042	0.043	0.935
20	PSAVERT	0.039	0.049	0.055	0.052	0.046	0.035	0.964
21	MZM	0.041	0.051	0.064	0.059	0.066	0.070	0.936
22	TB3MS	0.079	0.106	0.102	0.085	0.068	0.069	0.981
23	TB6MS	0.085	0.113	0.108	0.090	0.072	0.072	0.986
24	GS1	0.082	0.105	0.099	0.082	0.067	0.068	0.991
25	GS5	0.093	0.093	0.084	0.078	0.072	0.071	0.995
26	UMCSENT	0.013	0.025	0.018	0.015	0.016	0.019	0.919
27	LNS12032195	0.049	0.056	0.085	0.074	0.058	0.055	0.859
28	AAA	0.034	0.025	0.024	0.031	0.026	0.028	0.981
29	EMRATIO	0.020	0.052	0.090	0.097	0.074	0.066	0.916
30	OILPRICE	0.052	0.046	0.064	0.060	0.053	0.054	0.957
31	DSPIC96	0.028	0.023	0.028	0.047	0.047	0.046	0.804
32	MORTG	0.040	0.032	0.028	0.027	0.023	0.027	0.992
33	CURRENCY	0.011	0.013	0.052	0.085	0.089	0.085	0.894
34	BAA	0.014	0.010	0.014	0.017	0.012	0.012	0.976
35	PCE	0.035	0.037	0.076	0.081	0.069	0.065	0.960
36	TOTALSL	0.072	0.123	0.116	0.097	0.077	0.059	0.950
37	GPDI	0.025	0.034	0.087	0.087	0.065	0.061	0.929
38	NAPMII	0.058	0.052	0.043	0.034	0.039	0.036	0.763
39	NAPMNOI	0.050	0.035	0.031	0.043	0.045	0.043	0.905
40	NAPMEI	0.039	0.028	0.024	0.027	0.037	0.035	0.940
41	NAPMSDI	0.023	0.020	0.021	0.039	0.043	0.041	0.878
42	NAPMPRI	0.048	0.043	0.039	0.046	0.047	0.043	0.920
43	NAPMPI	0.052	0.038	0.033	0.046	0.049	0.046	0.941
44	CPIUFDNS	0.034	0.069	0.061	0.051	0.046	0.043	0.798
45	CUSR0000SAC	0.036	0.035	0.041	0.039	0.036	0.036	0.955
46	CUSR0000SEHF	0.001	0.008	0.042	0.067	0.070	0.069	0.903
47	CUSR0000SAS4	0.028	0.138	0.143	0.148	0.143	0.128	0.795
48	PPIITM	0.018	0.029	0.038	0.038	0.033	0.038	0.936
49	GS7	0.081	0.077	0.069	0.070	0.067	0.066	0.994
50	GS3	0.101	0.106	0.096	0.083	0.072	0.072	0.995
51	PCEPI	0.041	0.032	0.047	0.046	0.042	0.042	0.988
52	PCEPILFE	0.100	0.155	0.164	0.147	0.125	0.101	0.899
53	PCEDG	0.003	0.007	0.013	0.016	0.015	0.021	0.836
54	PCEND	0.040	0.037	0.051	0.048	0.043	0.045	0.936
55	PCES	0.048	0.121	0.171	0.184	0.158	0.135	0.914
56	NONREVSL	0.061	0.153	0.157	0.134	0.100	0.076	0.958
57	TWEXMMTH	0.061	0.038	0.032	0.028	0.023	0.019	0.954
58	MZMV	0.031	0.035	0.034	0.028	0.042	0.077	0.988
59	M2V	0.040	0.081	0.098	0.089	0.065	0.055	0.948
60	M1V	0.071	0.090	0.116	0.123	0.122	0.088	0.965

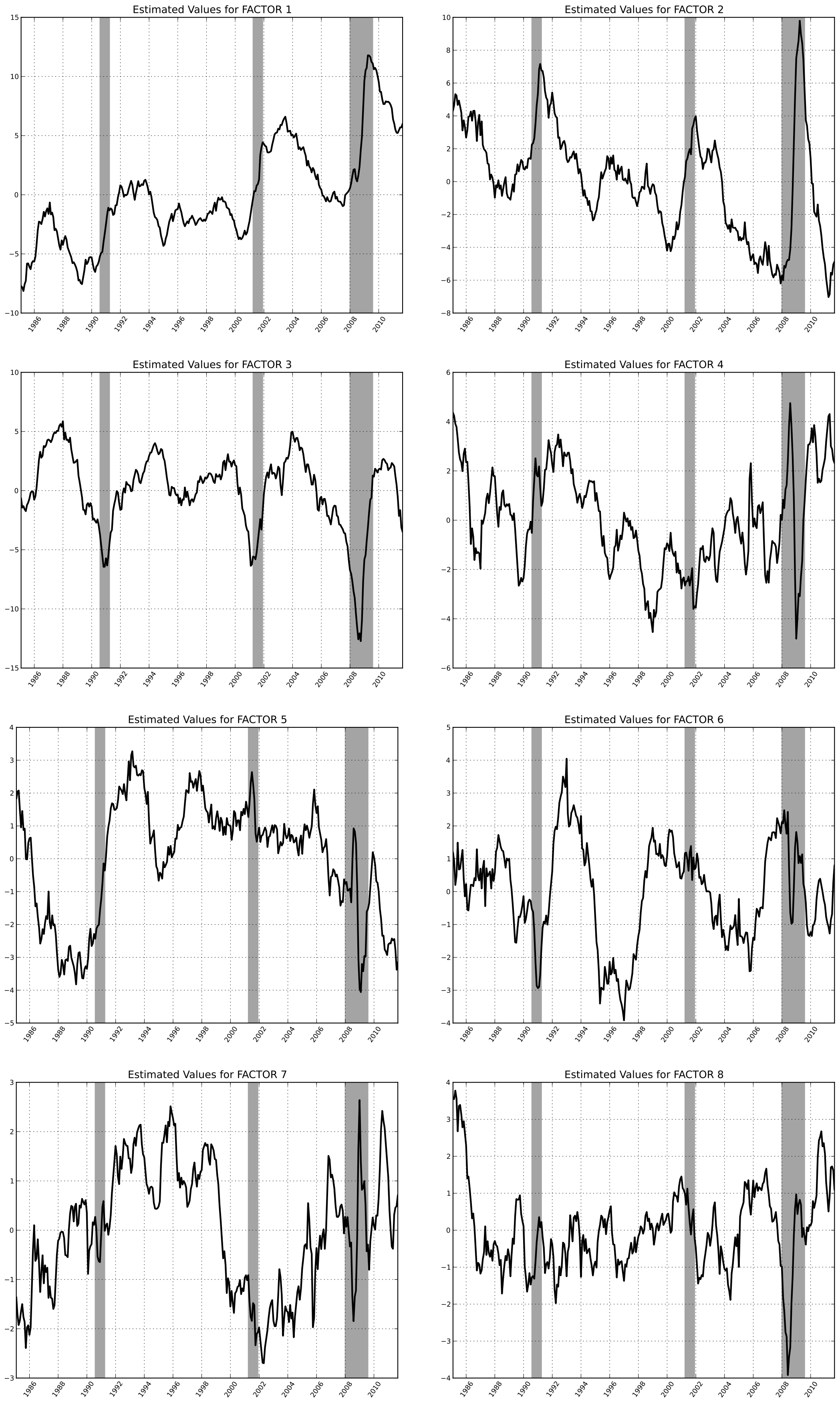
Notes: Right-hand side column shows R^2 from regression of variables on factors.

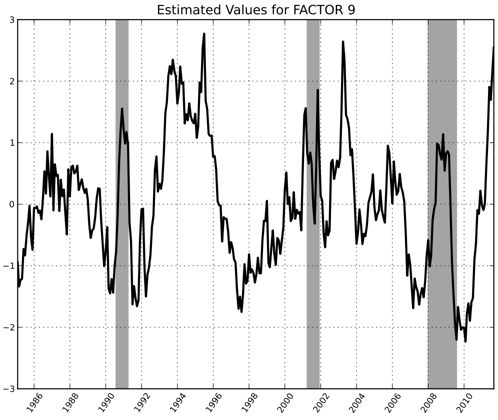
Table 4: Contribution of Policy Uncertainty Shock to Variance of Forecasts
Only commodities and survey data ordered first

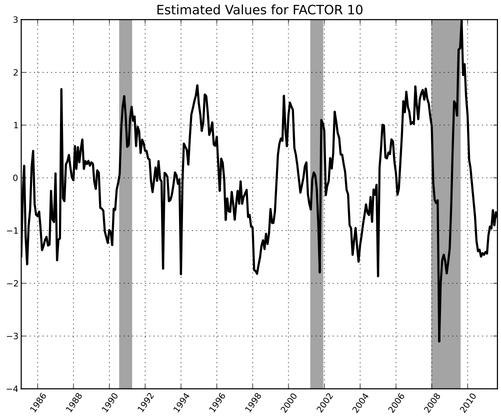
		Variance Decomposition at h						
No.	Variable	h=6	h=12	h=18	h=24	h=36	h=60	R^2
0	UNCERT	0.706	0.611	0.538	0.485	0.407	0.339	1.000
1	SPINDEX	0.071	0.056	0.050	0.045	0.034	0.025	0.967
2	FFR	0.017	0.044	0.052	0.046	0.035	0.033	0.976
3	EMP	0.062	0.064	0.081	0.076	0.056	0.048	0.954
4	IP	0.065	0.071	0.089	0.072	0.056	0.053	0.886
5	COPPER	0.024	0.036	0.046	0.040	0.036	0.032	0.962
6	GS2	0.055	0.071	0.072	0.060	0.048	0.041	0.994
7	GS10	0.064	0.065	0.063	0.060	0.051	0.042	0.992
8	PPIFGS	0.045	0.049	0.042	0.038	0.034	0.034	0.946
9	CPIAUCSL	0.033	0.029	0.030	0.027	0.025	0.025	0.977
10	CPILFESL	0.032	0.037	0.030	0.024	0.021	0.020	0.847
11	M2SL	0.023	0.037	0.061	0.054	0.059	0.058	0.833
12	CFNAI	0.054	0.033	0.024	0.025	0.028	0.029	0.812
13	IPDCONGD	0.092	0.059	0.054	0.041	0.033	0.033	0.867
14	TCU	0.023	0.032	0.043	0.031	0.029	0.040	0.978
15	MCUMFN	0.020	0.029	0.036	0.026	0.027	0.038	0.985
16	HOUST	0.115	0.080	0.059	0.045	0.033	0.028	0.843
17	NAPM	0.127	0.093	0.075	0.074	0.063	0.055	0.980
18	USSLIND	0.068	0.043	0.031	0.029	0.034	0.034	0.919
19	IC4WSA	0.060	0.072	0.068	0.050	0.037	0.037	0.935
20	PSAVERT	0.017	0.016	0.016	0.016	0.015	0.013	0.964
21	MZM	0.011	0.010	0.018	0.017	0.025	0.030	0.936
22	TB3MS	0.026	0.051	0.058	0.050	0.039	0.036	0.981
23	TB6MS	0.029	0.058	0.065	0.055	0.043	0.039	0.986
24	GS1	0.031	0.057	0.063	0.053	0.041	0.037	0.991
25	GS5	0.071	0.078	0.076	0.068	0.056	0.047	0.995
26	UMCSENT	0.020	0.028	0.020	0.017	0.016	0.018	0.919
27	LNS12032195	0.060	0.056	0.068	0.056	0.043	0.041	0.859
28	AAA	0.031	0.035	0.034	0.031	0.024	0.019	0.981
29	EMRATIO	0.053	0.066	0.082	0.077	0.058	0.050	0.916
30	OILPRICE	0.077	0.061	0.062	0.056	0.050	0.047	0.957
31	DSPIC96	0.022	0.025	0.033	0.040	0.036	0.036	0.804
32	MORTG	0.042	0.045	0.045	0.038	0.028	0.023	0.992
33	CURRENCY	0.024	0.020	0.025	0.036	0.039	0.038	0.894
34	BAA	0.020	0.026	0.023	0.019	0.017	0.014	0.976
35	PCE	0.044	0.043	0.065	0.064	0.055	0.052	0.960
36	TOTALSL	0.068	0.139	0.139	0.115	0.090	0.064	0.950
37	GPDI	0.047	0.049	0.078	0.067	0.049	0.047	0.929
38	NAPMII	0.122	0.090	0.074	0.057	0.048	0.039	0.763
39	NAPMNOI	0.159	0.108	0.086	0.085	0.070	0.063	0.905
40	NAPMEI	0.117	0.082	0.062	0.057	0.052	0.045	0.940
41	NAPMSDI	0.032	0.032	0.031	0.044	0.042	0.038	0.878
42	NAPMPRI	0.067	0.055	0.052	0.054	0.051	0.047	0.920
43	NAPMPI	0.154	0.107	0.087	0.087	0.073	0.065	0.941
44	CPIUFDNS	0.043	0.067	0.057	0.048	0.039	0.035	0.798
45	CUSR0000SAC	0.050	0.042	0.040	0.037	0.034	0.034	0.955
46	CUSR0000SEHF	0.003	0.007	0.022	0.036	0.038	0.038	0.903
47	CUSR0000SAS4	0.022	0.120	0.124	0.129	0.124	0.112	0.795
48	PPIITM	0.025	0.030	0.030	0.027	0.023	0.026	0.936
49	GS7	0.069	0.073	0.071	0.065	0.055	0.045	0.994
50	GS3	0.064	0.075	0.074	0.063	0.051	0.043	0.995
51	PCEPI	0.045	0.034	0.038	0.035	0.032	0.031	0.988
52	PCEPILFE	0.035	0.084	0.091	0.079	0.065	0.052	0.899
53	PCEDG	0.020	0.016	0.016	0.019	0.018	0.020	0.836
54	PCEND	0.066	0.050	0.051	0.045	0.040	0.040	0.936
55	PCES	0.035	0.121	0.156	0.155	0.129	0.112	0.914
56	NONREVSL	0.045	0.158	0.165	0.141	0.109	0.079	0.958
57	TWEXMMTH	0.052	0.033	0.027	0.025	0.022	0.018	0.954
58	MZMV	0.008	0.010	0.012	0.010	0.019	0.035	0.988
59	M2V	0.014	0.031	0.035	0.030	0.028	0.036	0.948
60	M1V	0.075	0.078	0.082	0.078	0.072	0.051	0.965

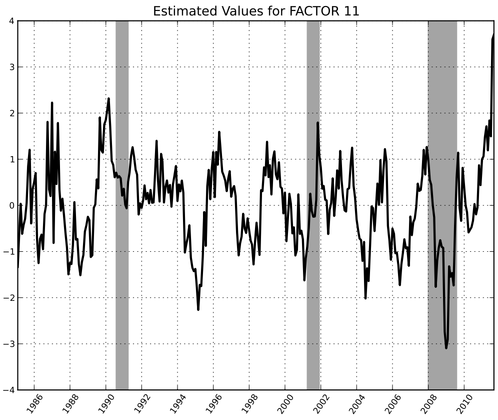
Notes: Right-hand side column shows R^2 from regression of variables on factors.

Estimated Factors and economic contractions




Estimated Values for FACTOR 9


Estimated Values for FACTOR 10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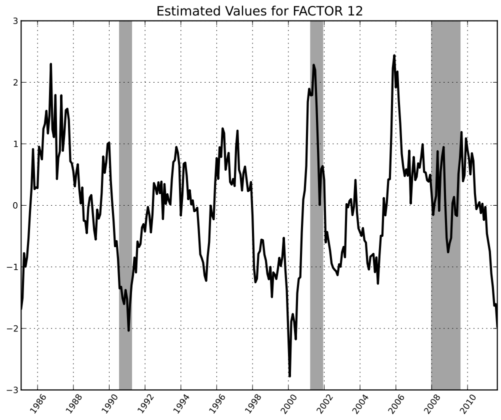
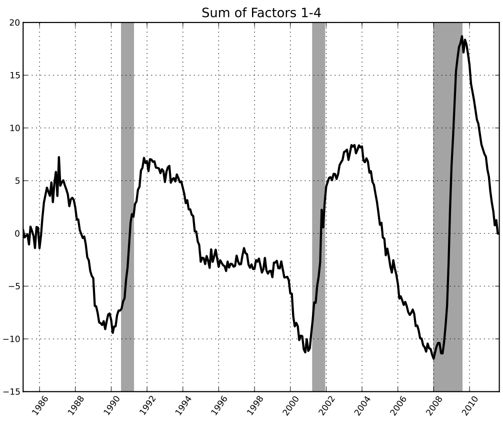
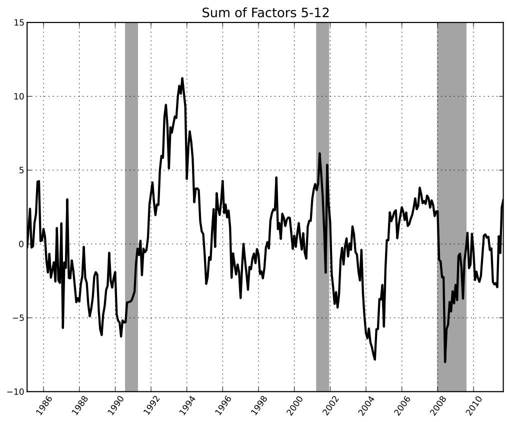
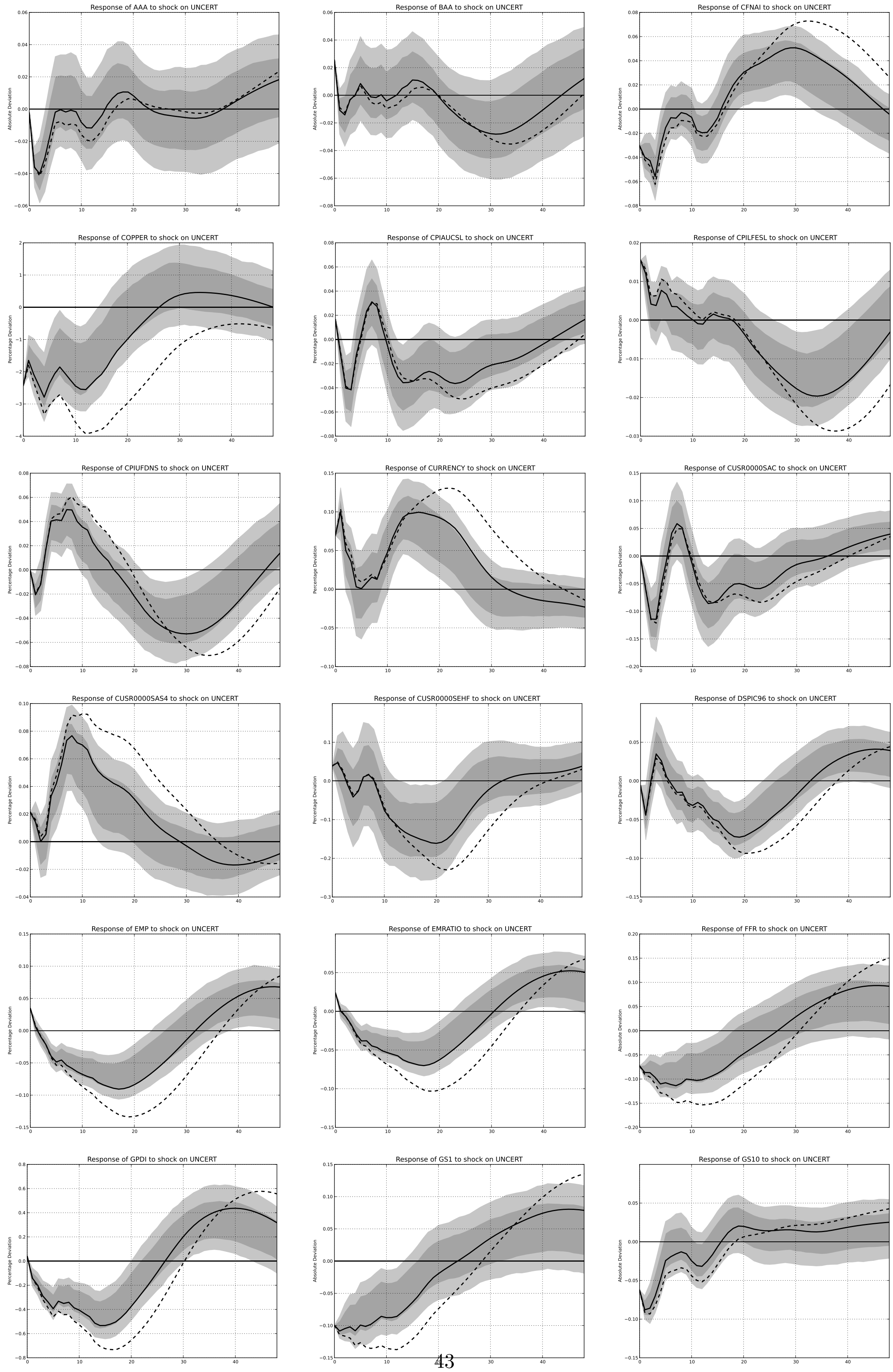
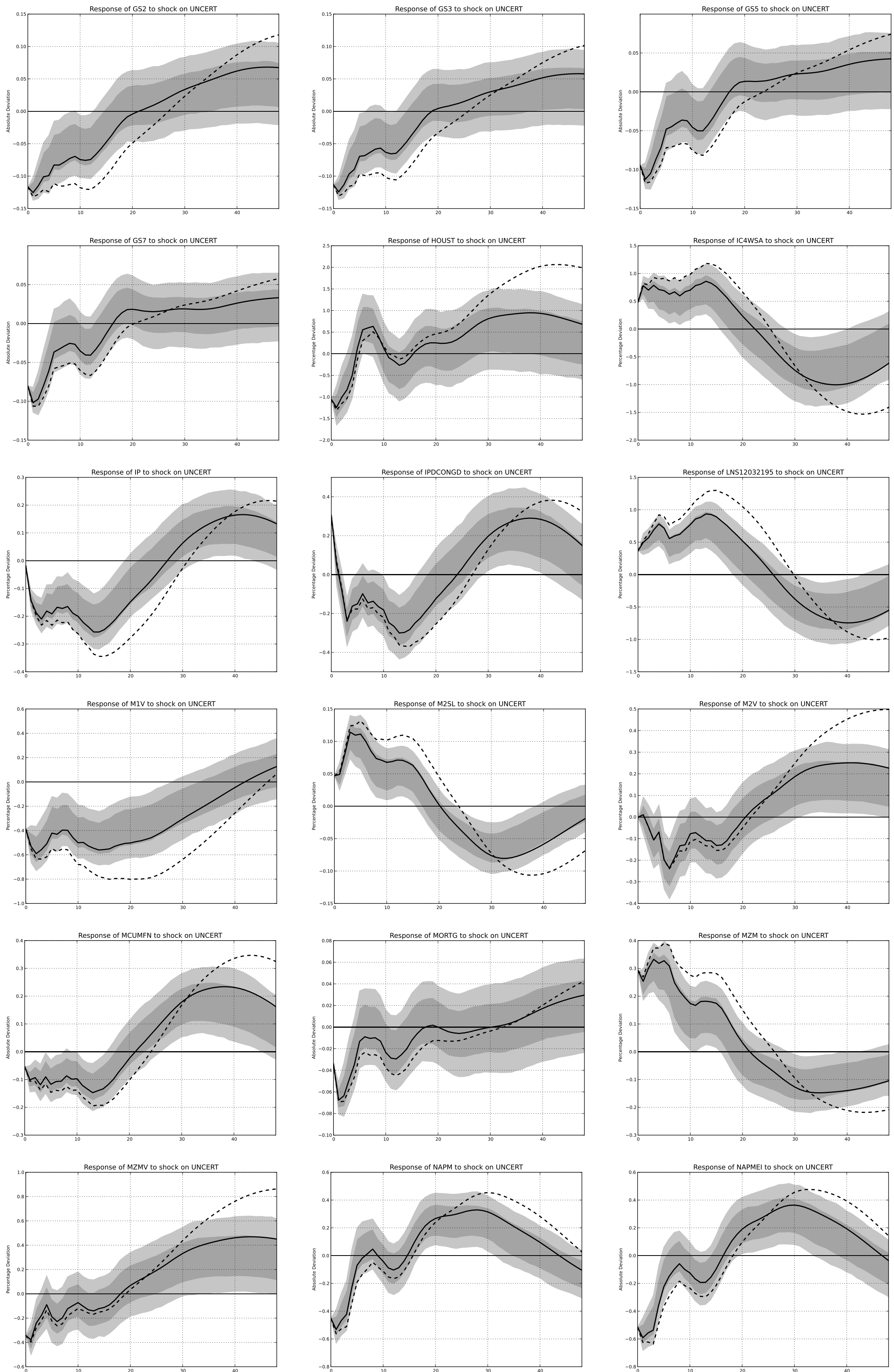

Estimated Values for FACTOR 12

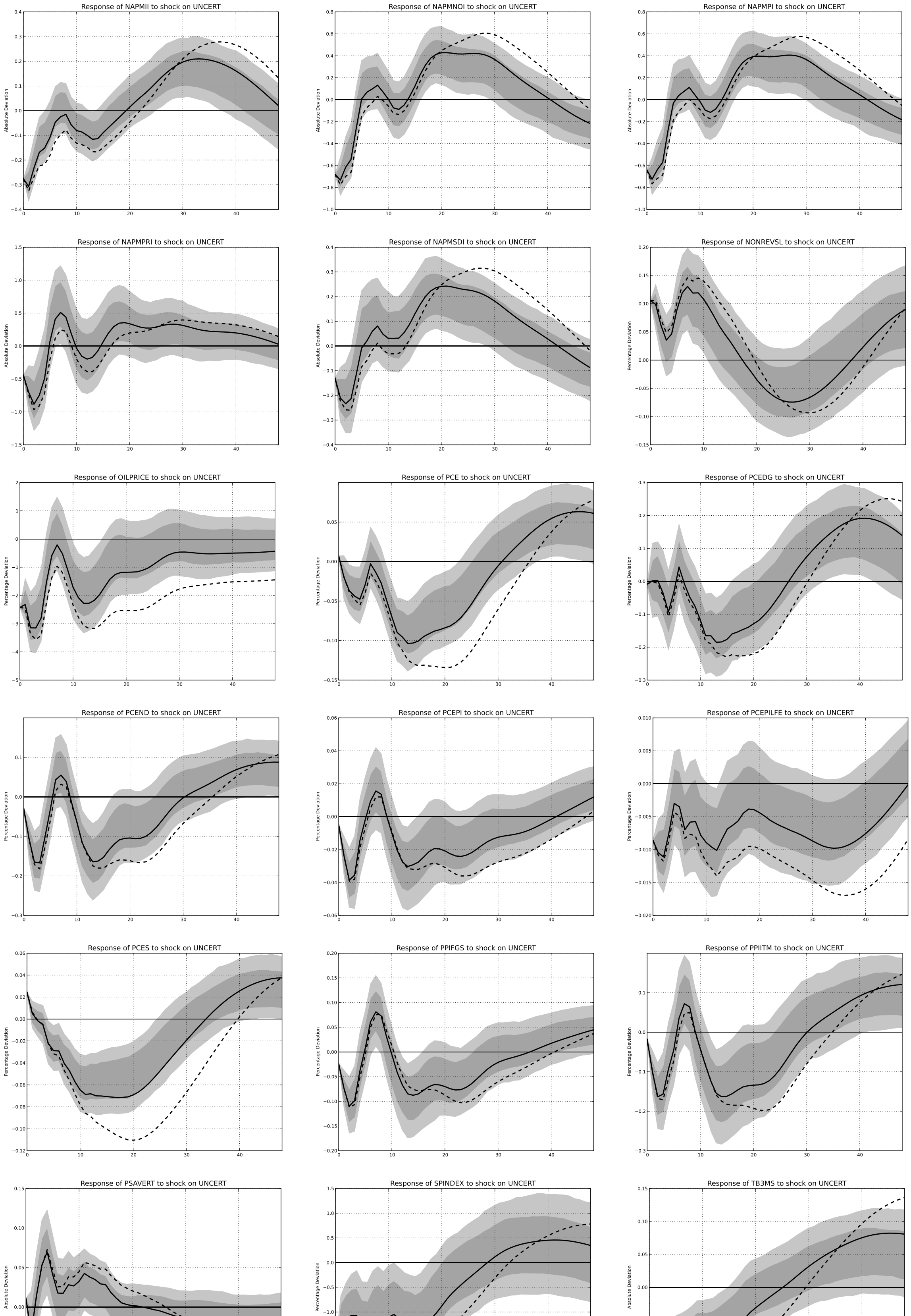

Sum of Factors 1-4

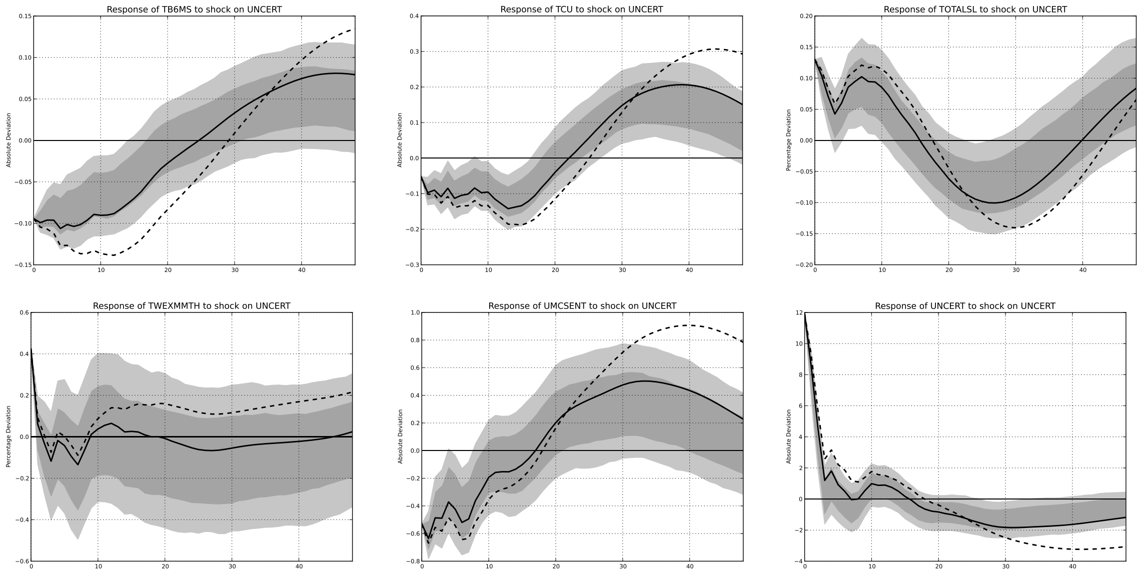

Sum of Factors 5-12

Impulse responses from policy uncertainty shock (Benchmark ordering)

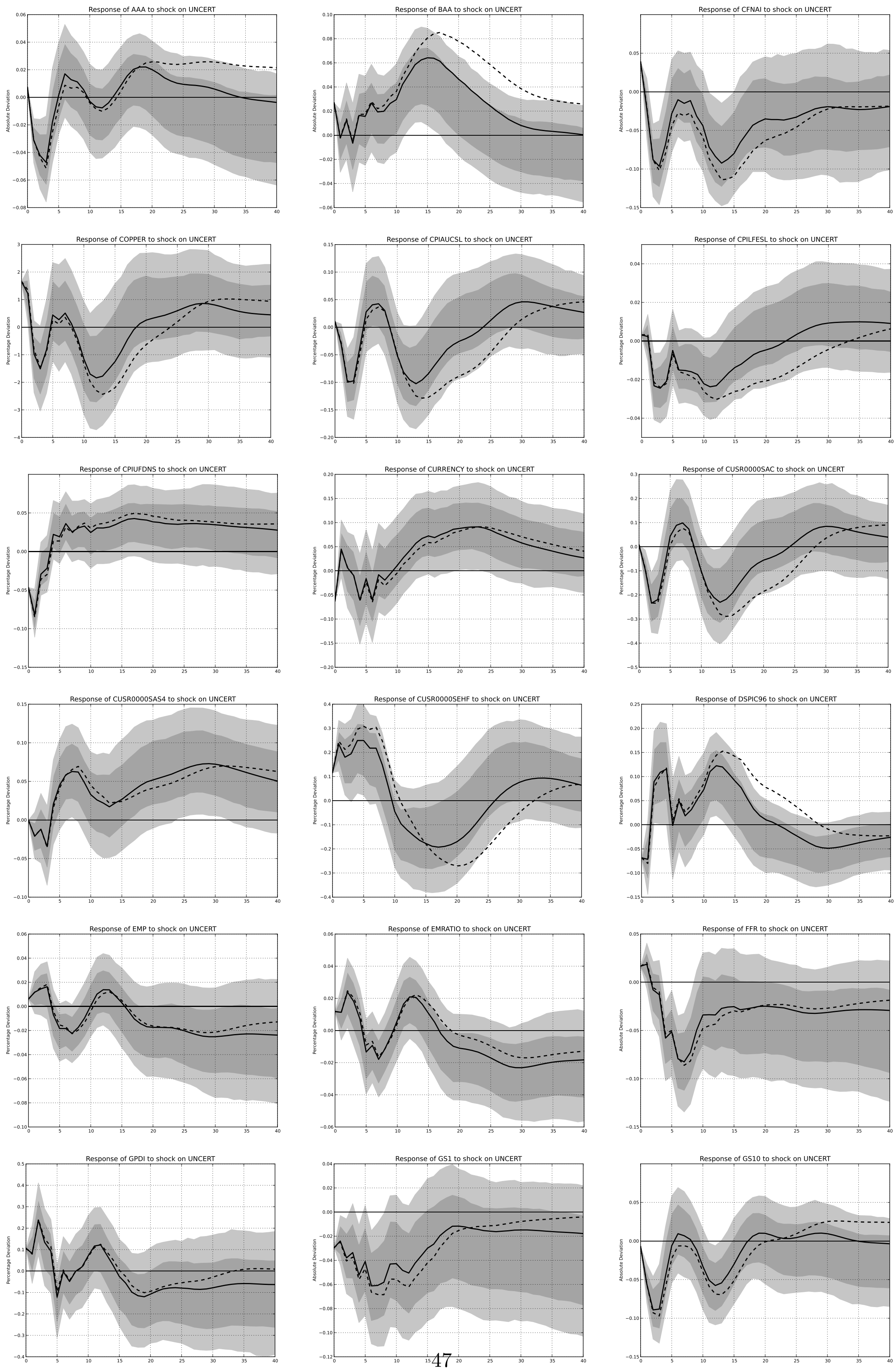


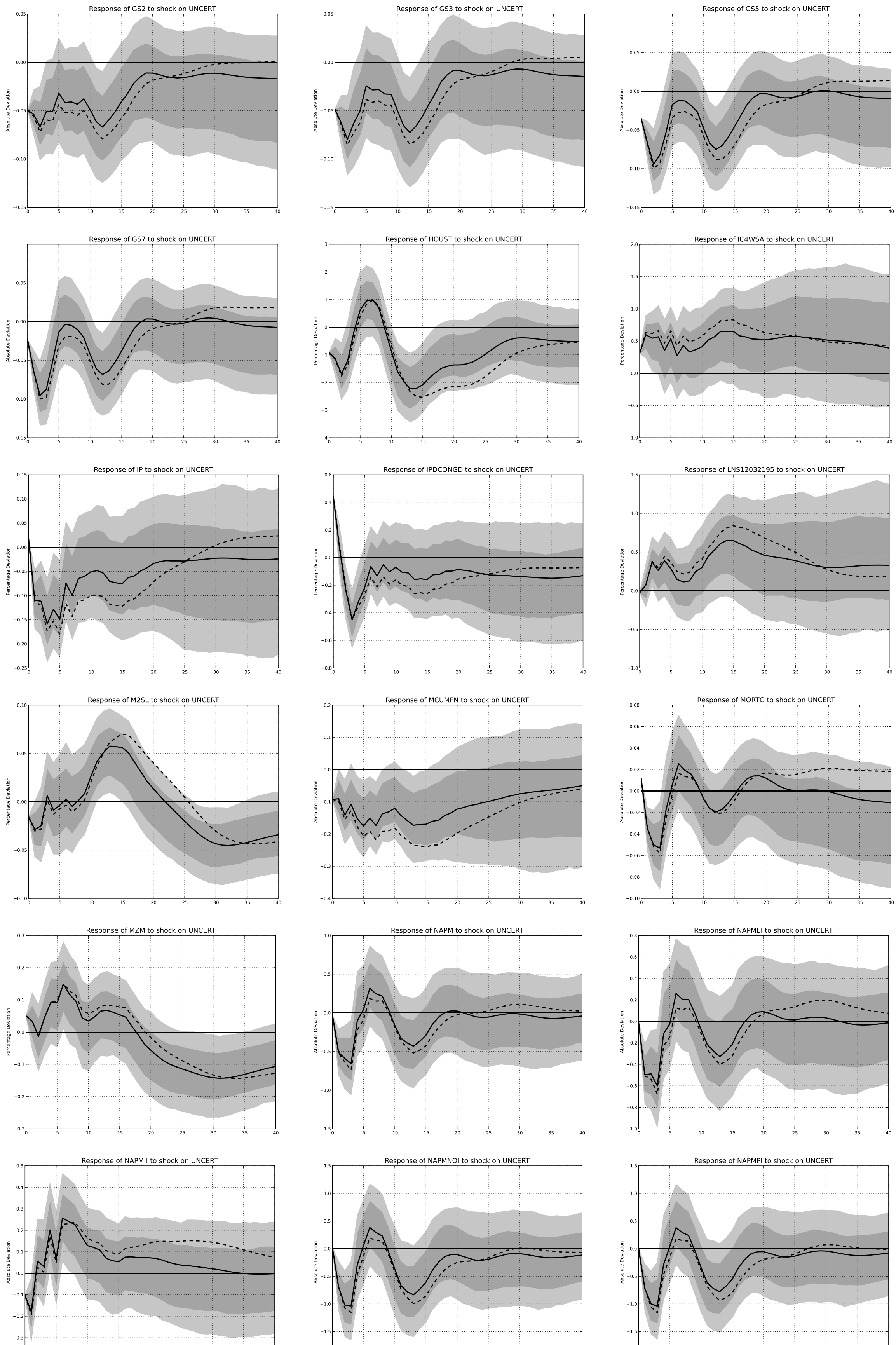

Response of GS2 to shock on UNCERT
Response of GS3 to shock on UNCERT
Response of GS5 to shock on UNCERT
Response of GS7 to shock on UNCERT
Response of HOUST to shock on UNCERT
Response of IC4WSA to shock on UNCERT
Response of IP to shock on UNCERT
Response of IPDCONGD to shock on UNCERT
Response of LNS12032195 to shock on UNCERT
Response of M1V to shock on UNCERT
Response of M2SL to shock on UNCERT
Response of M2V to shock on UNCERT
Response of MCUMFN to shock on UNCERT
Response of MORTG to shock on UNCERT
Response of MZM to shock on UNCERT
Response of MZMV to shock on UNCERT
Response of NAPM to shock on UNCERT
Response of NAPMEI to shock on UNCERT
Absolute Deviation
Percentage Deviation

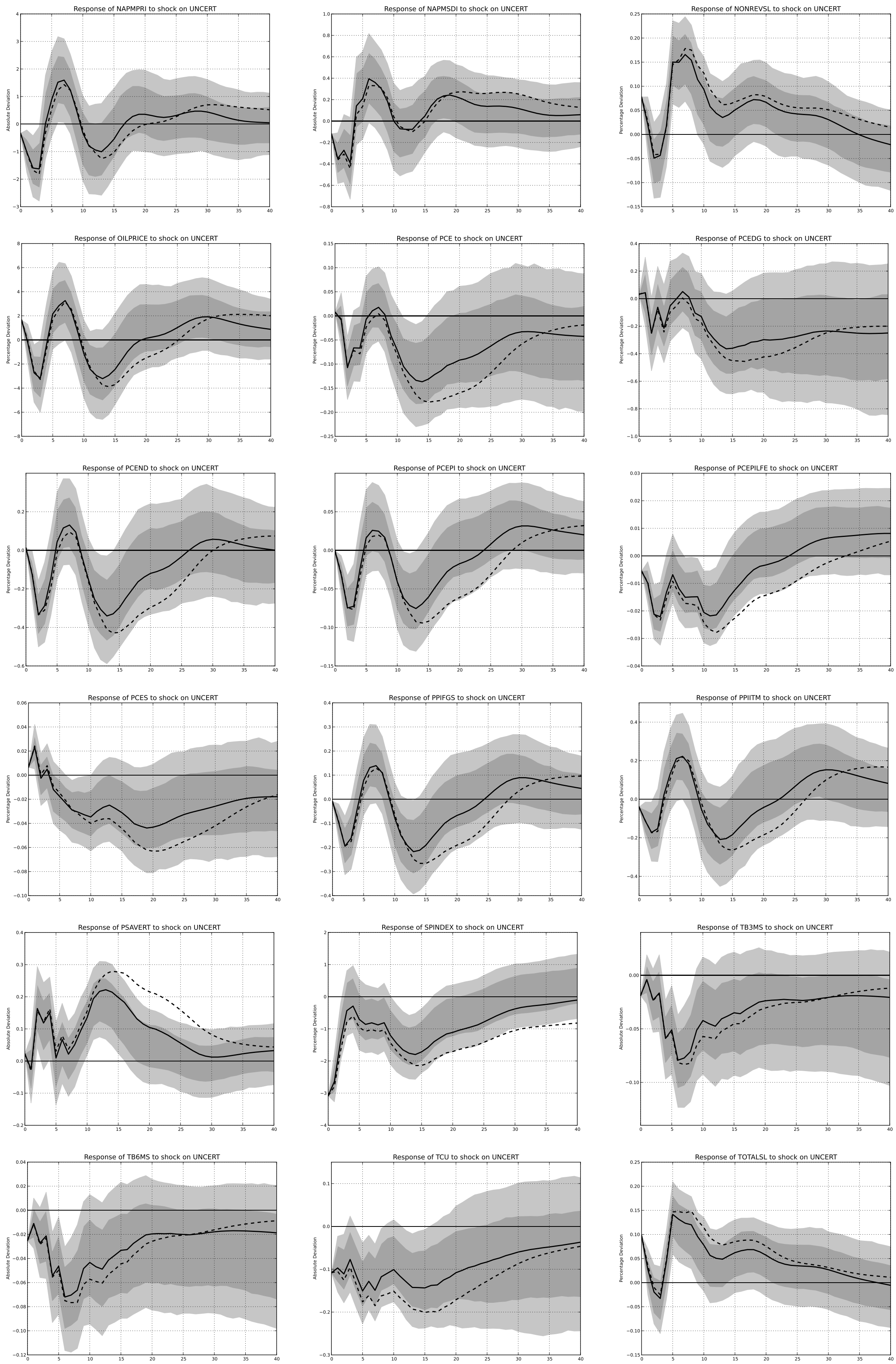

Response of NAPMII to shock on UNCERT
Absolute Deviation
Response of NAPMNOI to shock on UNCERT
Absolute Deviation
Response of NAPMPI to shock on UNCERT
Absolute Deviation
Response of NAPMPRI to shock on UNCERT
Absolute Deviation
Response of NAPMSDI to shock on UNCERT
Absolute Deviation
Response of NONREVSL to shock on UNCERT
Percentage Deviation
Response of OILPRICE to shock on UNCERT
Percentage Deviation
Response of PCE to shock on UNCERT
Percentage Deviation
Response of PCEDG to shock on UNCERT
Percentage Deviation
Response of PCEND to shock on UNCERT
Percentage Deviation
Response of PCEPI to shock on UNCERT
Percentage Deviation
Response of PCEPILFE to shock on UNCERT
Percentage Deviation
Response of PCES to shock on UNCERT
Percentage Deviation
Response of PPIFGS to shock on UNCERT
Percentage Deviation
Response of PPIITM to shock on UNCERT
Percentage Deviation
Response of PSAVERT to shock on UNCERT
Absolute Deviation
Response of SPINDEX to shock on UNCERT
Percentage Deviation
Response of TB3MS to shock on UNCERT
Absolute Deviation

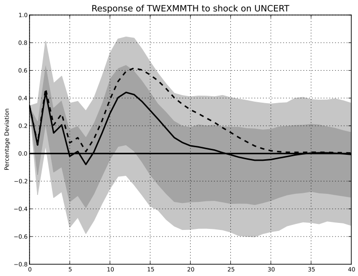

Response of TB6MS to shock on UNCERT
Absolute Deviation
Response of TCU to shock on UNCERT
Absolute Deviation
Response of TOTALSL to shock on UNCERT
Percentage Deviation
Response of TWEXMMTH to shock on UNCERT
Percentage Deviation
Response of UMCSENT to shock on UNCERT
Absolute Deviation
Response of UNCERT to shock on UNCERT
Absolute Deviation

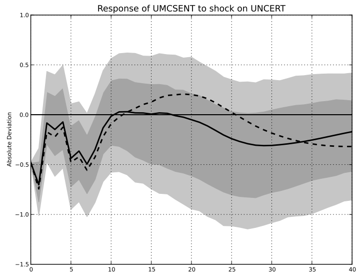
Impulse responses from policy uncertainty shock
(Only commodities ordered first)

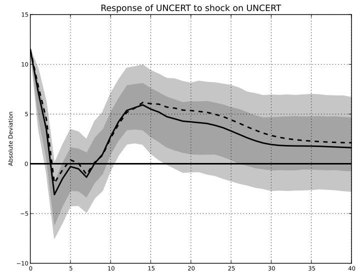



Response of GS2 to shock on UNCERT
Response of GS3 to shock on UNCERT
Response of GS5 to shock on UNCERT
Response of GS7 to shock on UNCERT
Response of HOUST to shock on UNCERT
Response of IC4WSA to shock on UNCERT
Response of IP to shock on UNCERT
Response of IPDCONGD to shock on UNCERT
Response of LNS12032195 to shock on UNCERT
Response of M2SL to shock on UNCERT
Response of MCUMFN to shock on UNCERT
Response of MORTG to shock on UNCERT
Response of MZM to shock on UNCERT
Response of NAPM to shock on UNCERT
Response of NAPMEI to shock on UNCERT
Response of NAPMII to shock on UNCERT
Response of NAPMNOI to shock on UNCERT
Response of NAPMPI to shock on UNCERT
Absolute Deviation
Percentage Deviation

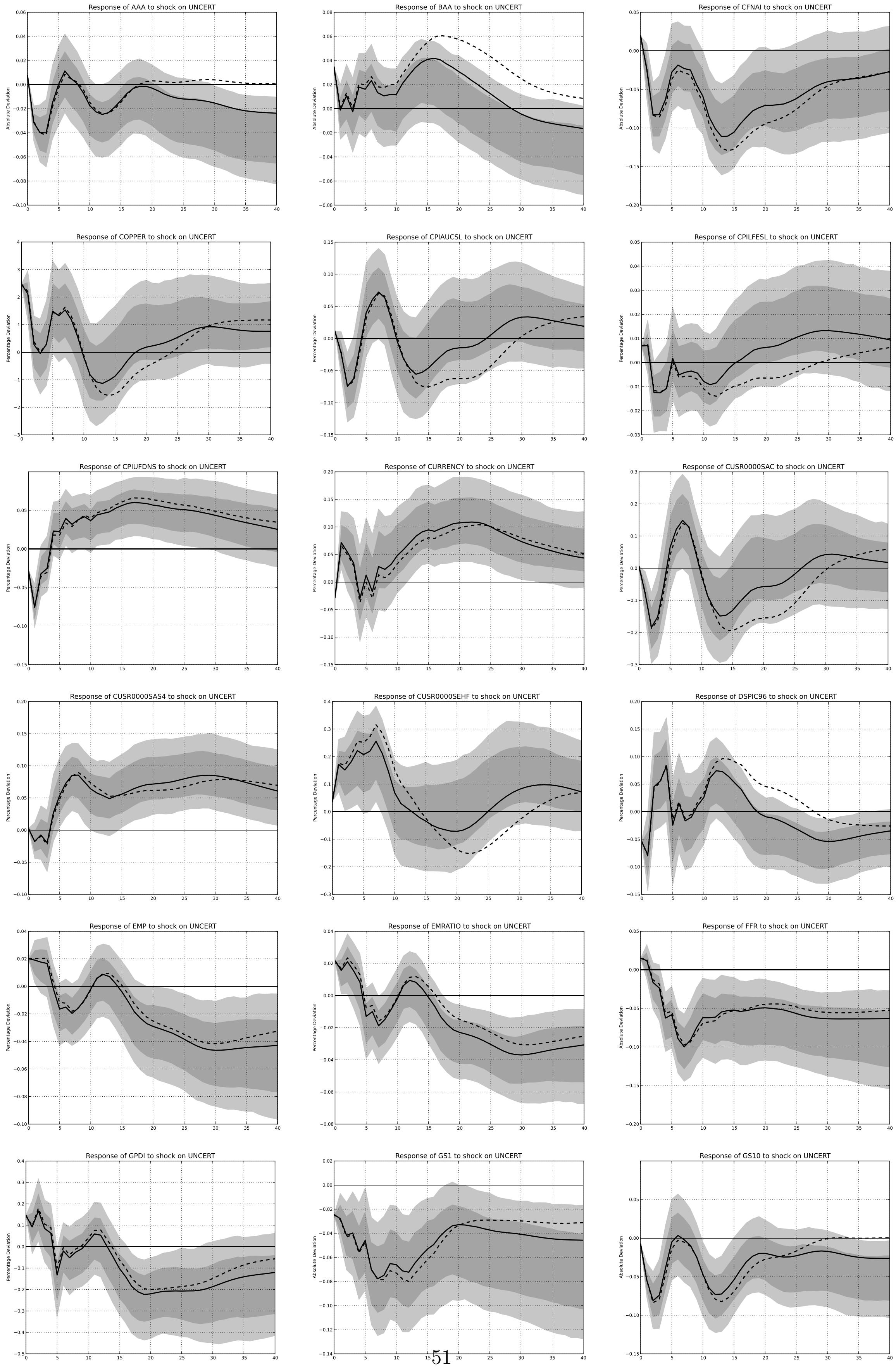

Response of NAPMPRI to shock on UNCERT
Absolute Deviation
Response of NAPMSDI to shock on UNCERT
Absolute Deviation
Response of NONREVSL to shock on UNCERT
Percentage Deviation
Response of OILPRICE to shock on UNCERT
Percentage Deviation
Response of PCE to shock on UNCERT
Percentage Deviation
Response of PCEDG to shock on UNCERT
Percentage Deviation
Response of PCEND to shock on UNCERT
Percentage Deviation
Response of PCEPI to shock on UNCERT
Percentage Deviation
Response of PCEPILFE to shock on UNCERT
Percentage Deviation
Response of PCES to shock on UNCERT
Percentage Deviation
Response of PPIFGS to shock on UNCERT
Percentage Deviation
Response of PPIITM to shock on UNCERT
Percentage Deviation
Response of PSAVERT to shock on UNCERT
Absolute Deviation
Response of SPINDEX to shock on UNCERT
Percentage Deviation
Response of TB3MS to shock on UNCERT
Absolute Deviation
Response of TB6MS to shock on UNCERT
Absolute Deviation
Response of TCU to shock on UNCERT
Absolute Deviation
Response of TOTALSL to shock on UNCERT
Percentage Deviation

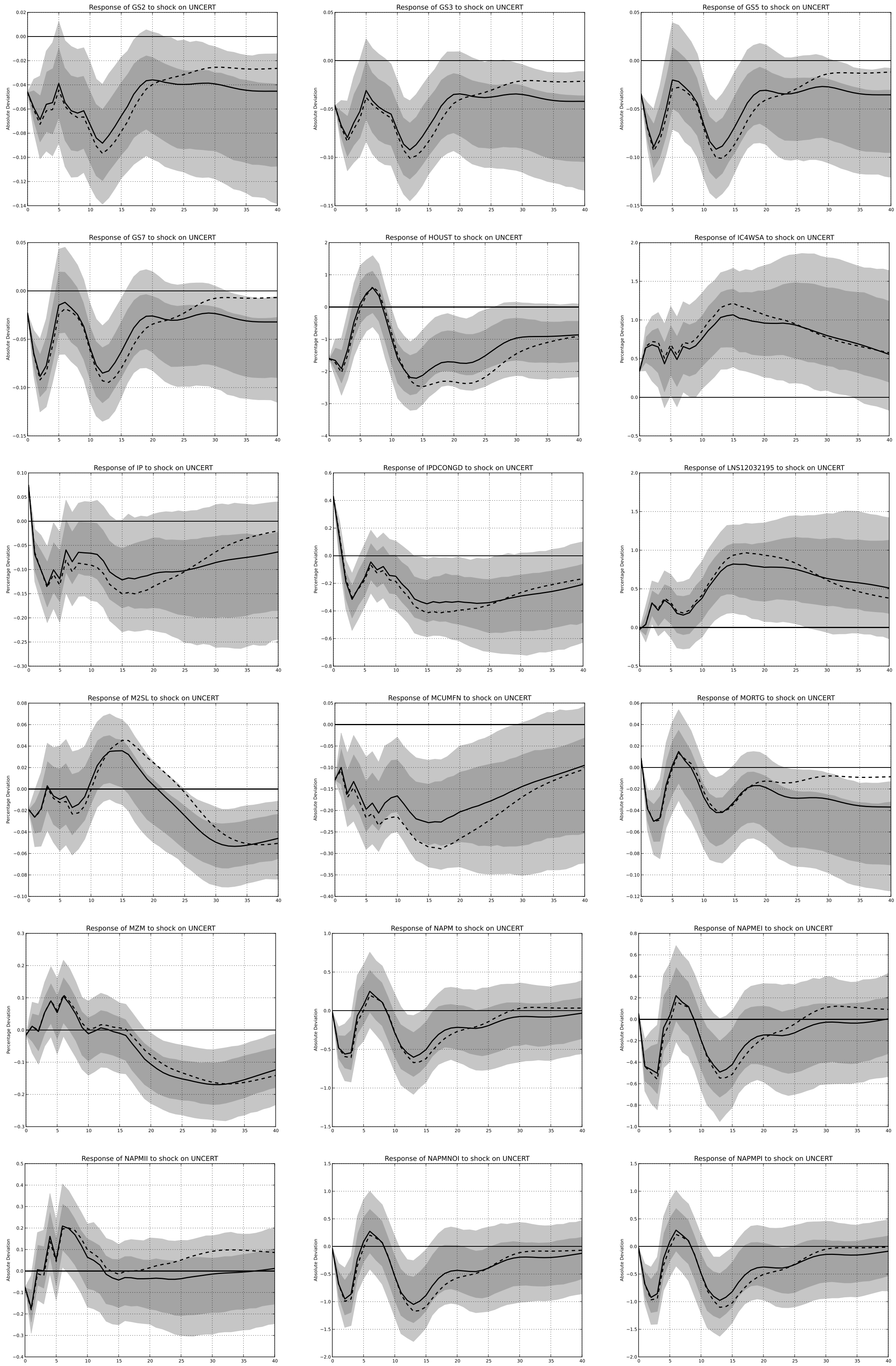

Response of TWEXMMTH to shock on UNCERT
Percentage Deviation


Response of UMCSENT to shock on UNCERT
Absolute Deviation


Response of UNCERT to shock on UNCERT
Absolute Deviation

Impulse responses from policy uncertainty shock
(Only commodities & survey data ordered first)




Response of GS2 to shock on UNCERT
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Response of GS5 to shock on UNCERT
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Response of HOUST to shock on UNCERT
Response of IC4WSA to shock on UNCERT
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Response of LNS12032195 to shock on UNCERT
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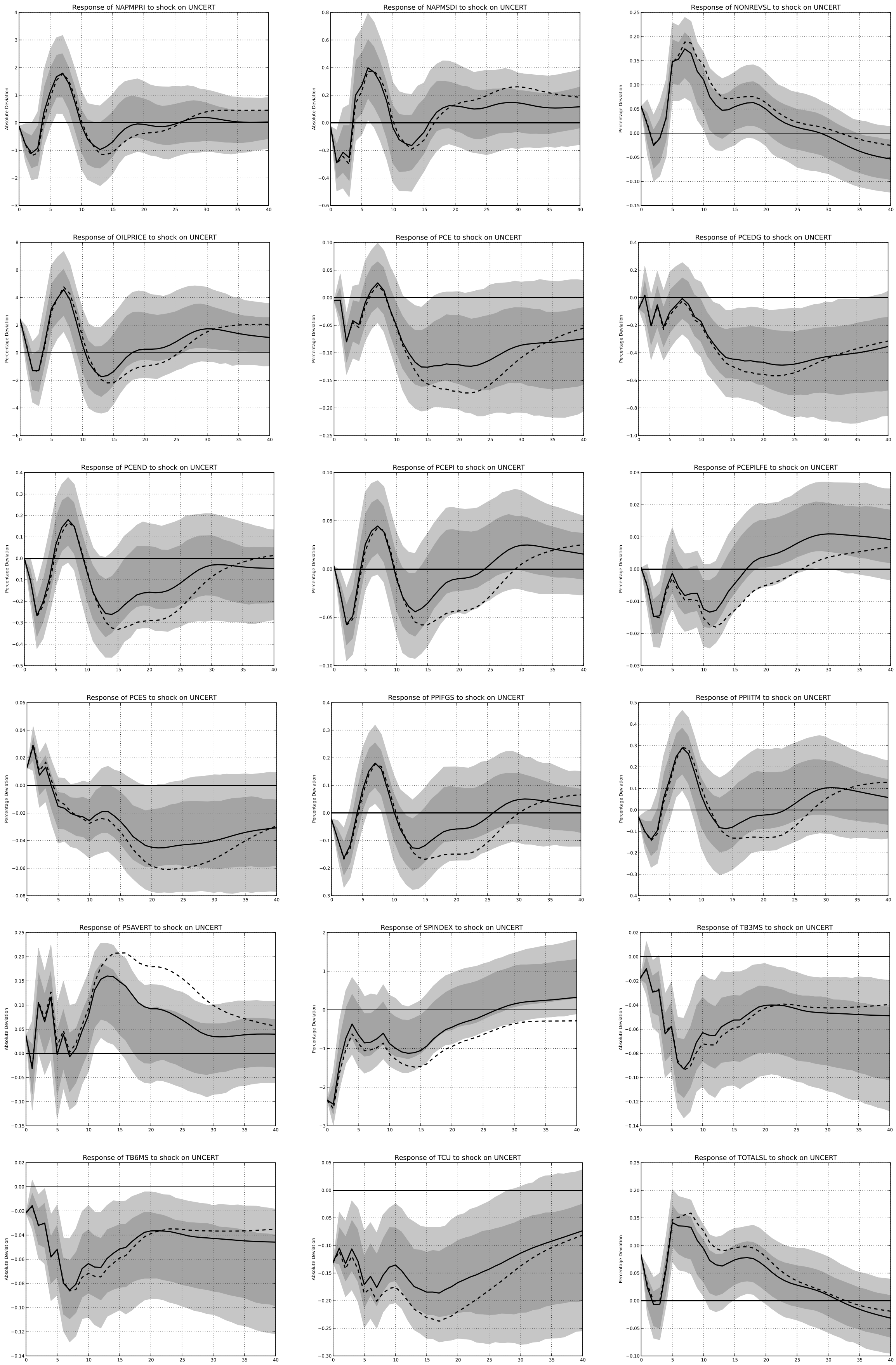
Response of MCUMFN to shock on UNCERT
Response of MORTG to shock on UNCERT
Response of MZM to shock on UNCERT
Response of NAPM to shock on UNCERT
Response of NAPMEI to shock on UNCERT
Response of NAPMII to shock on UNCERT
Response of NAPMNOI to shock on UNCERT
Response of NAPMPI to shock on UNCERT
Absolute Deviation
Percentage Deviation


Response of NAPMPRI to shock on UNCERT
Response of NAPMSDI to shock on UNCERT
Response of NONREVSL to shock on UNCERT
Response of OILPRICE to shock on UNCERT
Response of PCE to shock on UNCERT
Response of PCEDG to shock on UNCERT
Response of PCEND to shock on UNCERT
Response of PCEPI to shock on UNCERT
Response of PCEPILFE to shock on UNCERT
Response of PCES to shock on UNCERT
Response of PPIFGS to shock on UNCERT
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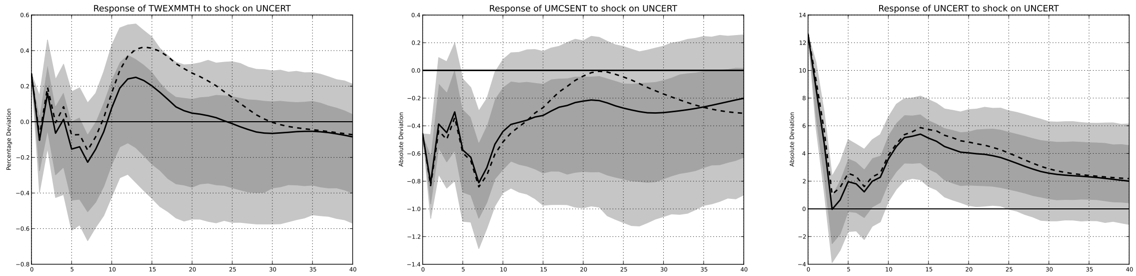
Response of PSAVERT to shock on UNCERT
Response of SPINDEX to shock on UNCERT
Response of TB3MS to shock on UNCERT
Response of TB6MS to shock on UNCERT
Response of TCU to shock on UNCERT
Response of TOTALSL to shock on UNCERT
Absolute Deviation
Percentage Deviation


Response of TWEXMMTH to shock on UNCERT
Percentage Deviation
Response of UMCSENT to shock on UNCERT
Absolute Deviation
Response of UNCERT to shock on UNCERT
Absolute Deviation

Scree Plots

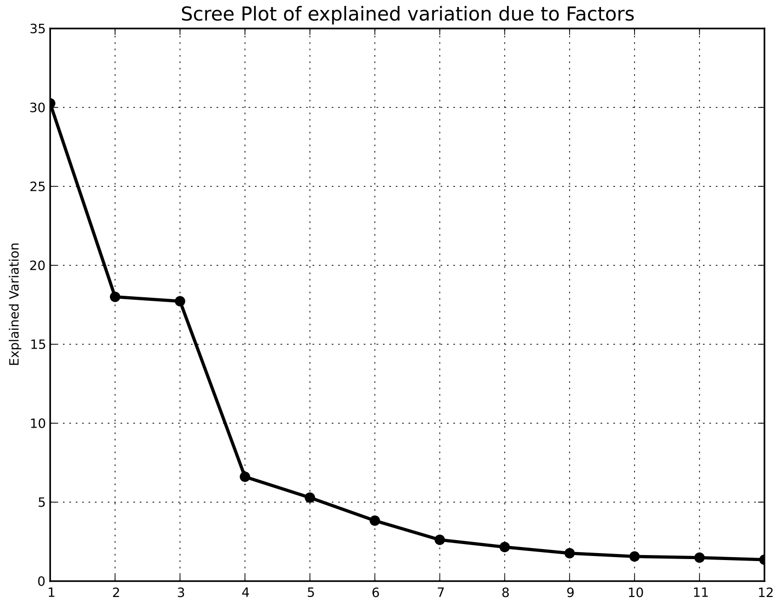


Figure 12: Scree plot plotting explained variation of data against number of extracted factors

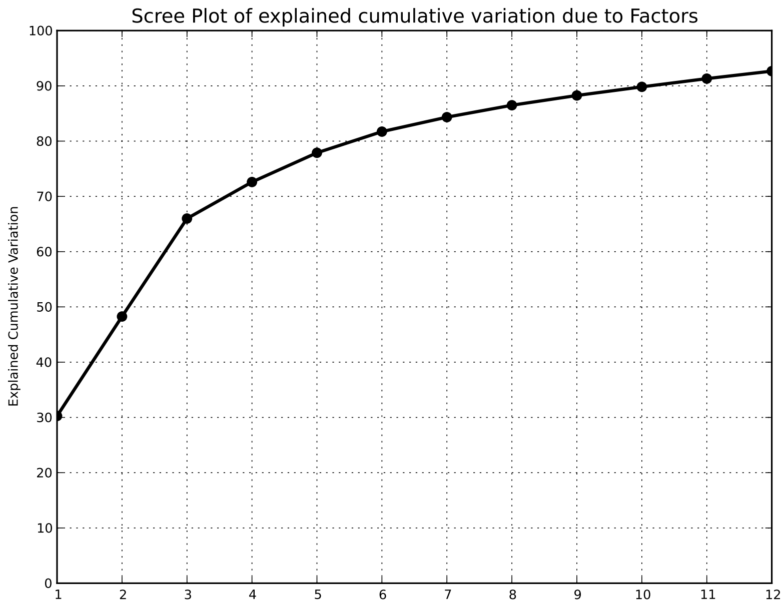


Figure 13: Scree plot plotting cumulative explained variation of data against number of extracted factors