ESSAYS ON MACROECONOMIC UNCERTAINTY AND MONETARY POLICY

by

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Abstract

This dissertation is composed of three chapters. In the first chapter, I introduce subjective and model-free measures of macroeconomic uncertainty, which are based on belief distributions for future inflation and output growth from the Survey of Professional Forecasters. I find that quantitatively important uncertainty episodes are rare, but persistent. My estimates of macroeconomic uncertainty exhibit strikingly different dynamics compared to existing uncertainty measures, suggesting that much of the variation in these measures is not driven by macroeconomic uncertainty. By re-examining recent empirical work on the relationship between macroeconomic uncertainty and real economic activity, I find that macroeconomic uncertainty shocks have a large and persistent effect on real activity, without an evidence of subsequent overshooting. Due to its model-free and subjective nature, I believe that my measure of uncertainty provides a natural benchmark to distinguish among several competing hypotheses about the association between macroeconomic uncertainty and economic activity.

The second chapter investigates the effects of an expansionary monetary policy shock that results in a 1% long-run increase in the price level on output, the bilateral real exchange rate with the United States and the price level in developing economies with inflation targeting. With an empirical panel-VAR model, we show that such a shock leads to a temporary increase in output, a temporary depreciation in the real exchange rate with the United States and a half percent contemporaneous increase in the price level. A multi-sector model with a staggered wage-setting mechanism and asymmetries among sectors with respect to the frequency of price changes is capable of explaining these aggregate dynamics.

The third, and the last, chapter uses quotes on options written on crude oil futures to construct nonparametric risk-neutral probability distribution functions (pdfs) for crude oil prices. Based on these pdfs, first, I show that the skewness and the extreme percentiles of these distributions are affected by U.S. macroeconomic news surprises, but the mean is not. Second, I find that these pdfs perform significantly better than density forecasts generated by popular time-series models at 1 to 3 months horizons. Finally, I show that options-implied volatility and skewness help with point prediction of future oil prices.

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To my lovely wife *Gizem*,
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Chapter 1

Measuring Uncertainty and Evaluating its Impacts on Macroeconomic Fluctuations

1.1 Introduction

The seminal contribution by Bloom (2009) and recent economic events have led researchers to estimate and evaluate the role of time-varying uncertainty on economic activity. Yet, uncertainty is an unobserved process. Therefore, to examine the relationship between uncertainty and economic activity, researchers have relied on different proxies for uncertainty[1]. While a consistent theme of this literature is the negative association between uncertainty and real activity, studies disagree on other empirical properties of uncertainty and its role in explaining economic fluctuations. Furthermore, existing uncertainty measures are tightly

[1]See Leahy and Whited (1996); Campbell, Lettau, Malkiel, and Xu (2001); Bloom, Bond, and Van Reenen (2007); Bloom (2009) for stock market related; Bloom (2009); Berger and Vavra (2010); Kehrig (2010); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012); Bachmann and Bayer (2013) for firms related; Ferderer (1993); Leahy and Whited (1996); Bomberger (1996); Giordani and Söderlind (2003); Popescu and Smets (2010); Bachmann, Elstner, and Sims (2013); Baker, Bloom, and Davis (2012) for cross sectional dispersion of survey based forecasts related; and Alexopoulos and Cohen (2009); Baker, Bloom, and Davis (2012) for news related uncertainty proxies that are proposed in the literature.

linked to agents' perception of macroeconomic uncertainty only under very restrictive assumptions. For instance, option-implied stock market volatility, a widely used uncertainty measure, can change due to reasons besides macroeconomic uncertainty such as changes in expected stock returns or changes in risk aversion. Similarly, changes in cross-sectional dispersion of subjective forecasts, another widely used uncertainty measure, are reflective of disagreement, rather than how uncertain forecasters feel when producing their subjective forecasts.

In this paper, I provide model-free measures of macroeconomic uncertainty that are derived from the subjective density forecasts of experts from the Survey of Professional Forecasters (SPF) for future inflation and output growth. More specifically, I extract the common subjective uncertainty component, which I call the Subjective Consensus Uncertainty (SCU), across experts both for inflation and output growth. Consistent with uncertainty-based theories of the business cycle, the SCU measure captures the common variation perceived by all agents assuming the SPF truly elicits the subjective belief distribution of experts. Accordingly, I use inflation and output growth SCU estimates as the benchmark macroeconomic uncertainty estimates in my analysis.

I emphasize three novel features of the SCUs. First, they are ex-ante measures of economic uncertainty that capture common movements in the subjective ex-ante predictability about future values of either inflation or output growth. Second, the SCUs do not have to be tightly linked with fluctuations in aggregate or idiosyncratic volatility of realized economic outcomes. Typically, empirical macroeconomic uncertainty measurement literature derives uncertainty proxies that are associated with volatility in aggregate or idiosyncratic conditions (e.g. see Bloom (2009), Arellano, Bai, and Kehoe (2012), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), and Gilchrist, Sim, and Zakrajšek (2014)). However, in this paper, I estimate subjective macroeconomic uncertainty measures that are perceived by economic agents. Finally, the SCUs are model-free in nature, so rather than assuming a specific model to estimate macroeconomic uncertainty, the density forecasts of experts provide a direct way to estimate these objects for inflation and output growth.

The Survey of Professional Forecasters (SPF) provides density forecasts for future deflator inflation and output growth for a panel of macroeconomic forecasters. In each quarter, experts assign their subjective probabilities to some pre-assigned bins both for inflation and output growth. Naturally, the standard deviations of these distributions represent how uncertain forecaster are when making the forecast. However, it is not straightforward to work with these density forecasts so estimation of the SCUs from these distributions involves two key steps. First, following Engelberg, Manski, and Williams (2009), I fit a generalized beta distribution to experts' discretized subjective densities to back out the standard deviation of each forecast distribution. Second, I estimate the common component from these subjective forecast uncertainties by considering several structural changes in the SPF that I explain in detail later on.

The main results can be summarized as follows. First, I find significant independent variation in the existing uncertainty proxies as opposed to the SCU estimates. I demonstrate that uncertainty episodes are far less frequent than what is inferred from other commonly used uncertainty measures, such as the option-implied stock market volatility, measures of cross sectional dispersion of subjective forecasts or firms' asset returns and profits. In particular, the SCU estimates reveal four big uncertainty episodes in US macroeconomic history, which coincide with the deepest recessions in the US: one during the 1973-74 recession, two during the 1980-82 recessions and one during the 2007-09 recession. Second, the SCU estimates are far more persistent than other conventional uncertainty proxies. For instance, the inflation and the output growth SCUs have an AR(1) coefficient of 0.96 and 0.92 respectively whereas the corresponding values for conventional uncertainty measures are in 0.8 to 0.25 range. Third, I show that during economic downturns the SCUs can explain approximately half of the movements in the individual subjective forecast uncertainties of experts as opposed to one third during normal times. This is consistent with uncertainty-based theories that predict agents discount new information more heavily and adjust their subjective uncertainty slowly during economic downturns Van Nieuwerburgh and Veldkamp (2006); Orlik and Veldkamp (2013); Fajgelbaum, Schaal, and Taschereau-Dumouchel (2014). Overall, these findings imply that a large fraction of the movements in popular uncertainty proxies, such as implied stock market volatility or disagreement, are mainly driven by factors that are not associated with ex-ante subjective macroeconomic uncertainty.

Turning to the dynamic relationship between uncertainty and economic activity, I estimate an 8-variable recursively identified VAR model where uncertainty is ordered as the second variable as in Bloom (2009). A large disturbance to uncertainty measured by commonly used empirical uncertainty proxies leads to short-lived declines in the real activity followed often by a statistically significant "volatility overshoot", i.e. the rebound in real activity following the initial decline after a positive uncertainty shock. In contrast, I show that uncertainty measured by the SCUs leads to sizable and protracted declines in production and employment without exhibiting the subsequent overshooting pattern. Using the 8-variable benchmark VAR model, I show that the SCU disturbances account for 25 - 32% of the forecast error variance of industrial production whereas implied stock market volatility and output growth disagreement can account for a maximum 11.7 - 12% of the forecast error variance of industrial production.

Yet, there are two major concerns regarding the identification of uncertainty shocks in the benchmark empirical VAR analysis. First, the identification is achieved purely by the ordering of variables assuming a particular causal chain, i.e. shocks instantaneously affect first the stock market, then uncertainty, prices and finally real variables. While this is one of the likely economic interpretations that may happen, other alternatives, such as the hypothesis that uncertainty is more a consequence of depressed economic activity than a cause are disregarded in this specification Bachmann and Bayer (2013, 2014). Second, Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2013) and Gilchrist, Sim, and Zakrajšek (2014) show that financial channel is key in the transmission of uncertainty shocks, so including financial fragility along with uncertainty into the same VAR substantially weaken the impact of uncertainty shocks on economic activity. An obvious solution to this claim is to include financial fragility to the 8-variable empirical VAR model. Due to contemporaneous feedback mechanisms between uncertainty and financial fragility, however, it is hard to defend identification of shocks to macroeconomic uncertainty that is based on the ordering of variables in the VAR. In an attempt to make progress in these aspects, I propose a small scale sign-identified VAR model that includes both uncertainty measured by either inflation or output growth SCU along with a proxy for financial fragility. I show that while the bigger fraction of the fluctuations in production can be explained by innovations to financial conditions, the structural shocks to uncertainty still leads statistically significant and persistent declines in real economic activity.

The rest of the paper is organized as follows. Section 2 briefly introduces the SPF's probabilistic data that I use to construct inflation and output growth SCUs. Section 3 introduces the notion of subjective forecast uncertainty along with the econometric methodology conducted to estimate the SCUs. Section 4 presents inflation and output growth SCU estimates, and compares their relationship with commonly used uncertainty measures. Section 5 documents the dynamic relationship between uncertainty and real economic activity under two different identification schemes within the framework of a structural VAR. Finally, section 6 concludes.

1.2 The SPF Data

The belief distributions of agents that I use to compute the Subjective Consensus Uncertainty (SCU) are rarely available for economic research. The Survey of Professional Forecasters (SPF) fortunately provides them for deflator inflation and output growth for experts starting from 1968Q4 and 1981Q3, respectively. This section briefly describes the survey question format and points out the major properties of the probabilistic forecast data that I need to take into account for the estimation of the SCUs.

1.2.1 The SPF Data Description

The American Statistical Association started and managed the SPF from 1968 to 1990 before the Federal Reserve Bank of Philadelphia took it over in 1990. The panel of forecasters, which includes academics and researchers from both industry and government, provides point forecast for various US macroeconomic series in different horizons and at a quarterly frequency. In addition to these point forecasts, the SPF also asks panel members to make probabilistic forecasts of annual output growth and deflator inflation.

In each quarter during a calendar year, participants are asked to provide their belief distributions for the percentage change in annual real GDP and GDP deflator between previous/current years and current/next years. The former is called the current year whereas the latter is called the next year probabilistic forecast. The experts participating in the SPF assign their subjective probabilistic forecasts of inflation and output growth to some pre-assigned bins.

Currently, the SPF provides 10 bins for inflation: ($-\infty$, 0%), 8 intervals with 1% interval length from 0% to 8% and [8%, ∞). For output growth, the SPF provides 11 bins: ($-\infty$, -3%), 9 intervals with 1% interval length from -3% to 6% and [6%, ∞) at present. Therefore, the SPF's probabilistic forecast coverage is always from minus to plus infinity, which requires the lowest and highest intervals to be open-ended, i.e. bottom or top-coded.

The SPF experienced significant structural changes in its history[2]. First, while survey participants were asked to report GNP deflator inflation and real growth prior 1992Q1, afterwards they are asked for the GDP counterparts of these variables. Second, for inflation, the number of available intervals were from 15 prior to 1981, to 6 throughout the 80s, and finally increased to 10 in 1992. Furthermore, the typical interval width, which excludes the open-ended lowest and highest extreme intervals, is equal to 1% except in the 80s when it was equal to 2%. For output growth, probabilistic forecasts started from 1981Q3 and followed the same pattern as inflation, except that the available number of intervals increased from 10 to 11 starting 2009Q2.

I restrict the empirical analysis to current year probabilistic forecasts for both inflation and output growth because their time series dimension is longer. Furthermore, I drop the surveys from the sample if (i) the assigned subjective

[2] The table A.1 at the appendix roughly summarizes these changes both for deflator inflation and output growth. For the history of the survey and other details mentioned in this paragraph, see Croushore (1993); Lahiri and Liu (2006); Rich and Tracy (2010) and the following SPF documentation provided by the Federal Reserve Bank of Philadelphia: http://www.phil.frb.org/research-and-data/real-time-center/survey-of-professional-forecasters/spf-documentation.pdf.

probabilistic forecasts do not sum to unity, and (*ii*) a respondent participated just once in the life of the survey. After these restrictions, I have 6539 individual probabilistic surveys for inflation and 4197 for output growth. This corresponds to a quarterly average of 36 and 32 individual surveys for inflation and output growth respectively (see table A.3 at the appendix for details).

1.2.2 Other Data Considerations

Agents' belief distributions for future inflation and output growth are available for calendar year forecasts, so they tend to be tighter mechanically as the year progresses. For example, in February the calendar year forecast horizon is longer than in May. Consequently, forecast uncertainty regarding the first quarter is lower than the one in second quarter as more information is revealed about the target variable in the second quarter. The suggested solution to this problem is to execute deterministic seasonality adjustment (Lahiri and Liu, 2006; Rich and Tracy, 2010; Andrade, Ghysels, and Idier, 2012).

The SPF embodies temporal variation in aggregate predictions partly due to changes in panel compositions (Engelberg, Manski, and Williams, 2011). This is not a problem for the interpretation of an aggregate statistic if forecasters are selected randomly to the SPF and experience is not a significant determinant of the forecasters' performance. Nevertheless, if either of these conditions does not hold, any aggregate statistic will conflate fluctuations in aggregate behaviour with temporal fluctuations in the survey structure (Engelberg, Manski, and Williams, 2011). To illustrate the effects of a changing panel composition, consider the following simple hypothetical example. Suppose there are four forecasters in the SPF, all of who expect annual growth of 2%, with two having a standard deviation of 1% and the rest of 2%. This implies that the hypothetical representative (i.e. average) forecaster expects annual output growth rate is 2% with a subjective standard deviation of 1.5%. If in the next quarter, all forecasters continue to hold the same beliefs, but the two forecasters (the ones with lower standard deviations) fall out of the sample, expected annual output growth rate would remain at 2% while the standard deviation would fall from 1.5 to 1%. While this is just an artifact of changing panel composition in the SPF, the representative forecast makes it appear that forecasters have become less uncertain about future inflation[3].

Yet, in the absence of knowledge of the participation process of forecasters, there is no direct evidence to justify how important this problem is in the SPF. However, there are three pieces of evidence in the SPF showing that this effect might be present. First, the survey size varies over time. For instance, the survey size changed from about 100 in the late 60s to 14 in the early 90s for inflation; 10 in early 90s to 50 in mid-2000 for output growth. Secondly, on average 36 (33) forecasters participated, 10 (7) exited, and entered in each survey for inflation (output growth). This means that on average about 70 to 80% of the forecasters participated in the former survey participates in the current one, whereas the rest participated only once in either of these surveys. Finally, while some experts participate the SPF regularly, other do so less frequently: only 196 forecasters (out of 412) for inflation and 123 forecasters (out of 238)

[3]This example is tailored from Engelberg, Manski, and Williams (2011) to address the effects of changing panel composition for consensus subjective uncertainty in the SPF.

for output growth participated more than 10 times in the SPF[4].

The problem of changing panel decomposition and forecaster heterogeneity are well documented problems for several other surveys besides the SPF such as Michigan Household Survey, CESifo World Economic Survey or Confederation of British Industry's Small and Medium enterprises survey (see Pesaran and Weale (2006) and Engelberg, Manski, and Williams (2011) for details). In an attempt to handle these problems, the panel structure of the SPF becomes crucial and I will control for these effects with a set of dummy variables.

Abstracting from the problems stated so far, some surveys are not comparable with others due to incompatible forecast horizons (Rich and Tracy, 2010). Therefore, all the surveys in 1972:Q3, 1974:Q4, 1979:Q2-Q3, 1980:Q4, 1985:Q1 and 1986:Q1 are reported as missing in the estimation. To fill out these missing observations, I proceed in two steps. First, I aggregate the surveys and provide a macroeconomic uncertainty estimate either for inflation or output growth for each quarter. Next, I propose a time series model in state-space form and estimate these missing observations via Kalman filter and smoother (Harvey, 1993). The details of this model appear in section 1.3.2 below.

1.3 Estimation Method

This section explains how I estimate the inflation and output growth Subjective Consensus Uncertainties (SCUs) from discretized probability distributions provided by the SPF. To compute the SCUs, I proceed in three steps. First,

[4]See figures A.1 and A.2 at the appendix for details.

I estimate subjective forecast uncertainties of each expert in the SPF panel by following the approach of Engelberg, Manski, and Williams (2009) who match generalized beta distributions to the individual discrete histograms. I provide some motivation and intuition for this procedure in subsection 1.3.1. In the second step, I estimate the inflation and output growth SCUs from these subjective uncertainties in subsection 1.3.2, briefly explaining how I control for potential biases in the SCU estimates that are raised in section 1.2. In the final step, I fill out the SCUs which are recorded as missing due to occasional errors made by the SPF. Finally, in subsection 1.3.3, I discuss the motivation for using other commonly used empirical uncertainty measures and compare them with the SCUs.

To conserve some space, the full description of fitting generalized beta distribution to individual histograms, the estimation of the missing SCU values, and several robustness exercises designed to check sensitivity of my results to assumptions regarding the SCU estimates are provided in the Supplementary On-Line Appendix in Karaca (2014)[5].

1.3.1 Estimation of Subjective Forecast Uncertainties of Experts

For illustrative purposes, suppose $F_{it}^{h}(x)$ is the forecaster i's subjective cumulative distribution function conditional on date t information for the target

[5] The Supplementary On-Line Appendix can be downloaded from my webpage: https://goo.gl/CG3uXs

variable x_t at horizon h quarters:

$$F_{it}^{h}(x) = \mathbb{P}\left(x_{t+h} \leq x | \Omega_{it}\right)$$

where Ω_{it} is the information set of individual i at time t. Moreover, let μ_{it} and $\sigma_{i,t}^2$ denote date t subjective mean and variance of the point forecast of the target variable x at horizon h (notice that the target variable and the horizon are suppressed from this point onwards) quarters of a forecaster i defined as:

$$\mu_{i,t} = \int_{-\infty}^{\infty} x_{t+h}\, dF_{it}^{h} \qquad\qquad \sigma_{i,t}^2 = \int_{-\infty}^{\infty} \left(x_{t+h} - \mu_{it}\right)^2 \, dF_{it}^{h}$$

The subjective uncertainty ($\sigma_{i,t}$) defined above is the dispersion of the subjective belief distribution of an expert. By definition, the notion of subjective uncertainty differs from what is used in most of the uncertainty-driven business cycle literature where uncertainty is associated with volatility about either idiosyncratic or aggregate conditions. In this paper, rather than imposing any *a priori* structure about the relationship between volatility and subjective uncertainty, I allow for the possibility that subjective uncertainty could be high even if actual volatility is low or vice versa.

I then construct an aggregate measure of macroeconomic uncertainty, i.e. the SCU by aggregating subjective uncertainties (i.e. standard deviations) at each date t for all forecasters:

$$\sigma_t = \mathbb{E}_i\left[\sigma_{it}\right] \tag{1.1}$$

where $\mathbb{E}_i$ is the expectation across individual forecasters i.

The SCU defined in equation 1.1 has three important properties. First, fluctuations in the SCU measure capture the common subjective ex-ante uncertainty movements perceived by all agents. Assuming these belief distributions correctly characterize the uncertainty that agents face, the SCU perfectly lines with most uncertainty based theories of business cycles that require the existence of common movements which simultaneously affect all agents in the economy. Second, fluctuations in the SCU do not have to be tightly linked with the fluctuations in actual volatility. Typically, uncertainty is defined as the volatility of either aggregate or idiosyncratic productivity shocks (e.g. Bloom (2009); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012)) but here I define it as the standard deviation of agents' beliefs about future macroeconomic developments. This enables me to dissociate subjective uncertainty from volatility, so that with the SCU, I allow the possibility of periods of high uncertainty with low volatility or vice versa[6]. Finally, fluctuations in the SCU are model-free, so any structural shock affecting subjective uncertainty of all experts will be recorded as a rise in the SCUs. Therefore, SCUs allow me to consider all sources of fluctuations of uncertainty rather than just focussing on volatility, which is just one aspect of uncertainty.

The objective of this paper is to provide estimates for: (i) subjective uncertainty of each expert, i.e. $\sigma_{i,t}$[7] and, (ii) the Subjective Consensus Uncertainty,

[6] Fajgelbaum, Schaal, and Taschereau-Dumouchel (2014) show that option value of waiting due to irreversibilities may lead to endogenous movements in subjective uncertainty resulting long lasting recessions as in 2007-09 even if no volatility is observed in economic data.

[7] My approach in this paper relies on individual belief distributions on future inflation and output growth. Alternatively, some researchers relied on aggregate (cross-sectional average) belief distributions and use its standard deviation as a measure of forecast uncertainty.

i.e. σ_t. However, the estimation of these objects depends critically on the availability of belief distributions. Fortunately, the SPF provides the discretized belief distributions of experts for two key macroeconomic variables: inflation and output growth, so I can utilize these belief distributions to estimate experts' subjective uncertainties. To make these belief distributions operational, I estimate the continuous counterparts of these belief distributions and back out the standard deviation.

I assume that the generalized beta distribution characterizes the discretized belief distributions of experts (Engelberg, Manski, and Williams, 2009), and estimate its parameters by minimizing the sum of squared deviations between the empirical distribution (i.e. discretized belief distributions) and the continuously distributed theoretical distribution. The generalized beta distribution is an appropriate choice for approximating the empirical distribution of beliefs for two reasons. First, it is flexible and parsimonious enough to characterize these empirical distributions without any *a priori* restrictions on their higher order moments. Giordani and Söderlind (2003), for instance, assume that experts' beliefs are normally distributed. Not surprisingly, this assumption does not hold in the data (see for example Engelberg, Manski, and Williams (2009), Andrade, Ghysels, and Idier (2012) and Engelberg, Manski, and Williams (2011) for an evidence in favor of heterogeneity or time-variation in these moments).

However, as shown by Wallis (2005), the variance of aggregate belief distribution can be decomposed into average forecast uncertainty and the disagreement among the participants. Therefore, using aggregate distribution conflates disagreement with the subjective forecast uncertainty, potentially masks the individual characteristics of the subjective distributions due to central limit theorem type arguments.

Second, the generalized beta distribution has bounded support. Therefore, if an expert assigns a positive probability to either (or both) of the open-ended intervals, this introduces one (or two) more parameter(s) to be estimated. Meanwhile, if an expert does not assign a positive probability to either of the open-ended intervals, I take the support of the distribution to be the left and right endpoints of the intervals with positive probability. While forecasters do not assign a positive probability to these open-ended intervals 80% of the time, during some economic downturns, notably during the 1980-82 and 2007-09 recessions, most of the forecasters assign non-zero probabilities to the lowest open-ended interval. For example, the (cross-sectional) average probability assigned to the lowest open-ended intervals in these recessions jumps to 8 and 18 percentage points respectively for inflation, whereas the same magnitudes for output growth are 18 and 33 percentage points[8]. In this context, non-parametric fitting methods such as uniform smoothing, i.e. assuming probability mass in each interval is uniformly distributed, are hard to defend. On the one hand, uniform smoothing tends to inflate the standard deviations of the belief distributions of experts during normal times (Rich and Tracy, 2010). On the other hand, during economic downturns, particularly the 1980-82 and the 2007-09 recessions, standard deviation estimates depend critically on how open-ended intervals are closed as most of the survey participants assign positive probabilities to the open-ended bins[9].

[8]See figure A.3 at the Appendix A.1.2.

[9]Some researchers using SPF's probabilistic data assume that the width of an open-ended interval is equal to twice the size of a mid-interval (for example see Lahiri and Liu (2006); Andrade, Ghysels, and Idier (2012)) and apply uniform smoothing to these histograms to calculate the moments of these belief distributions. However, this assumption causes the width of these open-ended bins to be 4% during the 80s and 2% after 90s due to changes in the bin width in the life of the SPF. Noting that average cross-sectional probability assigned

1.3.2 Estimation of the SCUs

Once I obtain the individual subjective forecast uncertainty estimates, the next step is extracting their common component, i.e. the SCUs. As discussed in section 1.2, the simple cross-sectional average (in line with equation 1.1) may lead to biased SCU estimates. In this section, I briefly discuss how I handle these problems and explain how I estimate the SCUs for inflation and output growth.

Traditional practice of aggregate time series analysis of the SPF conflates changes in the subjective expectations of individual forecasters with both changes in panel composition (Engelberg, Manski, and Williams, 2011) and forecaster heterogeneity (Keane and Runkle, 1990). The possibility of systematic differences due to different information sets or systemic biases in subjective expectations are extensively studied in the literature (Zarnowitz and Lambros, 1987; Keane and Runkle, 1990; Engelberg, Manski, and Williams, 2009). Frequent exiting and entering behavior of professional forecasters adds another layer of complication to the interpretation of an aggregate statistic, such as the consensus forecast or the consensus uncertainty. For example, Engelberg, Manski, and Williams (2011) compare the consensus inflation forecasts of two groups of forecasters in the SPF: experts participated in at least two consecutive surveys against the

to these bins are approximately two times during the Great Recession, this assumption adds another layer of complication to compare these numbers during different periods of the SPF. Nonetheless, as a robustness check, the SCU estimates are also constructed from subjective uncertainties of experts that are assumed to be characterized by a three parameter functional form following (Clements, 2004). The parameters of these distributions are estimated by minimizing the sum of squared deviations between the observed empirical distributions and theoretical distribution.

composite (consists of all participants). They find that the differences in the inflation forecasts of these groups are sometimes as high as 0.5 percentage points after 1992, a relatively low inflation period compared to the whole sample. Similarly, by comparing the average (cross-sectional) standard deviations of these two groups, I find that the difference is sometimes more than 0.5% both for inflation and output growth[10]. In order to control for the temporal fluctuations in subjective forecast uncertainties, I use the panel structure of the SPF and include a set of respondent fixed-effects in equation 1.2.

I have already elaborated on the reasons for why experts' subjective uncertainties experience the mechanical intra-year declines as the year progresses and how the changes in panel composition can lead to biased SCU estimates. To explore how these two forces affect SCU estimates for different time periods that are determined by the changes in the survey design (i.e. changes number of bins and changes in bin width) further, I run two types of regressions: (i) the *panel regression* of individual subjective uncertainties on seasonal and forecaster fixed effect dummies and, (ii) the *time series regression* of cross-sectional average subjective forecast uncertainties on seasonal dummies. The former adjusts for the temporal fluctuations in the survey by introducing forecaster fixed effects whereas the latter does not. Furthermore, I run these regressions both for the whole and the different sub-samples determined by the structural changes in the SPF[11].

[10]This is more than 25% of the average subjective standard deviation of inflation or output growth uncertainty of the composite sample. See figure A.4 in the Appendix A.1.2 for details.

[11] If there is a change in the number of pre-assigned intervals by the SPF or if there is a change in the length of intervals, I consider this as a structural change in the survey. Table A.1 demonstrates that there are 6 and 3 of such episodes for inflation and output growth subjective

These regressions flesh out two properties regarding the deterministic seasonality coefficients. First, the coefficients from the panel and the time-series regressions are significantly different form each other in the sense that 90% confidence intervals do not overlap. Second, the estimated deterministic seasonality coefficients across different subsamples are often significantly different from each other, i.e. once again the 90% confidence intervals do not overlap. Therefore, in order to provide comparable subjective uncertainties of experts between different periods, it is important to control for the three sources of potential bias (i.e. seasonality, structural breaks, and changing panel composition) at the same time. Consequently, in my preferred specification, in addition to forecaster fixed effects and mechanical declines seasonality coefficients, I introduce 20 seasonal dummies for inflation (4 per quarter, and 5 for changes in the SPF design) and 12 for output growth (4 per quarter and 3 for changes in SPF design) to take effects of the structural breaks into account[12].

To control for the panel composition, forecaster heterogeneity and structural changes in the deterministic seasonality patterns, I estimate the panel regression appearing in equation 1.2 both for inflation and output growth. The subjective

forecasts respectively. However, as 1973Q2-1974Q4 episode is too short to separately identify the deterministic seasonality structure for inflation, so I treat 1968Q4-1973Q1 & 1973Q2-1974Q4 as a single period. Therefore, I have 5 structurally different subsamples for inflation probabilistic forecasts.

[12] Andrade, Ghysels, and Idier (2012) points out the time-variation in deterministic seasonality coefficients only for average subjective uncertainty estimates. Apart from that, these patterns in subjective forecast uncertainties are mostly overlooked in the literature. See tables A.6 and A.7 for the exact seasonality coefficient estimates of the *panel regression* of individual subjective uncertainties and the *time series regression* of cross-sectional average subjective forecast uncertainties both for the whole and the subsamples.

forecast uncertainty in regression 1.2 is in logs to prevent subjective forecast uncertainty to be greater than zero at all times. Furthermore, forecasters who participated just once in the SPF and the occasional survey error periods (see footnote 14 provides these periods) are dropped from this regression.

$$\ln \sigma_{i,t} \quad = \quad \sum_{j=1}^{4}\sum_{k=1}^{P_x} \beta_{jk}\,\mathrm{D}_j \times B_k + \sum_{i=1}^{I_x} \gamma_i\,\mathrm{F}_i + u_{i,t} \tag{1.2}$$

$$\mathrm{SCU}_t \quad = \quad \frac{1}{N_t}\sum_{i=1}^{N_t} \exp\left(\hat{u}_{i,t}\right) \tag{1.3}$$

where P_x is equal to 5 for inflation and 3 for output growth (see footnote 11 on how these values are determined), D_j is a seasonal dummy (equal to 1 in quarter j), B_k is the interaction dummy (equal to 1 in subsample k), β_{jk}'s are deterministic seasonality coefficients that are allowed to change in different subsamples, I_x is the number of distinct forecasters (312 for inflation and 206 for output growth uncertainties) in the SPF panel, and $\hat{u}_{i,t}$ are fitted values from eq. The exponential of the error terms in equation 1.2 are subjective forecast uncertainties that are adjusted for the three problems mentioned above. Therefore, the cross-sectional averages of these terms are the benchmark inflation and output growth SCUs (equation 1.3.3)[13].

In the final step, I estimate the missing SCU observations. As I mentioned in section 1.2.2, I report all individual surveys in some dates of the SPF as

[13]Instead of the cross-sectional average, I also explored taking the median. Unlike the SCU estimates that are based on the averages, the ones based on the median are slightly less persistent with AR(1) coefficients 0.91 for inflation and 0.89 for output growth. Apart from this difference, the SCU estimates based on the median produce quantitatively similar dynamics as the ones based on the mean so I don't report median estimates in the paper to preserve space.

missing because of differences in the SPF's intended and experts' requested forecast horizon[14] which makes these dates incomparable with the rest of the observations in the SPF. To fill out those missing values, I utilize the next year inflation and output growth empirical forecast distributions provided by the SPF. Following the same procedure that I have explained above, first, I estimate the next year inflation and output growth SCUs (data starts from 1981Q3) and then, I estimate a state-space model to fill out those missing values[15].

1.3.3 Discussion

The existing empirical uncertainty literature has so far relied primarily on measures of volatility and dispersion as proxies or indicators of uncertainty. While most of these measures have the advantage of being observable, there are various factors besides economic uncertainty that cause changes in these indicators. In this section, I classify these empirical measures into 4 categories and briefly elaborate on their relationship with the SCUs.

Observed Empirical Proxies: The examples of observed proxies are option-implied stock market volatility and mentions of phrases like "uncertain" and/or "uncertainty" in the press[16]. Bloom (2009) used the VXO index, which measures the risk neutral expected stock market volatility with a horizon of 30

[14] These dates are 1972:Q3, 1974:Q4, 1979:Q2-Q3 and 1980:Q4 only for current inflation; 1985:Q1 and 1986:Q1 for both current inflation and output growth. See Rich and Tracy (2010) for details.

[15] I provide the details of the estimation method in the online appendix.

[16] Bloom (2009); Baker and Bloom (2013) use implied or realized stock market volatility to measure uncertainty, whereas Alexopoulos and Cohen (2009); Baker and Bloom (2013) use newspapers such as New York Times or Wall Street Journal to count "uncertainty-related" keywords

calender days (22 trading days) from options written on the S&P100 index to proxy macroeconomic uncertainty[17]. While implied stock market volatility is also model-free and ex-ante similar to the SCUs, it is most closely associated with uncertainty about the stock market returns, not about the macroeconomy. Additionally, time-varying risk aversion is an important component of the VXO index (Bekaert, Hoerova, and Lo Duca, 2013), and certain events can cause spikes in risk aversion but the not the uncertainty (see the subsection 4.2 about a detailed discussion on this issue).

Subjective Cross-Sectional Dispersion (DIS): Several researchers used the cross sectional dispersion in agents' subjective point forecasts, i.e. disagreement, of a particular target variable:

$$\mathrm{DIS}_t = \sqrt{\sum_{i=1}^{N_t} \left[(x_{t+h} - \mathbb{E}_{it}(x_{t+h}))^2 \right]} \tag{1.4}$$

where N_t is the number of participants at survey date t, x is the target variable and $\mathbb{E}_{it}(x_{t+h})$ is the subjective point estimate of the target variable x at date t for forecaster i. In order to make equation 1.4 operational, the h-period ahead value of the target variable (x_{t+h}) is replaced by the consensus forecast $(\mathbb{E}_i(\mu_{it})))$.

There are several known drawbacks of subjective cross-sectional dispersions. First, disagreement in surveys could reflect differences in opinions (Mankiw, Reis, and Wolfers, 2004) or differences in firms loadings on aggregate shocks in

[17] The VXO index is unavailable before 1986, so Bloom (2009) combines it with actual stock market return volatility.

the absence of time-varying volatility (Jurado, Ludvigson, and Ng, 2013) rather than macroeconomic uncertainty. While disagreement is also subjective similar to the SCUs, the relationship between disagreement and the average subjective uncertainty is generally weak and unstable (Lahiri and Liu, 2006; Boero, Smith, and Wallis, 2008; Rich and Tracy, 2010; Rich, Song, and Tracy, 2012). Second, point forecasts of experts tend to be more optimistic than the central tendency measures (mean/median/mode) of probabilistic belief distributions (Engelberg, Manski, and Williams, 2009). As disagreement is computed from point forecasts as opposed to probabilistic distributions, it is also contaminated by these inconsistencies.

Realized Cross-Sectional Dispersion (DISP): Alternatively, some researchers focus on the realized values instead of subjective forecasts:

$$\mathrm{DISP}_t = \sqrt{\frac{1}{N_t}\sum_{j=1}^{N_t}\left[(x_{jt}-\overline{x}_t)^2\right]} \tag{1.5}$$

where $\overline{x}_t$ is the cross-sectional average of a particular variable at time t, x_{jt} is the realized value of the variable at time t for agent j (usually a firm) and N_t is the total number of agents (i.e. panel dimension) at time t. In particular, Bloom (2009) and Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) argue in favor of using unconditional cross sectional dispersion in firm-level earnings (the Profits), sectoral industrial production (the QIQR) or firms' stock returns (the CRSP) to measure uncertainty. Unlike the SCUs, all of these empirical measures of uncertainty are realized and several factors such as heterogeneity in the cyclicality of firms business activity or heterogeneity in the access to credit and firms' financial conditions causes DISP to change without a change in macroeconomic uncertainty.

Time series estimates: Time series methods provide an alternative way of measuring uncertainty. By specifying a parametric structure for the underlying target variable and the volatility process, researchers can estimate the uncertainty regarding the underlying target variable. Stochastic volatility or GARCH type time series models are famous examples of this approach. In contrast to the SCUs, assuming the postulated model is the correct representation of how the world works, time series models provide ex-post uncertainty estimates based on the information set of the econometrician, not the agents in the economy. Furthermore, it is always a possible that the postulated model can be misspecified. To overcome the problem of dependency of underlying uncertainty on parameters of a model, Jurado, Ludvigson, and Ng (2013) construct an aggregate uncertainty measure by extracting the common component in forecast errors in hundreds of different economic time series. While their approach breaks reliance of uncertainty estimates on a specific model, their macroeconomic uncertainty measure is still based on the information set of the econometrician. On the other hand, this paper focuses on the common component of the ex-ante subjective uncertainties faced by experts, so it is complementary to Jurado, Ludvigson, and Ng (2013)'s analysis on measuring macroeconomic uncertainty.

1.4 Empirical Subjective Consensus Uncertainty Estimates

I now turn to the Subjective Consensus Uncertainty (SCU) estimates and document three sets of findings about them. First, in contrast to one of the recurrent themes of the uncertainty measurement literature, in section 1.4.1, I demonstrate that uncertainty episodes are less frequent and persistently negatively correlated with economic activity. The deepest recessions in US macroeconomic history coincide with large increases in the estimated subjective consensus uncertainty, while the modest declines do not. I show, in section 4.2, that other commonly used uncertainty measures, in contrast, frequent spikes, both during recessionary and non-recessionary episodes. Second, in section 1.4.1, I show that the SCUs can explain more than half of the fluctuations in the subjective individual forecast uncertainties of experts during recessions. In normal times, however, SCUs explain about 30-35% of the common movement in the subjective forecast uncertainties. Finally, in section 4.2, I show that there are significant independent variations in commonly used empirical uncertainty measures and the SCUs, most of which cannot be attributed to fluctuations in macroeconomic uncertainty.

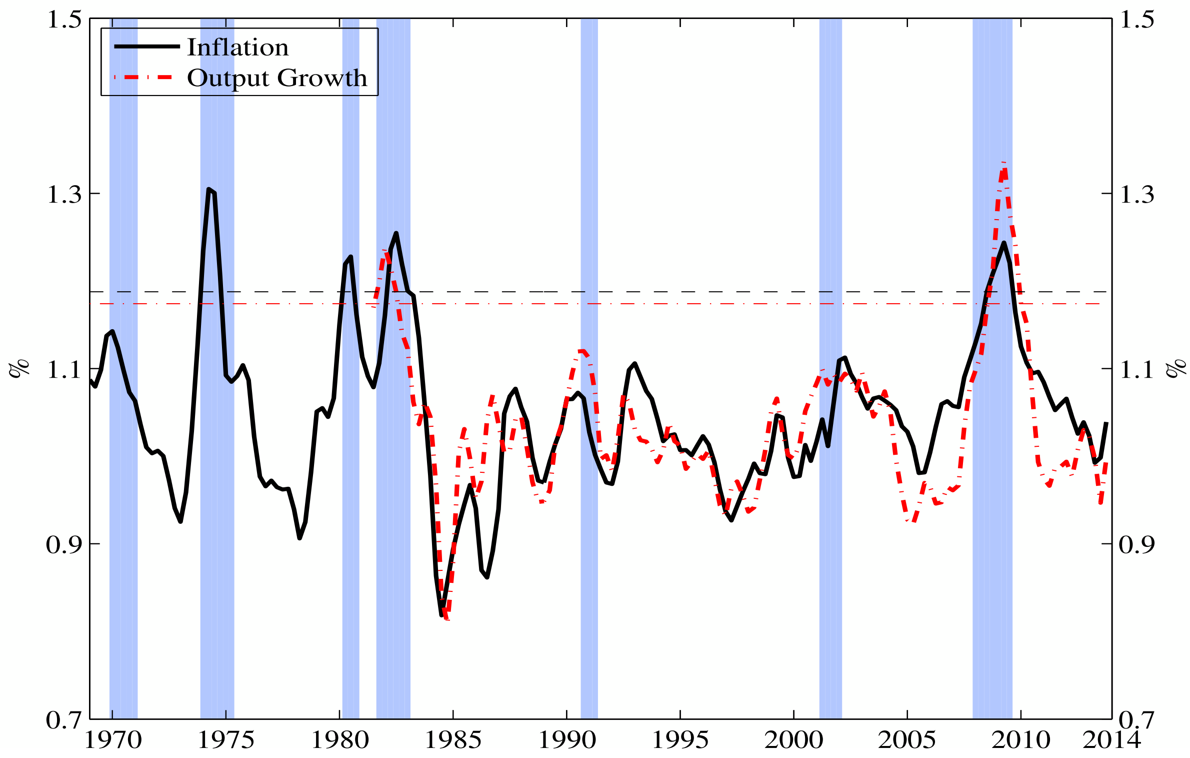
1.4.1 Estimates of Subjective Consensus Uncertainty

Figure 1.1 plots time series estimates of inflation and output growth SCUs together with NBER recession dates represented by the shaded blue bars. The matching color horizontal lines correspond to 1.65 standard deviations above the mean for each series. Figure 1.1 shows that uncertainty represented by either the inflation or the output growth SCU is strongly countercyclical. A bivariate regression between the SCUs and NBER recession index or HP-detrended industrial production confirms a significant negative relationship that is observed in figure 1.1[18]. Moreover, inflation and output growth uncertainty estimates are

[18]Table A.8 in Appendix A provides bivariate regressions between the SCUs and several HP-detrended macroeconomic variables such as the consumer price index, federal funds rate,

moving in lockstep with a correlation coefficient equal to 75%. Even though, I compute them from the empirical belief distributions of experts for inflation and output growth separately, this observation suggests that aggregate ex-ante predictability in inflation and output growth is mainly proxy the same factor, which is the aggregate unobserved subjective macroeconomic uncertainty.

Figure 1.1: *Inflation and Output Growth SCU Estimates*



Note: Inflation (solid black line) and output growth (dash-dot red line) subjective consensus uncertainty (SCU) estimates are based on the methodology explained in section 1.3. Data for inflation and output growth SCUs start from 1968Q4 and 1981Q3 respectively. Horizontal (dash or dash-dot) lines indicate 1.65 standard deviations above the unconditional mean of each series (matching colors and matching for inflation and output growth SCU). The shaded blue bars are recessions defined according to the NBER Business Cycle Dating Committee.

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total employment in manufacturing sector and S&P500 index. Coefficient estimates from these regressions suggest that unlike other commonly used empirical uncertainty measures, the SCUs are significantly correlated with most of these macroeconomic aggregates.

Interestingly, the SCUs experience a rise during all US recessions, but certain recessions are more pronounced compared to others. The inflation SCU experience four heightened uncertainty episodes: one during the 1973-74, two during the 1980-82 recessions and finally one during the 2007-09 Great Recession as in Jurado, Ludvigson, and Ng (2013). On the other hand, the output growth SCU estimate experienced only two of such episodes: one during the 1980-1982 recessions and the other one during the Great Recession[19]. During all heightened uncertainty episodes identified by the inflation SCU, uncertainty levels are fairly close to each other, with the highest in the 1973-74 recession followed by the 1981-82 as close second, and the Great Recession as third. In terms of the output growth SCU, figure 1.1 shows roughly the same picture with one major difference. That is, the Great Recession clearly represents the most striking episode of heightened uncertainty while the 1981-82 episode is second. Due to data availability, however, it is not possible to compare with the 1973-74 recession in terms of the output growth uncertainty as the empirical belief distributions of experts for output growth starts in 1981Q3. Overall, these findings are consistent with the historical account of the 1973-74 energy crisis, 1980-82 global economic recession and contractionary monetary policy, and the 2007-09 global financial crises.

Table 1.2 lays out several salient features of the inflation and output growth SCU estimates. First, both the inflation and output growth SCUs suggest that macroeconomic uncertainty is a highly persistent process unlike what is

[19] I define heightened uncertainty episodes in excess of 1.65 standard deviations above their HP-detrended mean following Bloom (2009).

suggested by conventional uncertainty proxies. According to Table 1.2, the estimates of the half-life of an innovation from a univariate autoregression of inflation or output growth SCUs are 12.5 and 10 quarters, whereas the corresponding values for the inflation disagreement and the implied stock market volatility (VXO) are equal to 1.3 and 2 quarters. The half life estimates of the SCUs are slightly higher than the ones in Jurado, Ludvigson, and Ng (2013), where they estimate the half-life of macro uncertainty as 10 quarters. Second, the SCUs are positively skewed but the kurtosis estimates are mostly smaller compared to other measures such as the implied stock market volatility or measures of dispersion. This implies that the SCUs experience less frequent spikes (less extreme values), which is also consistent with figures 1.1 and 1.2[20].

Third, the SCUs are persistently countercyclical with respect to industrial production. In particular, their contemporaneous correlation with HP-detrended industrial production is equal to -0.51 and -0.64 for inflation and output growth respectively[21]. Even though most of the comovement between uncertainty and economic activity is associated with their contemporaneous correlation, a significant part of the comovement between them can also be attributed to uncertainty both leading and lagging real activity[22]. For example, the correlation between current uncertainty and 1 quarter ahead real activity is equal to -0.6 whereas

[20]Appendix A.2 provides figures for the standardized (i.e. with mean zero and standard deviation one) commonly used uncertainty measures against the SCUs. Consistent with high kurtosis and low AR(1) coefficient estimates, other commonly used empirical uncertainty measures experience frequent spikes both during the recessions and normal times.

[21]I choose the smoothing parameter (i.e. λ) for the HP-filter as 129,600. However, the bivariate regressions in table A.8 or cross-correlograms in figure A.5 quantitatively give close results whether I utilize HP-detrended industrial production or the quarterly industrial production growth.

[22]For details, see figure A.5 at the appendix A.5

the same number for current real activity and 1 quarter ahead uncertainty is equal to -0.61. Qualitatively, similar results hold for the inflation SCU as well. That said, these are all unconditional correlations and do not tell us anything about causality, but it seems that there is a strong relation between the SCUs and real activity.

An interesting question about empirical analysis of uncertainty is whether uncertainty shocks are persistent enough to explain prolonged periods of below-trend economic growth. Typically, in models where uncertainty plays a key role in explaining business cycle dynamics calibrate uncertainty as a strongly persistent process (e.g. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012); Schaal (2012)). However, existing empirical uncertainty proxies such as the (implied) stock market volatility, cross sectional dispersion in firms' profits, stock returns or production differences are not persistent enough to prolonged periods of below-trend economic growth and unemployment, in particular (during and) the post-Great Recession era. However, the SCU estimates suggest that subjective uncertainty is a highly persistent process and is strongly associated with industrial production, which also aligns with the macro uncertainty estimates in Jurado, Ludvigson, and Ng (2013).

The SCUs are model-free macroeconomic uncertainty measures that are defined as the common movements in the ex-ante predictability about future values of inflation or the output growth. A question that may arise about this common component is whether its explanatory power in summarizing the variations in subjective forecast uncertainties of experts is constant in different subsamples.

Table 1.1: *Marginal R^2s from Regression of Subjective Forecast Uncertainties on SCUs*

σ_{it}s	**Whole Sample**	**Non-Recession**	**Recession**
π Current Year	0.359	0.290	0.479
Δy Current Year	0.414	0.312	0.491
π Next Year	0.315	0.261	0.435
Δy Next Year	0.303	0.235	0.421

Note: Marginal R^2 describes the proportion of variance of current/next year inflation or output growth subjective forecast uncertainties explained by the SCU factor(s) alone. Regressing current/next year inflation or output growth subjective forecast uncertainties, i.e. $\sigma_{i,t}$, on either fixed effects dummies (i.e. subsample interacted deterministic seasonal dummies - $\sum_{j=1}^{4}\sum_{k=1}^{P_x}\beta_{jk}\ \mathrm{D}_j \times B_k$ where D_j is a seasonal dummy interacted with subsample dummy B_k and P_x is equal to 5 for current year inflation and 3 for the others) or fixed effects dummies and the current year inflation or the output growth SCUs respectively, I calculate the contribution of SCUs on the increase in R^2. These regressions discard forecasters participated just once in the SPF and the occasional survey error periods similar to equation 1.2. Recessions are defined according to the NBER Business Cycle Dating Committee.

To answer this question, I regress the current and the next year subjective forecast uncertainties on the SCUs using the whole, the recession or the non-recession samples. If the importance of the SCUs in explaining the proportion of variance of inflation or output growth subjective forecast uncertainties, this would be revealed in the estimated marginal R^2 values.

Table 1.1 shows that the explanatory power of the SCUs on the current and the next year subjective forecast uncertainties increases during recessions[23]. For instance, inflation SCU increases the proportion of variance in current year inflation subjective forecast uncertainties of experts by 36% for the whole sample,

[23]As explained in section 1.2.1, the SPF also provides discretized belief distributions of experts for the next year inflation and output growth probabilistic forecasts as well. Therefore, I estimate the experts' subjective uncertainties from the next year inflation and output growth empirical belief distributions following the estimation methodology outlined in section 1.3.1. The next year regressions provided in Table 1.1 use next year subjective forecast uncertainties of experts as the dependent and the current year SCU as the independent variable.

whereas during recessions, marginal R^2 jumps to 48%. For the next year inflation subjective forecast uncertainties of experts, the increase in the explanatory power of the inflation inflation is approximately 12 percentage points as well, i.e. from 31% to 43%. Similar tendency holds for output growth subjective uncertainty of experts.

1.4.2 The SCUs versus Other Commonly Used Uncertainty Proxies

Researchers so far have relied on various empirical uncertainty measures to document the relationship between economic uncertainty and economic activity. While implied or actual stock market volatility stands out as the most popular one, other empirical uncertainty measures are also extensively used in the literature. In this section, I compare the empirical properties of the SCU estimates with these uncertainty measures, particularly focusing on option-implied stock market volatility and disagreement.

To compare the fluctuations in implied stock market volatility against the SCUs, I update the VXO index used by Bloom (2009) and plot the standardized values of these series in figure 1.2. Bloom (2009) constructed his benchmark measure of uncertainty shocks by selecting 17 months with VXO that is 1.65 standard deviation above its HP-detrended mean[24]. Here, I followed the same strategy with the VXO index in quarterly frequency and I identified 9 quarters which are shown as vertical lines in figure 1.2.

[24]Bloom finds 17 of such months in his paper. However, extending the sample period to 2013Q3 introduces one more spike in VXO that happened in September 2011, which seems to be also apparent in quarterly frequency as well. Identified uncertainty episodes in terms of monthly and quarterly frequency are reported in table A.9 at the Appendix.

Table 1.2: *Summary Statistics*

Statistic	Uncertainty Measured By: π SCU	Δy SCU	VXO	EPU	CRSP	Profits	QIQR	π DIS	Δy DIS
AR(1)	0.95	0.94	0.71	0.81	0.71	0.85	0.76	0.58	0.25
Half-Life	14.07	11.34	2.04	3.31	2.03	4.25	2.57	1.26	0.51
Std	0.08	0.08	6.87	30.58	0.02	0.39	0.01	0.20	0.14
Skewness	0.47	0.82	2.00	0.83	1.45	0.37	2.36	1.17	0.85
Kurtosis	3.75	4.40	10.57	3.36	5.77	3.18	9.12	4.12	3.87
$\lvert\mathrm{corr}(\mathrm{IP},\mathrm{U})\rvert$	-0.44	-0.59	-0.36	-0.31	-0.43	-0.17	-0.52	-0.20	-0.41
$\max_k \lvert\mathrm{corr}(\mathrm{IP},\mathrm{U})\rvert$	-0.45	-0.64	-0.40	-0.40	-0.43	-0.28	-0.52	-0.20	-0.41
$k=$	-1	-1	1	-10	0	-3	0	0	0
Obs.	180	129	180	115	180	180	167	180	129

Note:

1. This table summarizes various descriptive statistics for the inflation and output growth SCUs along with other commonly used empirical uncertainty measures. Commonly used empirical uncertainty measures presented in this table are: (*i*) the VXO index, i.e. the option-implied stock market volatility index derived from options written on S&P100 stock market index, (*ii*) Google News index, i.e. the subindex that is the economic uncertainty component of economic policy uncertainty index of Baker, Bloom, and Davis (2012), (*iii*) Profits, i.e. the within-quarter cross-sectional spread of profit growth rates normalized by average sales (Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), (*iv*) QIQR, i.e. the interquartile range of the industrial production growth for manufacturing industries (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), (*v*) CRSP, i.e. the within quarter cross-sectional standard deviation of firm-level stock returns for firms with 500+ months of data in the Center for Research in Securities Prices (Bloom, 2009) and, (*vi*) π DIS and Δy DIS, i.e. the cross sectional standard deviation of mean probabilistic forecasts for inflation or output growth derived from the fitted distributions by the methodology explained in section 1.3.1.
2. The half-lives are based on the response of an uncertainty measure (U) governed by columns of table 1.2 to its own innovation from a univariate AR(1) model. $\lvert\mathrm{corr}(\Delta(\log IP), U)\rvert$ is the absolute contemporaneous correlation coefficient between HP-detrended log industrial production and the U. On the other hand, $\max_k \lvert\mathrm{corr}(\Delta(\mathrm{IP}),\mathrm{U})\rvert$ is the absolute cross-correlation coefficient between U in period t and quarterly log industrial production growth in period $t+k$, i.e. $\lvert\mathrm{corr}(\Delta(\mathrm{IP}),\mathrm{U})\rvert = \max_{-8\le k\le 8} \lvert\mathrm{corr}(\mathrm{IP}_{t+k}),\mathrm{U}_t)\rvert$. $\mathrm{argmax}_k \lvert\mathrm{corr}(\Delta(\mathrm{IP}),\mathrm{U})\rvert$ is the k that maximizes cross-correlation between HP-detrended log industrial production and the relevant U. A positive (negative) k means the relevant uncertainty measure is correlated with the future (past) industrial production growth. Finally, Obs. is the number of observations that I have for each U.

While implied stock market volatility and the SCUs are positively correlated, with correlation coefficients 0.35 and 0.55 for inflation and output growth respectively, the VXO index experiences many sharp spikes. Interestingly, most of these spikes in the VXO index are not picked up by the SCUs. For example, "Black Monday" spike in October 1987, which includes the largest single day decline recorded in stock market, is easily identified by the VXO index. Although this may be an indication of a dramatic rise in stock market uncertainty, the SCU estimates reflecting the subjective macroeconomic uncertainty barely increase in October 1987. More importantly, the level of macroeconomic uncertainty, which is proxied by the VXO index, is historically at its second highest peak even if 1987 is not a recession year. Besides "Black Monday", there are other important episodes that the VXO index and the SCU estimates substantially disagree. In particular, the VXO index surges during other non-recessionary periods such as during the LTCM crisis in 1998Q3, Enron scandal in 2002Q3 or the Debt-ceiling crisis in 2011Q3. While all of them can be considered as heightened stock market uncertainty episodes, it is hard to interpret them as heightened macroeconomic uncertainty episodes.

Table 1.3: ***SCU Regressed on Other Uncertainty Proxies***

	Different Uncertainty Proxies					
SCU:	VXO	QIQR	Profits	CRSP	Google	Disagreement
corr(π, U)	0.342	0.530	0.067	0.344	0.359	0.309
# of Obs.	180	167	180	180	115	180
corr(Δy, U)	0.555	0.607	0.210	0.556	0.412	0.495
# of Obs.	129	129	129	129	115	129

Notes: This table reports the correlations between either inflation (π) or output growth (Δy) SCU against various empirical uncertainty measures (U) governed by each column of the table 1.3. These empirical uncertainty measures are explained in detail in table 1.2 above. Disagreement in the last column of table 1.3 is inflation disagreement or output growth disagreement matching inflation or output growth SCU measure.

There are various reasons for surges in the implied stock market volatility besides economic uncertainty. First, these increases are mainly related with stock market returns but rarely with macroeconomic variables. Second, implied stock market volatility appears to have a large component primarily driven by factors associated with time-varying risk aversion rather than economic uncertainty Bekaert, Hoerova, and Lo Duca (2013). To understand the role of time-varying risk aversion during the heightened uncertainty episodes, following Bekaert, Hoerova, and Lo Duca (2013), I project the future monthly realized variances (derived by 5-minute returns of the S&P500 index) on the current realized volatility and the implied volatility measured by the VIX index[25]. The fitted values from this regression are time-varying uncertainty whereas the residual, i.e. the difference between the actual and the fitted volatilities, is time-varying risk aversion. While the details of this procedure explained in Appendix A.2.1, Table 1.4 demonstrates the levels and the contribution of the time-varying risk aversion and the stock market uncertainty to the jumps in the VIX index for some of Bloom's heightened uncertainty episodes.

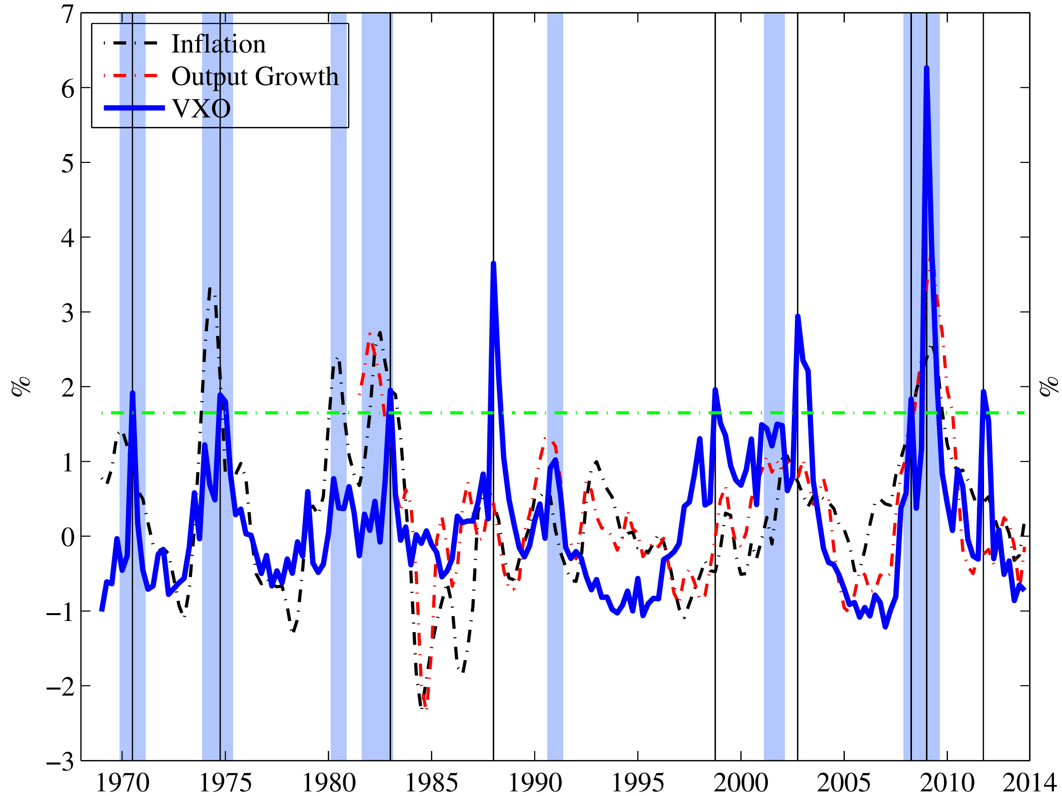
Table 1.4: ***The Risk Aversion vs The Stock Market Uncertainty***

	RA	**RA/VIX (%)**	**UC**	**UC/VIX (%)**
Average	7.42	26.99	17.72	73.01
1998Q2	19.54	50.93	18.83	49.07
2002Q2	15.63	31.52	33.97	68.48
2008Q1	9.84	29.38	23.65	70.62
2008Q4	30.82	35.94	54.94	64.06
2011Q2	16.32	41.87	22.66	58.13

Note: Table 1.4 presents the levels and part of the spike in the VIX index that is associated with time-varying risk aversion and stock market uncertainty as a percentage of the VIX index for fairly recent heightened uncertainty episodes identified by Bloom (2009). Time-varying stock market uncertainty is identified by projecting future realized stock market variance (derived by 5-minute returns of the S&P500 index) into current realized stock market variance and the squared VIX index. On the other hand, the time-varying risk aversion is the residual of the difference between the squared VIX and the stock market uncertainty term. The details of this decomposition appears in the Appendix A.2.1. The sample period for the estimation is January 3, 1994 - December 31, 2013.

[25]The VIX index is constructed from the prices on a hypothetical at the money option contracts written on the S&P500 Index rather than the S&P100 Index as is the case for the VXO. Although the VIX and the VXO indices are slightly different empirical measures of implied stock market volatility, they have quite similar time series properties. For instance, the correlation level between these objects is equal to 98% and this is the main reason why I treat these indices as close substitutes.

Figure 1.2: ***SCUs and Implied Stock Market Volatility***



Note: The VXO Index, inflation and output growth SCU estimates are presented in standardized units. Bloom counts uncertainty episodes by the number of times the stock market volatility index exceeds 1.65 standard deviations above its Hodrick and Prescott (1997) filtered trend in monthly frequency. Extending his sample to current date and applying his methodology in quarterly frequency identifies 9 heightened uncertainty episodes shown by black vertical lines in figure 1.2. Table A.9 at the appendix provides the heightened uncertainty dates both in monthly and quarterly frequency. The horizontal (green) dashed-line corresponds to 1.65 standard deviations above the unconditional mean of each series (which has been normalized to zero). The shaded bars are recessions defined according to the NBER Business Cycle Dating Committee.

Table 1.4 shows that time-varying risk aversion can explain approximately one third of the fluctuations in the VIX index during the years 1993 - 2013[26]. While the lion's share of the fluctuations in the VIX index can be attributed to stock market uncertainty, the contribution of risk aversion as a percentage of the VIX index significantly increases during Bloom's heightened uncertainty episodes.

[26]Due to data availability, I only focus on the recent heightened uncertainty episodes identified by Bloom (2009).

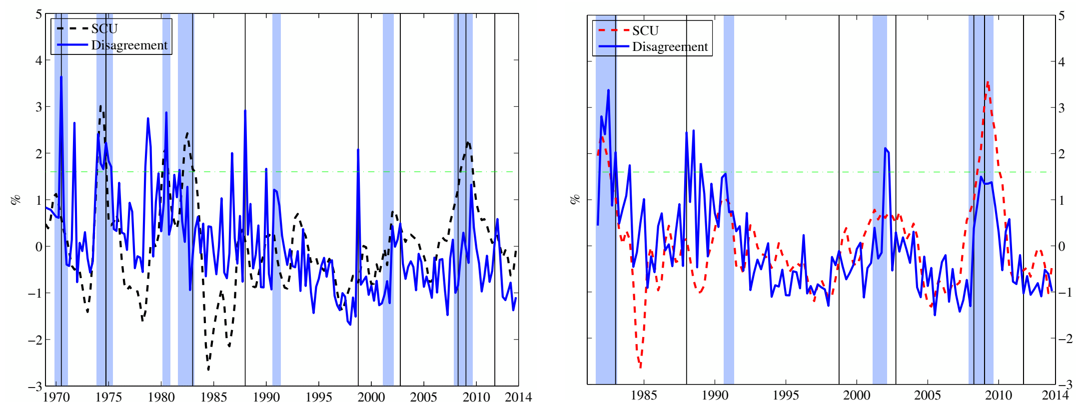
The spikes in risk aversion, for instance, can explain on average more than half of the spikes in the VIX index in these episodes. In particular, during the LTCM crisis in 1998Q2, 64% the jump in the VXO index is attributed to spike in time-varying risk aversion. Even during the Great Recession, half of the jump in the VIX index can be attributed to the jump in risk aversion. On the other hand, the SCUs experience minor increases during these episodes except for the Great Recession. All said, it seems the jumps in the risk aversion explain significant portion of the spikes in the VIX index, so heightened uncertainty episodes identified by Bloom (2009) are mainly driven by fluctuations in the risk aversion rather than stock market uncertainty.

Another commonly used empirical uncertainty proxy is disagreement[27] even though, the evidence regarding the relationship between the two is generally weak. While the contemporaneous correlation in these series seem to be in the 0.33-0.48 range, similar to the VXO index, both inflation and output growth disagreement series experience frequent spikes as presented in Figure 1.3. For instance, 1986-1988 episode, which includes "Black Monday", stands out to be a period of high disagreement but low macroeconomic uncertainty (as measured by either of the SCUs).

One simple way to summarize the differences in opinions and subjective uncertainties at a point in time is to create a two-dimensional plot with subjective

[27]Several papers including Ferderer (1993); Leahy and Whited (1996); Bomberger (1996); Giordani and Söderlind (2003); Boero, Smith, and Wallis (2008); Popescu and Smets (2010) and Baker, Bloom, and Davis (2012) used disagreement as a proxy for macroeconomic uncertainty.

Figure 1.3: ***Non-Zero Probability Assigned to the Lowest-Extreme Bin***

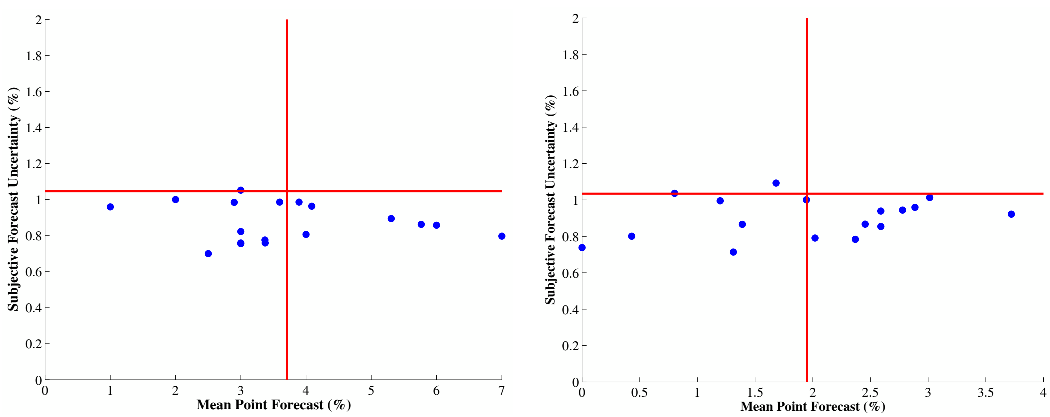


(a) ***Inflation*** **(b)** ***Output Growth***

Note: Figure 1.3a present inflation disagreement and inflation SCU estimates, whereas figure 1.3b present output growth disagreement and output growth SCU estimates in standardized units. The horizontal (green) dashed-line corresponds to 1.65 standard deviations above the unconditional mean of each series (which has been normalized to zero). The solid lines in both these figures are disagreement whereas the dashed lines are the SCU estimates. The shaded bars are recessions defined according to the NBER Business Cycle Dating Committee.

mean point forecast in one axis and the subjective forecast uncertainty in the other. To illustrate the differences in opinions against subjective forecast uncertainties, figure 1.4 presents two separate plots for inflation and output growth in 1987Q4. In each figure, I plot the subjective forecast uncertainties of experts that are adjusted for forecaster heterogeneity and structural changes in the deterministic seasonality patterns (i.e. equation 1.3.3) on the y-axis against the subjective mean probabilistic forecast that are derived from empirical belief distributions of experts on the x-axis. Therefore, each point represents a unique forecaster participated in the SPF in 1987Q4 survey. The intersection of the two straight lines in these figures represent the historical average of inflation or output growth SCU estimate against the consensus forecast in 1987Q4 about the next year's inflation or output growth. When the points are dispersed horizontally, disagreement in the central tendency of forecasts is high, whereas if the points cluster towards the top, forecasters tend to feel more uncertain compared to historical averages of the SCUs. Consistent with the time series estimates of the disagreement and the SCUs, figure 1.4 confirms that forecasters in the SPF highly disagree about the next year's inflation and output growth in 1987Q4. However, majority of the points are below the historical averages of the relevant SCU measure, suggesting that they feel less uncertain about their subjective mean point forecast.

Figure 1.4: *Subjective Forecast Uncertainty against Subjective Mean Forecast: 1987Q4*



(a) ***Inflation*** (b) ***Output Growth***

Note: Scatter plots of subjective forecast uncertainty and subjective mean point forecasts of experts both for inflation and output growth in 1987Q4. Subjective forecast uncertainties are the exponential of the error terms in equation 1.2 whereas subjective mean point forecasts derived from the fitted generalized beta distributions explained in section 1.3.1. The vertical red lines are the consensus forecasts (cross sectional averages) of the next year inflation or output growth subjective mean point forecasts. The horizontal lines are the historical averages of either the inflation or the output growth SCU estimates.

Tables 1.2 and 1.3 show the descriptive statistics and correlations between commonly used uncertainty proxies against the SCUs. First, realized cross-sectional dispersion measures (derived from micro level firm data) exhibit mostly lower and/or less persistent correlation with the HP-detrended industrial production. Second, their correlation with the SCUs are in 0.1 - 0.57 range but they all experience more frequent spikes than the SCUs. For instance, almost all of these empirical uncertainty measures experience a major spike during 2001, even though this recession is less severe than the 1980-82 or 2007-09 recessions. On the other hand, the SCUs experience a minor increase compared to their unconditional average. Taken together, these findings suggest that commonly used uncertainty measures are weakly associated with movements in macroeconomic uncertainty, whereas factors such as heterogeneity in the cyclicality of firms business activity, disagreement in opinions or time varying risk aversion seem to be important drivers in these proxies.

1.5 Economic Uncertainty and Macroeconomic Dynamics

Apart from uncertainty proxies being countercyclical, the existing empirical research on uncertainty often finds important dynamics between fluctuations in economic uncertainty and real activity. In subsection 1.5.1, I compare the dynamic relationship between the SCUs and other commonly used uncertainty measures against macroeconomic aggregates. To do so, I use an 8 variable recursively identified VAR model that has been previously employed in the uncertainty literature as in Bloom (2009). In his work, Bloom (2009) found a strong countercyclical relationship between real activity and uncertainty measured by the VXO index. His VAR estimates suggest that an innovation to uncertainty first sharply depresses real activity with effects remaining significantly below the long-run trend for the first six to seven months, and then real activity significantly overshoots its long-run trend in the medium term. While this pattern is consistent with the predictions of the theories that consider uncertainty as a driving force of business cycle fluctuations, I show that this empirical prediction depends on the empirical uncertainty measure that is used to proxy macroeconomic uncertainty. In contrast to Bloom (2009), I demonstrate that an innovation to uncertainty measured by either of the SCUs leads to sizable and protracted declines in production and employment without exhibiting a "volatility overshoot".

An important unresolved issue for empirical analysis of uncertainty concerns whether heightened economic uncertainty is a symptom rather than a cause of macroeconomic fluctuations (e.g. Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2012), Gilchrist, Sim, and Zakrajšek (2014) and Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2013)). However, the baseline specification that is presented in subsection 1.5.1 implicitly assumes that uncertainty is cause. To make progress with this problem, in subsection 1.5.2, I propose a small scale sign-identified VAR model that identifies structural uncertainty shocks conditioning on financial fragility. The results suggest that while innovations to uncertainty leads to protracted declines in production, the magnitudes of the declines are much smaller compared to baseline VAR estimates. In fact, the bigger fraction of the fluctuations in production can be explained by innovations to financial conditions rather than the innovations to uncertainty similar to Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2013).

Furthermore, online appendix[28] provides results of a large number of robustness exercises ranging from alternative ordering schemes for Cholesky identification to broad macroeconomic variables rather than using manufacturing sector related variables as in this section. Overall, results presented in the online appendix are qualitatively consistent the ones presented in this section.

1.5.1 Benchmark VAR

In this section, following the existing empirical research, I use VARs to investigate the dynamic relationship between two key macroeconomic variables: production and employment against an innovation to macroeconomic uncertainty which is either measured by the inflation or the output growth SCUs. To put these results into perspective, I re-estimate the same VAR with different empirical uncertainty measures that are presented in subsection 30, and compare the results with the ones generated by the SCUs. I generally refer these innovations as uncertainty shocks, but this depends on the ordering of the variables as identification achieved by Cholesky orthogonalization. Bloom (2009) traced out the responses of production and employment to a 4 standard deviation shock to uncertainty, which is measured by the VXO index, from a VAR that consists of the following 8 variables: the log of the S&P 500 index, an uncertainty measure, federal funds rate, log of wages, log of Consumer Price Index, log of hours worked, log of employment and log of industrial production

[28] Provide the link for the online appendix from my webpage.

index in that order. Here, I take his identification scheme as given and use several uncertainty measures as well as implied stock market volatility.[29].

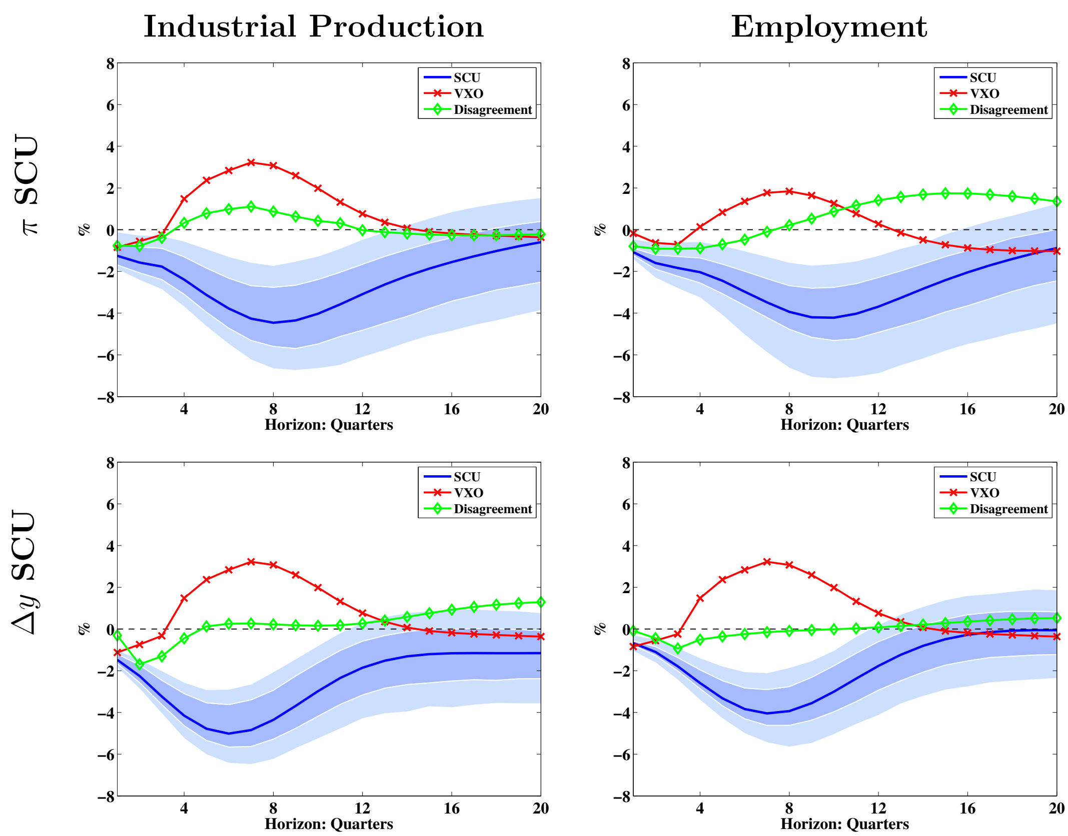
Figure 1.5 shows the dynamic responses of industrial production and employment in the baseline recursively identified 8 variable VAR model. Shocks to uncertainty are measured either by inflation or output growth SCU lead to slowly-building and economically significant declines in production and employment with effects remaining statistically significant up to 4 years. The solid red (with cross) and green (with diamond) lines compare the point estimate of the responses of the same variables when either the VXO index or disagreement (inflation disagreement for the first row of figure 1.5 whereas the output growth disagreement for the second row) is used as a proxy for uncertainty. While both of these proxies lead to contractions in real activity measures and the initial responses generated by them are statistically indistinguishable, the difference in magnitude and the persistence of the responses of production and employment strikingly different from each other particularly after the third quarter that uncertainty shock hits to economy. This once again underscores two findings of the section 4.2: (i) the persistent nature of SCUs compared to other uncertainty proxies, (ii) the persistent correlations of the SCUs with the economic activity[30]. In particular, the response of employment to a VXO or disagreement disturbance is barely statistically different when the shock is realized[31]

[29] All VARs reported in this section have 4 lags and for each case identification is achieved by recursive ordering. Finally, similar to Bloom (2009), I detrend all variables besides the empirical uncertainty measure by using Hodrick and Prescott (1997) filter with the smoothing parameter $\lambda = 129,600$.

[30] See table 1.2 in section and figure A.5 in appendix A.2 for details.

[31] Instead of providing the confidence intervals of employment or production response to VXO or disagreement shock, I provide point estimates of the impulse responses to make these

Figure 1.5: ***IR of Production and Employment: Shock to the SCU, VXO or Disagreement***

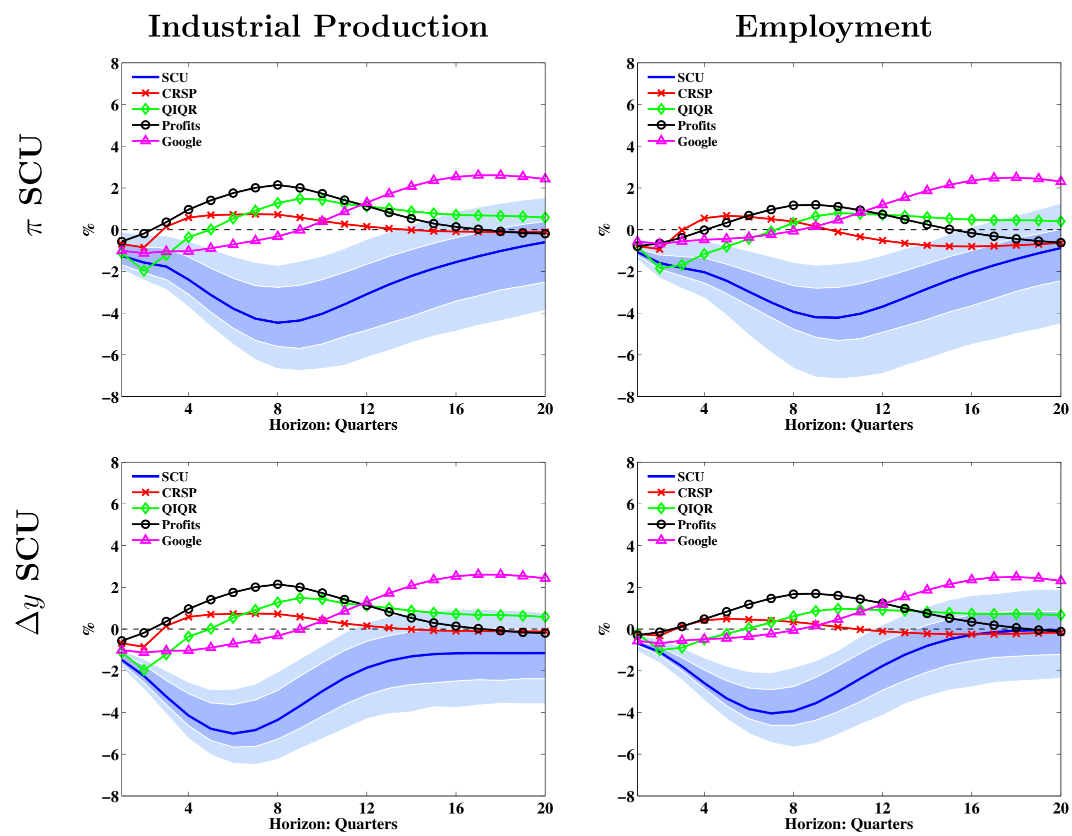


Note: The baseline VAR estimation consists of 8 variables identified by Cholesky decomposition. The order of variables is log of S&P 500 index, uncertainty proxy, federal funds rate, log of wages (manufacturing sector), log of Consumer Price Index, log of hours worked (manufacturing sector), log of employment (manufacturing sector) and log of industrial production index. Impulse response functions trace out the dynamics of Industrial Production and manufacturing employment to a 4 standard deviation shock to the relevant uncertainty proxy, which can be either the inflation (π) or the output growth (Δy) SCU, VXO or the disagreement (i.e. the inflation disagreement for figures in the first row and the output growth disagreement otherwise). For all figures, the coverage of dark shaded areas are 66% while the coverage of dark and light shaded ones are 90% confidence intervals using Kilian (1998) bias-corrected bootstrap.

but they quickly rebound within 2 to 3 quarters. However, as also documented by Bloom (2009), a shock to VXO index leads statistically significant "volatility

magnitudes comparable to the ones generated by the SCUs.

Figure 1.6: ***IR of Production and Employment: the SCUs and Other Uncertainty Proxies***



Note: The baseline VAR estimation consists of 8 variables identified by Cholesky decomposition. The order of variables is log of S&P 500 index, uncertainty proxy, federal funds rate, log of wages (manufacturing sector), log of Consumer Price Index, log of hours worked (manufacturing sector), log of employment (manufacturing sector) and log of industrial production index. Impulse response functions trace out the dynamics of Industrial Production and manufacturing employment to a 4 standard edition shock to the relevant uncertainty proxy: (*i*) the inflation (π) or the output growth (Δy) SCU, (*ii*) the Google News index (Baker, Bloom, and Davis, 2012), (*iii*) the Profits, i.e. the cross-sectional standard deviation of firm profits (Bloom, 2009), (*iv*) the QIQR, i.e. the interquantile range of the industrial production growth for manufacturing industries (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), and (*v*) the CRSP, i.e. the within quarter cross-sectional standard deviation of firm-level stock returns for rm with 500+ months of data in the Center for Research in Securities Prices (Bloom, 2009). The details of these uncertainty proxies are provided in section 30. For all figures, the coverage of dark shaded areas are 66% while the coverage of dark and light shaded ones are 90% confidence intervals using Kilian (1998) bias-corrected bootstrap.

overshoot" in both the real activity and the employment following the initial decline after a positive uncertainty shock. Interestingly, this "volatility overshoot" pattern generated by a VXO disturbance is a robust finding that continues to hold under different VAR specifications[32].

On the other hand, figure 1.6 documents the responses of the same macroeconomic variables to an innovation to uncertainty measured by other empirical uncertainty proxies, besides implied stock market volatility or disagreement. Overall, these measures generate broadly similar responses in production and employment as the VXO index. In particular, the initial responses of employment and production are statistically indistinguishable during first two to three quarters. Once the maximum decline in economic activity is materialized, depending on the uncertainty measure, production either goes back to its long run level or overshoots it[33]. For employment, on the other hand, innovations generated by different uncertainty measures have roughly the same pattern as production. Besides the QIQR, all empirical uncertainty measures generate small increases in employment. This finding, however, sharply contrasts with uncertainty innovations originated from the SCUs which are in line with the type of employment and production responses that Jurado, Ludvigson, and Ng (2013) documents in their VAR applications. Finally, the responses to uncertainty shocks governed by other commonly used uncertainty indices are not as large as the ones generated by the SCUs.

To evaluate the importance of uncertainty shocks in explaining macroeconomic dynamics, table 1.5 documents the forecast error variance decomposition for

[32] These results are presented in the online appendix.

[33] While I do not present the confidence intervals for employment and production responses to an innovation to either one of the commonly used uncertainty measure, the overshooting responses of production are mostly significant in 66% confidence intervals.

production and employment for the baseline recursively identified 8 variable VAR. In this table, h represents the forecast horizon where I report the fraction of the VAR forecast error variance that is attributable to different uncertainty measures. Specifically, each column represents a VAR using different uncertainty measure. Finally, Max is the greatest fraction of VAR forecast error variance of the employment and production that can be explained by an uncertainty disturbance at the horizon h (denoted by h at Max in the table 1.5).

Table 1.5 reports that the SCU shocks are associated with much larger fraction of the variance of in real activity then with other empirical uncertainty proxies. For instance, shocks to implied stock market volatility are associated with a maximum of 11.7% of the forecast error variance in production and 7.6% of the forecast error variance in employment. On the other hand, the corresponding values for the inflation and output growth SCUs are in the 25% - 33% range, which are almost twice the size of the forecast error variance that can be explained by the implied stock market volatility. Broadly speaking, this pattern holds for all other commonly used uncertainty measures. Furthermore, the explanatory power of the SCUs on the forecast error variance of production and employment is slowly building up which is once again consistent with the persistent nature of these series.

Of course, the variance decomposition results presented in Table 1.5 are specific to ordering of the variables that are included in the VAR. An alternative approach is to place uncertainty as the last variable and document the effects of uncertainty shocks once I remove the endogenous variations that are attributed to other variables. These results are presented at the online appendix but I discuss some of them here. When I order uncertainty as the last variable in the 8 variable VAR presented above, innovations to uncertainty measured either by inflation or output growth SCU can explain approximately 15-20% of the forecast error variance in production and employment, which is approximately the twice the size of the forecast error variance that can be explained by anyone of the commonly used uncertainty proxies. These variance decomposition results are quantitatively similar to ones reported here even if I include both the inflation (or output growth) SCU and another commonly used uncertainty proxy and re-estimate the VAR with 9 instead of 8 variables[34]. From such VARs, it seems that shocks to any one of the commonly used uncertainty proxy mainly explained by shocks to itself rather than shocks to either inflation or output growth uncertainty. For the 9 variable VAR specification, on the other hand, the SCU (either inflation or output growth) can explain bigger fraction of the forecast error variance in production and employment compared to anyone of the commonly used uncertainty proxies.

These results reinforces two important findings. First, fluctuations in commonly used uncertainty proxies are driven largely by shocks other than fluctuations in macroeconomic uncertainty. Second, the effects of uncertainty shocks can still explain a non-trivial share of forecast error variance of production and employment, which aligns with the theories showing macroeconomic uncertainty has important implications for economic activity.

[34]For these VARs, the commonly used uncertainty proxy is ordered as the second whereas the SCU (either inflation or output growth) is ordered as the third variable.

Table 1.5: ***Relative Importance of Different Uncertainty Measures in the VAR***

	π SCU	Δy SCU	VXO	CRSP	Google	Profits	QIQR	DISInf	DISGrw
					Industrial Production				
$h = 1$	1.15	6.81	0.38	1.97	4.49	0.97	11.66	2.47	3.55
$h = 4$	4.43	24.72	4.20	1.38	4.38	0.90	10.74	1.10	9.20
$h = 8$	18.68	32.27	11.72	0.95	3.34	4.65	6.53	0.79	12.02
$h = \infty$	24.86	22.53	10.34	1.08	13.35	6.05	5.36	3.27	8.86
Max	25.82	32.80	11.74	2.67	13.35	6.32	16.15	3.74	12.02
h at Max	16	8	10	3	24	14	3	1	9
					Employment				
$h = 1$	1.71	3.07	2.15	1.53	5.65	0.55	8.00	4.24	2.42
$h = 4$	4.04	20.78	1.52	0.67	2.76	0.34	8.79	1.16	5.15
$h = 8$	17.54	35.75	6.10	0.39	1.37	3.46	5.46	0.63	8.34
$h = \infty$	23.74	24.68	7.64	1.17	17.20	5.88	3.91	3.62	6.57
Max	25.74	35.75	7.64	1.53	17.20	6.31	12.14	5.86	8.41
h at Max	14	9	24	2	24	15	3	1	10

Note: The baseline VAR estimation consists of 8 variables, all of which (beside the empirical uncertainty measure) detrended by the filter of Hodrick and Prescott (1997), identified by Cholesky decomposition. The order of variables is log of S&P 500 index, uncertainty proxy, federal funds rate, log of wages (manufacturing sector), log of Consumer Price Index, log of hours worked (manufacturing sector), log of employment (manufacturing sector) and log of industrial production index. The uncertainty proxies are: (*i*) inflation (π) or output growth (Δy) SCU, (*ii*) Economic Policy Uncertainty (EPU) Index of Baker, Bloom, and Davis (2012), (*iii*) Profits is the cross-sectional standard deviation of firm profits (Bloom, 2009), (*iv*) QIQR is the interquantile range of the industrial production growth for manufacturing industries (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), (*v*) CRSP is the within quarter cross-sectional standard deviation of rm-level stock returns for rm with 500+ months of data in the Center for Research in Securities Prices (Bloom, 2009) and, (*vi*) disagreement is the mean point forecasts of density histograms adjusted for deterministic seasonality where first row is the inflation and second row is the output growth disagreement. Each column shows the fraction of forecast-error variance of the variable given in the panel title at VAR forecast horizon h that is explained by the uncertainty measure named in the column. The row denoted "max" gives the the maximum fraction of forecast error variance that uncertainty variable named in the column explains forecast error variance of either industrial production or employment in the manufacturing sector. The raw "h at Max" gives the horizon h that fraction of the maximum forecast error variance explained at "max".

1.5.2 Sign-Identified VAR

There are two fundamental concerns regarding the identification of the structural uncertainty shocks by a recursively identified VAR. First one is about which variables to be included into the empirical method. While the baseline VAR specification presented in subsection 1.5.1 closely follows Bloom (2009), this empirical specification assumes that fluctuations in uncertainty is a cause rather than the result of macroeconomic fluctuations. However, several researchers suggest alternative mechanisms leading to endogenous increases in macroeconomic uncertainty (e.g. Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2012), Gilchrist, Sim, and Zakrajšek (2014), and Fajgelbaum, Schaal, and Taschereau-Dumouchel (2014)). A promising mechanism that has been suggested by Gilchrist and Zakrajsek (2012) and Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2013) is the role of financial fragility for generating endogenous increases in macroeconomic uncertainty. However, as documented by Stock and Watson (2012), financial distress and macroeconomic uncertainty are highly contemporaneously correlated, this makes the identification of structural uncertainty and financial fragility shocks a hard problem to solve. In particular, as the indicators of these variables are relatively fast moving, it is highly controversial to identify these shocks by means of equality restrictions as in the recursively identified VAR.

Second, Bloom (2009) assumes that causality starts from an innovation to uncertainty, which is controlled by first moment shocks that are captured by stock market, then runs into the prices and finally affects the real variables. Even without including a variable that measures the financial conditions, zero restrictions in this setup not easy to defend in economic grounds.

Instead of leaning on the equality restrictions as in subsection 1.5.1 which are rarely supported by economic theory, here I provide an alternative identification mechanism to recover the structural uncertainty shocks with an empirical VAR model. The identification strategy relies on economically motivated inequality (sign) restrictions on the impulse response functions. However, this strategy comes with a cost; that is, I can only achieve a set identification that consists of several structural models whereas Cholesky decomposition provides a unique model.

To recover the structural uncertainty shocks, I employ a quarterly 5-variable VAR of lag order 4. The variables in the empirical VAR model consists of log of CPI, log of production, FFR, either the inflation or the output growth SCU and the Excess Bond Premium (EBP) index of Gilchrist and Zakrajsek (2012) to capture the dynamics in the financial fragility. Similar to benchmark VAR estimates, I detrend all variables besides the SCU and the EBP. I normalize both the sign and the scale of the contemporaneous impact of structural shocks on their own variable. Finally, I explore the dynamic effects of a 4 standard deviation shocks to uncertainty and financial fragility on production.

Rationale for This Specification

There are three variables that are included in the VAR model to capture the macroeconomic dynamics in the US: consumer prices and industrial production, representing the non-policy block and the federal funds rate, representing the policy block. While most of the literature has preferred larger sets of variables, there are a few existing papers that characterize the macroeconomic dynamics with only three variables similar to mine[35]. Here, the choice is mostly due to computational reasons, whereas the alternative would be to use a wider set of variables at the cost of the computational time. I extend this framework by including the baseline uncertainty measure (the SCU) and a variable that captures the conditions in financial fragility, i.e. Excess Bond Premium - EBP (Gilchrist and Zakrajsek, 2012). In short, a previously studied small scale VAR allows for the use of sensible, relatively well-understood identification techniques to parsimoniously estimate the dynamic impacts of structural shocks to uncertainty or financial fragility on the production.

Potential Identifying Restrictions

There are three sets of restriction that recover two structural shocks in the 5-variable VAR presented above. These structural shocks are either structural uncertainty or financial fragility shocks identified by the following restrictions:

1. **Effects of Uncertainty on Production and Financial Conditions:**

   I assume that a positive structural shock to uncertainty does not raise

[35] See Primiceri (2005) and references therein for the papers that identifies monetary policy shocks in small and large scale empirical VAR models.

production and does not improve the financial conditions[36]. In intuitive terms, these set of sign restrictions are easily justifiable on the basis of economic theory. In theory, as long as there is a curvature in the objective function of an agent and actions are at least partially irreversible, increases in uncertainty depresses hiring, investment, or consumption (Bloom, 2014). When uncertainty increases, either due to risk aversion or real option dynamics, agents become more cautious and wait uncertainty to dissolve. On the other hand, in the presence of financial constraints, a rise in uncertainty leads tighter financial constraints which binds the investment or consumption expenditure of agents (Meghir and Pistaferri, 2004; Arellano, Bai, and Kehoe, 2012).

2. **Effects of Financial Conditions on Production and Uncertainty:** A positive structural shock to financial fragility does not raise production, does not decrease economic uncertainty and does not tighten monetary policy.

   These sign restrictions can also be justified on the grounds of economic theory. To the extent that an increase in the excess bond premium reflects a reduction in the effective risk-bearing capacity of the financial sector, this leads a contraction in the supply of credit (He and Krishnamurthy, 2013). As a result, consistent with the financial accelerator mechanisms

[36] I also try to impose a positive structural shock to uncertainty does not tighten the monetary policy. Both quantitatively and qualitatively, however, the results do not seem to change with or without this restriction. Therefore, I prefer not to impose this restriction in the baseline case

emphasized in Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1999), the reduction in credit availability significantly contracts real activity. The non-tightening nature of responses of the federal funds rate to a shock to financial fragility is consistent with a systematic easing of monetary policy in reaction to lower economic activity. Consequently, this can be rationalized easily within the framework of the workhorse financial accelerator model as in Bernanke and Gertler (1995).

3. **Effects of Production on Uncertainty and Financial Fragility:** A negative shock to production does not decrease uncertainty and does not improve financial conditions.

The third class of restrictions entertains the possibility that a slowdown in production cannot improve the financial conditions and macroeconomic uncertainty. In theory, a decline in production due to a negative aggregate demand or productivity shock implies a deterioration in financial conditions due to a decline in the net worth of borrowers (financial accelerator mechanism at work) or a deterioration in asset prices (feedback effect to agents balance sheets from fire sales prices). Therefore, even a small decline in production is enough for generating a negative feedback mechanism between financial conditions and real activity (Krishnamurthy, 2010). The recent literature on learning and business cycle dynamics precisely underscores how uncertainty is endogenously generated due to sharp contractions in real activity (Van Nieuwerburgh and Veldkamp, 2006; Fajgelbaum, Schaal, and Taschereau-Dumouchel, 2014). When economic activity slows down, the diffusion of information among agents also slows down. This leads to an increase in the subjective uncertainty which is measured by belief distributions of agents.

Estimation Method

I impose the sign restrictions in 4 steps following the general methods of Faust (1998) and Uhlig (2005) as modified by Inoue and Kilian (2013)[37]. In the first step, I address the estimation uncertainty in the parameters assuming a diffuse prior over the reduced form VAR coefficients so the resulting posterior has a closed form solution. In the second step, I draw a large number of structural models following the methodology provided by Rubio-Ramirez, Waggoner, and Zha (2010). Third, I throw out all the models that do not satisfy the sign restrictions provided above and compute the posterior likelihood of the remaining structural models. Finally, I construct the 90% confidence interval from the models whose posterior probability sum to 90% of the total probability mass. The outer envelope of the set of most likely remaining (admissible) structural models is the joint confidence set that are presented in figure 1.7.

By characterizing the posterior probability of each structural model, I address two shortcomings of the standard, point-wise summaries of results. First, for sign-identified models, point-wise measures of central tendency are misleading. Consider the most commonly used point-wise measure of central tendency, i.e.

[37]The details of the computational algorithm appears in the online appendix.

the median. The median response function is constructed by taking the median of the distribution of all admissible models at each horizon, and stacking the medians into a single vector. However, it is very unlikely for this structural model to be actually observed in the data. Moreover, even if the point-wise median does correspond to a single structural model, there is no compelling reason to focus on that particular model as it is just one of many admissible models. Second, the point-wise confidence sets are misleading and may understate the true uncertainty regarding impulse response functions. Therefore, point-wise sets do not take into account the dependence of impulse responses across horizons, whereas joint confidence sets do.

Estimation Results

The set of sign restrictions demonstrates that limited, easily justifiable restrictions are adequate to identify economically important impacts of the structural uncertainty and financial fragility shocks on production. However, the magnitudes of the responses in production to a large uncertainty shock are much lower compared to the benchmark 8 variable recursively identified VAR.

In the empirical analysis, I apply three sets of sign restrictions on the impulse responses to an exogenous 4 standard deviations shocks to either uncertainty or financial fragility and trace out the responses of the industrial production in figure 7. In brief, it appears that a surprise increase in uncertainty lowers the industrial production initially, and it takes approximately 1 year for production to reach its lowest level. Then, production gradually recovers and it takes approximately 4 years for production to go back to its initial level. This pattern holds for both the 90% nominal coverage intervals and the modal (most likely) model. Interestingly, the production responses to a structural shock to uncertainty either measured by the inflation and the output growth SCU produce exactly the same pattern for industrial production.

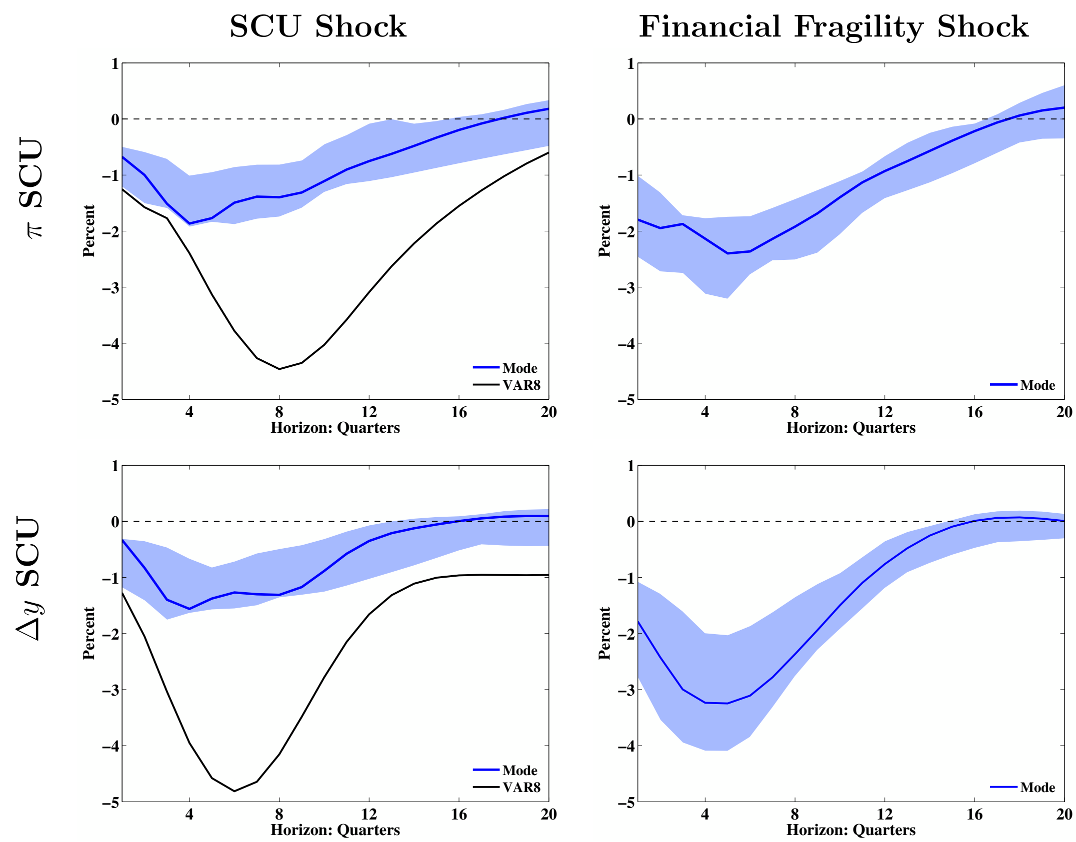
On the other hand, a surprise shock to financial fragility leads to a substantial drop in industrial production. Similar to a structural uncertainty shock, the decline in production slowly builds up and the lowest level is achieved in the sixth quarter after the shock. Then, production gradually goes back to its initial level and the 90% nominal coverage intervals of the impulse response of production continues to stay below the pre-shock level 4 years after the structural shock.

Figure 7 also provides the impulse responses of an uncertainty shock from the recursively identified 8-variable VAR model. While the magnitudes of the uncertainty shocks are the same in whether inflation or output growth SCU is used to proxy macroeconomic uncertainty, the responses of production from the sign or the recursively identified models are quite different in magnitudes. This is not surprising mainly because of two reasons. First, sign identified VAR introduces the EBP which has a contemporaneous correlation with the SCUs in 0.45-0.55 range, so it picks up some of the variation in uncertainty that is attributable to shocks to financial fragility. Second, I do not impose zero restrictions about the timing of the variables besides the contemporaneous sign restrictions, so the variation in uncertainty that is attributable to shocks to the macroeconomic block in the 5 variable VAR also pick some of the effects in uncertainty shocks as well.

Besides the possibility that causality is running in both directions between production and uncertainty, financial fragility appears to be a key channel to understand how the structural uncertainty shocks are affecting the business cycle dynamics. In particular, introducing the EBP index into a small-scale VAR model significantly reduces the effect of a structural shock uncertainty on production. For instance, the point estimate of the response of production to a structural uncertainty shock identified by the benchmark VAR (solid black line in figure 1.7) causes a 4% decline in production approximately in 8 quarters. At that point, the sign identified modal model shows that the maximum decline in production to a structural uncertainty shock is approximately 2% in 4 quarters after the shock.

Therefore, the results suggest that while uncertainty shocks have a significant on effects on production, compared to benchmark (8 variable VAR) estimates, the impact of uncertainty shocks on economic activity is substantially attenuated. Furthermore, structural shocks to financial fragility significantly reduces the production where effects remain significant up to 3 to 4 years with magnitudes (based on sign-identified modal model) higher than the structural shocks to uncertainty.

Figure 1.7: *Production Responses to a Structural Shock to SCU or EBP*



Note: The sign-identified VAR estimation consists of 5 variables: the inflation or the output growth SCU, federal funds rate, log of Consumer Price Index, log of industrial production index and the Excess Bond Premium. Impulse response functions trace out the dynamics of the industrial production to a 4 standard deviation structural shock to either the uncertainty or the financial fragility. The bold blue lines are the modal model and the confidence intervals in blue are 90% nominal coverage intervals whereas the black lines are the responses of production to an uncertainty shock derived from recursively identified 8-variable VAR model presented in figure 1.5. In the first row, the inflation SCU is the uncertainty measure used in the estimation whereas the output growth SCU used in the second.

1.6 Conclusion

In this paper, I introduced new measures of macroeconomic uncertainty that were derived from subjective density forecasts for inflation and output growth provided by the Survey of Professional Forecasters. I estimated these subjective macroeconomic uncertainty estimates in several steps in order to ensure that the problems in the SPF such as structural changes in survey, the fluctuations in the panel composition (due to frequent entering and exiting behavior of experts) or occasional errors do not lead any biases in my subjective macroeconomic estimates. I estimated the macroeconomic uncertainty perceived by agents which is the common subjective uncertainty component, i.e. Subjective Consensus Uncertainty (SCU), perceived by all agents in the economy. Furthermore, I also revisited the recent empirical work on the relationship between macroeconomic uncertainty and real economic activity.

I demonstrated that the resulting SCU estimates display surprisingly different dynamics compared to commonly used measures of uncertainty that are derived from implied stock market volatility, disagreement in survey forecasts, or realized cross sectional dispersion of firm's activities. In particular, I showed that the SCU estimates imply fewer important uncertainty episodes compared to other popular measures of uncertainty. Bloom (2009) documented 17 months of important uncertainty episode based on option-implied stock market volatility (i.e. VXO index) in US macroeconomic history. By extending his analysis to the current date and changing it to quarterly frequency, I show that there are 9 quantitatively important uncertainty episodes based on the VXO index, most of which are not apparent in the SCU estimates. Based on the SCU estimates, I recover four quantitatively important uncertainty episodes: the 1973-74 recession, two during the 1980-82 recessions and the 2007-09 recession. Further investigation on the empirical properties of other commonly used uncertainty proxies show that there are other factors besides economic uncertainty that drive fluctuations in these proxies. For instance, time varying risk aversion in the case of stock market volatility, or differences in opinions rather than forecast uncertainty in the case of survey based forecasts are important reasons to observe large fluctuations in these series rather than macroeconomic uncertainty.

In terms of dynamics, the SCU estimates reveal a strong negative association between measures of real activity and economic uncertainty. I show that while all empirical uncertainty measures recover the negative relationship between production and uncertainty in the short term, only the SCU estimates leads to sizable and protracted declines in production and employment without a "volatility overshoot" as in Jurado, Ludvigson, and Ng (2013). The SCU estimates reveal that macroeconomic uncertainty can explain about a quarter of the VAR forecast error variance in production and employment which is twice as much as other proxies can explain. Overall, as opposed to other conventional uncertainty estimates, subjective macroeconomic uncertainty estimates are more persistent, and shocks to them can explain larger fraction of the fluctuations in real activity.

While it is already hard to defend zero contemporaneous restrictions postulated by the ordering of the variables in a VAR, several researchers (e.g. see

(Gilchrist, Sim, and Zakrajšek, 2014; Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek, 2013)) suggested that fluctuations in uncertainty is a symptom of financial fragility, which leads to even further problems in identification of uncertainty shocks. In an attempt to make progress in these aspects, I propose a small scale sign-identified VAR model that includes both the SCU along with a proxy for financial fragility. I show that while the larger fraction of the fluctuations in production can be explained by innovations to financial conditions, the structural shocks to uncertainty still leads statistically significant and persistent declines in real economic activity.

Chapter 2

Identification of Monetary Shocks in Developing Countries: Evidence Based on Long-Run Restrictions

2.1 Introduction

There are many developing countries that have been exploring alternative monetary regimes after years of high and variable inflation. However there remains considerable debate regarding the appropriate framework for analyzing monetary policy in such an environment. Our goal in this paper is to develop a model which is appropriate for monetary policy analysis in developing economies. When developing such a model, Christiano, Eichenbaum, and Evans (1998) suggest applying the Lucas program. In our paper, we follow their advice and apply the Lucas program using monetary shocks. This involves three steps. First, we isolate monetary shocks in developing economies which adopted an inflation targeting regime. In the second step, we study the dynamic behavior of output, the real and nominal exchange rates, and the price level in developing economies following an expansionary monetary shock that results in a 1% increase in the price level in the long-run. In the last step, the same experiment is conducted in two different model environments and the outcomes in these models are compared with those in the actual economies.

Now, we elaborate on each of these steps. In the first step, we make two assumptions to identify monetary shocks in developing countries adopted inflation targeting regime. First, we assume that monetary shocks have no effect on the level of real variables in the long-term. This assumption is consistent with a broad class of models where monetary shocks have no long-run effect on real variables. Second, we assume that monetary shocks in developing economies do not affect the aggregate price level in the United States in the long-term. This assumption is in conformity with the small-country assumption for developing economies which is often made in the literature. With these assumptions, we show that monetary shocks can be isolated.

Having isolated monetary shocks in developing economies, we characterize our experiment in the second step of the Lucas program. We study how output, the bilateral real and nominal exchange rates with the United States, and consumer prices move in developing countries under inflation targeting after an expansionary domestic monetary shock that results in a 1% long-run increase in the price level. We find this shock is characterized by a temporary rise in output, a short-lived depreciation in the real exchange rate, a sizable overshooting of the nominal exchange rate, and a 0.5% contemporaneous increase in the consumer prices in these countries.

Our findings of short-lived effects from monetary shocks on output and the real exchange rate in developing economies contrast sharply with the persistent effects of monetary shocks on such variables in advanced economies. For example, while Christiano, Eichenbaum, and Evans (2005) find the effect of a monetary shock on output in the United States dissipates in about three years, we find the effect of monetary shock on output becomes negligible in less than one year in developing economies. Furthermore, we also show that shocks to the real exchange rate in developing economies have a half-life of less than a year whereas Rogoff (1996) documents that they have a half-life of three to five years in developed ones.

Another difference between developed and developing countries is the speed of price adjustment. While the inertial character of inflation results in a slow price-adjustment in advanced countries, we find price-adjustment is fast in developing countries. Specifically, prices adjust half-way, or more, within the same period as the shock and the full price-adjustment occurs in only one year.

There are three potential reasons to explain such short-lived real effects and faster price adjustment following a monetary shock in developing economies: (*i*) the higher pass-through of exchange rates into imports' prices, (*ii*) the less persistent shocks to monetary policy, and (*iii*) the more frequent changes in prices. The role played by the second and third factors leading to less persistent real effects of monetary policy shocks in developing economies are easy to understand. Yet, the role played by the first factor is more subtle and may occur if monetary policy is represented by a Taylor rule. Specifically, note that an unanticipated fall in interest rates is likely to be followed by rapid nominal depreciation. However, due to a larger exchange rate pass-through coefficient, this results in a stronger increase in inflation leading central banks in developing economies to raise their policy rates soon after they cause them to fall unexpectedly. Clearly, this behaviour of interest rates induces less persistent effects on output and the real exchange rate compared to ones in advanced economies.

In the last step of the Lucas program, we turn to assess the ability of two dynamic stochastic general equilibrium (DSGE) models to explain these findings. The first model is a one-sector model with identical firms that have the same frequency of price changes. In contrast, the second-model is a multi-sector model with heterogeneous firms which have different frequencies of price changes, so that prices can frequently change only in some sectors. Yet, they do not change frequently in other sectors. The common features in these models are: (*i*) Calvo-type nominal price contracts, (*ii*) heterogeneity in the frequency of price changes between the home and foreign countries, (*iii*) the price rigidity in terms of the price that firms set their prices regardless of firm being domestic or foreign, (*iv*) incomplete insurance of households in home and domestic countries, (*v*) variable capacity utilization, and (*vi*) a novel staggered wage-setting mechanism of households.

Yet, since it is standard practice in the literature to assume wages in developing economies respond fast to shocks, our staggered wage-setting assumption may invoke debate. In this regard, it is useful to discuss some evidence which supports the staggered wage-setting assumption in developing economies. To illustrate, a half of workers with social security benefits is paid the minimum wage which remains unchanged over a quarter in Turkey. Similarly, Kzdi and Knya (2009) note that 70% of wages are re-set in a specific month of a year in Hungary, which suggests that these wages are unchanged over one year duration. Such evidence supports our assumption that wages in developing economies have some rigidity.

Besides aligning with the wage-setting practices in developing economies, the staggered wage-setting assumption also helps the models successfully account for the findings in Li (2011). That is, with wage-setting mechanism that we introduce in this work, developing economies have an average contemporaneous correlation of 0.41 between detrended real wages and real GDP and that real wages are responsive to business cycles and lag the cycle by an average of one quarter. As a matter of fact, dropping the staggered wage-setting assumption and assuming instead wages are flexible results in the models predicting real wages and real GDP have an almost perfect correlation and that real wages closely follow business cycles without any lag.

After the discussion of the models' features, we compare the outcomes in the one- and multi-sector models to those in the actual economies after the monetary shock which causes a 1% long-run increase in the price-level. We find the latter is particularly accurate in accounting for the aggregate dynamics in the actual economies. A striking difference between the one- and multi-sector models is that the full price-adjustment takes a shorter duration in the one-sector model compared with that in the multi-sector model after the monetary shock. Regarding output and the real exchange rate, in line with the finding in Carvalho and Nechio (2011), we show that output and the real exchange rate in the one-sector model show less persistent dynamics than those in the multi-sector model.

The organization of the paper is as follows. Section 2.2 presents our empirical strategy for isolating monetary shocks in developing economies and reports our findings on the consequences of monetary shocks in developing economies with the inflation targeting regime. Section 2.3 introduces two dynamic stochastic sticky-price small-open economy models. Section 2.4 describes the estimation and calibration of the models' parameters. Section 2.5 evaluates the success of the models in accounting for the outcomes of a domestic monetary shock in the actual economies that are reported in Section 2.2. The last section concludes.

2.2 Empirical Section

The goal of this section is to develop an empirical model for studying the dynamics of output, the real exchange rate and the price level in developing countries under inflation targeting following a positive monetary shock. We introduce two different empirical models to identify these shocks. The former model closely follows the empirical strategy introduced in Clarida and Gali (1994) without seperetaly identifying monetary shocks in developing countries and the United

States. In latter one however, we develop an empirical model that separately these shocks in both developing countries and United States.

2.2.1 Empirical Models

2.2.1.1 Empirical Model I

By employing a Blanchard and Quah (1989) type decomposition, Clarida and Gali (1994) identify various structural shocks in four developed countries. In contrast to their concentration on developed countries, our focus is on developing economies. We first consider an empirical model based on the strategy in Clarida and Gali (1994). However, as opposed to estimating a VAR model for each country as in Clarida and Gali (1994), we estimate the following panel VAR model for the group of developing countries under inflation targeting.

$$X_{i,t} = \sum_{p=1}^{p_{max}} B_p X_{i,t-p} + \mu_i + u_{i,t} \tag{2.1}$$

where μ_i is the time-invariant country-specific fixed-effect term and p_{max} denotes the number of lags included in the panel VAR regression. We use both quarterly and monthly data to estimate (2.1) with the lag lengths chosen to be four and twelve, respectively. The endogenous variables in the panel VAR system of (2.1), X_{it}, consist of three variables:

$$X_{i,t} = \begin{bmatrix} \Delta\mathcal{Y}_{i,t} - \Delta\mathcal{Y}_t^* \\ \Delta Q_{i,t} \\ \Delta P_{i,t} - \Delta P_t^* \end{bmatrix} \tag{2.2}$$

where $\Delta\mathcal{Y}_{i,t} - \Delta\mathcal{Y}_t^*$ is the difference between the log changes in economic activity in the country of interest and the United States. For the quarterly data, we measure $\Delta\mathcal{Y}_{i,t} - \Delta\mathcal{Y}_t^*$ with real GDP differences in Economy i and the United States as in Clarida and Gali (1994). For the monthly data, on the other hand, we measure it with the differences in industrial production indexes between Economy i and the United States.[1]. The second variable in (2.2), $\Delta Q_{i,t}$, denotes the percentage change in the bilateral real exchange rate of the country of interest with the United States. $Q_{i,t}$ is defined as the cost of the consumption basket in the United States relative to that in the country of interest in the same currency.[2] Lastly, $\Delta P_{i,t} - \Delta P_t^*$ denotes inflation differences in consumer prices between the country of interest and the United States.

Clarida and Gali (1994) presume three different structural shocks which account for the movements of the variables in $X_{i,t}$. These are: *supply difference shocks* in the country of interest and the United States ($\epsilon_{i,t}^p - \epsilon_t^{p^*}$); *demand difference shocks* in the United States and the country of interest ($\epsilon_t^{d^*} - \epsilon_{i,t}^d$); and, *money difference shocks* in the country of interest and the United States ($\epsilon_{i,t}^m - \epsilon_t^{m^*}$). Demand shocks can be regarded as government spending shock or any other demand shock apart from money shocks.

The identification of structural shocks is achieved by placing restrictions on the long-run response matrix. To explain the identification method, let $u_{i,t} \sim N(0, \Omega)$ where Ω is the non-diagonal variance-covariance matrix of $u_{i,t}$. Also,

[1]Where data for seasonally adjusted series are available, we used these series. Otherwise, we obtained seasonally adjusted series from non-seasonally adjusted series by using the *Demetra+* program from Eurostat.

[2]Let $\mathcal{E}_{i,t}$ be the home currency price of the United States dollar in economy i. Also denote P_t^* and $P_{i,t}$ as indexes of the consumption basket in the United States and Economy i, respectively. We measure $\mathcal{Q}_{i,t}$ as $\frac{\mathcal{E}_{i,t} P_t^*}{P_{i,t}}$. Hence, a rise in $Q_{i,t}$ is associated with a depreciation of the real exchange rate vis-a-vis the United States.

suppose that $u_{i,t}$ is related to the structural shocks in the following way.

$$u_{i,t} = C_0 \epsilon_{i,t}, \quad \epsilon_{i,t} = \begin{vmatrix} \epsilon_{i,t}^{p} - \epsilon_{t}^{p^*} \\ \epsilon_{t}^{d^*} - \epsilon_{i,t}^{d} \\ \epsilon_{i,t}^{m} - \epsilon_{t}^{m^*} \end{vmatrix}, \quad \epsilon_{i,t} \sim N\left(0, C_0^{-1} \Omega C_0^{-1\prime}\right) \tag{2.3}$$

where C_0 is a 3×3 matrix of the contemporaneous responses of the variables to shocks. It is notable that due to the assumption of independence among different type of structural shocks, the variance-covariance matrix, $C_0^{-1} \Omega C_0^{-1\prime}$, is diagonal. Furthermore, under the normalization that the variance-covariance matrix of structural shocks is an identity matrix, the following equality has to hold:

$$C_0 C_0{}' = \Omega \tag{2.4}$$

Clarida and Gali (1994) identify structural shocks by imposing restrictions on the effects of these shocks on the level of the output difference, the real exchange rate and the price level difference in the long-run. Denoting the matrix of the long-run impulse responses by $\mathcal{D}$, Clarida and Gali (1994) isolate structural shocks by assuming that $\mathcal{D}$ is lower triangular.

$$\mathcal{D} = \begin{vmatrix} d_{11} & 0 & 0 \\ d_{21} & d_{22} & 0 \\ d_{31} & d_{32} & d_{33} \end{vmatrix} \tag{2.5}$$

The ordering of the variables in (2.2) implies only supply shocks influence the level of the output difference in the long-run. Neither demand nor money shocks have a permanent effect on the *level* of the output difference. Regarding the real exchange rate, its level is affected permanently by supply or demand shocks. Lastly, all three shocks have a long-run impact on the *level* of the CPI difference.

Yet, the lower triangularity of the long-run matrix is not enough to uniquely recover structural shocks. Accordingly, we impose sign restrictions on $\mathcal{D}$ as well.

In particular, we assume that a larger supply and monetary shock in Economy i compared to the United States are assumed to increase the long-run levels of GDP and CPI in Economy i relative to the United States, respectively ($d_{11} > 0$, $d_{33} > 0$). In addition, a larger demand shock in Economy i compared to the United States is assumed to *appreciate* the long-run level of the real exchange rate of Economy i relative to the United States ($d_{22} > 0$). This can happen if government spending mostly fall on non-traded goods.

Some restrictions on the long-run impact matrix in Clarida and Gali (1994) are debatable. For example, the sign restriction that an expansionary fiscal shock in Economy i appreciates the real exchange rate in the long-run should necessarily be taken with a grain of salt (For example, see Ravn, Schmitt-Groh, and Uribe (2007) for counter evidence). Similarly, the exclusion restriction in Clarida and Gali (1994), that the fiscal shocks have no long-run effect on the level of output, is subject to criticism because it is quite likely that fiscal shocks such as spending shocks on education and infrastructure impact the long-run output level in a country. Based on these considerations, we slightly modify the long-run impact response matrix. Indeed, as in Clarida and Gali (1994), we assume monetary shocks have a long-run impact on neither output level nor the real exchange rate level. Yet, we do not place any restriction regarding the long-run impact of productivity and demand shocks on the level of any of the variables. Let $\vec{\mathfrak{D}}$ denote the modified long-run impact matrix of structural shocks with the above noted restrictions on the level of the variables. This matrix can then be written as

$$\vec{\mathfrak{D}} = \left| \begin{array}{ccc} \vec{d}_{11} & \vec{d}_{12} & 0 \\ \vec{d}_{21} & \vec{d}_{22} & 0 \\ \vec{d}_{31} & \vec{d}_{32} & \vec{d}_{33} \end{array} \right| \tag{2.6}$$

In addition to the restrictions in (2.6), it can be shown that $\vec{\mathfrak{D}}$ must also satisfy

$$\vec{\mathfrak{D}}\vec{\mathfrak{D}}' = \left(I - \sum_{p=1}^{p_{max}} B_p \right)^{-1} \Omega \left(I - \sum_{p=1}^{p_{max}} B_p \right)^{\prime -1} \tag{2.7}$$

The modified long-run impact matrix of structural shocks, $\vec{\mathfrak{D}}$, has seven free parameters whereas $\vec{\mathfrak{D}}\vec{\mathfrak{D}}'$ is symmetric so it has only six independent elements. Hence, it is not possible to uniquely recover all the parameters of the $\vec{\mathfrak{D}}$ matrix. In particular, an analysis of the dynamic responses of the variables following *productivity* and *demand* shocks necessitates knowing the elements in the first and second columns of (2.6), respectively. Yet, such an analysis is not feasible as the elements in these columns are unidentifiable given the structure of $\vec{\mathfrak{D}}$. However, the third column can be uniquely recovered. This allows us to investigate dynamic responses of the variables to monetary shocks. To prove this, note first that since the model is not uniquely identified, there are many matrices satisfying (2.7). Letting $\vec{\mathfrak{D}}$ and $\vec{\mathfrak{D}}^A$ be two of such matrices (i.e. both $\vec{\mathfrak{D}}$ and $\vec{\mathfrak{D}}^A$ are block lower-triangular as stated in (2.6) and satisfy (2.7)), we can always find a square block lower-triangular orthonormal matrix $\vec{\omega}$ such that (2.8) holds.

$$\vec{\mathfrak{D}}^A = \vec{\mathfrak{D}}\vec{\omega} \tag{2.8}$$

One can show the reason for $\vec{\omega}$ matrix to be block lower-triangular and orthonormal in three steps. First, we show $\vec{\omega}$ is orthonormal. Since $\vec{\mathfrak{D}}$ and $\vec{\mathfrak{D}}^A$ satisfy (2.7), the following equation has to hold:

$$\vec{\mathfrak{D}}\vec{\omega}\vec{\omega}'\vec{\mathfrak{D}}' = \vec{\mathfrak{D}}\vec{\mathfrak{D}}' \tag{2.9}$$

Multiplying both sides with $\vec{\mathfrak{D}}^{-1}$ from the left and with $\vec{\mathfrak{D}}^{-1'}$ from the right yields $\vec{\omega}\vec{\omega}' = I$ where $\vec{\mathfrak{D}}$ is invertible by assumption. The implication being that $\vec{\omega}$ has to be an orthonormal matrix.

Second, note that $\vec{\omega} = \vec{\mathfrak{D}}^{-1}\vec{\mathfrak{D}}^{A}$. Since the product of two block lower-triangular matrices has to be block lower-triangular, $\vec{\omega}$ has to be block lower-triangular, as well. Hence, one can write $\vec{\omega}$ as

$$\vec{\omega} = \begin{vmatrix} \vec{\omega}_{11} & \vec{\omega}_{12} & 0 \\ \vec{\omega}_{21} & \vec{\omega}_{22} & 0 \\ \vec{\omega}_{31} & \vec{\omega}_{32} & \vec{\omega}_{33} \end{vmatrix} \tag{2.10}$$

Third, multiplying both sides of (2.8) with $\vec{\omega}'$ and using the fact that $\vec{\omega}$ is orthonormal yields $\vec{\mathfrak{D}}^{A}\vec{\omega}' = \vec{\mathfrak{D}}$. Since $\vec{\mathfrak{D}}^{A^{-1}}$ and $\vec{\mathfrak{D}}$ are block lower-triangular, $\vec{\omega}' = \vec{\mathfrak{D}}^{A^{-1}}\vec{\mathfrak{D}}$, $\vec{\omega}'$ must also be block lower-triangular. This implies $\vec{\omega}_{31}$ and $\vec{\omega}_{32}$ are equal to zero as well. Furthermore, since $\vec{\omega}$ is orthonormal, $\vec{\omega}$ has to be in the form of one of two matrices:

$$\vec{\omega} = \begin{vmatrix} \vec{\omega}_{11} & \vec{\omega}_{12} & 0 \\ \vec{\omega}_{21} & \vec{\omega}_{22} & 0 \\ 0 & 0 & -1 \end{vmatrix} \quad \text{or} \quad \vec{\omega} = \begin{vmatrix} \vec{\omega}_{11} & \vec{\omega}_{12} & 0 \\ \vec{\omega}_{21} & \vec{\omega}_{22} & 0 \\ 0 & 0 & 1 \end{vmatrix} \tag{2.11}$$

Lastly, the final step in uniquely identifying the monetary shock requires the assumption that an expansionary monetary shock results in a permanent rise in price level differences between the developing economies and the United States.[3] This sign restriction uniquely identifies the third column by ensuring $\vec{\omega}_{33} = 1$. Therefore, even if there are many matrices satisfying both (2.7) and (2.9), their third column must be the same. Identifying the elements of the third column this way enables us to analyze dynamic responses of the variables to monetary

[3]Therefore, $\vec{d}_{33}$ is positive in (2.6)

shocks.[4]

2.2.1.2 Empirical Model II

Clarida and Gali (1994) employ their strategy for isolating structural shocks in developed economies. In comparison to developed countries, an analysis of the dynamic responses of variables to structural shocks in developing countries may require more demanding assumptions. In particular, note that Clarida and Gali (1994) isolate differences in structural shocks between the country of interest and the United States, $\epsilon^{m}_{i,t} - \epsilon^{m^*}_{t}$, *rather than isolating them separately,* $\epsilon^{m}_{i,t}$ and $\epsilon^{m^*}_{t}$. When only differences in shocks are isolated, a 1% expansionary monetary shock in the country of interest is implicitly assumed to induce the same dynamics as a 1% contractionary monetary shock in the United States. Under the symmetric-country assumption, this may be a plausible assumption if one studies the movements in $\mathcal{Y}_{i,t} - \mathcal{Y}^*_t$, $\mathcal{Q}_{i,t}$ and $P_{i,t} - P^*_t$ between a developed economy and the United States. Yet, it is not realistic to maintain the symmetric-country assumption for a developing economy and the United States. For example, the coefficients of exchange rate pass-through into import and consumer prices in

[4] Here, it is natural to ask whether structural monetary shocks can be identified by placing restrictions only on the long-run responses matrix to monetary shocks. By writing the equation for the structural shock explicitly in (2.12), we show that this is not possible:

$$\epsilon_{i,t} = C_0^{-1} u_{i,t} = \vec{\mathcal{D}}^{-1} \left(I - \sum_{p=1}^{p_{max}} B_p \right) u_{i,t} \tag{2.12}$$

Since monetary shocks are ordered as the third element of $\epsilon_{i,t}$, recovering them requires the *third row of the inverse of* $\vec{\mathcal{D}}$ in (2.12). Yet, the third row cannot be identified by placing restrictions only in the long-run effects of monetary shocks on the level of output differences and the real exchange rate between the United States and the developing country. Consequently, structural monetary shocks are unidentifiable in *Empirical Model I.*

developing economies and the United States are markedly dissimilar. Furthermore, the frequencies of price changes among sectors in developing economies contrast with those in the United States. These asymmetric features may cause the dynamics of $\mathcal{Y}_{i,t} - \mathcal{Y}_t^*$, $\mathcal{Q}_{i,t}$ and $P_{i,t} - P_t^*$ between developing economies and the United States to differ significantly between a 1% *expansionary monetary shock* in developing economies and a 1% *contractionary monetary shock* in the United States.[5]

For this reason, we believe it is more plausible to study the consequences of monetary shocks in developing economies and the United States separately. To achieve this, we consider the same panel VAR model in (2.1), yet the vector of variables, $X_{i,t}$, is now given as

$$X_{i,t} = \begin{bmatrix} \Delta\mathcal{Y}_t^* \\ \Delta\mathcal{Y}_{i,t} \\ \Delta Q_{i,t} \\ \Delta P_t^* \\ \Delta P_{i,t} \end{bmatrix} \tag{2.13}$$

Here, $\Delta\mathcal{Y}_t^*$ ($\Delta\mathcal{Y}_{i,t}$) and ΔP_t^* ($\Delta P_{i,t}$) denote the log change in output and the consumer price level in the United States (the country of interest), respectively. Fluctuations in the vector of variables in *Empirical Model II* are assumed to be driven by five structural shocks in the following order:

1. Supply shocks in the United States ($\epsilon_t^{p^*}$)

2. Supply shocks in developing economies ($\epsilon_{i,t}^{p}$)

[5] Apart from these asymmetric features, a difference in the monetary shock process between developing economies and the United States may also result in the dynamics of $\mathcal{Y}_{i,t} - \mathcal{Y}_t^*$, $\mathcal{Q}_{i,t}$ and $P_{i,t} - P_t^*$ between developing economies and the United States differing significantly between a 1% *expansionary monetary shock* in developing economies and a 1% *contractionary monetary shock* in the United States.

3. General preference shocks ($\epsilon_{i,t}^{d}$)

4. Monetary shocks in the United States ($\epsilon_{t}^{m^*}$)

5. Monetary shocks in developing economies ($\epsilon_{i,t}^{m}$)

Our goal is to analyze dynamic responses of the variables to monetary shocks in the United States and developing countries separately. This can be achieved if the following assumptions are made regarding the $\check{\mathfrak{D}}$ matrix which shows the long-run level responses of the variables in developing economies to each shock in Empirical Model II:

$$\check{\mathfrak{D}} = \begin{vmatrix} \check{d}_{11} & \check{d}_{12} & \check{d}_{13} & 0 & 0 \\ \check{d}_{21} & \check{d}_{22} & \check{d}_{23} & 0 & 0 \\ \check{d}_{31} & \check{d}_{32} & \check{d}_{33} & 0 & 0 \\ \check{d}_{41} & \check{d}_{42} & \check{d}_{43} & \check{d}_{44} & 0 \\ \check{d}_{51} & \check{d}_{52} & \check{d}_{53} & \check{d}_{54} & \check{d}_{55} \end{vmatrix} \tag{2.14}$$

In the structure of (2.14), monetary shocks in the United States have been constrained to have no impact on the long-run level of output in both economies and the real exchange rate. In addition to these constraints, monetary shocks in the developing economies are restricted to have no permanent impact on the price level in the United States. This assumption is consistent with both the small-country assumption for developing economies and the standard practice of modeling the United States as a closed economy in the literature. In fact, our maintained assumption in *Empirical Model II* regarding the effect of domestic monetary shocks in developing economies is weaker than the small-country assumption in our theoretical models presented in Section 2.3. Indeed, while the assumption in *Empirical Model II* constrains domestic monetary shocks in developing economies to have *no long-term* impact on the price level in the

United States, the small-country assumption in our theoretical model imposes that they have a negligible impact on the price level in the United States in the *short-* and *long-terms*.

Now, we aim to separately analyze the dynamic responses of the variables to monetary shocks in the United States and developing economies. This can be achieved if the elements of the fourth and fifth columns of (2.14) are known. By following the same arguments in Section 2.2.1.1, it can be shown that *Empirical Model II* is unidentified and there are many matrices satisfying (2.14) and (2.15).

$$\check{\mathfrak{D}}\check{\mathfrak{D}}' = \left(I - \sum_{p=1}^{p_{max}} B_p\right)^{-1} \Omega \left(I - \sum_{p=1}^{p_{max}} B_p\right)^{\prime -1} \tag{2.15}$$

By following exactly the same arguments in Section 2.2.1.1, it is easy to show that any two such matrices $\check{\mathfrak{D}}$ and $\check{\mathfrak{D}}^A$ have the same fourth and fifth columns. This results from the fact that the orthonormal square matrix, $\breve{\omega}$, linking these two matrices must be in the following form:

$$\breve{\omega} = \begin{vmatrix} \breve{\omega}_{11} & \breve{\omega}_{12} & \breve{\omega}_{13} & 0 & 0 \\ \breve{\omega}_{21} & \breve{\omega}_{22} & \breve{\omega}_{23} & 0 & 0 \\ \breve{\omega}_{31} & \breve{\omega}_{32} & \breve{\omega}_{33} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{vmatrix} \tag{2.16}$$

Having identified the fourth and fifth columns of (2.14) this way, an analysis of the dynamic responses of the variables to the monetary shocks in the United States and the developing economies is straightforward.

Lastly, before discussing our empirical findings, it is notable that as an alternative to long-term restrictions in our paper, one may suggest using the recursive assumption which identifies monetary shocks with short-run restrictions on the contemporaneous response of variables. At this point, it is useful to discuss the reasons why adopting the recursive assumption may be unsuitable for isolating monetary shocks in developing countries. In the recursive assumption, the monetary authority is assumed to set its operating instrument by observing the movements in two different sets of variables. The first set of variables contains variables that may respond only with a lag to monetary policy shocks and whose current values are known to central banks before a decision on its operating instrument is made. The second set of variables, on the other hand, consists of variables that may contemporaneously respond to monetary policy shocks and whose current values are unknown to central banks before setting its operating instrument. The necessity of including variables in one of these sets lies at the root of the controversy over the recursive assumption for identifying shocks to monetary policy in developing economies. For example, in which set should the price level be included? Including it in the first set implies prices are sluggish in responding to monetary policy shocks. Such an assumption would be in conflict with the fact that a considerable share of prices change in a typical month in developing economies. Additionally, because of the fast response of exchange rates to monetary policy shocks and the strong pass-through of exchange rates into import prices in developing countries, it is plausible to assume that monetary shocks affect prices contemporaneously through their effect on exchange rates. Consequently, including the price level in the first set of variables is questionable. Including it in the second set of variables is also questionable since including the price level in this set implies central banks set their operating instrument without knowing the current price level. However, they collect data on a large volume of prices and are likely to predict the general trend in prices over any period. In our view, the price level in developing economies belongs to neither the first nor the second set of variables. Yet, since the recursive assumption requires it to be included in either of the two sets, we have abandoned this strategy and identified monetary shocks with the long-term restrictions.

2.2.2 Empirical Results

This section presents our findings on the responses of domestic economic activity, the bilateral real exchange rate with the United States and prices after domestic monetary shocks in developing countries under an inflation targeting regime. Since the adoption dates of the inflation targeting regime were not the same among the countries in our sample, we have an unbalanced panel data. As stated in Arellano and Bond (1991), this does not fundamentally change our analysis since we only require the assumption that observations are independently distributed in the initial cross-section and that subsequent additions and deletions occur randomly. Table 2.1 reports the adoption dates of inflation targeting in the developing countries contained in our sample for which we have quarterly or monthly data.

Our source of data on the level of economic activity, bilateral nominal exchange rates with the United States and consumer prices in our sample of countries is the IMF's *International Finance Statistics* data. Our data spans the post-inflation targeting period for each country until March, 2013. Due to data limitations on industrial production index for some developing countries at the monthly frequency, Chile, Colombia, Guatemala, Indonesia, Peru, Philippines and South Africa are dropped from the sample *at the monthly frequency.* Instead

Table 2.1: *Adoption Dates of Inflation Targeting in Developing Economies*

	Monthly Data	Quarterly Data
Country	*Effective IT adoption date*	*Effective IT adoption date*
Poland	1998-M10	1998-Q4
Brazil	1999-M6	1999-Q2
Chile	1999-M9	1999-Q3
Colombia	1999-M9	1999-Q3
South Africa	2000-M2	2000-Q1
Thailand	2000-M5	2000-Q2
Mexico	2001-M1	2001-Q1
Hungary	2001-M6	2001-Q2
Peru	2002-M1	2002-Q1
Philippines	2002-M1	2002-Q1
Guatemala	2005-M1	2005-Q1
Indonesia	2005-M7	2005-Q3
Romania	2005-M8	2005-Q3
Turkey	2006-M1	2006-Q1
Serbia	2006-M9	2006-Q3

Source: Roger (2009)

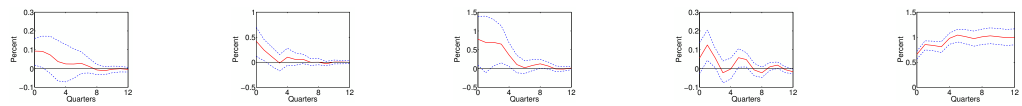
of the industrial production index, real GDP is used *at the quarterly frequency.* Since the series of real GDP are available for most sample countries, our quarterly data contains a larger sample of economies.[6]

[6]Before presenting our results, it is essential that logged real exchange rates of developing economies compared to the United States, $\mathcal{Q}_{i,t}$, the logged real GDP and CPI in Economy i and the United States (denoted by $\mathcal{Y}_{i,t}$, $\mathcal{Y}^*_t$, $P_{i,t}$ and P^*_t, respectively) all have unit roots. For the series pertaining to developing economies, we estimated a panel auto-regression equation with country-specific fixed effects containing four and twelve lags for the quarterly and monthly data, respectively. With the level specification, we perform the augmented Dickey-Fuller test. The unreported results indicate that one cannot reject the null that all five series contains a unit-root at the 5% significance level. With the growth specification, on the other hand, the null is rejected strongly at the 5% significance level. Hence, we conclude that all five series have unit roots.

Figure 2.1: *Impulse Responses to Monetary Shocks in Developing Economies (Empirical Model II)*

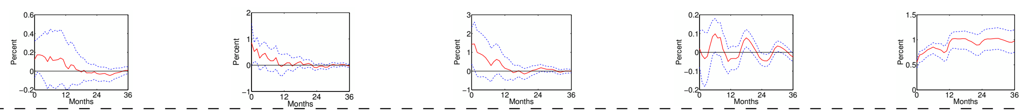
Quarterly

(a) $\mathcal{Y}^*$ **(b)** $\mathcal{Y}_i$ **(c)** $\mathcal{Q}_i$ **(d)** P^* **(e)** P_i



Monthly

(f) $\mathcal{Y}^*$ **(g)** $\mathcal{Y}_i$ **(h)** $\mathcal{Q}_i$ **(i)** P^* **(j)** P_i



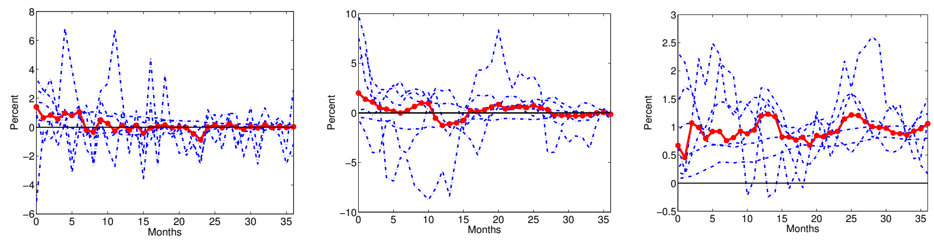
Note: Our calculations are based on the IMF's *International Finance Statistics*. The solid lines indicate the estimated point-wise impulse responses. The area between the dashed lines shows the 90% confidence interval estimated using the Bayesian method suggested by Sims and Zha (1999).

We now study the aggregate dynamics after an expansionary domestic monetary shock in developing economies using *Empirical Model II*. [7] These aggregate dynamics are displayed in Figure 2.1. It is evident from this figure that an expansionary monetary shock in developing economies (i) causes a modest, short-lived impact on output in the United States, (ii) induces an increase in the level of output in developing countries relative to its undistorted path which

[7]We study aggregate dynamics following monetary shocks in *Empirical Model I* and following monetary shocks in the United States in *Empirical Model II* in Appendix B.1.

Figure 2.2: *Impulse Responses in Each Country to Monetary Shocks in Developing Economies (The VAR Model with Monthly Data)*

(a) $\mathcal{Y}_i$ **(b)** $\mathcal{Q}_i$ **(c)** P_i



Note: Our calculations are based on the IMF's *International Finance Statistics*. The solid line marked with circles indicates the median of the estimated point-wise impulse response functions in the group in each period. The dot-dashed line shows the country-specific impulse response functions separately estimated for each country in the group using the VAR version of *Emprical Model II*.

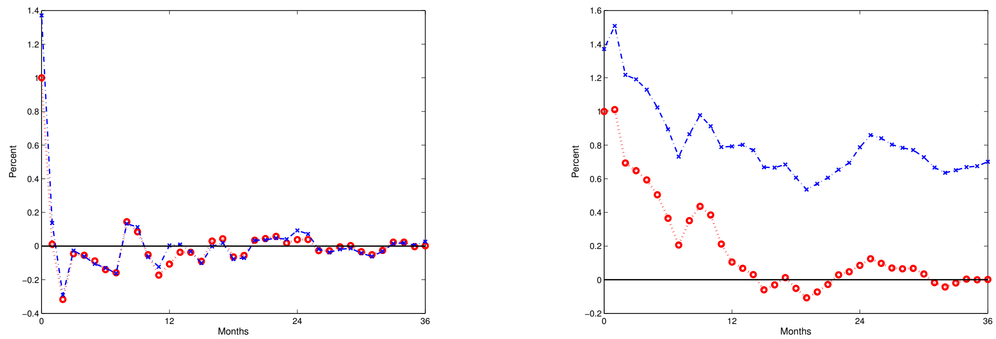
lasts for about one year, (*iii*) depreciates the real exchange rate on impact, implying that the goods from the developing economies is worth less in terms of the goods from the United States[8], (*iv*) leads to either a small, temporary increase or no change at all in the price level of the United States, and (*v*) results in a permanent increase of the price level in the developing economies.

Such findings only show the *average* impulse response functions for the group of developing countries which adopted an inflation targeting regime. However, the impulse response functions of the variables to an expansionary domestic monetary shock in each country in the group differ radically from the average

[8]The dissipation of the shock takes about one and half years both at the monthly and quarterly frequency.

Figure 2.3: *Conditional Movements of the Real and Nominal Exchange Rates*
(Empirical Model II with Monthly Data)

(a) ΔQ_i *and* $\Delta \mathcal{E}_i$ **(b)** Q_i *and* $\mathcal{E}_i$



Note: Our calculations are based on the IMF's *International Finance Statistics*. The dotted lines marked with circles in Panel (a) and Panel (b) indicate the log-change and the level impulse response functions of the real exchange rate to the domestic monetary shock, respectively. The dot-dashed lines marked with asterisks in Panel (a) and Panel (b) show the log-change and the level impulse response functions of the nominal exchange rate to the domestic monetary shock, respectively.

impulse response functions. Figure 2.2 illustrates this point. The impulse response functions of output, the real exchange rate and the price level to an expansionary monetary shock in each country is obtained separately by considering the country-specific VAR model version of *Empirical Model II* with monthly data. The size of the shock in each country is normalized to induce the same long-run response in the price level. It is evident from this figure that the impulse response functions of all three variables in the individual countries differ radically from the median impulse functions in the group.

2.2.2.1 The Conditional Co-movements of the Real and Nominal Exchange Rates

Next, we show the co-movements of the real and nominal exchange rates conditional on the domestic monetary shock in the *Empirical Model II* with monthly data. The impulse response functions of the nominal exchange rates ($\hat{\mathcal{E}}$) are obtained as $\hat{Q} + \hat{P} - \hat{P}^*$. It is evident from Panel (a) of Figure 2.3 that conditional on the domestic monetary shock, the deviation (in percent) of the log-change in the nominal and real exchange rates from their undistorted path follow a similar pattern. Such co-movements are also noticeable from the common pattern of the impulse response functions of the level nominal and real exchange rates in Panel (b).

2.3 Theoretical Models

In this section, we present two small-open economy DSGE models. Specifically, we study the consequences of a monetary shock that causes a 1% increase in the price level in the long-term for each model, and compare the outcomes in these models with those in the actual economies to the same shock. The details of how we derive these models as well as their extension in positive inflation steady-state environments are provided in Karaca and Tugan (2015)[9]. We start by presenting models with the problem of Home and Foreign households.

[9]In deriving statedly state equations, we assume that steady-state inflation rate for developing countries is also zero like the United States. However, this may a strong assumption and we would like to thank to anonymous referee to brought this extension to our attention. The Supplementary On-line Appendix can be downloaded from the following link: https://goo.gl/kLq0XU

2.3.1 The Problem of Home and Foreign Households

There is a continuum of infinitely-lived households in each country with a mass of one and indexed with h. Each household is comprised of two members. They aim to maximize their joint lifetime discounted utility with the discount factor given by β. In period t, the members of the h^{th} household in the Home country have to make a sequence of decisions. First, they have to choose how much to consume from the home-country non-traded final consumption good (C_t). Second, they optimally choose how intensively they supply their capital (u_t) in each period. Third, they decide on the amount of investment (I_t), and therefore, on the next period's capital stock (K_{t+1}). Fourth, they have to decide on the amount of optimal holdings of a one-period risk-free foreign bond (B_{t+1}) which pays a gross nominal return of R_t^B. Lastly, only one of the household members obtains a chance to renegotiate its wage contract each period. The wage contract made in any period lasts for two periods and has to be signed before observing the shock. The problem of the Home household can be put more compactly as follows:

$$\max_{C_t, u_t, I_t, K_{t+1}, B_{t+1}, x_t} E_t \sum_{s=0}^{\infty} \beta^{t+s} \left(\frac{C_{t+s}^{1-\sigma_c} - 1}{1-\sigma_c} - \frac{\tilde{n}_{t+s,i}^{1+\sigma_n}}{1+\sigma_n} - \frac{n_{t+s,i}^{1+\sigma_n}}{1+\sigma_n} \right) \tag{2.17}$$

where $\tilde{n}_{t,i}$ and $n_{t,i}$ are the hours worked by the members of the household whose wage-contracts are signed in period t and $t-1$, respectively. σ_c and σ_n stand for the *reciprocal* of the intertemporal elasticity of substitution and the Frisch-elasticity of substitution, respectively. In solving 2.17, the household has the following budget constraint:

$$
\begin{aligned}
&P_{t+s}\Big(C_{t+s} + I_{t+s} + a(u_{t+s})K_{t+s}\Big) + \mathcal{E}_{t+s}B_{t+1+s} \\
&= x_{t+s,i}\tilde{n}_{t+s,i} + x_{t-1+s,i}n_{t+s,i} + R^k_{t+s}u_{t+s}K_{t+s} + R^B_{\mathcal{H},t-1+s}\mathcal{E}_{t+s}B_{t+s} + \Pi_{t+s}
\end{aligned} \tag{2.18}
$$

In writing (2.18), we follow Christiano, Eichenbaum, and Evans (2005) and assume that increasing capacity utilization (u_t) involves real costs in units of the final good denoted by $a(u_t)$.[10]. The price of the home non-traded final good is denoted by P_t. $\mathcal{E}_t$ stands for the nominal exchange rate between the currency of the home-country (¢) and the foreign-country (¢*). R^k_t denotes the rental rate of capital paid to the owners of capital stock. The gross nominal return on the holdings of last period's foreign risk-free bonds is shown with $R^B_{\mathcal{H},t-1}$. $x_{t,i}$ and $x_{t-1,i}$ in (2.18) represent the hourly-wage earnings of the household member who negotiates his wage in period t and $t-1$, respectively. Lastly, Π_t shows the profits of firms which belong to the household. In sum, the representative household earns wage, capital, profit and interest income. The household uses its resources to finance purchases of the final consumption good, investment, the cost associated with varying u_t and purchases of foreign bonds.

The law of motion for capital in the home-country is given as:

$$
K_{t+1} = (1-\delta)K_t + \phi\left(\frac{I_t}{K_t}\right)K_t \tag{2.19}
$$

where $\phi\left(\frac{I_t}{K_t}\right)K_t$ shows the additional capital-stock which new investment in

[10]Let the bar symbol over the variables show the steady-state values of these variables. At the steady-state, capital is fully-utilized, $\bar{u} = 1$. The function $a(u)$ has the following properties: $a(1) = 0$, $a'(u) > 0$ and $a''(u) > 0$.

the current period makes available for the next period.[11].

The problem of the foreign household is similar. Her optimization problem and flow-budget constraint can be written as:

$$\max_{C_t^*,u_t^*,I_t^*,B_{t+1}^*} E_t \sum_{s=0}^{\infty} \beta^{t+s} \left(\frac{C_{t+s}^{*\,1-\sigma_c} - 1}{1-\sigma_c} - \frac{\tilde{n}_{t+s,i}^{*\,1+\sigma_n}}{1+\sigma_n} - \frac{n_{t+s,i}^{*\,1+\sigma_n}}{1+\sigma_n} \right) \tag{2.20}$$

$$\begin{aligned} &P_{t+s}^*\Big(C_{t+s}^* + I_{t+s}^* + a(u_{t+s}^*)K_{t+s}^*\Big) + B_{t+1+s}^* = \\ &x_{t+s,i}^*\tilde{n}_{t+s,i}^* + x_{t-1+s,i}^* n_{t+s,i}^* + R_{t+s}^{*^k} u_{t+s}^* K_{t+s}^* + R_{\mathcal{F},t-1+s}^B B_{t+s}^* + \Pi_{t+s}^* \end{aligned} \tag{2.21}$$

where the variables denoted with the superscript * represent the foreign-counterparts of the home variables. It is notable that the gross nominal return pertinent to the holdings of the risk-free bond in the foreign-country in (2.21), $R_{\mathcal{F},t-1}^B$, may differ from $R_{\mathcal{H},t-1}^B$ in (2.18). Following Devereux and Smith (2005), we assume that countries face a debt-elastic interest rate. Let the net position of the home-country in the risk-free bond be given as $\mathcal{B}_t$. The debtor country has to pay a higher interest rate than the lender country due to upward-sloping bond supply in international financial markets. The differential between $R_{\mathcal{F},t-1}^B$ and $R_{\mathcal{H},t-1}^B$ depends on the net bond holdings of the countries in the following way:

$$R_{\mathcal{H},t}^B = \Theta\Big(\mathcal{B}_{t+1} - \bar{\mathcal{B}}\Big) R_{\mathcal{F},t}^B \tag{2.22}$$

where $\Theta\left(\mathcal{B}_{t+1} - \bar{\mathcal{B}}\right)$ satisfies $\Theta(0) = 1$ and $\Theta'(.) < 0$. Since there is a continuum of households in both countries, bond holdings of any individual household (B_{t+1}) has only a negligible effect on the net position of countries' bond-holdings

[11] At the steady-state, $\bar{I} = \delta\bar{K}$. The function $\phi\left(\frac{I_t}{K_t}\right)$ has the following properties. $\phi(\delta) = \delta$, $\phi'(\delta) = 1$, $\phi'(.) > 0$ and $\phi''(.) < 0$. The last assumption implies that $\phi''(.)$ is concave that emanates from the fact that new investment is subject to adjustment costs.

$(\mathcal{B}_{t+1})$. Thus, households *do not internalize* the interest rate country faces.[12].

The optimality conditions for the Home household with respect to C_t, u_t, I_t, K_{t+1} and B_t are given as:

$$C_t^{-\sigma_c} = \lambda_t P_t \tag{2.23}$$

$$a'(u_t) = r_t^k,\ r_t^k = R_t^k / P_t \tag{2.24}$$

$$\lambda_t P_t = \mu_t \phi' \left(\frac{I_t}{K_t} \right) \tag{2.25}$$

$$\begin{aligned} \mu_t \quad = \quad & \beta E_t \left[-\lambda_{t+1} P_{t+1} a(u_{t+1}) + \lambda_{t+1} R_{t+1}^k u_{t+1} + \mu_{t+1} \left((1-\delta) \right. \right. \\ & \left. \left. -\phi' \left(\tfrac{I_{t+1}}{K_{t+1}} \right) \tfrac{I_{t+1}}{K_{t+1}} + \phi \left(\tfrac{I_{t+1}}{K_{t+1}} \right) \right) \right] \end{aligned} \tag{2.26}$$

$$\lambda_t \mathcal{E}_t = \beta E_t \lambda_{t+1} R_{\mathcal{H},t}^B \mathcal{E}_{t+1} \tag{2.27}$$

where λ_t and r_t^k are the marginal utility of nominal income and the real rental price of capital in the home country, respectively. μ_t, on the other hand, stands for the shadow value of having one more unit of next period's capital stock. In other words, it shows the amount of the final good the household is willing to forgo in the current-period to have one more unit of capital stock in the next-period. The condition (2.23) states that the household equates the marginal utility of consumption with its marginal cost. As well, the condition (2.24) implies that incremental variations in u_t would cost $a'(u_t)K_t$ in resources but since it allows the household to supply more capital services in the current period,

[12]Assuming a debt-elastic differential in the two countries' interest rates is a standard way to circumvent the problem of multiple steady-states in imperfect financial markets. Without such an assumption, stationarity of the model would not be ensured as when a shock is introduced into the model, the model oscillates between different steady-states without ever reaching a stable equilibrium. For a more complete description, see Schmitt-Grohe and Uribe (2003) and Boileau and Normandin (2008) who describe the problem of multiple steady-states in the small- and large-open economy models with imperfect financial markets, respectively. They also evaluate different methods to circumvent this problem.

the real income of the household rises by $r_t^k K_t$. At the optimal u_t, these two should be equal. In (2.25), the left-hand side is the opportunity cost of investing an incremental amount. At optimum, this is equated to the utility gained from making that incremental investment as it allows the household to have $\phi'\left(\frac{I_t}{K_t}\right)$ more capital in the next period. The condition (2.26) indicates that the marginal utility of having an extra unit of capital stock in the next period is the sum of three terms. $-\beta\lambda_{t+1}P_{t+1}a(u_{t+1})$ is the utility cost associated with the deviation of the capacity utilization rate in the next period from its steady-state. The second term, $\beta\lambda_{t+1}R_{t+1}^k u_{t+1}$, indicates that having an extra unit of capital stock in the next period would increase nominal income by $R_{t+1}^k u_{t+1}$. The third term, $\beta\mu_{t+1}\left((1-\delta)-\phi'\left(\frac{I_{t+1}}{K_{t+1}}\right)\frac{I_{t+1}}{K_{t+1}}+\phi\left(\frac{I_{t+1}}{K_{t+1}}\right)\right)$ denotes the utility gain of retaining the extra unit of capital in period $t+2$. Lastly, the optimal bond holdings equation in equation (2.27) states that purchasing an extra unit of foreign risk-free bonds would cost $\mathcal{E}_t$ in period t and would yield $R_{\mathcal{H},t}^B\mathcal{E}_{t+1}$ of nominal income in period $t+1$. Regarding the equivalent problem of households in the foreign country, all of the first-order conditions, except that of the bond-holdings, are similar. The optimality condition for the foreign-household's bond-holdings, on the other hand, can be written as follows:

$$\lambda_t^* = \beta E_t \lambda_{t+1}^* R_{\mathcal{F},t}^B \tag{2.28}$$

Using (2.23) and (2.27) along with their counterparts for the foreign-household, the equation for the real exchange rate between the home- and foreign-country ($\mathcal{Q}_t$) can be written as:

$$\sigma_c\left[E_t\left(\hat{C}_{t+1}-\hat{C}_t\right)-E_t\left(\hat{C}_{t+1}^*-\hat{C}_t^*\right)\right] = E_t\hat{Q}_{t+1}-\hat{Q}_t+\Theta'(0)\bar{Y}\hat{B}_{t+1} \tag{2.29}$$

where $Q_{t+1} = \frac{\mathcal{E}_t P_t^*}{P_t}$. In our paper, the bars and hats over the variables stand for the steady-state values and the log-deviation of the variables from their steady-states, respectively. The only exception is $\hat{B}_{t+1}$ which is defined as $\frac{B_t - \bar{B}}{\bar{Y}}$ where $\bar{Y}$ is the steady-state value of the aggregate final-good output. Defining $\hat{B}_{t+1}$ this way makes it convenient to take a log-linear approximation of the domestic budget constraint.

2.3.1.1 Aggregate Wage Equation

It is notable that the existing models of staggered-wage setting such as the Erceg, Henderson, and Levin (2000) and Huang and Liu (2002) models are not particularly suitable for studying developing countries. The reason is that these models require a complete financial markets assumption, whereas financial markets in developing economies are infant and lack sophistication. For this reason, we develop a novel structural staggered wage-setting model with incomplete insurance. To explain the difficulty of incorporating staggered wages with incomplete insurance, suppose households hold only non-state contingent bonds. Since workers renew their wage contracts in different periods under the staggered wage setting, their wage income must differ after a monetary shock. This, together with the absence of state-contingent bonds with incomplete insurance, results in budget-constraints being different among households. Consequently, the problem of households in the economy with incomplete insurance might not be reduced to that of the "representative-household" since households' budget constraints would not be alike after the shock. Solving such a model involves the difficult task of following the non-degenerate income distribution period-by-period which can be computationally demanding.

Both Erceg, Henderson, and Levin (2000) and Huang and Liu (2002) circumvent this problem by assuming complete financial markets. Under complete insurance, state-contingent assets are traded to eliminate idiosyncratic risks among households. In staggered wage-setting environments, these risks are associated with uncertainty about the timing of wage contract renewals. For example, when an expansionary monetary shock happens, in the absence of full insurance, workers whose contracts are renewed soon may be in an advantageous position compared to workers whose contracts are renewed late. However, under complete financial markets, these idiosyncratic risks are eliminated since income transfers through state-contingent bonds exactly offset wage income differences among households so that they have the same income in all periods. In other words, there is a single budget constraint among households and income distribution is degenerate with complete insurance.

To the best of our knowledge, what is left unexplored in the literature is that idiosyncratic risks under staggered wage-setting can be eliminated even when insurance is incomplete. This can be explained as follows: In our DSGE model, households contain two members, the wife and the husband, who negotiate their wages with employers in even and odd periods, respectively. Since some wages may not be re-contracted immediately after a monetary shock, wage adjustment in our model is staggered. Despite this, households' budget constraints in our model will be identical after a monetary shock. To explain this, firstly note that since wives in all households re-contract their wages in the same period, their wage income will be alike after this shock. By the same logic, the wage income of husbands in all households will also be the same. Since households? total wage income is equal to the sum of wives? and husbands? wages, even in the absence of income transfers through financial assets, households? total income will be alike in all periods after the monetary shock. Consequently, there is a single budget-constraint among households and the income distribution of households is degenerate since they all have the same income. This allows us to consider only the problem of the "representative-household" instead of considering household-specific maximization problems. Achieving staggered wage-setting without sacrificing the incomplete financial market assumption in developing countries adds realism to our model.

Now, we describe the home wage-setting environment in detail. Our model of staggered wage-setting is a modified version of the Huang and Liu (2002) model. Indeed, while households contain one member in the Huang and Liu (2002) model, they contain two members, the wife and the husband, in our model. There is a continuum of employment-offices with a mass of one in the home economy. They combine the differentiated hours of work supplied by the members of households ($\tilde{n}_{t,i}$ and $n_{t,i}$)[13] into a composite labor of (N_t) and sell it to the firms. The employment-offices use the following technology to form the composite of labor:

$$N_t = \left(\int_0^1 \tilde{n}_{t,i}^{(\theta_w - 1)/\theta_w} di + \int_0^1 n_{t,i}^{(\theta_w - 1)/\theta_w} di \right)^{\theta_w/(\theta_w - 1)} \tag{2.30}$$

The optimization problem of employment offices can be written as:

$$\max_{\tilde{n}_{t,i}, n_{t,i}} W_t N_t - \int_0^1 x_{t,i} \tilde{n}_{t,i} di - \int_0^1 x_{t-1,i} n_{t,i} di \tag{2.31}$$

where, because of the assumption of a continuum of employment offices, individual offices do not have an effect on the aggregate wage (W_t) and the wages

[13]For definitions of $\tilde{n}_{t,i}$ and $n_{t,i}$, see (2.17).

set by the owners of the differentiated labors in period t and $t-1$ ($x_{t,i}$ and $x_{t-1,i}$). Employment offices' demand for differentiated labor of workers whose wages are set in period t and $t-1$ are given by:

$$\tilde{n}_{t,i} = \left(\frac{x_{t,i}}{W_t}\right)^{-\theta_w} N_t \qquad ; \qquad n_{t,i} = \left(\frac{x_{t-1,i}}{W_t}\right)^{-\theta_w} N_t \tag{2.32}$$

From (2.32), it is clear that θ_w is the wage-elasticity of substitution among differentiated hours. In period t, one member of the households sets his wage *before observing the shock* that will remain fixed in period t and period $t+1$. Hence, his optimality problem can be written as:[14]

$$\max_{x_{t,i}} E_{t-1}\left[\left(-\frac{\tilde{n}_{t,i}^{1+\sigma_n}}{1+\sigma_n} + \lambda_t x_{t,i}\tilde{n}_{t,i}\right) + \beta\left(-\frac{n_{t+1,i}^{1+\sigma_n}}{1+\sigma_n} + \lambda_{t+1} x_{t,i} n_{t+1,i}\right)\right] \tag{2.33}$$

Having renegotiated his wage in period t, the household member must supply differentiated hours of work as demanded by the employment offices due to the binding wage-contract in period t and period $t+1$. Due to the continuum of differentiated hours supplied, each individual worker has negligible effect on the aggregate wage. Using this and the fact that households' budget constraints are identical, the contracted wage in period t for all workers is the same, allowing us to drop the subscript i in $x_{t,i}$ and write x_t:

$$x_t^{1+\theta_w\sigma_n} = \frac{\theta_w}{\theta_w - 1}\frac{E_{t-1}W_t^{\theta_w+\theta_w\sigma_n}N_t^{1+\sigma_n} + \beta E_{t-1}\left(W_{t+1}^{\theta_w+\theta_w\sigma_n}N_{t+1}^{1+\sigma_n}\right)}{E_{t-1}\left(\lambda_t W_t^{\theta_w}N_t\right) + \beta E_t\left(\lambda_{t+1}W_{t+1}^{\theta_w}N_{t+1}\right)} \tag{2.34}$$

[14]It is notable that in our notation, the hours supplied by the workers who do not renegotiate their wages are shown without a tilde over n. Since it is not possible to renegotiate the wage in period $t+1$ once wage is set at period t, the hours supplied by the worker in the next period who set a wage at period t is shown with $n_{t+1,i}$ not with $\tilde{n}_{t+1,i}$.

By using (2.30), (2.32) and the fact that all of the contracted wages are equal, one can show that the aggregate wage equation is given by:

$$W_t = \left(x_t^{1-\theta_w} + x_{t-1}^{1-\theta_w} \right)^{\frac{1}{1-\theta_w}} \tag{2.35}$$

The wage-setting behavior of the owners of differentiated labor types in the foreign-country is the same, yielding similar equations for the contracted and aggregate wages.

2.3.2 The Objective of Firms in the Home- and Foreign-Country

2.3.2.1 Firms Producing the Final Good in the Home- and Foreign-Country

The non-traded final goods in both of the countries are produced by a continuum of perfectly-competitive firms. Firms produce the final goods by using the following technology which involves combining goods from different sectors:

$$Y_t = \left(\sum_{k=1}^{k_{max}} f_k^{1/\eta} Y_{k,t}^{(\eta-1)/\eta} \right)^{\frac{\eta}{\eta-1}} \tag{2.36}$$

where Y_t and $Y_{k,t}$ denote the amount of the final good produced by firms and the output of Sector k, respectively. f_k, η and k_{max} denote the sectoral weight, constant elasticity-of-substitution for sectoral goods in the final good production and the total number of sectors in the home-country, respectively. It is easy to show that the demand for sectoral goods and the aggregate price index (P_t) are given by:

$$Y_{k,t} = f_k \left(\frac{P_{k,t}}{P_t} \right)^{-\eta} Y_t \tag{2.37}$$

$$P_t = \left(\sum_{k=1}^{K} f_k P_{k,t}^{1-\eta}\right)^{\frac{1}{1-\eta}} \tag{2.38}$$

where $P_{k,t}$ denotes the aggregate price index of sector k. Since the final-good firms in the foreign-country solve a similar problem, for the sake of brevity, we omit writing the equations for the sector-specific foreign-demand ($Y^*_{k,t}$) and the foreign aggregate price (P^*_t).

2.3.2.2 Firms Producing Sector k Output in the Home and Foreign Countries

In both countries, sectoral goods are produced by an infinitely large number of perfectly-competitive firms. The home-firms producing sectoral goods combine domestic-goods ($Y_{\mathcal{H},k,t}$) and import-goods ($Y_{\mathcal{F},k,t}$) to produce sectoral output ($Y_{k,t}$) with the following technology:

$$Y_{k,t} = \left((1-\psi)^{\frac{1}{\rho}} Y_{\mathcal{H},k,t}^{(\rho-1)/\rho} + \psi^{\frac{1}{\rho}} Y_{\mathcal{F},k,t}^{(\rho-1)/\rho}\right)^{\frac{\rho}{\rho-1}} \tag{2.39}$$

where ψ and ρ represent the steady-state weight of the import-good in the home country and the elasticity of substitution between the domestic and import-goods, respectively. It is straightforward to show the demands for the domestic goods and those imported by the home country in sector k are given as:

$$Y_{\mathcal{H},k,t} = (1-\psi)\left(\frac{P_{\mathcal{H},k,t}}{P_{k,t}}\right)^{-\rho} Y_{k,t} \quad ; \quad Y_{\mathcal{F},k,t} = \psi\left(\frac{P_{\mathcal{F},k,t}}{P_{k,t}}\right)^{-\rho} Y_{k,t} \tag{2.40}$$

where $P_{\mathcal{H},k,t}$ and $P_{\mathcal{F},k,t}$ denote domestic and import price indexes in sector k in the home country, respectively. Using (2.39) and (2.40), one can write the sector

k price index in the home country ($P_{k,t}$) as the weighted average of domestic and import price indexes in sector k:

$$P_{k,t} = \left((1-\psi)P_{\mathcal{H},k,t}^{1-\rho} + \psi P_{\mathcal{F},k,t}^{1-\rho}\right)^{\frac{1}{1-\rho}} \tag{2.41}$$

Sector k's good in the foreign-country is again produced by perfectly-competitive firms. Yet, the technology combining home and foreign-goods in sector k to produce its output may involve a lower steady-state share of imports in the foreign country than in the home country. Indeed, the foreign-technology is given by:

$$Y_{k,t}^{*} = \left(\left(1-\frac{\psi}{\tau}\right)^{\frac{1}{\rho}} Y_{\mathcal{F},k,t}^{*(\rho-1)/\rho} + \left(\frac{\psi}{\tau}\right)^{\frac{1}{\rho}} Y_{\mathcal{H},k,t}^{*(\rho-1)/\rho}\right)^{\frac{\rho}{\rho-1}} \tag{2.42}$$

It is clear from (2.42) that the steady-state import-share in the foreign-country is $\left(\frac{\psi}{\tau}\right)$, which is smaller than the steady-state import-share in the home-country ψ when $\tau \geq 1$. This assumption is convenient since it allows us to study small- and large-open economies within the same model. Indeed, for a large economy, one can take $\tau = 1$. For a small economy, on the other hand, one can assume τ is *arbitrarily large* as the size of its trading-partners is much larger compared to its size.

We also give sector k's price index and the demands for the foreign- and home-goods in sector k in the foreign-country as:

$$P_{k,t}^{*} = \left(\left(1-\frac{\psi}{\tau}\right)P_{\mathcal{F},k,t}^{*1-\rho} + \left(\frac{\psi}{\tau}\right) P_{\mathcal{H},k,t}^{*1-\rho}\right)^{\frac{1}{1-\rho}} \tag{2.43}$$

$$Y^*_{\mathcal{F},k,t} = \left(1 - \frac{\psi}{\tau}\right)\left(\frac{P^*_{\mathcal{F},k,t}}{P^*_{k,t}}\right)^{-\rho} Y^*_{k,t} \quad ; \quad Y^*_{\mathcal{H},k,t} = \left(\frac{\psi}{\tau}\right)\left(\frac{P^*_{\mathcal{H},k,t}}{P^*_{k,t}}\right)^{-\rho} Y^*_{k,t} \tag{2.44}$$

where the variables denoted with asterisks ($*$) show the foreign counterparts of the home-variables.

2.3.2.3 The Invoice Currency and Pricing of Internationally Traded Goods

The home-import good in sector k ($Y_{\mathcal{F},k,t}$) is produced by perfectly-competitive home- import firms. Producing the home-import good involves combining intermediate foreign-goods which are invoiced in different currencies. Indeed, while some intermediate goods are invoiced in the home-currency (¢), others are invoiced in the foreign-currency (¢*). In producing the home-import good in Sector k, the home-import firm combines output from the foreign firms which set prices in the home- and foreign-currency (denoted by $Y_{F,¢,k,t}$ and $Y_{F,¢^*,k,t}$, respectively) with the following technology:

$$Y_{\mathcal{F},k,t} = \left((1-\omega^*_{¢^*})^{\frac{1}{\theta_p}} Y^{(\theta_p-1)/\theta_p}_{F,¢,k,t} + \omega^{*\,\frac{1}{\theta_p}}_{¢^*} Y^{(\theta_p-1)/\theta_p}_{F,¢^*,k,t}\right)^{\frac{\theta_p}{\theta_p-1}} \tag{2.45}$$

where θ_p stands for the elasticity-of-substitution between intermediate foreign-goods invoiced in different currencies and $\omega^*_{¢^*}$ denotes the steady-state weight of the foreign-currency-invoiced intermediate foreign-goods in the home-import price index of sector k. It is easy to show that the price index for the home-import good (denoted by $P_{\mathcal{F},k,t}$ and expressed in the home-currency) and the demand for the intermediate foreign-goods are given as:

$$P_{\mathcal{F},k,t} = \left((1-\omega^*_{¢^*})P^{1-\theta_p}_{F,¢,k,t} + \omega^*_{¢^*}\left(\mathcal{E}_t P_{F,¢^*,k,t}\right)^{1-\theta_p}\right)^{\frac{1}{1-\theta_p}} \tag{2.46}$$

$$
\begin{aligned}
Y_{F,\cent,k,t} &= (1-\omega^*_{\cent^*})\left(\tfrac{P_{F,\cent,k,t}}{P_{\mathcal{F},k,t}}\right)^{-\theta_p} Y_{\mathcal{F},k,t} \\
Y_{F,\cent^*,k,t} &= \omega^*_{\cent^*}\left(\tfrac{\mathcal{E}_t P_{F,\cent^*,k,t}}{P_{\mathcal{F},k,t}}\right)^{-\theta_p} Y_{\mathcal{F},k,t}
\end{aligned}
\tag{2.47}
$$

where $P_{F,\cent,k,t}$ and $P_{F,\cent^*,k,t}$ represent the prices set for the intermediate foreign-goods that are invoiced in the home- and foreign-currency, respectively.

The home-export good is produced similarly. Indeed, perfectly-competitive foreign importers in sector k combine output from the home firms which set prices in the home- and foreign-currency (denoted by $Y^*_{H,\cent,k,t}$ and $Y^*_{H,\cent^*,k,t}$, respectively) with the following technology:

$$
Y^*_{\mathcal{H},k,t} = \left(\omega_{\cent}^{\frac{1}{\theta_p}} {Y^*_{H,\cent,k,t}}^{(\theta_p-1)/\theta_p} + (1-\omega_{\cent})^{\frac{1}{\theta_p}} {Y^*_{H,\cent^*,k,t}}^{(\theta_p-1)/\theta_p}\right)^{\frac{\theta_p}{\theta_p-1}} \tag{2.48}
$$

where $\omega_{\cent}$ is the steady-state share in sector k's foreign-import price index of the home-currency-priced intermediate home-export goods. The foreign-import price index (denoted by $P^*_{\mathcal{H},k,t}$ and expressed in the foreign-currency) and the demands for the intermediate home-export goods can be written as:

$$
P^*_{\mathcal{H},k,t} = \left(\omega_{\cent}\left(\frac{1}{\mathcal{E}_t} P^*_{H,\cent,k,t}\right)^{1-\theta_p} + (1-\omega_{\cent}) {P^*_{H,\cent^*,k,t}}^{1-\theta_p}\right)^{\frac{1}{1-\theta_p}} \tag{2.49}
$$

$$
\begin{aligned}
Y^*_{H,\cent,k,t} &= \omega_{\cent}\left(\frac{\frac{1}{\mathcal{E}_t} P^*_{H,\cent,k,t}}{P^*_{\mathcal{H},k,t}}\right)^{-\theta_p} Y^*_{\mathcal{H},k,t} \\
Y^*_{H,\cent^*,k,t} &= (1-\omega_{\cent})\left(\tfrac{P^*_{H,\cent^*,k,t}}{P^*_{\mathcal{H},k,t}}\right)^{-\theta_p} Y^*_{\mathcal{H},k,t}
\end{aligned}
\tag{2.50}
$$

where $P^*_{H,\cent,k,t}$ and $P^*_{H,\cent^*,k,t}$ denote the prices set for the intermediate home-export goods whose prices are invoiced in the home- and foreign-currency, respectively.

2.3.2.4 Home- and Foreign-Firms Producing Varieties for Intermediate Goods

The intermediate domestic and import goods in both the home and foreign countries are composite goods composed of a variety of goods produced by firms engaging in monopolistic competition. The production technology used in the production of intermediate domestic goods is given as:

$$Y_{\mathcal{H},k,t} = \left(\int_0^1 Y_{H,k,j,t}{}^{(\theta_p - 1)/\theta_p} dj \right)^{\frac{\theta_p}{\theta_p - 1}} \tag{2.51}$$

where $Y_{H,k,j,t}$ denotes demand for variety j of the firm producing the domestic intermediate good in the home-country in sector k. One can show that $Y_{H,k,j,t}$ and the price-index for the domestic-intermediate good in the home-country in sector k ($P_{\mathcal{H},k,t}$) can be written as:

$$Y_{H,k,j,t} = \left(\frac{P_{H,k,j,t}}{P_{\mathcal{H},k,t}} \right)^{-\theta_p} Y_{\mathcal{H},k,t} \tag{2.52}$$

$$P_{\mathcal{H},k,t} = \left(\int_0^1 P_{H,k,j,t}{}^{1-\theta_p} \right)^{\frac{1}{1-\theta_p}} \tag{2.53}$$

where $P_{H,k,j,t}$ is the price set by the monopolistically-competitive firm producing variety j of the domestic intermediate-good. When producing variety j, the firm employs the composite labor ($N_{H,k,j,t}$) together with capital ($K_{H,k,j,t}$) and uses the following production function:

$$Y_{H,k,j,t} = K_{H,k,j,t}^{1-\chi} N_{H,k,j,t}^{\chi} \tag{2.54}$$

where χ is the steady-state share of labor in the home-country. In each period, only a fraction of the firms producing different varieties in sector k obtains a price-change signal. When firms obtain such a signal, they set prices with their intermediate domestic-goods suppliers. These prices remain constant until a new price-change signal is obtained. During this time, firms are obliged to supply any quantity demanded of their varieties. In the one-sector model, it is assumed sectors have the same frequency of price-change which is given by the weighted average of the frequencies of price-change in sectors. In the multi-sector model, on the other hand, the probability of receiving such a signal differs by sector. For the varieties of domestic sector k's good in the home country, let $1-\alpha_k$ indicate the probability of receiving the price-change signal in each period. Then, the objective of the firm producing variety j which obtains a price-change signal in period t can be written as:

$$E_t \sum_{s=0}^{\infty} \beta^s \alpha_k^s \left(X_{H,k,j,t} Y_{H,k,j,t+s} - W_{t+s} N_{H,k,j,t+s} - R_{t+s}^k K_{H,k,j,t+s} \right) \tag{2.55}$$

where $X_{H,k,j,t}$ denotes the contracted-price for the home-variety j in sector k's domestic good in the home-country. Let $\Lambda_{\mathcal{H},k,t}$ be defined as:

$$\Lambda_{\mathcal{H},k,t} = \left(\frac{1}{P_{\mathcal{H},k,t}} \right)^{-\theta_p} \left(\frac{P_{\mathcal{H},k,t}}{P_{k,t}} \right)^{-\rho} \left(\frac{P_{k,t}}{P_t} \right)^{-\eta} Y_t \tag{2.56}$$

Then, from the first-order condition of (2.55), $X_{H,k,j,t}$ can be written as:

$$X_{H,k,j,t} = \frac{\theta_p}{\theta_p - 1} \left(\frac{1}{1-\chi} \right)^{1-\chi} \left(\frac{1}{\chi} \right)^{\chi} \frac{E_t \sum_{s=0}^{\infty} \beta^s \alpha_k^s \left(W_{t+s}^{\chi} {R_{t+s}^k}^{1-\chi} \Lambda_{\mathcal{H},k,t+s} \right)}{E_t \sum_{s=0}^{\infty} \beta^s \alpha_k^s \Lambda_{\mathcal{H},k,t+s}} \tag{2.57}$$

Since the objective-function is identical across the firms that produce differentiated goods in sector k and that obtain a price-change signal in the same period, their contracted prices are the same ($X_{H,k,j,t} = X_{H,k,t}$). This, together with the Calvo-type randomization assumption, implies that $P_{\mathcal{H},k,t}$ can be rewritten as:

$$P_{\mathcal{H},k,t} = (1 - \alpha_{H,k}) X_{H,k,t} + \alpha_{H,k} P_{\mathcal{H},k,t-1} \tag{2.58}$$

Similar to the domestic intermediate-good, the home-export goods are composite goods made up of a continuum of varieties produced by monopolistically-competitive firms:

$$\begin{aligned} Y^*_{H,¢,k,t} &= \left(\int_0^1 {Y^*_{H,¢,k,j,t}}^{(\theta_p - 1)/\theta_p} dj \right)^{\frac{\theta_p}{\theta_p - 1}} \\ Y^*_{H,¢^*,k,t} &= \left(\int_0^1 {Y^*_{H,¢^*,k,j,t}}^{(\theta_p - 1)/\theta_p} dj \right)^{\frac{\theta_p}{\theta_p - 1}} \end{aligned} \tag{2.59}$$

where the demand for the home-export variety of j priced in home-currency (the foreign-currency) is denoted by $Y^*_{H,¢,k,j,t}$ ($Y^*_{H,¢^*,k,j,t}$).

The monopolistically-competitive firm producing variety j and the aggregator firm demanding this variety invoice in the same currency. It is also notable that while the varieties produced for the home-export firms are allowed to be invoiced in different currencies in the model, the demand elasticity between any two home-export varieties is not affected by the invoice currency. Indeed, the demand elasticity between any two home-export varieties is equal to θ_p, regardless of whether they are priced in the same or different currencies.[15].

Next, we write the maximization problem of the firm that produces variety j

[15] See Equation (2.45) and (2.59).

for the home-exporters and that set prices in the home-currency (the foreign-currency) as (2.60) ((2.61)):

$$E_t \sum_{s=0}^{\infty} \beta^s \alpha_k^s \left(X^*_{H,\cent,k,j,t} Y^*_{H,\cent,k,j,t+s} - W_{t+s} N^*_{H,\cent,k,j,t+s} - R^k_{t+s} K^*_{H,\cent,k,j,t+s} \right) \tag{2.60}$$

$$\begin{aligned} E_t \sum_{s=0}^{\infty} \beta^s {\alpha_k^*}^s \Big(& \mathcal{E}_{t+s} X^*_{H,\cent^*,k,j,t} Y^*_{H,\cent^*,k,j,t+s} \\ & - W_{t+s} N^*_{H,\cent^*,k,j,t+s} - R^k_{t+s} K^*_{H,\cent^*,k,j,t+s} \Big) \end{aligned} \tag{2.61}$$

where 1-α_k^* is the constant probability of receiving a price-change signal in *the foreign-sector* k, which is allowed to differ from that in *the home-sector* k (1-α_k). In writing (2.60) and (2.61), we make an important assumption that the invoice currency of monopolistically-competitive home-export firms also determines the price-rigidity which the firms face. Indeed, while the prices set in the home-currency remain fixed with the probability of α_k in each period, those set in the foreign-currency are subject to the price-rigidity in *the foreign-sector* k and remain fixed with the probability of α_k^*. We also make an analogous assumption for the monopolistically-competitive home-import firms.

One can show that the optimal prices set for the home-export varieties j which are invoiced in the home-currency ($X^*_{H,\cent,k,j,t}$) and the foreign-currency ($X^*_{H,\cent^*,k,j,t}$) can be written as:

$$X^*_{H,\cent,k,j,t} = \frac{\theta_p}{\theta_p - 1} \left(\frac{1}{1-\chi} \right)^{1-\chi} \left(\frac{1}{\chi} \right)^{\chi} \frac{E_t \sum_{s=0}^{\infty} \beta^s \alpha_k^s \left(W^{\chi}_{t+s} {R^k_{t+s}}^{1-\chi} \Lambda^*_{H,\cent,k,t+s} \right)}{E_t \sum_{s=0}^{\infty} \beta^s \alpha_k^s \Lambda^*_{H,\cent,k,t+s}} \tag{2.62}$$

$$X^*_{H,\cent^*,k,j,t} = \frac{\theta_p}{\theta_p - 1} \left(\frac{1}{1-\chi} \right)^{1-\chi} \left(\frac{1}{\chi} \right)^{\chi} \frac{E_t \sum_{s=0}^{\infty} \beta^s {\alpha_k^*}^s \left(W^{\chi}_{t+s} {R^k_{t+s}}^{1-\chi} \Lambda^*_{H,\cent^*,k,t+s} \right)}{E_t \sum_{s=0}^{\infty} \beta^s {\alpha_k^*}^s \mathcal{E}_{t+s} \Lambda^*_{H,\cent^*,k,t+s}} \tag{2.63}$$

where $\Lambda^*_{H,\not{c},k,t+s}$ and $\Lambda^*_{H,\not{c}^*,k,t+s}$ are defined as:

$$\Lambda^*_{H,\not{c},k,t+s} = \left(\frac{1}{P^*_{H,\not{c},k,t+s}}\right)^{-\theta_p} \left(\frac{\frac{1}{\mathcal{E}_t} P^*_{H,\not{c},k,t+s}}{P^*_{\mathcal{H},k,t+s}}\right)^{-\theta_p} \left(\frac{P^*_{\mathcal{H},k,t+s}}{P^*_{k,t+s}}\right)^{-\rho} \left(\frac{P^*_{k,t+s}}{P^*_t}\right)^{-\eta} Y^*_t \tag{2.64}$$

$$\Lambda^*_{H,\not{c}^*,k,t+s} = \left(\frac{1}{P^*_{H,\not{c}^*,k,t+s}}\right)^{-\theta_p} \left(\frac{P^*_{H,\not{c}^*,k,t+s}}{P^*_{\mathcal{H},k,t+s}}\right)^{-\theta_p} \left(\frac{P^*_{\mathcal{H},k,t+s}}{P^*_{k,t+s}}\right)^{-\rho} \left(\frac{P^*_{k,t+s}}{P^*_t}\right)^{-\eta} Y^*_t \tag{2.65}$$

The maximization problem of foreign-firms can analogously be written.

2.3.3 Closing the Model

Our first approach to close the model is to assume the growth of nominal spending follows an exogenous process in both countries:

$$\begin{array}{rl} logZ_t - logZ_{t-1} = \rho_z(logZ_{t-1} - logZ_{t-2}) + \epsilon_t^z & \quad \epsilon_t^z \sim N(0, \sigma_\epsilon^{z^2}) \\ logZ^*_t - logZ^*_{t-1} = \rho_z(logZ^*_{t-1} - logZ^*_{t-2}) + \epsilon_t^{z^*} & \quad \epsilon_t \sim N(0, \sigma_\epsilon^{z^{*2}}) \end{array} \tag{2.66}$$

where $Z_t = P_t Y_t$ and $Z^*_t = P^*_t Y^*_t$ denote nominal spending in the home- and foreign-country, respectively.

2.4 Calibration and Estimation

This section discusses calibration of the models' parameters. It should be noted that since monthly frequencies of price changes are readily available, whereas quarterly frequencies are not, we assess the ability of the models by comparing the outcomes from the models with those in the actual economies using monthly data. In Table B.1 of Section B.2 of the appendix, we present calibrated parameter values along with a source on which we base our calibration for these parameters. We start with θ_p. It is taken to be equal to 11, implying an average markup of 10%, which is the estimated markup rate for the auto-industry of the United States in Bresnahan (1981). We set $\delta = 0.008$, implying an annual rate of depreciation of 10%, which is the estimated annual rate of depreciation in the United States in Christiano and Eichenbaum (1992). We calibrate the values for σ_c, σ_n, σ_a, σ_ϕ, $\Theta'\bar{Y}$, ρ, η and χ directly from the sources outlined in Table B.1. β is set to $1.03^{\frac{-1}{12}}$, which implies an annual real interest rate of 3%.

Next, we calibrate the frequency of price changes in each sector. It is noteworthy that since the main trading partners of developing economies are advanced countries, the price-stickiness parameters and sectoral weights in the foreign-country (denoted by α_k^* and f_k) need to be calibrated as those in advanced countries when we study aggregate dynamics following monetary shocks in developing economies in our model. When calibrating these parameters, we rely on the estimates reported in Carvalho and Nechio (2011).[16] They estimate the weighted average of the frequency-of-price adjustments ($\sum_{k=1}^{67} f_k(1-\alpha_k^*)$) in the United States as 0.21. Based on this, we take the foreign price-stickiness, α_k^*, in the one-sector model as 0.79.

The home frequency of price changes, $1-\alpha_k$, in the one-sector model is calibrated as 27.2%. That is, on average, 27.2% of prices change in each month in developing economies, which is in line with the estimates of the mean frequency of price changes in Mexico in Gagnon (2009) when inflation remained between 4%

[16] It is notable that while Carvalho and Nechio (2011) use the data from Nakamura and Steinsson (2008) who report the frequency of price changes and the expenditure share for 271 categories of goods and services in the United States, to make their model computationally manageable, Carvalho and Nechio (2011) only include 67 sectors in their model by aggregating some sectors.

and 14%. We do not have estimates of sectoral frequency of price-adjustments in developing economies. In calibrating sectoral price-stickiness in developing economies for the multi-sector model, we ensure that $\sum_1^{67} f_k(1-\alpha_k) = 0.272$. We also assume that the expected duration of price contracts in a home sector is shorter than that in its foreign counterpart by some factor, say by D. If D is taken as 1.45, we find that the aforementioned condition is met. That is, if sectoral prices in these economies changes 1.45 times more frequently than those in the United States, the condition that $\sum_1^{67} f_k(1-\alpha_k) = 0.272$ is met. With such an assumption, the sectoral frequency of price changes in the home-country can be calibrated using the following steps. First, estimate the expected duration of price-contracts in a sector in the United States with the following formula:

$$d_k^* = -\frac{1}{ln\alpha_k^*}$$

Second, estimate the expected duration of sectoral price contracts in the home-country by assuming that it is 1.45 times shorter than that in the United States

$$d_k = \frac{d_k^*}{1.45}$$

In the last step, estimate sectoral price stickiness in developing economies with

$$\alpha_k = e^{\frac{-1}{d_k}}$$ [17]

Even if the frequency of price changes is calibrated for 67 sectors, we only include 3 sectors in our multi-sector model. The reason is that we have to estimate some parameters using minimum distance estimation in our paper and it is not computationally feasible to do estimation with 67 sectors. In reducing the number of sectors to three, we first order the sectors according to their frequencies

[17] This follows from $d_k = \frac{-1}{ln\alpha_k}$

of price changes. Next, we include the sectors whose frequency of price changes lies in [0, 33],[34, 66] and [66,100] percentiles of frequencies of price changes in the first, second and third group, respectively. The frequency of price changes that represents each group is approximated by the median frequency of price changes in each group. The expenditure share of each group (f_k), on the other hand, is taken as the sum of the expenditure shares of the sectors forming the group.

In calibrating the shares of final consumption (s_c), investment (s_m) and home-imports (ψ) in GDP, we use data for these series from the World Bank's *World Development Indicators* in 2002. s_c, s_m and ψ are taken as the median values in the group. τ which denotes the economic size of the foreign-country relative to that of the home-country is taken as 1000. τ is set to be very high for developing economies, in line with the common small-country assumption for these countries in the literature. It is notable that setting τ to a large value for developing economies, together with the assumption of no international borrowing at the steady-state, requires that the steady-state shares of exports and imports in the foreign-country be only $\frac{1}{\tau}$ as big as those in the home-country. This is the essence of the small-country assumption in our model. The share of the home-exports priced in the home-currency ($\omega_{¢}$) and the share of the home-imports priced in the foreign-currency ($\omega_{¢}^{*}$) are calibrated based on the findings in Section B.2.1 for Turkey.

Lastly, in order to calibrate ρ_z, which represents the persistence in the exogenous nominal spending growth process in (2.66), the Panel AR(12) model for log changes in the monetary aggregates M1 and M2 are estimated for our sample using monthly data with country-fixed effects. The sum of AR coefficients for M1 and M2 are estimated as 0.35 and 0.29, respectively. Based on this, we set $\rho_z = 0.32$.

To study dynamics after nominal spending shocks, both models are log-linearized around the zero-inflation and zero-debt steady-state.

2.5 Quantitative Results

In this section, our aim is to evaluate the ability of the one- and multi-sector models to account for the dynamics of output, the price level, the real and nominal exchange rates after monetary shocks in developing economies which adopted an inflation targeting regime.

2.5.1 Output and Price Level Dynamics

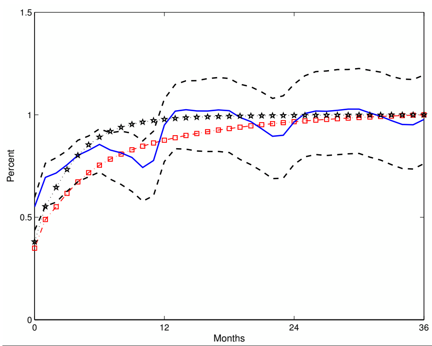
Figure 2.4 displays the model- and panel-VAR-based impulse response functions of output ($\hat{\mathcal{Y}}_t$) and the price level (P_t) in the home-country.[18] In this figure, the dashed lines with pentagrams and dotted line with squares show the impulse response functions to a domestic expansionary shock in the one- and multi-sector models, respectively. The panel-VAR-based impulse responses of the variables in developing economies obtained in *Empirical Model II* with the monthly data

[18] It is notable that real spending (denoted by Y_t) differs from domestic output. We denote domestic output in the home country as $\hat{\mathcal{Y}}_t$. $\hat{\mathcal{Y}}_t$ can be written as:

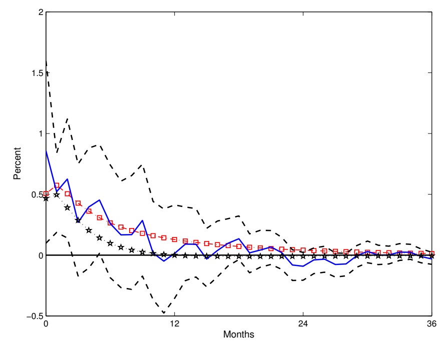
$$\hat{\mathcal{Y}}_t = \sum_{k=1}^{K} f_k(1-\psi)\hat{Y}_{\mathcal{H},k,t} + \sum_{k=1}^{K} f_k\psi\omega_{\mathcal{C}}\hat{Y}^*_{H,\mathcal{C},k,t} + \sum_{k=1}^{K} f_k\psi(1-\omega_{\mathcal{C}})\hat{Y}^*_{H,\mathcal{C}^*,k,t}$$

Figure 2.4: *Model- and VAR-Based Impulse Responses of P and $\mathcal{Y}$ to ϵ^z*

(a) *Price Level (P)*



(b) *Output ($\mathcal{Y}$)*



Note: Our calculations are based on the IMF's *International Finance Statistics*. The dotted lines with pentagrams and the dashed lines with squares indicate the model-based impulse response functions in the one- and multi-sector models, respectively. The solid lines show the estimated point-wise panel-VAR-based impulse response functions. The area between the dotted lines shows the 90% confidence interval estimated with the method suggested by Sims and Zha (1999).

are displayed with the solid lines. Lastly, the area between the dotted lines show the 90% confidence interval of the panel-VAR-based impulse response functions estimated with the method suggested by Sims and Zha (1999). It is notable that for both the model- and panel-VAR-based impulse response functions, we consider a monetary shock in developing economies that results in a 1% long-run increase in P.

We first discuss the price level dynamics. A striking observation in Figure 2.4 is that the price level responses in the multi-sector model stays muted compared to those in the one-sector model. This point is explained succinctly in Nakamura and Steinsson (2013) for the case of no strategic interaction among firms. Suppose that an economy has two sectors. Let the first sector have a low frequency of price changes so that it takes quite a while for firms in this sector to respond to an aggregate shock (the sticky-price sector). Let the second sector have high price-flexibility so that prices may respond fast to an aggregate shock in this sector (the flexible-price sector). It can be argued that firms in the flexible-price sector might have a chance to change their prices several times before firms in the sticky-price sector do so for the first time. However, apart from the period in which firms in the flexible-price sector obtain a chance to change their prices for the first time, the price adjustment in this sector in accompanying periods adds little to the aggregate price adjustment since firms adjust fully to the shock when they first obtain a chance to respond. In other words, apart from the first responses, all other price responses in the flexible-price sector are "wasted". For the complete aggregate price adjustment, it is crucial that firms in the sticky-price sector obtain a chance to change their prices at least once after the shock. Nakamura and Steinsson (2013) note that if it were possible to have a more even distribution of the frequency of price changes among sectors, the aggregate price adjustment would be much faster. This conjecture is supported by our findings. Indeed, in the one-sector model, by taking the weighted average of the frequencies of price changes among sectors as the frequency of price changes in the economy, some price changes are implicitly re-allocated from the flexible-price sector to the sticky-price sector. As a result, it is not surprising to observe a stronger contemporaneous response of the aggregate price level and faster price adjustment in the one-sector model than in the multi-sector model.

Regarding output, it is clear in Figure 2.4 that output shows less persistent dynamics in the one-sector model than the multi-sector model. This can be accounted for by a faster price adjustment in the former.

2.5.2 Real and Nominal Exchange Rate Dynamics

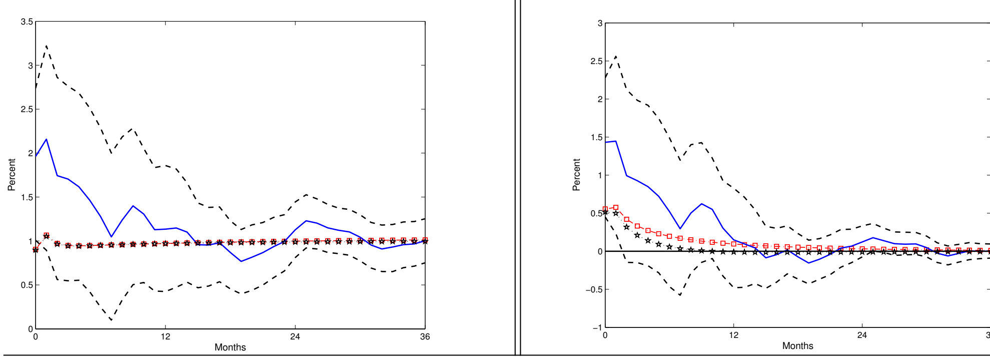
Figure 2.5 displays the dynamics of nominal and real exchange rate in the one- and multi-sector models along with their panel-VAR-based dynamics.[19] It is evident that the nominal exchange rate undershoots its new long-run level, which contrasts with a sizable overshooting of the nominal exchange rate in the actual economies shown in this figure. This mainly results from the muted initial impulse response functions of the real exchange rate.

Our findings regarding the models indicate that both the one- and multi-sector models are of limited ability in explaining the aggregate dynamics in developing economies following a monetary shock. Indeed, some impulse response functions stay out of 90% confidence intervals. Particularly, nominal exchange dynamics in the actual economies are poorly predicted by these models.

How can the predictions of the one- and multi-sector models be improved? We show in the next section that when adjustment costs of new capital are so large that they prohibit investment, the extent to which the exchange rate overshoots

[19] To obtain 90% confidence intervals for the impulse response functions of the nominal exchange rate, we first obtain 1000 randomly generated impulse response functions of the nominal exchange rate over 36 months ($\mathcal{E}^i$) as $\mathcal{E}^i = \mathcal{Q}^i - P^i - P^{*^i}$ where $\mathcal{Q}^i$, P^i, P^{*^i} denote randomly generated impulse functions of the real exchange rate, the price level in developing economies and the United States, respectively. The area that stays within the 5th and 95th percentile of the distribution of randomly generated impulse response functions of the nominal exchange rate is reported in Figure 2.4 as the 90% confidence interval for the impulse response functions of the nominal exchange rate.

Figure 2.5: *Model- and Panel-VAR-Based Impulse Responses of $\mathcal{E}$ and $\mathcal{Q}$ to ϵ^z*



(a) *Nominal Exchange Rate ($\mathcal{E}$)*

(b) *Real Exchange Rate ($\mathcal{Q}$)*

Note: Our calculations are based on the IMF's *International Finance Statistics*. The dotted lines with pentagrams and the dashed lines with squares indicate the model-based impulse response functions in the one- and multi-sector models, respectively. The solid lines show the estimated point-wise panel-VAR-based impulse response functions. The area between the dotted lines shows the 90% confidence interval estimated with the method suggested by Sims and Zha (1999).

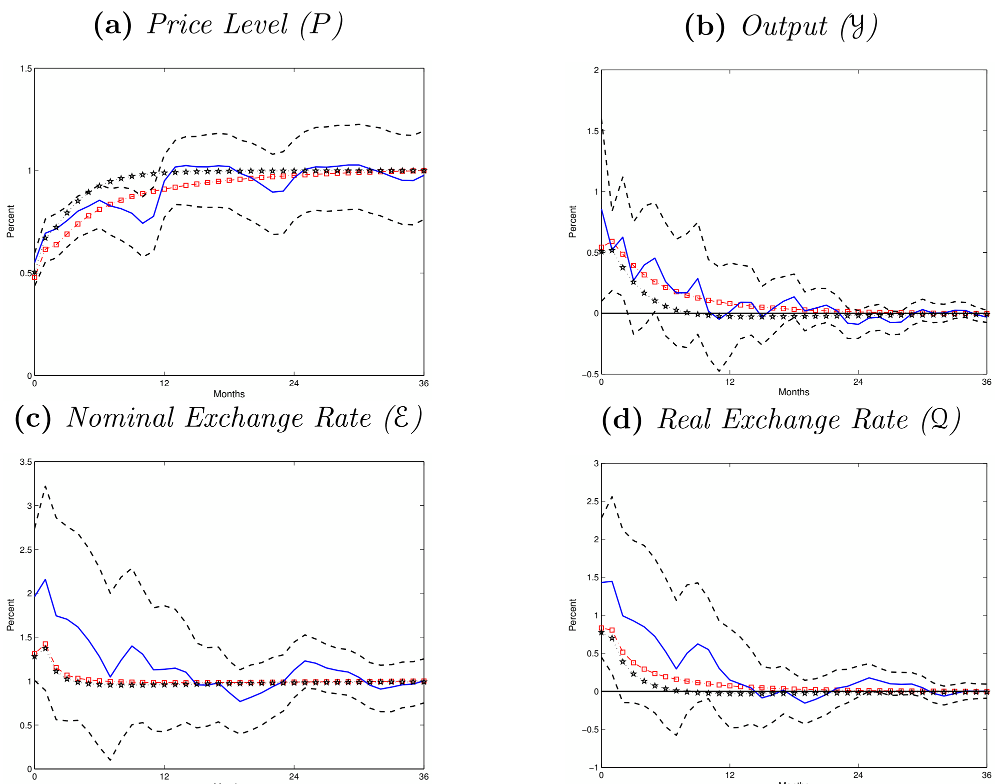
increases and the models' performance improves to a certain degree.

2.5.3 One- and Multi-Sector Models without Investment

To understand the reason for the limited degree of exchange rate overshooting in the models, it is useful to consider the real exchange rate equation in the model. It can be shown from (2.29) that the % deviation of the real exchange rate ($\hat{Q}_t$) from its steady-state in the models is given by

$$\begin{aligned} \hat{Q}_t &= \textstyle\sum_{s=0}^{\infty} \sigma_c \left[E_t \left(\hat{C}_{t+s} - \hat{C}_{t+1+s} \right) - E_t \left(\hat{C}^*_{t+s} - \hat{C}^*_{t+1+s} \right) \right] + \textstyle\sum_{s=0}^{\infty} \Theta'(0) \bar{Y} \hat{B}_{t+1+s} \\ &= \sigma_c E_t \left(\hat{C}_t - \hat{C}^*_t \right) + \textstyle\sum_{s=0}^{\infty} \Theta'(0) \bar{Y} \hat{B}_{t+1+s} \end{aligned} \tag{2.67}$$

Figure 2.6: *Model- and Panel-VAR-Based Impulse Responses of P, $\mathcal{Y}$, $\mathcal{E}$ and $\mathcal{Q}$ to ϵ^z*
(Without Investment)



Note: Our calculations are based on the IMF's *International Finance Statistics*. The dotted lines with pentagrams and the dashed lines with squares indicate the model-based impulse response functions in the one- and multi-sector models, respectively. The solid lines show the estimated point-wise panel-VAR-based impulse response functions. The area between the dotted lines shows the 90% confidence interval estimated with the method suggested by Sims and Zha (1999).

Since we maintain the small-country assumption, the impulse response functions of foreign consumption should be negligible after a monetary shock in developing economies ($\hat{C}_t^* \approx 0$). This, together with the small value of calibrated interest elasticity of foreign debt ($\Theta'(0)\bar{Y}$), implies that

$$\hat{Q}_t \approx \sigma_c \hat{C}_t \tag{2.68}$$

From (2.68), the weak contemporaneous response of the real and nominal exchange rates in the models can therefore be traced to a weak contemporaneous response of consumption. Put differently, should the contemporaneous response of consumption have increased, the undesirable outcome of exchange-rate undershooting in the models would be avoided. To this end, it is useful to consider the resource constraint in the home country:

$$s_C \hat{C}_t + s_I \hat{I}_t + \frac{s_I}{\delta}\left(\frac{1}{\beta} - (1-\delta)\right)\hat{u}_t = \hat{Y}_t \tag{2.69}$$

where s_C and s_I are the steady-state shares of consumption and investment in real spending in the home-country, respectively. We conjecture that by increasing the contemporaneous response of C_t for some given Y_t, excluding investment in the models may result in a more profound contemporaneous response of Q_t, which may help the models to predict an overshooting of the exchange rates after monetary shocks.

Figure 2.6 offers supporting evidence for our conjecture that when investment is excluded from the models, Q_t gives a stronger contemporaneous response. This helps the models predict the nominal exchange rate overshoots its long-run level after the monetary shocks as found in the actual economies. Moreover, unlike the price dynamics in the one-sector model, the price dynamics in the multi-sector model never stay out of 90% confidence intervals of the impulse-response functions of the aggregate variables in the actual economies when investment is too costly to make.

Lastly, one may argue that instead of excluding investment, the one- and multi-sector models without a variable rate of capacity utilization (u_t) would produce a higher exchange rate overshooting in the real and nominal exchange rates since the contemporaneous response of consumption would be stronger without a variable capacity utilization. However, we find excluding the variable u_t has a negligible effect on the extent of overshooting. The reason is that when capacity is fully utilized in all periods ($\hat{u}_t = 0$), the rental rate of capital increases immediately when an expansionary monetary shock occurs, causing a stronger contemporaneous response of the price level and a weaker contemporaneous response of real spending. Consequently, when capital is assumed to be fully utilized in all periods, both $\hat{u}_t$ and $\hat{Y}_t$ fall, causing a small change in $\hat{C}_t$. This results in the nominal and real exchange rate overshooting being limited after the monetary shock (see (2.68)).

2.5.4 The Real Wage Dynamics in the Multi-Sector Model

Before concluding the paper, we analyze the real wage dynamics in the multi-sector model under both staggered and flexible wage-setting. In Table 2.2, we present the estimates of the correlation between real wages and real GDP in developing economies reported in Agnor, McDermott, and Prasad (2000) and Li (2011) along with those in the multi-sector model under both staggered and flexible wages. The correlation under flexible wages is almost perfect which contrasts with a moderate correlation of 0.49 or lower in data. The correlation of 0.59 under staggered wages may also be regarded as high compared to that in the data. Yet, it is clear that our staggered wage-setting assumption brings the

Table 2.2: *Correlation of the Real Wage with Output in Developing Economies*

			$\rho_{w,y}$
Data			
	Agnor, McDermott, and Prasad (2000)		
		HP	0.49
		BP	0.27
	Li (2011)		
		HP	0.41
Multi-Sector Model			
		Flexible Wages	0.99
		Staggered Wages	0.59

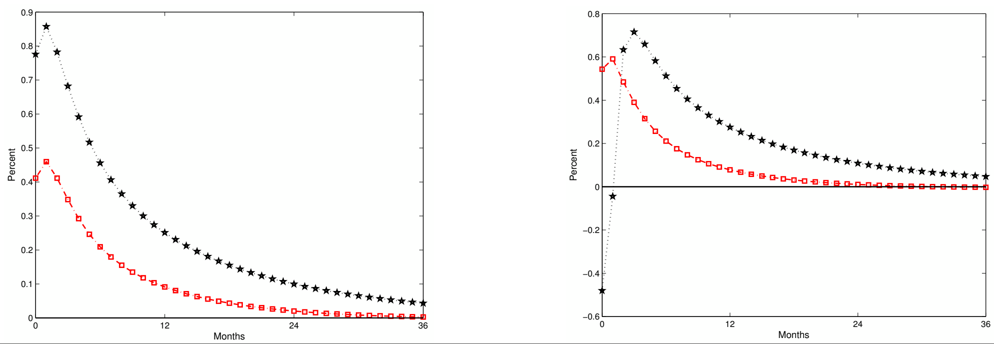
Note: HP and BP refer to the estimates of the *quarterly* correlation between real wages and real GDP which are filtered with the Hodrick-Prescott and band-pass filters, respectively. In both Agnor, McDermott, and Prasad (2000) and Li (2011), the reported correlations denote the simple mean of the correlations in the developing economies contained in their sample. We estimate the *quarterly* model-based correlations using the 3-month average of the monthly impulse responses of the real wage and output in the multi-sector model under both staggered and flexible wages.

correlation in the model closer to the estimates of the correlation in the data.

We also study the co-movements of the real wage and output in the multi-sector model under flexible and staggered wages in Figure 2.7. Under flexible wages, workers' ability to respond fast to shocks results in the real wage increasing strongly in tandem with output following the shock. Consequently, the movements in the real wage closely follow those in output in the multi-sector model under flexible wages. Yet, while output strongly increases, the real wage falls under staggered wages as wages are predetermined and prices increase after the

Figure 2.7: *Model-Based Impulse Responses of w and $\mathcal{Y}$ to ϵ^z*

(a) *Flexible Wages* **(b)** *Staggered Wages*



Note: The dashed lines with squares and the dotted lines with pentagrams indicate the model-based impulse response functions of output and the real wage in the multi-sector model, respectively.

shock. In the accompanying two months, since workers obtain a chance to reset their wages at least once after the shock, the real wage increases and peaks about a quarter after the peak in output following the shock, which is consistent with the finding in Li (2011) that real wages lag business cycles by a quarter in developing economies.

2.6 Conclusion

In this paper, we have studied what happens to output, the price level, the real and nominal exchange rates after a positive domestic monetary shock in developing economies under an inflation targeting regime. We have found such a shock causes a short-lived rise in output, a temporary real exchange rate depreciation, a sizable overshooting of the nominal exchange rate and an increase in the price level in the short- and long-terms in these countries. Then, we have compared these findings with the outcomes in the one- and multi-sector models under staggered-wages. When adjustment costs of acquiring new capital is low, neither the former nor the latter can successfully account for the nominal exchange rate overshooting following domestic monetary shocks in the actual economies. However, when such costs are large, we have found the multi-sector model can successfully explain the aggregate dynamics following domestic monetary shocks in developing economies.

Chapter 3

Information Content of the Options-Implied Crude Oil PDFs

3.1 Introduction

Financial markets provide a wide range of instruments that enable market participants to speculate or hedge against potential changes in asset prices. As these instruments provide rich and timely information that is inherently forward looking, researchers and practitioners frequently analyze financial data to infer market participants' beliefs about future movements in asset prices or probabilities of certain outcomes. Options, in particular, are a powerful source of direct market-based measures of investors' beliefs about the price of an underlying asset. So far, many researchers have attempted to estimate these densities for stock market indices, exchange rates, interest rates or even inflation, but only a few have estimated these densities for commodities, particularly crude oil.

Yet, crude oil options written on oil futures are particularly interesting for at least three reasons. First, crude oil is one of the key variables in generating macroeconomic projections and in assessing macroeconomic risks. As famously argued by Hamilton (2008), almost all of the U.S. recessions since World War II were preceded by a spike in the oil price. Therefore, gaining further insights about the expected path of crude oil prices can be helpful in predicting the future course of the US economy. Second, one of the widely accepted reasons for the upward trend in oil prices since 2000 is the surge in global demand (Kilian, 2009). This means, a better understanding of the expected crude oil prices can be useful for inferring the expected global economic conditions. Third, fluctuations in oil prices are relevant for the way to conduct monetary policy. For instance, whether a shock to crude oil prices is temporary or permanent is vital for policy makers to update their current stance on monetary policy. Pooling information from market participants about the expected path of oil prices can shed light on the nature of these shocks.

In this paper, I estimate an options-implied probability distribution function (pdf) for Western Texas Intermediate (WTI) crude oil futures and document the empirical properties of its first 4 moments as well as its extreme percentiles. Second, I investigate the dynamics of these pdfs around particular events and evaluate their reactions. As an extension, I implement an event-study analysis and assess the effects of U.S. macroeconomic news on these pdfs. Finally, I evaluate the information content of these pdfs by designing forecasting exercises in two different but complementary directions. In the former one, I treat these pdfs as density forecasts and compare their predictive accuracy against other density forecasts generated by popular time-series models. In the latter one, I evaluate both in-sample and out-of-sample information content of these pdfs in point forecasting of oil prices.

My contribution to the literature is threefold. First, I demonstrate that while the expected price of oil futures (i.e. the mean of the options-implied oil pdf) does not significantly respond to U.S. macroeconomic news, especially at short maturities as in Kilian and Vega (2011), the skewness and the 95^{th} percentile of these pdfs do react to U.S. macroeconomic news at almost all maturities. Market perceptions of oil price risk do react to surprises in U.S. macroeconomic fundamentals, even if the short-term futures or spot prices do not. Second, I show that options-implied oil pdfs are generally better density forecasts than their standard time-series counterparts, particularly at shorter horizons (i.e. less than 6 months). This provides evidence that pooling agents' perceptions about future oil prices can provide useful density forecasts. Finally, the fluctuations in options-implied volatility and skewness contain valuable information in the point forecast of oil prices. In particular, I show that these moments improve the out-of-sample predictive performance of the common oil price forecasting models. While the predictive content of higher order moments has been documented in the context of equities or stock market indices (Bollerslev, Tauchen, and Zhou, 2009; Goyal and Saretto, 2009), the possibility of such a link has not been explored for crude oil. This paper quantifies several aspects of oil price risk including volatility and skewness using options-implied pdfs and fills these gaps for crude oil.

I derive the options-implied pdfs in two steps following Ait-Sahalia and Duarte

(2003). In the first step, I filter the options data, by replacing the price of options by the closest prices that satisfy convexity and shape restrictions. In the second step, I compute options-implied pdfs by estimating a locally linear regression function.

The appeal of extracting densities from options prices to assess the market based expectations is not new. The first examples of this kind go back to Breeden and Litzenberger (1978). However, this literature mostly focussed on options on foreign exchange market (Campa and Chang, 1996; Campa, Chang, and Refalo, 2002), interest rates (Amin and Ng, 1997; Longstaff, Santa-Clara, and Schwartz, 2001), and stock market indices or individual equities (Gemmill and Saflekos, 2000; Kang and Kim, 2006; Kostakis, Panigirtzoglou, and Skiadopoulos, 2011). There are only handful of papers that have extracted options-implied pdfs for commodities (for crude oil Melick and Thomas (1997); Pan (2012), and Datta, Londono, and Ross (2015), and for agricultural commodities Fackler and King (1990)). While Datta, Londono, and Ross (2015) examined the performances of these pdfs around important market events like this paper, all of these papers remain silent about the systematic reaction of these pdfs to U.S. macroeconomic news announcements and their information content in predicting future oil prices. This paper fills these gaps in the literature.

The rest of the paper is organized as follows. In Section 3.2, I provide details of the estimation method and introduce the options data that is used in this paper. In Section 3.3, I document several empirical regularities of options-implied moments, their reactions to U.S. macroeconomic news, and finally their information content in predicting future oil prices. Section 3.4 concludes.

3.2 Option-Implied PDFs

In this section, I briefly discuss how I estimated the options-implied pdfs for oil futures. Then, I discuss how to estimate the key moments and percentiles from these distributions along with some discussion about the robustness of these measures. Finally, I introduce the options and futures data that are used to estimate these oil pdfs.

3.2.1 Estimating Options-Implied Pdfs

In forming the option-implied pdfs, I follow the well known approach introduced by Breeden and Litzenberger (1978). Suppose at time t, there is a European call option, C, written on a futures contract $F_{t,T}$ maturing at time T with the strike price X. We usually rely on the price dynamics of underlying assets under the risk-neutral measure and under this measure, a European call option is priced by equation 3.1:

$$\begin{aligned} C(X,T) &= e^{-rT}\int_0^{\infty} \max\left(S_T - X, 0\right) f(S_T)\, dS_T \\ &= e^{-rT}\int_X^{\infty} \left(S_T - X\right) f(S_T)\, dS_T \end{aligned} \tag{3.1}$$

Breeden and Litzenberger (1978) demonstrate that the second derivative of the price of a call option with respect to the strike price represents the risk-neutral (options-implied) probability distribution function ($f(S_T)$ where $S_T = X$):

$$\frac{\partial^2 C(X,T)}{\partial X^2} = e^{-rT} f(X) \tag{3.2}$$

where r is the risk-free rate and T is the maturity of the option. Equation 3.2 is derived for European calls, but the variables of interest, i.e. options written of WTI futures, are American calls and puts. In the benchmark method, I assume that this relationship holds also for American options, so I treat them as if they are European options[1].

In general, out-of-the money options are more liquid compared to their in-the-money counterparts (see Voit (2003) for a discussion about the differences between in-the-money and out-of-the-money options). Consequently, researchers prefer to use out-of-the money puts rather than in-the-money calls in estimating options-implied pdfs. Yet, equations 3.1 and 3.2 are both derived for call options. In practice, it is always possible to find the price of a call as long as there is a put option with the same maturity and the strike price. This is achieved by the put-call parity relationship[2].

[1]One implication of this assumption is that the prices of European and American options would be the same. Yet, in theory (and also in practice) the price of American option is slightly higher than a European one. However, this assumption implies that it is never attractive to exercise the American call which is indeed a reasonable assumption for short horizons and low interest rates (Chaudhury and Wei, 1994; Melick and Thomas, 1997). For commodity options, particularly in a liquid market such as crude oil, Trolle and Schwartz (2009) show that the approximation errors, due to the treatment of American options as Europeans, are approximately zero in maturities less than 3 months and they are approximately less than one fifteenth of the price of the option for maturities longer than one year.

[2]Notice that the original put-call parity equation holds only for European options. Since American options can be exercised at any time prior the expiration date, the same put-call parity cannot be used for American options. However, it is possible to rearrange this equation into an inequality for the American options too. It will give us upper and lower bounds for the price of the American put option with the same maturity date and strike price as the American call option. Here is the formula that defines these limits:

$$S_0 - X \leq C(X,T) - P(X,T) \leq S_0 - X\ e^{-r\ T}$$

Because I am treating American options as if they were European, I need to choose either of the two available choices with different shortcomings: (i) I can either use more liquid options (i.e. out-of-the money puts instead of in-the-money calls) and introduce a noise due to the

Options-implied pdfs are formed based on equation 3.2, which is the second derivative of the price of the call option price with respect to its exercise price. In practice, however, call prices are available only for a discrete number of strike prices, so I need an approximation to derive the risk neutral pdfs from the observed prices of options. Secondly, options have fixed expiration dates, so the options-implied pdfs mechanically shrink (i.e. the uncertainty regrading oil futures goes down) as we approach to expiration date. Throughout the paper, besides the event study analysis of option implied moments in subsection 3.3.3 and forecasting exercises that are provided in subsection 3.3.4, I use fixed-horizon options-implied pdfs to derive time-series estimates of the relevant percentiles and their moments[3].

Consider a set of M crude oil call options in ascending order with respect to the strike price on a given day at a given maturity. Let C_i be the price of the ith call option[4] with a strike price that is equal to X_i. The estimation problem is then first to replace the actual call prices with the ones that satisfy no-arbitrage conditions. This is the constrained least squares estimation step of Ait-Sahalia and Duarte (2003). Next, I approximate the price of a call option written

form of the put-call parity for American options, (*ii*) I can stick just with the calls (and drop all the puts from the sample) and introduce another type of noise due to liquidity differences between in-the-money calls and out-of-the-money puts. As there is no perfect fix to this problem, in the benchmark estimation, I continue to treat these options as European and implement the put-call parity as usual.

[3]The literature provides several ways to interpolate option implied pdfs across time. In this paper, I use total variance interpolation method as described in Carr and Wu (2010). In simple terms, it is a weighted average of two pdfs where one has a shorter, the other has a longer maturity compared to hypothetical fixed maturity pdf.

[4]For the notational simplicity, instead of writing $C(X_i, T)$, I suppress the maturity and the strike price for the call option and write it as C_i.

on oil futures at a strike price X' in a neighbour around X. The estimation is conducted by a locally linear function $\beta_0(X)+\beta_1(X)\,(X'-X)$, which is the local polynomial regression step of Ait-Sahalia and Duarte (2003). The parameters of interest, i.e. $\beta_0(X)$ and $\beta_1(X)$, can be estimated by using the following kernel regression:

$$\hat{\beta}_0(X), \hat{\beta}_1(X) = \arg\min_{\beta_0(X),\beta_1(X)} \sum_{i=1}^{M} \left(C_i - \beta_0(X) - \beta_1(X)\,(X_i - X)\right)^2 k_i \tag{3.3}$$

$$k_i = \frac{K\left((X_i - X)/h\right)}{h}$$

where $K(.)$ is the kernel function and h is the bandwidth. The second partial derivative of the call price, C, with respect to exercise price, X, (i.e. options-implied risk neutral pdf) is given by $\hat{\beta}_1'(X)$ which the first derivative of $\hat{\beta}_1(X)$ with respect to X as in equation 3.4:

$$\hat{\beta}_1'(X) = \frac{\sum_{i=1}^{M-1}\sum_{j=i+1}^{M} (X_i - X_j)\,(C_i - C_j)\left(k_i'\,k_j + k_i\,k_j'\right)}{\sum_{i=1}^{M-1}\sum_{j=i+1}^{M} (X_i - X_j)^2\,\left(k_i'\,k_j + k_i\,k_j'\right)} \tag{3.4}$$

where $k_i' = K'\left((X_i - X)/h\right)/h$, i.e. first derivative of the kernel function with respect to X.

The estimation of equations 3.3 and 3.4 hinges on (i) the functional form for the kernel function $(K(.))$ and (ii) the bandwidth (h). Following the standard practice in the literature, I assume a Gaussian kernel function for $K(.)$. For the choice of bandwidth, I follow Li and Zhao (2009) and numerically minimize the finite sample integrated Mean Square Error (MSE) of the locally linear estimation via simulation[5] and optimally choose h. All the estimation results in this paper are based on this optimal bandwidth.

Finally, to estimate an options-implied risk neutral pdf, I need the risk-free Treasury rates (see equation 3.2). Using the nominal Treasury term structure data set of Gürkaynak, Sack, and Wright (2007), I obtain the risk free n-period yields and I derive the oil pdfs under the forward measure[6]. Therefore, with this method, I can construct the probability on a single day at a single maturity from options at different strike prices.

Once I estimate these distributions, I can easily obtain their summary measures, particularly the options-implied moments and extreme percentiles. The odds of observing a large number of outliers and high variability in the moment measures in a highly liquid market such as crude oil is less likely. However, I still observe large jumps particularly higher order moments of options-implied pdfs. Therefore, rather than estimating the moments of the estimated pdfs, I compute the quantile counterparts of these magnitudes as the benchmark because the quantile moments are more prone to outliers. Specifically, defining the options-implied cumulative distribution as $F(X)$ and the quantile associated with the probability level p as $q(p)$[7], I define the quantile based moments, i.e.

[5] The exact numerical algorithm that I use to calculate the bandwidth is provided in Pan (2012).

[6] A forward measure is an equivalent martingale measure similar to risk-neutral measure. However, rather than using the uncertain money market rate as in risk neutral measure, it uses the non-random forward rates to discount future payoffs. I use the forward measure rather than risk neutral one throughout the paper.

[7] Notice that, for the notational simplicity, instead of writing the cumulative distribution

median, volatility, skewness and kurtosis in equations 3.5 and 3.6 respectively[8].

$$\text{MED} = q(50) \qquad \text{IVOL} = q(75) - q(25) \tag{3.5}$$

$$\text{SKEW} = \frac{(q(90) - q(50)) - (q(50) - q(10))}{q(75) - q(25)} \qquad \text{KURT} = \frac{q(95) - q(5)}{q(75) - q(25)} \tag{3.6}$$

3.2.2 Data Description

In this study, I use daily futures on Western Texas Intermediate (WTI) crude oil and options on these futures contracts that were traded formerly at New York Mercantile Exchange (NYMEX), and now under the Chicago Mercantile Exchange (CME) Group. This exchange offers institutional features that allow traders to transact anonymously. Futures contracts traded in this market are for delivery at Cushing, OK and traditionally, they have been the most liquid and the largest volume market for crude oil trading. Similar to the NYMEX oil futures, the options written on them are by far the most liquid options market where underlying is a commodity futures.

Trading for futures contracts ends 4 days prior to the 25^{th} calendar day preceding the delivery month. If the 25^{th} is not a business day, trading ends on the fourth business day prior to the last business day before the 25^{th} calendar day. On the other hand, options written on these futures expire in three business

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as $F_{t,T}(X)$, I suppress the maturity and the time so write it as $F(X)$. This is true for $q(p)$ as well. Finally, the relationship between $q(p)$ and $F(X)$ can be represented as follows: $p = \mathbb{P}\left(x \leq q(p)\right) = F(q(p)) \quad \Rightarrow \quad q(p) = F^{-1}(p)$

[8] When abstracting from these outliers (i.e. after I trim above and below 5% of daily moments data), the options-implied moments derived from quantiles and usual methods are highly correlated. This is particularly true for the lower-order moments, such as mean and volatility. After trimming the series for outliers, the average pairwise correlation is equal to 0.95 for the mean and 0.92 for the volatilities over the entire sample. On the other hand, the correlation for skewness and kurtosis decline to 0.85 and 0.78, respectively.

days prior to the expiration date of futures contract. Furthermore, these options are American-style contracts and at the expiry date, the payoffs of these options are settled in cash[9].

To reduce data and pricing errors, I clean the data by removing options that are priced at 1 cent as very cheap options might add too much noise to the estimation of the options-implied pdf[10]. While the constrained least squares estimation step of Ait-Sahalia and Duarte (2003) method partially irons this problem out, this noise can be still be a serious problem especially if we move further away form the center and approach the tails of the pdf (e.g. see Høg and Tsiaras (2011), Christoffersen, Jacobs, and Chang (2013), and Datta, Londono, and Ross (2015)).

Even after I clean the data, the number of options and their moneyness[11] range remain quite large. Table 3.1 reports that there are 43 calls and 50 puts maturing in a month, but there are only 31 calls and 30 puts maturing in a year. Figure 3.1 shows that rather than being stable, the number of options traded display an upward trend through time. For example, before 2000s, the available strike prices often cover 20 to 25 US dollars range with increments of 1 dollar whereas recently the coverage increases to 200-250 US dollars with increments

[9]Here is a link that provides the details of the NYMEX crude oil futures and options written on them:
http://www.cmegroup.com/trading/energy/crude-oil/light-sweet-crude_contract_specifications.html

[10]The options on WTI futures are priced with increments of 1 cent, so 1 cent is the minimum price of an option if that option is traded in the market at any point in time.

[11]In this context, moneyness is defined as the relative position (so a ratio) of the price of an underlying asset, which is the oil futures, with respect to the strike price of a call option or a put option.

of 50 cents (see Figure 3.2)[12]. Furthermore, call moneyness ranges from an average daily minimum of 0.84 to an average daily maximum of 1.27 for the options maturing in a month. This means that market participants can, on average, hedge against price changes between a roughly 15 percent decrease and 25 percent increase in the price of oil during the next month. Not surprisingly, the moneyness range of calls widens as the maturity of options increases, reflecting the differences in market participants opinions or hedging needs for future crude oil price developments. Broadly speaking, the put options have similar characteristics as the calls which are shown by Table 3.1.

3.3 Estimation Results

This section presents empirical regularities regarding the oil pdfs. I first report the stylized facts, specifically time series and cross sectional properties of the options-implied moments of oil futures. Next, I analyze changes in market participants' beliefs about oil price movements around major market events as well as their systematic reactions to U.S. macroeconomic news announcements. Finally, I study the accuracy of these risk-neutral distributions as density forecasts and their information content in point forecasting oil prices.

[12] The increase in the range spanned by options with minimum and maximum strikes got accelerated even more after 2006. Anecdotal reports suggest that there is an influx of cash by financial institutions to oil options and futures markets in all maturities especially after 2006. Clearly, this tendency also coincides with the "Financialization (Master's) Hypothesis". This hypothesis postulates that the financialization of oil leads to influx of cash to oil futures and options market, which in the end affect the real price of oil in physical oil markets (for further discussions on this channel, see Fattouh, Kilian, and Mahadeva (2013)). While the validity of this hypothesis is still unresolved in the literature, the widening in the moneyness of options would suggest the recent influx of cash in oil futures and options markets.

3.3.1 Options-Implied Risk Neutral Moments: Some Stylized Facts

Crude oil options are by far the most liquid and actively traded options among other commodities. Surprisingly, crude oil options have not been studied in detail[13]. Indeed, the literature (to the best of my knowledge) lacks stylized facts regarding the descriptive properties of distribution of oil futures as implied by options.

Figure 3.3 displays the recent behaviour (2000 and onwards) of the volatility, skewness and kurtosis of the options-implied oil pdfs in daily frequency for 30 and 90 days fixed-horizon maturities. Clearly, there are only a handful of extreme events in the crude oil market that sharply increases the implied volatility. Not surprisingly, the Great Recession is one of them, and during this period, the level of implied volatility reached its highest level in its history. Furthermore, the implied volatility of oil experienced a sharp increase due to supply interruptions or geopolitical tensions such as the Libyan production interruptions in 2011 or U.S. tensions with Iran in 2012.

Another source of information about the options-implied pdfs is the time series behaviour of skewness and kurtosis (also documented in Figure 3.3). First, both of these moments are time-varying, similar to the implied volatility. Having said that, the kurtosis experiences several hikes which suggests a higher probability of extreme events. Combined with the empirical behavior of skewness, higher order options-implied moments can provide useful insights about the market

[13] There are handful of recent papers using crude oil options data to document the behavior of options-implied pdfs or compare the predictive performance of different pdf fitting methods, such as Høg and Tsiaras (2011); Pan (2012); Datta, Londono, and Ross (2015).

participants' perception of oil price risk. For instance, when the price of crude oil reached its peak in the early second half of 2008 (before Lehman Brothers declared its bankruptcy in September 2008), market participants were assigning increased probability to a major decline in oil prices. In particular, during the second half of 2008, kurtosis reached fresh highs whereas skewness reached new lows compared to their historical values strongly indicating higher probability of a left extreme event.

The last piece of information provided in Figure 3.3 is the average term structure behaviour of empirical moments of oil pdfs. First, there is a volatility premium for longer maturities in the implied volatility of oil, which is on average true for the oil futures as well (Alquist, Kilian, and Vigfusson, 2013). Second, the skewness is negative on average and it decreases as we move further along in the term structure of skewness. This possibly represents the increased price of hedging the tail risk as we move farther in the future (Bakshi, Kapadia, and Madan, 2003).

Alternatively, Table 3.2 confirms the average term structure behaviour in the higher order moments of oil pdfs that is shown in Figure 3.3, such as the volatility risk premium and the decreasing skewness in the term structure. However, unlike the mean or the implied volatility, skewness and kurtosis have lower autoregressive coefficients. As confirmed in the forecasting regressions in subsection 3.3.4, this is likely an indication of the richer information content in the skewness about the empirical behaviour of future oil prices.

3.3.2 Option-Implied Pdfs and Important Market Events

In this subsection, I present two case studies that focus on rapid and unexpected changes in market sentiment proxied by the reaction of options-implied pdfs of oil futures: (i) the fall in Libyan crude oil production and (ii) the unanticipated announcements of future large-scale asset purchases (or QE) programs. Assuming risk neutrality, the estimated fixed-maturity options-implied pdfs reflects market participants' beliefs about the oil futures for different maturities at any point in time. However, risk neutrality is a strong assumption and caution should be taken in interpreting these densities as representing actual (physical) probabilities of future events[14].

3.3.2.1 Libyan Oil Production Disruptions in 2011 and 2013

Oil prices increased because of two major conflicts that broke out and escalated in Libya in 2011 and 2013. During both of these episodes, particularly from mid-February to end of April in 2011 and beginning of June to mid September in 2013, crude oil prices experienced visible jumps (see Figure 3.5). These jumps coincided with news related to increasing probability of lasting interruption to Libyan oil supply such as the first reports of production cuts (February 23), the low (or even no) exports (March 7), and sabotages of oil fields (April 8) in 2011. Figures 3.4 and 3.5 show that oil price increases particularly in February and March do lead to a minor increase in volatility but major increases in skewness and the 95^{th} percentile of the risk-neutral distribution. On the other hand, when oil prices reached \$115 in early April, volatility, skewness, and kurtosis started

[14] There is a vast amount evidence for asset prices showing that observed asset returns do not follow risk-neutral dynamics, which are therefore not directly observable.

to decline, which suggests a decreasing probability of a spike in oil prices. In other words, further price increases were seen as less likely according to market participants. This means that the sabotage of oil fields in April 8 did not lead to any change in the distribution.

In 2013, oil prices experienced similar jumps as in 2011 due to another wave of turmoil in Libya. For example, these jumps in oil prices (see Figure 3.5) align with another round of increased civil strife (July 5), entire port blockades by militias (August 12), and partial resolution of decline in port activity in Libya (September 10). Interestingly, these events follow exactly the same pattern as the ones in 2011. The ones in July 5 and August 12 lead to increases in the volatility and the skewness, whereas the September 10 do not lead to any visible change in these moments (see Figure 3.4 for the daily reaction of these pdfs).

3.3.2.2 Quantitative Easing Announcements in the US

Oil pdfs can also help to clarify how sudden changes in monetary policy can affect the beliefs of oil market participants about the future path of oil prices. For example, after the recent financial crises, the Federal Reserve launched several rounds of monetary policy expansion mechanisms such as buying a large volume of Treasury securities (known as QE2) and extension of the maturity of the Feds Treasury holdings as well as the reinvestment of maturing mortgage-backed securities (known as QE3). These programs were publicly announced in several steps in the speeches of the chairman and the FOMC statements that are published by the Fed. Here, I focus on only four of these statements/speeches about the introduction of these programs which are arguably the most important ones[15]. These dates are August 10, 2010 (FOMC meeting) and August 27, 2010 (chairman Bernanke's speech in the annual Jackson Hall conference) for the QE2 program, and August 26, 2011 (chairman Bernanke's speech in the annual Jackson Hall conference) and September 27, 2011 (FOMC meeting) for the QE3 program.

Figure 3.7 shows the effect of important QE2 announcements on crude oil pdfs. As in Glick and Leduc (2012), I confirm that (important) QE2 announcements lead to a decline in mean of option-implied crude oil pdfs. However, these declines become less apparent for longer maturities. For instance, as shown in Figure 3.7, the decline in the mean is less obvious for 90 day maturities as opposed to the 30 day fixed maturity risk-neutral pdf. Alternatively, Rosa (2013) and Basistha and Kurov (2015) show that the effects of unconventional monetary policies could be attenuated if identification of these shocks are achieved with daily rather than intraday data. It is true that the options-implied analysis has the drawback of using daily data, but they are helpful to understand how certain percentiles of the distribution react to QE type announcements. For instance, Figure 3.7 shows that not only the mean but also the volatility and skewness of the oil pdfs react to those announcements. On the other hand, these announcements lead to a decline in the skewness but an increase in the volatility of crude oil prices (Figure 3.8) for all maturities. Combining the increase in the

[15] Wright (2012) identified 21 of such announcement dates for the US among which 7 are treated as the most important ones for the introduction and implementation of QE2 and QE3 programs. Here, I pick only 4 of them and document the behaviour of oil pdfs just before and after these dates. However, the ones that I haven't included in my analysis delivered roughly similar results as the ones I study in this paper.

5^{th} (from \$57 to \$61) and 95^{th} percentiles (from \$93 to \$95), the results seem to be consistent with the view that QE2 announcement decreases the possibility of major decline in crude oil prices (below \$60) but increase the possibility of a major increase.

3.3.3 Events that Move Crude Oil Pdfs

It is hard to disentangle causality in macroeconomics and finance. One promising approach to solve this is to make use of the public information and approach the causal identification problem by looking at the high frequency reaction of asset prices on macroeconomic news announcements. Typically, in a small window around a major news announcement, the surprise component will dominate all other available information, so the recovered effect will be the an important insight of the surprise on financial market participants' beliefs.

Most researchers exploiting event study methodology use short windows around the data release; typically 30 to 60 minutes. This aligns with the empirical evidence as the jump in conditional mean following a news announcement happens typically within 10 minutes (Andersen, Bollerslev, Diebold, and Vega, 2003). Accordingly, I relate the changes in the moments and extreme quantiles of the options-implied oil pdf to 24 leading macroeconomic news announcements. Due to data availability, however, the window size that I use in this analysis is daily.

In subsection 3.3.2, I document a few case studies that focuses on rapid and unexpected changes in oil pdfs. Alternatively, rather than focusing on just handful of announcements, one can examine the systematic reactions of these pdfs to macroeconomic surprises. In this subsection, I move in this direction and complement the previous analysis with an event-study exercise. The goal is to recover the reaction of higher order moments and percentiles of risk-neutral oil pdfs to these surprises.

Table 3.3 lists the announcements, their frequency and units. For all announcements, the surprise component is measured as the difference between real-time actual value less the median expectation from the survey conducted by Money Market Services (MMS) on the previous Friday before the data release. The event study regression that I run has the form in equation (9):

$$\Delta x_{n,t}(q) = \sum_{i=1}^{I} \beta_i s_{it} + \varepsilon_t \tag{3.7}$$

where $x_{k,n,t}(q)$ is either the moment (the mean, volatility, skewness or kurtosis), 5^{th} (if $q = 5$), or 95^{th} (if $q = 95$) percentile of the pdf over the next n months as of day t, s_{it} denotes the surprise component of an announcement of type i, I denotes the total number of announcements (24 in my case) and finally Δ is the difference operator. Similar to Kitsul and Wright (2013), I run this regression over all days when there is at least one news announcement and the surprise is set to zero for news types for which there is not an announcement on that day.

The reaction of the options-implied mean, volatility, skewness and kurtosis are shown in Tables 3.4, 3.5, 3.6, and 3.7, respectively. To complement this analysis, I also provide the responses of the 5^{th} and the 95^{th} percentiles of the pdf to the macroeconomic surprises in Tables 3.8 and 3.9 respectively. For example, the effect of one percent PPI surprise on the mean of the distribution is reported as 0.707 at 3 months horizon (see Table 3.4). This means that if the PPI is realized in one percentage point above expectations, then the mean of the oil pdf derived from options maturing in 3 months will fall by $ 0.71.

All the parameter estimates of the conditional mean to 24 macroeconomic announcements in Table 3.4 are insignificant at shorter horizons and only some of these estimates have the signs predicted by the theory. This perfectly aligns with Kilian and Vega (2011) where they test the identifying assumption that energy prices are predetermined with respect to U.S. macroeconomic aggregates by using an event-study approach and regressing daily energy price returns on U.S. macroeconomic news[16]. On the other hand, some of the macroeconomic surprises have significant effects on the conditional mean at longer maturities (6 months or more)[17]. For instance, as can be seen from Table 3.4, positive surprises to Non-Farm Payrolls, ISM Manufacturing, Industrial Production, GDP advanced estimate and PPI all have significant effects on the mean of the fixed horizon pdfs with horizons 6 months or more.

Surprisingly, U.S. macroeconomic announcements have significant effects on some of the higher order moments of the oil pdfs at various maturities. While

[16] One weak point about Kilian and Vega (2011)'s exercise is the window size, which is a day in their study. However, Rosa (2013) showed that using an hour as the window, it is possible to show macroeconomic surprises have significant effects on energy prices.

[17] The importance of this discussion goes back to the problem of whether energy prices are predetermined with respect to U.S. macroeconomic aggregates. In the VAR or SVAR models including energy prices as a variable, the most commonly used identifying assumption is that energy prices are predetermined with respect to U.S. macroeconomic aggregates (see Kilian (2009) and the references therein). Kilian and Vega (2011) investigate the validity of this hypothesis the spot oil prices or 1 month oil futures. However, they did not worry about whether oil futures prices are predetermined in longer maturities of the oil futures as none of these VAR models use futures with maturities beyond 1 month.

implied volatility of the oil pdfs is generally unaffected by U.S. macroeconomic surprises (as documented in Table 3.5), some of these news surprises have significant effects on skewness of the oil pdfs. Better than expected data (that indicates stronger growth for US economy) increases the skewness of the oil pdfs, which indicates an increased probability of the extreme values on the right tail. For instance, the effect of one percent real GDP growth surprise on the skewness of risk-neutral distribution is reported as 0.024 at the 3 months horizon (see Table 3.6). While this is a big surprise in terms of real GDP growth, the increase in skewness is non-trivial as well, because the change in skewness is slightly higher than one third of its standard deviation.

Related to studying the effect of macroeconomic announcements on moments, one can also examine their effects on the upper and lower extreme values of the oil distribution. Tables 3.8 and 3.9 report the effects of the U.S. macro news on the 5^{th} and 95^{th} percentiles of the pdfs respectively. Positive aggregate demand surprises such as real GDP growth, Initial Jobless Claims, Non-Farm Payrolls, Retail Sales, and Capacity Utilization significantly raise the 95^{th} percentile of the distribution. This finding is also true for forward-looking indicators such as Chicago PMI, Consumer Sentiment, and Business Outlook Survey (BOS). On the other hand, besides the real GDP growth surprises, the 5^{th} percentile does not respond to macroeconomic surprises. Thus, it seems that the right extreme percentile is more sensitive to macroeconomic surprises than the left one.

3.3.4 Forecasting with Oil Pdfs

This subsection assesses the information that one can extract from these pdfs in two dimensions. First, I investigate their performance as density forecasts and I compare them with density forecasts generated by standard time-series models. Second, I evaluate whether information that can be obtained from these risk-neutral densities is valuable in point forecasting of future oil prices. This assessment is based on standard predictive regressions in the context of both in-sample and out-of-sample exercises.

Typically, the predictive regression exercises in this literature rely on monthly oil futures data. While this approach is useful, it does not utilize all available information from oil futures. More importantly, statistical tests using daily data will have more accurate size and higher power as one can pool the daily information both from oil futures and options markets. This approach does have some drawbacks, however. For instance, the price of a futures contract for delivery in h months can never be exact. In fact, as we approach to the maturity, the number of days remaining decreases. Additionally, it is not easy to work with daily data due to its sparse nature in many days. Despite the drawbacks of using daily data, in this subsection I conduct forecasting exercises at the daily frequency in order to achieve two things: (*i*) obtain all available information from both of these markets and (*ii*) to be consistent with previous parts of the paper.

3.3.4.1 Evaluating Density Forecasts

The forecast densities of crude oil are based on either time-series methods or options on WTI oil futures. Time-series models use only past return information and I consider 2 fairly popular GARCH models. Specifically, I estimate the historical densities from Generalized AutoRegressive Conditional Heteroscedasticity Model (GARCH) (1,1) and an Exponential GARCH (EGARCH) (1,1) models. The exact formulation of these models are provided in equations 3.8 and 3.9 respectively.

$$\begin{aligned} r_t &= \kappa + \rho_1 r_{t-1} + \sigma_t \varepsilon_t \\ \sigma_t^2 &= \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \\ \varepsilon_t &\sim N(0,1) \end{aligned} \tag{3.8}$$

$$\begin{aligned} r_t &= \kappa + \rho_1 r_{t-1} + \sigma_t \varepsilon_t \\ \log\left(\sigma_t^2\right) &= \omega + \alpha \log\left(\sigma_{t-1}^2\right) + \beta\left[\theta \varepsilon_t + \left(|\varepsilon_t| + (2/\pi)^{0.5}\right)\right] \\ \varepsilon_t &\sim N(0,1) \end{aligned} \tag{3.9}$$

where r denotes either the daily return of WTI Spot price. I assume that GARCH(1,1) and EGARCH(1,1) correctly capture the dynamics of the oil prices. However, to inspect the adequacy of our standard GARCH model structure, I also try higher order models as well. For this purpose, every time I estimate the GARCH(1,1) model, I test whether the standardized errors are uncorrelated using the Ljung-Box test. When one of these tests indicated a rejection of the null I have included additional parameters in the mean/variance equations and selected the best model according to the Bayesian Information Criterion[18].

In order to construct the GARCH and EGARCH based density forecasts, I use the following procedure. For each observation time t, at which a forecast density corresponding to some future time $t+h$ must be estimated, I estimate the parameters of each model by maximum likelihood with all the available data up to (and including) day t. Next, I draw a random number from the standard normal distribution and multiply it by σ_t to generate a new ε_t residual, which is then used to update the conditional variance equation and define the simulated logarithmic return and corresponding asset price. Repeating this process h times provides the terminal price of the reference asset at time $t+h$. In order to get a smooth estimate of the forecast density, I simulate 10000 terminal prices similarly and fit a Gaussian kernel density in order to obtain the required density[19]. Notice that I provide time-series density forecasts using oil spot prices, and compare the performance them with the corresponding risk-neutral distribution.

To compare the out-of-sample predictive ability of time-series model (either

[18]There are few occasions in the sample where a higher order model would be preferable. Nevertheless, I chose to maintain our standard GARCH(1,1) model because the rejections are sporadic and unsystematic, so that the end user would probably be reluctant to temporarily switch from one specification to another.

[19]As in Rosenberg and Engle (2002), I choose bandwidth equal to 0.9 $N^{-1/5}\Sigma$ where Σ is the standard deviation of the simulated terminal values, and N is the number of simulations (10,000 in this case).

EGARCH or GARCH) against risk-neutral pdf, I used the predictive likelihood (AG) test proposed by Amisano and Giacomini (2007). Assuming $f_t(Y_{t+h})$ and $g_t(Y_{t+h})$ are two competing forecast densities where h and Y_{t+h} are denoting the number of out-of sample periods and the realized price of the underlying asset as of time $t+h$ respectively, the difference in the predictive likelihoods is equal to $\sum_{i=1}^{h} \log(f_t(Y_{t+h})) - \log(g_t(Y_{t+h}))$[20]. Specifically, the AG-test statistic takes the form of a t-statistic as in equation 3.10.

$$AG_{t,h} = \frac{\sum_{t=1}^{T} (\log(f_t(S_{t+h})) - \log(g_t(S_{t+h})))}{\hat{\sigma}/\sqrt{T-h}} \tag{3.10}$$

where $\hat{\sigma}$ is the Newey-West HAC consistent estimator for the asymptotic variance.

Table 3.10 provides the AG-test results for the time-series based density forecast using daily returns of spot oil prices and risk-neutral distribution. In Table 3.10, I evaluate the performance of these models for maturities 1, 3, 6, 9, and 12 months in the second to sixth columns. A positive significant AG-test statistic

[20]Notice that, options-implied pdfs are only available for so-called calendar forecast, i.e. forecasts for the 7 business days before the expiration of the future contract. This means that as we approach to maturity, the dispersion of density forecasts mechanically shrink. Due to this problem, in subsection 3.3.1, I present fixed-horizon options-implied pdfs. There, I interpolate these pdfs across time as well (see subsection 3.2.1 for details of the interpolation). However, risk-neutral densities that I use for density forecast evaluation in this sections are not interpolated across time, i.e. they are in altering horizons. For example, the horizon for risk-neutral pdf maturing in a month is between 1 to 22 business days whereas for 3 months maturity, it is between 45 to 66 business days. Since I evaluate these density forecasts in real-time, I have not interpolated these density forecasts across time. Specifically, I take h as multiples of 22 business days for maturity horizons. Specifically, as I assess these time-series sand options implied densities in 1, 3, 6, 9 and 12 months maturities, I take $h = 22, 66, 132, 198, 264$ days respectively.

displays that risk-neutral density significantly outperforms the relevant time-series model in the given horizon whereas a negative significant AG-test does the other way round.

Overall, two results stand out from Table 3.10. First, in shorter maturities, there is an evidence in favor of risk-neutral distributions in delivering better density forecasts compared to time-series methods. However, at relatively longer horizons, i.e. 6, 9, and 12 months, it seems that risk-neutral distributions provide equally good or only slightly better density forecasts as their time-series counterparts. The main reason for the difference in the performance of risk-neutral density in different horizons might be the liquidity of the options market. In particular, for the horizons that options are heavily traded, risk-neutral distributions do fairly well compared to time-series based methods. Assuming the coverage of the strike prices is an indicator of liquidity at any given point time, options maturing in 1 and 3 months are better compared to others (as in Figure 3.2). Alternatively, as the risk premium at shorter maturities is close to zero, risk-neutral distribution is almost the same as the physical distribution so it accurately reflects the market participants beliefs about future oil prices. In fact, several studies have shown superior performance of risk neutral pdfs in other options markets (see for instance Gemmill and Saflekos (2002); Shackleton, Taylor, and Yu (2010)).

3.3.4.2 Evaluating Point Forecasts

As an alternative for treating risk-neutral densities as density forecasts and comparing them with usual time-series based density forecasts, one can assess how valuable the information content of these pdfs are in forecasting future oil prices. Accordingly, in this subsection I investigate their information content by predictive regressions in the context of an in-sample as well as an out-of-sample forecasting exercises.

In-Sample Analysis: While out-of-sample performance is more relevant for practical forecasting purposes, in-sample regressions are also informative and have the advantage of exploiting the full sample. Therefore, it is useful to evaluate the in-sample performance of information content of risk-neutral densities of oil. To investigate whether the higher order moments contain information about future inflation realizations, I rely on regressions in the spirit of Mincer and Zarnowitz (1969) as in equation 3.11.

$$S_{t+h} = \alpha_h + \beta_h F_t^h + \gamma_h \,\mathrm{IVOL}_t^h + \delta_h \,\mathrm{SKEW}_t^h + C_h Z_t + \varepsilon_{t+h} \quad (3.11)$$

where S_{t+h} denotes the realized future oil prices at some future date $t+h$, F_t^h denotes oil futures at the same horizon h, IVOL and SKEW are the volatility and the skewness of computed from risk neutral pdfs. In all of the following regressions, I use the usual controls Z_t, i.e. general or sub indices (Goldman Sachs Commodity Indices) of Commodity Prices to control for the general tendency in commodity markets, Baltic Dry Index to control for global demand conditions, the Crack Spread (the difference between products and crude oil prices) to control for oil related product markets, and the lagged value of the realized oil prices. All these controls are at the daily frequency and available in Bloomberg.

While the purpose of these regressions is to evaluate whether an expected value of a target variable incorporates all available information, here I use them to evaluate the information content of the quantile moments in forecasting oil prices. In order to do that, first I need a good enough estimate for the expected value of future oil prices. Since the analysis is conducted in daily frequency and there is a widespread tendency to use oil futures as the conditional expectation or the best predictors of future oil spot prices, I use the futures oil prices, i.e. F_t^h as an estimate for the conditional expected values of future oil prices in equation 3.11[21].

The empirical results for the regression specification 3.11 are reported in Table 3.11 at 1, 3, 6, 9 and 12 months horizons. As a reference point, in the first column in Table 3.11, I regress the realized future oil prices on the oil futures. In columns 2 and 3, I add implied volatility and skewness indicators one by one. The dispersion in the implied volatility measure has a negative and significant impact on the future oil prices, whereas the skewness, after taking into account expected inflation, has a positive and significant impact on future oil prices. Notice that including both implied skewness and volatility separately helps decreasing the root mean square error (RMSE) at various horizons.

[21]Typically, researchers forecasts of crude oil from surveys such as the Bluechip or the Survey of Professional Forecasters (SPF), but they are available only at monthly (or quarterly) frequencies and their quality is questioned in several papers. Even though there is a massive evidence showing that surveys are very good in forecasting inflation (see Faust and Wright (2013) for a recent review), for crude oil prices evidence usually can go to the other way (see Alquist, Kilian, and Vigfusson (2013) for a recent survey). Furthermore, many institutions such as ECB, IMF, and several central banks are using oil futures as their forecasts of oil prices. Therefore, I choose the futures oil prices as the estimates of conditional expectation.

In the forth column of Table 3.11, I include both of these variables in the same regression. It is interesting to note that these variables are significant at both 1 month and 3 months horizons, but beyond, only skewness remains significant. In terms of RMSE ratios, it seems skewness leads to larger declines as opposed to volatility. Furthermore, the fifth and sixth columns in Table 3.11 report the results when one adds the controls Z_t including both volatility and skewness. Overall, these controls qualitatively do not alter the results in columns 2-4.

Several researchers argue that volatility helps to explain macroeconomic cycles and oil price dynamics (e.g. Hamilton (2003); Baumeister and Peersman (2013), and Jo (2014)). These papers show that ignoring the effects of oil price volatility can distort the effectiveness of a policy designed under the presumption of linearity in the oil price-economic activity relationship. The findings in Table 3.11 go one step further and suggests that the oil price skewness contains information about future oil prices beyond the usual indicators such as oil futures, oil price volatility and a set of standard high frequency indicators extensively used in the literature. This is true even at the one year horizon[22].

These results are also important in economic terms as well. The tail risk or the volatility regarding the oil prices are important risks which may have disastrous impacts on macroeconomic dynamics. These risks, however, are not fully

[22]One particular reason that I don't go beyond one year maturity is the liquidly concerns regarding the crude oil options market. For instance, in the CME there were in total 425 options (both call and put with different strike prices) that have been traded in January 2012 that will expire within a month. On the other hand, there were only 65 options that have been traded in the CME that have a maturity of one year at the same time. While I don't have exact volume of these options but there is no reason for maturities one year or more to be very liquid.

incorporated in the futures prices alone. It may be that oil futures are biased indicators of expected future spot prices and there is no reason to expect them to pool all the information in the economy. In fact there are several compelling reasons and evidences for why oil futures should be the biased estimators of future oil prices. For example, assuming inventories of crude oil serve to avoid interruptions of the production process or to meet unexpected shifts in demand, oil importers may either want to hold inventories or buy oil futures to insure themselves against adverse movement in the oil prices as in Alquist and Kilian (2010). In their model, an increase in the oil price volatility and skewness, which is an indication of an increased probability of a spike in oil prices, could lead spot oil prices to overshoot. Alquist and Kilian (2010) show that oil futures will also increase but not as much as the spot price, so the futures spread (the difference between the oil futures and the spot prices) can be viewed as an indicator of fluctuations in the spot price of crude oil driven by shifts in precautionary demand or risk premium for oil. Alternatively, one can interpret the skewness and volatility as indicators of risk premia or precautionary demand as well as the indicators of a increased probability of a spike in oil prices.

Out-Of-Sample Analysis: The previous analysis involved in-sample prediction performance. Now, I complement this exercise with an evaluation of the out-of-sample performance of the skewness and volatility measures estimated from risk-neutral densities of crude oil. More precisely, I use a set of reference models in which I incorporate the skewness and volatility measures to construct pseudo out-of-sample forecasts. For each case, I compare the performance of each model that includes these measures with the one that does not.

In the literature, several studies have shown that oil futures usually cannot improve the no change, i.e. random walk, forecast in monthly frequency but the results do alter for some maturities (such as 6 months or 1 year) at the daily frequency (Alquist, Kilian, and Vigfusson, 2013). Typically, models performing well out-of-sample are usually parsimonious as parameter proliferation tends to deteriorate out-of-sample forecast accuracy. Therefore, I consider three simple univariate specifications as in Alquist, Kilian, and Vigfusson (2013), but unlike their work, I slightly modify these models in order to test whether the information content of options-implied moment is valuable in forecasting oil prices. Specifically, I augment all of these models with the volatility and the skewness derived from oil pdfs. The models that I use for the forecasting horserace are: (*i*) the "Random Walk (RW)" without drift (equation 3.12), (*ii*) the "Futures Model (FM)" that assumes oil futures are the best available predictors of future oil prices (equation 3.13), and (*iii*) the "Futures Spread (FS) Model" that uses futures spread and the spot price of oil as the predictors of future oil prices (equation 3.14).

$$\hat{S}_{t+h|t} = S_t + \gamma_1 \mathrm{IVOL}_t + \gamma_2 \mathrm{SKEW}_t \tag{3.12}$$

$$\hat{S}_{t+h|t} = F_t^h + \gamma_1 \mathrm{VOL}_t + \gamma_2 \mathrm{SKEW}_t \tag{3.13}$$

$$\hat{S}_{t+h|t} = S_t \left(1 + \ln\left(F_t^h / S_t\right)\right) + \gamma_1 \mathrm{IVOL}_t + \gamma_2 \mathrm{SKEW}_t \tag{3.14}$$

where F_t^h denotes the current nominal price of the futures contract that matures in h periods, S_t i the current spot price of oil, VOL_t denotes the volatility, and SKEW_t denotes the skewness computed from options-implied distribution.

I compare the performance of these reference models (presented in equations 3.12 - 3.14) that incorporate measures of oil price risk with the models without the oil price risk measures. For example, I forecast future oil prices based on both the RW model with oil price risk measures (equation 3.12) and RW model without oil price risk measures (a version of equation 3.12 where $\gamma_1 = \gamma_2 = 0$). Then, I compare the performances of both of these models to assess if the oil price risk measures improve the forecast performance compared to the RW model that does not include them. I follow this procedure for the FM and the FS models as well.

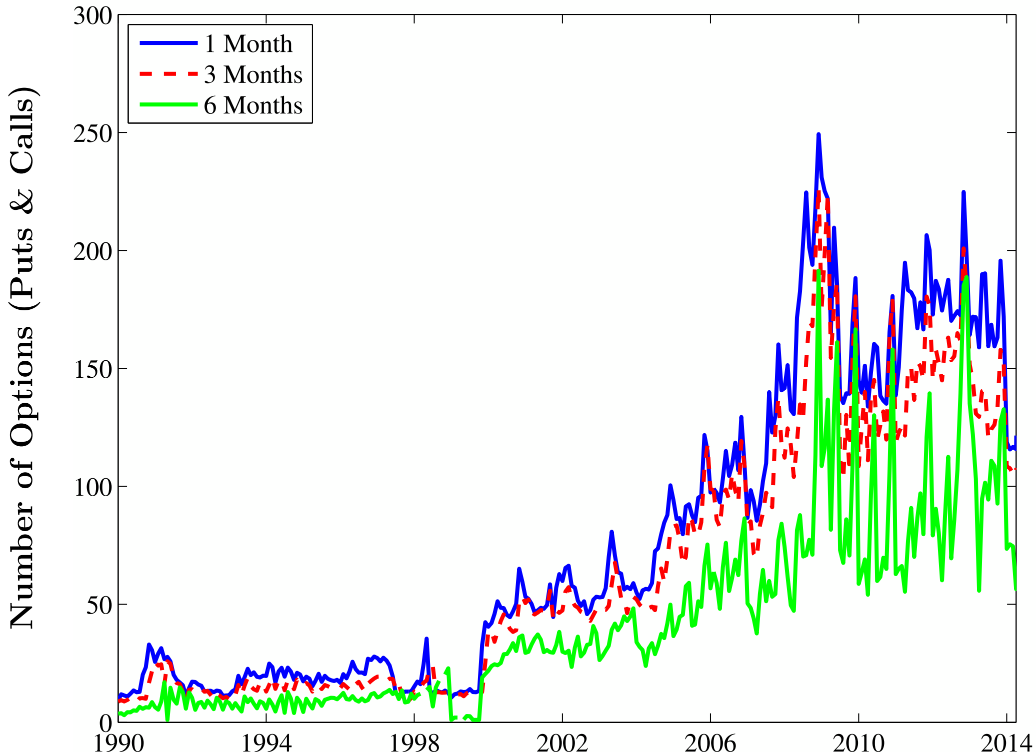
Table 3.12 assesses the predictive accuracy of all three forecasting models against the benchmark model for horizons of 1, 3, 6, 9, and 12 months. The forecast evaluation period is January 4, 2004 to May 22, 2014 whereas the initial estimation window starts from January 2, 1991 for maturities 1 to 9 months, whereas it starts from January 2, 1996 for options maturing in 12 months. For each model, I report the results for the MSPE ratio for the model including the skewness and the volatility as the explanatory variables relative to the model that does not include them as explanatory variables. However, since the assessment of which forecasting model is accurate may depend on the loss function of the forecaster (Elliott and Timmermann, 2008), for each horizon I also test whether a forecast correctly predicts the sign of the change in the spot price following the success ratio statistic of Pesaran and Timmermann (1992). Finally, the p-values for MSPE ratio test is constructed based on Clark and West (2006).

Columns 1, 3, 5, 7 and 9 show that adding skewness and implied volatility to the models presented in equations 3.12 - 3.14 produces lower MSPE than the appropriate model without these measures. For instance, options-implied moments leads to an improvement of 5 to 10 % reduction in the Futures Model (equation 3.13 and row three in Table 3.12) in 1 to 3 months horizons. This is also true for Random Walk and Futures Spread models as well. Options-implied moments once again lead to improvements in the forecast performance and these improvements are more visible (in terms of reductions in MSPE) especially at 1, 3, and 6 months horizons. In terms of statistical significance, the models including volatility and skewness as additional variables (as opposed to the one that do not include them) are significant at not all but in most of the horizons. In particular, option implied moments improve the forecasting performance of all 3 of the empirical models especially in 3, 6 and 12 months horizons. The improvements are slightly more visible in terms of success ratios. In particular, these options-implied moments are quite helpful in predicting the right direction of the change in the future spot prices.

3.4 Conclusion

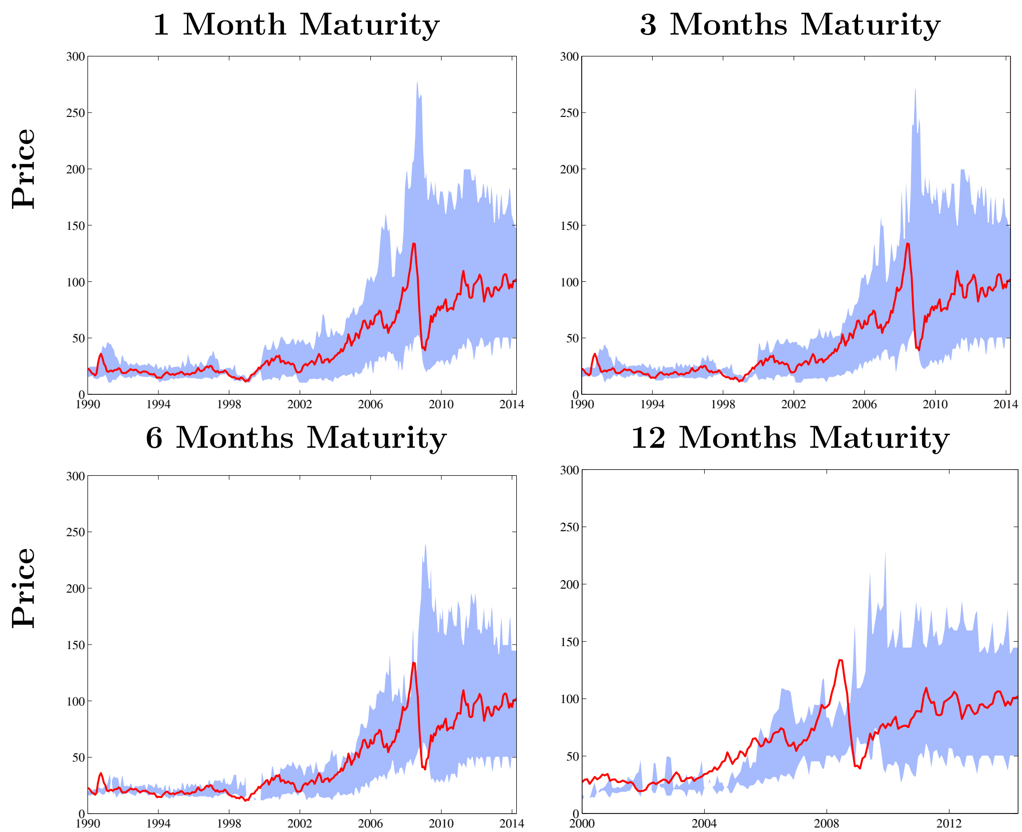
In this paper, I use the options on WTI crude oil futures to construct daily risk neutral probability densities for oil prices between August 1990 and May 2014. Using these oil pdfs, I first derive their higher order moments and extreme percentiles. Second, I examine changes in market participants' beliefs about oil price movements around a few important events. Complementary to this analysis, I study the systematic reactions of these summary statistics to announcements regarding US macroeconomic fundamentals. While the bulk of the movement in these pdfs cannot be tied to the surprise component of macroeconomic news announcements regarding U.S. fundamentals, skewness and the 95^{th} percentile of these pdfs are significantly related to these announcements. Third, I find that oil pdfs based on market information perform better than density forecasts based on standard time-series models, especially at shorter horizons. Finally, I show that different components of oil price risks (implied volatility and skewness) have valuable information for the future realizations of oil prices. Specifically, taking into account of volatility and skewness improves the point forecasts of oil prices.

Figure 3.1: ***Availability of Options Written on WTI Futures***



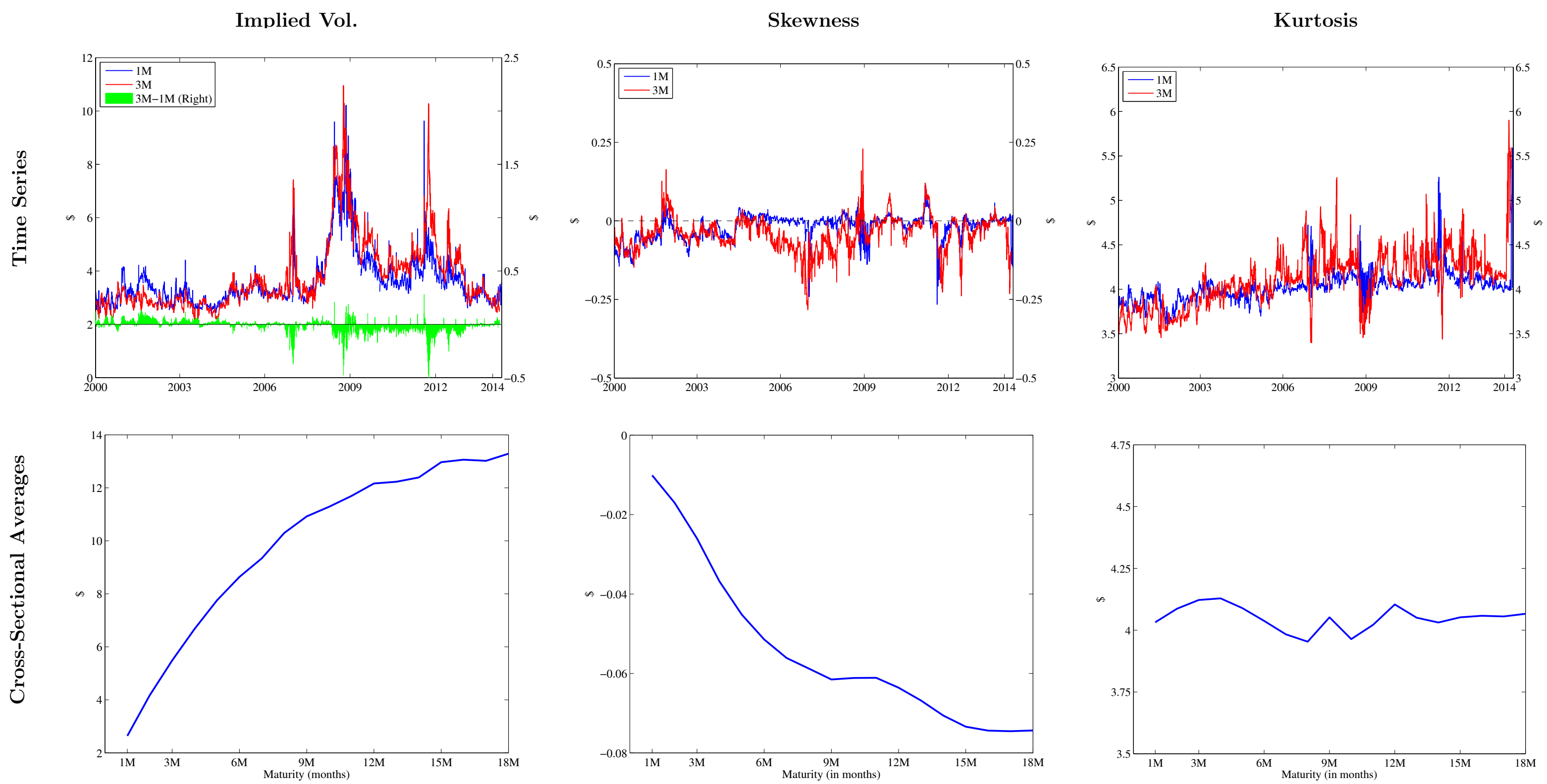
Note: This Figure shows the average number of available American put and call options written on the WTI futures that are traded in CME Group in monthly frequency. The options that are plotted in Figure 3.1 are only ones that are maturing within 1, 3, and 6 months. These are the options that I use to estimate risk neutral pdfs in Section 3.3 which includes both out-of-the-money puts and out-of-the-money calls as explained in section 3.2.2. The sample period is between January 1990 and May 2015.

Figure 3.2: ***WTI Spot Price and Options Coverage (Min and Max)***



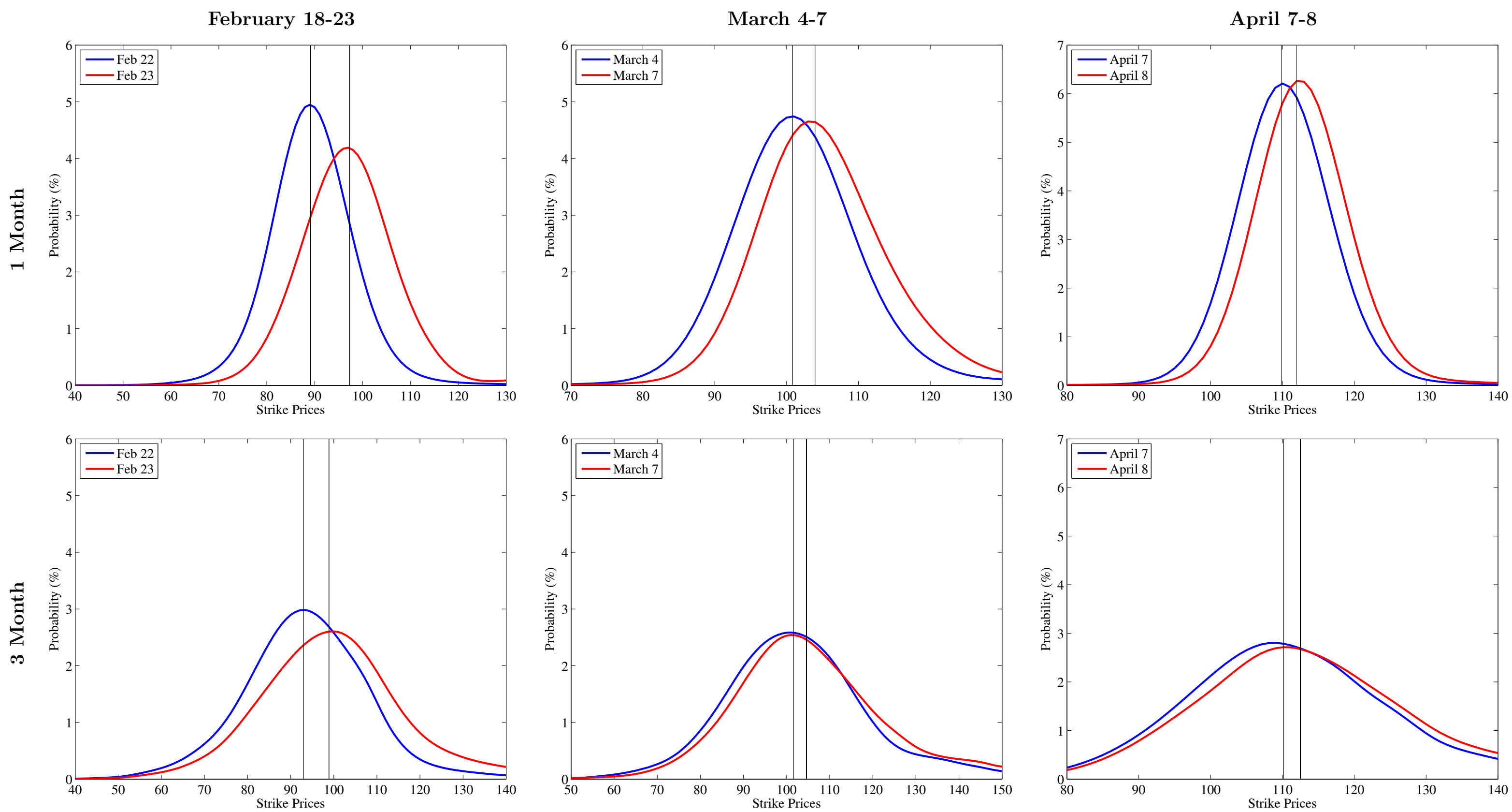
Note: This Figure shows the WTI futures available for delivery at Cushing, OK and both the minimum and maximum strike price of options (that are used to estimate risk-neutral pdfs in Section 3.3) within 1, 3, 6, and 12 months expiration. The strike prices of options as well as the future prices are quoted in monthly frequency, so they are computed by taking the averages of daily strikes (for options) and prices (for futures). To calculate the monthly minimum and maximum strike prices, however, I first find options with the minimum and maximum strike prices each business day, then take daily averages of strike prices of these options. Therefore, the options with highest and lowest strike prices may not be traded everyday (For instance, if the price of a option is equal to 1 cent, it is deleted from the sample, so the min/max strike prices may be different for consecutive days).

Figure 3.3: *Higher Order Moments of Option Implied Pdfs*



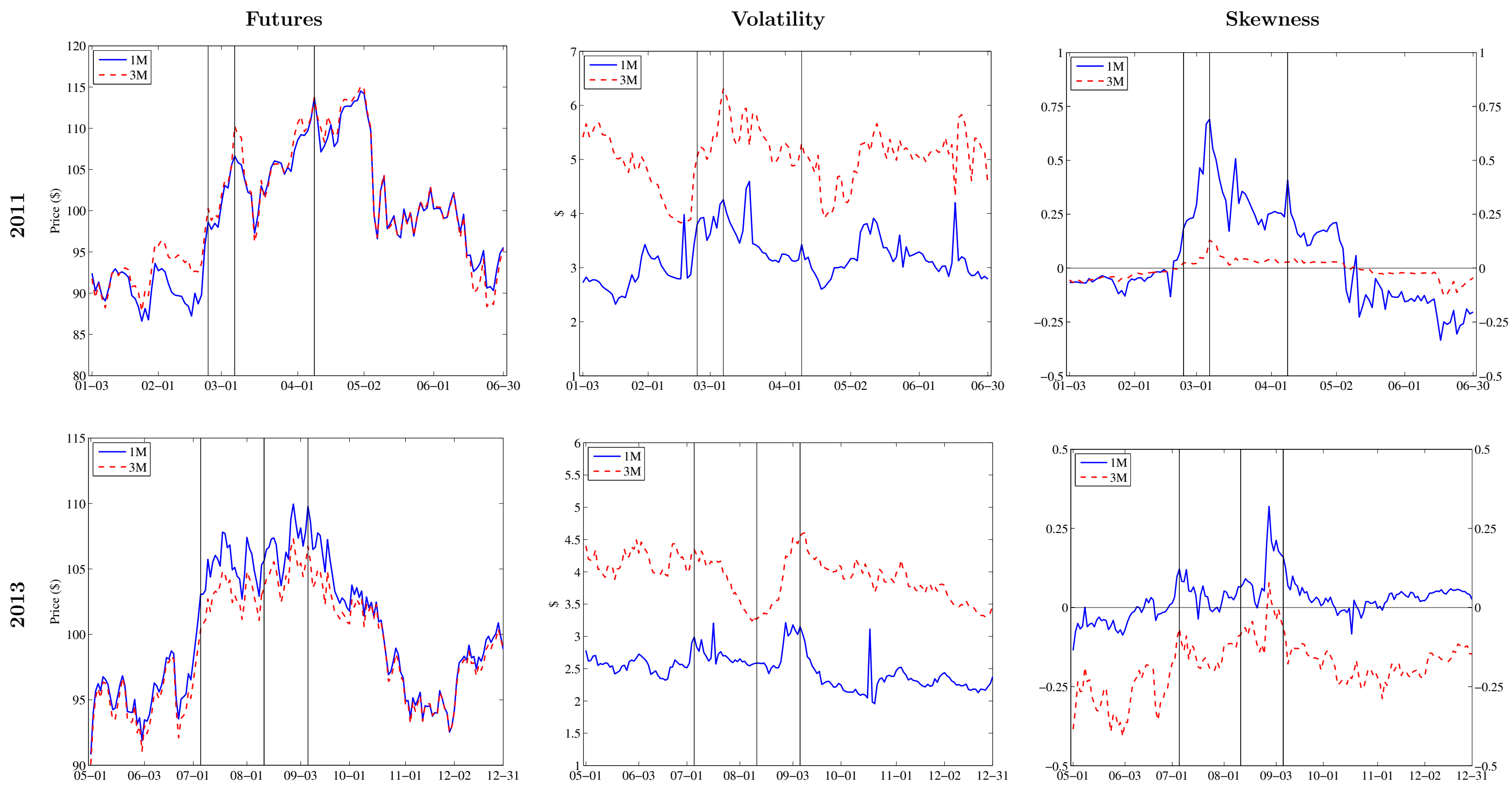
Note: Figure (3.3) displays the time series and the average term structure of options-implied higher order moments. The moments of the options-implied oil pdfs are percentile moments and the exact formulas to compute these moments are defined in equations 3.5 - 3.6 in Subsection 3.2.1. The figures that are in the first row show the time series whereas the ones in the second row show the average cross-sectional (term structure) dynamics of options implied moments.

Figure 3.4: *Reaction of Options-Implied Pdfs During Libyan Civil War I: 2011*



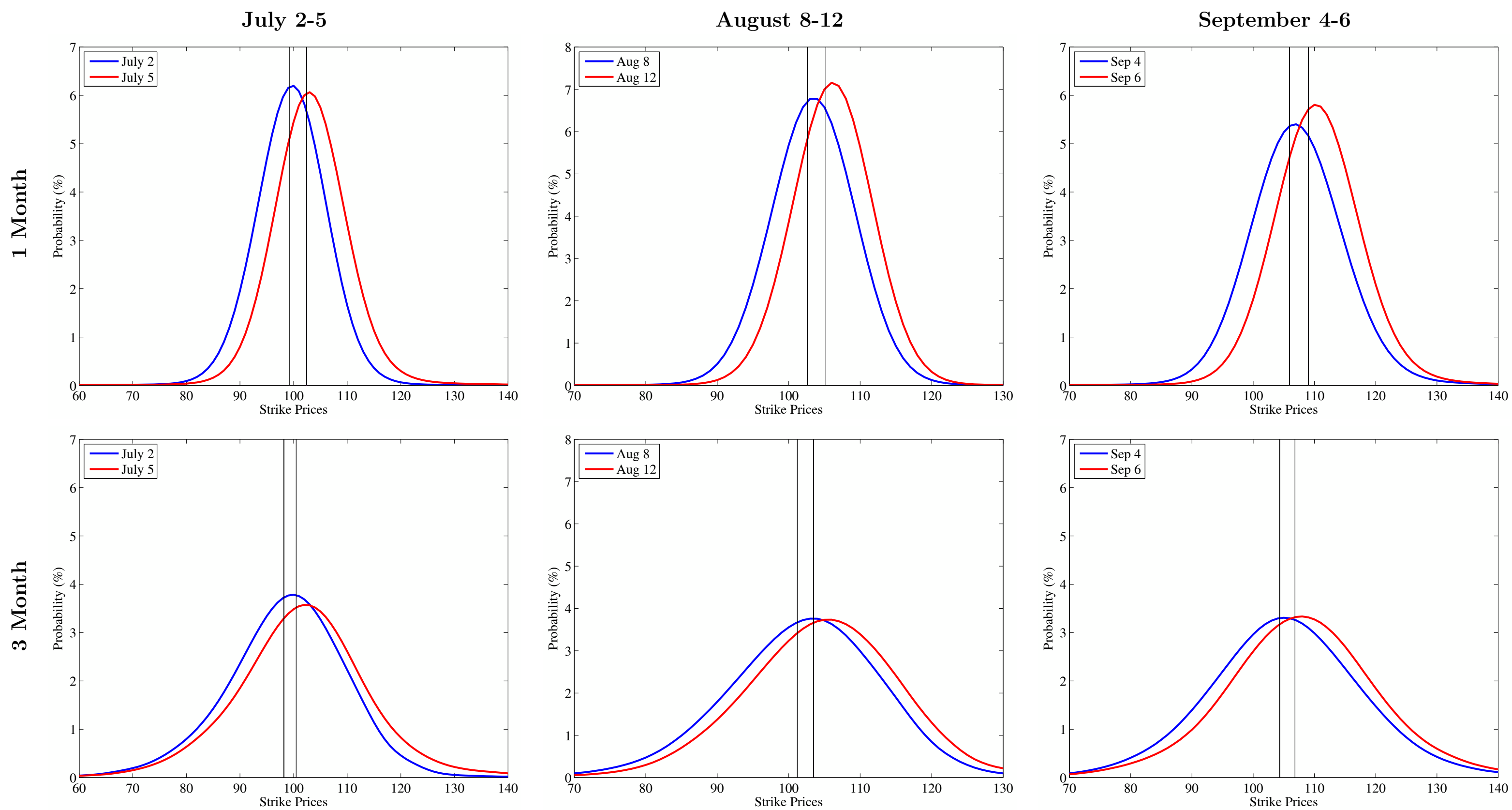
Note: Figure (3.4) shows a set of information extracted from the PDFs several days before and after the major news related to Libyan civil war in 2011. Figure 3.4 includes 6 panels. The first row documents the reaction of option implied pdfs to these major news for a fixed maturity of 30 days whereas the second row shows for a fixed maturity of 90 days. Since the option implied pdfs have the fixed horizon structure, I interpolate the data across maturities as explained in the Section 3.2.1. In each Figure, the pdf in blue corresponds to the distribution function one business day before the news whereas the one is red corresponds to the day of the news (for all trading days, the trading ends at 5 pm in Eastern Time). Finally the vertical lines in each figure are the median value of each pdf at the particular trading day. The pdfs are estimated using the local polynomial regression method as in Ait-Sahalia and Duarte (2003).

Figure 3.5: ***Reaction of Options-Implied Moments During Libyan Civil War II: 2011***



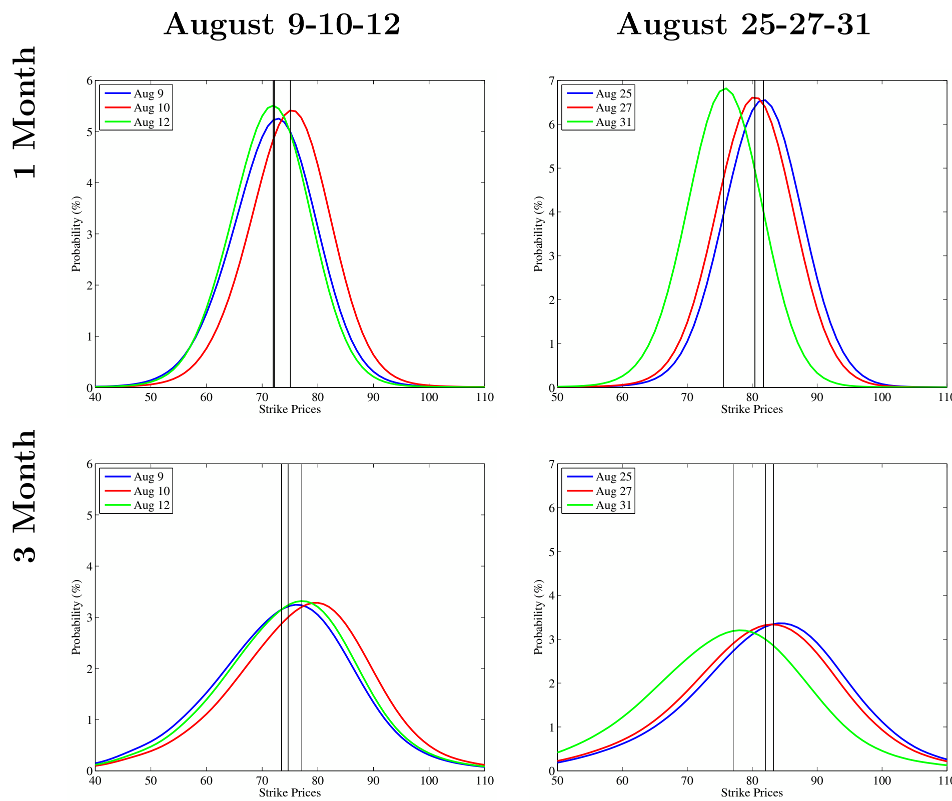
Note: Figure (3.5) show time series in interpolated 1 and 3 months fixed maturities in the option implied moments only in 2011 and 2013 respectively. The first column shows the interpolated 30 and 90-day futures price, the second column shows implied volatility moments, and finally the last column shows the skewness for the option implied distributions. The vertical lines in the first row are important events explained in section (3.3.2) (as in Datta, Londono, and Ross (2015)): the first reports of interruptions in production (February 23), the halting of exports (March 7), and the sabotaging of oil fields (April 8). The figures in the second row are the corresponding figures for 2013 and the important dates are second round of increased production interruptions (July 5), major slowdown news in the exports to Europe (August 12) and finally major decline in production once again September 10. The moments are computed using equations 3.5 - 3.6 in Subsection 3.2.1, which are computed from the oil pdfs that are estimated using the local polynomial regression method as in Ait-Sahalia and Duarte (2003).

Figure 3.6: *Reaction of Option Implied Pdfs During Libyan Civil War I: 2013*



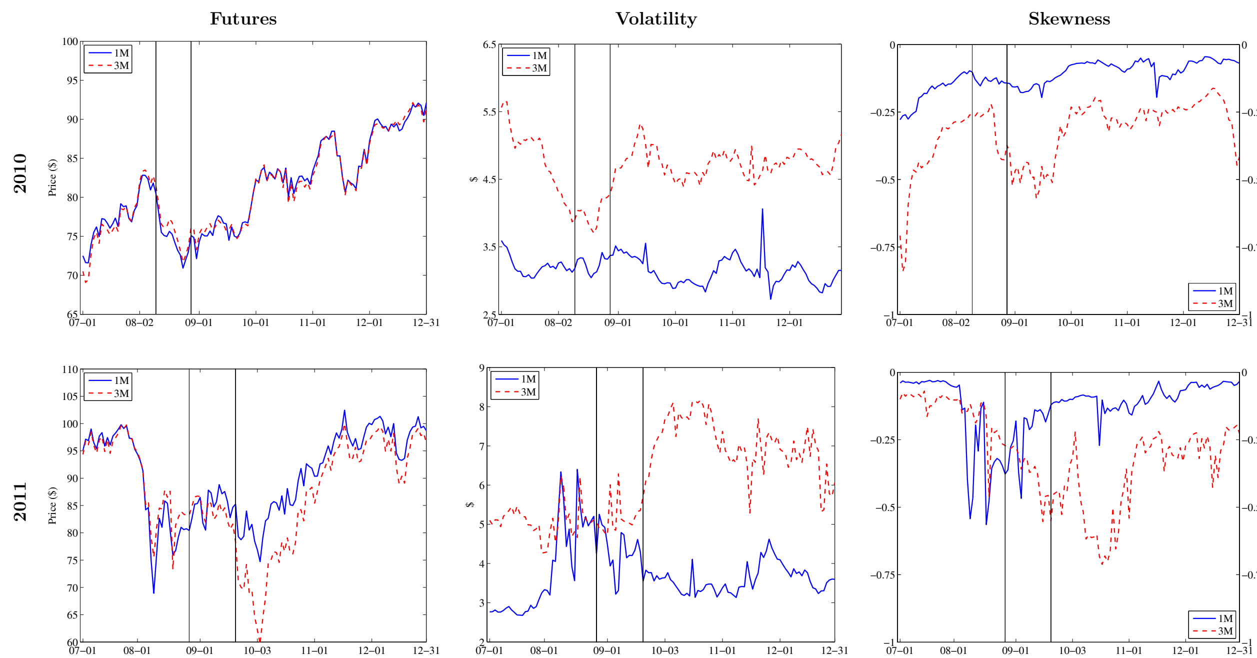
Note: Figure (3.6) show a set of information extracted from the PDFs several days before and after the major news related to Libyan civil war in 2013. Figure 3.6 includes 6 panels. The first row documents the reaction of option implied pdfs to these major news for a fixed maturity of 30 days whereas the second row shows for a fixed maturity of 90 days. Since the option implied pdfs have the fixed horizon structure, I interpolate the data across maturities as explained in the Section 3.2.1. In each Figure, the pdf in blue corresponds to the distribution function one business day before the news whereas the one is red corresponds to the day of the news (for all trading days, the trading ends at 5 pm in Eastern Time). Finally the vertical lines in each figure are the median value of each pdf at the particular trading day. The pdfs are estimated using the local polynomial regression method as in Ait-Sahalia and Duarte (2003).

Figure 3.7: ***Reaction of Option Implied Pdfs to QE2 Announcements***



Note: Figure (3.7) show a set of options-implied moments extracted from the PDFs several days before and after the major news related to QE2 and QE3 announcements in 2010 and 2011. It has 4 panels and documents the reaction of option implied pdfs to 2 important QE2 related events: FOMC statement in August 10, 2010 where the Fed committed to keep its benchmark interest rate close to zero for an "extended period", and Bernanke's August 27, 2010 Jackson Hall speech where he names "conducting additional purchases of longer-term securities" as a tool, "is prepared to provide additional monetary accommodation through unconventional measures". The first row documents the reaction of option implied pdfs to these major news for a fixed maturity of 30 whereas the second row shows 90 days. Since the option implied pdfs have the fixed horizon structure, I interpolate the data across maturities as explained in the Section 3.2.1. In each Figure, the pdf in blue corresponds to the distribution function one business day before the news whereas the one is red corresponds to the day of the news (for all trading days, the trading ends at 5 pm in Eastern Time). Finally the vertical lines in each figure are the median value of each pdf at the particular trading day. The pdfs are estimated using the local polynomial regression method as in Ait-Sahalia and Duarte (2003).

Figure 3.8: *Reaction of Option Implied Moments During Important QE2 Announcements*



Note: Figure 3.8 shows options-implied moments extracted from the PDFs several days before and after the major news related to Quantitative Easing Announcements. Figure (3.8) includes 6 panels. The first row documents the reaction of option implied pdfs to these major news for a fixed maturity of 30 days whereas the second row shows for a fixed maturity of 90 days. Since the option implied pdfs have the fixed horizon structure, I interpolate the data across maturities as explained in the Section 3.2.1. In each Figure, the pdf in blue corresponds to the distribution function one business day before the news whereas the one is red corresponds to the day of the news (for all trading days, the trading ends at 5 pm in Eastern Time). Finally the vertical lines in each figure are the median value of each pdf at the particular trading day. The vertical lines in the first row are important events explained in section (3.3.2). The pdfs are estimated using the local polynomial regression method as in Ait-Sahalia and Duarte (2003).

Table 3.1: *Summary Statistics for Options on WTI Futures Contracts*

	Calls	Puts	Min. Call	Max. Call	Min. Put	Max. Put
Maturity: 1 Month						
Mean	42.79	49.91	0.84	1.27	0.81	1.24
Std Dev.	31.64	36.49	0.19	0.61	0.18	0.45
Min	5	3	0.14	1.12	0.22	0.95
Max	168	216	1.12	3.23	1.02	2.69
Maturity: 3 Months						
Mean	47.70	43.73	0.69	1.52	0.62	1.42
Std Dev.	38.34	39.55	0.19	0.51	0.17	1.04
Min	4	6	0.65	1.09	0.20	0.73
Max	232	219	1.24	2.84	1.12	3.89
Maturity: 6 Months						
Mean	38.33	36.19	0.62	1.63	0.61	1.59
Std Dev.	23.05	23.30	0.18	0.47	0.17	0.80
Min	3	5	0.56	0.65	0.21	0.43
Max	231	200	1.50	2.44	1.32	3.59
Maturity: 12 Months						
Mean	31.46	30.90	0.86	1.55	0.65	1.17
Std Dev.	19.24	16.74	0.17	0.48	0.16	0.32
Min	4	5	0.29	0.79	0.24	0.45
Max	170	184	1.92	2.72	1.60	3.46

Notes: This table shows a set of summary statistics for the availability of put and call options for the maturities with 1, 3, 6, and 12 months. Columns 2 and 3 report the summary statistics for the total number of options available for the estimation of the pdfs whereas Columns 4 to 7 report the summary statistics for the minimum and maximum degree of moneyness (calculated as a ratio between the option's strike price and the underlying WTI futures price) for the options available for estimation. The sample period runs from January 1990 to May 2015 for options maturing in 1, 3, and 6 months, March 1991 to May 2015 for options maturing in 9 months and finally November 1996 to May 2015 for options maturing in 12 months.

Table 3.2: ***Descriptive Statistics for Option Implied Moments from Oil Pdfs***

Relevant Moment: Mean

	1M	3M	6M	9M	12M	15M	18M
Average	48.897	49.664	52.835	51.670	54.175	59.797	65.461
Stdev.	34.010	33.854	32.542	31.191	30.862	30.879	31.088
Rho	0.999	0.999	0.999	0.998	0.997	0.997	0.997
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NObs	4931	4768	4048	3896	3606	3112	2643

Relevant Moment: Implied Volatility

	1M	3M	6M	9M	12M	15M	18M
Average	12.081	16.913	24.252	28.457	29.655	32.256	35.666
Stdev.	3.205	6.460	10.238	12.725	13.928	15.552	18.306
Rho	0.968	0.989	0.989	0.982	0.982	0.987	0.984
	(0.007)	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)	(0.006)
NObs	4931	4768	4048	3896	3606	3112	2643

Relevant Moment: Skewness

	1M	3M	6M	9M	12M	15M	18M
Average	-0.034	-0.070	-0.151	-0.183	-0.200	-0.238	-0.250
Stdev.	0.050	0.066	0.118	0.155	0.166	0.176	0.199
Rho	0.942	0.943	0.957	0.875	0.890	0.931	0.903
	(0.010)	(0.014)	(0.010)	(0.030)	(0.019)	(0.014)	(0.028)
NObs	4931	4768	4048	3896	3606	3112	2643

Relevant Moment: Kurtosis

	1M	3M	6M	9M	12M	15M	18M
Average	2.372	2.439	2.410	2.400	2.464	2.483	2.552
Stdev.	0.294	0.395	0.445	1.908	1.566	0.595	0.673
Rho	0.973	0.981	0.977	0.974	0.982	0.830	0.876
	(0.006)	(0.003)	(0.007)	(0.032)	(0.026)	(0.075)	(0.046)
NObs	4931	4768	4048	3896	3606	3112	2643

Notes: Table (3.2) reports the descriptive statistics for options-implied moments computed from crude oil pdfs, which are estimated using the local polynomial regression method as in Ait-Sahalia and Duarte (2003). The moments of the options-implied oil pdfs are calculated using equations 3.5 - 3.6 which are displayed in Subsection 3.2.1. This Table reports the Average, Stdev (standard deviation), Rho where the latter being the first order autocorrelation coefficient for all four moments computed from oil pdfs. The numbers reported in parenthesis below the Rho statistic are the Newey-West adjusted standard deviations for the Rho coefficients of each moment. The columns of table reports these statistics for maturities 1, 3, 6, 9, 12, 15, and 18 months.

Table 3.3: *US Macroeconomic News Announcements*

Data Release	**Source**	**Frequency**	**Units**
CPI (Core)	BLS	Monthly	Percent Change (MoM)
Capacity Utilization	Fed - Board	Monthly	Percent of Capacity
Chicago PMI	ISM	Monthly	Percent
Consumer Confidence	Conference Board	Monthly	Index
Durable Goods Orders	Census	Monthly	Percent Change (MoM)
ECI Civilian Workers	Census	Quarterly	Percent Change (QoQ)
Existing Home Sales	NAR	Monthly	Millions
Factory Orders		Monthly	Percent Change (MoM)
GDP (Advanced Estimate)	BEA	Quarterly	Percent Change (QoQ), AR
Hourly Earnings	BLS	Monthly	Percent Change (MoM)
Housing Starts	Census	Monthly	Thousands
ISM	ISM	Monthly	Index
Industrial Production	Fed	Monthly	Percent Change (MoM)
Initial Claims	ET Admin.	Weekly	Thousands
Leading Economic Indicators	Fed - Philadelphia	Monthly	Percent Change (MoM)
Michigan Consumer Sentiment	Univ. of Michigan	Monthly	Index
New Home Sales	Census	Monthly	Hundred Thousands
Nonfarm Payrolls	BLS	Monthly	Thousands
PCE	BEA	Monthly	Percent Change (MoM)
PPI (Core)	BLS	Monthly	Percent Change (MoM)
Philadelphia Fed Business Outlook	Fed - Philadelphia	Monthly	Index
Retail Sales	Census	Monthly	Percent Change (MoM)
Retail Sales x Autos	Census	Monthly	Percent Change (MoM)
Unemployment	BLS	Monthly	Percent

Notes: In Table (3.3), CPI is the Consumer Price Index, PMI is the Purchasing Managers Index, ECI is the Employment Cost Index, ISM is the Institute of Supply Management, PCE is the Personal Consumption Expenditures, PPI is the Producers Price Index, and Retail Sales X Autos is the Retail Sales Excluding Automobile sales are Data Sources. On the other hand, BLS is the Bureau of Labor Statistics, Census is the Bureau of the Census, Fed-Board is the Federal Reserve Board of Governors, Fed - Philadelphia is the Federal Reserve Bank of Philadelphia, NAR is the National Association of Realtors, UoM is the University of Michigan, ET Admin. is the US. Employment and Training Administration. Finally, for the units, MoM is the Month over Month, QoQ is the Quarter over Quarter, and the AR is the annualized rate.

Table 3.4: *Event Study Regression: The Mean on Macro Surprises*

Data Release	1M	3M	6M	9M	12M	15M	18M
CPI (Core)	-0.981	1.107	0.450	-2.199	4.632	9.598	-4.584
	(-0.197)	(1.144)	(0.313)	(-1.110)	(1.569)	(1.165)	(-1.559)
Capacity Utilization	1.512	0.557	0.666	1.608	0.507	2.492	0.690
	(0.410)	(1.130)	(1.086)	(1.906)	(0.638)	(1.153)	(0.641)
Chicago PMI	-0.013	-0.059	-0.008	-0.045	-0.013	-0.043	-0.092
	(-0.067)	(-1.571)	(-0.224)	(-1.246)	(-0.273)	(-0.757)	(-1.527)
Consumer Confidence	0.074	0.004	0.005	0.017	0.004	-0.112	0.033
	(1.292)	(0.226)	(0.227)	(0.755)	(0.093)	(-1.854)	(0.483)
Durable Goods Orders	0.034	-0.059	-0.052	0.028	0.025	**0.441**	0.051
	(0.299)	(-1.441)	(-1.434)	(0.356)	(0.275)	**(2.093)**	(0.656)
ECI Civilian Workers	-0.045	-0.178	-0.017	-0.641	**0.842**	-0.736	-2.759
	(-0.008)	(-0.300)	(-0.024)	(-0.750)	**(2.042)**	(-0.493)	(-1.878)
Existing Home Sales	-0.074	0.239	-0.324	0.045	-0.726	-2.072	-2.054
	(-0.028)	(0.315)	(-0.406)	(0.049)	(-0.315)	(-1.235)	(-0.999)
Factory Orders	-0.503	-0.139	-0.381	-0.389	-0.211	0.051	0.543
	(-0.463)	(-0.980)	(-1.716)	(-1.739)	(-0.749)	(0.121)	(0.653)
GDP (Advanced Estimate)	-0.476	0.088	**0.552**	**0.634**	**0.929**	**0.883**	**1.106**
	(-0.276)	(-1.441)	**(2.434)**	**(5.463)**	**(4.450)**	**(7.467)**	**(4.933)**
Hourly Earnings	-5.086	-0.598	-0.543	-0.439	-2.837	-0.423	0.690
	(-0.231)	(-0.784)	(-0.527)	(-0.353)	(-1.501)	(-0.270)	(0.270)
Housing Starts	-8.460	0.018	-0.325	-0.452	6.615	-3.424	-3.504
	(-0.709)	(0.017)	(-0.165)	(-0.206)	(1.574)	(-1.071)	(-1.137)
ISM Manufacturing	-0.401	0.118	**0.043**	**0.133**	**0.272**	**0.138**	**0.193**
	(-0.574)	(1.857)	**(2.039)**	**(2.759)**	**(2.293)**	**(3.268)**	**(3.174)**
Industrial Production	-0.232	-0.097	0.136	-0.261	**0.484**	**0.541**	**0.558**
	(-0.087)	(-0.186)	(0.208)	(-0.360)	**(3.399)**	**(5.239)**	**(4.379)**
Initial Claims	-0.197	**-0.007**	-0.001	0.003	-0.005	-0.005	-0.027
	(-0.261)	**(-2.106)**	(-0.286)	(0.311)	(-0.453)	(-0.878)	(-1.454)
Leading Economic Indicators	2.740	-0.061	-0.512	0.650	-0.818	-0.671	-0.477
	(0.376)	(-0.092)	(-0.832)	(0.779)	(-0.268)	(-0.697)	(-0.493)
Michigan Consumer Sentiment	2.220	-0.048	-0.010	-0.072	0.003	-0.199	-0.461
	(0.892)	(-0.604)	(-0.170)	(-1.196)	(0.022)	(-1.562)	(-1.857)
New Home Sales	-0.006	-0.000	-0.001	0.002	-0.005	0.025	0.003
	(-0.584)	(-0.288)	(-0.643)	(0.713)	(-1.331)	(1.537)	(0.449)
Nonfarm Payrolls	-0.016	0.002	**0.002**	0.001	**0.005**	**0.002**	0.002
	(-1.402)	(1.898)	**(2.115)**	(0.741)	**(2.500)**	**(3.139)**	(0.461)
PCE	0.814	0.271	0.751	0.174	1.535	1.980	-0.239
	(0.925)	(0.627)	(1.174)	(0.232)	(1.110)	(1.252)	(-0.108)
PPI (Core)	0.770	**0.707**	**2.251**	**1.199**	-2.201	-0.704	0.797
	(0.976)	**(2.077)**	**(2.093)**	**(2.130)**	(-1.698)	(-0.488)	(0.803)
Philadelphia Fed BOS	-0.017	**0.081**	0.028	**0.073**	0.040	0.039	**0.040**
	(-0.131)	**(3.061)**	(1.533)	**(2.509)**	(0.875)	(0.965)	**(2.043)**
Retail Sales	-0.178	-0.047	-0.207	0.419	0.726	3.762	0.297
	(-0.138)	(-0.159)	(-1.300)	(0.610)	(0.807)	(1.062)	(0.540)
Retail Sales (Excl. Autos)	-1.364	0.454	0.283	0.558	0.006	-2.774	**1.267**
	(-0.886)	(1.304)	(1.053)	(0.728)	(0.010)	(-0.750)	**(3.185)**
Unemployment	-7.311	0.639	0.401	2.471	8.506	-1.447	1.787
	(-0.876)	(0.704)	(0.397)	(1.100)	(1.133)	(-1.239)	(1.157)

Notes: This table reports estimates of the regressions of daily changes in the options-implied mean of crude oil prices over different horizons (1, 3, 6, 9, 12, 15, and 18 months) onto macroeconomic surprises. The implied volatility values are defined in terms of dollar amounts and the units of macroeconomic surprises are given in Table (3.3). T-statistic values computed with heteroskedasticity-robust standard errors are in parenthesis and the bold numbers are significant at least at the 5% level. For the explanation of macroeconomic variables, see Table (3.3).

Table 3.5: *Event Study Regression: The Volatility on Macro Surprises*

Data Release	1M	3M	6M	9M	12M	15M	18M
CPI (Core)	-1.153	-0.141	-0.144	3.816	-0.148	**6.851**	-4.341
	(-1.052)	(-0.231)	(-0.178)	(1.276)	(-0.065)	**(2.043)**	(-1.148)
Capacity Utilization	-0.412	0.685	**0.853**	1.623	**2.255**	**1.337**	1.223
	(-0.305)	(1.646)	**(2.726)**	(1.533)	**(2.329)**	**(2.206)**	(1.679)
Chicago PMI	-0.013	0.026	0.012	-0.087	-0.020	-0.037	0.011
	(-1.493)	(0.658)	(0.476)	(-1.891)	(-0.403)	(-0.729)	(0.204)
Consumer Confidence	0.015	-0.001	0.022	-0.025	0.009	0.001	-0.123
	(1.714)	(-0.150)	(1.419)	(-0.832)	(0.260)	(0.032)	(-1.593)
Durable Goods Orders	0.002	-0.003	0.018	-0.077	0.050	-0.045	-0.171
	(0.224)	(-0.285)	(0.644)	(-1.741)	(0.422)	(-0.827)	(-0.635)
ECI Civilian Workers	0.031	-0.187	-0.911	3.661	2.421	-0.482	-5.618
	(0.168)	(-0.429)	(-0.851)	(1.605)	(1.647)	(-0.339)	(-1.684)
Existing Home Sales	-0.155	0.057	-0.086	0.820	-0.168	-3.112	**-1.265**
	(-0.599)	(0.153)	(-0.151)	(0.415)	(-0.177)	(-1.046)	**(-2.755)**
Factory Orders	-0.032	-0.018	0.340	0.478	0.360	-0.503	-1.117
	(-0.624)	(-0.153)	(1.849)	(1.141)	(0.792)	(-0.804)	(-1.104)
GDP (Advanced Estimate)	0.021	0.023	-0.033	0.103	0.133	0.119	-0.064
	(1.954)	(1.090)	(-1.180)	(0.964)	(1.292)	(1.955)	(-1.011)
Hourly Earnings	-0.135	-0.371	0.138	-1.283	-1.778	-4.768	**-7.037**
	(-0.691)	(-1.239)	(0.160)	(-1.391)	(-1.046)	(-1.556)	**(-2.280)**
Housing Starts	-0.988	-1.512	-0.624	-3.011	-2.701	-1.618	5.503
	(-0.483)	(-0.893)	(-0.612)	(-0.783)	(-1.367)	(-0.489)	(0.653)
ISM Manufacturing	-0.000	0.018	0.012	0.066	**0.178**	-0.040	-0.160
	(-0.003)	(0.348)	(0.352)	(1.137)	**(1.995)**	(-0.403)	(-0.840)
Industrial Production	1.129	-0.570	-0.494	-0.309	**-0.982**	0.357	**1.405**
	(0.656)	(-1.551)	(-1.710)	(-0.556)	**(-2.493)**	(0.652)	**(2.409)**
Initial Claims	-0.003	-0.001	0.000	**-0.011**	-0.001	-0.015	-0.028
	(-1.560)	(-0.979)	(0.224)	**(-2.781)**	(-0.185)	(-1.017)	(-1.517)
Leading Economic Indicators	-0.422	1.474	-0.284	0.577	-0.480	-2.145	**3.300**
	(-0.843)	(1.595)	(-0.361)	(0.615)	(-0.529)	(-0.990)	**(2.815)**
Michigan Consumer Sentiment	0.010	-0.036	-0.097	0.020	-0.117	0.079	0.076
	(0.291)	(-1.206)	(-1.711)	(0.364)	(-0.809)	(0.690)	(0.689)
New Home Sales	-0.000	-0.001	0.001	0.002	-0.005	-0.001	0.002
	(-0.177)	(-1.268)	(0.838)	(0.867)	(-0.926)	(-0.190)	(0.473)
Nonfarm Payrolls	0.000	-0.000	-0.001	-0.002	-0.003	0.004	0.003
	(0.863)	(-0.303)	(-0.509)	(-1.108)	(-0.888)	(1.494)	(1.155)
PCE	-0.109	0.140	-0.838	1.169	-1.896	1.056	-0.624
	(-0.722)	(0.698)	(-0.959)	(0.943)	(-1.393)	(1.124)	(-0.534)
PPI (Core)	-0.471	0.124	-0.495	-0.974	-0.027	0.421	-0.722
	(-0.752)	(0.716)	(-1.322)	(-0.577)	(-0.027)	(0.339)	(-1.275)
Philadelphia Fed BOS	**-0.066**	0.029	-0.020	0.008	-0.017	0.016	0.029
	(-2.778)	(1.105)	(-0.695)	(0.320)	(-0.728)	(0.641)	(1.538)
Retail Sales	0.091	-0.008	**-0.392**	-0.312	0.102	-0.309	-1.423
	(0.426)	(-0.135)	**(-2.962)**	(-1.507)	(0.166)	(-0.518)	(-0.678)
Retail Sales (Excl. Autos)	-0.028	-0.109	**0.765**	0.379	0.700	0.480	2.058
	(-0.093)	(-1.054)	**(3.433)**	(1.244)	(1.304)	(0.876)	(0.852)
Unemployment	0.314	0.430	-0.072	1.933	2.694	1.409	5.974
	(1.515)	(1.166)	(-0.101)	(0.604)	(1.606)	(0.444)	(1.502)

Notes: This table reports estimates of the regressions of daily changes in the options-implied volatility of crude oil prices over different horizons (1, 3, 6, 9, 12, 15, and 18 months) onto macroeconomic surprises. The implied volatility values are defined in terms of dollar amounts and the units of macroeconomic surprises are given in Table (3.3). T-statistic values computed with heteroskedasticity-robust standard errors are in parenthesis and the bold numbers are significant at least at the 5% level. For the explanation of macroeconomic variables, see Table (3.3).

Table 3.6: *Event Study Regression: The Skewness on Macro Surprises*

Data Release	1M	3M	6M	9M	12M	15M	18M
CPI (Core)	0.030	-0.016	-0.005	-0.121	0.028	0.052	0.046
	(1.197)	(-1.593)	(-0.329)	(-1.374)	(0.320)	(0.631)	(0.662)
Capacity Utilization	0.006	**0.009**	**0.004**	**0.002**	**0.001**	**0.002**	0.001
	(1.027)	**(3.050)**	**(3.369)**	**(3.660)**	**(4.213)**	**(2.189)**	(0.063)
Chicago PMI	-0.000	0.000	0.001	0.003	0.002	0.000	-0.000
	(-0.369)	(0.689)	(0.897)	(1.188)	(0.883)	(0.091)	(-0.315)
Consumer Confidence	0.000	-0.000	0.000	-0.000	0.001	0.000	-0.000
	(0.142)	(-0.381)	(1.145)	(-0.251)	(0.727)	(0.542)	(-0.263)
Durable Goods Orders	0.000	0.000	0.000	-0.001	-0.003	0.008	-0.000
	(0.055)	(1.039)	(0.313)	(-0.532)	(-0.657)	(1.267)	(-0.031)
ECI Civilian Workers	-0.001	-0.006	-0.034	0.041	0.059	**0.036**	0.056
	(-0.180)	(-0.848)	(-0.794)	(0.448)	(1.943)	**(2.175)**	(0.792)
Existing Home Sales	0.007	**0.001**	0.003	0.013	**0.009**	**0.002**	0.008
	(1.336)	**(2.958)**	(0.374)	(0.357)	**(3.004)**	**(2.520)**	(0.449)
Factory Orders	0.001	-0.007	-0.001	-0.023	0.013	0.022	0.045
	(0.507)	(-1.608)	(-0.228)	(-1.222)	(0.735)	(1.699)	(1.306)
GDP (Advanced Estimate)	**0.015**	**0.024**	**0.026**	**0.038**	**0.040**	**0.033**	**0.010**
	(2.142)	**(3.039)**	**(4.012)**	**(2.902)**	**(3.833)**	**(4.524)**	**(2.550)**
Hourly Earnings	-0.004	-0.004	0.005	**0.052**	0.067	**0.012**	**0.021**
	(-0.436)	(-0.419)	(0.208)	**(2.026)**	(1.817)	**(2.563)**	**(2.041)**
Housing Starts	-0.044	-0.032	0.022	-0.035	**0.018**	0.151	-0.067
	(-1.907)	(-1.500)	(1.149)	(-0.330)	**(2.121)**	(1.030)	(-0.434)
ISM Manufacturing	-0.000	-0.001	0.001	-0.002	0.002	-0.004	0.007
	(-0.614)	(-0.481)	(1.324)	(-0.912)	(0.703)	(-1.146)	(0.863)
Industrial Production	-0.008	-0.003	-0.003	0.008	0.014	0.001	-0.033
	(-0.644)	(-0.544)	(-0.333)	(0.749)	(1.060)	(0.097)	(-1.620)
Initial Claims	0.000	-0.000	0.000	0.000	-0.000	0.000	0.000
	(0.993)	(-1.253)	(0.330)	(0.056)	(-0.679)	(0.444)	(0.523)
Leading Economic Indicators	0.005	0.003	0.003	0.020	0.023	0.026	-0.010
	(0.443)	(0.424)	(0.297)	(0.695)	(1.316)	(0.413)	(-0.444)
Michigan Consumer Sentiment	-0.000	0.000	0.002	0.002	-0.002	-0.003	-0.002
	(-1.147)	(0.538)	(1.618)	(0.701)	(-0.767)	(-0.755)	(-0.550)
New Home Sales	0.000	**0.000**	0.000	-0.000	-0.000	0.000	-0.000
	(0.382)	**(2.141)**	(0.995)	(-0.322)	(-0.259)	(0.907)	(-0.021)
Nonfarm Payrolls	**0.001**	**0.004**	**0.006**	**0.005**	0.000	**0.010**	**0.013**
	(3.969)	**(4.145)**	**(4.138)**	**(3.478)**	(0.626)	**(4.205)**	**(4.234)**
PCE	-0.006	0.003	-0.012	-0.020	0.040	0.072	-0.045
	(-1.467)	(0.413)	(-1.219)	(-0.546)	(0.883)	(1.753)	(-0.513)
PPI (Core)	-0.006	0.000	-0.005	-0.062	0.000	0.004	-0.005
	(-0.853)	(0.070)	(-0.821)	(-1.395)	(0.001)	(0.147)	(-0.360)
Philadelphia Fed BOS	0.001	**0.001**	-0.000	0.001	-0.000	0.001	-0.001
	(1.861)	**(2.177)**	(-0.605)	(0.944)	(-0.072)	(1.736)	(-0.719)
Retail Sales	**0.008**	0.002	-0.001	0.011	0.003	-0.018	0.086
	(2.713)	(0.700)	(-0.406)	(1.647)	(0.183)	(-0.986)	(0.996)
Retail Sales (Excl. Autos)	0.007	-0.002	-0.003	**0.019**	**0.036**	-0.004	0.110
	(1.304)	(-0.640)	(-0.520)	**(2.639)**	**(2.574)**	(-0.168)	(1.091)
Unemployment	0.007	0.007	0.004	-0.061	0.008	0.118	0.137
	(1.661)	(1.039)	(0.327)	(-1.054)	(0.099)	(1.216)	(1.288)

Notes: This table reports estimates of the regressions of daily changes in the options-implied skewness of crude oil prices over different horizons (1, 3, 6, 9, 12, 15, and 18 months) onto macroeconomic surprises. The implied volatility values are defined in terms of dollar amounts and the units of macroeconomic surprises are given in Table (3.3). T-statistic values computed with heteroskedasticity-robust standard errors are in parenthesis and the bold numbers are significant at least at the 5% level. For the explanation of macroeconomic variables, see Table (3.3).

Table 3.7: *Event Study Regression: The Kurtosis on Macro Surprises*

Data Release	1M	3M	6M	9M	12M	15M	18M
CPI (Core)	0.030	-0.028	-0.068	0.069	**0.272**	0.069	-0.140
	(0.659)	(-0.577)	(-1.326)	(0.760)	**(2.813)**	(0.455)	(-0.491)
Capacity Utilization	-0.046	0.018	0.037	0.003	-0.066	0.003	-0.033
	(-1.400)	(0.489)	(1.270)	(0.116)	(-1.378)	(0.060)	(-0.533)
Chicago PMI	-0.001	-0.002	-0.001	0.008	-0.003	-0.003	0.001
	(-1.283)	(-1.064)	(-0.817)	(1.695)	(-0.846)	(-0.678)	(0.183)
Consumer Confidence	0.000	0.001	-0.001	0.001	-0.001	0.002	**0.009**
	(0.704)	(0.981)	(-1.274)	(0.525)	(-0.499)	(0.858)	**(2.494)**
Durable Goods Orders	-0.000	-0.002	-0.000	0.000	-0.005	-0.002	0.010
	(-0.361)	(-0.932)	(-0.041)	(0.065)	(-0.737)	(-0.170)	(0.983)
ECI Civilian Workers	-0.009	0.002	0.013	-0.118	-0.016	-0.020	0.043
	(-0.596)	(0.107)	(0.343)	(-1.219)	(-0.272)	(-0.223)	(0.664)
Existing Home Sales	-0.058	-0.044	-0.064	-0.019	0.097	0.214	0.223
	(-1.172)	(-1.573)	(-1.144)	(-0.293)	(0.912)	(1.245)	(0.925)
Factory Orders	0.003	-0.003	**-0.021**	0.003	0.015	0.016	0.006
	(0.423)	(-0.229)	**(-2.648)**	(0.064)	(0.589)	(0.411)	(0.105)
GDP (Advanced Estimate)	-0.001	-0.001	0.001	-0.003	0.009	-0.002	-0.002
	(-1.159)	(-0.345)	(0.322)	(-0.892)	(1.005)	(-0.274)	(-0.462)
Hourly Earnings	-0.047	**0.094**	0.041	0.226	0.073	0.212	0.456
	(-1.876)	**(2.194)**	(1.237)	(0.734)	(0.516)	(0.740)	(1.087)
Housing Starts	-0.002	-0.199	0.066	-0.420	0.142	-0.077	-0.008
	(-0.041)	(-1.547)	(0.959)	(-0.512)	(0.812)	(-0.436)	(-0.021)
ISM Manufacturing	0.001	0.002	0.001	0.025	0.008	0.011	0.005
	(0.289)	(0.786)	(0.341)	(1.156)	(0.846)	(1.181)	(0.563)
Industrial Production	-0.016	-0.004	0.006	-0.017	0.032	-0.086	-0.121
	(-0.838)	(-0.127)	(0.275)	(-0.519)	(0.890)	(-1.658)	(-1.191)
Initial Claims	0.000	0.000	0.000	-0.000	-0.001	0.000	-0.000
	(1.094)	(0.141)	(0.386)	(-0.516)	(-1.400)	(0.055)	(-0.557)
Leading Economic Indicators	0.016	-0.029	0.067	-0.119	0.077	-0.040	-0.016
	(0.479)	(-0.638)	(1.862)	(-1.058)	(1.510)	(-0.817)	(-0.359)
Michigan Consumer Sentiment	-0.001	-0.001	-0.014	0.005	0.009	-0.009	-0.002
	(-0.417)	(-0.249)	(-0.731)	(0.499)	(1.130)	(-0.815)	(-0.307)
New Home Sales	0.000	0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.049)	(0.288)	(-1.529)	(1.247)	(-0.371)	(-0.130)	(-0.593)
Nonfarm Payrolls	0.000	0.000	**0.000**	0.000	-0.000	-0.000	-0.000
	(0.159)	(1.021)	**(2.590)**	(1.157)	(-0.116)	(-0.877)	(-0.975)
PCE	0.002	-0.017	0.009	0.101	0.037	0.079	0.052
	(0.140)	(-0.954)	(0.274)	(0.469)	(0.523)	(1.009)	(0.834)
PPI (Core)	0.016	0.010	0.026	-0.021	0.007	-0.085	-0.127
	(0.770)	(0.512)	(0.905)	(-0.373)	(0.232)	(-1.219)	(-1.012)
Philadelphia Fed BOS	-0.004	0.003	0.002	**0.009**	-0.001	0.001	-0.002
	(-1.297)	(1.760)	(1.523)	**(2.297)**	(-0.554)	(0.438)	(-0.853)
Retail Sales	-0.007	-0.002	0.001	0.027	-0.006	-0.038	-0.079
	(-0.906)	(-0.252)	(0.111)	(1.050)	(-0.424)	(-0.834)	(-0.831)
Retail Sales (Excl. Autos)	0.000	0.006	0.005	-0.098	0.024	0.093	0.145
	(0.004)	(0.414)	(0.294)	(-1.536)	(0.881)	(1.289)	(1.012)
Unemployment	0.023	-0.010	0.021	-0.083	-0.296	1.131	-0.343
	(1.102)	(-0.295)	(0.647)	(-0.698)	(-1.495)	(0.944)	(-1.514)

Notes: This table reports estimates of the regressions of daily changes in the options-implied kurtosis of crude oil prices over different horizons (1, 3, 6, 9, 12, 15, and 18 months) onto macroeconomic surprises. The implied volatility values are defined in terms of dollar amounts and the units of macroeconomic surprises are given in Table (3.3). T-statistic values computed with heteroskedasticity-robust standard errors are in parenthesis and the bold numbers are significant at least at the 5% level. For the explanation of macroeconomic variables, see Table (3.3)

Table 3.8: ***Event Study Regression: The 5th Percentile on Macro Surprises***

Data Release	**1M**	**3M**	**6M**	**9M**	**12M**	**15M**	**18M**
CPI (Core)	4.774	1.505	0.857	-6.052	0.181	-8.718	3.707
	(1.933)	(1.089)	(0.601)	(-1.423)	(0.100)	(-1.112)	(0.603)
Capacity Utilization	1.350	-0.230	-0.673	0.001	-0.465	-1.188	0.213
	(0.606)	(-0.284)	(-1.075)	(0.001)	(-0.484)	(-0.566)	(0.225)
Chicago PMI	0.036	0.061	0.032	0.071	0.076	-0.135	**0.095**
	(1.843)	(1.106)	(1.721)	0.298)	(1.329)	(0.651)	**(2.960)**
Consumer Confidence	-0.034	0.018	-0.041	0.028	-0.032	-0.118	0.123
	(-1.024)	(0.738)	(-1.594)	(0.723)	(-0.704)	(-1.308)	(1.067)
Durable Goods Orders	-0.045	-0.027	**0.075**	0.044	0.092	0.025	-0.031
	(-1.338)	(1.733)	**(2.289)**	(-1.771)	(-1.912)	(-0.394)	(0.394)
ECI Civilian Workers	-0.160	0.324	1.158	-2.980	-1.088	-0.777	1.397
	(-0.245)	(0.413)	(0.934)	(-1.028)	(-0.790)	(-0.517)	(0.294)
Existing Home Sales	0.809	-0.824	0.488	-0.625	-2.472	1.030	0.439
	(0.726)	(-0.644)	(0.389)	(-0.219)	(-1.388)	(0.985)	(0.844)
Factory Orders	0.040	0.098	-0.649	-0.962	-0.216	-0.138	2.264
	(0.206)	(0.314)	**(-1.976)**	(-1.269)	(-0.423)	(-0.277)	(1.331)
GDP (Advanced Estimate)	0.092	0.119	0.029	**0.140**	0.160	**0.186**	-0.029
	(4.319)	(3.995)	(1.047)	**(2.990)**	(3.089)	**(2.772)**	(-0.557)
Hourly Earnings	-0.598	-0.733	-1.348	-0.605	-0.730	5.431	3.881
	(-0.830)	(-0.906)	(-0.957)	(-0.413)	(-0.567)	(1.087)	(0.764)
Housing Starts	-0.383	-1.537	2.895	1.153	0.857	6.286	-4.384
	(-0.142)	(-0.398)	(1.173)	(0.298)	(0.376)	(1.642)	(-0.818)
ISM Manufacturing	0.081	**0.187**	0.091	-0.011	-0.012	0.104	0.423
	(1.340)	**(2.495)**	(1.191)	(-0.152)	(-0.177)	(0.988)	(1.366)
Industrial Production	-1.985	0.812	0.631	1.217	0.900	-1.493	-1.298
	(-0.787)	(0.825)	(1.025)	(1.468)	(1.030)	(-0.970)	1.069)
Initial Claims	0.001	-0.005	-0.005	0.000	**-0.010**	-0.004	-0.008
	(0.306)	**(-2.750)**	(-1.899)	(0.127)	(-1.730)	(-0.766)	(-1.219)
Leading Economic Indicators	0.387	-1.523	-0.299	2.199	**1.623**	2.861	-1.794
	(0.284)	(-1.043)	(-0.354)	(0.902)	**(1.971)**	(0.993)	(-1.956)
Michigan Consumer Sentiment	-0.058	0.049	0.098	-0.026	**0.172**	0.118	-0.188
	(-1.189)	(1.228)	(2.559)	(-0.698)	**(-3.762)**	(-2.223)	(-1.933)
New Home Sales	0.000	0.001	0.000	-0.001	-0.005	0.046	-0.004
	(0.159)	(0.334)	(0.051)	(-0.510)	(-0.720)	(1.097)	(-0.681)
Nonfarm Payrolls	0.000	0.001	0.004	0.002	0.009	0.000	-0.001
	(0.266)	(1.099)	(1.164)	(0.846)	(0.974)	(0.083)	(-0.270)
PCE	0.319	0.467	0.886	-1.215	0.899	-2.464	2.163
	(0.526)	(0.684)	(0.609)	(-0.716)	(1.095)	(-0.970)	(0.986)
PPI (Core)	0.805	0.299	0.705	-1.186	1.062	3.000	**2.039**
	(0.847)	(0.694)	(1.430)	(-0.431)	(1.728)	(1.958)	**(2.940)**
Philadelphia Fed BOS	0.213	-0.126	0.088	0.074	0.007	**0.052**	0.018
	(1.606)	(-1.894)	(1.427)	(2.192)	(0.290)	**(1.995)**	(0.620)
Retail Sales	-0.200	-0.203	-0.045	0.507	-0.701	**-1.350**	5.661
	(-0.431)	(-1.030)	(-0.229)	(1.043)	(-1.199)	**(-2.272)**	(1.226)
Retail Sales (Excl. Autos)	0.495	0.659	0.015	-0.290	0.642	1.160	-6.206
	(0.624)	(2.155)	(0.050)	(-0.447)	(1.126)	(1.836)	(-1.153)
Unemployment	0.292	0.031	1.437	2.581	-2.199	-5.254	-6.326
	(0.401)	(0.042)	(1.299)	(1.323)	(-1.434)	(-0.991)	(-1.554)

Notes: This table reports estimates of the regressions of daily changes in the options-implied 95th percentile of crude oil prices over different horizons (1, 3, 6, 9, 12, 15, and 18 months) onto macroeconomic surprises. The implied volatility values are defined in terms of dollar amounts and the units of macroeconomic surprises are given in Table (3.3). T-statistic values computed with heteroskedasticity-robust standard errors are in parenthesis and the bold numbers are significant at least at the 5% level. For the explanation of macroeconomic variables, see Table (3.3)

Table 3.9: *Event Study Regression: The 95th Percentile on Macro Surprises*

Data Release	**1M**	**3M**	**6M**	**9M**	**12M**	**15M**	**18M**
CPI (Core)	2.396	1.106	0.757	0.613	3.776	-3.737	-2.193
	(1.859)	(1.170)	(0.725)	(0.323)	(1.242)	(-0.993)	(-0.443)
Capacity Utilization	0.745	0.544	0.595	**0.647**	**0.806**	1.052	1.359
	(1.143)	(1.015)	(1.180)	**(2.040)**	**(2.041)**	(0.647)	(0.905)
Chicago PMI	**0.066**	**0.074**	**0.067**	0.066	0.091	0.059	0.144
	(2.330)	**(2.080)**	**(2.340)**	(1.835)	(1.517)	(1.467)	(1.388)
Consumer Confidence	0.012	0.012	-0.014	0.020	-0.043	-0.063	0.217
	(0.843)	(0.772)	(-0.791)	(0.725)	(-0.518)	(-1.606)	(1.426)
Durable Goods Orders	0.051	**0.076**	**0.119**	**0.083**	-0.176	0.040	0.392
	(1.930)	**(2.684)**	**(3.285)**	**(2.135)**	(-1.214)	(0.727)	(1.584)
ECI Civilian Workers	-0.149	0.217	0.664	-0.723	0.278	-2.180	-5.208
	(-0.238)	(0.322)	(0.929)	(-0.998)	(0.123)	(-1.050)	(-1.043)
Existing Home Sales	0.015	-0.339	0.104	0.052	-0.457	-0.162	0.570
	(0.022)	(-0.430)	(0.147)	(0.053)	(-0.424)	(-0.115)	(0.387)
Factory Orders	-0.030	-0.012	-0.382	-0.381	-0.351	0.029	3.263
	(-0.191)	(-0.067)	(-1.600)	(-0.907)	(-0.275)	(0.061)	(1.469)
GDP (Advanced Estimate)	**0.053**	**0.082**	0.035	**0.168**	**0.304**	0.020	-0.052
	(2.634)	**(3.498)**	(1.449)	**(5.889)**	**(4.482)**	(0.669)	(-1.066)
Hourly Earnings	-0.839	-0.555	-1.411	-1.299	-0.678	-0.622	-19.667
	(-1.256)	(-0.756)	(-1.665)	(-1.110)	(-0.355)	(-0.285)	(-1.889)
Housing Starts	-2.356	-1.102	-0.523	1.538	-0.522	7.897	0.554
	(-1.059)	(-0.586)	(-0.219)	(0.859)	(-0.135)	(1.191)	(0.090)
ISM Manufacturing	0.077	0.222	0.087	0.108	**0.228**	0.099	0.138
	(1.315)	(1.759)	(1.219)	(1.130)	**(2.419)**	(0.679)	(0.865)
Industrial Production	-0.181	-0.119	0.157	-0.732	-1.506	0.132	-1.574
	(-0.183)	(-0.195)	(0.323)	(-1.011)	(-1.708)	(0.117)	(-1.304)
Initial Claims	**0.008**	**0.006**	**0.009**	**0.014**	**0.023**	**0.048**	**0.116**
	(4.825)	**(3.660)**	**(4.376)**	**(4.562)**	**(3.329)**	**(1.996)**	**(2.586)**
Leading Economic Indicators	-0.508	-0.021	-1.109	3.906	1.824	-0.258	**3.295**
	(-0.767)	(-0.023)	(-1.031)	(1.330)	(1.394)	(-0.137)	**(2.527)**
Michigan Consumer Sentiment	0.038	0.039	0.047	**0.113**	**0.866**	0.121	-0.075
	(1.332)	(1.328)	(1.200)	**(3.022)**	**(2.201)**	(1.523)	(-0.832)
New Home Sales	0.000	-0.000	0.000	0.000	-0.005	**0.006**	-0.006
	(0.145)	(-0.231)	(0.048)	(0.021)	(-1.349)	**(2.392)**	(-0.926)
Nonfarm Payrolls	**0.011**	**0.014**	**0.023**	0.012	**0.022**	**0.028**	-0.002
	(2.496)	**(3.572)**	**(3.955)**	(1.845)	**(1.591)**	**(2.911)**	(-0.631)
PCE	0.220	0.321	0.408	0.310	-0.963	0.431	0.720
	(0.509)	(0.717)	(0.632)	(0.371)	(-0.525)	(0.258)	(0.862)
PPI (Core)	-0.042	0.568	0.693	1.334	2.500	7.544	0.133
	(-0.072)	(1.945)	(1.745)	(1.841)	(1.488)	(1.737)	(0.093)
Philadelphia Fed BOS	0.040	0.035	**0.072**	0.041	-0.039	0.164	0.015
	(1.497)	(1.477)	**(3.938)**	(1.687)	(-1.106)	(1.526)	(0.374)
Retail Sales	0.164	**0.358**	**0.786**	0.110	0.416	**2.569**	-1.766
	(1.573)	**(4.186)**	**(5.147)**	(0.700)	(1.483)	**(6.512)**	(-1.744)
Retail Sales (Excl. Autos)	0.576	**0.729**	**1.102**	0.533	1.392	**3.692**	-0.026
	(1.528)	**(2.279)**	**(2.664)**	(1.217)	(1.753)	**(3.157)**	(-0.017)
Unemployment	0.879	0.943	1.664	2.475	-1.840	-2.399	-3.700
	(0.869)	(0.778)	(1.218)	(1.165)	(-1.075)	(-1.333)	(-0.526)

Notes: This table reports estimates of the regressions of daily changes in the options-implied 95th percentile of crude oil prices over different horizons (1, 3, 6, 9, 12, 15, and 18 months) onto macroeconomic surprises. The implied volatility values are defined in terms of dollar amounts and the units of macroeconomic surprises are given in Table (3.3). T-statistic values computed with heteroskedasticity-robust standard errors are in parenthesis and the bold numbers are significant at least at the 5% level. For the explanation of macroeconomic variables, see Table (3.3)

Table 3.10: ***AG-Test Results of Oil Spot Prices: Time Series Density Forecasts vs. Forward Density***

Models		**1M**	**3M**	**6M**	**9M**	**12M**
f:	Forward	**2.82**	**3.02**	1.44	**1.95**	1.01
g:	GARCH	**(0.001)**	**(0.000)**	(0.052)	**(0.011)**	(0.213)
f:	Forward	**3.01**	**2.75**	1.49	1.34	1.21
g:	EGARCH	**(0.000)**	**(0.000)**	(0.079)	(0.102)	(0.143)

Notes: This Table reports the AG-Test results for the forward density vs the time series forecast density.

1. The time series models that are used to generate these densities are either GARCH and EGARCH models (see the equations (3.8) and (3.9) for the exact parametric assumption for these models respectively). The returns of oil spot prices for the GARCH and EGARCH models at maturities 1, 3, 6, 9 and 12 are computed using the oil spot prices.

2. The AG test statistic is computed using equation (3.10) presented in Subsection 3.3.4.1.

3. Due to calendar forecast nature of options-implied pdfs, the number of days in the same maturity class have different days. Specifically, 1 month maturity includes all options with horizons ranging 1 to 22 business days, 3 months maturity includes all options with horizons ranging 45 to 66 business days, 6 months maturity includes all options with horizons ranging 111 to 132 business days, 9 months maturity includes all options with horizons ranging 177 to 198 business, and finally 12 maturity includes all options with horizons ranging 245 to 264 business days. The corresponding time series density forecast perfectly aligns with this calender forecast nature of the options-implied pdfs. The values in parenthesis are p-values and the bold numbers are significant at 5% level or less.

Table 3.11: ***The Effect of Oil Price Risk on Oil Price Realizations***

	No Controls				*Controls*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
1 Month						
Futures	1.013	1.105	0.998	1.052	0.739	0.708
	(41.091)	(43.875)	(47.073)	(39.982)	(8.531)	(10.177)
Volatility		-0.345		-0.271		-0.189
		(-6.143)		(-4.168)		(-3.121)
Skewness			11.345	8.892		4.775
			(8.195)	(6.781)		(4.712)
R^2	0.578	0.593	0.614	0.626	0.618	0.649
RMSE Ratio	0.994	0.981	0.977	0.951	0.947	0.935
3 Month						
Futures	0.993	1.009	0.984	0.972	0.711	0.693
	(32.355)	(34.196)	(36.621)	(31.288)	(7.112)	(5.121)
Volatility		-0.391		-0.304		-0.217
		(-5.489)		(-4.637)		(-2.989)
Skewness			11.727	8.788		4.838
			(9.332)	(7.332)		(5.211)
R^2	0.491	0.503	0.539	0.561	0.545	0.593
RMSE Ratio	1.003	0.987	0.975	0.967	0.974	0.949
6 Months						
Futures	0.985	0.993	0.973	0.961	0.697	0.676
	(29.912)	(31.882)	(33.929)	(28.911)	(11.349)	(7.955)
Volatility		-0.207		-0.157		-0.094
		(-3.621)		(-2.155)		(-1.211)
Skewness			9.933	7.323		3.992
			(8.112)	(6.277)		(4.199)
R^2	0.488	0.503	0.539	0.561	0.545	0.593
RMSE Ratio	0.979	0.962	0.949	0.937	0.942	0.911
12 Months						
Futures	0.961	0.982	0.969	0.952	0.653	0.631
	(25.453)	(26.123)	(26.997)	(27.212)	(13.211)	(9.855)
Volatility		-0.217		-0.145		-0.101
		(-5.166)		(-2.003)		(-1.257)
Skewness			10.737	8.112		4.122
			(9.677)	(8.219)		(5.221)
R^2	0.414	0.420	0.429	0.445	0.501	0.521
RMSE Ratio	0.951	0.945	0.933	0.929	0.921	0.902

Notes: OLS estimation of equation (3.11). The options-implied volatility and skewness are computed using equations **??** and 3.6 that are derived from pdfs, which are estimated using the local polynomial regression method as in Ait-Sahalia and Duarte (2003). The controls include general or sub indices (I used Goldman Sachs commodity indices) of Commodity Prices, Baltic Dry Index, the Crack Spread, and lagged oil prices. Estimation involves overlapping horizons, so standard errors are obtained via a HAC Newey-West procedure. I use a Bartlett kernel and a bandwidth of $k1$, with k the forecasting horizon (where $k = 22$business days $\times$ #of months). The sample runs from January 3, 1990 to May 22, 2014 for 1, 3, and 6 months maturities, March 17, 1991 to May 22, 2014 for 9 months maturity and finally November 13, 1996 to May 22, 2014 for 12 months maturity.

Table 3.12: ***Out of Sample Forecast of Nominal WTI Price of Oil***

	1M		3M		6M		9M		12M	
	MPSR	**SR**	**MPSR**	**SR**	**MPSR**	**SR**	**MPSR**	**SR**	**MPSR**	**SR**
S_t	0.952	0.534	0.931	0.523	0.943	0.531	0.966	0.527	0.977	0.519
	(0.009)	**(0.040)**	**(0.053)**	**(0.072)**	**(0.077)**	**(0.012)**	**(0.063)**	**(0.007)**	**(0.000)**	**(0.003)**
F_t^h	0.946	0.553	0.959	0.521	0.961	0.525	0.934	0.531	0.939	0.533
	(0.003)	**(0.001)**	**(0.002)**	**(0.005)**	**(0.001)**	**(0.007)**	**(0.001)**	**(0.002)**	**(0.006)**	**(0.000)**
$S_t\left(1+\ln\left(F_t^h/S_t\right)\right)$	0.923	0.567	0.934	0.573	0.942	0.551	0.965	0.527	0.954	0.559
	(0.002)	**(0.021)**	**(0.031)**	**(0.019)**	**(0.057)**	**(0.009)**	**(0.031)**	**(0.013)**	**(0.000)**	**(0.011)**

Notes: The forecast evaluation period is January 4, 2004 to May 22, 2014 whereas the initial estimation window starts from August 8, 1990. The sample runs from January 3, 1990 to May 22, 2014 for 1, 3, and 6 months maturities, March 17, 1991 to May 22, 2014 for 9 months maturity and finally November 13, 1996 to May 22, 2014 for 12 months maturity. F_t^h is the futures price that matures in h periods. All Mean Square Prediction Error results are presented as ratios relative to the model without the skewness and volatility variables. The success ratio is defined as the fraction of forecasts that correctly predict the sign of the change in the price of oil. Results that are statistically significant at the 10% level are shown in boldface. All tests of statistical significance refer to pairwise tests of the null of equal predictive accuracy with the same model without the skewness and volatility variables. Since all the models are nested, model comparisons with estimated parameters are obtained Nested model comparisons with estimated parameters are based on Clark and West (2006). The success ratio is defined as the fraction of forecasts that correctly predict the sign of the change in the price of oil. The sign test in the last column is based on Pesaran and Timmermann (1992).

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Appendix A

Appendix for Chapter 1

A.1 SPF Data

A.1.1 Survey Designs for Deflator Inflation and Output Growth

Table A.1: ***Survey Design for Deflator Inflation***

Sample Period	68Q4-73Q1	73Q2-74Q3	74Q4-81Q2	81Q3-85Q1	85Q2-91Q4	92Q1-Present
Target Variable	GNP Deflator (YoY Inflation)					GDP Deflator (YoY Inflation)
Number of Bins	15			6		10
Bin Width	1 %			2 %		1 %
Maximum Value	10 %	12 %	16 %	12 %	10 %	8 %
Minimum Value	-3 %	-1 %	3 %	4 %	2 %	0 %

Note: This table is provided by the Philadelphia Fed. The left and right extreme bins are by construction open-ended, i.e. top or bottom coded.

Table A.2: ***Survey Design for Output Growth***

Sample Period	81Q3-91Q4	92Q1-09Q1	09Q2-Present
Target Variable	GNP (YoY Growth)	GDP (YoY Growth)	
Number of Bins	6	10	11
Bin Width	2 %	1 %	
Maximum Value	6 %		
Minimum Value	-2 %		-3 %

Note: This table is provided by the Philadelphia Fed. The left and right extreme bins are by construction open-ended.

A.1.2 Some Characteristics of the SPF and SPF Respondents

Table A.3: *Descriptive Characteristics of the SPF Data*

	Current Deflator Inflation	**Current Output Growth**
Total Surveys	6539	4197
Quarter Average	36	32
Quarter Average (≥ 5)	35	31
Quarter Average (≥ 10)	34	29

Notes: Table A.3 presents total and quarterly average (based on several criteria) number of probabilistic surveys both for current period deflator inflation and output growth utilized in this study. This table excludes, however, any respondent (*i*) who at a given horizon do not report density forecast probabilities (*ii*) whose assigned probabilities for the histogram that do not sum to unity, and (*iii*) who participated just once in the survey. Table A.3 shows: (*i*) the average number of surveys (quarter average), (*ii*) the average number of surveys with forecasters participating at least 5 times or more (i.e. quarter average (≥ 5)), and (*iii*) the average number of surveys with forecasters participating at least 10 times or more (i.e. quarter average (≥ 10)).

Table A.4: *Classification of Micro Subjective Forecast Histograms for Inflation*

	Total	**Lowest Extreme**	**Highest Extreme**	**Both Extremes**	**None**
Case1	283	19	0	NaN	264
Case2	1492	125	0	0	1367
Case3	4683	691	86	137	3769

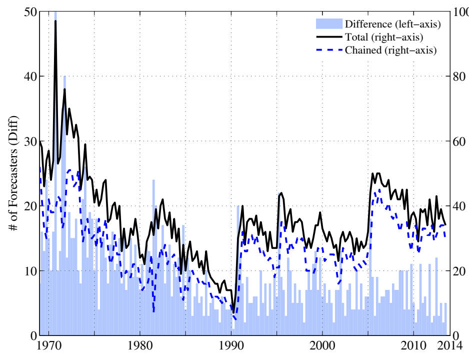
Table A.5: *Classification of Micro Subjective Forecast Histograms for Output Growth*

	Total	**Lowest Extreme**	**Highest Extreme**	**Both Extremes**	**None**
Case1	270	8	28	NaN	234
Case2	1010	50	41	0	919
Case3	2896	301	268	191	2136

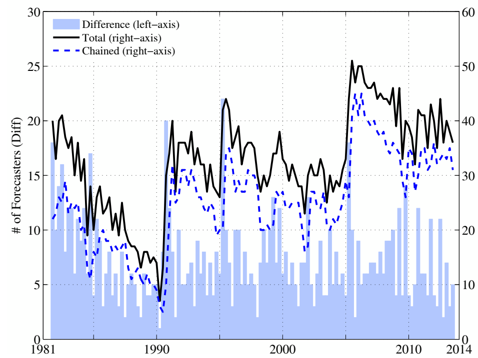
Notes for Tables A.4 and A.5: Case 1 and Case 2 refer whether a respondent to SPF attaches positive probability to one or two bins respectively. On the other hand, Case 3 refers to surveys where a forecaster assigns positive probabilities to more than two bins. In addition, I further categorize each case based on whether an observation has a positive probability on either (or both) of the extreme bins or not. The total number of micro observations is equal to 6539 and 4197 in current year inflation and output growth empirical forecast density histograms respectively.

Figure A.1: *Frequent Entry/Exit Patterns of Experts*

(a) *Output Growth*



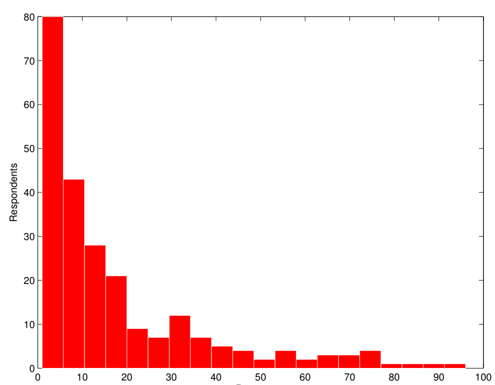
(b) *Inflation*



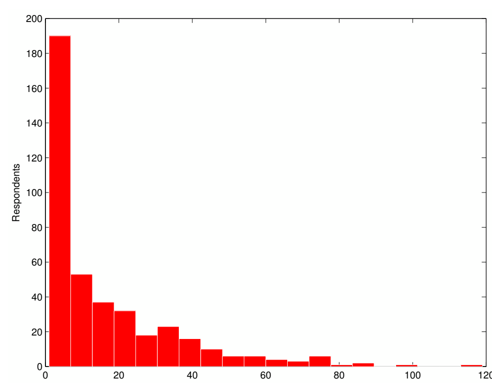
Note: Figures A.1b and A.1a show experts' participation patterns for the whole sample and the chained sub-sample both for inflation and output growth. The whole sample includes all 6539 surveys of inflation and 4197 surveys of output growth, which are presented as the solid (black) lines in figures A.1b and A.1a. The chained sample includes all forecasters who participate current quarter only if she participated in the previous quarter as well. It is shown as the dashed (blue) line both for inflation and output growth. Finally, the shaded regions are quarterly difference in the survey sizes of chained and whole surveys, which can be read from left-axis.

Figure A.2: *Total Participation of Experts*

(a) *Output Growth*

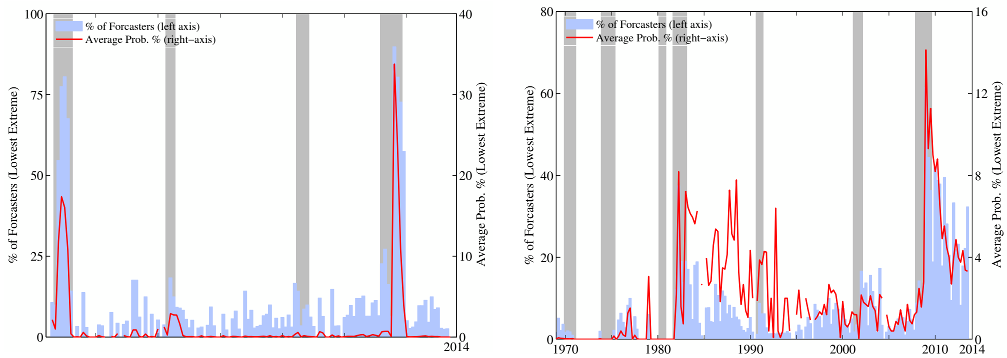


(b) *Inflation*



Note: Figures A.2a and A.2b indicate the number of responses for probabilistic current inflation or output growth by each forecaster over the sample for inflation and output growth separately. Each bin corresponds to multiple of 5 responses, so an expert participated 13 times to the SPF lies in the third bin (from the left) in figure A.2a or A.2b.

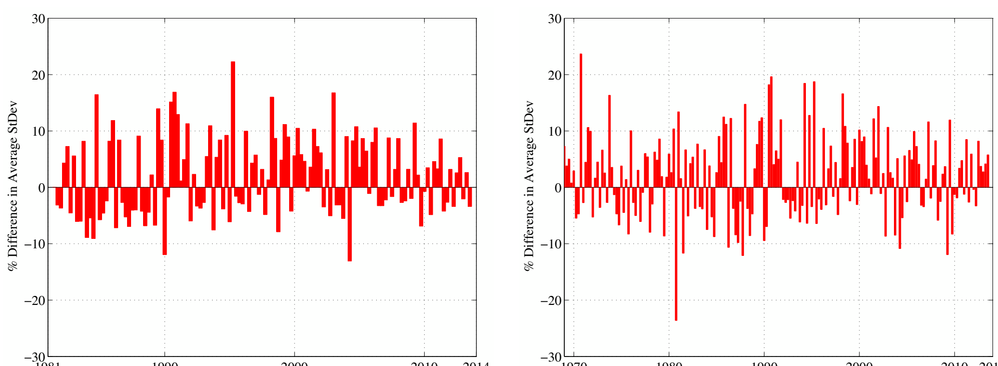
Figure A.3: *Non-Zero Probability Assigned to the Lowest-Extreme Bin*



(a) ***Current Output Growth*** (b) ***Current Inflation***

Note: Figures A.3a and A.3a show the frequency of forecasters that assign non-zero probabilities to lowest open-ended bin (light blue bar with the values can be read on the left-axis) and average probability weight attached to that lowest open-ended bin (solid red line with the values can be read on the right-axis) for output growth and inflation forecast density histograms respectively. The shaded blue bars are recessions defined according to the NBER Business Cycle Dating Committee.

Figure A.4: *Panel Compositon: Chained vs. Composite Samples*



(a) ***Current Output Growth*** (b) ***Current Inflation***

Note: Figures A.4a and A.4a show the percentage difference in average (cross-sectional) standard deviation between the chained sample (includes all forecasters who participate current quarter only if she participated in the previous quarter as well) and composite sample (that consists of all forecasters). Therefore, if the the difference is positive, the average standard deviation in the chained sample is greater than the average standard deviation for the composite sample.

A.1.3 Deterministic Seasonality Estimates for Current Inflation and Output Growth

Table A.6: ***Inflation Uncertainty: Estimated Deterministic Seasonal Dummies***

	Quarter 1					**Quarter 2**					**Quarter 3**					**Quarter 4**				
Estimation Type	**S1**	**S2**	**S3**	**S4**	**S5**	**S1**	**S2**	**S3**	**S4**	**S5**	**S1**	**S2**	**S3**	**S4**	**S5**	**S1**	**S2**	**S3**	**S4**	**S5**
Micro Breaks	1.01	0.67	0.74	0.98	0.80	0.98	0.61	0.70	0.89	0.75	0.96	0.52	0.72	0.84	0.70	1.04	0.56	0.57	0.76	0.57
	(0.93, 1.09)	(0.59, 0.75)	(0.60, 0.88)	(0.89, 1.07)	(0.76, 0.84)	(0.90, 1.05)	(0.53, 0.70)	(0.55, 0.84)	(0.80, 0.98)	(0.71, 0.80)	(0.88, 1.03)	(0.44, 0.61)	(0.58, 0.86)	(0.75, 0.93)	(0.66, 0.74)	(0.96, 1.11)	(0.48, 0.64)	(0.43, 0.71)	(0.67, 0.85)	(0.53,- 0.61)
Micro No Breaks			0.73					0.68					0.63					0.53		
			(0.69,0.77)					(0.64,0.72)					(0.59,0.67)					(0.54,0.63)		
Macro Breaks	0.71	0.85	0.92	0.85	0.72	0.67	0.78	0.86	0.76	0.68	0.66	0.67	0.90	0.73	0.61	0.75	0.71	0.78	0.63	0.49
	(0.67,0.76)	(0.79,0.91)	(0.77,1.07)	(0.76,0.93)	(0.70,0.74)	(0.63,0.71)	(0.72,0.84)	(0.69,1.03)	(0.69,0.84)	(0.65,0.70)	(0.62,0.70)	(0.61,0.74)	(0.75,1.05)	(0.65,0.81)	(0.59,0.64)	(0.71,0.79)	(0.64,0.77)	(0.63,0.92)	(0.55,0.71)	(0.46, 0.51)
Macro No Breaks			0.77					0.72					0.67					0.53		
			(0.74, 0.80)					(0.69, 0.75)					(0.64, 0.70)					(0.57, 0.64)		

Notes: Table A.6 presents estimated deterministic seasonal dummies based on 4 different regressions where inflation uncertainty is the dependent variable. The sub-samples are: 1968Q4-1974Q3 (S1), 1974Q4-1981Q2 (S2), 1981Q3-1985Q1 (S3), 1985Q2-1991Q4 (S4) and 1992Q1-2013Q3 (S5). Unlike table A.1, S1 combines 1968Q4-1973Q1 and 1973Q2-1974Q3 periods as latter period does not have enough observation to identify deterministic seasonal effects. Regressions are either estimated with micro (unbalanced panel) data (including forecaster fixed effects and dropping the forecasters participated only once) or the macro (aggregate) data (cross sectional average) dropping the forecasters participated only once). For each of the micro and macro regressions, I regress inflation uncertainty on either the full sample (no breaks) or the 5 different sub-samples (breaks) explained above. $3^{rd}, 5^{th}, 7^{th}$ and 9^{th} lines provide point estimates whereas following lines provide the 90% asymptotic confidence intervals for the relevant point estimates.

Table A.7: ***Output Growth Uncertainty: Estimated Seasonal Deterministic Dummies***

	Quarter 1			Quarter 2			Quarter 3			Quarter 4		
Estimation Type	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
Micro Breaks	1.09	0.83	0.90	1.04	0.76	0.86	0.92	0.65	0.74	0.73	0.47	0.58
	(1.00, 1.18)	(0.78, 0.89)	(0.80, 0.99)	(0.95, 1.13)	(0.71, 0.82)	(0.76, 0.96)	(0.83, 1.01)	(0.60, 0.70)	(0.64, 0.84)	(0.64, 0.82)	(0.42, 0.52)	(0.48,- 0.68)
Micro No Breaks	0.85			0.79			0.68			0.45		
	(0.79,0.91)			(0.73,0.85)			(0.62,0.74)			(0.44,0.56)		
Macro Breaks	0.97	0.84	0.85	0.94	0.77	0.81	0.82	0.65	0.70	0.64	0.48	0.53
	(0.90,1.04)	(0.81,0.87)	(0.79,0.91)	(0.87,1.00)	(0.74,0.80)	(0.76,0.86)	(0.75,0.89)	(0.62,0.68)	(0.65,0.75)	(0.57,0.70)	(0.44,0.51)	(0.48, 0.59)
Macro No Breaks	0.88			0.83			0.71			0.45		
	(0.85, 0.92)			(0.79, 0.86)			(0.68, 0.75)			(0.50, 0.57)		

Notes: Table A.7 presents estimated deterministic seasonal dummies based on 4 different regressions where inflation uncertainty is the dependent variable. The sub-samples are: 1981Q3-1991Q4 (S1), 1992Q1-2009Q1 (S2) and 2009Q2-2013Q3 (S3). Regressions are either estimated with micro (unbalanced panel) data (including forecaster fixed effects and dropping the forecasters participated only once) or the macro (aggregate) data (cross sectional average) dropping the forecasters participated only once). For each of the micro and macro regressions, I regress inflation uncertainty on either the full sample (no breaks) or the 3 different sub-samples (breaks) explained above. $3^{rd}, 5^{th}, 7^{th}$ and 9^{th} lines provide point estimates whereas following lines provide the 90% asymptotic confidence intervals for the relevant point estimates.

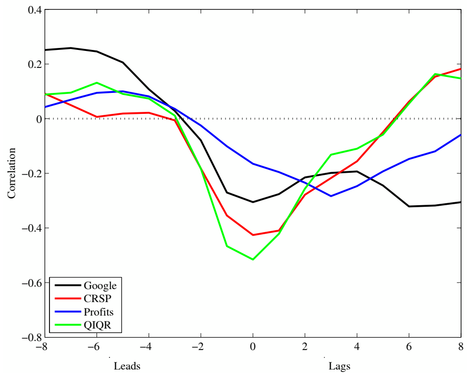
A.2 Additional Results on Other Uncertainty Indices

Table A.8: ***Uncertainty Measures: Correlation with other variables***

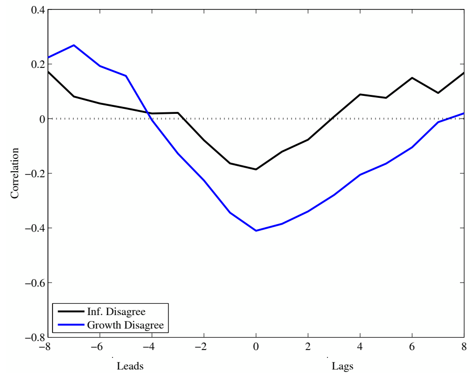
	Regressors					
U:	CPI	IP	NBER	FFR	S&P500	Employment
π **SCU**	2.649	-0.376	0.067	-0.014	-0.169	-0.151
	(4.660)	(-3.732)	(11.786)	(-4.332)	(-3.689)	(-1.297)
Δy **SCU**	3.183	-1.225	0.078	0.017	-0.401	-1.245
	(3.170)	(-7.418)	(11.494)	(3.125)	(-5.625)	(-7.074)
VXO	49.534	-19.418	3.502	0.167	-21.835	3.931
	(1.409)	(-0.824)	(3.274)	(0.366)	(-2.086)	(0.168)
Google	-47.475	-360.628	10.927	-8.706	-93.330	-342.967
	(-0.111)	(-3.585)	(2.560)	(-3.271)	(-3.228)	(-2.145)
CRSP	0.332	-0.120	0.013	0.000	-0.034	-0.016
	(2.169)	(-1.339)	(3.957)	(0.319)	(-0.922)	(-0.178)
Profits	4.817	-2.983	-0.009	-0.030	-0.524	-2.837
	(1.078)	(-1.778)	(-0.134)	(-0.979)	(-1.140)	(-1.295)
QIQR	0.429	-0.111	0.013	0.001	-0.041	-0.023
	(3.071)	(-2.226)	(5.628)	(1.229)	(-1.883)	(-0.375)
π **Disagree**	3.143	-0.734	0.123	0.026	-0.625	-0.209
	(1.018)	(-0.752)	(2.524)	(1.242)	(-2.406)	(-0.166)
Δy **Disagree**	5.992	-1.908	0.161	0.001	-0.512	-1.101
	(1.305)	(-2.167)	(3.817)	(0.028)	(-2.092)	(-1.059)

Note: Bivariate regression analysis. Entries are slope coefficient estimates, t-statistics utilizing newey-west robust standard errors of regressions for various empirical uncertainty measures involving a constant and a set of macroeconomic variables as single regressors. For the exact definitions of empirical uncertainty uncertainty measure see figure A.5. All macroeconomic variables are HP-detrended with a smoothing parameter that is equal to 129600 in quarterly frequency.

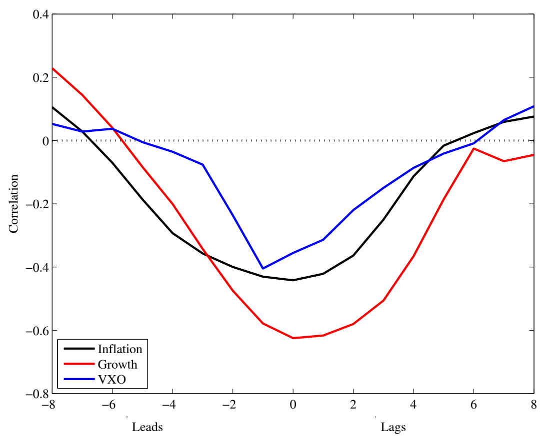
Figure A.5: *Cross-Correlograms: Uncertainty vs Industrial Production*



(a) *EPU/CRSP/Profits/QIQR*



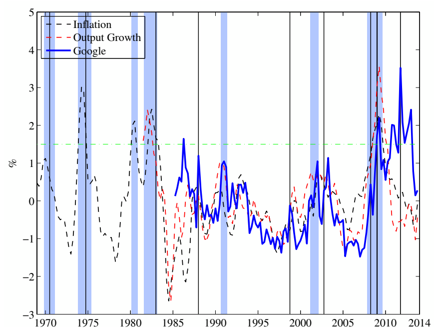
(b) *Disagreements*



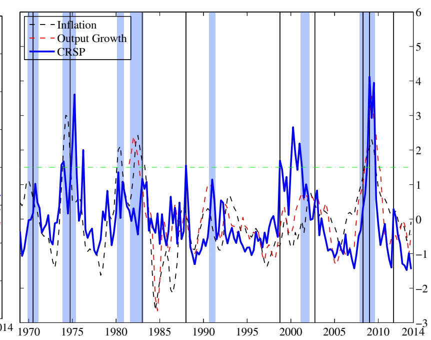
(c) *The SCUs and VXO*

Note: This figure displays the cross correlations between various uncertainty proxies against deviation of HP-detrended industrial production (with a smoothing parameter that is equal to 129600) in quarterly frequency. These correlations are computer for +/- 8 window of leads and lags for the relevant uncertainty proxy. The negative values are lagged whereas positive values are lead (future) uncertainty against deviation of industrial production from its HP-filtered trend. The empirical uncertainty measures are: (*i*) inflation and output growth SCU estimates (figure A.5c), (*ii*) implied stock market volatility index derived from options written on S&P100 stock market index extended by actual monthly returns volatilities of S&P500 for pre 1986 period following Bloom (2009), i.e. VXO (figure A.5c), (*iii*) the Economic Policy Uncertainty Index (Baker, Bloom, and Davis, 2012), i.e. EPU (figure A.5a), (*iv*) the within-quarter cross-sectional spread of profit growth rates normalized by average sales (Bloom, 2009; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), i.e. Profits (figure A.5a), (*v*) the interquartile range of the industrial production growth for manufacturing industries (Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2012), i.e. QIQR (figure A.5a), (*vi*) the within quarter cross-sectional standard deviation of firm-level stock returns for rms with 500+ months of data in the Center for Research in Securities Prices (Bloom, 2009), i.e. Profits (figure A.5a), (*vii*) the cross sectional standard deviation of mean probabilistic forecasts for inflation or output growth from the SPF, i.e. Inf. Disagree and Growth Disagree (figure A.5b).

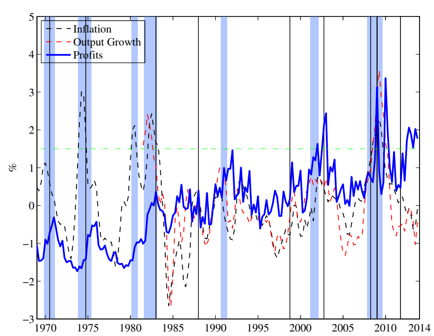
Figure A.6: *The SCUs and Other Uncertainty Proxies*



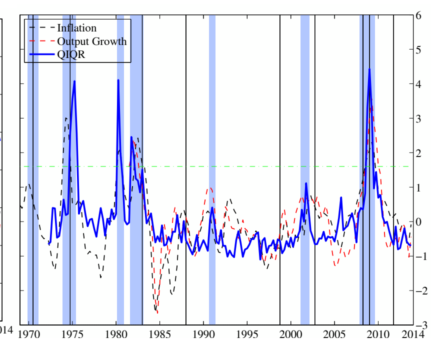
(a) ***EPU***



(b) ***CRSP***



(c) ***Profits***



(d) ***QIQR***

Note: Commonly used Uncertainty Indices Against the SCUs: This plot shows the inflation and output growth SCU estimates against various empirical uncertainty measures which are explained in figure A.5. All uncertainty measures are presented in standardized units and the horizontal (green) lines corresponds to 1.65 standard deviations above the unconditional mean of each series (which has been normalized to zero). The vertical lines correspond to the 9 heightened uncertainty episodes identified as dates in which VXO index exceeds 1.65 standard deviations above its hp-filtered mean in quarterly frequency (Bloom, 2009). Bloom (2009) identified 17 heightened uncertainty episodes in monthly frequency but some of these episodes are washed out in quarterly frequency. The shaded grey bars are recession quarters defined according to the NBER Business Cycle Dating Committee.

Table A.9: *Major Stock Market Volatility Shocks*

Monthly Frequency	
Max. Volatility Date	First Volatility Date
October 1962	October 1962
November 1963	November 1963
August 1966	August 1966
May 1970	May 1970
December 1973	December 1973
October 1974	September 1974
November 1978	Novermber 1978
March 1980	March 1980
October 1982	August 1982
November 1987	October 1987
October 1990	September 1990
November 1997	November 1997
September 1998	September 1998
September 2001	September 2001
September 2002	July 2002
February 2003	February 2003
October 2008	August 2007
September 2011	August 2011

Quarterly Frequency	
1966Q3	1966Q3
1970Q2	1970Q2
1974Q3	1974Q3
1982Q4	1982Q4
1987Q4	1987Q4
1998Q3	1998Q3
2002Q3	2002Q3
2008Q1	2008Q1
2008Q3	2008Q3
2011Q3	2011Q3

Note: Following Bloom (2009), the major uncertainty episodes are chosen as those with stock-market volatility more than 1.65 standard deviations above the hp-detrended ($\lambda = 129600$ for monthly and $\lambda = 1600$ for quarterly data) mean of the stock-market volatility series. Some of the spikes in stock market volatility are either 1 month/quarter episodes whereas others span more than 1 month/quarter. Quarterly VXO index is calculated by taking monthly averages. This smooths some volatility spikes that are visible in the monthly data, leaving less spikes in quarterly VXO series.

A.2.1 Decomposing VIX into Uncertainty and Risk Aversion

Following Bekaert, Hoerova, and Lo Duca (2013), one can decompose VIX index into two separate components: risk aversion and uncertainty. VIX index represents the option implied expected volatility on the S&P500 index with a horizon of 30 calendar (22 trading) days. This is an "implied" or "risk-neutral" volatility as opposed to the actual (or the "physical") volatility. The main difference between actual and the implied volatility is that the physical volatility would use the actual state probabilities to arrive at the physical expected volatility whereas the implied one would be adjusted for the price of risk. While VIX contains information about the the stock market uncertainty, it conceptually harbor information about the risk and risk aversion, i.e. Variance Premium, as well. Fortunately, Carr and Wu (2009) show that the time-varying variance premium satisfies equation 6.

$$\mathrm{VP}_t = \mathrm{VIX}^2 - \mathbb{E}_t\left(\mathrm{RV}_{t+1}^{22}\right) \tag{A.1}$$

where VIX is the VIX Index, VP is the variance premium[1], RV_{t+1}^{22} is the realized variance over the next month (22 trading days). In equation A.1, VIX index is observed (as it is a traded contract in the market) whereas the expected future realized variance ($\mathbb{E}_t\left(\mathrm{RV}_{t+1}^{22}\right)$) is not, so it should be estimated. I estimate it in three steps. First, I compute the current monthly realized variance by using squared 5-minute returns of the S&P500 index for the period January 3, 1994 - December 2013. Next, using daily data I project the future (1 month ahead) realized monthly variances onto a set of current instruments including the squared VIX, the dividend yield, real three-month T-Bill rate. Finally, I conduct a forecasting horserace between 8 different models[2] suggested by Bekaert, Hoerova, and Lo Duca (2013), and pick the model that gives the minimum root mean square error. The coefficient estimates of the winner model from this forecasting horserace are as follows:

$$\mathrm{RVAR}_t = \underset{(0.00037)}{0.00002} + \underset{(0.0618)}{0.3154}\,\mathrm{VIX}_{t-22}^2 + \underset{(0.1190)}{0.4753}\,\mathrm{RVAR}_{t-22} \tag{A.2}$$

[1] Similar to Bekaert, Hoerova, and Lo Duca (2013), I take the negative of variance premium so the estimated variance premium tends to increase with risk aversion.

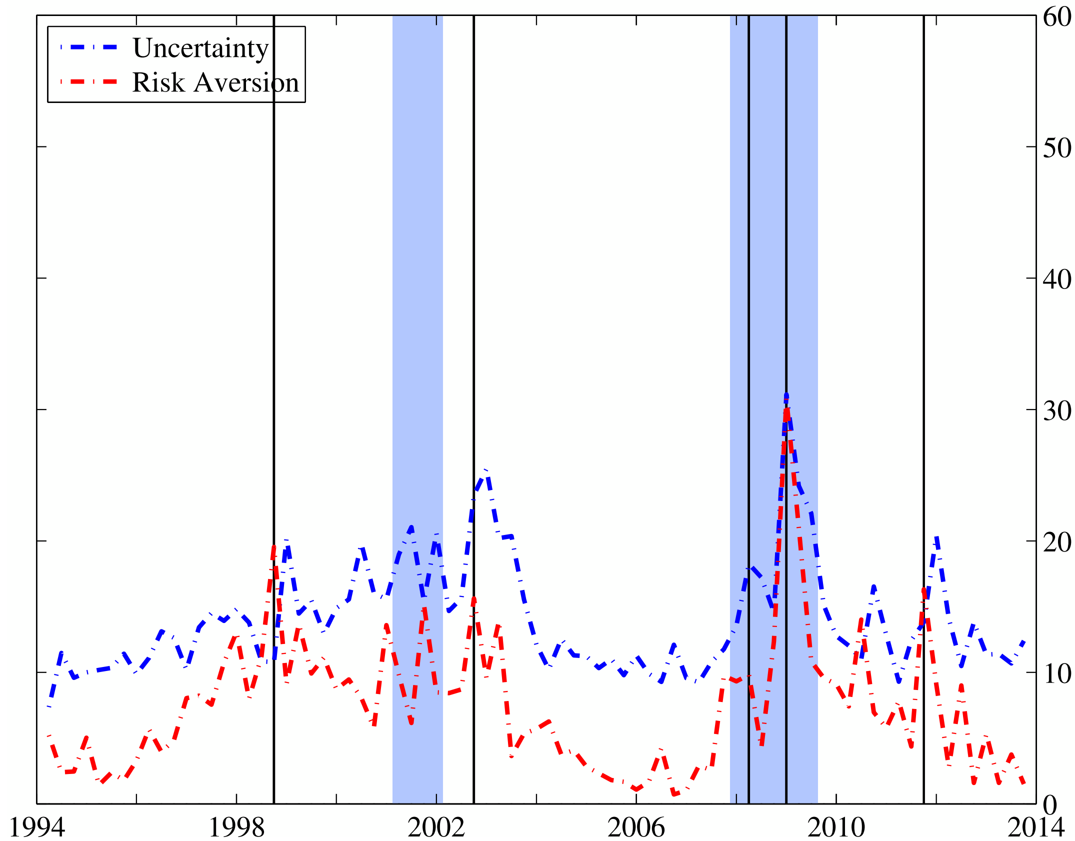
[2] These models are: one-variable model with either the past realized variance or the squared VIX; a two-variable model with both the squared VIX and the past realized variance; three-variable model either with the past dividend yield or the real three-month T-Bill rate; and a four-variable model adding the past real three month T-Bill rate; two models that do not require estimation, i.e. half-half weights on the past squared VIX and past realized variance or the past realized variance.

where RVAR is the monthly realized variance and the standard errors reported in parentheses are corrected for serial correlation using 30 Newey and West (1987) lags. The fitted values from equation A.2 is the estimated conditional variance measure of "uncertainty". Using equation 6, the difference between squared VIX and the conditional variance from above regression is the estimated measure of "risk aversion".

The quarterly averages of the square roots of resulting estimates are presented in figure A.7 along with four heightened uncertainty episodes (following Bloom (2009)) and US recessions that overlaps with the sample period. While the resulting uncertainty and risk aversion estimates have a 80 % correlation, their dynamics for some of the heightened uncertainty episodes are different from each other. According to table 1.4, on average, time-varying in risk aversion can explain 27% of the fluctuations of the VIX index. However, the explanatory power of time-varying risk aversion jumps to 50% during the height of the LTCM crisis in 1998Q2. Similarly, in the height of debt-ceiling crisis in US (July 2011, i.e. 2011Q3), there is a similar jump in the explanatory power of risk aversion. Notice that, both of these dates are identified as heightened uncertainty episodes by Bloom (2009). While it is possible to decompose VIX index into uncertainty and risk aversion for the whole sample period (1968Q4 - 2013Q3) in this paper[3], it seems risk aversion component of the VIX index is an important determinant particularly during heightened uncertainty episodes. Bekaert, Hoerova, and Lo Duca (2013) demonstrates that unlike the risk aversion, the uncertainty component of the VIX index is closely related to the business cycle fluctuations. However, the risk aversion component is strongly associated with the monetary policy or the stock market fluctuations, not with the business cycle dynamics. In that, identifying heightened uncertainty episodes by the VIX index can be misleading as during some of these episodes (i.e. the LTCM or the US debt-ceiling crises) the rise in the VIX index substantially explained by the rise in the risk aversion instead of the stock market uncertainty. Yet, this seems to be another reason for why VIX index is a noisy estimate of economic uncertainty.

[3]The data for VIX index published starting from 1990.

Figure A.7: ***Risk Aversion and Stock Market Uncertainty***



Note: This figure presents the decomposition of the squared VIX into two components (quarterly averages of monthly figures in percentage points): the square root of expected stock market variance (stock market uncertainty) and the residual, i.e. the square root of risk aversion proxy (the difference between the squared VIX and uncertainty from equation 6. The sample period is January1994 September 2013. The shaded blue bars are recessions defined according to the NBER Business Cycle Dating Committee and the vertical black lines are the identified uncertainty dates according to Bloom (2009).

Appendix B

Appendix for Chapter 2

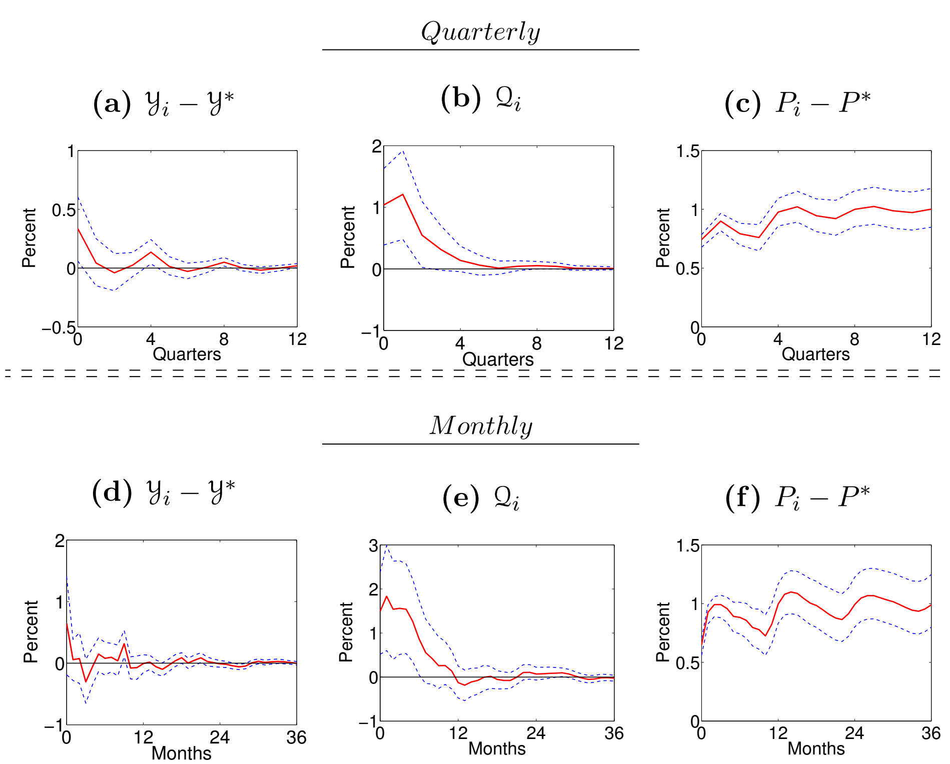
B.1 Aggregate Dynamics after Monetary Shocks

B.1.1 Aggregate Dynamics in *Empirical Model I* after Monetary Shocks

Here, we report our findings on aggregate dynamics in *Empirical Model I* after monetary shocks.

Aggregate dynamic responses are displayed in Figure B.1 over five years at the quarterly and monthly frequencies. It is evident from this figure that a higher monetary shock in developing economies, relative to one in the United States, is associated with a short-lived increase in the level of output in the former relative to that of the United States. It quickly falls again to the level of the undistorted path. Similarly, the real exchange rate exhibits a temporary upward movement after the shock, indicating a temporary depreciation in the real exchange rate against developing economies. At the quarterly (monthly) frequency, our results for *Empirical Model I* suggest that the real exchange rate stays depreciated relative to its undistorted path for about 6 quarters (12 months) after the shock. It can also be seen that the real exchange rate exhibits hump-shaped dynamics after the shock. These dynamics are also found by Clarida and Gali (1994) and Eichenbaum and Evans (1995) for the bilateral real exchange rates between the United States and other developed countries. Lastly, a positive monetary shock causes the price level in developing economies to rise relative to the price level in the United States on impact.

Figure B.1: *Impulse Responses to Monetary Shocks in Empirical Model I*



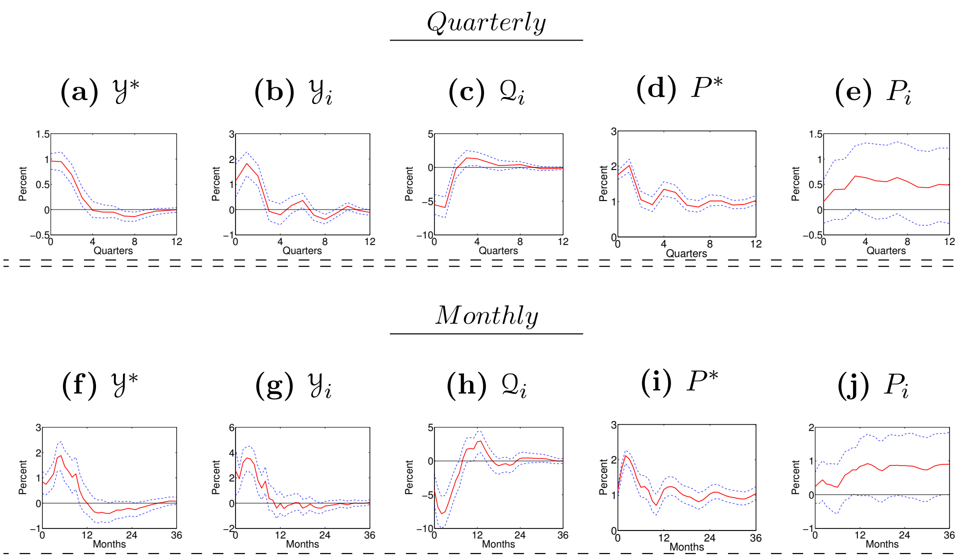
Note: Our calculations are based on the IMF's *International Finance Statistics*. The solid lines indicate the estimated point-wise impulse responses. The area between the dashed lines shows the 90% confidence interval estimated using the Bayesian method suggested by Sims and Zha (1999).

B.1.2 Aggregate Dynamics in *Empirical Model II* after Monetary Shocks in the United States

We have discussed aggregate dynamics after *an expansionary domestic monetary shock in developing countries* in *Empirical Model II* in Section 2.2.2. This section, on the other hand, discusses our findings on aggregate dynamics after *an expansionary monetary shock in the United States* in *Empirical Model II*. The results are presented in Figure B.2. Following a monetary shock in the United States:

- output in both developing economies and the United States stays above its undistorted level for about a year;

Figure B.2: *Impulse Responses to Monetary Shocks in the United States (Empirical Model II)*



Note: Our calculations are based on the IMF's *International Finance Statistics*. The solid lines indicate the estimated point-wise impulse responses. The area between the dashed lines shows the 90% confidence interval estimated using the Bayesian method suggested by Sims and Zha (1999).

- the real exchange rate appreciates on impact, and compared to the undistorted path, it stays appreciated for about 9 months; and,
- the price level in both developing economies and the United States contemporaneously rises.

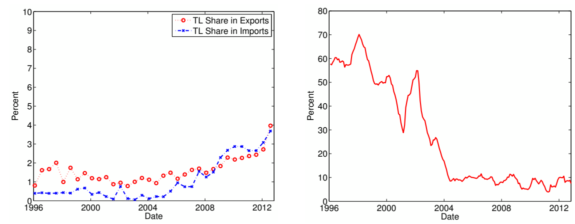
B.2 Calibration of Models' Parameters

Table B.1: *Calibration and Estimation*

Parameters	Description	Values	Source
θ_p	Price elasticity of demand for varieties within the same sector	11	Bresnahan (1981)
θ_w	Wage elasticity of labor demand	4	Huang and Liu (2002)
σ_c	Inverse of elasticity of inter-temporal substitution	5	Hall (1988)
σ_n	Inverse of Frisch-elasticity of labor supply	1	Carvalho and Nechio (2011)
σ_a	Inverse of the elasticity of capacity utilization with respect to the rental rate of capital	0.01	Christiano, Eichenbaum, and Evans (2005)
$\sigma_\phi = \frac{\phi'' \frac{\bar{I}}{\bar{K}}}{\phi'}$	The elasticity of the adjustment cost technology for investment with respect to $\frac{I_t}{K_t}$	-0.75	Devereux and Hnatkovska (2011)
$\Theta' \bar{Y}$	Elasticity of interest rate to net foreign assets	-0.01	Devereux and Smith (2005)
ρ	Elasticity of substitution between the home- and foreign-goods	1.5	Carvalho and Nechio (2011)
η	Elasticity of substitution between different sector-goods	1	Carvalho and Nechio (2011)
χ	Labor share in GDP	0.66	Christiano, Eichenbaum, and Evans (2005)
β	Discount factor	$1.03^{-\frac{1}{12}}$	Christiano, Eichenbaum, and Evans (2005)
α_k and α_k^*	Price-stickiness in sectors	See text	Carvalho and Nechio (2011)
f_k	Expenditure share of sectors	See text	Carvalho and Nechio (2011)
δ	Monthly rate of depreciation on capital	0.008	Christiano and Eichenbaum (1992)
ρ_z	The persistence in nominal spending growth shocks	0.32	See text
τ	Relative size of the foreign-country	1000	See text
s_c	% Share of final consumption expenditure in GDP	66	See text
s_i	% Share of investment in GDP	20	See text
$\omega_{\mathfrak{c}}$	Share of home-exports invoiced in the home-currency	0.05	See text
$\omega^*_{\mathfrak{c}^*}$	Share of home-imports priced in the foreign-currency	0.95	See text
ψ	Share of home-country imports in GDP	0.35	See text

Figure B.3: *Consumer Prices Inflation and the Turkish Lira Share in External Trade in Turkey*

(a) *TL Shares in External Trade* **(b)** *Consumer Prices Inflation*



Note: Our calculations are based on the Turkish Statistical Institute data. In Panel A, the dotted lines with circles and the dashed lines with multiplication signs indicate the share of TL-denominated exports in total Turkish exports and the share of TL-denominated imports in total Turkish imports, respectively.

B.2.1 Asymmetry in Currency Invoicing in International Trade between Developing and Advanced Economies

It is a well-known fact that there is an asymmetry between developing and advanced economies in regards to the currency in which exports and imports are denominated. Indeed, while exports and imports are largely denominated in *home currencies* in advanced economies, they are largely denominated in *foreign currencies* in developing economies. For example, in their study of pricing decision of the exports and imports in the United States, Gopinath and Rigobon (2008) report that 97% of exports and 90% of imports are priced in the United States dollar. To exemplify the pricing practices of exporters and importers in developing economies, we look at exports and imports by currency in Turkey. In Figure B.3, we illustrate the share of exports (imports) priced in the Turkish Lira(TL) in total exports (imports) as well as the inflation in consumer prices between 1996 and 2012. Inflation is measured as the percentage change in CPI over the last twelve months. It is notable that the remarkable success in bringing down inflation has produced only a modest rise in the shares of TL denominated exports and imports over the recent years. Indeed, the shares of TL-denominated exports and imports have stayed at very low levels below 5% during this period. Our conjecture is that this finding holds generally for all developing economies and currency invoicing in international trade happens largely with the foreign currencies in this group.

B.3 The One- and Multi-Sector Models' Dynamics with a Taylor-Type Rule

In this section, we analyze aggregate dynamics in the one- and multi-sector models without investment by considering a Taylor-type interest rate rule in the home- and foreign-country instead of considering exogenous nominal spending growth. In doing so, we assume that in addition to the international foreign bond (B_{t+1}), there is a domestic bond (D_{t+1}) which is traded only domestically, supplied in zero net supply and pays a gross nominal interest of R_t. The interest rates in the home-country (R_t) and in the foreign-country ($R^{B^*}_{\mathcal{F},t}$) are set according to the following rules:

$$\begin{gathered}\hat{R}_t = \phi_\pi \times \pi_t + \phi_y \times \hat{\mathcal{Y}}_t + \epsilon^r_t \\ \text{where } \epsilon^r_t = \rho_r \epsilon^r_{t-1} + \eta_t \text{ and } \eta_t \sim N(0, \sigma^2_\eta) \\ \hat{R}^B_{\mathcal{F},t} = 0.79 \times \hat{R}^B_{\mathcal{F},t-1} + (1\text{-}0.79) \times 2.15 \times \pi^*_t + (1\text{-}0.79) \times 0.93 \times \hat{\mathcal{Y}}^*_t + \epsilon^{r^*}_t \\ \text{where } \epsilon^{r^*}_t \sim N(0, \sigma^2_{\epsilon^{r*}})\end{gathered} \tag{B.1}$$

The coefficients for the foreign-interest rate rule reflect the estimates of the Taylor-rule coefficients in Clarida, Gali, and Gertler (1999) for the Volcker-Greenspan periods. The coefficients in the home interest-rate rule, on the other hand, have to be estimated since we do not have the estimates of the reaction function of the monetary authorities under inflation-targeting in developing economies. Two cases are considered when estimating the parameters. The first is that ε_t is a white-noise ($\rho_r = 0$). The second is that the shock to the home-interest rate can be persistent ($\rho_r > 0$). In the first case, the estimated vector of parameters ($\mathcal{P}$) consists of $\mathcal{P} = \begin{bmatrix} \phi_\pi & \phi_y \end{bmatrix}$. In the second case, it includes $\mathcal{P} = \begin{bmatrix} \phi_\pi & \phi_y & \rho_r \end{bmatrix}$. Let $f(\mathcal{P})$ denote the impulse response functions of the price level, output, the real exchange rate and the nominal exchange rate in developing economies for some $\mathcal{P}$ between the 0^{th} and 12^{th} months. We estimate $\mathcal{P}$ as the classical minimum distance estimator and denote it with $\hat{\mathcal{P}}(\hat{A}_n)$:

$$\hat{\mathcal{P}}(\hat{A}_n) = \arg\min_{\mathcal{P}} (\hat{h}_n - f(\mathcal{P}))' \hat{A}'_n \hat{A}_n (\hat{h}_n - f(\mathcal{P})) \tag{B.2}$$

where $\hat{A}_n$ is the weighting matrix used. $\hat{h}_n$ shows the impulse response functions of the price level, output, the nominal and real exchange rates in the actual economies between the 0^{th} and 12^{th} months. Lastly, n stands for the sample size of the data used to estimate the VAR-based impulse response functions. Since using different weighting matrices would yield different estimators, $\hat{\mathcal{P}}$ is

Table B.2: *Estimated Parameters of the Taylor Rule*

	Transitory Shocks		Persistent Shocks	
	One-Sector	*Multi-Sector*	*One-Sector*	*Multi-Sector*
ϕ_π	1.00*	1.00*	1.12 (0.004)	1.64 (0.002)
ϕ_y	0.24 (0.14)	2.00*	0.15 (0.035)	1.52 (0.990)
ρ_r	0	0	0.61 (0.006)	0.79 (0.004)
Obj. Func.	619.36	1986.26	78.80	65.41

Note: The numbers in parentheses denote estimated model-based standard errors. The numbers with an asterisk indicate that standard-errors are not reported since the estimates of the parameters are close to either its lower-bound or its upper-bound as discussed in Footnote 1. Obj. Func. indicates the value of the objective specified in (B.2).

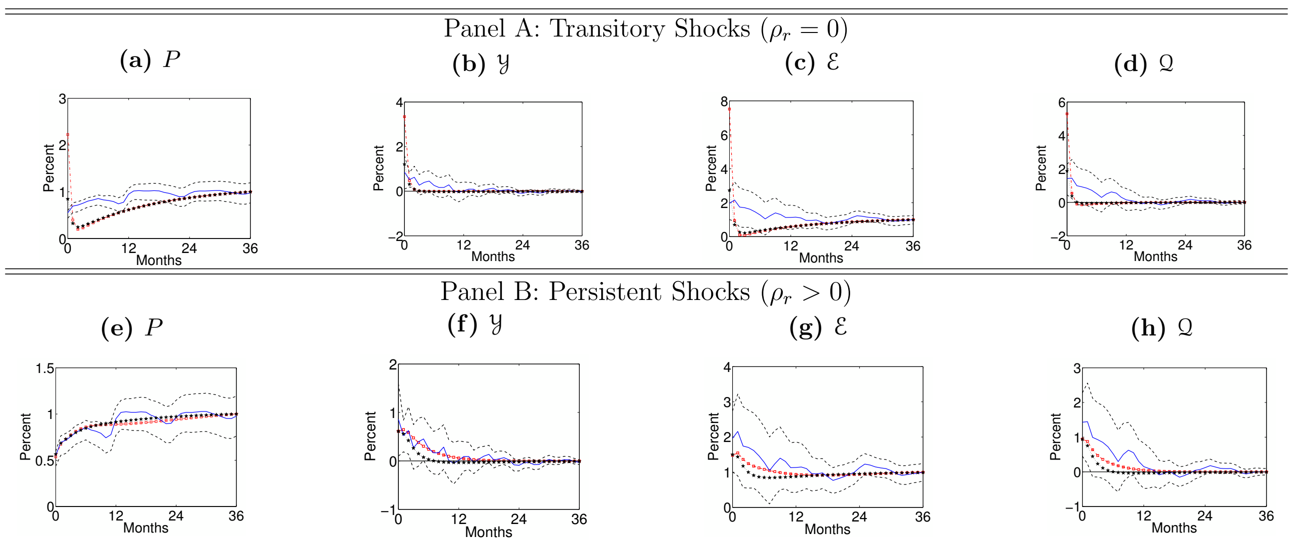
written as a function of $\hat{A}_n$. As a weighting matrix, we choose the widely-used diagonal matrix whose diagonal elements are given as the inverse of standard deviations of empirical impulse responses.(See, for example, Christiano, Eichenbaum, and Evans (2005) and Giannoni and Woodford (2003)). This weighting matrix ensures more precisely estimated impulse response functions are given more importance than the less precisely estimated ones.[1]

Table B.2 shows the estimated parameters of the Taylor rule specified in B.1. Allowing persistence in the shocks to the interest rate in the home-country significantly improves both the one- and multi-sector models' performance as it leads to a sharp fall in the weighted distance between the model- and VAR-based impulse response functions (See Obj. Func. in the table). Figure B.4 visualizes this. In Panel A of this figure, the impulse response functions of the aggregate variables to an expansionary white-noise shock to the home-interest rate rule in (B.1) are illustrated. Both the one- and multi-sector models are incapable of explaining the aggregate dynamics when shocks to the interest rate in the home-country are transitory.

[1] To do the estimation, the lower and upper bounds for the parameters have to be entered in the computer program. For the parameters $\begin{bmatrix} \phi_\pi & \phi_y & \rho_r \end{bmatrix}$, we set the lower and upper bounds as [1.00,2.14], [0,2.00],[0,0.99], respectively.

Next, we consider that the shocks to the interest-rate in the home-country are persistent. Panel B of Figure B.4 shows the model- and VAR-based impulse response functions with a persistent interest-rate rule. It is clear from this figure that with such a high persistence in the shocks, the dynamics of the price level, output and the nominal and real exchange rates after the monetary shock in both the one- and multi-sector models align quite well with those found in the data. While the model-based impulse-response functions in both the former and the latter stay within the 90% confidence intervals for the panel VAR-based impulse response functions, it is evident that the latter is more successful than the former in explaining the movements of output, the real and nominal exchange rates in the actual economies following the monetary shock.

Figure B.4: *One- and Multi-Sector Models with a Taylor-Type Rule*



Note: Our calculations are based on the IMF's *International Finance Statistics*. The dotted lines with pentagrams and the dashed lines with squares indicate the model-based impulse response functions in the one- and multi-sector models, respectively. The solid lines show the estimated point-wise panel-VAR-based impulse response functions. The area between the dotted lines shows the 90% confidence interval estimated with the method suggested by Sims and Zha (1999).

Curriculum Vitae

Emek Karaca received his B.Sc and M.Sc degrees in Economics from the Middle East Technical University, Turkey in 2004 and 2008, respectively. He also worked as a Research Economist in the Research and Monetary Policy Department at Central Bank of Turkey between 2005-2009. He later received the Ph.D. Fellowship from the Central Bank of Turkey and started the Ph.D program in Economics at Johns Hopkins University. His research interests lie in the field of empirical macroeconomics with a special focus on macroeconomic uncertainty, identification of monetary policy shocks, and evaluation of the forecasting records of options-implied crude oil pdfs. While he mostly utilizes applied time series methods in his research, he is also interested in understanding the mechanisms implied by the empirical results by means of applied economic theory.

Starting June 2015, he'll work at JP Morgan and Chase as a Modeling and Analytics Associate.