ARTICLE IN PRESS

Journal of International Money and Finance xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Journal of International Money and Finance

journal homepage: www.elsevier.com/locate/jimf

Measuring global and country-specific uncertainty

Ezgi O. Ozturk [a], Xuguang Simon Sheng [b,*]

[a] International Monetary Fund, USA
[b] American University, USA

ARTICLE INFO

Article history:
Available online xxxx

JEL classification:
E24
E32

Keywords:
Capital asset pricing model
Common uncertainty
Consensus forecasts
Idiosyncratic uncertainty
Global uncertainty
Survey forecast

ABSTRACT

Motivated by the literature on the capital asset pricing model, we decompose the uncertainty of a typical forecaster into common and idiosyncratic uncertainty. Using individual survey data from the *Consensus Forecasts* over the period of 1989–2014, we develop monthly measures of macroeconomic uncertainty covering 45 countries and construct a measure of global uncertainty as the weighted average of country-specific uncertainties. Our measure captures perceived uncertainty of market participants and derives from two components that are shown to exhibit strikingly different behavior. Common uncertainty shocks produce the large and persistent negative response in real economic activity, whereas the contributions of idiosyncratic uncertainty shocks are negligible.

1. Introduction

Heightened economic uncertainty, at both national and global levels, greatly contributed to the 2007–09 recession and shaped the speed of the subsequent recovery. Eight years after the end of the recession, there is still no sign of a complete global recovery. Advanced economies are uncertain about the effects of monetary policy normalization and emerging market economies are uncertain about the growth challenges ahead. Surrounded with unprecedentedly high uncertainty, economists face great challenges in understanding the origins of economic uncertainty and analyzing its causal impacts on real economy, e.g. Stock and Watson (2012).

Since there is no objective measure of uncertainty, economists have used numerous different proxies. A ubiquitous proxy is the implied or realized volatility in stock markets, such as VIX, e.g. Bloom (2009). However, the volatility in Wall Street might not reflect uncertainty in Main Street. For instance, changes in the VIX might be due to leverage or financial stress, despite low levels of economic uncertainty; see Bekaert et al. (2013). Jurado et al. (2015) develop an alternative measure of economic uncertainty: the common variation in uncertainty across hundreds of economic series. Their measure reflects uncertainty around objective statistical forecasts, rather than perceived uncertainty by market participants. Moreover, as they focus on common, not idiosyncratic, uncertainty, there is no role for private information and heterogeneous agent models. A third leading proxy is based on the frequency of references to policy-related uncertainty in the newspapers, e.g. Baker et al. (2016). But, like all measurements of this type, this news-based uncertainty measure puts a high bar for the attentiveness of reporters and editors, who might miss uncertainty events if they neglect to write a story on the subject. The fourth

* Corresponding author at: Department of Economics, American University, 4400 Massachusetts Avenue NW, Washington, DC 20016, USA.
E-mail address: sheng@american.edu (X.S. Sheng).

http://dx.doi.org/10.1016/j.jimonfin.2017.07.014

proxy for uncertainty is cross-sectional disagreement of economic agents, calculated as the dispersion in directional or point forecasts, e.g. Bachmann et al. (2013). When disagreement is taken to indicate uncertainty, the underlying assumption is that this inter-personal dispersion measure is an acceptable proxy for the average dispersion of intra-personal uncertainty. As shown by Lahiri and Sheng (2010), however, disagreement is only a part of uncertainty and misses an important component: the volatility of aggregate shocks.

To address some of the limitations in the existing measures, we develop a comprehensive measure of economic uncertainty by incorporating rich information reflected in the surveys of professional forecasters. Similar to Jo and Sekkel (2015), Rossi and Sekhposyan (2015) and Scotti (2016), our measure is based on subjective forecasts of market participants and reflects their perceived uncertainty. In contrast to these three papers, our uncertainty measure includes two components: common uncertainty as emphasized in Jurado et al. (2015) and idiosyncratic uncertainty as documented in the macroeconomics literature. Our decomposition of uncertainty of a typical forecaster into common and idiosyncratic parts is similar to Campbell et al. (2001) that decompose the volatility of a typical stock into market and firm-level volatility. We estimate the common component as the perceived variability of future aggregate shocks and idiosyncratic component as the disagreement among professional forecasters across three different layers. First, we estimate the variable-specific uncertainty for eight nominal and real economic indicators. Second, we measure the country-specific uncertainty as the weighted average of standardized components of variable-specific uncertainty measures. Finally, we propose an index of global uncertainty, which is a rather new concept in the literature.[1] Constructed from a large set of countries, corresponding to more than 90 percent of the world economy, this global measure is more comprehensive than the previously proposed measures, e.g. Berger and Herz (2014).

Our main findings are summarized as follows. All uncertainty measures are countercyclical and at all layers, combined uncertainty is more countercyclical than its common or idiosyncratic component. A comparison of our country-specific uncertainty measures with alternative leading measures from the literature for a subset of countries shows that our measures have fewer peaks, all around the recessions, and have persistent and heightened uncertainty during the recession episodes. Shocks to our measures of uncertainty are associated with large and persistent drops in real activity at both national and global levels. Further investigation shows that common uncertainty shocks produce large and persistent responses in real activity, whereas the contributions of idiosyncratic uncertainty shocks are negligible.

The rest of the paper is organized as follows. Section 2 details the methodology on measuring uncertainty. Section 3 introduces the data used in this paper. Section 4 describes the properties of economic uncertainty measures. Section 5 presents the dynamic relationship between uncertainty and economic activity and Section 6 concludes. The online appendix includes detailed information on the dataset, alternative measures of country-specific uncertainty using principal component analysis and regional measures of uncertainty.

2. Methodology: estimating uncertainty

2.1. Uncertainty decomposition

Our decomposition of the uncertainty of a typical forecaster is motivated by the literature on the capital asset pricing model (CAPM) that decomposes the return volatility of a typical stock into market volatility and firm-specific volatility. We start off by presenting the traditional CAPM decomposition that requires estimation of firm-specific betas and then move to the approach in Campbell et al. (2001) that does not require any information about individual betas on the aggregate level.

Let e_{it} be individual i's forecast error at time t. Then, consensus forecast error, e_t, is defined as the weighted average of individual forecast errors:

$$e_t = \sum_{i=1}^{N} w_{it} e_{it}, \tag{1}$$

where w_{it} is the weight of individual forecast error in consensus forecast error. Parallel to the CAPM literature that connects firm-specific return to market return, we specify the relationship between individual and consensus forecast errors as follows

$$e_{it} = \beta_i e_t + \varepsilon_{it}, \tag{2}$$

where β_i measures individual i's tendency to respond to common shocks, as proxied by consensus forecast error e_t. Beta is important since it captures the risk arising from exposure to general economic conditions as opposed to idiosyncratic factors. The β_i below 1 indicates that an individual forecast error is not highly correlated with consensus forecast error. In Eq. (2), ε_{it} is orthogonal by construction to e_t. Eqs. (1) and (2) together impose the following restriction $\sum_{i=1}^{N} w_{it}\beta_i = 1$, which is the standard assumption in the CAPM literature that the weighted sums of the different betas equal unity. Eq. (2) permits a simple variance decomposition in which the covariance term is zero:

$$Var(e_{it}) = \beta_i^2 Var(e_t) + Var(\varepsilon_{it}). \tag{3}$$

[1] Our data are available at monthly frequencies on http://www.american.edu/cas/faculty/sheng.cfm.