Surprise and Uncertainty Indexes: Real-time Aggregation of Real-Activity Macro Surprises

Chiara Scotti*

Federal Reserve Board

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Abstract

I construct two real-time, real activity indexes: (i) a surprise index that summarizes recent economic data surprises and measures deviation from consensus expectations, and (ii) an uncertainty index that measures uncertainty related to the state of the economy. The indexes, on a given day, are weighted averages of the surprises or squared surprises from a set of macro releases, where the weights depend on the contribution of the associated real activity indicator to a business condition index a la Aruoba, Diebold, and Scotti (2009). I apply this methodology to construct indexes for the United States, Euro Area, the United Kingdom, Canada, Japan, and the aggregate of the five countries. I show various applications for those indexes: measuring the impact of news surprises on FX, computing the response of employment to uncertainty shocks, and disentangling the part of implied volatility, as measured by the VIX, due to economic uncertainty.

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1 Introduction

This paper proposes a new methodology to construct two real-time, real activity indexes: (i) a surprise index that summarizes recent economic data surprises and measures deviation from consensus expectations and (ii) an uncertainty index that measures uncertainty related to the state of the economy. The indexes, on a given day, are weighted averages of the surprises or squared surprises from a set of releases, where the weights depend on the contribution of the associated real activity indicator to a business condition index *a la* Aruoba, Diebold, and Scotti (2009). The surprise index measures whether agents are more optimistic or pessimist about the real economy than indicated by actual data releases. A positive (negative) reading of the surprise index suggests that economic releases have on balance been higher (lower) than consensus, meaning that agents were more pessimistic (optimistic) about the economy. The uncertainty index measures how uncertain agents are about current real activity conditions. A greater (smaller) reading of the uncertainty index suggests that agents have on balance been more (less) uncertain about the state of the economy. I apply this methodology to construct surprise indexes for the United States, Euro Area, the United Kingdom, Canada, Japan, and an aggregate if the five countries.

The Aruoba, Diebold, and Scotti (ADS) index maintained by the Federal Reserve Bank of Philadelphia has proven to be a successful economic indicator and as such it has been classified by the Wall Street Journal among the 50 economic indicators that really matter (Constable and Wright, 2011) and has been added by Bloomberg to the data that can be followed in real time through its platform (ADS BCI Index).[1] However, the ADS index measures the state of the economy, and financial markets are interested in more than that. For example, asset prices reacts to the surprise component of macroeconomic announcements rather than the announcement itself. Similarly, economic uncertainty can have a big impact on growth because it causes firms to temporarily pause their investments and hiring, and consequently uncertainty can also have an effect on financial market prices. To this end, the surprise index presented in this paper aggregates the information contained in the surprises to construct a summary measure of the deviation of the real economy from consensus expectations, and the uncertainty index quantifies economic uncertainty, which is otherwise challenging to measure. The indexes are not competitors but complements to the existing business condition indicators such as the ADS index.

I use a dynamic factor model to construct monthly business condition indexes for the aforementioned countries and compute the weights representing the contribution of the economic indicators to these business condition indexes. I then use those weights to average the surprises or squared surprises in order to construct the surprise and the uncertainty indexes. The weights

[1] http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index/

depend on (i) the time elapsed since the release of the associated information and (ii) the unbalancedness pattern of the underlying releases. The former is a time decay feature that reduces the contribution of each surprise over time. The latter is a missing data characteristic that sets to zero the contributions of an indicator in months in which no data is available.

This paper relates to several branches of the literature. First, it relates to those papers which use similar factors models to extract a business condition index or to nowcast GDP such as Aruoba, Diebold, and Scotti (2009), Banbura, Giannone, and Reichlin (2010), and the seminal Stock and Watson paper (1989). Second, this paper employs the idea of forecasting weights developed in Koopman and Harvey (2003) and applied by Banbura and Rünstler (2010) and Camacho and Perez-Quiros (2010), among others, to study the impact of news releases on GDP forecast revisions. Third, it relates to the branch of literature that studies the impact of news surprises on asset price such as Andersen, Bollerslev, Diebold and Vega (2003, 2007), and Gilbert, Scotti, Strasser and Vega (2012). Finally, this work also relates to Bloom's work and its uncertainty measures (see Bloom 2009, and Bloom and Fernandez-Villaverde 2012).

Interestingly, the surprise index constructed in the paper also relates to instruments that are used in the financial markets community. In fact, Citigroup provides the so-called "Citigroup Economic Surprise Indexes" which are also a quantitative measure of economic surprises. These indexes are defined as weighted historical standard deviations of data surprises where the weights of economic indicators are derived from the impact that these data surprises have on foreign exchange markets. As such, my index has the advantage that it is more objective in that its weights do not depend on the surprise impact on asset prices and could therefore potentially be used in applications where there is a desire to control for the effect of macroeconomic surprises on asset prices. Macroeconomic uncertainty has been traditionally measured using stock return volatility, news mention of uncertainty, forecast disagreement, and economic policy uncertainty (Baker, Bloom and Davis 2012). However, these measures tend to combine economic uncertainty with other notions. For example, stock return volatility combines information about stock market volatility with economic uncertainty and forecast disagreement measures divergence of opinions among forecasters rather than just the underlying uncertainty about the economy. My uncertainty measure is instead a cleaner measure of the uncertainty regarding the current state of the economy.

The results are interesting. The surprise indexes tend to be negative during the recession associated with the 2008 financial crisis, suggesting that agents were probably too optimistic about the real economy than it turned out to be the case. Unfortunately, we are not able to see whether this is a characteristic of all recessions because the surprise indexes only start in 2003 and hence only cover one recession episode. There appear to be other episodes when the indexes were negative. Of note are the most recent decline in the euro-area surprise index, the sharp drop in the Japanese surprise index after the March 2011 earthquake, and the prolonged low

levels of the U.K. index in 2010 and 2011. On the other hand, there are also several instances where the surprise indexes are positive, especially coming out of the recession in the United States, the United Kingdom and Canada.

The uncertainty indexes tend to be higher during recession periods. Interestingly, the euro-area uncertainty index reaches its highest values just before and after the 2008-2009 recession, suggesting that agents were more uncertain about the economy as the euro-zone was entering and exiting the recession.

Two by-products of the paper are the construction of monthly business condition indexes in real time for the five countries and the analysis of the forecasting weights used to average the surprises in order to construct the surprise indexes. The forecasting weights show the relative importance of the macroeconomic indicators in understanding the state of the economy. Industrial production and employment/unemployment are the most important indicators across countries and over time. However, survey indicators such as the euro-area flash purchasing managers index (PMI) and the Japanese Tankan survey gain momentum when no other information for the current month or quarter is released.

The remainder of the paper is organized as follows: section 2 presents the details of the dynamic factor model, the forecasting weights and the construction of the surprise and uncertainty indexes; section 3 presents the data; section 4 covers the estimation details; section 5 presents the results; section 6 shows a couple of simple applications; and section 7 concludes.

2 The Model

I use a standard dynamic factor model at monthly frequency which explicitly accounts for missing data and temporal aggregation.

2.1 The Dynamic Factor Model

I model the unobserved factor as a VAR process of order p:

$$x_{t+1} = \Lambda x_t + \eta_t, \tag{1}$$

$$\eta_t \sim i.i.d.N(0, \sigma_\eta). \tag{2}$$

The model includes both monthly and quarterly variables. The monthly variables y_t^M follow a single factor model representation of the type:

$$y_t^M = \mu^M + Z^M x_t + \varepsilon_t^M \tag{3}$$

$$\varepsilon_t^M = \alpha \varepsilon_{t-1}^M + e_t^M \tag{4}$$

where x_t represents the underlying real activity factor, ε_t is a vector of idiosyncratic components, and Z^M represent the factor loadings for the monthly variables. ε_t follows an $AR(1)$ process, as shown in equation (4), and $e_t^M \sim i.i.d.N(0, \Sigma_e^M)$.

The quarterly variables y_t^Q follow a similar factor model representation:

$$y_t^Q = \mu^Q + Z^Q x_t + \varepsilon_t^Q \tag{5}$$
$$\varepsilon_t^Q = \rho \varepsilon_{t-1}^Q + e_t^Q \tag{6}$$

with $e_t^Q \sim i.i.d.N(0, \Sigma_e^Q)$. Quarterly variables in the model are GDPs for all countries and the Japanese Tankan survey. I follow Mariano and Murasawa (2003) in the way I incorporate quarterly GDP into the monthly factor model. GDP is a level series in my dataset. I define $Y_t^Q = 100 \log(GDP)$, then

$$y_t^Q = \begin{cases} Y_t^Q - Y_{t-3}^Q & \text{if } t = 3, 6, 9, 12 \\ NA & \text{otherwise,} \end{cases} \tag{7}$$

and using the Mariano and Murasawa (2003) approximation I get that for $t = 3, 6, 9, 12$

$$Y_t^Q - Y_{t-3}^Q \approx (Y_t^M + Y_{t-1}^M + Y_{t-2}^M) - (Y_{t-3}^M + Y_{t-4}^M + Y_{t-5}^M) = y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4}. \tag{8}$$

Based on this I can link the quarterly variables to the monthly factor as

$$\begin{aligned} y_t^Q = \; & \mu^Q + Z_t^Q x_t + 2Z_t^Q x_{t-1} + 3Z_t^Q x_{t-2} + 2Z_t^Q x_{t-3} + Z_t^Q x_{t-4} \\ & + \varepsilon_t^Q + 2\varepsilon_{t-1}^Q + 3\varepsilon_{t-2}^Q + 2\varepsilon_{t-3}^Q + \varepsilon_{t-4}^Q \end{aligned} \tag{9}$$

A similar treatment can be applied to any other quarterly series in the dataset.[2]

Stacking monthly and quarterly variables, this model can be easily cast in a state space representation:[3]

$$y_t = \mu + Z\alpha_t \tag{10}$$
$$\alpha_t = T\alpha_{t-1} + u_t, \qquad u_t \sim i.i.d.N(0, \Sigma) \tag{11}$$

where $y_t = (y_t^M, y_t^Q)'$, $\mu = (\mu^M, \mu^Q)'$ and the state vector includes both the common factor and the idiosyncratic components:

[2]The other quarterly series in the dataset is the Japanese Tankan survey. Because it is an index, I do not compute the *log* difference (growth rate) as for GDP. By defining $Y_t^Q = Tankan_t$ and $y_t^Q = Y_t^Q - Y_{t-3}^Q = Tankan_t - Tankan_{t-3}$, the same argument goes through and equation (8) holds exactly.

[3]Details about the state space representation can be found in the appendix.

$$\alpha_t = \left(x_t, x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, \varepsilon_t^M, \varepsilon_t^Q, \varepsilon_{t-1}^Q, \varepsilon_{t-2}^Q, \varepsilon_{t-3}^Q, \varepsilon_{t-4}^Q\right)' \tag{12}$$

We define the total number of indicators as n^{MQ}. Interestingly, the model could be extended to a multiple factor model.

2.2 Forecast Weights

With the dynamic factor model approach described above, each of the real activity variables is used to extract information about the common (unobserved) factor. The contribution of each series to the determination of the factor represents the weight applied to construct the surprise index. As shown in Koopman and Harvey (2003), the weights $w_j(a_{t|t})$ are used to calculate the estimator of the state vector based on information available as of time t and can therefore be used to compute the contribution of variable y_j^i in forecasting the factor x at time t:

$$x_{t|t} = \sum_{j=1}^{t-1} w_j(x_{t|t}) y_j. \tag{13}$$

As in the previous section, y_t can contain vectors of monthly or quarterly series (y_t^M, y_t^Q). Each series is indicated by y^i.

I consider the real-time release schedule of each real activity series y^i. For example, if I want to calculate the factor for the month of January 2012, information about that month will be released gradually. For example, if we consider the case of the United States, the ISM index will be the first series to be released, most likely followed by employment, retail sales, industrial production, and personal income. The advance reading of GDP for the first quarter (i.e., the one which includes January) will be released with an average delay of 29 days from the end of the quarter. Based on this real-time schedule I can recursively compute the underlying unobserved factor at time t based on the data availability until day t, that is $x_{t|t}$. Equation (13) displays the factor at time t as a weighted average of the data y released between day 1 and t. The weights implicitly display a time decay feature with more recent data exhibiting higher importance in determining the factor.

For each data series included in y, say y^i, there exist a time series of weights w_j^i, so that cumulative forecast weights can be computed as in Banbura and Rünstler (2010)

$$w_{cum}^i = \sum_{j=1}^{t} w_j^i. \tag{14}$$

Interestingly, forecast weights do not depend on time t, but depend on the forecast horizon and

the real-time release pattern of the data.

In this paper, I abstract from data revisions as my index wants to represent over/under optimism of the first data announcements.

2.3 The Surprise Index

Financial markets are particularly attentive every time new data are released. As already mentioned, market participants are generally interested in how a certain data release compares with market expectation for that particular announcement. Asset prices efficiently incorporate news as they become available. The expected value of a data release, $E[y^i|\mathcal{F}_t]$ has already been incorporated into prices at time t. What moves markets is the surprise component, that is

$$s_t^i = y_t^i - E[y_t^i|\mathcal{F}_t] \tag{15}$$

where $\mathcal{F}_t$ is the available information set as of time t. Hence the interest in developing a surprise index that summarizes information about announcement surprises.

I construct the surprise index based on equation (13). With the idea that forecast weights represent the importance of the series in determining the underlying unobservable factor, I use those same weights to combine the standardized surprises so that the surprise index $\mathcal{S}$ at time t is:

$$\mathcal{S}_t = \sum_{j=1}^{t} w_j s_j \tag{16}$$

where $s_j = (s_t^M, s_t^Q)'$ contains the vectors of the standardized surprise s^i corresponding to each data series y^i. In the application, I construct the underlying series that feed into the factor so that a higher (lower) number means that the economy is doing better (worse). Likewise, I construct each surprise such that a positive surprise means good (bad) news for the economy. This implies that the weights should be positive.

2.4 The Uncertainty Index

The uncertainty index is computed by averaging squared surprises

$$\mathcal{U}_t = \sqrt{\sum_{j=1}^{t} w_j s_j^2}. \tag{17}$$

The link with realized volatility is straightforward. Just like realized volatility is computed as the square root of the average of squared returns, $vol = \sqrt{\frac{1}{n}\sum_{i=1}^{n} return_i^2}$, the uncertainty index

is computed as the square root of the weighted average of the squared surprises.[4] The weights are not simply $1/n$ but are time varying. Moreover, unlike the volatility which is computed on one instrument at a time using the history from $t = 1, \ldots, n$, the uncertainty index is computed across different instruments/surprises as well as across time.

3 Data

Our analysis for the news surprise index and the uncertainty index covers the period from May 15, 2003 through June 15, 2012. However, a longer dataset is used to estimate the underlying business condition indexes: January 1980 to June 15, 2012, except for the Euro area where the sample starts on January 1985. Five countries are analyzed: the United States, the Euro Area, the United Kingdom, Canada, and Japan. I use five indicators for each country, except the United States for which I use six. Several considerations guide our choice of variables. First, I want to use the variables that are regarded as the main real activity indicators and as such followed by the business community, governments, and central banks as indication of the state of the economy. Second, I choose indicators for which analysts form expectations that are publicly available. This allows us to be able to compute surprises as defined in equation (15).

Table 1 lists the indicators, together with their frequency, publication lags and transformations that I use to construct the real activity factor. The two rightmost columns list the source of the data series that I use to construct the factor and the corresponding Bloomberg data series that I use to construct the surprise index.

The first indicator is quarterly real gross domestic product (GDP). For each country, the first GDP release for the corresponding quarter is used. The second indicator is industrial production (IP), which is a monthly indicator. The third indicator is employees on nonagricultural payrolls, when available, or the unemployment rate.[5] The former tends to be more timely than the latter, but unfortunately it is not available for all countries. To avoid confusion, because for all the indicators a higher number means that the economy is doing good, I feed the negative of the unemployment rate into the model. The fourth indicator is retail sales, which is another monthly variable. The fifth indicator is a survey measure of the manufacturing sector or the overall economy (composite) depending on the availability of the Bloomberg consensus. I use theISM manufacturing index the United States, the composite PMI for the euro area, the manufacturing PMI for the United Kingdom and Canada (Ivey survey), and the Tankan survey for Japan.

[4] Realized volatility is more precisely defined as $vol = \sqrt{\frac{1}{n}\sum return_i^2 - \left(\frac{1}{n}\sum return_i\right)^2}$ but because the second term, the average return, tends to be zero it is frequently dropped. Similarly, we abstract from using the second term, $\left(\sum_{j=1}^{t} w_j s_j\right)^2$ in the definition of the uncertainty index. In practice, this term is very close to zero.

[5] Employment data and expectations are available only for the United States and Canada. For the other countries we use the unemployment rate.

Table 1: Summary information of the real activity indicators used in the paper to construct the surprise index for the United States, Euro Area, United Kingdom, Canada, and Japan

Country	Series Name	Description	Frequency	Publication Lag(days)	Transformation for factor	Source	Bloomberg Mnemonic
United States	GDP	Real GDP, level	Q	29	log diff	BEA	GDP CQOQ
	IP	Index, level	M	16	log diff	FRB	IP CHNG
	Employment	Level	M	5	log diff	BLS	USURTOT
	Retail Sales	Level	M	13	log diff	ISM	RSTAMOM
	ISM Manufacturing	Index	M	2	diff	ISM	NAPMPMI
	Personal Income	level	M	29	log diff	BEA	PITLCHNG
Euro Area	GDP	Real GDP, level	Q	48	log diff	EUROSTAT	EUGNEMUQ
	IP	Index, level	M	46	log diff	EUROSTAT	EUITEMUM
	Unemployment rate	Level, percent	M	32	log diff	EUROSTAT	UMRTEMU
	Retail Sales	Level	M	41	log diff	EUROSTAT	RSSAEMUM
	PMI Composite (Flash)	Index	M	-9	diff	Markit	ECPMICOU
United Kingdom	GDP	Real GDP, level	Q	24	log diff	UK ONS	UKGRABIQ
	IP	Index, level	M	38	log diff	UK ONS	UKIPIMOM
	Unemployment rate	Level, percent	M	15	log diff	UK ONS	UKUER
	Retail Sales	Level	M	20	log diff	UK ONS	UKRVAMOM
	PMI Manufacturing	Index	M	2	diff	Markit	PMITMUK
Canada	GDP	Real GDP, level	Q	61	log diff	STCA	CGE9ANN
	IP (monthly GDP)	Index, level	M	60	log diff	STCA	CAIPMOM
	Employment	Level	M	7	log diff	STCA	CANLNETJ
	Retail Sales	Level	M	52	log diff	STCA	CARSCHNG
	Ivey PMI	Index	M	6	diff	PMAC	IVEY
Japan	GDP	Real GDP, level	Q	46	log diff	ESRI	JGDPAGDP
	IP	Index, level	M	28	log diff	METI	JNIPMOM
	Unemployment rate	Level, percent	M	28	log diff	MIC	JNUE
	Retail Sales	Level	M	27	log diff	METI	JNRETMOM
	Tankan Survey	Index	Q	-4	diff	BoJ	JNTSMFG

The Tankan survey is a quarterly series, whereas the other surveys are all monthly series.[6] Although monthly series are generally preferred when available, the Tankan survey has the advantage of being very timely, as it is released on average four days before the end of the quarter it refers to. The average publication lag for the other series vary a lot as shown in table 1. Survey measures are the most timely of all: the euro-area Flash composite PMI is the first indicator to be released, followed by the Japanese Tankan survey, the U.S. ISM and the U.K. PMI.[7] On the other hand, GDP and IP data tend to be the last information to be released in every country.

The additional indicator for the United States is the BEA personal income. Although household income or personal income are generally available for the other countries, given that their expectation is not, I drop them from the dataset.

Announcement surprises are computed as the difference between announcement realizations (y_t^i) and their corresponding Bloomberg expectations ($E[y_t^i|\mathcal{F}_t]$). Because units of measurement vary across macroeconomic variables, I standardize the resulting surprises by dividing each of them by their sample standard deviation (σ^j). The standardized news surprise associated with the macroeconomic indicator y^j at time t is therefore computed as:

$$s_t^i = \frac{y_t^i - E[y_t^i|\mathcal{F}_t]}{\sigma^j}. \tag{18}$$

4 Estimation

The construction of the indexes requires three steps:

(i) estimation of the state space model of equations (10) and (11),

(ii) determination of the weights $w_j(\alpha_{t|t-1})$ as defined in equation (13) and

(iii) construction of the indexes as for equations (16) and (17).

For step (i), the estimation of the model in equations (10) and (11) requires estimation of the parameters $\theta = \{\mu, Z, T, \Sigma\}$. The missing data pattern complicates the estimation of the model. Missing data occur both because the data are at different frequencies and because indicators are released at different times after the end of the reference period (ragged edge). A number of papers have dealt with different frequencies and missing observations either within a Kalman

[6] For Canada, Bloomberg used to provide expectations for the non-seasonally-adjusted IVEY index, but as of March 2011, it started to provide expectations for the seasonally adjusted series. I splice the two series series together being aware of the break point.

[7] Although the Tankan survey has an average publication lag of -4 days, only Q4 numbers are released before the end of the quarter (normally around mid-December). Releases for the other quarters generally occur at the beginning of the following quarter.

filter framework (see among others Aruoba, Diebold, and Scotti (2008), Giannone, Reichlin and Small (2008), and Banbura and Modugno (2010)) or within a mixed data sampling (MIDAS) regression framework (Andreou, Kourtellos, and Ghysels (2011)). I estimate the parameters by maximum likelihood implemented by the Expectation Maximization (EM) algorithm as proposed by Doz, Giannone, and Reichlin (2012) and extended by Banbura and Modugno (2010) to deal with missing observations and idiosyncratic dynamics.[8] The EM algorithm iterates over two steps: in the expectation step, the log-likelihood conditional on the data is calculated using the estimated parameters from the previous iteration; in the maximization step, the parameters are re-estimated by maximizing the expected log-likelihood with respect to θ. Following Doz, Giannone, and Reichlin (2011, 2012), the initial parameters $\theta(0)$ are obtained through principal components and the iteration between the two steps is stopped when the increase in likelihood between two steps is small.

In step (ii), once the parameters θ are estimated, the weights can be computed by running the algorithm defined in Koopman and Harvey (2003) to get the smoothed weights. The history of weights $w_j(\alpha_{t|t})$ for $j = 1, ..., t$ is computed in real time for any time for any t based on the information available up until that time. Finally, in step (iii), the surprise and uncertainty indexes are computed based on (16) and (17).

Each country is estimated separately from the others. The estimation of the underlying business condition index is based on the longest common sample across countries (1980-2012), except for the euro area due for which not enough indicators are available before 1985. The Kalman filter is then run based on the estimated parameters in a real time framework (i.e. based on data that are released sequentially), and steps (ii) and (iii) are repeated to get the smoothed weight matrix and the real-time surprise and uncertainty indexes for each day from May 15, 2003 to June 15, 2012.[9] Step (i) is run over the entire sample, unlike steps (ii) and (iii), because for countries in which data series become available later in the sample estimates are not accurate at first. For the United States, where there are no issues of data availability, there are no significant differences in the surprise indexes constructed according to the two methodologies.

5 Results

Here I discuss the results following the steps described in the estimation section.

[8] I thank Banbura, Giannone and Reichlin for sharing their EM codes.

[9] The surprise index is computed on a shorter sample due to the limited availability of expectation data for all the countries.

5.1 Real Activity Indexes

The real activity indexes that I estimate based on the indicators listed in table (1) are displayed in figure 1. As mentioned, I use a longer history for the estimation of these factors in order to have more reliable estimates. The figure shows the latest factors, which include information as of June 15, 2012, for the United States, the Euro Area, the United Kingdom, Canada, and Japan.

The average value of each index is zero by construction. Therefore, a value of zero is interpreted as average economic activity for that country, whereas progressively bigger positive values indicate progressively better-than-average conditions and progressively more negative values indicate progressively worse-than-average conditions. Importantly, average conditions differ across countries. For example, a value of zero for Japan corresponds to a number akin to 0.7 percent annual real GDP growth while a value of zero in the United States corresponds to around 2.5 percent annual real GDP growth. The shaded areas in the panels represent official recessions as defined by the NBER, CEPR, and ECRI. The indexes fall sharply during recessions and tend to reach relatively high values during good times, for example the late 1990s. As expected, the U.S. business condition index is very similar to the Aruoba, Diebold, and Scotti (ADS) index maintained by the Federal Reserve Bank of Philadelphia, with the difference that the ADS index is daily and also includes weekly data such as initial jobless claims. Because the other countries do not have relevant weekly data, I opted here for a monthly frequency. The last panel shows the aggregate business condition index, which is created by aggregating the other indexes weighting them by GDP.

5.2 Weights

To gauge the importance of the various indicators in constructing the surprise and uncertainty indexes, I consider two different standpoints in analyzing the weights: (i) I construct the cumulative weights as in equation (14) and (ii) I analyze, at each time t, the vector of $t \times 1$ weights, w_t^j, that are multiplied by the announcements to get the time t surprise index based on equation (16).

To be clear, for $t = \widetilde{t}$, the variable w that represents the weights in equation (16) is a matrix of dimension $\widetilde{t} \times MQ$ which contains those weights applied to all the announcements available up to time $\widetilde{t}$ that are used in the construction of the index. The sum of these weights over time represents the cumulative weight for indicator i at time $\widetilde{t}$, that is $w_{cum}^i = \sum_{j=1}^{\widetilde{t}} w_j^i$.[10]

The average cumulative weights are reported in table 2.[11] The weights are averages because

[10] The idea is that w_j^i represents the bars in figure 3, while w_{cum}^i represent the lines in figure 2. Because w_j^i in figure 3 are computed as of March 31, 2012, the sum of the bars for each indicator represents the last value of the corresponding line in figure 2.

[11] For comparability across countries, the table shows standardized weights so that the sum of all weights in

I calculate the mean of w^{cum} over the last five years of the sample. The choice of the five years is arbitrary to some extent and is linked to the availability of PMI data in the euro area and in the United Kingdom.[12] Based on this measure, employment (or unemployment) and industrial production have the highest weight in the United States, the Euro Area, and in the United Kingdom. In Canada, most of the weight (92 percent) is concentrated on employment. In Japan, industrial production is the most important series followed by unemployment and retail sales.

Cumulative weights, however, are not constant over time and therefore looking at their mean is not enough. They are affected by the pattern of missing observations due to the different release schedule of the underlying indicators (ragged edge). Figure 2 shows the evolution of the cumulative forecast weights w^i_{cum} for each indicator over the first quarter of 2012. Each panel in the figure displays the weights for a specific country. A clear pattern stands out: as soon as new information about an indicator becomes available, the contribution of that particular indicator increases. So, for example, the weight of the U.S. nonfarm payroll series (NFP), represented by the green line in the top leftmost panel, increases on January 6, February 3, and March 9 (solid vertical lines) when the December, January and February figures are announced. Until the IP numbers are released (dotted vertical lines), nonfarm payroll has the biggest weight. With the release of the IP figures, the weight for IP (red line) increases and becomes the highest of all. However, as additional information about real activity in the United States is released, nonfarm payroll and IP weights start to decline gradually. A similar pattern can be observed in the other countries: as the more timely information becomes available, its weight jumps up and it declines as other indicators are subsequently released. In the euro area (the top rightmost panel), unemployment tends to have the highest weight overall, but when IP numbers are released, IP weights become slightly bigger than those of the unemployment data. In the United Kingdom, IP weights are always bigger than any other weight. In Canada unemployment is consistently and by far the highest weight. Finally, in Japan, the Tankan survey has the highest weight at the beginning of the quarter when it represents the only available information for that quarter, but its weight is immediately overtaken as other information become available and, in particular, as IP numbers are released.

Turning to (ii), figure 3 shows the weights w when computed on March 31, 2012 for the six months prior to that day. The weights in all the countries display a time decay feature. For the United States, nonfarm payroll and IP (the green and red bars) have the highest weight for the month of February based on information as of March 31, 2012. Interestingly, IP weights are more persistent than the others, suggesting that past IP information continues to be important whereas the nonfarm payroll information value is limited to the latest available month. Because

each country is equal to 1.

[12] Euro-area flash PMI becomes available in June 2007 and U.K. PMI becomes available in March 2006.

Table 2: Average cumulative weights for each indicator used to construct the surprise index. For comparability across countries, weights are standardized so that the sum of all weights in each country is equal to 1. The average is computed over the last five years of the sample when all the indicators are available.

	United States	**Euro area**	**United Kingdom**	**Canada**	**Japan**
GDP	0.04	0.06	0.13	0.00	0.01
IP	0.35	0.31	0.39	0.02	0.57
Employment/Unemployment	0.30	0.40	0.30	0.92	0.17
Retail Sales	0.14	0.15	0.11	0.01	0.13
PMI	0.12	0.09	0.08	0.04	0.12
Personal Income	0.05				

no data about March are released as of March 31, all the weights are zero for the month of March. Weights are close to zero for all indicators after about six months. Of note, the time decay feature can technically complicate the interpretation of the index because an increase in the index might be due to a smaller weight given to an old negative surprise or to a new positive surprise.

The Euro Area represents an interesting case because as of March 31, flash euro-area PMI numbers for February and March are available, whereas any other real activity information refers to January. While past PMI numbers have a very small weight, the February and March PMI figures have a relatively high weight. Once more, the weights for IP are the slowest to decline and the last available unemployment data displays the highest weight.

The United Kingdom seems to have the slowest time decay in its weights compared to the other countries. In Canada, the employment weights dominate every other weight. Japan displays the quickest time decay with weights reaching practically zero already after only four months. Unlike the other countries, unemployment does not have the highest weight.

These weights are computed based on the available information as of March 31, 2012. Of course, the pattern would be different if the weights were to be computed on another day when different information was available.

5.3 Surprise Indexes

The news surprise indexes for the United States, the Euro area, the United Kingdom, Canada, Japan and the aggregate of the five countries are displayed in figure 4 (solid lines).[13] A positive (negative) reading of the surprise index suggests that economic releases have on balance been

[13]The indexes continue to be updated daily and are available from the author upon request.

higher (lower) than consensus, meaning that agents were more pessimistic (optimistic) about the economy. A positive number does not mean the economy is doing well on any ordinary measure, but merely that economic forecasts were overly pessimistic. The surprise index reaches its lowest value during the global financial crisis of 2008-2009 in all the countries. This suggests that, as the crisis was unfolding, agents were less pessimistic about its possible outcome and its impact on the real economy, while the actual data turned out to depict a grimmer picture of the stance of economic activity around the globe.

The euro-area surprise index dropped sharply in March 2012. As agents became more optimistic on a resolution of the European debt crisis with the bond exchange taking place in Greece, real activity indicators for 2012 that were released in March were disappointing. The January unemployment rate, released on March 1, was 10.70 percent versus an expectation of 10.40 percent. The February and March euro-area PMIs released on February 22 and March 22 were 49.70 and 48.70 respectively, versus expected values of 50.50 and 49.60, respectively. Finally, based on data released on March 14, euro-area industrial production increased 0.2 percent from December 2011 to January 2012 versus an expectation of a 0.5 increase.

Interestingly, the U.K. index dropped sharply on January 25, 2011 when a very disappointing Q4 GDP for 2010 was released (-0.5 percent versus an expectation of +0.5 percent). Although subsequent data helped the index to move higher, it continued to be depressed until the second half of 2011. Agents reportedly attributed the slowdown to a series of temporary factors (such as bad weather, the Japanese earthquake, and the royal wedding) that were believed to be short-lived. The transitory nature of these events most probably made agents mark up their economic outlook, but as a series of temporary factors occurred, these expectation were always disappointed.

The Japanese surprise index dropped sharply on April 27, 2011 as the actual number for IP turned out to be a lot lower than expected following the March earthquake: IP decreased 15.30 percent between February and March versus expectation of a 10.60 percent decrease.

On the other hand, there are also several instances where the surprise indexes are positive, especially coming out of the recession in the United States, the United Kingdom, and Canada.

For comparison the dotted lines in figure 4 show the Citi Economic Surprise Indexes (CESI). Although CESIs also measure economic news, they are constructed based on a different methodology. CESIs are defined as weighted historical standard deviations of data surprises (actual releases versus Bloomberg median survey) and are calculated daily in a rolling three-month window. The weights of the economic indicators are derived from relative high-frequency spot foreign exchange impacts of 1 standard deviation data surprises adjusted to include a time decay feature so as to replicate the limited memory of markets. Because the index constructed in this paper does not rely on the impact that macroeconomic surprises have on asset prices, it represents a more objective measure of deviation from consensus expectations. Although the

two indexes follow very similar patterns for all the countries, they also present some differences because both the set of indicators and the weights are different. For example, the euro-area surprise index tends to lag the CESI especially during the shaded area which represents the 2008-2009 recession.

5.4 Uncertainty Indexes

The uncertainty indexes for the United States, the Euro area, the United Kingdom, Canada, Japan and the aggregate of the five countries are displayed in figure 5 (solid lines). These indexes measure how uncertain agents are about current real activity conditions. A greater (smaller) reading of the uncertainty index suggests that agents have on balance been more (less) uncertain about the state of the economy. The indexes tend to be elevated during recessions, although there are other episodes when the indexes spike up. In the United States, economic uncertainty was also relatively high in 2004 and a big jump was observed at the end of 2005. The euro-area uncertainty index reaches its highest values just before and after the 2008-2009 recession, suggesting that agents were more uncertain about the economy as the euro-zone was entering and exiting the recession. Increased uncertainty characterized also the beginning of 2010 when the Greece "problem" started to be in prime time and the period between the end of 2011 and the start of 2012. Uncertainty in the United Kingdom has been particularly elevated since early 2009, when compared to its value in the first part of the sample. Canada has experienced several episodes of elevated economic uncertainty, whereas in Japan, the period after the March 2011 earthquake was by far the one with the highest uncertainty regarding the state of the Japanese economy. The dotted lines in the top panels show the VIX and the VSTOXX implied volatilities. Interestingly, especially in the latter part of the sample, the uncertainty index and the VIX are very similar, whereas the uncertainty index of the euro area differs somewhat from the VSTOXX. The two measures (implied volatility and uncertainty index) are constructed in completely independent ways. Implied volatility, a forward-looking measure, is computed from option prices. The uncertainty index, an historical measure, is calculated from current and past macroeconomic news surprises. The former is a wider measure that combines information about risk aversion and future stock market volatility, and to the extent that these two move with news surprises, the VIX also contains information about current and future economic uncertainty. On the other hand, the uncertainty index presented here is a clean measure of agents' uncertainty about the current state of the economy.

Table 3: Results of univariate regressions in which exchange rate returns are regressed on the surprise index

$$dlog(FX_t) = \alpha + \beta * d(\mathcal{S}_t) + \varepsilon_t$$

	Euro/$		**GBP/$**		**CAD/$**		**JPY/$**	
	$\boldsymbol{\beta}$	$\mathbf{R}^2$	$\boldsymbol{\beta}$	$\mathbf{R}^2$	$\boldsymbol{\beta}$	$\mathbf{R}^2$	$\boldsymbol{\beta}$	$\mathbf{R}^2$
US surprise index	0.290**	0.021	0.213***	0.013	-0.074	0.002	0.355***	0.032
Foreign surprise index	-0.313***	0.015	-0.335	0.005	-0.607***	0.042	0.086	0.002

** 5 percent significance, *** 1 percent significance

6 Applications

In this section, I show a couple of straightforward applications for the surprise and uncertainty indexes.

6.1 News Impact on Foreign Exchanges

A wide literature has documented the asset price response to macroeconomic news announcements. Andersen, Bollerslev, Diebold and Vega (2003, 2007) and Gilbert, Scotti, Strasser and Vega (2012) among others have looked into this question. Most papers study the impact of macroeconomic news announcement in a univariate regression or choose a subset of announcements in multivariate regressions. The surprise index presented here represents a nice summary measure that can be used to parsimoniously control for news announcement surprises in more general models.

Table 3 presents the results of a set of regression where the euro/$, GBP/$, CAD/$, and JPY/$ exchange rate returns are regressed on the U.S. surprise index or the respective foreign surprise index, i.e. the euro/$ return is regressed on the U.S surprise index and the euro-area surprise index, the GBP/$ return is regressed on the U.S surprise index and the U.K. surprise index, etc. I cover the sample period for which the surprise indexes are available (May 15, 2003 to June 15, 2012). As shown, the surprise indexes tend to have the right sign and be significant: a positive change in the U.S. surprise index (i.e. the U.S. economy doing better than expected) appreciates the U.S. dollar versus the euro, whereas a positive change in the euro-area surprise index depreciated the U.S. dollar. On the other hand the R^2 tends to be low.

For comparison, table 4 displays the results of univariate regressions of foreign exchange returns on the individual macro announcement surprises over the same sample period. These results do not necessarily correspond to what reported in the existing literature because of the different samples used. [comparison with ABDV results]

Table 4: Results of univariate regressions in which exchange rate returns are regressed on each individual macroeconomic news announcement surprise

$$dlog(FX_t) = \alpha + \beta * s_t^i + \varepsilon_t$$

	Euro/$		GBP/$		CAD/$		JPY/$	
	Beta	**R2**	**Beta**	**R2**	**Beta**	**R2**	**Beta**	**R2**
US								
IP	0.034	0.002	0.003	0.000	0.047**	0.005	-0.03	0.002
Employment	0.280**	0.115	0.203***	0.112	-0.042	0.004	0.374***	0.211
Retail sales	0.036	0.004	0.094**	0.026	-0.102**	0.026	0.219***	0.121
Personal income	0.012	0.000	-0.017	0.001	0.039	0.003	-0.056*	0.009
PMI	0.030	0.002	0.014	0.000	-0.026	0.001	0.097**	0.024
GDP	0.144**	0.044	-0.111**	0.031	0.058**	0.007	0.016	0.001
Foreign								
IP	-0.099***	0.028	-0.137**	0.056	0.001	0.000	0.114	0.021
Employment/unemployment	0.140***	0.036	-0.041	0.003	-0.275***	-0.129	0.023	0.002
Retail sales	-0.190***	0.081	-0.133**	0.042	-0.219***	0.093	-0.071**	0.012
PMI/Ivey/Tankan	0.033	0.001	-0.250***	0.086	-0.120***	0.025	-0.107*	0.031
GDP	-0.137**	0.056	-0.434***	0.340	-0.104	0.033	0.043	0.010

* 10 percent significance, ** 5 percent significance, and *** 1 percent significance

6.2 Uncertainty and the Business Cycle

Uncertainty can have a big role in firms' hiring decisions. To demonstrate this, I estimate a VAR on monthly data from May 2003 to May 2012. The variables in the estimations are employment (percentage change) and the uncertainty index (level). Figure 6 shows the generalized impulse response of employment (the solid blue line) to an uncertainty shock. The standard-error (Monte Carlo, 1000 repetitions) are also plotted. As shown in the top left panel, employment decreases after and uncertainty shock. The biggest effect occurs 2 to 3 months later and the effect is persistent over subsequent months.

6.3 Uncertainty and the VIX

As mentioned above, implied volatilities and uncertainty indexes potentially measure different objects. Implied volatility is a forward-looking measure that combines information about risk aversion, future stock market volatility, and to the extent that these move with news surprises, implied volatility also contains information about current and future economic uncertainty. On the other hand, the uncertainty index is an historical measure and represent a clean measure of agents' uncertainty about the current state of the economy. A straightforward application is

then to disentangle the part of the implied volatility that is related to uncertainty about the current state of the economy. Figure 7 shows such a measure plotted together with the VIX. While during the 2008-2009 recession most of the volatility was due to economic uncertainty, in the latter part of teh sample there were big spikes in the VIX that are not accounted for by the underlying economic uncertainty as measured by the uncertainty index.

7 Summary and Concluding Remarks

The goal of this paper is to construct objective measures of (i) real-time economic news and their deviation from consensus expectations and (ii) real-time uncertainty about the state of the economy. I view this paper as a "complement" to the Aruoba, Diebold and Scotti (2009) business condition index updated on a daily basis by the Federal Reserve Bank of Philadelphia. While the ADS index is a real time measurement of the state of the economy, the surprise index presented in this paper measures agents' optimism or pessimism about the economy by combining macroeconomic news surprises, and the uncertainty index measures agents' uncertainty about the current state of the economy.

I look forward to a variety of variations and extensions of this basic theme, including but not limited to:

- constructing indexes for nominal variables to gauge optimism/pessimism about inflation stance
- incorporating additional indicators and surprises for each country to construct a summary measure of real and nominal variables
- extending the framework to include U.S. macro surprises into foreign economies to exploit the correlation/causation across business cycles.

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Appendix – The State Space Representation

We report below the details of the state space representation as specified by equations (10) and (11) when the only quarterly variable is GDP:

$$\underbrace{\begin{bmatrix} y_t^M \\ y_t^Q \end{bmatrix}}_{y_t} = \underbrace{\begin{bmatrix} \mu^M \\ \mu^Q \end{bmatrix} + \begin{bmatrix} Z^M & 0 & 0 & 0 & 0 & I_{n^M} & 0 & 0 & 0 & 0 & 0 \\ Z^Q & 2Z^Q & 3Z^Q & 2Z^Q & Z^Q & 0 & 1 & 2 & 3 & 2 & 1 \end{bmatrix}}_{Z} \underbrace{\begin{bmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \\ \varepsilon_t^M \\ \varepsilon_t^Q \\ \varepsilon_{t-1}^Q \\ \varepsilon_{t-2}^Q \\ \varepsilon_{t-3}^Q \\ \varepsilon_{t-4}^Q \end{bmatrix}}_{\alpha_t}$$

$$\begin{bmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \\ \varepsilon_t^M \\ \varepsilon_t^Q \\ \varepsilon_{t-1}^Q \\ \varepsilon_{t-2}^Q \\ \varepsilon_{t-3}^Q \\ \varepsilon_{t-4}^Q \end{bmatrix} = \underbrace{\begin{bmatrix} \Lambda & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & diag(\alpha_1, ..., \alpha_{n^M}) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \alpha_Q & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}}_{T} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ x_{t-4} \\ x_{t-5} \\ \varepsilon_{t-1}^M \\ \varepsilon_{t-1}^Q \\ \varepsilon_{t-2}^Q \\ \varepsilon_{t-3}^Q \\ \varepsilon_{t-4}^Q \\ \varepsilon_{t-5}^Q \end{bmatrix} + \underbrace{\begin{bmatrix} \eta_t \\ 0 \\ 0 \\ 0 \\ 0 \\ e_t^M \\ e_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}}_{u_t}$$

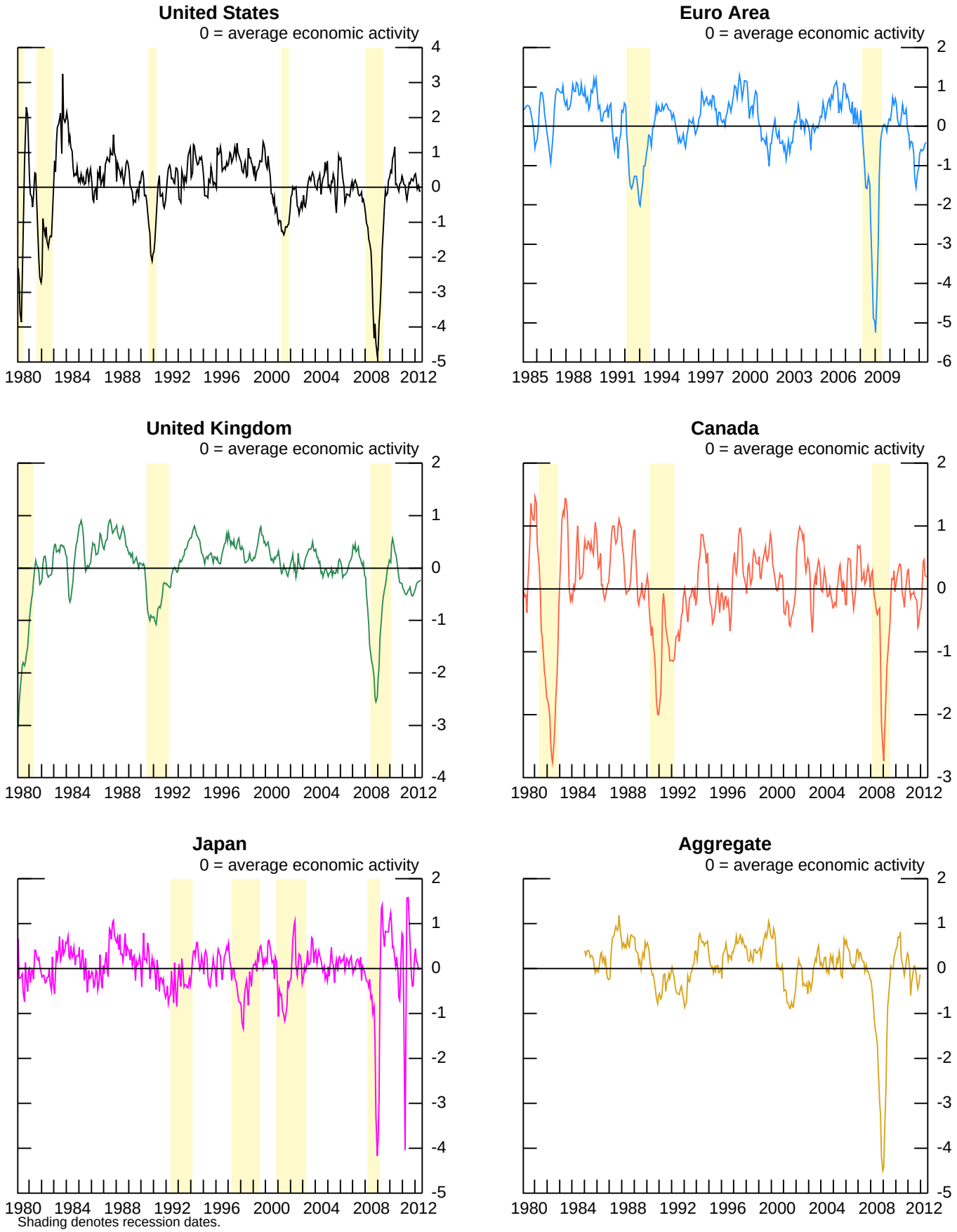
with n^M and n^Q representing the number of monthly and quarterly variables, $\varepsilon_t^M = \left(\varepsilon_t^{1^M}, ..., \varepsilon_t^{n^M}\right)'$, $e_t^M = \left(e_t^{1^M}, ..., e_t^{n^M}\right)'$, $\varepsilon_t^Q = \left(\varepsilon_t^{1^Q}, ..., \varepsilon_t^{n^Q}\right)'$ and $e_t^Q = \left(e_t^{1^Q}, ..., e_t^{n^Q}\right)'$. Because we are considering the case of only one quarterly variable, $\varepsilon_t^Q = \left(\varepsilon_t^{1^Q}\right)$ and $e_t^Q = \left(e_t^{1^Q}\right)$. Also $Z^M = \left(Z^{1^M}, ..., Z^{n^M}\right)$ and

$$Var(u_t) = \Sigma = \begin{pmatrix} \sigma_\eta & & \cdots & & 0 \\ & 0 & & & \\ \vdots & & \Sigma_e^M & & \vdots \\ & & & \sigma_e^Q & \\ 0 & & \cdots & & 0 \end{pmatrix} \text{ with } \Sigma_{e^M} = \begin{pmatrix} \sigma_{e^{1^M}} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_{e^{n^M}} \end{pmatrix}.^{14}$$

The parameters to be estimate are $\theta = \left\{\mu^M, \mu^Q, Z^M, Z^Q, \Lambda, \alpha_1, ..., \alpha_{n^M}, \alpha_Q, \sigma_\eta, \sigma_{e^1}^M, ..., \sigma_{e^{n^M}}^M, \sigma_e^Q\right\}$.

[14] We use the notation Σ to indicate a variance-covariance matrix and σ to indicate its elements.

Figure 1: Real Activity Indexes (factors) for the United States, Euro Area, United Kingdom, Canada, Japan, and aggregate of the 5 countries.



Shading denotes recession dates.

Figure 2: Average cumulative weights for the United States, Euro Area, United Kingdom, Canada, and Japan over the last quarter of the sample.

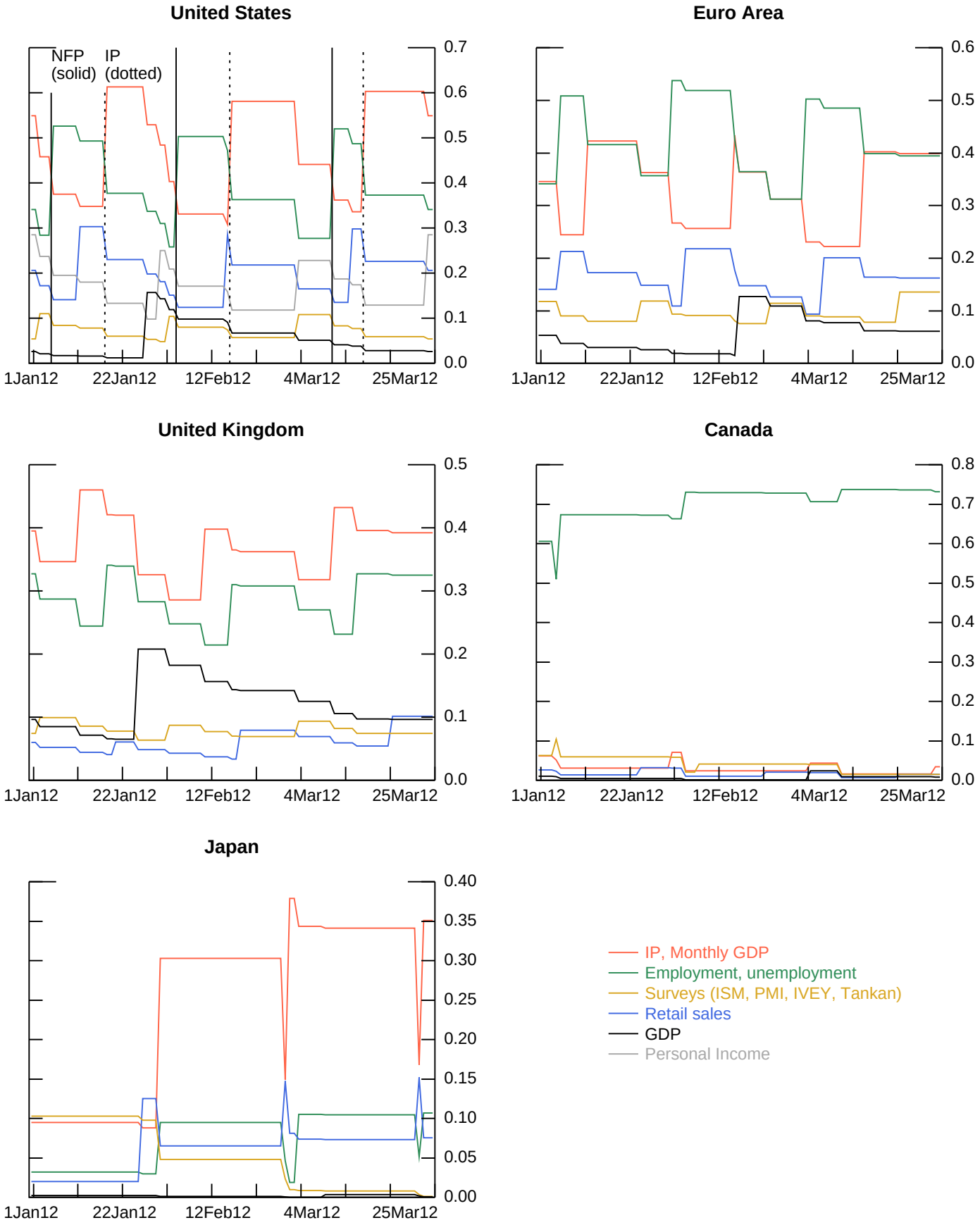


Figure 3: Time series of weights for each indicator based on the information available as of March 31, 2012.

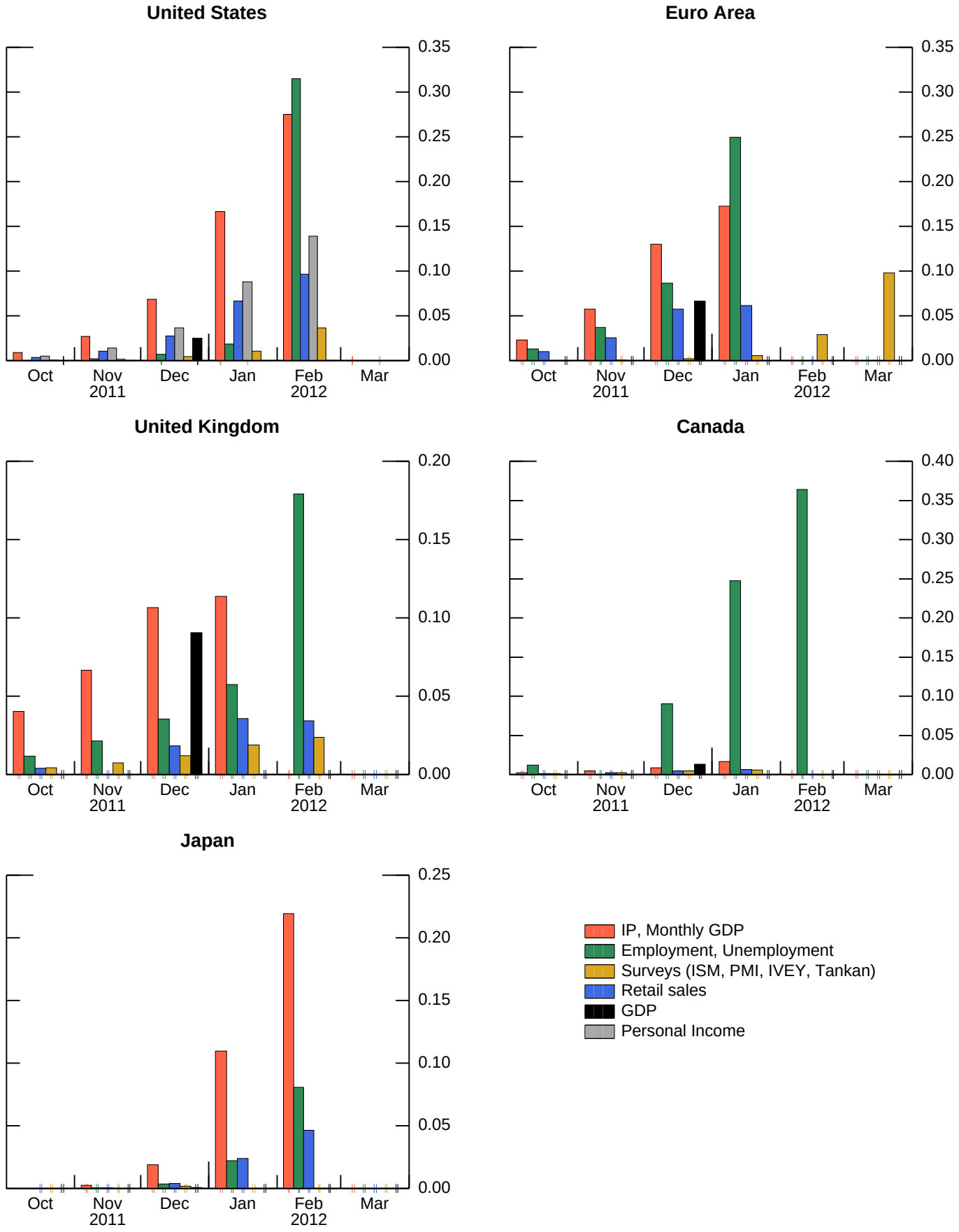
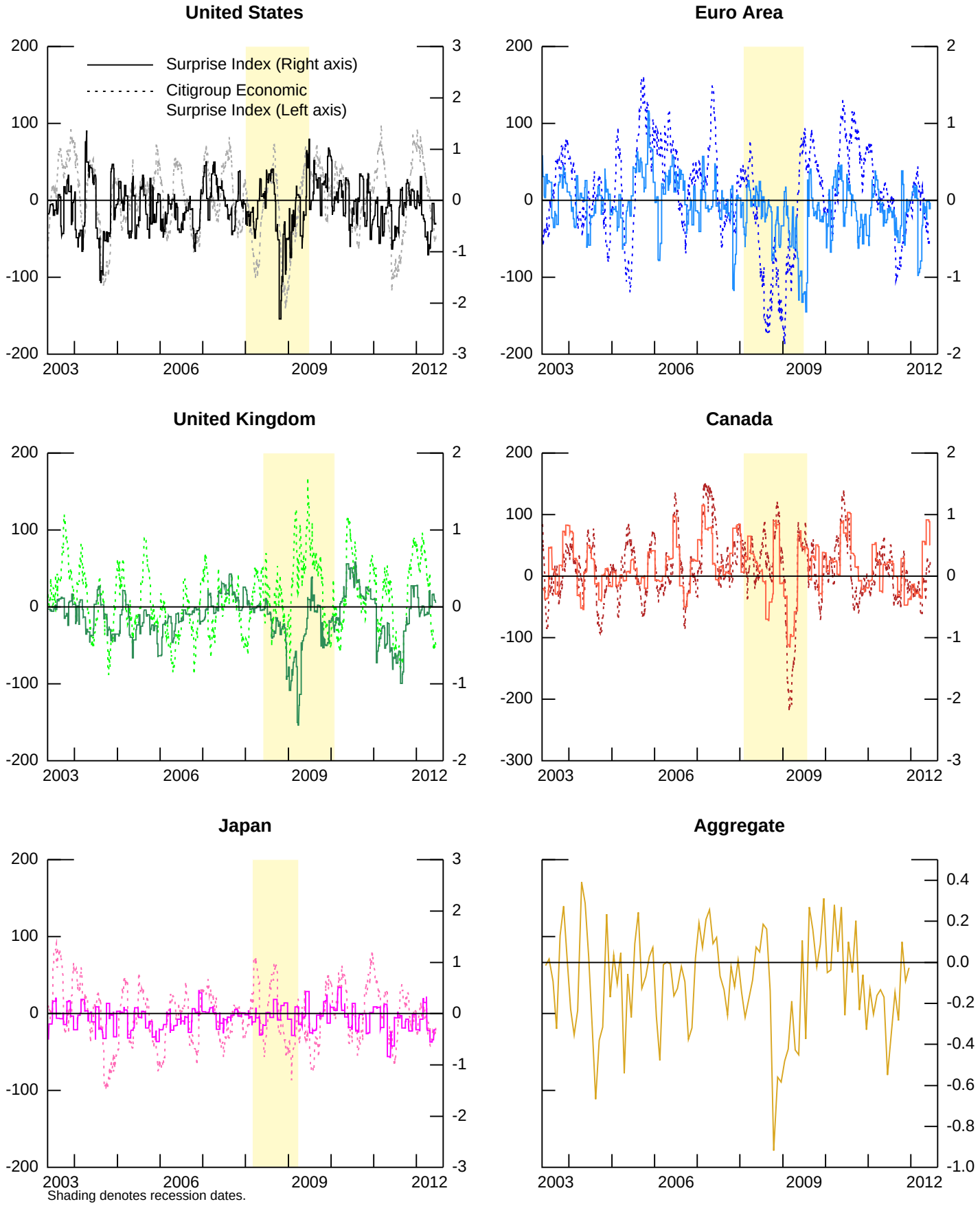
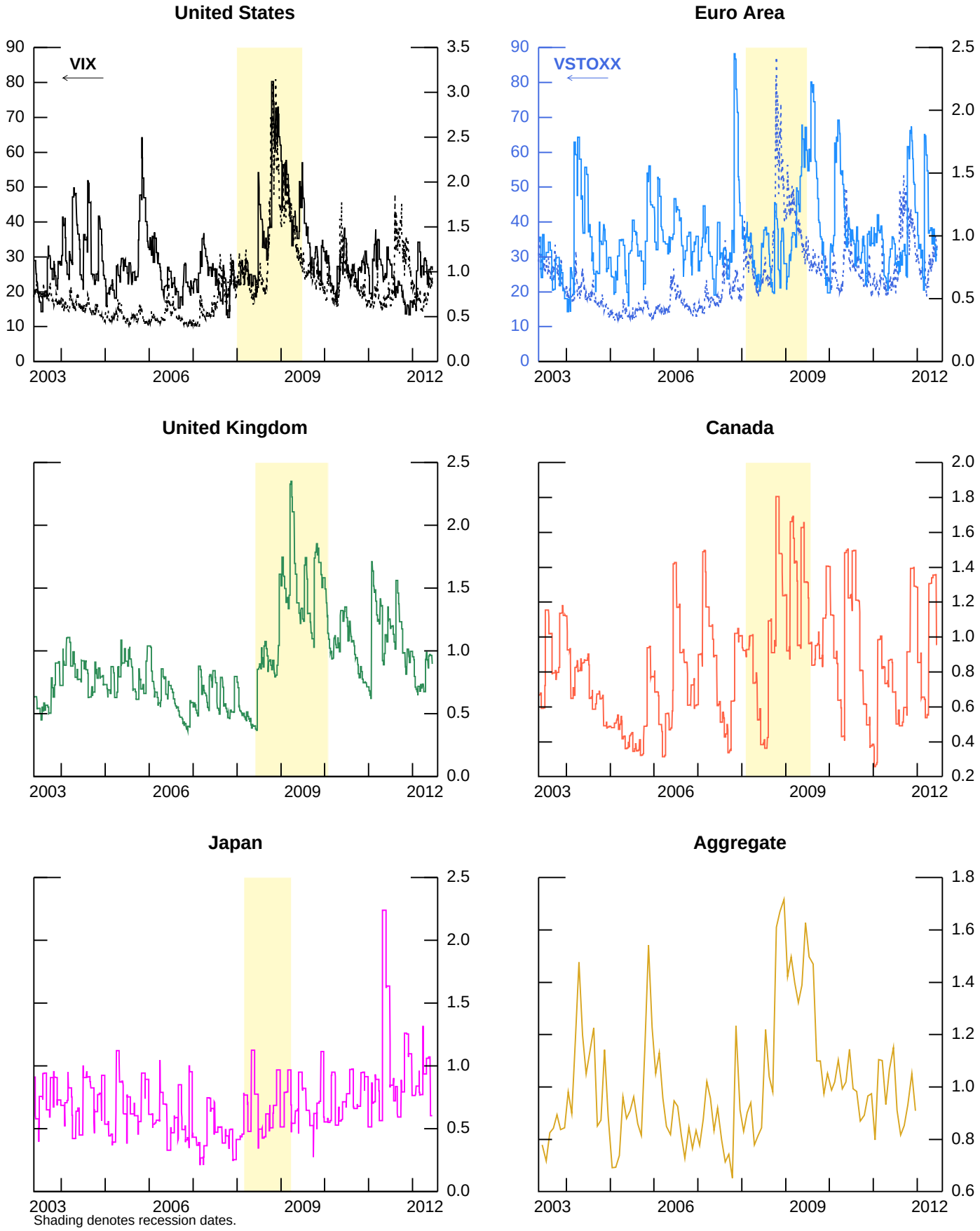


Figure 4: Surprise indexes for the United States, Euro Area, United Kingdom, Canada, Japan, and the aggregate of the 5 countries. The value of the index on a given day is weighted average of the surprises from a set of releases, where the weights depend on the contribution of the associated series to real activity index shown in Figure 1.



Shading denotes recession dates.

Figure 5: Uncertainty indexes for the United States, Euro Area, United Kingdom, Canada, Japan, and the aggregate of the 5 countries. The value of the index on a given day is weighted average of the squared surprises from a set of releases, where the weights depend on the contribution of the associated series to real activity index shown in Figure 1.



Shading denotes recession dates.

Figure 6: Employment response to a one SD uncertainty shock

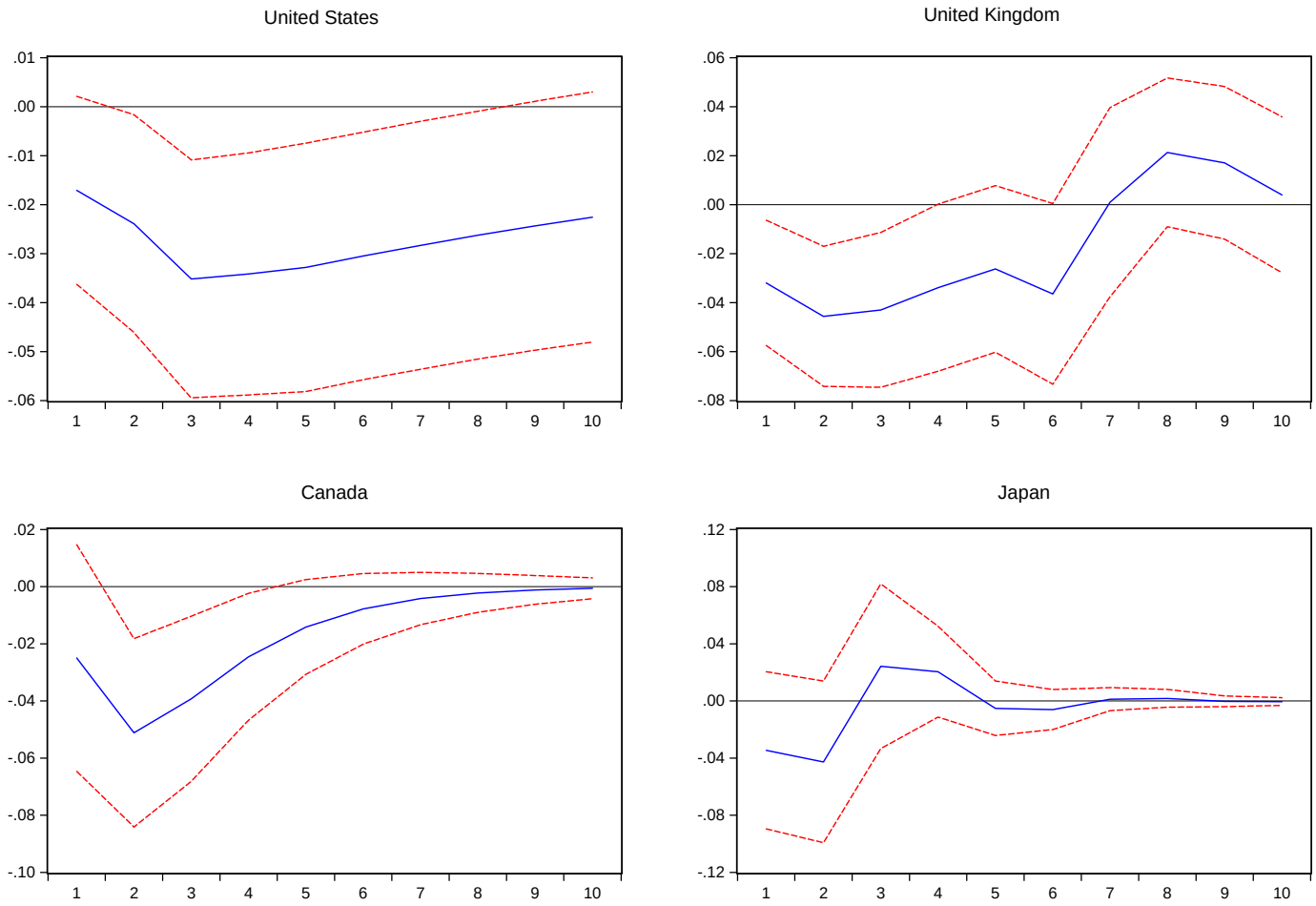
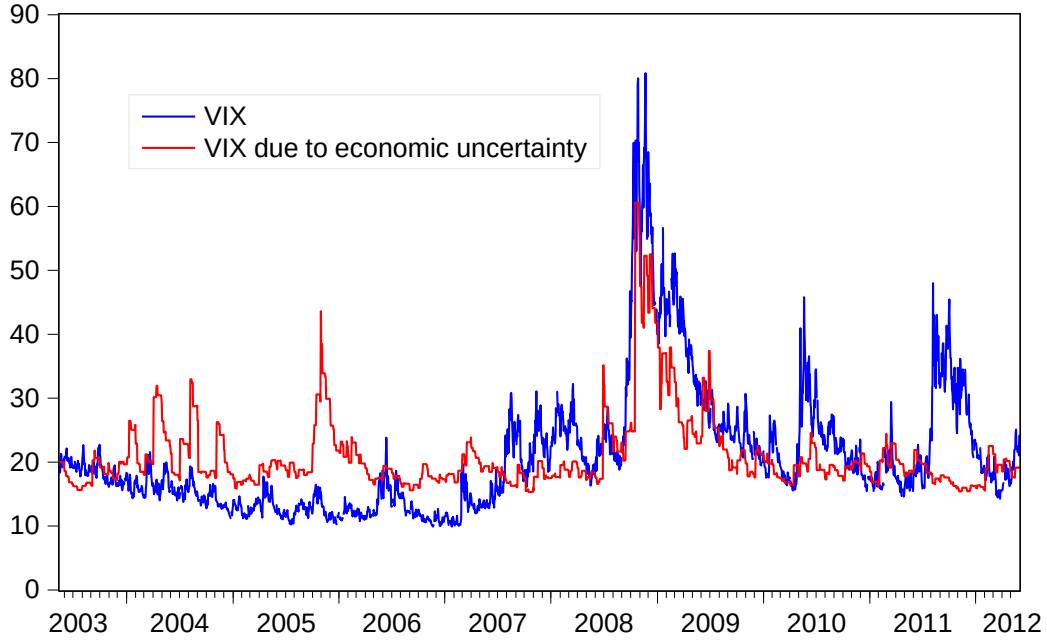



Figure 7: VIX and part of the VIX which is explained by economic uncertainty