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Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises ☆

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ABSTRACT

Two daily, real-time, real-activity indexes are constructed for the United States, euro area, United Kingdom, Canada, and Japan: (i) a surprise index summarizing recent economic data surprises and measuring optimism/pessimism about the state of the economy, and (ii) an uncertainty index measuring uncertainty related to the state of the economy. The surprise index parsimoniously preserves the properties of the underlying series when affecting asset prices. For the United States, the real-activity uncertainty index is compared to other uncertainty proxies to show that, when uncertainty is strictly related to real activity only, it has a potentially milder effect on economic activity.

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1. Introduction

Parsimonious measures of macroeconomic surprises and proxies of economic uncertainty have been of great interest over the past several years. A new methodology is proposed in this paper 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 *à la* Aruoba et al. (2009). The surprise index measures whether agents are *ex-post* more optimistic or pessimistic about the real economy than indicated by actual data releases.[1] 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 *ex-post* 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. This methodology is applied to construct indexes for the United States, euro area, the United Kingdom, Canada, Japan, and an aggregate of the five countries over the 2003–2016 period.[2]

☆ The views expressed in this paper are solely the responsibility of the author and should not be interpreted as reflecting the view of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

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[1] *Ex-post* optimism or pessimism differs from *ex-ante* optimism or pessimism. Considering the weather, for example, the optimal, model-consistent forecast for the temperature tomorrow could be 15 degrees Fahrenheit. A person could be ex-ante optimistic and expect it to be 20 degrees Fahrenheit. If the forecast turns out to be wildly wrong, and the temperature turns up to a toasty 25 degrees, that person was still ex-ante optimistic, even though, ex-post, her forecast looks pessimistic. Ex-post optimism or pessimism is neither necessary nor sufficient to say anything about ex-ante beliefs. Another definition that captures these measures well is *realized* optimism or pessimism.

[2] The indexes continue to be updated and are available from the author upon request or at chiarascotti.com.

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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 as being among the 50 economic indicators that really matter (Constable and Wright, 2011) and has been added to Bloomberg's real-time data that can be followed on its platform (ADS BCI Index).[3] The ADS index measures the state of the economy and serves as a summary statistic of the information that market participants have received thus far about real activity. However, in efficient markets, asset prices react to *new* information. Thus it is important to measure the surprise component of the information that has just arrived and the uncertainty surrounding that information. To this end, the surprise index presented here 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 existing business condition indicators such as the ADS index and to existing uncertainty indexes.

This paper relates to several branches of the literature. First and foremost is the uncertainty literature, which has thrived in recent years. Because uncertainty is not observable, a number of proxies have been used to measure it, ranging from stock market realized and implied volatilities (Bloom, 2009), to the cross-sectional dispersion of survey-based forecasts (Bachmann et al., 2013), the frequency of newspaper references to economic policy uncertainty (Baker et al., forthcoming), and the common variability in the purely unforecastable component of the future value of a big number of variables (Jurado et al., 2015). 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 could measure a divergence of opinions among forecasters rather than just the underlying uncertainty about the economy. My paper contributes to this literature by providing a *daily* macroeconomic information uncertainty measure which quantifies the part of uncertainty that specifically relates to the state of the real economy. It also contributes by helping to disentangle the effect of purely macro-uncertainty from more general uncertainty. The index is daily in that it gets updated every time new information about the state of the economy gets released. Second, this paper relates to those papers that study the effect of news surprises on asset prices, such as Andersen et al. (2003, 2007), and Gilbert et al. (2015), and contributes to this literature by providing a parsimonious summary measure of real-activity macroeconomic surprises. Also relevant are papers that use similar factors models to extract a business condition index (Aruoba et al., 2009, and Banbura et al., 2010, among others). The idea of forecasting weights developed in Koopman and Harvey (2003) and applied in Banbura and Runstler (2010) and Camacho and Perez-Quiroz (2009), among others, will be used here to study the impact of news releases on GDP forecast revisions.

In order to construct the surprise and uncertainty indexes, a dynamic factor model is employed to estimate monthly business condition indexes for the aforementioned countries and to compute the weights representing the contribution of the economic indicators to these business condition indexes. Those weights are then used to average the surprises or squared surprises in order to construct the surprise and uncertainty indexes, respectively. The weights depend on the time elapsed since the release of the associated information and 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.

I find that surprise indexes tend to be negative during the recession associated with the 2008 financial crisis, the so-called Great Recession, suggesting that agents were more optimistic about the real economy than warranted.[4] There appear to be other episodes when the indexes are negative. Of note are several declines in the euro-area surprise index after 2011, 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. 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 surprise index preserves the properties of the underlying series when affecting asset prices, with the advantage of being a parsimonious summary measure of real-activity surprises. In light of this, Demiralp et al. (2016) make use of it as a control variable when investigating the effects of political commentaries on policy rate decisions and policy expectations in the United States and the euro area, and find it to be a significant determinant of policy expectations. Similarly, Brunetti et al. (forthcoming) employ it as a control variable in studying the impact of speculation activity in the crude oil market.

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 area was entering and exiting the recession. The *daily* U.S. uncertainty index looks somewhat similar to the U.S. stock market implied volatility as measured by the VIX. Implied volatility, a forward-looking measure, is computed from option prices. The uncertainty index, a 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/uncertainty, and to the extent that these two move with news surprises, the VIX also contains information about current and future economic uncertainty. The VIX is also decomposed following Bakaert et al. (2013) into stock market uncertainty and variance risk premium, and it is found that the VIX patterns are mainly driven by the Bakaert et al. (2013)

[3] The updated ADS index can be found at http://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index/.

[4] Unfortunately, it is not clear whether this is a characteristic of all recessions because the surprise indexes only start in 2003 and hence only cover one recession episode. Expectation data are available from Bloomberg for all countries since 2003.

stock market uncertainty during the period analyzed.[5] However, understanding the exact linkages should be left to future studies.

A bivariate VAR exercise with employment and uncertainty proxies for the United States over the last decade shows that when uncertainty is strictly related to real activity as measured by the real-activity uncertainty index, it has a potentially milder impact on economic activity. By flipping the argument, when uncertainty is more generally related to economic and financial conditions as measured by the VIX or Bakaert et al. (2013) stock market uncertainty proxy, its impact on real-activity variables seems to be stronger and faster. This finding supports recent work by Caldara et al. (in press), which finds that the financial channel is key in the transmission of uncertainty shocks. Of course, the different effects could also be more generally due to the fact that the VIX measures a more wide-ranging notion of uncertainty.

The surprise and uncertainty indexes tend to be negatively correlated, meaning that bad news occurs together with increased volatility.[6] This result is similar to the inverse relationship between first and second moments of asset returns found in the financial literature, a phenomenon for which Fostel and Geanakoplos (2012) provide a theoretical explanation, together with explaining a decrease in leverage.

The remainder of the paper is organized as follows: Section 2 presents the data and the rationale behind using Bloomberg forecasts; Section 3 presents the details of the model's forecasting weights and the construction of the surprise and uncertainty indexes; Section 4 covers the estimation details; Section 5 presents the results; Section 6 shows some applications; and Section 7 concludes.

2. Data

Before getting into the model, this section presents information about the data used to construct the surprise and uncertainty indexes. Two different types of data are employed: the actual first release of the macroeconomic variable, say gross domestic product (GDP) or nonfarm payroll, and its forecast as measured by the Bloomberg median expectation. Note that Bloomberg expectations generally do not run the risk of being stale forecasts as they can be updated until 1 hour before the data release. The forecast is the latest one recorded by Bloomberg.[7] The actual releases of macroeconomic variables are used to estimate the underlying factor model from which the weights are gathered. The difference between actual releases and Bloomberg expectations, also known as news surprise or forecast error, is then used together with the weights to construct the surprise and uncertainty indexes. What follows describes the details of the data and some of the properties of the news surprises.

The analysis covers five countries – the United States, the euro area, the United Kingdom, Canada, and Japan – and five indicators for each country, excluding the United States; which has six. Several considerations guide the choice of variables. First, I want to use those 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 (see Table B1 in the online Appendix).[8]

The analysis for the surprise and uncertainty indexes covers the period from May 15, 2003 through March 31, 2016. However, a longer dataset is used to estimate the underlying business condition indexes: January 1980 to March 31, 2016, except for the euro area where the sample starts in January 1985.

The first indicator is quarterly real 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 non-agricultural payrolls, when available, or the unemployment rate.[9] The former tends to be timelier than the latter, but unfortunately it is not available for all countries.[10] 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 forecast: the ISM manufacturing index for the United States, the composite PMI for the euro area, the manufacturing PMI for the United Kingdom and Canada (Ivy survey), and the Tankan survey for Japan. The Tankan survey is a quarterly series, whereas the other surveys are all monthly.[11] 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

[5] The correlation between the daily U.S. uncertainty index and the VIX is 53 percent over the sample period analyzed.

[6] The correlation ranges between -0.26 and -0.45 for the United States, euro area, the United Kingdom and Japan, whereas it is positive in Canada over the sample period analyzed in the paper.

[7] The survey is done on a rolling basis and the Bloomberg news team runs tables every weekday morning, as they get the forecasts. Economists can usually make changes up to an hour before the release time.

[8] The table lists the indicators, together with their frequency, publication lags and transformations used to construct the real activity factor. The two rightmost columns list the source of the data series used to construct the factor, and the corresponding Bloomberg data series employed to construct the surprise and uncertainty indexes.

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

[10] To avoid confusion, because for all the indicators a higher number means that the economy is doing well, the negative of the unemployment rate is fed into the model.

[11] For Canada, Bloomberg used to provide expectations for the not seasonally adjusted IVY index, but as of March 2011, it started to provide expectations for the seasonally adjusted series. I splice the two series together being aware of the break point.

end of the quarter it refers to.[12] The average publication lag for the other series varies a lot as shown in Table B1 in the online Appendix. Survey measures are the timeliest 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. Conversely, GDP and IP data tend to be the last information to be released.

The additional indicator for the United States is the Bureau of Economic Analysis (BEA) personal income. Household income or personal income is generally available for the other countries but because its expectation is not, income is dropped from the dataset for foreign countries.

As already mentioned, while the announcement itself is used in constructing the real activity factor, the news surprise, that is the difference between announcement realizations (y_t^i) and their corresponding Bloomberg expectations ($E[y_t^i|\mathcal{F}_t]$), is used in constructing the surprise and uncertainty indexes. Because units of measurement vary across macroeconomic variables, the resulting surprises are standardized by dividing each of them by their sample standard deviation (σ^i). The standardized news surprise associated with the macroeconomic indicator y^i at time t is therefore computed as:

$$s_t^i = \frac{y_t^i - E[y_t^i|\mathcal{F}_t]}{\sigma^i}. \tag{1}$$

2.1. News surprises

Market participants watch and react to scheduled macroeconomic announcements because these announcements potentially contain new information that was not previously incorporated into market participants' expectations about the state of the economy. Several studies have looked into the forecast efficiency, or rationality, of market expectations. Under rationality, the surprise component, measured as the difference between the actual release and its forecast, should truly represent "news," meaning that market agents optimally use available information in forming their forecasts, and therefore the forecast error should be orthogonal to information available when the forecast is produced. This is equivalent to testing whether the error term ε_t^i is orthogonal to the forecast $y_t^{i,f} = E[y_t^i|\mathcal{F}_t]$ in the equation

$$y_t^{i,f} = y_t + \varepsilon_t^i. \tag{2}$$

In particular, testing for forecast efficiency boils down to testing that $\alpha^i = \beta^i = 0$ in the regression

$$s_t^i = \alpha^i + \beta^i y_t^{i,f} + u_t^i \tag{3}$$

where $s_t^i = y_t^i - y_t^{i,f}$ is the forecast error, or news surprise. This is sometimes known as the Mincer–Zarnowitz test (Mincer et al., 1969). Several earlier papers have applied these tests mainly using data revisions (among others, see Croushore and Stark, 2001; Faust et al., 2005). Table 1 reports evidence from the baseline tests of forecast rationality – tests of the hypothesis that $\alpha^i = \beta^i = 0$ in Eq. (3). As can be seen in the middle columns, α^i and β^i are very often significantly different from zero and the F test fails to reject the null hypothesis that $\alpha^i = \beta^i = 0$ only in one-third of the cases.

But given that Bloomberg median forecasts are not efficient, why are they so important? Why are they used rather than efficient forecasts that could be constructed within the factor model? The answer is simple: financial markets do not react to private forecasts; financial markets react to Bloomberg forecasts, which are public and can be seen by everyone.

A wide literature has documented the asset price response to macroeconomic news announcements. Andersen et al. (2007) and Gilbert et al. (2015) among others have looked into this question. Table 2 displays the results of univariate regressions of foreign exchange returns on the individual macro-announcement surprises over the sample period 2003–2016. These results do not necessarily correspond to what is reported in the existing literature because of the different samples used. However, they clearly state the point that Bloomberg forecasts (and surprises) are important because financial markets react to them.

3. The model

A standard dynamic factor model is used at a monthly frequency, explicitly accounting for missing data and temporal aggregation (details can be found in the appendix). With it, each of the real-activity variables is used to extract information about the common (unobserved) factor.

3.1. Forecasting weights

The contribution of each real-activity variable to the determination of the factor represents the weight applied to construct the surprise index. As shown in Koopman and Harvey (2003), the weights $w_j(\alpha_{t|t})$ are used to calculate the

[12] The Tankan survey has an average publication lag of -4 days, but only Q4 numbers are released before the end of the quarter (around mid-December). Other releases occur at the beginning of the following quarter.

Table 1
Forecast efficiency regression results (July 2003—March 2016).

$s_t^i = \alpha^i + \beta^i y_t^{i,f} + u_t^i$

Country	Series name	α	β	F	p value
United States	GDP	−0.05	−0.02	0.65	**0.53**
	IP	−0.09***	0.27***	12.55	0.00
	Employment	−12.70**	−0.01	2.87	0.06
	Retail Sales	−0.05	0.18***	5.15	0.01
	ISM	1.12	−0.02	0.67	**0.51**
	Personal Income	0.04*	−0.11***	4.17	0.02
Euro Area	GDP	−0.02	0.11***	3.31	0.04
	IP	−0.08*	−0.11**	3.81	0.02
	Unemployment	0.10**	−0.01**	3.13	0.05
	Retail Sales	−0.07	−0.13*	1.93	**0.15**
	PMI	1.03	−0.02	0.42	**0.66**
United Kingdom	GDP	−0.14***	0.26***	6.58	0.00
	IP	−0.21***	−0.01***	9.22	0.00
	Unemployment	0.05***	−0.02***	7.73	0.00
	Retail Sales	0.20***	0.11***	5.88	0.00
	PMI	3.28*	−0.06**	1.93	**0.15**
Canada	GDP	0.06	−0.01	0.23	**0.80**
	IP	−0.06***	0.06***	7.00	0.00
	Employment	5.17	0.12***	2.98	0.05
	Retail Sales	−0.07	0.35***	5.78	0.00
	Ivey Survey	19.95***	−0.34***	7.23	0.00
Japan	GDP	0.01	−0.05	0.25	**0.78**
	IP	−0.42***	0.04***	10.66	0.00
	Unemployment	0.17*	−0.05***	4.57	0.01
	Retail Sales	0.04	0.21***	6.02	0.00
	Tankan	0.16	0.01	0.27	**0.76**

* 10 percent, ** 5 percent, and *** 1 percent significance level, with Newey-West standard errors.

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:

$$x_{t|t} = \sum_{j=1}^{t-1} w_j(\alpha_{t|t}) y_j. \tag{4}$$

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. w_j is the vector of weights at time t referring to the monthly and quarterly series.

The real-time release schedule of each real activity series y^i is considered. For example, when calculating the factor for the month of March 2012, information about that month will be released gradually. In 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 advanced reading of GDP for the first quarter (that is the one that includes January) will be released with an average delay of 29 days from the end of the quarter. Based on this real-time schedule, the underlying unobserved factor at time t can be computed recursively based on the data availability until day t, that is $x_{t|t}$. Eq. (4) 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 Runstler (2010):

$$w_{cum}^i = \sum_{j=1}^{t} w_j^i. \tag{5}$$

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.

An alternative to using the forecast weights as outlined above, would be to use the weights as described in Banbura and Modugno (2014). In this case, the weights would have a different interpretation, as they would represent the contribution of the news releases to the factor revision from period t to $t+1$. The Banbura and Modugno (2014) weights are represented by

Table 2
Results of univariate regressions in which exchange rate returns are regressed on each individual macroeconomic news announcement surprise (July 2003–March 2016).

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

	Euro/$		**GBP/$**		**CAD/$**		**JPY/$**	
	β	R^2	β	R^2	β	R^2	β	R^2
US								
IP	0.029	0.003	0.021	0.001	0.043**	0.005	−0.034	0.003
Employment	0.271***	0.125	0.214***	0.130	0.002	0.000	0.342***	0.214
Retail sales	0.063	0.013	0.100***	0.030	−0.062	0.010	0.198***	0.099
Personal income	0.009	0.000	−0.040	0.004	0.020	0.001	−0.038	0.004
PMI	0.050	0.006	0.035	0.001	−0.013	0.000	0.169***	0.067
GDP	0.219***	0.097	0.017	0.000	0.084***	0.011	0.059	0.005
Foreign								
IP	−0.066***	0.023	−0.147***	0.059	−0.028	0.005	0.077	0.023
Empl/unempl	0.064	0.066	−0.039	0.006	−0.252***	−0.125	0.009	0.001
Retail sales	−0.106	0.023	−0.148***	0.069	−0.013	0.071	−0.013	0.004
PMI/Ivey/Tankan	0.005	0.000	−0.238***	0.110	−0.064	0.006	0.020	0.001
GDP	−0.113**	0.038	−0.371***	0.300	−0.090	0.025	−0.005	0.000

* 10 percent, ** 5 percent, and *** 1 percent significance level, with Newey-West standard errors.

$b_{\nu+1,j}$ in

$$E[x_t^i|\Omega_{\nu+1}] - E[x_t^i|\Omega_\nu] = \sum_{j=1}^{J_{\nu+1}} b_{\nu+1,j}(y_t - E[y_t^i|\Omega_\nu]) \tag{6}$$

where $E[x_t^i|\Omega_{\nu+1}] - E[x_t^i|\Omega_\nu]$ represents the revision to the factor implied by the new data release, $(y_t - E[y_t^i|\Omega_\nu])$ is the news surprise, and Ω_ν and $\Omega_{\nu+1}$ are two consecutive data vintages with $\Omega_\nu \subset \Omega_{\nu+1}$. In the Banbura and Modugno (2014) framework, $E[y_t^i|\Omega_\nu]$ is the model implied expectation of the variable y, whereas in my framework $E[y_t^i|\Omega_\nu]$ would be the Bloomberg expectation for the macro variable y. The advantage of their set-up is that the weights represent the effect of the news release of a variable y on the underlying factor forecast, rather than the importance of the underlying series y in determining the factor. The drawback, however, is that the weight b is practically the Kalman gain and as such, this set-up does not provide a time series of the weights similar to that in this framework. A way to overcome this issue could be to apply an arbitrary time decay feature similar to that applied by Citigroup to construct the so-called "Citigroup Economic Surprise Indexes." These indexes are defined as weighted historical standard deviations of data surprises where the weights of economic indicators are derived from the announcement's effect on the foreign exchange markets to which a subjective decay function is applied.

3.2. The surprise index

The surprise index is constructed starting from Eq. (4). With the idea that forecast weights represent the importance of the series in determining the underlying unobservable factor, those same weights are used to combine the standardized surprises so that the surprise index $\mathcal{S}$ at time t is:

$$\mathcal{S}_t = \sum_{j=1}^{t} w_j s_j \tag{7}$$

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.[13] In the application, the underlying series that feed into the factor are signed so that a higher (lower) number means that the economy is doing better (worse). Likewise, each surprise is constructed such that a positive surprise means good (bad) news for the economy. This implies that the weights should be positive.

The surprise indexes are *daily*: every time new information becomes available because new data are released, the surprise index gets updated. If there are no new data, the index is equal by construction to its value on the previous day. Of course, more data releases imply that the surprise index gets updated more frequently.

[13] Because s and w are vectors, this method is practically aggregating over variables (through the product of s and w) and over time (with $\sum_{j=1}^{t}$).

3.3. The uncertainty index

The uncertainty index is computed starting from Eq. (4) and averaging squared surprises

$$\mathcal{U}_t = \sqrt{\sum_{j=1}^{t} w_j s_j^2}. \tag{8}$$

The link with realized volatility is straightforward. Just like realized volatility is computed as the square root of the average of squared returns, $RV_n = \sqrt{\frac{1}{n}\sum_{t=1}^{n} ret_t^2}$, the uncertainty index is computed as the square root of the weighted average of the squared surprises.[14] 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.

As mentioned in the Introduction, these surprise and uncertainty indexes are ex-post, realized measures. Moreover, these indexes measure how optimistic, pessimistic or uncertain agents are about recent economic conditions. Bloomberg forecasts are constructed in such a way that contributors can submit and continuously revise their forecasts until one hour before the data release. The forecasts employed here are screen-shots of the latest submitted forecasts. For example, if we consider nonfarm payroll, a contributor can submit her forecast until 7:30 am ET on the first Friday of the month for the release of nonfarm payroll referring to the previous month. In this sense, these measures are backward looking measures as they use today's best guess (forecast) about the state of the economy in the recent past. Because the Bloomberg forecasts refer to the latest macroeconomic statistics only, it is not possible to compute these measures for different horizons, say $t+1, t+2, \ldots$ In fact, the macroeconomic announcements analyzed in this paper are all released with a reporting lag, meaning that they are announced after the end of the period they refer to. Practically, this uncertainty measure can even be considered as a nowcasting/backcasting exercise in that it uses weighed forecast errors from the recent past.

Similar to the surprise indexes, the uncertainty indexes are also daily and get updated every time new information become available.

4. Estimation

The construction of the indexes requires three steps:

1. estimation of the state space model,
2. determination of the weights w_j as defined in Eq. (4) and
3. construction of the indexes as for Eqs. (7) and (8).

For step (1), the estimation of the model described in the online appendix 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 filter framework (see among others Aruoba et al., 2009; Giannone et al., 2008; Banbura and Modugno, 2014) or within a mixed data sampling (MIDAS) regression framework (Andreou et al., 2011). The parameters are estimated using maximum likelihood implemented by the Expectation Maximization (EM) algorithm as proposed by Doz et al. (2012) and extended by Banbura and Modugno (2014) to deal with missing observations and idiosyncratic dynamics.[15] 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 et al. (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 (2), 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 $j = 1, \ldots, t$ is computed in real time for any t based on the information available up until that time.

Finally, in step (3), the surprise and uncertainty indexes are computed based on Eqs. (7) and (8).

Each country is estimated separately. The estimation of the underlying business condition index is based on the longest common sample across countries (1980–2012), except for the euro area 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 (that is, based on data that are released sequentially), and steps (2) and (3) are repeated to get the smoothed weight matrix and the real-time surprise

[14] Realized volatility is more precisely defined as $vol = \sqrt{\frac{1}{n}\sum ret_i^2 - \left(\frac{1}{n}\sum ret_i\right)^2}$ 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.

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

and uncertainty indexes for each day from May 15, 2003 to March 31, 2016.[16] Step (1) is run over the entire sample, unlike steps (2) and (3), because for countries in which data series become available later in the sample, estimates are not accurate at first.[17] 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.[18]

5. Results

This section discusses the results following the steps described in the estimation section.

5.1. Real activity indexes

The estimated real activity indexes based on the indicators described above are displayed in Fig. 1. As mentioned, a longer history for the estimation of these factors is used in order to have more reliable estimates. The figure shows the latest factors, which include information as of March 31, 2016, for the United States, the euro area, the United Kingdom, Canada, Japan, and an aggregate of the five countries.

The average value of each index is zero by construction. Therefore, a value of zero is interpreted as the 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 in the late 1990s. As expected, the U.S. business condition index is very similar to the 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, the indexes used here are constructed at a monthly frequency. The last panel shows the aggregate business condition index, which is created by aggregating the other indexes and weighing them by each country's GDP.

5.2. Weights

To gauge the importance of the various indicators in constructing the surprise and uncertainty indexes, two different standpoints are considered in analyzing the weights: (1) the cumulative weights as in Eq. (5) and (2) the vector of $t \times 1$ weights, w_t^j, at each time t, , which are multiplied by the announcements to get the time t surprise index based on Eq. (7).

To be clear, for $t = \tilde{t}$, the variable w that represents the weights in Eq. (7) is a matrix of dimension $\tilde{t} \times MQ$ which contains those weights applied to all the announcements available up to time $\tilde{t}$ 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 $\tilde{t}$, that is $w_{cum}^i = \sum_{j=1}^{\tilde{t}} w_j^i$.

Average cumulative weights computed over the 2003–2016 sample show that employment (or unemployment) and industrial production have the highest value in the United States, the euro area, and in the United Kingdom. In Canada, most of the weight is concentrated on employment. In Japan, industrial production is the most important series followed by unemployment and retail sales.[19] 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 schedules of the underlying indicators (ragged edge). Fig. 2 shows the evolution of the cumulative forecast weights w_{cum}^i 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), shown 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 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 larger than those of the unemployment data. In the United

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

[17] The underlying real activity factor is estimated on the full sample to avoid parameter instability problems due to the fact that, for some of the countries, some macroeconomic releases become available later in the sample (namely retail sales and PMI series).

[18] That means, running (1), (2) and (3) in real time versus running (1) over the entire sample, and (2) and (3) in real time does not give significant differences for the United States.

[19] Details of the average cumulative weights are reported in Table B2 in the online Appendix. For comparability across countries, the table shows standardized weights so that the sum of all weights in each country is equal to 1.

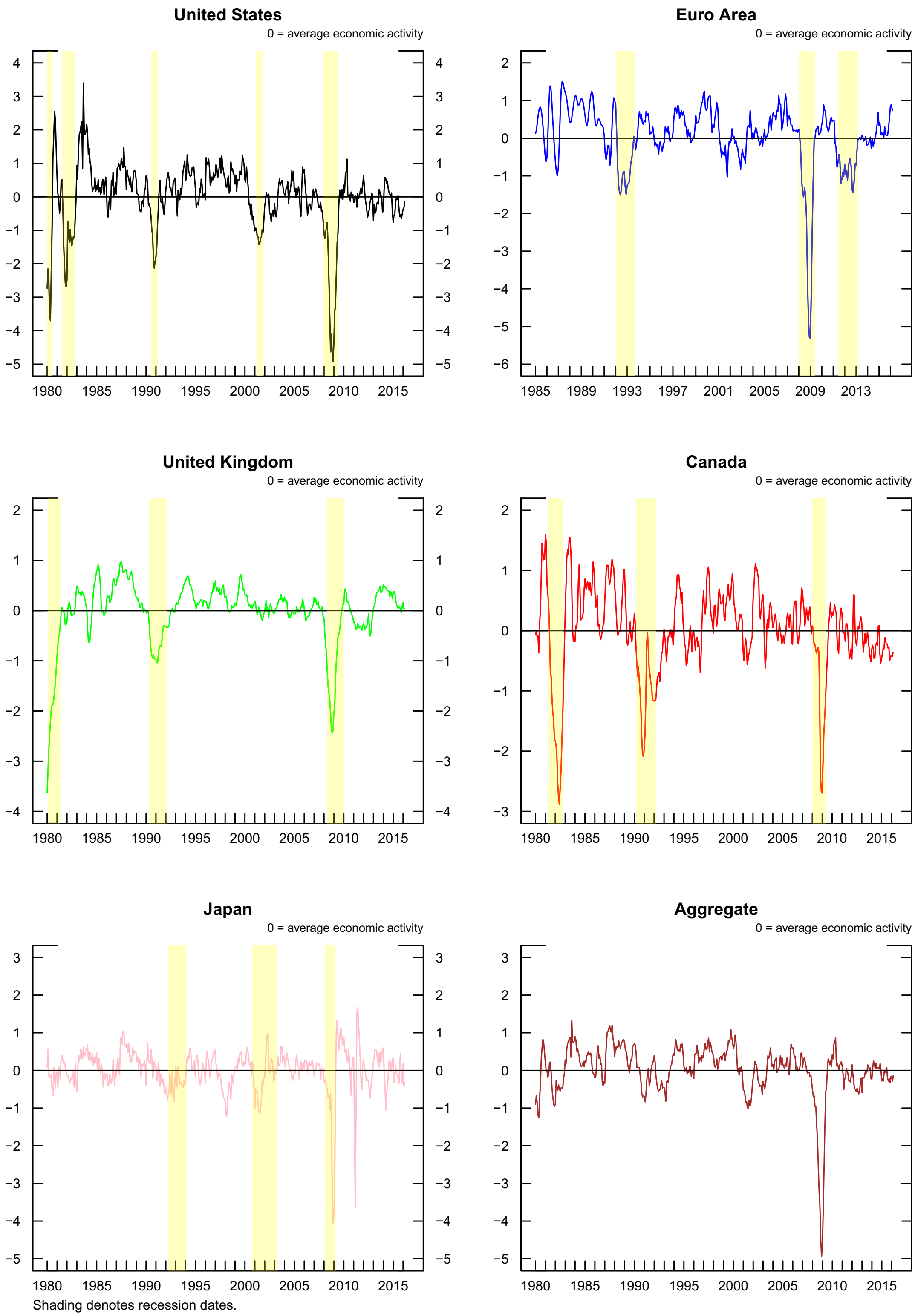

Fig. 1. Real Activity Indexes (factors) for the United States, euro area, United Kingdom, Canada, Japan, and aggregate of the five countries, as of March 31, 2016. The average value of each index is zero by construction. A value of zero is interpreted as average economic activity for that country, whereas progressively bigger (more negative) positive values indicate progressively better-than-average (worse-than-average) conditions.

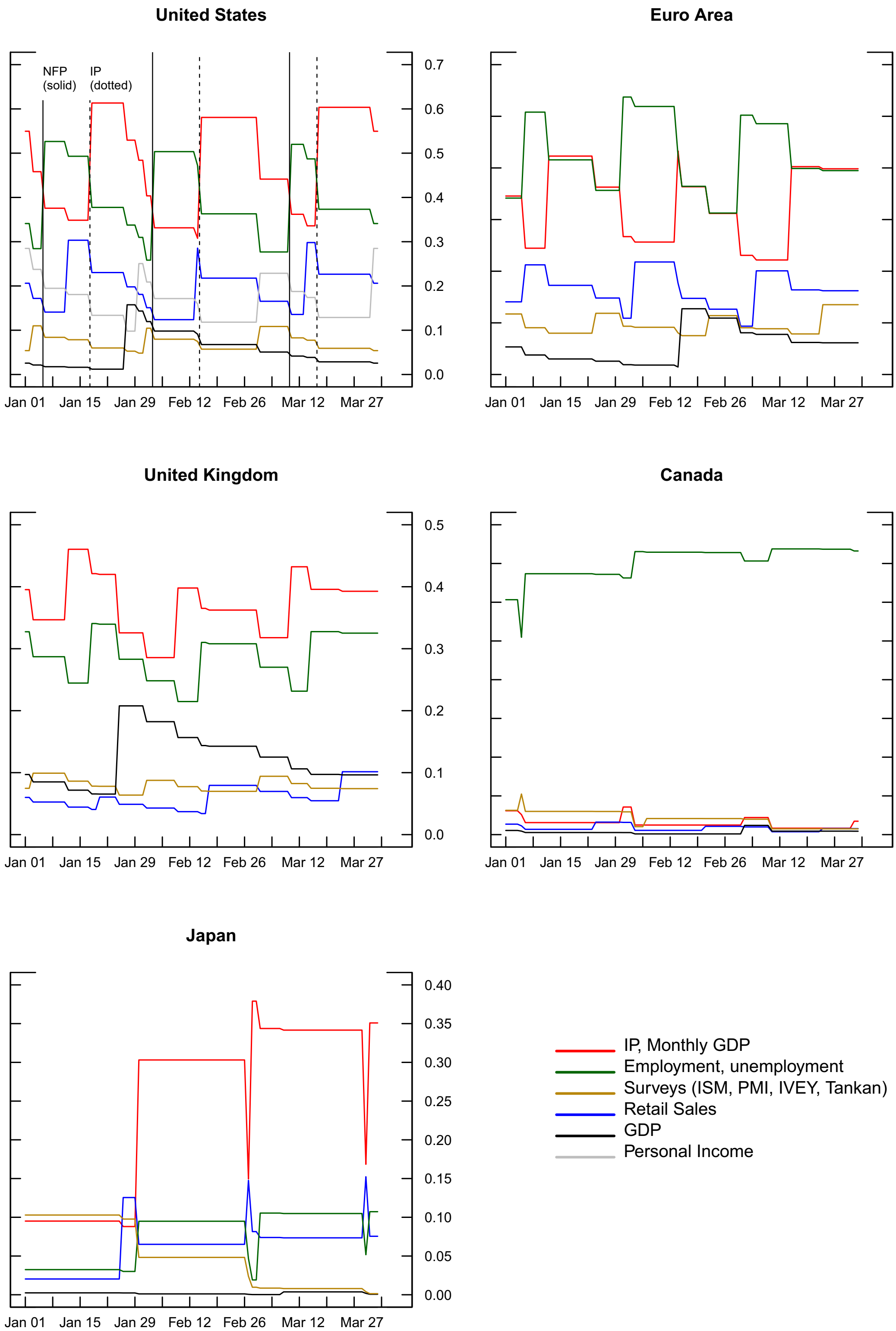

Fig. 2. Average cumulative weights for the United States, euro area, United Kingdom, Canada, and Japan over the first quarter of 2012.

Kingdom, IP weights are always larger 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 (2), Fig. 3 shows the weights w when computed on March 31, 2012 for the 6 months prior to that day.[20] The weights in all the countries display a time decay feature. For the United States, nonfarm payroll and IP have the highest weights 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 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 6 months. Of note, the time decay feature implies that 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, 2012, 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 large weight. Once more, the weights for IP are the slowest to decline, and the last available unemployment data display 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 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 Fig. 4 (solid lines). A positive (negative) reading of the surprise index suggests that economic releases have on balance been higher (lower) than consensus, meaning that agents were *ex-post* 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 most 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 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 percent 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 probably made agents mark up their economic outlook, but, as a series of temporary factors occurred, these expectations 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 2011 earthquake: IP decreased 15.30 percent between February and March versus the expectation of a 10.60 percent decrease.

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.

More generally, the surprise indexes seem to be autocorrelated. Part of this feature comes from the fact that old surprises continue to receive a positive weight for some time after their release. Except for Canada, the surprise indexes are on average slightly negative, with a more negative value during recessions suggesting that, in the period considered, agents were on average overly optimistic about the state of the economy.

For comparison, the dotted lines in Fig. 4 show the Citi Economic Surprise Indexes (CESIs). 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 the Bloomberg median survey) and are calculated daily in a rolling 3-month window. The weights of the economic indicators are derived from the corresponding high-frequency spot foreign

[20] The idea is that w_j^i represents the bars in Fig. 3, while w_{cum}^i represent the lines in Fig. 2.

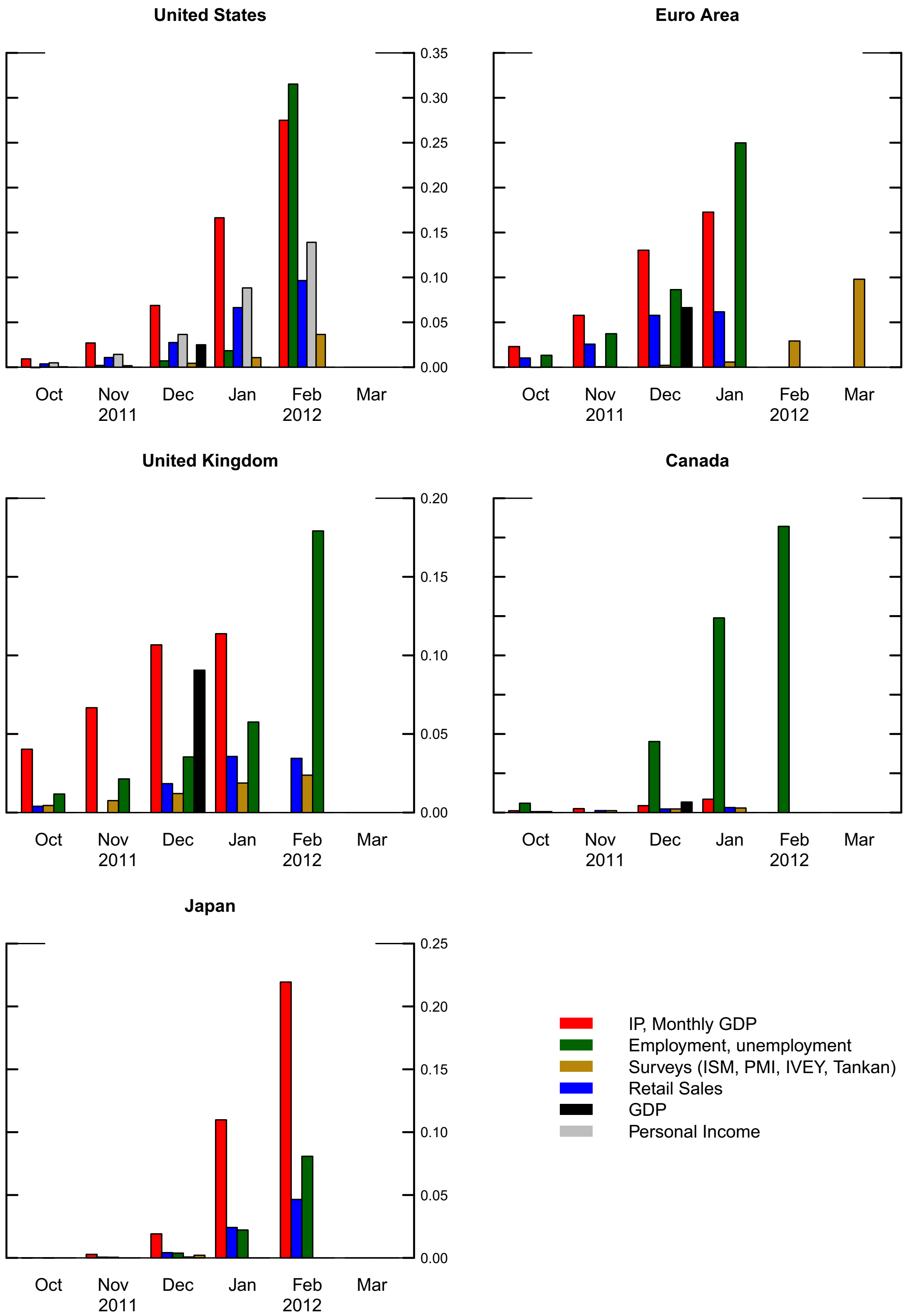

Fig. 3. Time series of weights for each indicator over the 6-month period October 2011–March 2012, based on the information available as of March 31, 2012.

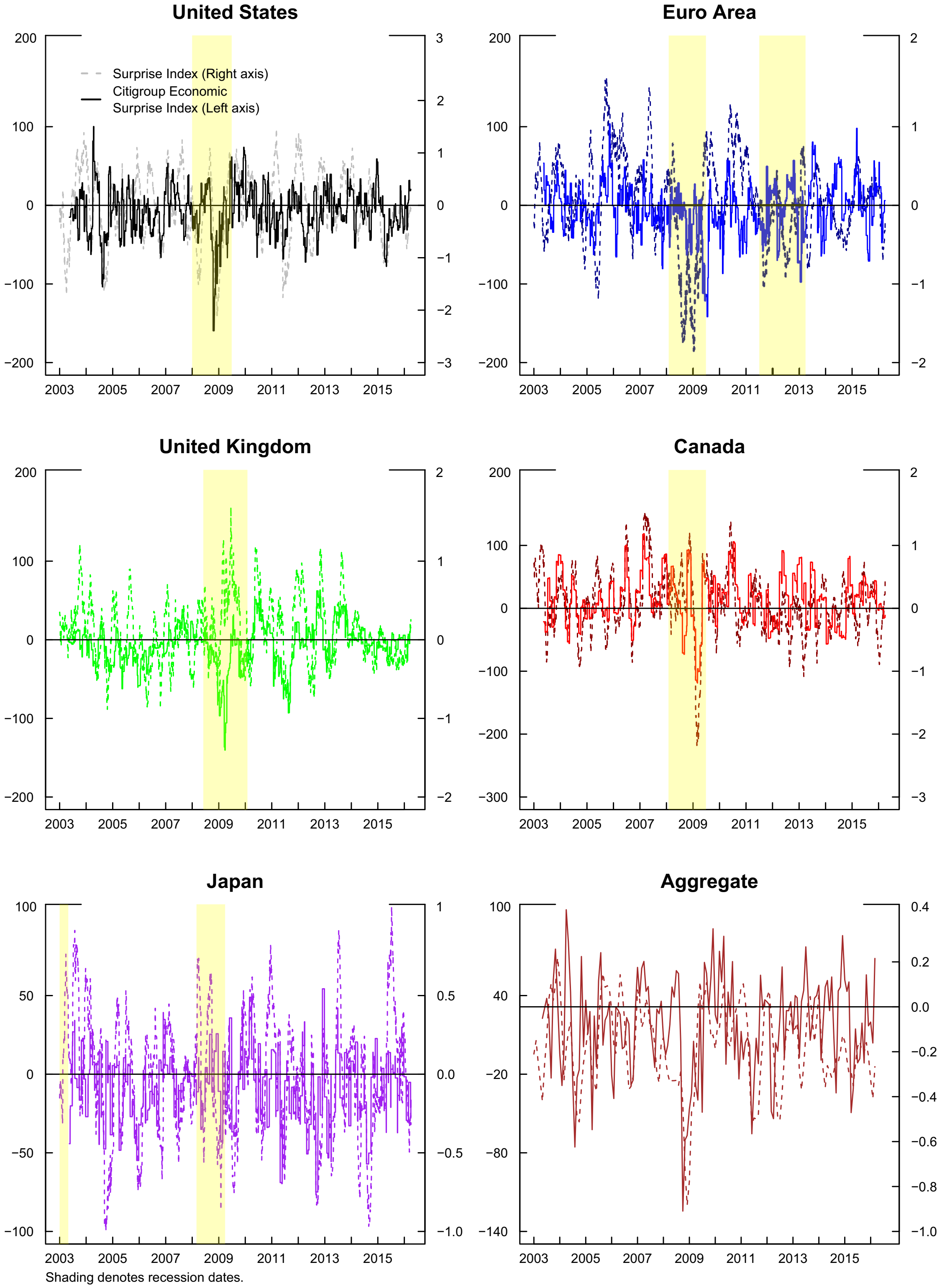

Fig. 4. The solid lines show the surprise indexes for the United States, euro area, United Kingdom, Canada, Japan, and the aggregate of the five countries, as of March 31, 2016. The dotted lines show the Citigroup Economic Surprise Indexes for the corresponding country (left axis). A positive (negative) reading of the surprise index suggests that economic releases have on balance been higher (lower) than consensus, meaning that agents were *ex-post* more pessimistic (optimistic) about the economy.

exchange effects of one-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 Fig. 5 (solid lines). These indexes measure how uncertain agents are about realized 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 current economy. The indexes tend to be elevated during recessions, although there are other episodes when the indexes spike. In the United States, economic uncertainty was also relatively high in 2004, and a big jump was observed at the end of 2005 and in 2012. 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 area was entering and exiting the recession. Increased macro-uncertainty also characterized the beginning of 2010, when the Greece “problem” started to emerge, 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, 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 had by far the highest uncertainty regarding the state of the Japanese economy. Interestingly, higher volatility is associated with negative surprises. The correlation between the surprise index and the uncertainty index tends to be stronger when the surprise index is negative.

The dotted lines in the panels show stock market implied volatilities in the United States, euro area, United Kingdom, Canada, and Japan as represented by the VIX, VSTOXX, VTFSE, VIXC and VXJ. The dashed lines display the stock market realized volatilities for the respective countries. Notably, especially in the latter part of the sample, the uncertainty index and the VIX look somewhat similar, whereas the uncertainty index of the euro area differs from the VSTOXX.[21] The two measures (implied volatility and the uncertainty index) are constructed in completely independent ways. Implied volatility, a forward-looking measure, is computed from option prices. The uncertainty index, a 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. Conversely, the uncertainty index presented here is a clean measure of agents’ uncertainty about the current state of the economy. In the analysis that follows, the VIX will be decomposed into stock market uncertainty and variance risk premium, following Bakaert et al. (2013), to use the part of the VIX that is most comparable to uncertainty.

6. Applications

This section presents a couple of applications for the surprise and uncertainty indexes. In the first application, replicating the regressions shown in Table 2, the surprise index is shown to preserve the properties of the underlying macro-series when affecting asset prices. Combining several macro-series into one, the surprise index has the advantage of being potentially easier to use and very parsimonious. In light of this, Demiralp et al. (2016) make use of it as a control variable when investigating the effects of political commentaries on policy rate decisions and policy expectations in the United States and the euro area, and find it to be a significant determinant of policy expectations. Similarly, Brunetti et al. (forthcoming) employ it as a control variable in studying the impact of speculative activity in commodity markets.

In the second application, the U.S. uncertainty index is compared to other uncertainty measures commonly used in the literature. The uncertainty index has a negative impact on real-activity series. Papers like Bloom (2009), Baker et al. (forthcoming), and Bachmann et al. (2013) have documented a similar analysis with different measures of uncertainty. I find that, in the United States over the last decade, when uncertainty is strictly related to the state of the economy as measured by real activity. It potentially has a milder impact on macro-activity than when the uncertainty is related to both the macro and the financial sectors as measured by the VIX.

6.1. Surprise indexes and news impact on foreign exchanges

As shown in Section 2, macroeconomic news announcements affect asset prices. The surprise index presented in this paper represents a nice summary measure that can be used to parsimoniously control for news announcement surprises in more general models.

[21] Table B3 in the online Appendix displays the correlation between the uncertainty measure and the implied and realized volatilities for each country.

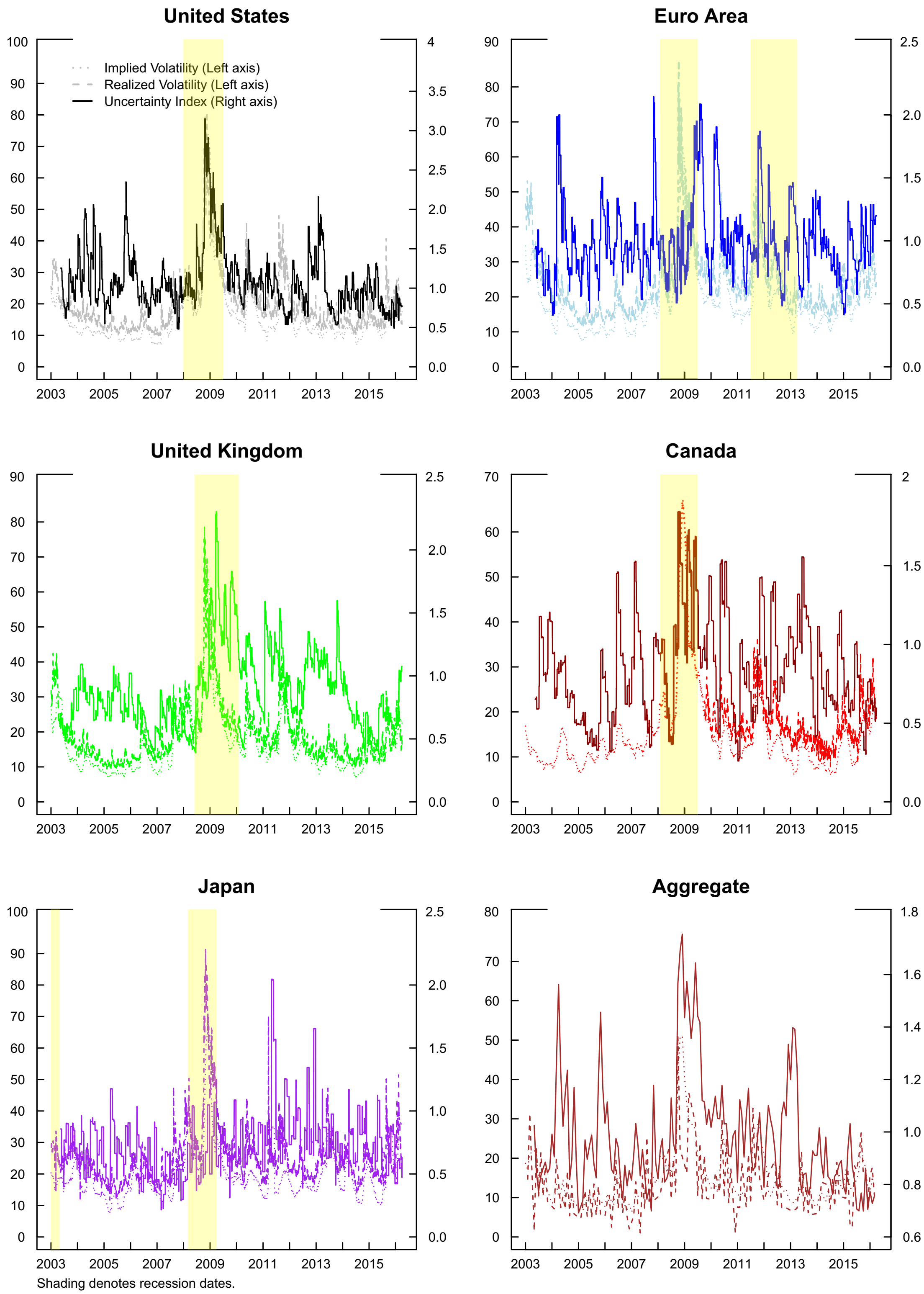

Fig. 5. The solid lines show the uncertainty indexes for the United States, euro area, United Kingdom, Canada, Japan, and the aggregate of the five countries, as of March 31, 2016. The dotted and dashed lines show stock market implied and realized volatilities respectively (left axis).

Table 3
Results of univariate regressions in which exchange rate returns are regressed on the change in the surprise index (July 2003–March 2016).

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

	Euro/$		**GBP/$**		**CAD/$**		**JPY/$**	
	β	R^2	β	R^2	β	R^2	β	R^2
US surprise index	0.418***	0.032	0.303***	0.019	−0.061	0.000	0.482***	0.037
Foreign surprise index	−0.358***	0.016	−0.424	0.005	−0.830***	0.048	0.114	0.000

* 10 percent, ** 5 percent, and *** 1 percent significance with Newey-West standard errors.

Table 3 presents the results of a set of regressions where the euro/$, GBP/$, CAD/$, and JPY/$ exchange rate returns are regressed on the U.S. surprise index and the respective foreign surprise index, that is, 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. The sample period is approximately the same for which the surprise indexes are available (July 2003–March 2016).[22] As shown in the table, the surprise indexes tend to have the right sign and be significant: a positive change in the U.S. surprise index (that is, the U.S. economy doing better than expected) appreciates the U.S. dollar versus the foreign currency, whereas a positive change in the foreign surprise index depreciates the U.S. dollar.

6.2. *Uncertainty measures and the business cycle*

A "true" measure of economic uncertainty does not exist, stock market realized and implied volatilities have been commonly used as proxies for uncertainty. Bloom (2009), for example, uses the Chicago Board of Option Exchange VXO index as a proxy for uncertainty.[23] More recently, a growing literature has focused on finding new measures of macroeconomic uncertainty. Bachmann et al. (2013) use survey expectation data to construct time-varying business-level uncertainty. For Germany and the United States, they construct a measure of uncertainty with forecast disagreement from the IFO Business Climate Survey and the Business Outlook Survey, respectively. Baker et al. (forthcoming) create an economic policy uncertainty (EPU) measure based on the frequency of newspaper references to economic policy uncertainty, the number and size of the federal tax code provisions set to expire in future years, and the disagreement among economic forecasters about policy relevant variables. Leduc and Liu (forthcoming) use a measure of perceived uncertainty of consumers and businesses from the Thomson Reuters/University of Michigan Surveys of Consumers in the United States and the Confederation of British Industry (CBI) Industrial Trends Survey in the United Kingdom. Bakaert et al. (2013) decompose the VIX into variance risk premium, a measure of risk aversion, and stock market uncertainty. Jurado et al. (2015) define uncertainty as the variability in the purely unforecastable component of the future value of a variable and measure macro-uncertainty as the uncertainty factors common to individual measures of uncertainty across a large number of series. Similar to Jurado et al. (2015), the real-activity uncertainty index uses forecast errors, which, however, are not the objective and efficient forecast errors from a model. Instead they are market-based forecast errors and as such, the uncertainty index in this paper measures the perceived uncertainty about the state of the economy. Agents base decisions on their perceived uncertainty rather than an objective uncertainty that they do not observe.

Fig. 6 compares the real-activity uncertainty index developed here against some of the available other measures of uncertainty for the United States. All proxies are de-meaned and standardized for comparison; they are all countercyclical, rising during economic downturns. The correlation of the uncertainty index ranges from about 20 percent between with the Baker et al. (forthcoming) EPU to over 60 percent with the VIX.[24] The uncertainty index exceeds 1.65 standard deviations above its mean only few times but the peaks do not always correspond with the peaks of the other series suggesting that these uncertainty measures might indeed carry slightly different information.

A growing literature has also focused on analyzing the relationship between real activity and uncertainty, and the latter has been generally found to have a significant role in firms' hiring decisions (employment) and output. To estimate such effects, I estimate a bivariate VAR with log employment and each one of the uncertainty proxies from Fig. 6, separately. Because of the short data set (monthly data from May 2003 to March 2016), the bivariate VAR represents a parsimonious way to model the joint dynamics between these variables. As shown in Bachmann et al. (2013), the results are robust to

[22] For comparison with the exercise in Table 2, the regression covers only days in which there are news releases.

[23] The VXO is equivalent to the VIX series in this paper. The VIX was launched in 1993. In 2003, its formula was modified substantially. Data from the new 2003 VIX formula, also used to reconstruct historical data going back to 1990, is known as the VIX. The data associated with the original and revised VIX formulae is known as VXO. In my sub-sample VIX and VXO coincide.

[24] The smallest correlation is between the Bachmann et al. (2013) and Baker et al. (forthcoming) measures (about 10 percent). The highest correlations are between the VIX and the Bakaert et al. (2013) uncertainty/variance risk premium decomposition of the VIX (about 85–90 percent), followed by the correlation between the VIX between Baker et al. (forthcoming) EPU measure (about 70 percent).

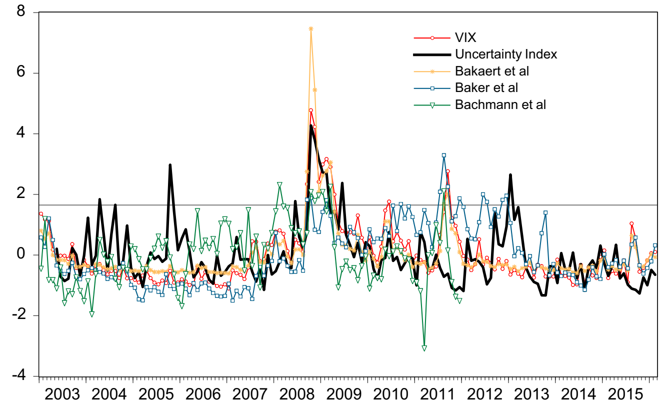

Fig. 6. The solid line represents the uncertainty index which is compared against other common proxies for uncertainty, namely (Bakaert et al., 2013) stock market uncertainty, Baker et al. (forthcoming) economic policy uncertainty index, Bachmann et al. (2013) dispersion measure and the VIX. All series are demeaned and standardized. The horizontal line represents the 1.65 standard deviation limit.

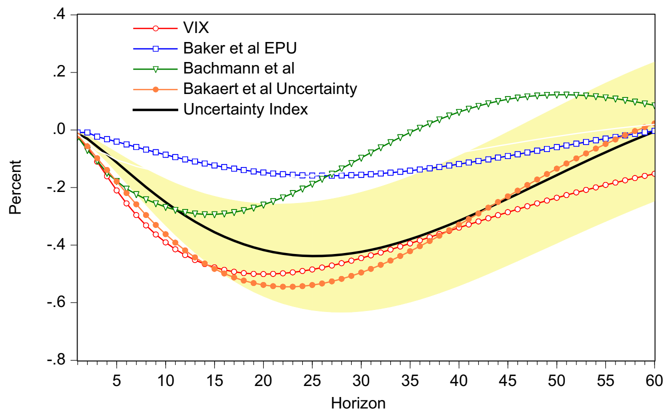

Fig. 7. Employment response to a 1 standard deviation shock in the different uncertainty proxies, namely the uncertainty index, the Bakaert et al. (2013) stock market uncertainty, Baker et al. (forthcoming) economic policy uncertainty index, Bachmann et al. (2013) dispersion measure and the VIX.

estimating a larger VAR similar to Bloom (2009).[25] Each VAR is estimated selecting the lag length based on the Schwarz Information Criterion; employment enters in log levels, while uncertainty measures in levels.

Fig. 7 shows the recursive impulse responses of employment to a one-standard-deviation uncertainty shock as measured by the different proxies, where uncertainty is ordered first. The shaded region is the $\pm$ one standard error confidence interval for the real-activity uncertainty shock. Employment decreases after an uncertainty shock, no matter which uncertainty proxy is used. However, how quickly and how deeply varies across measures, with shocks to the VIX or the Bakaert et al. (2013) stock market uncertainty being the most quick to materialize and the ones with the deepest trough. Shocks to the macroeconomic uncertainty index, to the Baker et al. (forthcoming) EPU measure and the Bachmann et al. (2013) dispersion measure elicit a progressively lower impact on employment over this period. This result suggests that when uncertainty is strictly related to real activity, it potentially has a milder impact on economic activity. By flipping the argument, when uncertainty is more generally related to economic as well as financial conditions as measured by the VIX or the Bakaert et al. (2013) measure of stock market uncertainty, its impact on real-activity variables appears to be stronger.[26] This finding supports recent work by Caldara et al. (in press) which finds that the financial channel is key in the transmission of uncertainty shocks. Although a financial channel is not explicitly introduced, using the real-activity uncertainty index, the VIX and the Bakaert et al. (2013) stock market uncertainty measure allows me to distinguish between purely macro versus the more general macro and financial uncertainty. Interestingly, the variance risk premium (not shown) does not seem to play a very important role.[27] An analysis of the fraction of the VAR forecast error variance of employment that is attributable to innovations in each of the uncertainty series over different forecast horizons confirms the results: the VIX and the Bakaert

[25] Given the short dataset, I only estimate the bivariate VAR.

[26] Fig. A1 shows the confidence intervals for the real-activity uncertainty index and the VIX.

[27] The variance risk premium, computed as in Bakaert et al. (2013), elicits an impulse response to employment similar to that of Baker et al. (forthcoming) EPU.

et al. (2013) stock market uncertainty decomposition explain about 2–3 times the share of the forecast error of employment compared to the real-activity uncertainty index.

For robustness, some alternative specifications are considered. The result just described holds true with other measures of real activity, such as industrial production or unemployment rate. Although a similar comparison is not shown for the other countries, the negative impact of an uncertainty shock on employment is generally significant across countries. As a robustness check, generalized impulse responses from Pesaran and Shin (1998), which do not depend on the ordering of the variables, are also employed and results remain quite consistent across uncertainty proxies and variables.

7. Summary and concluding remarks

The goal of this paper is to construct measures of (i) real-time economic news and their deviation from consensus expectations and (ii) real-time uncertainty about the state of the economy. This paper is a "complement" to the Aruoba et al. (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. This paper is also a "complement" to other papers that develop uncertainty measures in that it only measures perceived uncertainty about the 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, including vintages of data so that the indexes change not only when new information is released but also when past information is revised, expanding the dataset to construct indexes with a longer history, and analyzing in more depth the impact of different types of uncertainty.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jmoneco.2016.06.002.

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