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How Quickly is News Incorporated in Fiscal Forecasts?

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Abstract

This paper tests for the existence of information rigidities in private sector budget-balance forecasts in a multi-country context for a sample of G7 countries between 1993 and 2012. We find evidence of information rigidities in fiscal forecast as private forecasters fail to adjust their budget balance forecasts quick enough in response not only to domestic news, but also to news from abroad.

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1. Introduction

A known property of rational forecasts is that successive revisions of forecasts of the same event are uncorrelated (Nordhaus, 1987). If this was not the case then forecast revisions could be predicted on the basis of past revisions. In practice, Nordhaus found that revisions do tend to be serially correlated, a departure from full information rational expectations (FIRE). Over the last decade, two main classes of theories emerged to account for this departure and potentially explain the existence of "forecast smoothing" or "information rigidity". One theory, called 'sticky information', states that there are fixed costs of acquiring and updating information, which leads infrequent updating of forecasts (Mankiw and Reis, 2002). The other, called 'noisy information', states that forecasters continually update their information but, because they receive noisy signals about the underlying state, never get to the FIRE solution (Woodford, 2001; Sims, 2003). In an influential paper, Coibion and Gorodnichenko (2012) showed that these two classes of theories of information rigidities imply that the forecast error will be correlated with forecast revisions. This fact—that revisions to forecasts contain a large predictable component—provides evidence in favor of models emphasizing "the frictions and limitations faced by agents in the acquisition and processing of information."

There exists, in addition, the possibility that forecasters do not incorporate news from other countries in a timely manner. Given that globalization, in general, and both trade and financial integration, in particular, are expected to increase the cross-country correlations in economic activity (and, thus, in forecast revisions), it is of interest to know to what extent, and how speedily, news from abroad are absorbed into domestic's forecasts.

This paper contributes to this fledgling literature on the examination of forecasts' information rigidities by focusing on private-sector budget balance (*Consensus*) forecasts for the G7 countries between 1993 and 2012. We rely on private-sector forecasts given the considerable skepticism invoked by government forecasts of budget deficits. In fact, a prominent critic is Jeff Frankel whose column piece in the Project Syndicate mocks the "budgetary wishful thinking" of many government agencies.[1] Moreover, many other earlier studies in the literature have also pointed out the deficiencies (and biases) of government budget forecasts.[2] The findings of bias have led to demands that fiscal forecasts should be produced by stronger national fiscal institutions or independent agencies (Frankel and Schreger, 2013) [3] Another suggestion to curb bias is that government forecasts should be supplemented by private sector forecasts, which are presumably less subject to the political pressures that governments face and exhibit less bias than government forecasts (Frankel and Schreger, 2014).[4]

Based on a multi-country Panel VAR analysis, we find that information rigidities can also result from failure in accounting international linkages. Forecasts are then inefficient as forecasters

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[1] http://www.project-syndicate.org/commentary/budgetary-wishful-thinking

[2] Frankel (2011) analyzes official government forecasts and finds a positive bias. The survey by Leal et al. (2008) provides a discussion of previous studies.

[3] See Debrun, Hauner and Kumar (2009) for a survey of the literature on the performance of independent fiscal agencies. Muhleisen et al. (2005) find that countries with fiscal rules and strong budgetary institutions are more successful in their budget forecasting. Poplawski-Ribeiro and Rulke (2011) examine whether the adoption of the Stability and Growth Pact led to a convergence of private, national and EC forecasts.

[4] Jalles et al. (2015) analyze the general properties of private-sector budget balance forecasts in a sample 29 countries.

fail to adjust their budget balance predictions quick enough in response to domestic news and news from abroad.

The paper is organized as follows. Section 2 outlines the methodology for testing information rigidities in a multi-country setting. Section 3 discusses the data. Section 4 presents our main results.

2. Methodology: testing for information rigidities

In order to examine cross-country correlations in information rigidities (and forecast revisions), we follow Isiklar et al. (2006).[5] More specifically, we exploit the fact that we have a sequence of revised budget balance forecasts to learn something about how quickly forecasters absorb new information into their forecasts and how responsive they are to news from other countries. When the forecaster makes his first forecast for the budget balance in a given year, he presumably does so using all the relevant information. Next month, the forecast is revised, presumably because the forecaster has received some new information that has some bearing on the budget balance forecast. If the forecaster is efficient, the news should be reflected fully in this month's revision. In practice forecasters may not absorb all news instantly into their revisions; hence by studying the correlations across forecast revisions we can learn about how quickly news are absorbed into forecasts. And, similarly, studying correlations between the forecast revisions for one country and the forecasts revisions for other countries tells us to what extent and how speedily news from other economies is absorbed into a country's forecasts.

Mathematically, denoting the new information available at horizon *h* as $\varepsilon_{t,h}$, one can think of the forecast revision as the accumulation of past news components, so that:

$$r_{t,h} = \beta_0 \varepsilon_{t,h} + \beta_1 \varepsilon_{t,h+1} + \beta_2 \varepsilon_{t,h+2} + \ldots \qquad (1)$$

where β_s represents the use in today's revision of the new information that became available *s* periods, ago, $\varepsilon_{t,h+s}$. If forecasters are fully efficient, then $\beta_j = 0$ for all $j>0$ should be satisfied and all the new information is reflected immediately in today's revision. Rewriting equation (1) in a full autoregressive form:

$$r_{t,h} = c + B_1 r_{t,h+1} + B_2 r_{t,h+2} + \ldots + B_p r_{t,h+p} + \varepsilon_{t,h} \qquad (2)$$

where $r_{t,h}$ are vectors of revisions for all countries. All of the *B* coefficients should be zero under the null of full information.

Assuming that there are *J* countries in a system, $r_{t,h}$ in equation (2) is a $(J \times J)$ vector containing the forecast revisions of the *J* countries, B_k is the $(J \times J)$ matrix of coefficients of $r_{t,h+k}$ and *p* is the chosen lag length. The diagonal elements of the matrix tell us how quickly forecasters

[5] Loungani et al. (2013) employ the same approach to consensus forecasts of GDP growth in a sample of 46 countries.

absorb news from their own country, and the off-diagonal elements indicate how quickly they absorb news from other countries.

Note that equation (2) is in the form of a vector autoregressive model (VAR) where the variables are the forecast revisions of the J countries; hence, one can use the standard output from an estimated VAR. In particular, the estimated generalized impulse response functions (IRF) can be used to trace out the effect of a one standard deviation shock to forecast revisions for country i on the forecast revisions for country j.[6] We compute the speed at which forecasters absorb news over time by decomposing the variation in forecast revisions into the part accounted for by current innovations and the part accounted for by past innovations.

All in all, the approach followed here is in line with Dovern et al.'s (2015) test of information rigidities based on forecast revisions.[7] In contrast with Coibion and Gorodnichenko's (2012) test that requires the use of the outcomes, Dovern et al.'s (2015) test has the advantage that "because it relies on forecast revisions rather than forecast errors, the econometrician does not have to take a stand on which version of the ex-post data to use to construct forecast errors".

3. Data and Descriptive Statistics

In the past decade there has been a huge growth in published economic analysis emanating from banks, corporations and independent consultants around the world, and a parallel growth in "consensus forecasting" services which gather together information from these disparate private sources. Each month since 1989, the Consensus Economics service has published forecasts for major economic variables. For each country, the number of forecasters varies between about 10 and 30, and most forecasters are from the private sector. Our analysis is focused on the arithmetic mean of the forecasts—the "consensus". While individual private sector forecasts may be subject to various behavioral biases (Batchelor and Dua, 1992), many of these are likely to be eliminated by pooling forecasts from several forecasters.

Seven countries are represented in the sample, namely the "Group of 7" (USA, Japan, Germany, France, UK, Italy and Canada). We use forecasts of the budget balance for the current and next year for the period from February 1993 to December 2012. The event being forecasted is the average budget balance-to-GDP ratio for a given target year.[8] For each target year, the sequence of forecasts is the 24 forecasts made between January of the previous year and December of the

[6] We use generalized impulse responses and variance decompositions which are ordering-free (Pesaran and Shin, 1998).

[7] They show that both classes of models of information rigidities described earlier imply that regressions of forecast revisions on past revisions should yield a positive coefficient; in contrast, the FIRE model would predict a zero coefficient.

[8] Consensus Economics provides forecasts for the public sector budget balance in absolute numbers (local currency). As most fiscal criteria and rules for budgetary discipline are formulated in terms of the balance-to-GDP ratio, we construct these by using actual national GDP figures as the denominator. Alternatively, one could have followed Heppke-Falk and Hufner's (2004) approach: first, generate projected nominal GDP series (using information from Consensus' real GDP growth and inflation forecasts) and then take the respective ratio. In practice, the method of scaling is unlikely to make a big difference because much of the variation in the ratio comes from the numerator (the budget balance) rather than the denominator (level of GDP). As a robustness check, we used the latter method for a few countries; the correlation with the series based on our method exceeded 0.95 in all cases.

year in question. So, for example, the first forecast for the average budget balance-to-GDP ratio for 2012 is made in January 2011 and the last one in December 2012. We index the sequence of forecasts by the horizon (h), with $h=24$ corresponding to the first forecast made and $h=1$ corresponding to the last. The dataset also includes actual data on the budget balance-to-GDP ratio from the IMF's International Financial Statistics.

At this point a caveat should be made. Data revisions have worried economists for many years now (see Croushore, 2011 for a recent survey) and policy-makers have to base their decisions on preliminary (timely estimate based on limited information) and partially revised data, since the most recent data are usually the least reliable as it simply translates a noisy indicator for final values (Koenig et al., 2003).[9] We are aware that data revisions poses challenges to forecasters[10] and that forecast studies should reflect the true forecasting performance by using real-time data instead of final data (which can affect the forecasting results – Stark and Croushore, 2002; Castro et al., 2013). However, in the present case it is difficult to find reliable, consistent and comparable real-time vintages for the budget balance-to-GDP ratio for the countries in our dataset.

Before discussing our main results, we present some descriptive statistics of the set of forecasts under scrutiny. First, define, for each country i during year t, $e_{it} = A_{it} - F_{it}$, where e represents forecast error, F denotes the forecast, and A denotes its respective realization. Second, to assess forecasting performance we rely on the forecast average bias (ME), the mean absolute error (MAE) and the root mean squared error (RMSE). While these measures have a number of limitations, the RMSE has invariably been used as standard for judging the quality of predictions. A better approach for evaluating performance is to compare descriptive statistics with similar statistics obtained from a naive standard. Using a naive standard allows us to test whether a forecaster's errors are significantly smaller than those of the benchmark. A frequently used naive standard compares a forecaster's errors with those obtained from a no-change (random-walk) naive model. Theil's U-coefficient formalizes this comparison. If U is less than 1, the forecasts which are being evaluated have smaller errors than those of the naive model, but this result does not guarantee that the former are significantly better than the latter.

The ME, MAE, RMSE and Theil statistics are reported in Table 1. If we take the full sample period first, one can notice that the mean error is always smaller than one percentage point, and the absolute error is only slightly larger (with the highest value corresponding to Japan). Moreover, the mean error is generally negative suggesting "optimism" in predicting the budget balance. More interesting is to look at the year-ahead and current-year performance: the latter presents larger ME, MAE and RMSE vis-a-vis the former. This is theoretically expected given the fact that forecasters, at the one year-ahead horizon, possess much less information to allow them to make good guesses, relative to that available at the current-year horizon. Even though empirical evidence suggests the existence of "forecast smoothing" this tends to converge to zero as the forecast horizon is brought to zero. With respect to the Theil statistics we observe that they are generally below unity, therefore

[9] See McKenzie (2006) for 8 reasons underlying revisions of official statistics.

[10] Recent empirical work suggests that measurement errors have more complex dynamics than existing models of data revisions allow (see, Aruoba, 2008). With this in mind, Jacobs and van Norden (2011) propose a state-space model which allows for richer dynamics in these measurement errors, including the noise, news and spillover effects. Bouwman and Jacobs (2011) present a state-space model that can deal with publication lags and data revisions.

suggesting that the consensus forecasts are "preferred" to the random-walk model.[11] This looks like a relatively good performance on a country-by-country basis.

Table 1. Descriptive Statistics

Stat.	USA	Japan	Germany	France	Italy	UK	Canada
				Full Sample			
ME	-0.18	-0.47	0.20	-0.52	-0.37	-0.62	0.27
MAE	0.97	1.73	1.01	0.84	1.01	1.16	0.74
RMSE	2.50	5.02	1.79	1.61	2.09	3.00	1.03
				Year Ahead			
ME	-0.50	-0.65	0.02	-0.71	-0.17	-0.74	0.24
MAE	1.66	2.02	1.27	1.09	1.11	1.38	0.84
RMSE	5.46	6.70	2.57	2.51	1.97	4.13	1.34
Theil	0.45	0.45	0.42	0.34	0.32	0.41	0.40
				Current Year			
ME	0.01	-0.16	0.37	-0.33	-0.08	-0.41	0.30
MAE	0.56	1.24	0.75	0.59	0.62	0.79	0.57
RMSE	0.72	2.22	1.02	0.71	0.53	1.13	0.52
Theil	0.21	0.32	0.36	0.23	0.20	0.34	0.37

Notes: This table presents some descriptive statistics for 7 Developed countries. ME, MAE, RMSE and Theil stand for the mean forecast error, the mean absolute forecast error, the mean square forecast error and the U-Theil statistic, respectively. "Year ahead" forecasts are those conducted between January and December of the previous year; whereas "current year" forecasts are those carried out in the year in question.

4. Results: failure to account for cross-sectional linkages?

To test for information rigidities in a multi-country context, the VAR equation (2) is estimated with the lag length set at three, based on the Akaike Information Criterion.[12] Under perfect efficiency, forecast revisions should respond fully to the shocks immediately and the impulse response functions (IRFs) should be zero for longer horizons.[13] In other words, the speed with which forecasters absorb news into their forecasts can be gauged by how quickly the estimated IRF go to zero. In Figure 1 we trace out the (generalized) effect of a shock to forecast revisions for country i on the forecast revision of country j. In general, the impulse responses (bold lines, with 2 standard error bands—dashed lines) show a significant dependence of forecast revisions on own-country lagged revisions. The same applies to cross-country lagged revisions (Figure 2). For example, revisions of forecasts for the United States are correlated with past revisions of forecasts for the United States (Figure 1 top left panel), as well as those for Japan, Canada and the UK (not shown). For example, revisions of US forecasts prompt revisions of forecasts for Canada, the UK and Germany, albeit with different lags (Figure 2).

[11] We also tested for differences in forecast accuracy by means of the Diebold-Mariano test and confirmed consensus' forecasts superiority.

[12] When comparing models with different lag lengths we made sure that the same number of observations was used in the estimations.

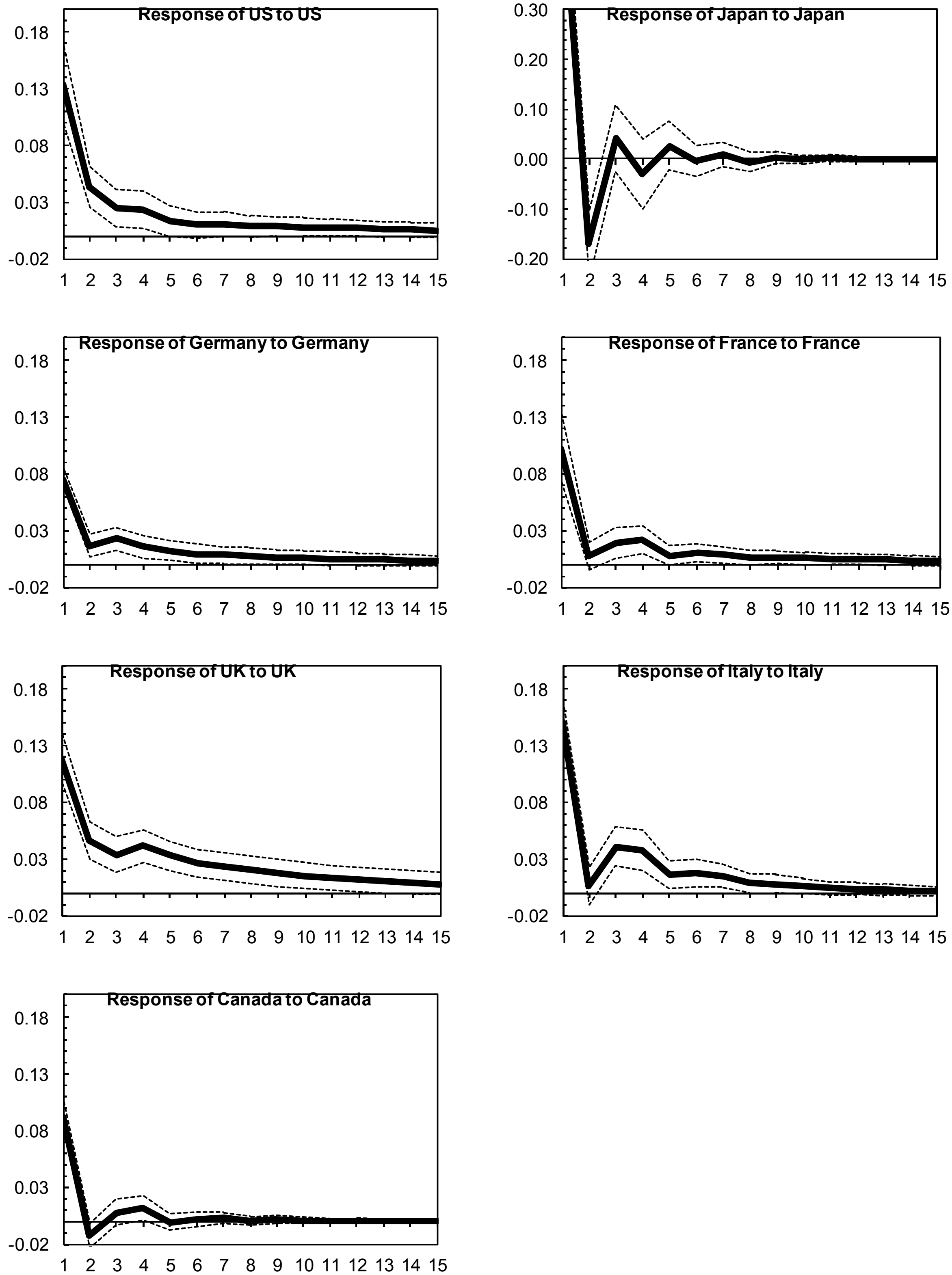
[13] If there are non-zero impulse response values at longer horizons, then forecasters are not efficiently using the information immediately, and some of the information is being used in the later forecast revisions.

Let us focus on some of the key results from the IRFs. Consider first responses to own-country shocks shown in Figure 1. Consistent with evidence gathered elsewhere (see Jalles et al., 2015), in all seven cases there is sluggishness in the absorption of information. The number of months it takes to absorb information fully ranges from about 8-9 months in Japan and Canada to more than 15 months in the US, Germany and UK. All in all, the multi-country analysis points to forecast inefficiency as forecasters fail to adjust their forecasts quick enough in response to domestic news and news from abroad. Next, consider the "off-diagonal" elements—the panels in Figure 2 that show the responses of the forecast revision of one country to the forecast revisions in other countries. First, countries where there is sluggishness in the absorption of own-country information also tend to be sluggish in absorbing foreign information. Second, most countries show sluggish responses to news emanating from the US, implying that departures from full information arise partly from an insufficient attention to news from this country.[14] This is particularly true in the case of Japan that is the least responsive to other countries' fiscal information (impulse response not statistically different from zero). Aggregate spillovers between countries are likely to be contained when fiscal multipliers and/or imports elasticities are small (Ivanova and Weber, 2011). First, Japan is the least integrated country among the G7, that is, where trade and/or financial linkages are the smallest. Second, several studies have found, using different methodologies, that the fiscal multiplier in Japan is generally low (Miyazaki, 2007; Afonso and Aubyn, 2008).

[14] The full set of results is available upon request. Mutatis mutandis, the same set of conclusions remains valid.

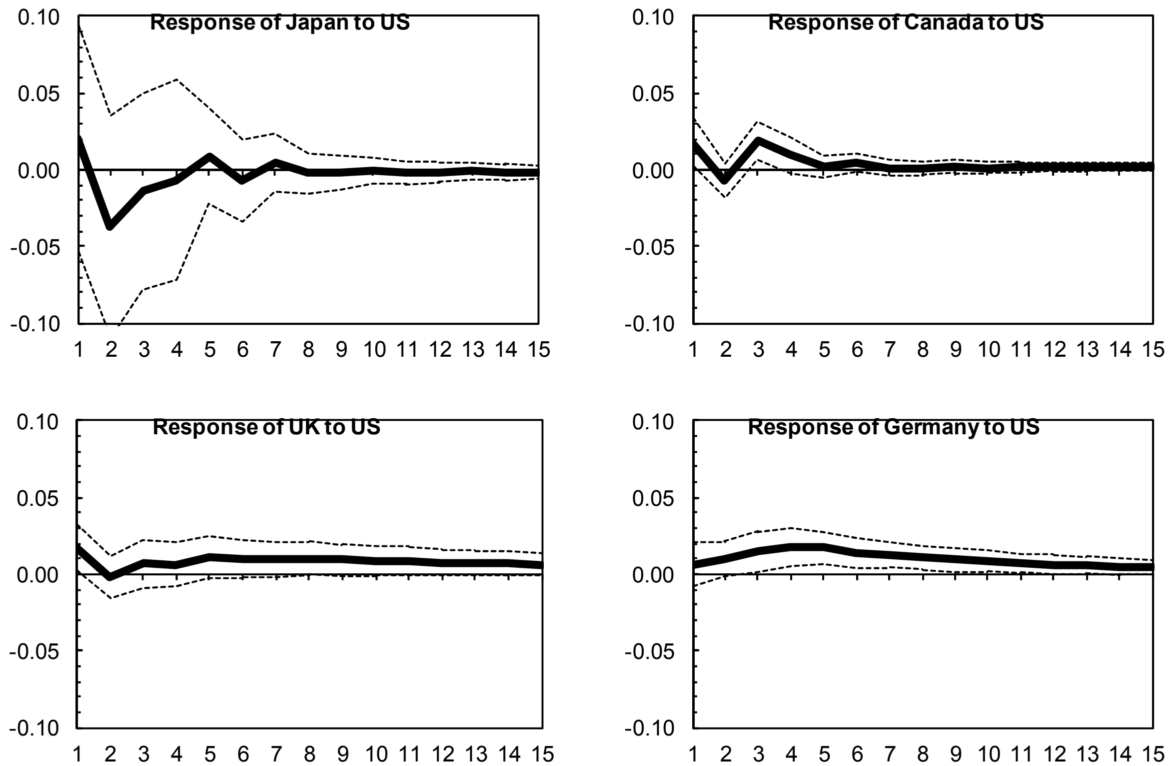
Figure 1: Generalized Impulse Response Functions of Forecast Revisions

(own-country responses, in percentage points)



Note: confidence bands correspond to two standard deviations.

Figure 2: Generalized Impulse Response Functions of Forecast Revisions
(responses to US revisions, in percentage points)



Note: confidence bands correspond to two standard deviations.

To quantify the relative importance of these shocks, we present in Table 2 the generalized forecast error variance decompositions.[15] The contribution of own-shocks ranges from about 54% in Germany to close to 95% in Japan. The off-diagonal terms show the considerable dependence of Germany forecast revisions on US revisions. There is also substantial dependence of revisions in Germany and France on UK revisions.

[15] Note that generalized variance decompositions do not necessarily add up to 100% due to non-zero covariances between the original country shocks (Pesaran and Shin, 1998). Our numbers are normalized so that the total adds up to 100.

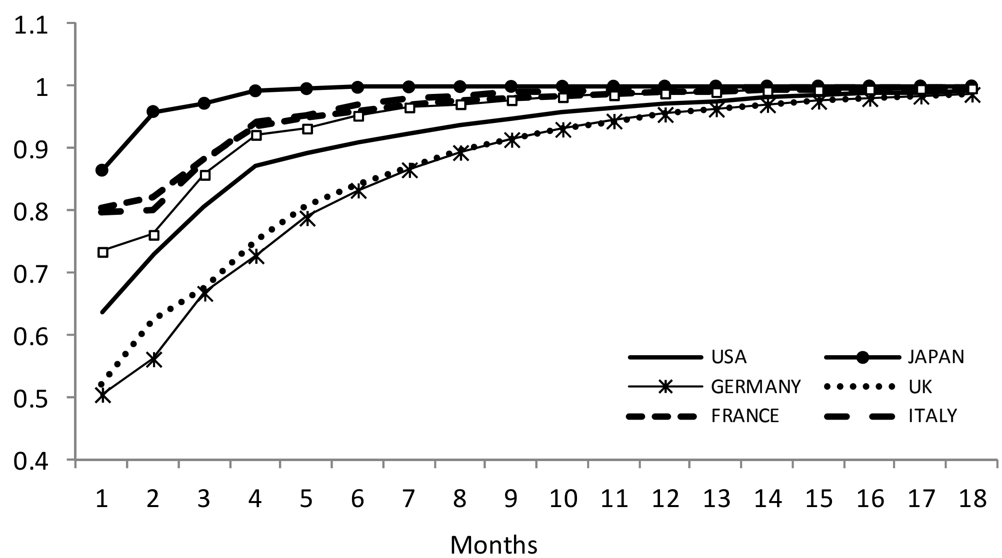
Table 2. Variance Decompositions: Panel-VAR

	USA	JAPAN	GERMANY	FRANCE	UK	ITALY	CANADA
USA	**70%**	6%	2%	10%	8%	1%	3%
JAPAN	1%	**95%**	1%	2%	0%	1%	1%
GERMANY	14%	1%	**54%**	5%	21%	4%	0%
FRANCE	5%	0%	3%	**75%**	15%	1%	1%
UK	8%	2%	3%	4%	**81%**	1%	1%
ITALY	3%	0%	4%	1%	1%	**88%**	2%
FRANCE	7%	1%	2%	14%	2%	3%	**71%**

Note: This table shows the generalized forecast error variance decompositions.. Diagonal elements show the contribution of own shocks. Off-diagonal elements should be read, for example, as follows: there is considerable dependence of forecast revisions in Germany on USA revisions.

Finally, in Figure 3 we show the speed of absorption of news of budget balance forecast revisions. As shown, there is a quite bit of variation across countries in the immediate absorption of news, ranging from 50% in Germany to 85% in Japan. Additionally, catch-up is fairly slow so that by 10-11 months, in all countries 90% of the news has been absorbed into forecasts.[16]

Figure 3: Speed of Absorption of News: Variance Decomposition



5. Concluding remarks

In this paper we uncovered yet another reason for information rigidity in revisions of fiscal forecasts: this originates from failure to properly account for international cross-country linkages in absorbing new information. In other words, our multi-country analysis points to forecast inefficiency as forecasters fail to adjust their forecasts quick enough in response to new arrivals of

[16] In contrast, in the case of GDP growth forecasts, the speed of absorption of news is considerably faster, taking 6 months to reach the 90% level (Loungani et al., 2013).

not only domestic news but also news from abroad. The correlation of forecast revisions with past revisions is consistent with theories of information rigidities, as discussed by Coibion and Gorodnichenko (2013) and Dovern et al. (2015). Hence, the evidence of forecast smoothing is inconsistent with full informational rational expectations. To sum up, while we support Frankel and Schreger's (2014) view that adding private sector forecasts in the policy process is useful (in addition to official government forecasts), our findings show that these also have several limitations and could be improved upon.

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