EXPECTATIONS AND ECONOMIC FLUCTUATIONS: AN ANALYSIS USING SURVEY DATA

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Abstract—Using survey-based measures of future U.S. economic activity from the Livingston Survey and the Survey of Professional Forecasters, we study how changes in expectations and their interaction with monetary policy contribute to fluctuations in macroeconomic aggregates. We find that changes in expected future economic activity are a quantitatively important driver of economic fluctuations: a perception that good times are ahead typically leads to a significant rise in current measures of economic activity and inflation. We also find that the short-term interest rate rises in response to expectations of good times as monetary policy tightens.

I. Introduction

THE idea that changes in expectations of future economic activity can be important drivers of economic fluctuations has received increased attention with the unfolding of boom-bust cycles around the world over the past twenty years. The experiences of Japan in the late 1980s, East Asia in the late 1990s, and the United States over the past fifteen years suggest that optimism about future growth prospects may help fuel booms and that subsequent downward revisions in expectations may help precipitate busts. In addition, these episodes have served to generate debate about the importance of the role played by monetary policy in boom-bust cycles: the episodes were often accompanied by heightened criticism of central banks for fueling the booms by keeping monetary policy too easy for too long.[1]

Although boom-bust cycles are interesting events that suggest the importance of expectations for economic fluctuations, there has been relatively little empirical analysis that attempts to formally quantify the role played by expectations for the cyclical behavior of the economy. In this paper, we add to this literature by introducing survey-based measures of future U.S. economic activity into simple empirical models to measure how changes in expectations, and their interaction with monetary policy, contribute to fluctuations in macroeconomic aggregates. We take expectations measures from two sources, the Livingston Survey and the Survey of Professional Forecasters, and introduce them into an otherwise conventional vector autoregression framework. Survey data remain relatively unused in empirical work on economic fluctuations, despite the fact that surveys are closely monitored by policymakers, who view them as important indicators of market participants' perceptions of future economic activity. A benefit of using survey data is that they provide an independent source of information about agents' perceptions of future economic activity. Consequently, one need not impose modeling assumptions to back out those expectations.

We exploit the timing of the surveys' construction to help identify structural shocks to expectations. To help mitigate difficult issues surrounding the use of ex post revised data in assessing the quantitative role of changes in expectations, our VARs are estimated using data that are not subject to revision over time. In particular, we use the unemployment rate as a measure of economic activity.

Our main finding is that changes in expectations about future economic activity contain quantitatively important information that helps account for economic fluctuations: a perception that good times are ahead, manifested as a drop in the expected unemployment rate, typically leads to a significant rise in current measures of real economic activity and inflation. In addition, the downward revision to the expected future unemployment rate leads to a contemporaneous rise in the short-term interest rate as monetary policy tightens. The results are robust across the two surveys, to forecasts over very different horizons of up to ten years ahead and to the inclusion of different forward-looking financial variables in the empirical models. Moreover, we show that our results are substantively unchanged when we measure expectations using data from the University of Michigan survey of households rather than survey measures from the professional forecasters. The Michigan survey data provide an important check on our findings since the respondent sample is larger and is not composed of professional forecasters.

Macroeconomic variables respond to a wide array of influences that are difficult to fully capture in small-scale VARs. Consequently, VAR models may suffer from misspecification due to omitted variables. This problem could potentially be mitigated through the introduction of survey expectations into the VAR framework since professional forecasters and households likely consider a wide range of variables when making forecasts of future economic activity. Our findings suggest that survey expectations contain important information, not directly included in the VARs, that is relevant for economic activity—even after controlling for movements in forward-looking financial variables. While our analysis is not geared to identifying specific factors that map into expectations shocks, one possibility is news that households receive about future fundamentals that is unrelated to current fundamentals and is thus unaccounted for by an econometrician

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[1] For instance, see Taylor (2008) for a criticism of the Federal Reserve's policies under chairmen Greenspan and Bernanke and Lionel Robbins's (1934) argument that the Federal Reserve kept interest rates below the natural rate for too long during the late 1920s. See also Okina and Shiratsuka (2001) concerning reasons that Japanese monetary policy may have been too loose in the period leading up to the burst of the stock market bubble at the beginning of 1990.

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(see, for example, the consumption shock and news shock in the empirical analysis of Cochrane, 1994).

Alternatively, to the extent that one successfully accounted for all the fundamentals that drive unemployment forecasts, our methodology would identify expectations shocks as autonomous changes in expectations of future activity. Those autonomous revisions to expectations ("animal spirits") could potentially influence current economic activity (see, for instance, the dynamic stochastic general equilibrium (DSGE) model with expectations shocks of Danthine, Donaldson, & Johnsen, 1998). However, identifying such shocks is a tall order. We prefer to interpret our results as indicating that expectations of future economic activity contain important information not otherwise included in the VAR and that this information matters for understanding movements in macroeconomic variables.

Our results also shed some light on the role played by monetary policy in fueling boom episodes in the United States. The conventional wisdom, as embodied in Bernanke and Gertler (2000), is that an inflation-targeting central bank will naturally act as a stabilizing force with respect to boom-bust cycles as it contracts monetary policy in response to factors that raise expected inflation and lower output gaps. In contrast, Christiano, Motto, and Rostagno (2006) point out that this need not be the case if nominal wages are sticky. For example, expectations of higher future productivity growth put upward pressure on the real wage. To the extent that the nominal wage is sticky, this is necessarily accomplished by a fall in prices, to which an inflation-targeting central bank responds by lowering the short-term nominal interest rate, thus feeding the boom. Our empirical results are more consistent with the conventional view: upward revisions to expectations about future economic performance are accompanied by a rise in current activity and inflation and a concomitant rise in the short-term interest rate, which tends to stabilize the economy. Though our findings are not derived exclusively from boom-bust episodes in the data, they nevertheless suggest that during times of economic optimism, the Federal Reserve tended not to run an expansionary monetary policy that amplified fluctuations.[2]

Along similar lines, our result that the economy expands in response to an upward revision in expectations of future activity squares well with the predictions of standard labor matching models regarding the impact of changes in expectations. In that framework, expectations that good times are ahead increase the marginal benefit of a match and lead to a fall in the current unemployment rate as more vacancies are being posted. Studying the effects of an anticipated increase in productivity in a labor search model, Den Haan and Kaltenbrunner (2009) find that it induces entrepreneurs to increase investment in new projects and post vacancies early and so induce an economic expansion.[3]

The remainder of the paper is organized as follows. Section II describes how we measure expectations and economic activity and presents the results from a baseline VAR. In section III, we investigate the impact of adding financial variables and other indicators of economic activity to the baseline VAR. Section IV analyzes the quantitative contribution of expectations shocks to the variances of the unemployment and inflation rates. Section V analyzes the robustness of the baseline VAR results to longer horizon forecasts, altered sample size, and the use of household expectations. Section VI concludes.

II. A Small Structural VAR

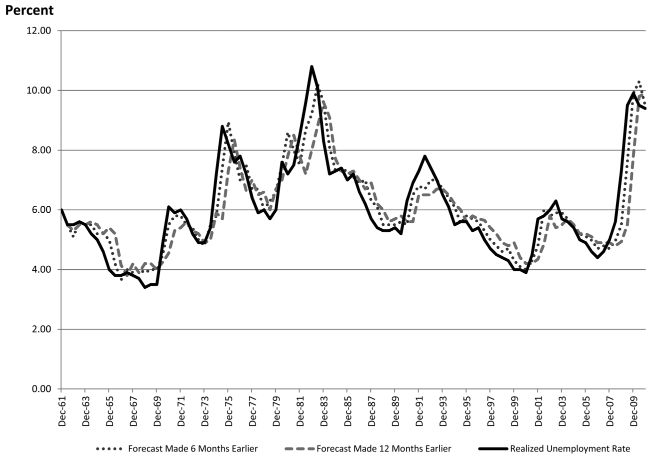
We are interested in quantifying the extent to which changes in agents' expectations about the future may affect current economic variables. We use data from two sources to measure expectations: the Survey of Professional Forecasters (SPF) and the Livingston Survey (LS). Both surveys collect predictions from professional forecasters (typically about fourty to fifty respondents per survey), and both are conducted by the Federal Reserve Bank of Philadelphia. The SPF is a quarterly survey that dates from 1968, at which time it was conducted by the American Statistical Association and the National Bureau of Economic Research (the Federal Reserve Bank of Philadelphia took over the survey in 1990). The SPF is released at the end of the second month of each quarter (or early in the next month). Survey participants provide forecasts of variables such as CPI inflation, the unemployment rate, real GDP growth, and nonfarm payroll growth over a five-quarter horizon. The LS, which was initiated in 1946, is conducted twice a year. Survey questionnaires go out in May and November, and the survey's results are made public in the second week of June and December. The survey started compiling forecasts of the unemployment rate in 1961, and it covers a somewhat broader set of macroeconomic variables than the SPF.

We use survey forecasts of the unemployment rate, to proxy expectations about future economic activity. The unemployment rate has the advantage that it is subject to only minor revisions, which are limited to changes in seasonal factors. By using forecasts of the unemployment rate, we can bypass difficult questions about real-time data and subsequent data revisions. For example, the use of expected and actual real

[2] Christiano et al. (2006) focus their analysis solely on boom-bust episodes. They identify three over the period 1870 to 2006: one that began in 1920 and ended at the start of the Great Depression, one that began in the mid-1950s and ended in the 1970s, and one that began in the mid-1990s and ended in the early 2000s.

[3] Under a news shock interpretation of an innovation to expectations, our findings are somewhat at odds with the predictions of the standard neoclassical business cycle model. In that model, expectations that good times are ahead, usually modeled as an anticipated increase in productivity, lead to a current period recession, as the positive wealth effect of the anticipated productivity increase induces an increase in leisure today. However, the standard model can be modified so that expectations of good times can generate business cycle booms, as shown by Beaudry and Portier (2006, 2007), Christiano et al. (2006), and Jaimovich and Rebelo (2009). Typically the modification involves adding complementarities in the production technology or adding certain types of adjustment costs, of which a labor-matching friction would be an example.

FIGURE 1.—LIVINGSTON SURVEY FORECASTS AND REALIZED UNEMPLOYMENT RATES



GDP growth (measured using the latest vintage of data) in our VARs would be problematic because real GDP revisions may incorporate information that is unavailable to forecasters at the time their forecasts were being made. Since the unemployment rate series is unrevised, we can include expected and actual unemployment in a VAR and not otherwise have to account for the possibility that the VAR conditioning set contains more information than forecasters had when making their predictions. That said, we will also investigate the robustness of our results to the inclusion of additional real-time activity measures such as a real-time measure of GDP growth and the Institute of Supply Management (ISM) activity index. We find that the results are similar to those that use the unemployment rate as the sole measure of real activity (see section IIIB).

Figure 1 plots the six-month-ahead and twelve-month-ahead LS forecasts of the unemployment rate, together with the realized unemployment rate. Notwithstanding the large increase in the unemployment rate to more than 10% in 1982 from 4% in the early 1970s, forecasters were able to predict the unemployment rate reasonably well at both horizons. However, as with inflation forecasts, forecasts of the unemployment rate tended to lag movements in the realized unemployment rate, particularly for the twelve-month-ahead forecasts (see the discussion of the inflation forecasts in Leduc, Sill & Stark, 2007). Thus, unemployment rate forecasts tended to be below the unemployment rate during most of the 1970s and above the unemployment rate during the 1980s.[4]

Consider now the implications of a baseline VAR model comprising the expected unemployment rate, the realized unemployment rate, the realized CPI inflation rate (annualized), and the realized nominal three-month Treasury bill rate (annualized).[5] The key specification issue for investigating the consequences of shifts in expectations is how to identify expectations shocks. We use a recursive identification scheme that places the expected unemployment rate first in the ordering so that there is no contemporaneous response of expected unemployment to other shocks in the system. Following Leduc et al. (2007), the placement of expected unemployment first in the recursive identification is motivated by the timing of the surveys and the way we have aligned the other data in the VAR. The known timing of the survey is critical in allowing us to order the expected unemployment rate first: when making forecasts at time t, the information set on which agents condition their forecasts will not include, by construction, the time t realizations of the unemployment rate and the other variables in our VAR (since forecasters did not have that information at the time they made their forecasts).

To elaborate, consider the SPF. The response deadline is generally the third week of the second month of the quarter (although the deadline does vary a bit over the survey sample period).[6] Based on the survey's timing, we redefine quarters of the year so that the first month of a quarter is the month that survey responses are filled out. Thus, the redefined first quarter is February, March, April. The second quarter becomes May, June, July, and so on. With this timing convention and associated data definition, the SPF is by construction conducted at the start (generally the second or third week) of each quarter. Consequently, the data are aligned so that agents have past values of the unemployment rate, inflation, and interest rates in their information set when the surveys are filled out, but they do not yet have the official data releases telling them contemporaneous quarter values of the unemployment rate and inflation. However, they do have some information on quarterly interest rates (the first two or three weeks of the quarterly realization).

We employ a similar strategy when constructing the data set for the VARs that use the Livingston Survey measure of expectations. Now, half-years are defined based on the timing of the Livingston Survey to mitigate the influence that contemporaneous realizations of the unemployment rate, inflation, and interest rates can have on forecasters' decisions about future unemployment rates. Since in this case the survey questionnaire is due back in May and November, we redefine half-years as running from April to October and from October to April. As with the SPF, this data alignment implies that the survey is conducted at the start of each period: May and November. The remaining variables in the VAR are then measured as the average monthly value of the corresponding six-month period.

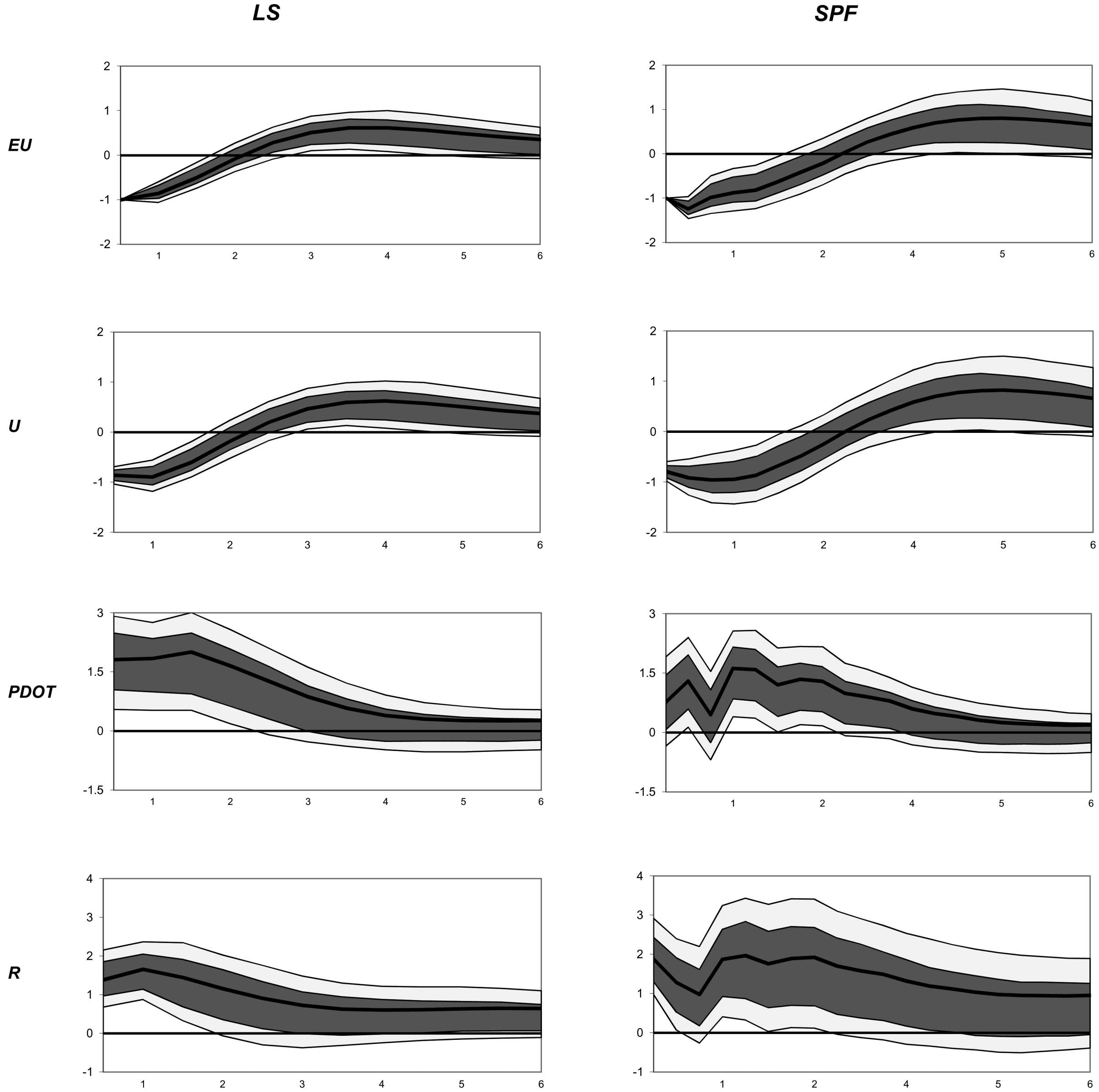
To summarize then, the baseline VARs contain four dynamic variables and use a recursive identification scheme that orders expectation variables first. The variables are

[4] A similar picture emerges for forecasts from the Survey of Professional Forecasters.

[5] Note that the CPI index is generally not revised over time, nor is the measured Treasury bill rate.

[6] For example, in 1995 the Q1 SPF respondents had to return the survey questionnaire by February 21. For the 1995Q2, survey responses were due by May 22. For 1995Q3, survey responses were due by August 22, and for 1995Q4 survey responses were due by November 20.

FIGURE 2.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT



The responses were generated from a VAR with expected unemployment (EU), actual unemployment (U), inflation (PDOT), and the three-month T bill rate (R). All the responses are expressed in percentage points. The x-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. The system with the LS survey is estimated over the period 1961H1–2008H2, while that using the SPF survey is estimated over the period 1968Q4–2008Q4.

ordered as the expected unemployment rate, the unemployment rate, inflation, and the nominal interest rate. The data used in the VAR are largely unrevised over time, and the definitions of quarters or half-years and the measurements of quarterly and biannual realizations are consistent with placing the expectations variable above the other model variables in the recursive ordering. We now turn to an analysis of the baseline VAR results.

A. *Results from a Baseline VAR*

Our interest focuses on the economy's response to an unanticipated shock to expectations of the future unemployment rate. The models are estimated over the sample period 1961H1 to 2008H2 for the Livingston Survey VAR (because the LS is biannual, we denote the first survey observation in a year as H1) and 1968Q4–2008Q4 for the SPF VAR. For our baseline results, the sample period runs to the end of 2008 to avoid potential misspecification issues arising from hitting the zero lower bound on nominal interest rates. However, we show below that the results are robust to extending the sample to 2010.

Figure 2 shows the impulse responses to a normalized 1 unit negative shock to the one-step-ahead expected unemployment rate (six-month-ahead forecast from the Livingston survey and the one-quarter-ahead forecast from the survey of professional forecasters) for the baseline VARs.[7] The panel on the left shows the impulses from a VAR that uses the Livingston Survey measure of expectations, while the panel on the right shows the responses from a VAR that uses the SPF expectations measure. Each panel of the figure shows the response of a variable to the expectations shock, as well as 68% and 90% confidence intervals that are generated using Kilian's (1998) bootstrap-within-bootstrap method.

On impact, the VARs indicate that a negative innovation that lowers the expected unemployment rate by 1 percentage point leads to a fall in the current unemployment rate of a similar magnitude, a roughly 1.5 percentage point increase in the inflation rate, and an increase in the three-month Treasury bill rate of between 1 and 2 percentage points. All responses are significantly different from 0 at the 90% confidence level. The unemployment rate is significantly below 0 for about two years, as is the increase in the nominal interest rate. The rise in inflation is somewhat more significant and persistent in the Livingston VAR than in the SPF VAR. Expected unemployment is quite persistent, staying significantly below 0 for roughly two years.

The two VARs largely tell the same story. An unaticipated downward revision to expected unemployment leads to a current boom in economic activity and a concomitant tightening of monetary policy. The estimated monetary policy response to a shock to the expected unemployment rate supports the story in Bernanke and Gertler (2000). More optimistic expectations of a future boom (in the form of a lower expected unemployment rate) coincide with an anticipatory monetary policy tightening. In this respect, the baseline specification suggests that on average, monetary policy over the sample period did not serve to amplify expectations-driven fluctuations. Rather, policymakers appear to have responded to anticipated booms and the associated higher near-term inflation by raising the short-term interest rate. The response is consistent with the view that a monetary policy that responds aggressively to changes in inflation serves to dampen economic fluctuations.

Our VARs indicate that shifts in expectations about future economic activity are a significant driver of economic fluctuations. One possible mechanism for this result is that survey expectations contain information that is relevant for economic activity but is not reflected in current fundamentals for the macroeconomy. For instance, the innovation to the expected unemployment rate could capture a shock to expected future aggregate conditions that is fully conditioned on current data releases: such a shock would reflect news about future conditions that is not tied to current fundamentals.

This interpretation of our results would fit the implications of the labor search model in Den Haan and Kaltenbrunner (2009). These authors study the impact of positive news about future productivity growth on the business cycle and argued that because of the matching friction central to these frameworks, such news can lead to comovements in macrovariables that resemble typical business cycles. As a result of the matching friction, firms post more vacancies in anticipation of better times ahead, which increases today's employment rate and lowers the number of unemployed workers. While our VAR-based findings do not provide direct evidence on the effects of revisions to expected productivity growth, the movement in the VAR's unemployment rate in response to revisions to expectations of future activity is qualitatively consistent with this model's predictions.[8]

An alternative to the news shock interpretation of our results is that the innovation to the expected unemployment rate reflects economically important information about current fundamentals used by forecasters but is not fully reflected in the other variables included in the VAR. It could be the case that agents condition their forecasts on variables that are omitted from the VAR and provide important information about the within-period realization of the unemployment rate, interest rates, and inflation. In the following sections, we investigate this view further by expanding the set of variables in the baseline VAR to include exogenous factors like oil and fiscal policy shocks, additional measures of real activity, as well as additional financial variables. The goal will be to see whether the inclusion of such variables reduces the impact of shocks to expectations on current economic activity. As we will see, these modifications of the baseline structure do not qualitatively change the results (though there is some small change in the quantitative responses).

Under either interpretation of the expectation shock, a negative shock to the expected unemployment rate (a lower expected unemployment rate) represents information that agents receive at the start of a quarter that leads them to become more optimistic about future economic conditions. We now turn to assessing the robustness of our results to the inclusion of additional variables in the VAR.

III. Extending the Baseline Model

A. *Controlling for Fiscal Policy and Oil Shocks*

To accurately assess the role of expectations shocks for economic fluctuations, it is important to control for exogenous shocks that may play a significant role in the system's dynamic behavior. Two obvious candidates for such shocks are oil price movements and fiscal stimulus and contractions. There is evidence that large upward movements in oil prices are associated with economic downturns (see Hamilton, 2003, and the references there). To control for exogenous, unanticipated increases in oil prices, we employ the quantitative dummy variable that Hamilton (2003) developed. The

[7] We use the one-step-ahead forecast in our baseline models to reduce the possibility of serial correlation in the errors. See Leduc et al. (2007) for a discussion of this issue. However, we also examine the implications of longer-horizon forecasts below.

[8] Since 1991, the SPF has asked survey respondents about their expectations of productivity growth ten years out. However, the question is asked only in the first quarter of each year and so leaves us relatively few data points to conduct a meaningful analysis.

quantitative dummy variable captures the disruptions in the oil market due to political events in the Middle East that are plausibly exogenous to developments in the U.S. economy. Hamilton identifies the following dates as being associated with exogenous declines (in parentheses) in world oil supply: November 1956 (10.1%), November 1973 (7.8%), December 1978 (8.9%), October 1980 (7.2%), and August 1990 (8.8%). Three of these episodes fall within the sample period of our baseline model: December 1978, October 1980, and August 1990. The quantitative dummy takes a value equal to the drop in world production during the period in which the episodes occur and is otherwise 0.[9]

To identify exogenous fiscal shocks, we appeal to the narrative approach of Ramey and Shapiro (1998) and its extension in Ramey (2011). They identify U.S. government spending shocks associated with military spending in four episodes in the postwar era: 1950Q3, associated with the Korean War; 1965Q1, associated with the Vietnam War; 1980Q1 associated with the Carter-Reagan military buildup; and 2001:Q3, associated with terrorist attack on September 11. Of these shocks, only the 1980Q1 and 2001Q3 episodes fall within our estimation period.

Figure 3 shows the impulse responses to an innovation in the expected unemployment rate in the baseline VARs that have been modified to include the oil and fiscal dummy variables (we maintain the same recursive ordering as in figure 2). Comparing the impulse responses to those in figure 2, controlling for exogenous oil and fiscal shocks has little effect on the dynamic response of the unemployment rate, inflation, and the nominal interest rate. The magnitudes of the responses are similar to those in figure 2: it remains the case that a fall in the expected unemployment rate leads to a contemporaneous decline in the current unemployment rate, a rise in the inflation rate, and an increase in the short-term interest rate.

B. *Additional Measures of Real Activity*

As a measure of real activity for the economy, the unemployment rate has the advantage that it does not get revised by much over time. However, it is not as comprehensive a measure of economic conditions as is a variable like real GDP. The problem with using real GDP in our analysis is that the series gets revised substantially over time, and the latest vintage data may contain information that was not available to forecasters at the time they made their projections. We compromise by adding a real-time measure of real GDP growth to the baseline VAR. Our series on real-time output is measured as the sequence of first releases of annualized real GDP growth over the sample period (and first releases only). Thus, we do not incorporate GDP revisions into the data series, even though that revised history would have been available to forecasters at the time they made their projections.

[9] Kilian (2009) argues that demand shocks are an important factor in accounting for oil price movements during these episodes.

We also investigate alternative specifications that use the Institute of Supply Management (ISM) index of economic activity in the manufacturing sector as a measure of real activity. This index offers a long data series that begins in 1948 (the broader ISM composite index, which includes both the manufacturing and nonmanufacturing sectors begins in 1997). The ISM manufacturing index is a diffusion index based on surveys of purchasing managers in the manufacturing sector. An index value above 50 generally indicates the manufacturing sector is expanding, while an index value below 50 indicates contraction. The index is not revised over time and is widely believed to reflect movements in real output.

Figures 4 and 5 show the impulse responses to an expectations shock when the additional real activity measures are included in the VAR (the expected unemployment rate is still ordered first, as in figures 2 and 3, and dummy variables for oil and fiscal shocks are also included). When expectations are measured using the Livingston Survey (figure 4), a negative innovation to the expected unemployment rate again leads to a fall in the current unemployment rate and an increase in the alternative real activity measures. Real GDP growth increases about 5 percentage point on impact (at an annual rate), while the ISM rises 0.2%, and both responses remain significantly above 0 for about six months before exhibiting a hump-shaped pattern that takes the activity measures significantly below 0 for about twelve months. In both cases, inflation rises on impact and short-term interest rates rise as the Fed tightens monetary policy. However, the response of the inflation rate is less significant over time compared to figures 2 and 3.

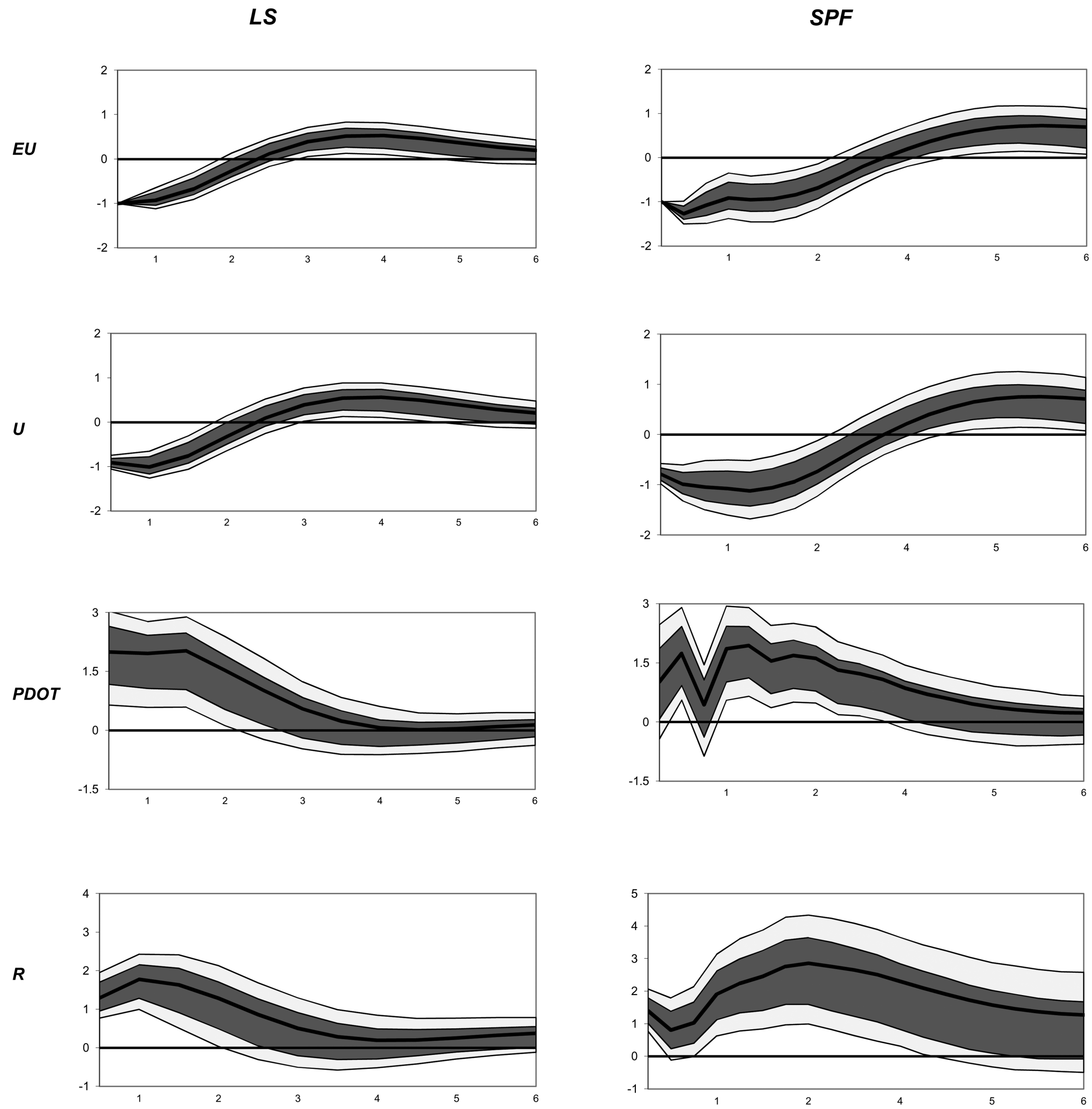
Using the SPF to measure expectations (figure 5) leads to similar results: an unanticipated decrease in the expected unemployment rate leads to a significant rise in real activity on impact, with a somewhat more persistent response of the unemployment rate than in Livingston Survey case. Consistent with the fall in the unemployment rate, real GDP growth increases by roughly 8 percentage points, slightly more than in figure 4.[10] We continue to find a significant tightening of monetary policy, although, compared to the baseline VAR result, the increase in inflation is less precisely estimated.

On balance, the impulse responses to expectations shocks when alternative real activity measures enter the VARs are quite similar (both qualitatively and quantitatively) to those exhibited in the baseline VAR (figure 2). The result that the alternative real activity measures rise in response to a negative innovation in the expected unemployment rate is consistent with baseline finding that the current unemployment rate falls.[11]

[10] Overall, the magnitude of the increase in GDP growth on impact in the SPF VAR (2 percentage points at a quarterly rate) is in line with Okun's law given the change in the unemployment rate (1 percentage point). In contrast, the VAR with the Livingston survey predicts a slightly smaller increase in real GDP growth on impact (1.25 percentage points at a quarterly rate) given the 1 percentage point fall in the unemployment rate.

[11] We also investigated the use of an unrevised industrial production index in the VARs and found the results to be very similar to those that use the real-time GDP growth measure and the ISM index. Similarly, the results are very similar if revised real GDP growth is instead included in the empirical model.

FIGURE 3.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT: CONTROLLING FOR OIL AND FISCAL SHOCKS



The responses were generated from a VAR with expected unemployment (EU), actual unemployment (U), inflation (PDOT), and the three-month T bill rate, and dummy variables for oil and fiscal shocks. All the responses are expressed in percentage ponts. The *x*-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. The system with the LS survey is estimated over the period 1961H1–2008H2, while that using the SPF survey is estimated over the period 1968Q4–2008Q4.

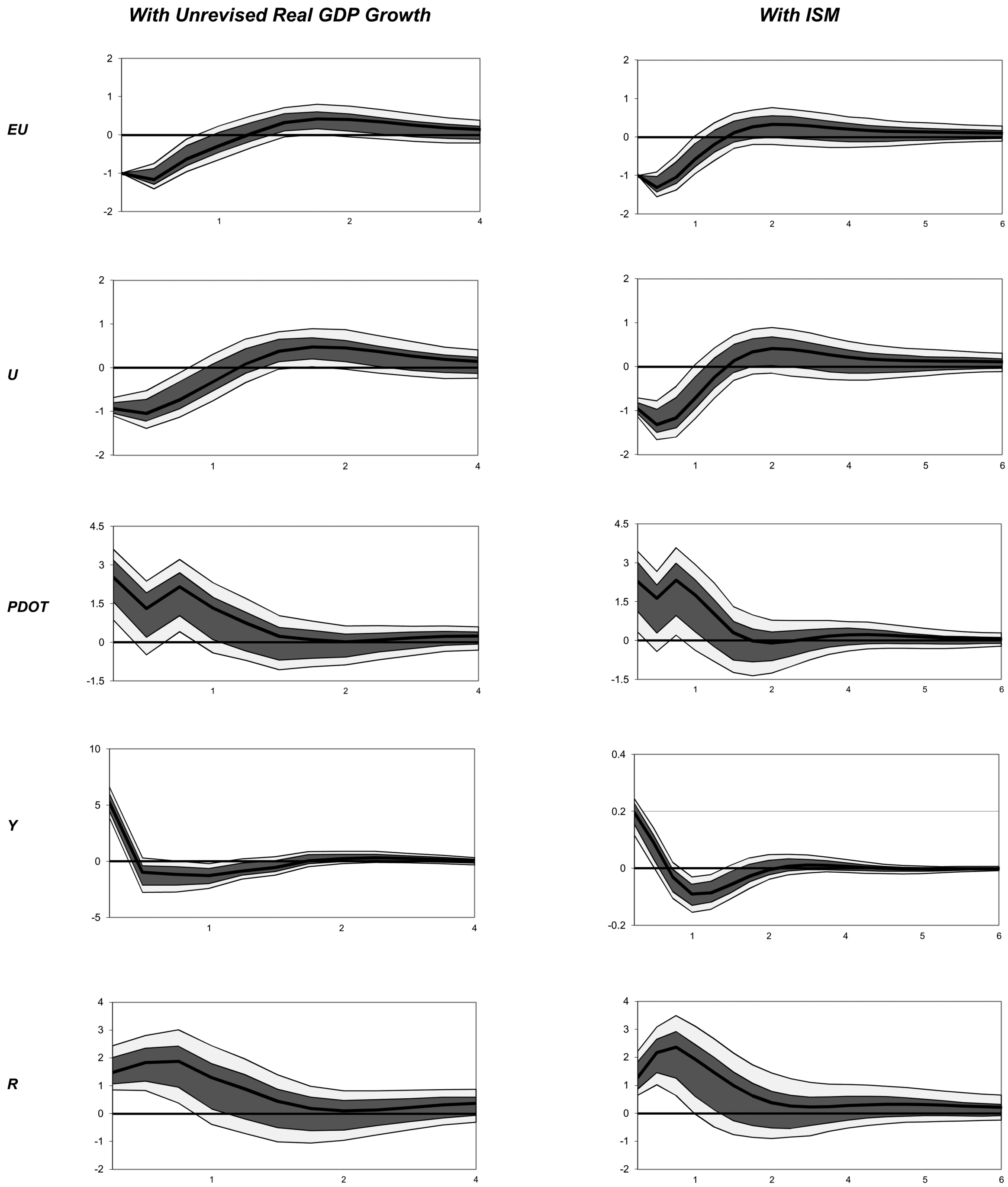
C. *Additional Financial Variables*

To further investigate the role that omitted information may play in accounting for our results we added more financial variables to the baseline VARs: stock returns as measured by the S&P 500 and long-term bond returns as measured by the yield on ten-year Treasury notes. Presumably important news about the current economy or its future would be reflected in such financial asset prices, and so conditioning on them is a straightforward, although somewhat crude, way to add omitted information to the VAR analysis. The financial data enter the VARs as period averages of daily data. Consequently, news that arrives in the time interval between the last observation of a variable and the date of the survey can potentially affect financial asset prices and be reflected in the VARs, so the measure is not without some concern vis-à-vis the identification assumption.

Figure 6 shows the impulse responses to an expectations shock in the baseline VARs augmented by the unrevised real GDP growth measure and the long-term interest rate series. (The results are similar when stock returns are added to the VAR in lieu of the long-term interest rate. See Leduc & Sill, 2010.) We again use a recursive identification scheme with the expected unemployment rate ordered first in the VAR. The responses for the unemployment rate and inflation are similar to those in figures 2 to 5. The long-term interest rate (LR) increases in response to a negative innovation to unemployment rate expectations and by less than the short-term

FIGURE 4.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT: REAL-TIME OUTPUT INDICATORS

LIVINGSTON SURVEY

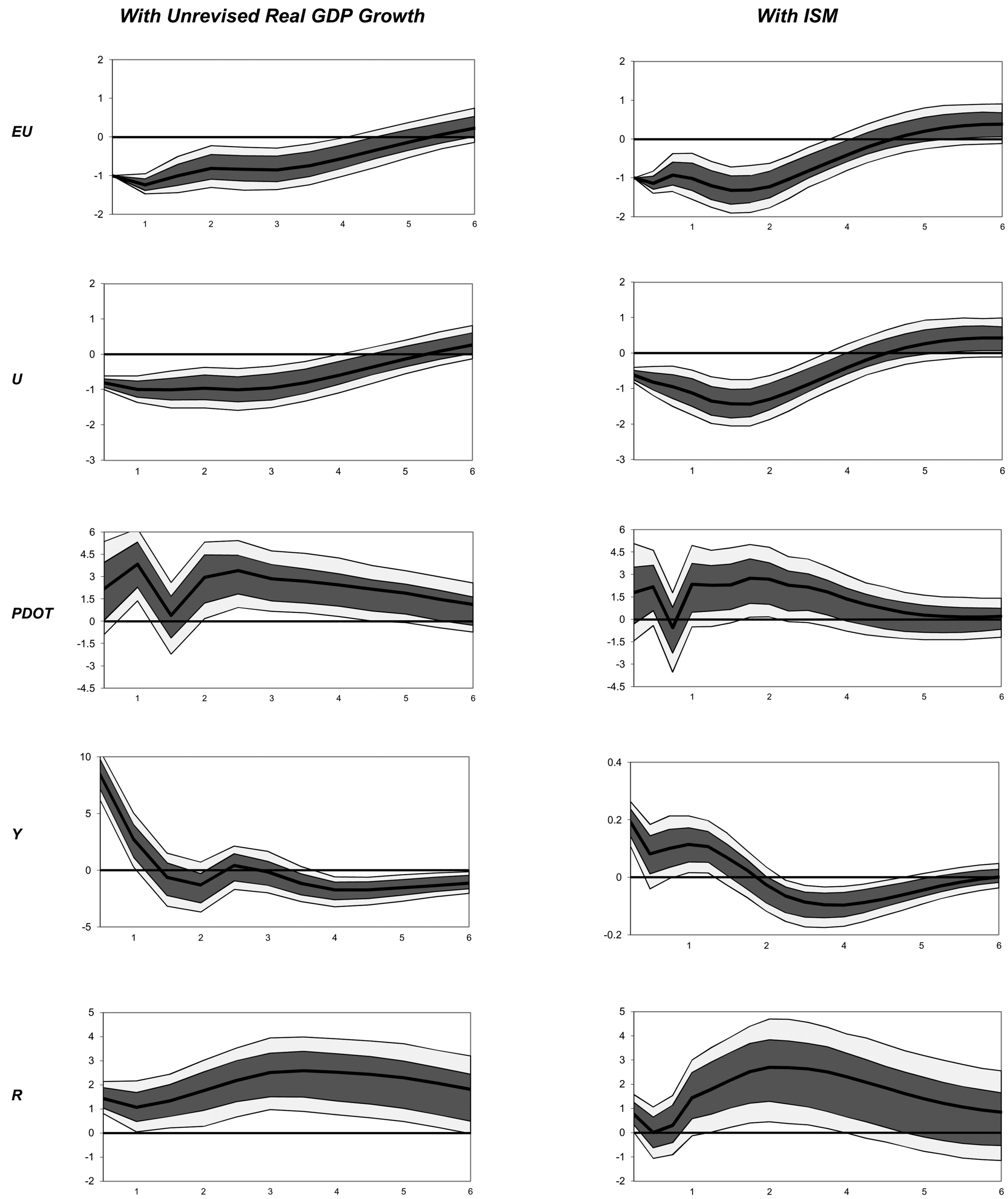


The responses were generated from a VAR with expected unemployment (EU), actual unemployment (U), inflation (PDOT), an output indicator (Y) equal real-time real GDP growth in the first column and to the ISM manufacturing index in the second column, the three-month T bill rate (R), and oil and fiscal dummy variables . All the responses are expressed in percentage points, except that of the ISM index, which is in percent. The x-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. Expectations of the unemployment rate are from the LS survey. The VARs are estimated over the period 1965H2–2008H2.

interest rate, with the response being slightly more significant in the VAR that uses the Livingston Survey measure of expectations.

The federal funds rate response is similar to that in the VARs that do not include long-term interest rates (figures 4 and 5) and continues to show a significant monetary policy tightening in response to expectations of a lower unemployment rate. On balance, the addition of the financial market variables does not much change the qualitative or quantitative results from the baseline VAR in figure 2. Consequently, we are more confident that the finding from the baseline VAR is robust.

FIGURE 5.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT: REAL-TIME OUTPUT INDICATORS
SURVEY OF PROFESSIONAL FORECASTERS

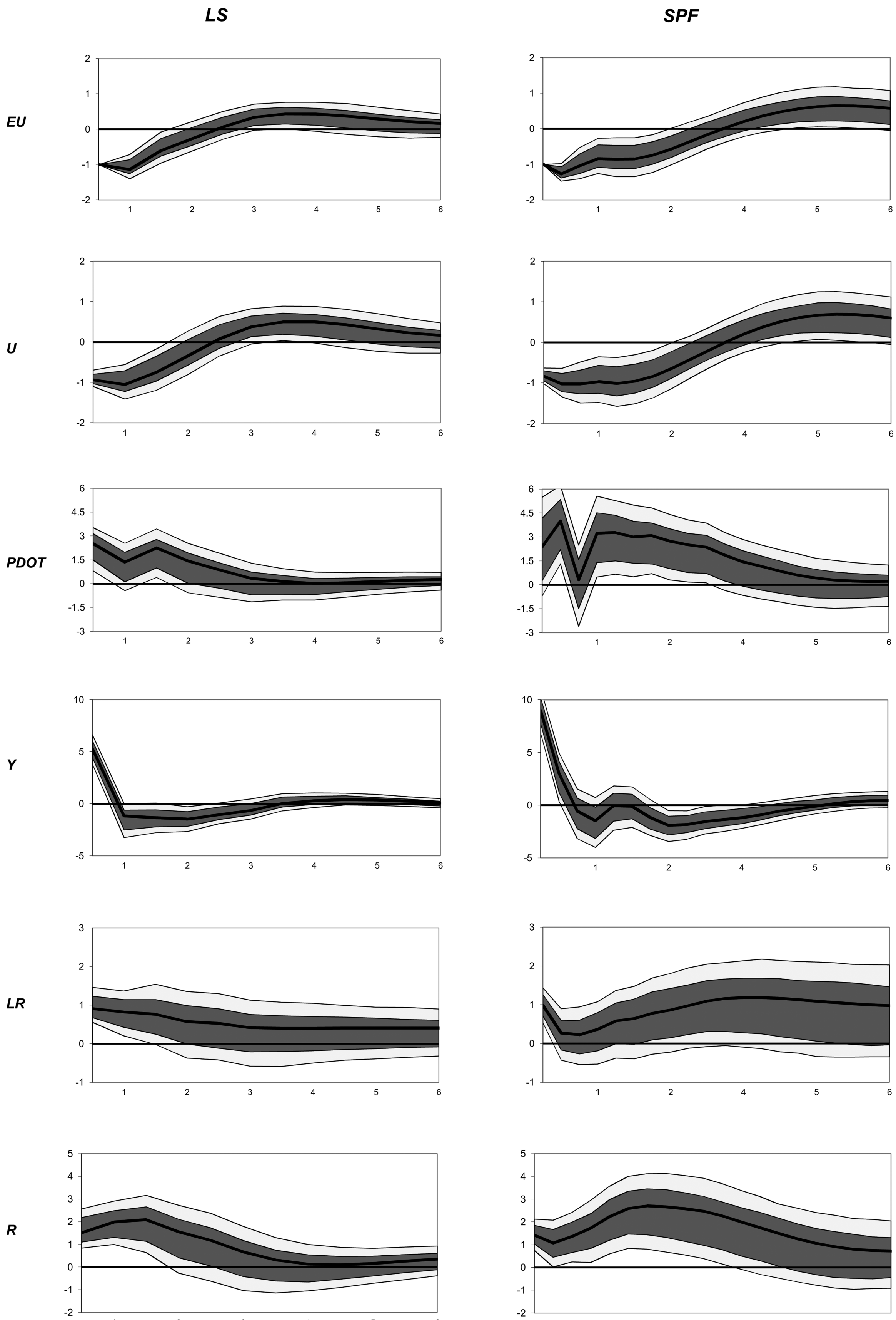


The responses were generated from a VAR with expected unemployment (EU), actual unemployment (U), inflation (PDOT), an output indicator (Y) equal to real-time real GDP growth in the first column and to the ISM manufacturing index in the second column, the three-month T bill rate (R), and oil and fiscal dummy variables. All the responses are expressed in percentage points, except that of the ISM index, which is in percent. The *x*-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. Expectations of the unemployment rate are from the SPF survey. The VARs are estimated over the period 1968Q4–2008Q4.

IV. Variance Decompositions and Prediction

An additional metric by which to gauge the significance of innovations to expectations for the dynamics of the VAR system is variance decomposition. Table 1 shows the contribution of shocks to the expected unemployment rate for the unemployment rate and inflation in the baseline four-variable and six-variable VARs. In the first two columns of the table, we report the one-year-ahead and five-year-ahead forecast error variance contributions for both the Livingston Survey and SPF VARs. The range of estimated contributions of expectations shocks to the forecast error variance of the actual

FIGURE 6.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT: LARGER SYSTEM



The responses were generated from a VAR with expected unemployment (EU), actual unemployment (U), inflation (PDOT), unrevised real GDP growth (Y), the ten-year T bond rate (LR), the three-month T bill rate, and oil and fiscal dummy variables. All the responses are expressed in percentage points. The *x*-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. The system with the LS survey is estimated over the period 1965H2–2008H2, while that using the SPF survey is estimated over the period 1968Q4–2008Q4.

TABLE 1.—CONTRIBUTION OF EXPECTATION SHOCKS TO THE VARIANCES OF UNEMPLOYMENT AND INFLATION

	LS	SPF	Michigan
Unemployment			
One-year ahead			
Four-variable system	41.6	21.0	51.4
Six-variable system	37.6	19.5	36.4
Five-year ahead			
Four-variable system	27.3	21.8	48.5
Six-variable system	23.7	16.9	46.9
Inflation			
One-year ahead			
Four-variable system	16.6	7.5	11.6
Six-variable system	15.1	7.8	17.4
Five-year ahead			
Four-variable system	20.2	15.0	22.0
Six-variable system	16.5	12.1	24.2

All entries are in percentages.

unemployment rate is somewhat wide. This variation is likely due in part to the fact that observations on the expectations measures, and thus the VAR estimation sample periods, start at different dates.

The first two columns of table 1 indicate that shocks to expectations are important for economic fluctuations. At the one-year horizon, these shocks account for between 19.5% and 41.6% of the forecast error variance of the unemployment rate, depending on the specification. While the contribution in general falls at the five-year horizon, it remains substantial. Under a "news shock" interpretation of our results, these variance decompositions are broadly in line with the VAR-based findings of Beaudry and Portier (2006) and the structural-model-based findings of Schmitt-Grohé and Uribe (2008), who estimate that news shocks account for more than 50% of aggregate fluctuations.

Shocks to expectations are important for the forecast error variance of the inflation rate, although that contribution is smaller than for the unemployment rate. For instance, table 1 indicates that the one-year-ahead contributions range from 7.5% to 16.6%, while at the five-year-ahead horizon, this range is between 12% and 20%.

We also consider how well the variables in the VARs predict expected unemployment rates. Granger-causality tests indicate that the variables in both the four-variable VAR and the six-variable VAR Granger-cause the 6-month-ahead expected unemployment rate. The P-values on all the tests were essentially 0 for the null hypothesis of no causality. We also examined how much the variance of residuals from a regression of the expected unemployment rate on a constant and two (four) of its own lags falls when we add inflation, the unemployment rate, and the short-term interest rate to the regression with the LS (SPF) measure. We find that the variance of the residual drops on the order of 55% to 60% for the SPF and LS measure of expectations, respectively. If the set of regressors includes long-term interest rates and the unrevised real GDP growth, the variance of the residual falls 73% for the SPF measure of expectations and 67% for the LS measure of expectations (the baseline remains a regression of the expected unemployment rate on itself only). Consequently, we are confident that the variables in our VARs are capturing important information forecasters use when making projections of the unemployment rate.[12]

V. Additional Robustness Checks

A. *Sample Size and Longer Horizon Forecast*

We also verified that the VAR results are stable over a sample period that includes the current financial crisis. We reestimated the five-variable VARs (i.e., the baseline VAR with the addition of the unrevised real GDP growth measure and dummy variables for oil and fiscal policy shocks) over the 1961H1–2010H1 period for the Livingston Survey VAR and 1968Q4–2010Q4 for the SPF VAR. The results, shown in figure 7, show little difference from those reported in figures 4 and 5, though the response of the inflation rate tends to be less significant than under our baseline specification in figure 2.

Moreover, we consider how the results might change if forecasts of the future unemployment rate were made for a longer horizon. Both the Livingston Survey and SPF have measures of expected unemployment twelve months ahead, and beginning in 1991 the Livingston Survey asked respondents to forecast average annual real GDP growth over the ten years following the survey. We replace our short-term expectations variable with these longer-term expectations in the VARs that include the unrevised real GDP growth and dummy variables for oil and fiscal shocks.[13] The impulse responses are reported in figure 8, and show that using twelve-month-ahead expectations in the VARs leads to similar results to those from the baseline VAR that has shorter-term expectations (though the contraction of monetary policy is found to be more short lived).

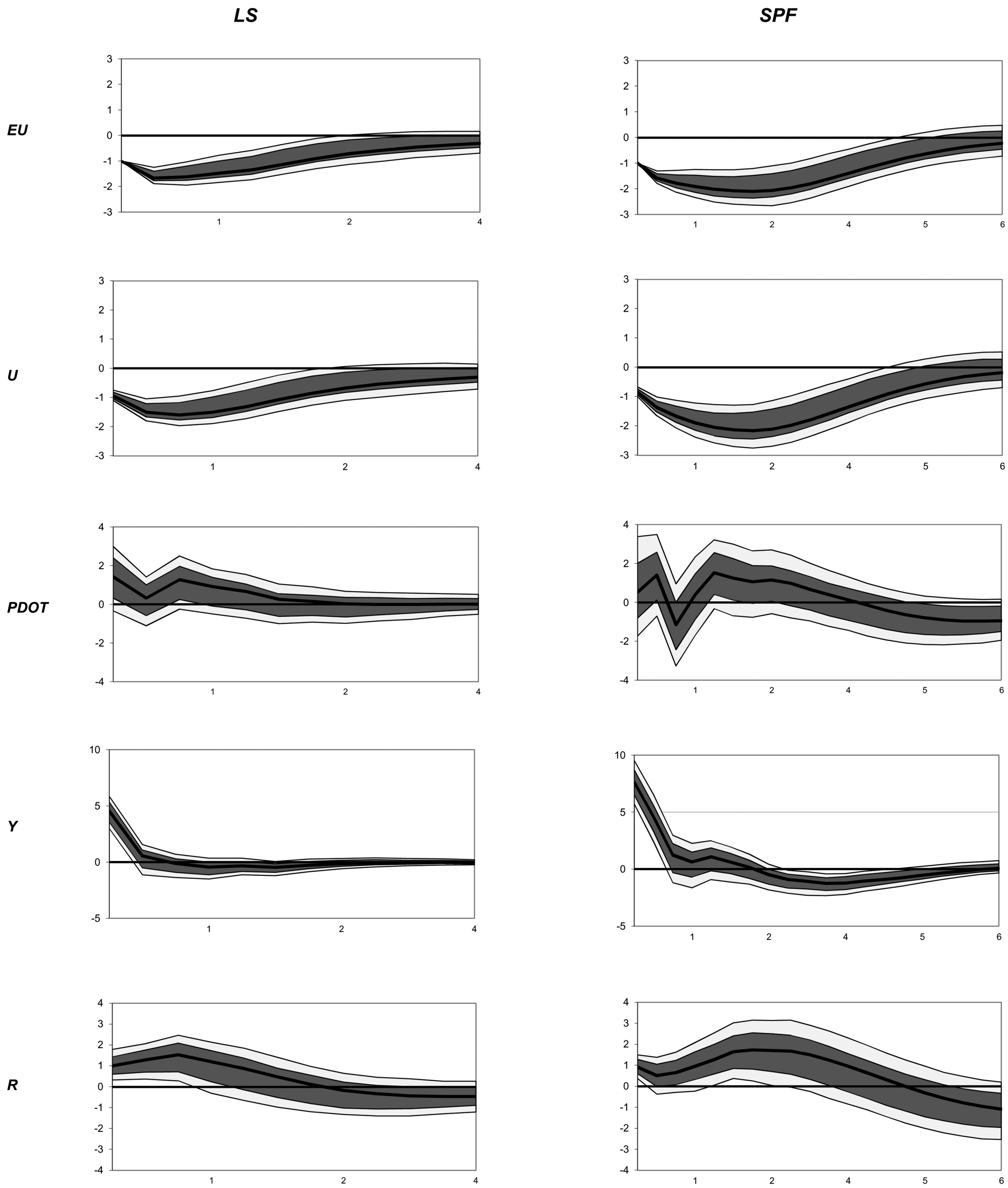
The last column of figure 8 shows that the qualitative story is much the same when expectations are measured using the long-term average output growth, though the impulse responses tend to be somewhat less significant.[14] An expected increase in the average annual real GDP growth over the next ten years leads to a fall in the current unemployment rate and a rise in current real GDP growth (both significant for one year following the shock), to which monetary policy responds by contracting on impact. That the pattern in the data remains similar to that in the baseline VAR is striking given that we have only twenty years of biannual data on this longer-term expectation measure.

[12] Because the unemployment rate tends to be very persistent, movements in the expected unemployment rate may be capturing the past more than future movements in the unemployment rate. To mitigate this concern, we also considered an alternative version of our baseline model with the actual and expected unemployment rates in first difference. In response to a sudden fall in expected unemployment, the results continue to show a fall in the actual unemployment rate and a rise in inflation and interest rates. To preserve space, we did not include the figure, but the results are available on request.

[13] For the SPF, we use three-quarter-ahead unemployment forecasts, since the four-quarter-ahead forecast series has some missing observations over the first five years.

[14] We used data through 2010 to estimate the VAR with the ten-year average GDP growth forecast because of that variable's shorter length time series.

FIGURE 7.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT: LONGER SAMPLE



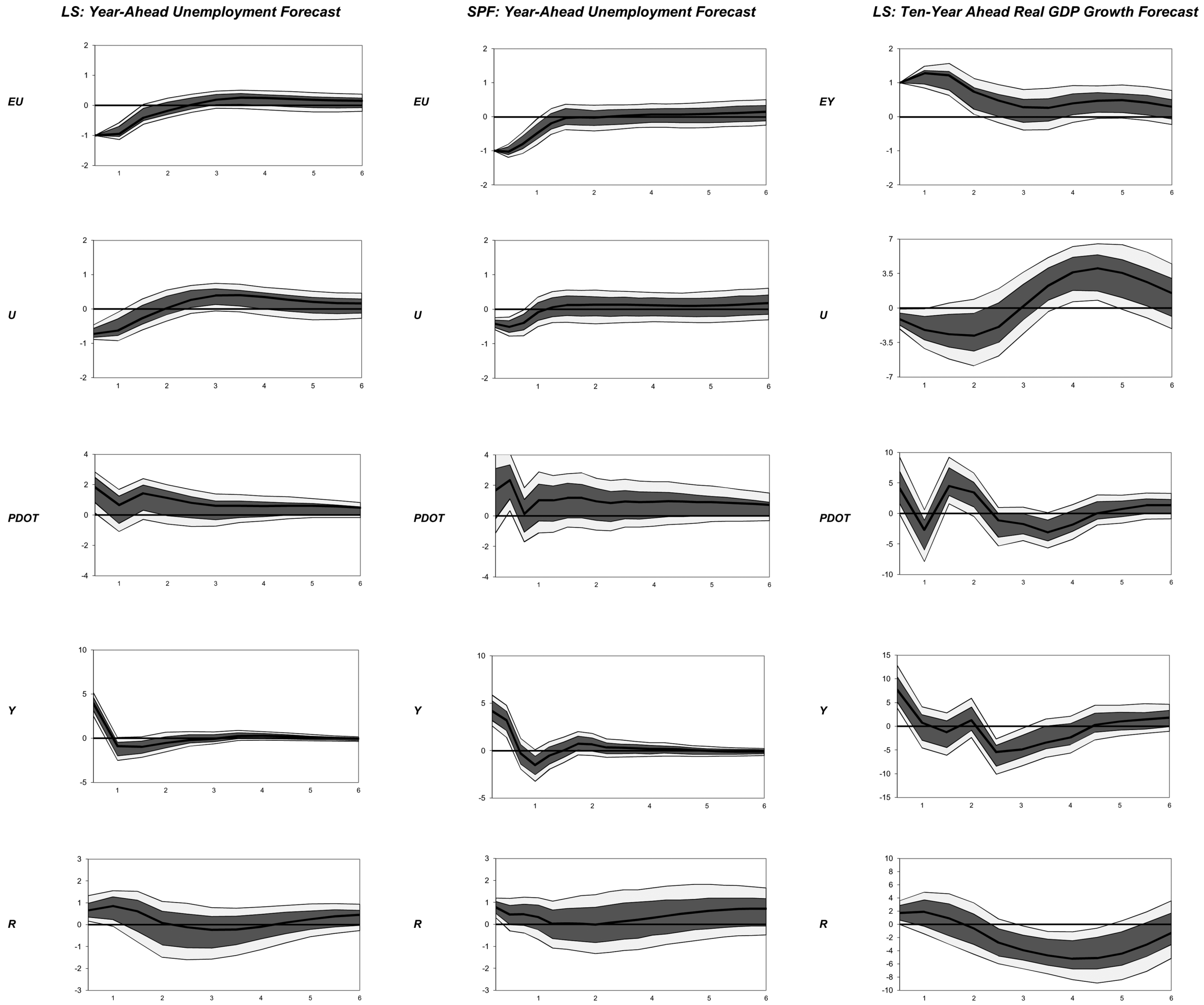
The responses were generated from a VAR with expected unemployment (EU), actual unemployment (U), inflation (PDOT), unrevised real GDP growth (Y), the three-month T bill rate, and oil and fiscal dummy variables. All the responses are expressed in percentage points. The *x*-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. The system with the LS survey is estimated over the period 1961H1–2010H1, while that using the SPF survey is estimated over the period 1968Q4–2010Q4.

Overall, the story told by the alternative VARs continues to be that expected good times ahead lead to a current fall in the unemployment rate, a rise in output growth, and a slightly more restrictive monetary policy on impact.

B. Measure of Household Expectations

Up to this point, our empirical results have been conditioned on using measures of unemployment expectations from surveys of professional forecasters. One possible issue with the use of such surveys is that their coverage, in terms of participants, is relatively small: the number of respondents in the LS or the SPF is typically on the order of fourty to fifty. An additional issue noted in Mankiw, Reis, and Wolfers (2003) is that professional and household forecasts can differ quite substantially along some important dimensions. For example, Mankiw et al. find that consumer forecasts of inflation tend

FIGURE 8.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT: LONGER HORIZON FORECASTS



The responses were generated from a VAR with expected unemployment (EU) or expectated real GDP growth (EY), actual unemployment (U), inflation (PDOT), unrevised real GDP growth (Y), and the three-month T bill rate (R). All the responses are expressed in percentage points. The *x*-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. The VAR with one-year-ahead unemployment expectations from the LS is estimated over the period 1965H2–2008H2. The SPF VAR is estimated from 1968:Q4 to 2008:Q4. Because of missing observations, we use the three-quarter-ahead forecast to proxy for year-ahead expectation. The VAR with the ten-year-ahead GDP growth expectation is estimated from 1991:H1 to 2010H1.

to be less efficient than professional forecasts: forecast errors of consumers are predictable based merely on past forecasts, while such is not the case for professional forecasts.

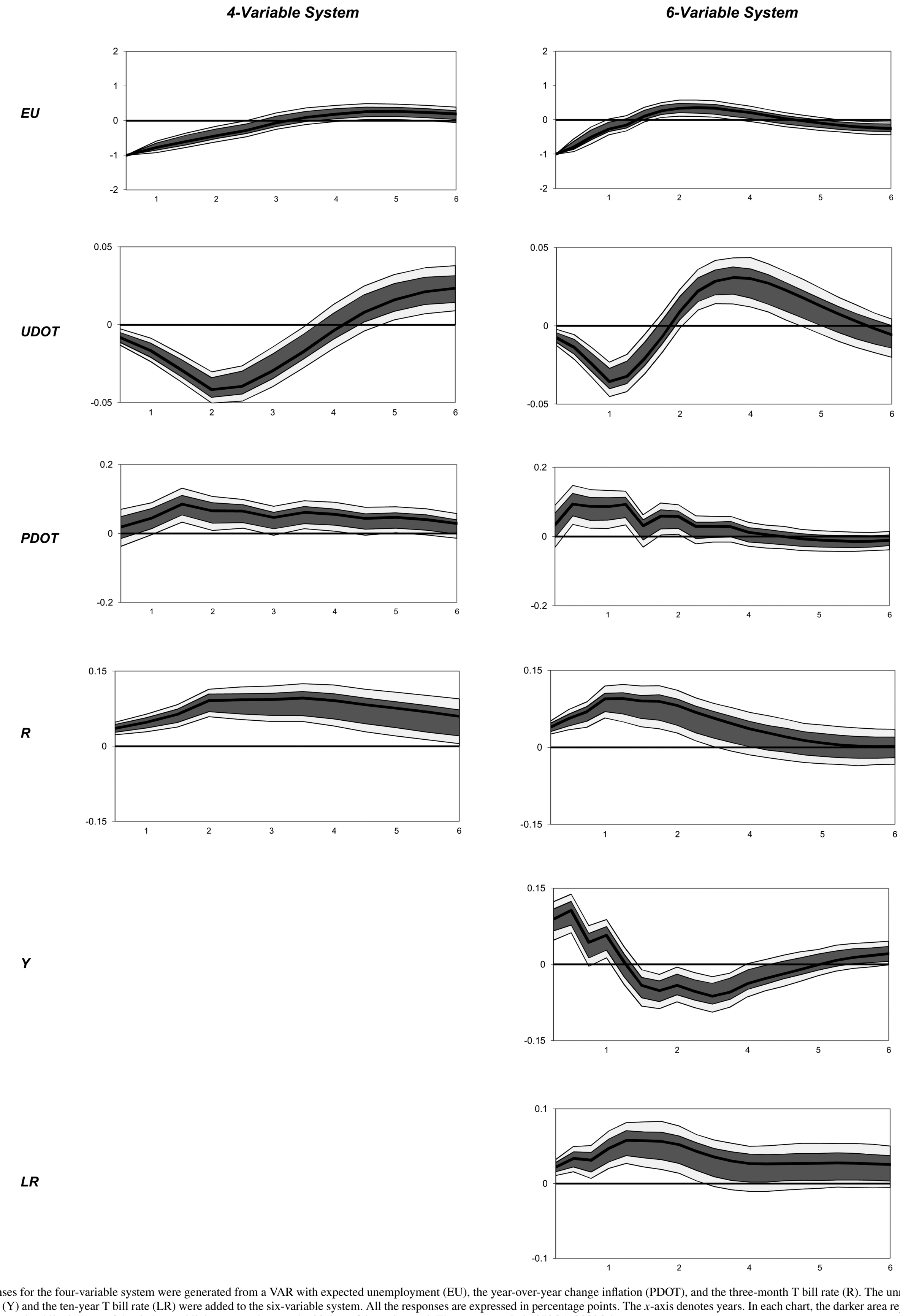
To investigate the robustness of our results to an alternative measure of survey expectations data, we reran our VARs using data from the Michigan survey of households. The Michigan survey asks roughly 500 households about their assessment of the economy and their expectations of a large number of economic variables. One drawback of the survey, and an important reason that we do not use it in our baseline model, is that it asks respondents only whether they think the unemployment rate will go up, down, or stay unchanged over the next twelve months.[15] Contrary to the LS or the SPF, the University of Michigan survey does not ask respondents to provide a point estimate for the unemployment rate.

Nevertheless, one measure of the survey tracks the changes in the unemployment rate quite well: the difference between

FIGURE 9.—MICHIGAN SURVEY UNEMPLOYMENT EXPECTATIONS VERSUS CHANGES IN THE UNEMPLOYMENT RATE

[15] More specifically, the survey asks respondents the following question: "How about people out of work during the coming 12 months—do you think that there will be more unemployment than now, about the same, or less?"

FIGURE 10.—RESPONSES TO A SHOCK TO EXPECTED UNEMPLOYMENT: MICHIGAN SURVEY



The responses for the four-variable system were generated from a VAR with expected unemployment (EU), the year-over-year change inflation (PDOT), and the three-month T bill rate (R). The unrevised real GDP growth index (Y) and the ten-year T bill rate (LR) were added to the six-variable system. All the responses are expressed in percentage points. The *x*-axis denotes years. In each chart, the darker area represents the 68% confidence interval, while the sum of the darker and lighter areas denotes the 90% confidence interval. The system period 1978Q1–2008Q4.

the percentage of households who thought the unemployment rate would increase minus the percentage who thought it would decline, normalized to 100. Figure 9 shows that this measure tracks the broad movements in the unemployment rate and tends to lead the changes in the actual unemployment rate. It appears, then, that this measure of household expectations has informational content that can be used in our empirical models.

Figure 10 shows the results from our baseline and six-variable models when we measure expectations using the Michigan survey of households instead of the professional forecasts. Since the survey of consumers asks respondents about the expected change in the unemployment rate over the next twelve month, we also modify the VARs so that they include the yearly change in the actual unemployment rate rather than its level. The other variables in the VAR are left unchanged. The survey of consumers has compiled quarterly data on expectations of unemployment changes since 1968 and at a monthly frequency since 1978. We use the monthly data since they allow us more flexibility in lining up the data to make the results more comparable to those with the SPF. Since the response deadline for the SPF is generally the third week of the second month of the quarter, we also use the survey of consumers conducted in that month.

Qualitatively, using household expectations instead of professional forecasts makes little difference to the results.[16] A sudden drop in expected unemployment is followed by a drop in the actual unemployment rate, a rise in inflation, and a tightening of monetary policy. In the six-variable VAR, a downward revision to expected unemployment also leads to increases in the growth rate of real GDP and long-term interest rates, just as was the case when expectations of professional forecasters were used. Quantitatively, the variance decomposition reported in table 1 shows that whether we use household forecasts or professional forecasts, the contribution of shocks to expectations for the variance of the unemployment and the inflation rates is substantial. For example, at the five-year horizon, shocks to expected unemployment account for roughly 50% of the forecast error variance of unemployment. The contribution to the forecast error variance of inflation is lower, at 22% to 24%. On balance, the results in table 1 point to a significant role for expectations shocks in accounting for variation in inflation and unemployment.

VI. Conclusion

Expectations play a key role in the determination of dynamic paths for economic variables in cogent equilibrium models of the economy. While recent applied theoretical work has suggested that expectations of future events may play an important role in economic fluctuations, the empirical evidence on how important expectations are for business cycles remains somewhat sparse. Existing studies have generally used economic data, such as asset price data, to infer expectations about the future. In contrast, we have examined this issue using actual expectations measures from surveys and used them to investigate how unanticipated shifts in expectations can influence movements in economic variables.

We find that changes in expectations of future economic activity are a quantitatively important driver of economic fluctuations. An anticipation of good times ahead leads to a fall in current unemployment, a rise in inflation, and a tighter monetary policy. These impulse responses hold across a variety of expectations measures, from professional forecasters to households, and a variety of VAR specifications. In this respect, our empirical evidence generally supports the findings of a recent generation of business cycle models that imply that expectations of good times in the future lead to current-period booms rather than busts. Our results also suggest that during these times of economic optimism, the Federal Reserve tended not to run an expansionary monetary policy that amplified fluctuations.

With policymakers' and market participants' interests in survey data increasing, existing surveys have expanded and new surveys have also been introduced. For instance, since 1992 the SPF tracks expectations for ten-year-ahead productivity once a year, while in 1999, the ECB introduced a survey of European forecasters similar to the SPF. As enough data become available, analyzing waves of optimism using these relatively newer data sources will be an interesting avenue for future research.

[16] Because our series for household expectations is a diffusion index and because it measures the expected change in the unemployment rate, the magnitude of the variable responses is not directly comparable to those in the previous figures.

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