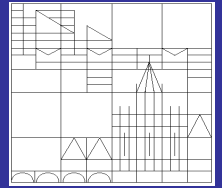University of Konstanz
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Commodity Price Shocks and the Business Cycle: Structural Evidence for the U.S.

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Commodity Price Shocks and the Business Cycle: Structural Evidence for the U.S.*

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Abstract

This paper develops a 9-dimensional SVAR to investigate the sources of the U.S. business cycle. We extend the standard set of identified shocks to include unexpected changes in commodity prices. Our main result is that commodity price shocks are a very important driving force of macroeconomic fluctuations, second only to investment-specific technology shocks. In particular, we find that commodity price shocks explain a large share of cyclical movements in inflation. Neutral technology shocks and monetary policy shocks seem less relevant at business cycle frequencies. The impulse response dynamics provide support for medium-scale DSGE models, but not for strong price rigidities.

JEL Classification: C32, E32, E52, Q43
Keywords: business cycles, commodity price shocks, structural VAR

1 Introduction

What are the sources of the U.S. business cycle? In recent years, a great body of research has addressed this question. The set of structural shocks often considered includes (neutral) technology shocks (Galí 1999), investment-specific technology shocks (Fisher 2006), and monetary policy shocks (Christiano et al. 1996). Alongside this debate, the macroeconomic effects of unexpected changes in commodity prices — particularly energy prices — have gained a great deal of attention (Kilian 2008). However, to our knowledge, no attempt has been made to estimate these four shocks in a single SVAR model so far. The present paper is meant to fill this gap.

As is well known, commodity price shocks are often blamed for the stagflation of the 1970s. An alternative explanation to this phenomenon has been offered by Barsky & Kilian (2001). They emphasize instead the effects of expansionary monetary policy, which is supposed to have contributed to the rise in commodity prices. On the contrary, Bernanke et al. (1997) argue that the recessionary effects of commodity price shocks are not due to the direct impact of higher producer prices, but rather due to the contractionary response of the Federal Reserve. Other authors stress the role of the productivity slowdown in that period (Bruno 1984). In contrast to previous studies, our model is designed to disentangle the effects of various shocks and, therefore, seems well suited to address this question.

The main aim of this paper is (i) to quantify the relative importance of the above-mentioned shocks in the U.S. business cycle and (ii) to derive modeling guidelines based on the estimated impulse response functions. Therefore, we develop a 9-dimensional VAR with four structural shocks. We use standard long-run restrictions (Galí 1999, Fisher 2006) in order to identify the neutral and the investment-specific technology shock. The monetary policy shock and the commodity price shock are identified using short-run restrictions, along the lines suggested by Christiano et al. (1996) and Rotemberg & Woodford (1996), respectively. In addition, our estimation strategy explicitly accounts for two types of distortions that may be responsible for the extreme sensitivity of the hours response to (neutral) technology shocks; i.e., the omitted-variable bias (Christiano et al. 2003) and the low-frequency bias (Fernald 2007, Canova et al. 2010).

The main result of our paper is that commodity price shocks are a very important driving force of the U.S. business cycle, second only to investment-specific technology shocks. In particular, we find that commodity price shocks explain a large share of cyclical movements in inflation. Sudden variations in the relative price of investment goods are the primary determinant of business cycle fluctuations in output and per-capita hours. Neutral technology shocks and monetary policy shocks, on the other hand, seem less relevant at business cycle frequencies. At low frequencies, however, neutral technology shocks do play an important role in explaining output variability. The historical decomposition of shocks indicates that commodity price shocks have played a significant role during

and after the first OPEC oil crisis. In this respect, the monetary policy feedback rule to changes in commodity prices seems to have amplified macroeconomic fluctuations. In addition, also investment-specific technology shocks appear to have contributed to the sharp recession of 1973-75 and the double-dip in the early 1980s.

We also examine the impulse response functions triggered by each of the four structural shocks. A permanent improvement in *neutral technology* generates positive responses in output, consumption and per-capita hours. The positive (even though not significant) response of per-capita hours is surprising, given that we control for low-frequency movements in the data (Canova et al. 2010). Further investigations show that, if the size of the information set is sufficiently large, the hours response becomes insignificant — irrespective of whether we control for low-frequency movements in the data or not. On the contrary, if the information set is small, the impact response of per-capita hours is indeed extremely sensitive to the treatment of the data. A sudden and permanent drop in the *relative price of investment goods* induces significant and hump-shaped responses in output, consumption, and per-capita hours. As explained by Justiniano et al. (2010), the strong comovement between macroeconomic aggregates cannot be reconciled with the standard RBC model. Instead, the evidence calls for modifications that drive a wedge between the marginal product of labor (MPL) and the marginal rate of substitution (MRS) between consumption and leisure. An expansionary *monetary policy* shock leads to significant and hump-shaped responses in output, consumption and per-capita hours. Consistent with Sims (1992), the impulse response of the inflation rate displays a temporary fall ("price puzzle"), followed by a slow and persistent rise ("inflation persistence"). The shape of the inflation response turns out to be robust to the inclusion of commodity prices. A sudden increase in *commodity prices* is characterized by significant U-shaped responses in output, consumption and per-capita hours. Most notably, the inflation rate displays a significant spike, followed by a rapid return to the initial level. Therefore, we are not able to confirm the conventional wisdom of unexpected changes in commodity prices as a driving force of sustained inflation (see also Barsky & Kilian 2001). The estimated dynamics turn out to be robust when we control for movements in external demand.

Given the importance of investment-specific technology shocks for the business cycle, the impulse response dynamics provide support for medium-scale DSGE models akin to Christiano et al. (2005). This class of models considers modifications like variable capital utilization or time-varying mark-ups that modify the relationship between the MPL and the MRS and, thus, may help to replicate the strong cyclical comovement of U.S. macroeconomic aggregates (Furlanetto & Seneca 2010). The flexibility of aggregate consumer prices, however, depends strongly on the type of disturbance. The consumer price index adjusts slowly to monetary policy and investment-specific technology shocks, somewhat faster to neutral technology shocks, and very fast to commodity price shocks (see also Boivin et al. 2009). This indicates that aggregate consumer prices *per se* are not very

sticky. Rather, decision makers might find it optimal to devote their attention primarily to changes in commodity prices. For this reason, models with rational inattention (Mackowiak & Wiederholt 2010) seem very promising.

Several robustness checks confirm our conclusions. In particular, we find that our results are robust to the data treatment prior to estimation. On the other hand, our results are *not* robust to the exclusion of the commodity price index or the consumption share in output. This indicates that the size of the information set is crucial in this context, thus echoing the results of Forni & Gambetti (2011). Furthermore, we examine robustness to the choice of the lag length, the selected sample period, and the inclusion of alternative disturbances — in particular, we add external demand shocks (Abbritti & Weber 2010), and we consider shocks to government spending (Blanchard & Perotti 2002) instead of commodity prices.

The remainder of this paper is organized as follows. Section 2 presents the identification and estimation strategies. Section 3 presents the results. Section 4 performs several robustness checks. Section 5 concludes.

2 Identification and Estimation Strategy

We estimate a VAR with four structural shocks (neutral technology, investment-specific technology, monetary policy, and commodity prices). Our strategy adopts standard identifying assumptions. We modify the code by Altig et al. (2011) to estimate the coefficients and compute the confidence intervals with a non-parametric bootstrap.[1] There are two novel aspects in our analysis. First, we add commodity price shocks to the standard set of structural shocks. Second, our estimation strategy explicitly accounts for two types of distortions that may be responsible for the extreme sensitivity of the hours response to (neutral) technology shocks. Therefore, we estimate the resulting SVAR using a large information set. In particular, the inclusion of the consumption and the investment share has been proven crucial to minimize omitted-variable bias toward a *negative* impact response (Christiano et al. 2003). In addition, we apply a one-sided bandpass filter prior to estimation (Canova et al. 2010). The novel feature of our analysis is that we filter not only per-capita hours, but *all* time series that enter the SVAR. This procedure allows us (*i*) to control for low-frequency movements in the data and (*ii*) to maintain spectral coherence (Granger 1969). As demonstrated by Fernald (2007), these low-frequency movements are likely to distort the estimation toward a *positive* impact response.

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[1]We thank Lawrence Christiano for making the code available on his website.

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2.1 Data

The sample period of this paper covers aggregate U.S. data between 1955Q3 and 2007Q4.[2] The following variables enter the SVAR: growth in the relative price of investment goods Δq_t, growth in labor productivity Δa_t (measured by the ratio of real output to hours per capita in the business sector), the CPI inflation rate π_t, hours per capita h_t, the consumption share in output c_t, the investment share in output i_t, the employment rate n_t, the Federal Funds rate r_t, and the PPI commodity price index p_t. All time series are seasonally adjusted (where applicable). Precise definitions can be found in the Appendix (Tables 1 and 2).

The discussion sparked by Galí (1999) and Francis & Ramey (2005) has shown that the response of hours worked to (neutral) technology shocks is extremely sensitive to the treatment of the data. When hours worked enter in first differences, the SVAR typically generates a *negative* impact response. The opposite holds true when the series enters in levels (Christiano et al. 2003, 2004, Uhlig 2004).[3] Since hours worked are borderline stationary, both choices can be justified on the basis of standard unit root tests. Even though the hours series is bounded, the presence of low-frequency movements may prevent the rejection of the null hypothesis of stationarity. These low-frequency movements, sometimes referred to as "long cycles", may be attributed to sectoral changes involving government and non-profit employment or the movement of the baby boom generation through the labor market (Francis & Ramey 2009).

As convincingly demonstrated by Fernald (2007), the presence of "long cycles" in per-capita hours may lead to significant distortions. The author illustrates the low-frequency bias by performing the following counterfactual exercise. Fernald removes the high and medium frequencies from the hours series, reverses their sign, and then adds both series together. Surprisingly, the impact response of hours worked to neutral technology shocks remains positive, although all high and medium frequencies are reversed. This indicates that the positive impact response in a bivariate VAR model is solely driven by the presence of low-frequency movements. Differencing removes the low-frequency movements from the data. This explains why we observe a negative impact response when hours worked are assumed to be non-stationary. Yet, differencing a bounded series (like per-capita hours) may involve misspecification issues (Hamilton 1994, p. 652). For this reason, Canova et al. (2010) evaluate several alternative filtering devices (e.g., bandpass filter, dummies) that are able to capture these long cycles in the data, but do not induce overdifferencing. Their three-dimensional SVAR identifies a neutral and an investment-specific technology shock. They conclude that all tested filtering methods produce results consistent with

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[2]The endpoint of our sample is due to limited availability of the quality-adjusted time series; i.e., consumption, investment, and the relative price of investment goods.

[3]Dedola & Neri (2007) question the above-mentioned sensitivity. Using a sign restriction approach, they show that a positive technology shock raises hours worked irrespective of the data transformation.

Galí (1999) and Francis & Ramey (2005). On impact, per-capita hours fall significantly in response to neutral technology shocks. After this, the function converges monotonically to its initial level.

With this in mind we treat the data as follows. First, we take the natural logarithm of all variables. Next, we difference labor productivity and the relative price of investment goods.[4] Then, in order to control for low-frequency movements in per-capita hours, we employ a one-sided bandpass filter (Christiano & Fitzgerald 2003) prior to estimation.[5] We prefer this particular filter since agents know only the past (Lucas 1980). Moreover, we apply the one-sided bandpass filter not only to per-capita hours, but to *all* series considered. Figure (1) illustrates that this procedure allows us to maintain spectral coherence between labor productivity growth and per-capita hours in our benchmark specification. When all series are filtered — as in the top panel — we are able to break the low-frequency comovement and minimize distortions at higher (particularly, at business cycle) frequencies. When only per-capita hours are filtered — as in the bottom panel — we are less successful in breaking the low-frequency comovement and distort the relationship at business cycle frequencies.

Using a trivariate SVAR, we are able to replicate the results of Canova et al. (2010) — both in terms of business cycle variance decomposition and estimated impulse response functions. However, we find significant correlation coefficients between the estimated neutral technology shock and the filtered series of the inflation rate, the Federal Funds rate and the index of commodity prices, respectively, at various leads and lags. Besides, the estimated investment-specific shock is significantly correlated with the filtered series of the consumption and the investment share (see Table 3). Therefore, we extend the trivariate VAR to these additional variables. Thus, we minimize the possibility of omitted-variable bias (Christiano et al. 2003). Furthermore, we note that the filtered series of the employment rate is not significantly correlated with either the neutral or the investment-specific technology shock. Nevertheless, we include this variable as a labor market indicator in our information set. In contrast to, for example, the unemployment rate, the employment rate corresponds to the business sector and, thus, allows us to examine employment adjustment consistently along the extensive vs. intensive margin. None of our results are affected if we exclude the employment rate from our system.[6] The extension of the

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[4] Our long-run identification strategy of the two technology shocks (see Section 2.2) requires that labor productivity and the relative price of investment goods enter the SVAR in first differences. Hence, we difference these variables first and then apply the bandpass filter. Section (4.1) shows that this choice is innocuous.

[5] To be precise, we first undrift the series and then apply the one-sided bandpass filter with following options: $p_l = 2$, $p_u = 52$, $root = 1$, $drift = 0$, $ifilt = 0$, $nfix = -1$, $thet = 1$. Where available, we use data from 1948Q1 to 2007Q4 and then drop the filtered data points prior to 1955Q3. The Federal Funds rate is only available from 1954Q3. Choosing $root = 0$ instead leads to less favorable coherence properties, but leaves the main conclusions unchanged.

[6] Alternatively, we have tested whether we can exclude single time series from our 9-dimensional SVAR. The resulting dynamic correlation pattern is consistent with the one presented in Table (3).

information set is also supported by the outcome of bivariate Granger (1969) causality tests (see Table 4).

2.2 Identification

We estimate four structural shocks using standard identifying assumptions. To begin with, we consider two kinds of technology shocks. Neutral technology shocks (Kydland & Prescott 1982) are able to replicate the cyclical comovement of output, hours worked, and consumption easily. For this reason, this type of disturbance has played a dominant role in the early RBC literature (King & Rebelo 1999). More recently, however, investment-specific technology shocks have gained a great deal of attention. This strand of the literature argues that movements in the relative price of investment goods are not only important in explaining postwar U.S. growth, but also macroeconomic fluctuations at business cycle frequencies (Greenwood et al. 1997, 2000). In addition to these two disturbances, we identify two non-technology shocks — innovations to monetary policy (Christiano et al. 1996) and unexpected changes in commodity prices (Rotemberg & Woodford 1996). The resulting identification procedure is equivalent to the model of Ravn & Simonelli (2008), with commodity prices instead of government spending.

Consequently, the reduced form VAR is given by:

$$x_t = a + B(L)x_{t-1} + e_t \tag{1}$$
$$x_t = \begin{bmatrix} \Delta q_t & \Delta a_t & z_t & r_t & p_t \end{bmatrix}'$$
$$z_t = \begin{bmatrix} \pi_t & h_t & c_t & i_t & n_t \end{bmatrix}'$$

where $B(L)$ is a lag polynomial of order M. By a premultiplication with β_0, one obtains the structural VAR:

$$\beta_0 x_t = \alpha + \beta(L)x_{t-1} + \epsilon_t \tag{2}$$

where ϵ_t denotes the vector of fundamental shocks. The orthogonality assumption implies that its covariance matrix $V_\epsilon = E(\epsilon_t' \epsilon_t)$ is diagonal. Moreover, we normalize the diagonal of β_0 to a 9x1 vector of ones.

Both technology shocks are identified using long-run restrictions (Shapiro & Watson 1988, Blanchard & Quah 1989). Following Fisher (2006), we assume that *only* investment-specific technology shocks affect the relative price of investment goods in the long run. The long-run level of aggregate productivity may be affected by both investment-specific *and* neutral technology shocks. No other shock has any long-run effect on the relative price of investment goods or the level of labor productivity (Galí 1999).

Our identification strategy of the two remaining shocks is based on short-run restrictions. We impose the constraint that no other variable may respond contemporaneously when the Fed's monetary policy — given by the Federal Funds rate — deviates from

its linear rule. This presumes that, when setting the nominal interest rate, the Fed's information set includes the contemporaneous values of all other variables included in the SVAR (Christiano et al. 1996). Moreover, we identify commodity price shocks by assuming that commodity prices are predetermined with respect to U.S. macroeconomic aggregates (Rotemberg & Woodford 1996).[7] This assumption is based on the perception that the sources of short-run commodity price fluctuations, such as political strife in the Middle East (Kilian 2008), are exogenous to the U.S. economy. However, this may be incorrect because the U.S. is a large economy, or because economic developments in the U.S. are correlated with global economic activity (Blanchard & Galí 2007). Indeed, Kilian (2008) surveys ample evidence that energy prices should be treated as endogenous. Nevertheless, he concludes that the *contemporaneous* exogeneity assumption provides a good approximation when working with quarterly data.[8] Blanchard & Galí (2007) relax the contemporaneous exogeneity assumption by allowing for immediate responses in energy prices to variations in two U.S. macroeconomic aggregates (output and employment). In line with Kilian (2008), they find that the estimated results are "nearly identical" under the two alternative identification schemes.[9]

Consequently, the process for the Federal Funds rate depends on the current and past values of all other variables, but no other process depends on its current realizations. This implies that the second-last column of β_0 consists of zeros, apart from the second-last element which is normalized to unity. The process for the commodity price, on the other hand, depends on the lagged values of commodity prices and all other variables, but not on the current realizations of any other variable. Consequently, the last row of β_0 consists of zeros, apart from the last element which is normalized to unity. Furthermore, the order of the variables included in the vector z_t imposes a number of additional short-run restrictions on β_0.

2.3 Estimation

The first equation of the structural VAR (equation 2):

$$p_t = \alpha^p + \sum_{j=1}^{M} \beta_{x,j}^p x_{t-j} + \epsilon_t^p \tag{3}$$

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[7]Most of the literature, as Rotemberg & Woodford (1996), focuses on energy prices rather than on the broader commodity price index. We find that the shape of the impulse response dynamics remains unchanged when we use the West Texas Intermediate spot oil price instead. Quantitatively, however, unexpected variations in the commodity price index seem more important for the cyclical behavior of U.S. macroeconomic aggregates.

[8]Hamilton (2003) emphasizes that the relationship between energy price changes and output growth may be nonlinear. The investigation of this aspect, however, is beyond the scope of this paper.

[9]In addition, Section 4.3 distinguishes between supply and demand-driven innovations. However, as commodity prices are denominated in U.S. dollars, we are not able to identify endogenous (real) exchange rate driven commodity price movements.

identifies the commodity price shock ϵ_t^p. We estimate equation (3) using ordinary least squares. The second equation of the SVAR:

$$\Delta q_t = \alpha^q + \sum_{j=1}^{M} \beta_{q,j}^q \Delta q_{t-j} + \sum_{j=0}^{M-1} \beta_{a,j}^q \Delta^2 a_{t-j} \tag{4}$$
$$+ \sum_{j=0}^{M-1} \beta_{z,j}^q \Delta z_{t-j} + \sum_{j=1}^{M-1} \beta_{r,j}^q \Delta r_{t-j} + \sum_{j=0}^{M-1} \beta_{p,j}^q \Delta p_{t-j} + \epsilon_t^q$$

identifies the investment-specific technology shock ϵ_t^q. The long-run restriction is imposed by differencing all the regressors in x_t apart from the relative investment goods price itself (note that Δ^2 is the second difference operator). Moreover, we exclude the contemporaneous value of the Federal Funds rate from this regression. This implements the short-run assumption on the Fed's information set. Since ϵ_t^q may be correlated with Δa_t (via equation 5) and z_t (via equation 7), we estimate equation (4) with 2SLS. The instruments are a constant, the vector $[\Delta q_{t-j}, \Delta a_{t-j}, z_{t-j}, r_{t-j}, p_{t-j}]_{j=1}^{M}$ and $\hat{\epsilon}_t^p$ (the estimate of ϵ_t^p). The third equation of the SVAR:

$$\Delta a_t = \alpha^a + \sum_{j=0}^{M} \beta_{q,j}^a \Delta q_{t-j} + \sum_{j=1}^{M} \beta_{a,j}^a \Delta a_{t-j} \tag{5}$$
$$+ \sum_{j=0}^{M-1} \beta_{z,j}^a \Delta z_{t-j} + \sum_{j=1}^{M-1} \beta_{r,j}^a \Delta r_{t-j} + \sum_{j=0}^{M-1} \beta_{p,j}^a \Delta p_{t-j} + \epsilon_t^a$$

identifies the neutral technology shock ϵ_t^a. Note that we difference all regressors — except for Δq_t and Δa_t — and exclude the contemporaneous value of the Federal Funds rate. We estimate equation (5) using 2SLS, given that ϵ_t^a may depend on z_t (via equation 7) and q_t (via equation 4). The instruments employed above are extended to include the estimate of ϵ_t^a; i.e., $\hat{\epsilon}_t^a$. The fourth equation of the SVAR:

$$r_t = \alpha^r - \beta_{q,0}^r \Delta q_t - \beta_{a,0}^r \Delta a_t - \beta_{z,0}^r z_t - \beta_{p,0}^r p_t + \sum_{j=1}^{M} \beta_{x,j}^r x_{t-j} + \epsilon_t^r \tag{6}$$

identifies the monetary policy shock ϵ_t^r. This equation is estimated with ordinary least squares.

Following Altig et al. (2011), we estimate the remaining parameters for the vector z_t. The components of z_t are denoted by z_t^i, $i = 1, \ldots, 5$. The parameters of the first equation are obtained by estimating:

$$z_t^1 = \alpha^1 + \sum_{j=0}^{M} \beta_{q,j}^1 \Delta q_{t-j} + \sum_{j=0}^{M} \beta_{a,j}^1 \Delta a_{t-j} \tag{7}$$
$$+ \sum_{j=1}^{M} \beta_{z,j}^1 z_{t-j} + \sum_{j=1}^{M} \beta_{r,j}^1 r_{t-j} + \sum_{j=0}^{M} \beta_{p,j}^1 p_{t-j} + \epsilon_t^1$$

employing the above-used instruments including the vector of estimated shocks $[\hat{\epsilon}_t^p, \hat{\epsilon}_t^q, \hat{\epsilon}_t^a]'$. The second equation extends the set of regressors with z_t^1 and the list of instruments with $\hat{\epsilon}_t^1$. We continue this procedure recursively for all the variables included in z_t.

3   Results

We apply standard lag selection tests in order to determine the optimal VAR order (M). These tests, however, yield inconsistent results. The information criteria by Akaike (3), Hannan-Quinn (2), and Schwarz (1) indicate a short lag length. Sequential likelihood ratio tests, on the other hand, suggest that the VAR order is rather large ($M = 5$).[10] Given that our identification strategy of technology shocks is based on long-run restrictions, we set the number of lags equal to $M = 5$.[11] The qualitative shape of the impulse response functions is not sensitive to this choice. Quantitatively, we note that the business cycle variance of output, per-capita hours, and the inflation rate which is explained by the four identified shocks rises when we increment the lag length from three to five (see Figure 2). We also check the bootstrapped multivariate Portmanteau (Q) statistics. We do not reject the null hypothesis of zero serial correlation when the lag length is set equal to $M = 5$.

3.1   Dynamic Responses to Structural Shocks

We examine the impulse responses at horizons up to 32 quarters. The graphs depict the responses based on bootstrap sampling over 3,000 replications, where the first 1,000 draws are used to correct for small sample bias and departures from non-normality (Kilian 1998a,b).[12] The solid line is the median estimate. The gray shaded areas represent the associated 60%, 70%, 80% and 90% non-centered confidence intervals. For the reader's convenience, Figures (3), (5)-(7) in the Appendix contrast the impulse responses of our benchmark specification (a panels) with the impulse responses of the level specification (b panels).

3.1.1   Neutral Technology Shocks

Figure (3) illustrates the impulse response functions to the identified neutral technology shock. We observe that a permanent improvement in labor productivity induces a long-lasting rise in output and consumption. On impact, both variables jump up and then remain well above their original value for the entire time horizon. Moreover, the shock

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[10]The standard sequential likelihood ratio test rejects $M = 4$ at the 5% significance level, the modified sequential likelihood ratio test (Sims 1980) rejects the same alternative hypothesis at the 10% significance level.

[11]Erceg et al. (2005) provide evidence that low-ordered VARs are able to approximate the true data generating process. Chari et al. (2008) conclude the opposite.

[12]The Jarque-Bera test statistics reject the null hypothesis that the commodity price shocks and the monetary policy shocks are normally distributed, at the 1% and 5% significance level, respectively.

produces a large and protracted hump-shaped response in investment. The inflation rate falls on impact and then asymptotes to its steady-state level within 4 years. There is also a modest increase in the relative price of investment goods, but the effect disappears relatively quickly. The impulse response of per-capita hours is positive, even though not significant at the 10% level. A very similar response can be observed for the employment rate. Hours per worker, on the other hand, rise on impact and then slowly return to their steady state. Quantitatively, however, the impact of the intensive margin is small. The estimated impulse responses differ only in one important respect from those obtained by Altig et al. (2011). We find that the increase in consumption is not gradual, but rather abrupt. The major implication of our result is that models assuming habit formation in aggregate consumption (Abel 1990) may not be able to replicate the dynamics of the U.S. economy.

Given that the response of hours worked to neutral technology shocks is extremely sensitive to the treatment of the data, we also examine the impact of alternative specifications in the following. Table (4) displays the hours response in our benchmark specification, the corresponding level specification, the corresponding difference specification, and in a dummy specification.[13] When the information set is large — as in the left panel — we observe that our results are very robust. Across all specifications, the entire dynamic response is not statistically significantly different from zero at the 10% level. The sign of the impact response is positive in all but one of the cases considered. Only the dummy specification predicts a negative response during the first few quarters, but the confidence intervals are wide. Interestingly, the hours response flips horizontally when all high and medium frequencies in per-capita hours are reversed (Fernald 2007).[14] These results indicate that the low-frequency bias (present in the level specification) and the misspecification error (induced by overdifferencing) become less important when the information set is sufficiently large. This conclusion is consistent with the results of Christiano et al. (2003) and Forni & Gambetti (2011).[15]

On the other hand, the right panel of Table (4) shows the impulse responses when the information set is reduced to three variables $\{q_t, a_t, h_t\}$. We observe that, in this case, the hours response becomes indeed extremely sensitive to the treatment of the data. If we remove the low-frequency movements, either by applying a one-sided bandpass filter, by taking first differences, or by including a time trend and two structural breaks in level and trend, the hours response is significantly *negative*. This confirms the results

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[13]*Level* specification: All series enter in levels, but the relative price of investment goods and labor productivity enter in first differences. *Difference* specification: Also per-capita hours enter in first differences. *Dummy* specification: We extend the level specification to include a time trend and two structural breaks in level and trend at the dates 1973Q2 and 1997Q2 (see Fernald 2007).

[14]Otherwise, the set-up is equivalent to the level specification.

[15]Using a trivariate VAR, Forni & Gambetti (2011) demonstrate that such a small model is not informationally sufficient. As in our SVAR, the impulse response of per-capita hours to technology shocks is hardly significantly different from zero when they include additional information.

of Galí (1999) and Canova et al. (2010). Instead, the response is significantly *positive* if per-capita hours enter the VAR in levels, thus echoing the findings of Christiano et al. (2003, 2004). Moreover, we are able to replicate the counterfactual exercise conducted by Fernald (2007). Even if all high and medium frequencies in per-capita hours are reversed, the trivariate SVAR generates a significant positive response. In summary, these results imply that the (downward) omitted-variable bias and the (upward) low-frequency bias lead to significant distortions only when the information set is insufficiently small.

The reason why the results of Galí (1999) and Francis & Ramey (2005) have gained a great deal of attention lies in their implications for DSGE modeling. In a New Keynesian environment, price rigidities prevent that aggregate demand adjusts as fast as aggregate supply. Hence, when the degree of price rigidity is sufficiently large, hours worked may fall in the aftermath of a positive productivity shock (Galí & Rabanal 2004). Furthermore, the fall in hours worked to neutral technology shocks implies that neutral technology shocks cannot be the main source of macroeconomic fluctuations — otherwise, hours worked would be countercyclical. Our results, however, do not provide strong support for this view. In contrast, the inflation rate drops significantly in response to neutral technology shocks. This suggests that price rigidities are rather moderate, causing only a small output gap.[16] Consequently, the median response of per-capita hours is greater than zero over the whole observation period.

3.1.2 Investment-Specific Technology Shocks

Figure (5) displays the effects of an investment-specific technology shock. This shock leads to a sudden and permanent drop in the relative price of investment goods. We observe that all variables (except labor productivity) move together in response to this type of disturbance. Their dynamic adjustment paths show a marked hump-shaped pattern, with peak effects occurring after 3-4 quarters. The impulse response of labor productivity is not statistically significant. This result illustrates that the amplitude of per-capita hours is of the same magnitude as aggregate output (also here, most variation in labor input is due to adjustments along the extensive margin). Thus, investment-specific technology shocks seem far more important for the cyclical behavior of the labor market than neutral technology shocks. Against this background, it is a little surprising that investment-specific technology shocks have not received more attention as a driving force of labor market fluctuations. Two of the exceptions are De Bock (2007) and Faccini & Ortigueira (2010) who both study the implications of frictional labor markets in this context. Overall, we note that these adjustment dynamics are virtually identical to the results of Altig et al. (2011).

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[16]Dupor et al. (2009) draw a similar conclusion.

The main reason why investment-specific technology shocks have not played a more important role in the literature has recently been pointed out by Justiniano et al. (2010). Their work explains why the standard RBC model fails to replicate the positive comovement between output, hours worked, and consumption over the business cycle. In such a frictionless environment, the marginal product of labor (MPL) equals the marginal rate of substitution (MRS) between consumption and leisure. Investment-specific technology shocks, however, have no direct impact on total factor productivity. This implies that consumption and leisure move in the same direction or, in other words, consumption and hours worked move in opposite directions. In the data, however, consumption and hours worked are positively correlated at business cycle frequencies. For this reason, investment-specific technology shocks were long considered not to be a main determinant of the business cycle (Barro & King 1984). Neutral technology shocks, on the contrary, are able to match the positive comovement easily. Hence, neutral technology shocks attracted most attention in the early RBC literature (King & Rebelo 1999).

Justiniano et al. (2010) also demonstrate how the standard RBC model can be reconciled with the empirical evidence. They suggest considering real frictions (or the like) that modify the relationship between the MPL and MRS. With variable capital utilization, for instance, investment-specific technology shocks may have a direct impact on the MPL. Consequently, consumption and per-capita hours do not necessarily move in opposite directions.[17] Moreover, in the presence of monopolistic competition, firms set prices as a mark-up over marginal costs. If the mark-up is time-variant (Rotemberg 2008), it may drive a wedge between the MPL and the MRS. Besides this, Justiniano et al. (2010) also consider habit formation in aggregate consumption (Abel 1990). This modification alters the marginal utility of consumption and, thus, the functional form of the MRS. The previous section, however, has shown that external habit formation is inconsistent with the dynamics of the U.S. economy in response to neutral technology shocks.

3.1.3 Monetary Policy Shocks

Figure (6) shows the responses to an expansionary shock in monetary policy. This shock represents a drop in the Federal Funds rate, due to an unexpected deviation from the Fed's linear policy rule. Our identifying assumptions imply that the shock has only a temporary effect. Nevertheless, the Federal Funds rate remains below its steady state level for more than seven quarters. In response to this, we observe that output, per-capita hours, employment, consumption, and investment rise gradually. Peak effects take place about 5-6 quarters after the monetary stimulus. At longer forecast horizons, the adjustment paths show a slight rebound. The response of the relative price of investment goods, on the other hand, is not significant. Overall, the shapes and elasticities of the

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[17]Furlanetto & Seneca (2010) examine under which parameter values medium-scale DSGE models are able to generate a positive consumption response to investment-specific technology shocks.

responses are in line with the estimates by Ravn & Simonelli (2008). Merely, labor input indicators behave slightly different. Employment seems somewhat less elastic. Hours per worker even display a very mild downturn.

Consistent with Sims (1992), the impulse response of the inflation rate drops on impact, followed by a slow and persistent increase. The former observation is often referred to as the "price puzzle", the latter as "inflation persistence". The slow speed of aggregate consumer price adjustment in the aftermath of monetary policy shocks has led to the development of medium-scale DSGE models, including nominal rigidities and several other departures from the standard RBC economy (Christiano et al. 2005). However, estimated versions of these models suggest that the degree of price rigidity is much larger than can be supported by micro data (see e.g., Bils & Klenow 2004). Hence, various extensions have been proposed to rationalize inflation persistence; for instance, deep habits (Ravn et al. 2010), firm-specific capital (Altig et al. 2011), or rational inattention (Mackowiak & Wiederholt 2010). Nevertheless, the temporary drop remains "puzzling". As explained by Eichenbaum (1992), it may be due to the presence of deflationary pressure already known to the Fed, but not captured by the information set of the VAR (Eichenbaum 1992). Therefore, we explicitly consider the PPI commodity price index. As this index is a forward-looking variable, our SVAR should be immune to this critique. However, we find out that the inclusion of the commodity price index reduces the size of the drop slightly, but leaves the shape of the inflation response unchanged.

Recently, Ravn et al. (2010) were able to match the shape of the inflation response to monetary policy shocks assuming "deep" habits over individual varieties of consumption goods (instead of aggregate consumption). In this set-up, mark-ups are endogenous. The authors show that, in response to a cut in the nominal interest rate, firms have an incentive to lower their mark-ups. The rationale behind this behavior is the following: When the expected value of future market shares is high, firms have large incentives to increase the stock of habits. Once the stock of habits has been built up, firms exploit the low price elasticity of demand. For this reason, we observe an initial drop in the inflation rate, followed by a protracted increase. Due to the presence of complementarities, the deep habits model requires — consistent with micro evidence — only a low to moderate degree of nominal rigidities to replicate the gradual response of the inflation rate. As pointed out by Justiniano et al. (2010), counter-cyclical mark-ups also help to replicate the positive comovement of output, hours worked, and consumption in response to investment-specific technology shocks. Hence, its seems promising to evaluate the deep habits model also in response to other structural shocks.[18]

Furthermore, we observe that an unexpected cut in the Federal Funds rate induces a slow, but persistent increase in commodity prices. The maximum impact does not

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[18]For instance, di Pace & Faccini (2010) introduce deep habits into a RBC model with frictional labor markets.

occur until four to five years after the shock. In comparison to Anzuini et al. (2010), our estimated impulse response is much more gradual and resembles (qualitatively as well as quantitatively) the impulse response of the consumer prices index (i.e., the cumulative response of the inflation rate). In other words, the commodity price index shows no significant movements in real terms.

3.1.4 Commodity Price Shocks

Figure (7) depicts the impulse responses to the identified commodity price shock.[19] We find that this shock triggers a temporary rise in the commodity price index, peaking about one year after the initial increase. After this, commodity prices slowly return to their steady state level. Moreover, we observe a spike in the inflation rate, indicating that aggregate consumer prices are very flexible in response to commodity price shocks. In the following periods, the inflation rate declines sharply. Therefore, we are not able to confirm the conventional wisdom of unexpected changes in commodity prices as a driving force of *sustained* inflation (see also Barsky & Kilian 2001). The sudden surge in the inflation rate prompts the Fed to elevate the nominal interest rate for a protracted period (about 6-8 quarters). Consequently, the inflation rate falls below normal about 10 quarters after the shock. We also note that the relative price of investment goods decreases slightly, but the effect disappears relatively quickly. The adjustment paths of output, per-capita hours, employment, consumption, and investment display significant U-shaped responses. Hours per worker, on the contrary, show no significant response.

The estimated impulse responses of output and employment are consistent with the results of Blanchard & Galí (2007) — output and employment decline persistently after a lag of 2-3 quarters and reach a trough after about 10 quarters.[20] Ordóñez et al. (2010) also find that energy price shocks cause upheaval in the labor market, albeit with a shorter lag. Rotemberg & Woodford (1996) argue that upward movements in the firms' mark-up play an important role in exacerbating economic downturns.[21]

Bernanke et al. (1997) have argued that the recessionary effects of commodity price shocks are not due to the direct impact of higher producer prices, but rather due to the contractionary response of the Federal Reserve. Hamilton & Herrera (2004) question this conclusion. In order to address this issue, we perform the following counterfactual exercise. We assume that the Federal Funds Rate is kept constant when the U.S. economy is hit by an unexpected increase in commodity prices. Figure (8) contrasts the impulse response functions of output, per-capita hours and the inflation rate in the benchmark specification (top panel) with the impulse responses under the counterfactual assumption

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[19]Section (4.3) provides a robustness analysis on the impact of demand-driven commodity price changes.

[20]In a similar context, Kilian (2008) explains through which channels higher energy prices may decrease economic activity.

[21]Blanchard & Galí (2007), on the contrary, emphasize the role of real wage rigidities.

(bottom panel). Indeed, we observe a much smaller downturn in output and per-capita hours if the Fed stayed passive. The decline in per-capita hours even becomes statistically insignificant. The initial spike in the inflation rate seems identical to the one estimated above. At medium horizons (10-20 quarters), however, the counterfactual response cannot replicate the significant rebound. In other words, aggregate consumer prices remain high. This explains why the median estimate of output requires four additional quarters to converge. Thus, we conclude that the monetary policy feedback rule leads to a deeper but shorter economic downturn in the aftermath of an unexpected rise in commodity prices.

In addition, Figure (9) illustrates the impulse responses of two CPI sub-indices; i.e. the so-called core inflation rate (all items less food and energy) and its counterpart (food and energy only). We observe that the spike in the (all items) inflation rate is mainly due to a sharp rise in food and energy prices. The core inflation rates, on the other hand, shows a lower — but still significant — and more persistent increase. This indicates that a little price rigidity at the level of intermediate goods may translate into persistent inflation movements in other sectors of the economy (Basu 1995) — so-called second-round effects. Moreover, by repeating the above-described counterfactual exercise, we notice that the initial increase in both sub-indices remained virtually unchanged if the Federal Reserve stayed passive. The significant rebound, however, disappears completely in both impulse responses. Therefore, we conclude that the Fed's contractionary monetary policy feedback rule is unable to avoid second-round effects in the short run. Yet, it exhibits medium-run disinflationary effects which help the Federal Reserve to achieve price stability (in terms of the core inflation rate) at longer forecast horizons.

3.2 Importance of the Structural Shocks

We now examine the relative importance of the four structural shocks for the variance of all variables included in our SVAR. First, we present the share of variation explained by each identified shock at different forecast horizons. However, as explained by Ravn & Simonelli (2008), these figures do not allow us to draw direct conclusions about the importance of these shocks at business cycle frequencies. Therefore, we also compute the variance decomposition at business cycle frequencies (8-32 quarters) following the method proposed by Altig et al. (2011). In addition, we present the historical decomposition of structural shocks for aggregate output in the postwar period.

3.2.1 Forecast Error Variance Decomposition

Figure (11) displays the forecast error variance decomposition of three key macroeconomic variables (output, per-capita hours, and the inflation rate) at different horizons. We observe that neutral technology shocks explain a large share of the variation in output,

particularly at long forecast horizons. Investment-specific technology shocks are the main determinant of fluctuations in per-capita hours, and the second most important determinant of fluctuations in output. Commodity price shocks appear to be the primary driving force of movements in the inflation rate. Monetary policy shocks, on the other hand, explain only small shares of macroeconomic fluctuations. The joint explanatory power of all four shocks lies between 38% (per-capita hours) and 48% (output) in the short run, and 57% (inflation rate) and 73% (output) in the long run.

3.2.2 Variance Decomposition at Business Cycle Frequencies

We now investigate the variance decomposition at business cycle frequencies (see Table 5). The results show that commodity price shocks are a principal driving force of macroeconomic fluctuations. In particular, we find that commodity price shocks explain a large share of cyclical movements in inflation. The commodity price shock also turns out to be a very important determinant of cyclical fluctuations in many other macroeconomic variables (e.g., output, per-capita hours, consumption, or investment), second only to investment-specific technology shocks. The neutral technology shock explains only a considerable share of the variation in labor productivity — the endogenous variable in the equation that identifies the shock. The monetary policy shock seems even less relevant. The fact that only 13% of the changes in the nominal interest rate are due to the unexpected shock indicates that the Fed's monetary policy has followed a rule-based approach over our sample period.

The importance of investment-specific technology shocks is in line with the results of several recent SVAR studies by Fisher (2006), Ravn & Simonelli (2008), Canova et al. (2010), and Altig et al. (2011).[22] Altogether, the four identified shocks account for 50%-71% of business cycle volatility in the data. At first glance, however, it seems surprising that neutral technology shocks do not explain larger shares at business cycle frequencies. Therefore, we analyze also the explanatory power of neutral technology shocks across the whole spectrum (Figure 12). Indeed, we find that neutral technology shocks play a very important role in explaining macroeconomic fluctuations (particularly, output, labor productivity, and consumption), but at low frequencies.

3.2.3 Historical Decomposition of Shocks

Figure (10) presents the historical decomposition of shocks for aggregate output. When all four structural shocks are considered, we observe that our SVAR model is able to replicate the cyclical behavior of output remarkably well. There are only two episodes in

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[22]Smets & Wouters (2007) as well as Mumtaz & Zanetti (2010) draw the opposite conclusion from a Bayesian VAR model using a data set that includes consumer durables in consumption (and not in investment). Schmitt-Grohé & Uribe (2011) argue that a common stochastic trend in neutral and investment-specific technology is the main driving force of the business cycle.

U.S. postwar history that exhibit a noticeable tracking error. The model explains neither the short recession in the late 1960s, nor the fast economic recovery after the burst of the so-called dotcom-bubble.

We also investigate the time series elicited by the four individual shocks. The graphs illustrate that their contribution varies considerably across different episodes in the U.S. postwar period. In line with our previous results, we are unable to find a systematic relationship between neutral productivity shocks and fluctuations in aggregate output at business cycle frequencies. Neutral technology shocks rather seem important at low frequencies. For example, neutral productivity shocks suggest a deep recession between 1976 and 1983, reflecting the productivity slowdown in that period (Bruno 1984), and two long-lasting economic booms — the first in the mid 1980s and the second in the late 1990s. Investment-specific technology shocks, on the contrary, appear to be a principal driving force of the 1960-61 recession and the following economic expansion, the 1973-75 recession and the double-dip in the early 1980s. Moreover, investment-specific technology shocks explain a large fraction of the economic expansion in the 1990s. Monetary policy shocks, on the other hand, seem to play a rather limited role in the postwar era. Apart from the double-dip in the early 1980s and the subsequent recovery, unexpected deviations from the Fed's monetary policy rule do not make a significant difference. Commodity price shocks, however, contribute substantially to the high degree of macroeconomic volatility in the 1970s, particularly during and after the first OPEC oil crisis. In addition, commodity price shocks are also an important determinant of the economic booms in the mid 1980s and in the late 1990s. Finally, we evaluate the impact of the Fed's response to commodity price shocks. Therefore, we examine the cyclical movements of aggregate output in the absence of its monetary policy feedback rule.[23] Interestingly, we observe that the monetary policy feedback rule — particularly the contractionary response during the first OPEC oil crisis and the subsequent monetary easing — seems to have amplified the output fluctuations caused by unexpected changes in commodity prices. In other words, our SVAR indicates that a contractionary monetary policy feedback rule may help to achieve price stability (in terms of the core inflation rate) at longer forecast horizons, yet at the cost of output destabilization.

4 Robustness Analysis

The following section presents a number of robustness checks. We investigate the sensitivity of our results to the data treatment, the choice of the lag length, the selected sample period, and the inclusion of alternative disturbances and variables — in particular, we add external demand shocks (Abbritti & Weber 2010) and we consider shocks

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[23]See Section (3.1.4) for details and motivation of this counterfactual exercise.

to government spending (Blanchard & Perotti 2002) instead of commodity prices.[24] We demonstrate that the results of our benchmark specification are robust across alternative model versions.

4.1 Data Treatment

The (b) panels of Figures (3), (5)-(7) and Table (5), respectively, display the impulse responses and the business cycle variance decomposition when we estimate the SVAR in levels.[25] We observe that all major conclusions drawn from the benchmark specification survive this type of test. Even the response of per-capita hours to neutral technology shocks remains virtually unchanged (see also Section 3.1.1). Only the cyclical variance decomposition statistics decrease slightly across most variables. Altogether, these results indicate that the low-frequency bias becomes less important when the information set is sufficiently large, thus echoing the findings of Christiano et al. (2003). Furthermore, the remarkable resemblance of the impulse responses suggests that bandpass filtering the data prior to estimation does not remove information necessary to identify the shocks using long-run restrictions (Gospodinov et al. 2009).

In addition, Table (6) provides the cyclical variance decomposition statistics of output, per-capita hours, and the inflation rate under different model specifications. The figures confirm that our findings are robust to different filtering methods (differences, dummies) or when the Federal Funds rate is not logarithmized prior to estimation.

4.2 Lag Length and Subsample Stability

Next, we assess whether the chosen lag length has any impact on our results. For this purpose, we reduce the order of our benchmark SVAR to $M = 4$. Table (6) shows that, in this case, the investment-specific technology shock becomes less important, but remains the principal driving force of cyclical fluctuations in output and per-capita hours. The contribution of commodity price shocks to the cyclical movements in the inflation rate even rises. Besides, we are unable to note any difference in the shape of the impulse responses (not shown here).

In addition, the present subsection examines the subsample stability of our benchmark specification. Therefore, we estimate our SVAR model separately before and after the appointment of Paul Volcker as chairman of the Board of Governors in August 1979. For this exercise — due to the smaller number of observations — we reduce the VAR order to $M = 3$. We find that most of our conclusions are independent of the chosen sample period with one exception: The impulse responses to a sudden and permanent drop in the relative price of investment goods become insignificant when we exclude the late 1990s Internet

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[24]In a companion paper (Gubler & Hertweck 2011), we additionally study the relevance of news shocks.
[25]See Footnote (13) for a definition of the level specification.

boom from our sample. We also observe that both technology shocks are somewhat more important in the late subsample. Overall, however, the business cycle variance decomposition statistics are consistent with the corresponding version ($M = 3$) of our benchmark model (not shown here). In particular, the explanatory power of commodity price shocks remains stable.

4.3 External Demand

The present identification procedure of the commodity price shock is unable to distinguish between supply- and demand-driven innovations (Kilian 2008). However, the assumption that commodity price shocks are contemporaneously exogenous to U.S. macroeconomic aggregates seems more defensible in the case of supply shocks (e.g., political strife in the Middle East) than in the case of demand shocks. Therefore, we extend our SVAR by adding a variable that captures variations in global demand for commodity goods. In particular, we choose to include the natural log of the ratio of real exports to real imports of goods & services (see Table 2).[26] Based on this series, we identify an external demand shock using short-run restrictions. Following Abbritti & Weber (2010), we assume that the process for the real export/import ratio is independent of the current realizations of all other variables but the commodity price index.

Figure (13a) illustrates the effects of the identified external demand shock. This shock represents a temporary but persistent rise in the real exports/imports ratio. We observe that the external demand shock causes a hump-shaped increase in the commodity price index, representing commodity price changes due to heightened global demand. All other variables show barely significant responses, which may be attributed to the fact that the U.S. is a relatively closed economy. The impulse responses generated by the four remaining shocks, particularly the commodity price shock (Figure 13b), remain virtually unchanged when we control for unexpected movements in external demand. In addition, the variance decomposition statistics at business cycle frequencies are remarkably robust (Table 6). We only note a mild reduction (about 6-7 percentage points) in the explanatory power of the commodity price shock with respect to cyclical movements in the inflation rate. Besides, the external demand shock is unable to explain significant shares in the business cycle variance of any variable but the real export/import ratio.

4.4 Government Spending Shocks

We also investigate the consequences of unexpected changes in government spending. Therefore, we adopt the assumption that government spending is predetermined; i.e.,

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[26]Alternatively, we have considered the "rest of the world" GDP series compiled by Enders et al. (2011) and the "global economic activity" index constructed by Kilian (2009). Both time series, however, do not cover our whole sample period. Subsample tests indicate that both indices yield similar results.

fiscal policy takes one quarter to adjust (Blanchard & Perotti 2002). In other words, government spending shocks are identified in exactly the same way as commodity price shocks. This implies that it is not feasible to estimate both structural shocks simultaneously. For this reason, we modify our benchmark specification to include real government expenditures per capita (see Table 2) instead of commodity prices. The resulting identification procedure of structural shocks is equivalent to Ravn & Simonelli (2008).

Figure (14) depicts the impulse responses to the identified government spending shock. This shock represents a long-lasting rise in government expenditures per capita, converging after four to five years. However, we observe that such a fiscal policy shock does not seem to cause any significant movements in U.S. macroeconomic aggregates.[27] Consistent with this result, Table (6) shows that variations in government spending explain only a small share of the movements in output, per-capita hours, and the inflation rate at business cycle frequencies. Apart from this, we note that the findings of our benchmark model are not sensitive to the inclusion of government spending shocks. Only the explanatory power of investment-specific technology shocks with respect to the inflation rate rises slightly when commodity price shocks are absent.

5 Summary and Conclusion

This paper develops a 9-dimensional SVAR to investigate the sources of the U.S. business cycle. We extend the standard set of identified shocks to include unexpected changes in commodity prices. Our main result is that commodity price shocks are a very important driving force of macroeconomic fluctuations, second only to investment-specific technology shocks. In particular, we find that commodity price shocks explain a large share of cyclical movements in inflation. Neutral technology shocks and monetary policy shocks seem less relevant at business cycle frequencies.

The impulse response analysis shows that commodity price shocks generate a spike in the inflation rate, followed by a rapid return to the initial level. Therefore, we are not able to confirm the conventional wisdom of unexpected changes in commodity prices as a driving force of *sustained* inflation (see also Barsky & Kilian 2001). Moreover, we observe that the sudden surge in the inflation rate prompts the Fed to elevate the nominal interest rate. Results of a counterfactual exercise indicate that the contractionary feedback rule achieves price stability (in terms of the core inflation rate) in the long run, yet at the cost of a deeper (and shorter) recession.

Furthermore, we confirm that investment-specific technology shocks induce a strong positive comovement between output, per-capita hours, and consumption. As demon-

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[27]Interestingly, we are able to replicate the negative sign of the consumption response to an expansionary government spending shock (Ramey 2011), even though our results are based on the standard identification strategy of Blanchard & Perotti (2002).

strated by Justiniano et al. (2010), this pattern cannot be reconciled with the standard RBC model. Medium-scale DSGE models (Christiano et al. 2005), however, consider modifications like variable capital utilization or time-varying mark-ups that modify the relationship between the marginal product of labor (MPL) and the marginal rate of substitution (MRS) between consumption and leisure. These modifications may help to replicate the strong cyclical comovement of U.S. macroeconomic aggregates (Furlanetto & Seneca 2010).

Given the importance of investment-specific technology shocks for the business cycle, our results provide support for medium-scale DSGE models. The flexibility of aggregate consumer prices, however, depends strongly on the type of disturbance. The consumer price index adjusts slowly to monetary policy and investment-specific technology shocks, somewhat faster to neutral technology shocks, and very fast to commodity price shocks (see also Boivin et al. 2009). This indicates that aggregate consumer prices *per se* are not very sticky. Rather, decision makers might find it optimal to devote their attention primarily to changes in commodity prices. For this reason, models with rational inattention (Mackowiak & Wiederholt 2010) seem very promising.

Our framework also addresses the extreme sensitivity of the hours response to neutral technology shocks. If the information set is small, the impact response of per-capita hours is significantly positive when the series enters the SVAR in levels. The opposite holds true when per-capita hours enter in first differences. On the contrary, our results suggest that, if the information set is sufficiently large, the hours response becomes insignificant — irrespective of whether we manipulate the data prior to estimation or not. Thus, we conclude that the (downward) omitted-variable bias and the (upward) low-frequency bias lead to significant distortions only when the information set is insufficiently small.

Several robustness checks confirm our conclusions. In particular, we find that our results are robust to the type of data manipulation (bandpass filter, levels, differences, dummies) prior to estimation. On the other hand, our results are *not* robust to the exclusion of the commodity price index or the consumption share in output. This indicates that the size of the information set is crucial in this context, thus echoing the results of Christiano et al. (2003) and Forni & Gambetti (2011). The exercise also points out that bandpass filtering the data prior to estimation does not remove information necessary to identify the shocks using long-run restrictions (Gospodinov et al. 2009).

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A   Tables

A.1   Sources and Definitions of Data

Series	Definition	Source	Mnemonic
POP	civilian non-institutional population 16+	FRED	CNP16OV
FFR	effective Federal Funds rate	FRED	FEDFUNDS
CPI	consumer price index (all urban consumers)	FRED	CPIAUCSL
PPI	producer price index (all commodities)	FRED	PPIACO
GOV	real government consumption expenditures & gross investment	FRED	GCEC96
EXP	real exports of goods & services	FRED	EXPGSC1
IMP	real imports of goods & services	FRED	IMPGSC1
HOU	hours in the business sector	BLS	PRS84006033
OUT	real output per hour in the business sector	BLS	PRS84006093
EMP	employment in the business sector	BLS	PRS84006013
RPI	quality-adjusted relative price of investment	DiCecio (2009)	p_i
CON	real personal consumption expenditures (nondurables & services)	DiCecio (2009)	cndq + csq
INV	real quality adjusted gross private fixed investment + PCE durables, divided by 100	DiCecio (2009)	r_inv

Table 1: This table displays the definitions of the raw series used. We thank Riccardo DiCecio for kindly sharing his data. The quality adjustment follows Gordon (1990), Cummins & Violante (2002), and Fisher (2006). Consumer durables are included in investment, but the change in inventories is not. We time-aggregate all monthly series to quarterly data.

A.2   Definition of Variables in the SVAR

Variable	Symbol	Definition
growth in labor p'tivity	Δa_t	first difference of log (OUT)
growth in RPI	Δq_t	first difference of log (RPI)
per-capita hours	h_t	log of (HOU/POP)
inflation rate	π_t	first difference of log (CPI)
nominal interest rate	r_t	log of (FFR)
employment rate	n_t	log of (EMP/POP)
commodity price index	p_t	log of (PPI)
consumption share	c_t	log of (CON/(CON+INV+GOV+EXP-IMP))
investment share	i_t	log of (INV/(CON+INV+GOV+EXP-IMP))
export/import ratio	d_t	log of (EXP/IMP)
government spending	g_t	log of (GOV/POP)

Table 2: This table displays the variables that enter the SVAR. The trivariate model (Canova et al. 2010) uses only the first three variables. The last two variables are only used for robustness checks.

A.3 Cross Correlations with Technology Shocks

		0	1	2	3	4	5
c_t	lag	0.090	0.080	0.091	0.082	0.093	0.058
	lead	0.090	0.107	0.107	0.068	0.030	0.033
n_t	lag	-0.092	-0.032	-0.018	-0.019	-0.012	-0.001
	lead	-0.092	-0.104	-0.119	-0.085	-0.064	-0.077
r_t	lag	-0.071	-0.035	0.008	0.036	0.033	0.050
	lead	-0.071	-0.091	-0.135	-0.155^*	-0.148^*	-0.134
π_t	lag	-0.279^{**}	-0.042	-0.048	-0.124	-0.070	-0.010
	lead	-0.279^{**}	-0.168^*	-0.140^*	-0.135	-0.104	-0.116
i_t	lag	0.001	-0.027	-0.013	-0.033	-0.045	-0.033
	lead	0.001	0.011	0.037	0.075	0.100	0.094
p_t	lag	-0.100	-0.032	-0.027	-0.028	-0.013	0.004
	lead	-0.100	-0.118	-0.152^*	-0.177^*	-0.169^*	-0.170^*

(a) neutral technology

		0	1	2	3	4	5
c_t	lag	-0.037	-0.142^*	-0.117	-0.148^*	-0.082	-0.099
	lead	-0.037	-0.015	0.018	0.032	0.044	0.065
n_t	lag	-0.019	0.011	0.022	0.007	0.004	0.003
	lead	-0.019	-0.037	-0.082	-0.112	-0.116	-0.092
r_t	lag	-0.009	0.005	-0.007	-0.067	-0.069	-0.079
	lead	-0.009	-0.023	-0.029	-0.027	-0.029	-0.046
π_t	lag	-0.088	0.190^{**}	0.171^*	0.018	0.158^*	0.121
	lead	-0.088	-0.017	-0.019	-0.136	-0.097	0.010
i_t	lag	-0.081	0.024	0.031	0.028	-0.001	0.016
	lead	-0.081	-0.103	-0.171^*	-0.177^*	-0.133	-0.103
p_t	lag	0.041	0.065	0.039	0.012	0.001	-0.011
	lead	0.041	0.039	0.024	0.001	-0.006	0.012

(b) investment-specific technology

Table 3: The table displays cross correlation coefficients with the two identified technology shocks at leads and lags ($\pm$ 5 quarters). Stars ($*$, $**$) indicate significance at the 5% and 1% level, respectively.

A.4 Granger Causality Tests

	c_t	n_t	r_t	π_t	i_t	p_t
q_t	0.03	0.73	0.41	0.00	0.62	0.45
a_t	0.79	0.86	0.12	0.06	0.70	0.54
h_t	0.80	0.30	0.00	0.10	0.00	0.04

Table 4: The table displays the Granger Causality/Block Exogeneity Wald Tests statistics. We obtain the p-values from bivariate VARs where the residuals of the trivariate model (in rows) are tested against potentially omitted variables (in columns). Numbers are rounded down to the nearest second decimal place.

A.5 Variance Decomposition at Business Cycle Frequencies

	investment specific	neutral tech	monetary policy	commodity prices	all four shocks
y_t	25 (13)	11 (7)	9 (6)	13 (8)	58 (12)
y_t/h_t	16 (11)	17 (10)	9 (6)	8 (6)	50 (13)
q_t	32 (15)	11 (8)	4 (4)	7 (5)	53 (14)
h_t	30 (15)	7 (6)	7 (6)	12 (8)	56 (13)
n_t	29 (16)	7 (6)	8 (6)	12 (8)	56 (14)
h_t/n_t	27 (13)	10 (7)	6 (5)	11 (7)	55 (12)
π_t	18 (12)	11 (8)	7 (6)	23 (9)	59 (12)
r_t	26 (14)	7 (6)	13 (7)	9 (6)	56 (13)
i_t	24 (13)	10 (7)	9 (6)	14 (8)	57 (12)
c_t	23 (12)	13 (8)	9 (6)	14 (8)	59 (12)
p_t	16 (11)	7 (7)	9 (6)	39 (13)	71 (11)

(a) Benchmark Specification

	investment specific	neutral tech	monetary policy	commodity prices	all four shocks
y_t	23 (14)	12 (8)	7 (5)	10 (6)	52 (14)
y_t/h_t	19 (14)	18 (13)	5 (4)	6 (5)	49 (16)
q_t	22 (18)	12 (9)	3 (2)	7 (5)	44 (18)
h_t	26 (16)	9 (8)	6 (5)	8 (5)	48 (17)
n_t	27 (17)	9 (9)	6 (5)	7 (5)	49 (17)
h_t/n_t	21 (14)	11 (9)	4 (3)	8 (5)	44 (15)
π_t	19 (14)	8 (7)	4 (4)	19 (8)	51 (15)
r_t	25 (16)	9 (8)	10 (5)	7 (5)	51 (15)
i_t	25 (13)	10 (8)	7 (5)	9 (6)	52 (14)
c_t	22 (13)	12 (8)	7 (5)	11 (6)	52 (14)
p_t	15 (13)	7 (7)	5 (4)	34 (12)	62 (14)

(b) Level Specification

Table 5: The table displays the decomposition of variance at business cycle frequencies based on estimated spectral densities (following Altig et al. 2011). Numbers are means of point estimates across bootstrap simulations, numbers in parentheses are the corresponding standard deviations.

A.6 Robustness

	investment specific	neutral tech		monetary policy	commodity prices		all four shocks
				Benchmark Specification			
y_t	25 (13)	11	(7)	9 (6)	13	(8)	58 (12)
h_t	30 (15)	7	(6)	7 (6)	12	(8)	56 (13)
π_t	18 (12)	11	(8)	7 (6)	23	(9)	59 (12)
				Level Specification			
y_t	23 (14)	12	(8)	7 (5)	10	(6)	52 (14)
h_t	26 (16)	9	(8)	6 (5)	8	(5)	48 (17)
π_t	19 (14)	8	(7)	4 (4)	19	(8)	51 (15)
				Difference Specification			
y_t	17 (11)	10	(7)	8 (5)	12	(6)	48 (12)
h_t	19 (13)	7	(6)	7 (5)	11	(6)	44 (14)
π_t	14 (11)	7	(6)	6 (4)	22	(8)	49 (12)
				Dummy Specification			
y_t	22 (12)	9	(6)	10 (7)	7	(5)	48 (12)
h_t	24 (13)	8	(6)	7 (6)	7	(5)	45 (13)
π_t	19 (10)	10	(7)	8 (6)	19	(8)	56 (11)
				Level Specification, but r_t is not logged prior to estimation			
y_t	18 (11)	13	(9)	8 (4)	12	(7)	51 (12)
h_t	21 (13)	9	(8)	6 (4)	11	(7)	47 (13)
π_t	19 (12)	6	(5)	4 (3)	24	(9)	54 (12)
				Benchmark Specification with 4 Lags			
y_t	18 (11)	10	(6)	8 (5)	12	(7)	47 (12)
h_t	21 (12)	6	(5)	7 (5)	10	(7)	44 (12)
π_t	8	(7)	9 (7)	8 (5)	26	(10)	52 (11)
				Early Sub-Sample (1955Q3-1979Q2)			
y_t	10	(8)	9 (7)	10 (6)	18	(12)	48 (14)
h_t	10	(7)	7 (5)	9 (6)	19	(12)	45 (14)
π_t	10	(8)	6 (6)	8 (6)	27	(14)	51 (14)
				Late Sub-Sample (1979Q3-2007Q4)			
y_t	14 (11)	17	(12)	4 (3)	16	(10)	51 (14)
h_t	19 (15)	12	(11)	5 (4)	12	(9)	48 (15)
π_t	12	(9)	9 (7)	5 (4)	31	(13)	56 (14)
				External Demand Shock			
y_t	25 (14)	11	(7)	9 (7)	10	(6)	61† (12)
h_t	31 (15)	8	(7)	8 (6)	9	(6)	62† (13)
π_t	21 (13)	10	(8)	7 (6)	16	(7)	60† (12)
				Government Spending Shock			
y_t	26 (14)	12	(8)	9 (7)	*	(*)	50 (16)
h_t	33 (16)	8	(6)	8 (6)	*	(*)	52 (16)
π_t	24 (14)	11	(8)	6 (5)	*	(*)	45 (15)

Table 6: The table displays the decomposition of variance at business cycle frequencies based on estimated spectral densities (following Altig et al. 2011). Numbers are means of point estimates across bootstrap simulations, numbers in parentheses are the corresponding standard deviations. The "external demand shock" specification includes five shocks in total (denoted by a dag symbol †). The "government spending shock" specification does not include the commodity price shock (denoted by an asterisk *).

B Figures

B.1 Coherence Analysis

(a) all series are filtered

(b) only per-capita hours are filtered
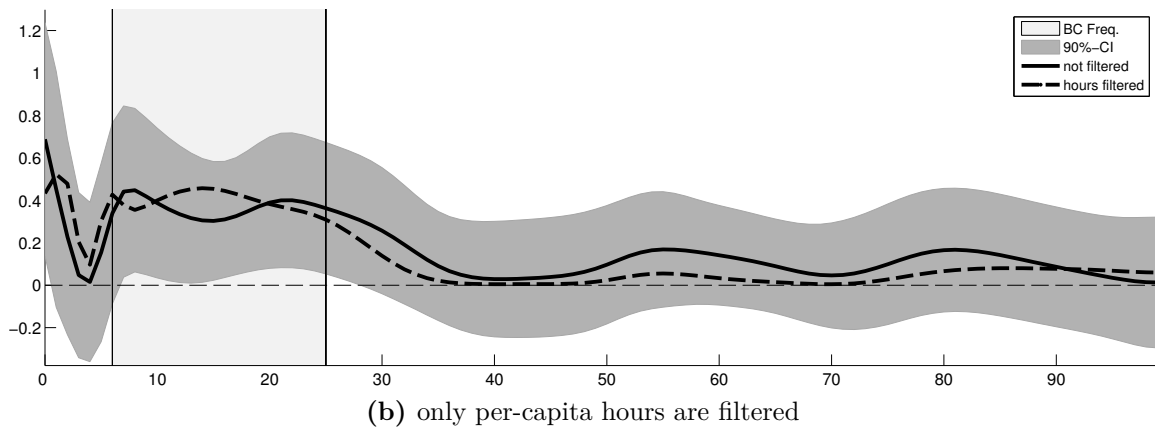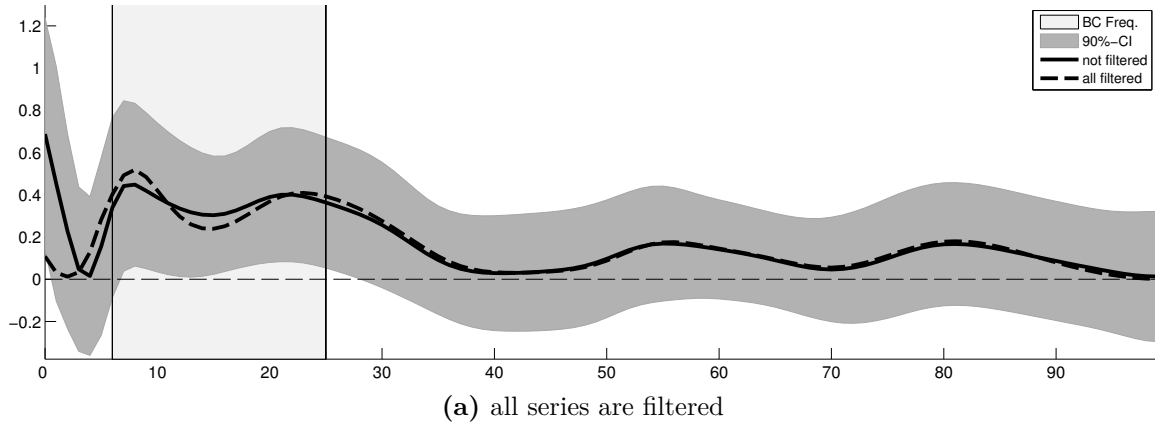
Figure 1: The figure illustrates the coherence between labor productivity growth and per-capita hours, estimated with five lags.

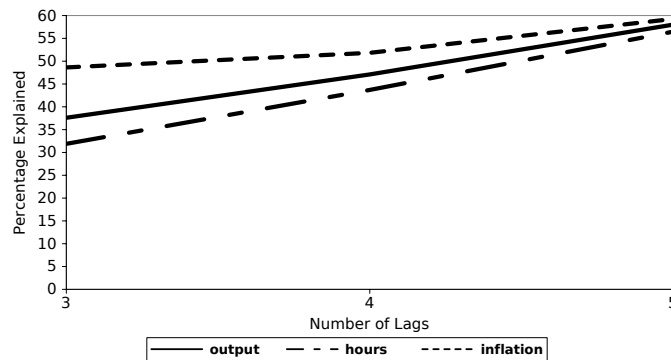## B.2 Lag Length and Business Cycle Variance Decomposition

Figure 2: The figure illustrates the share of business cycle variance explained by the four structural shocks when the lag length increases from three to five.
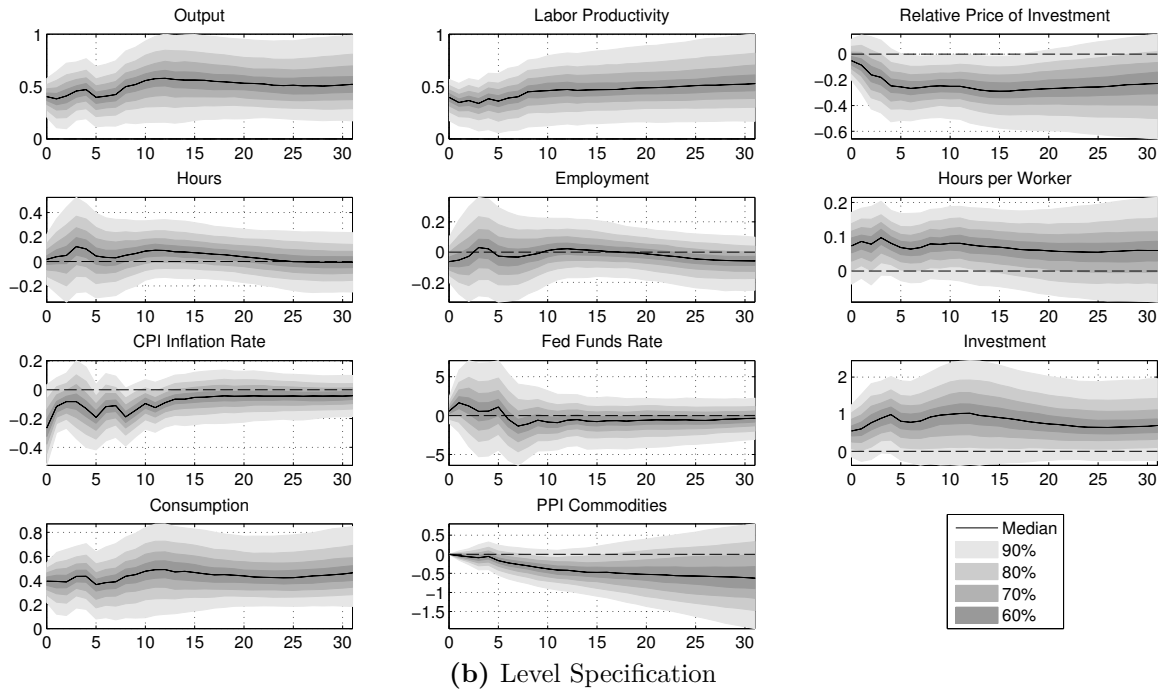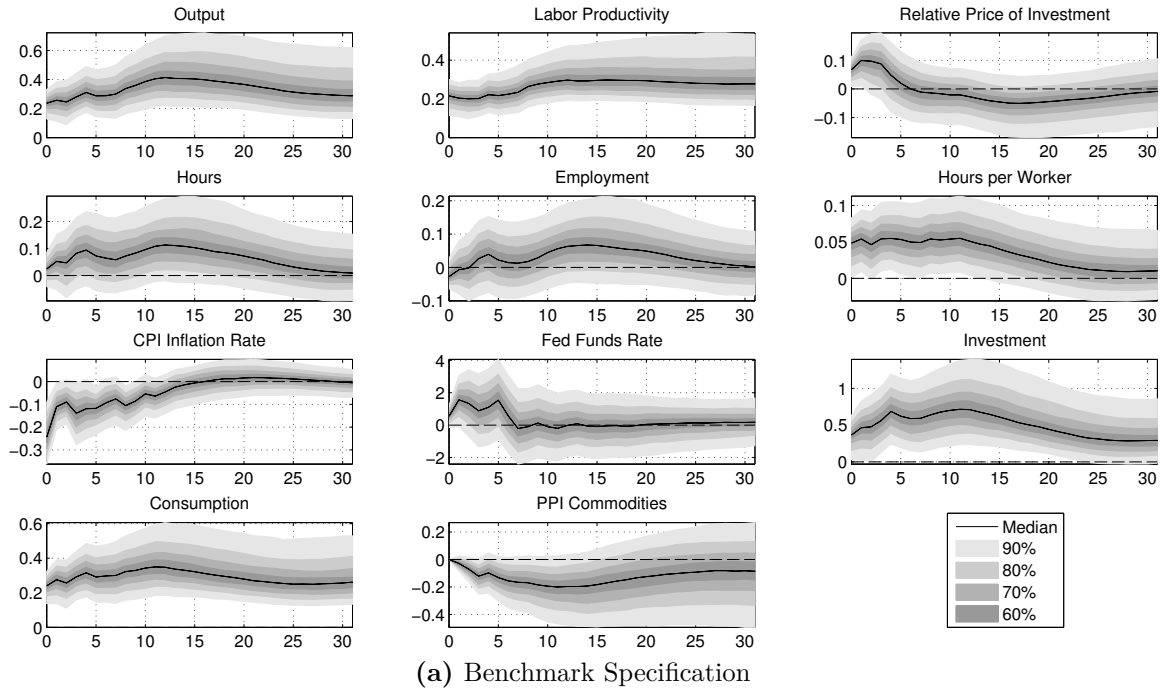
B.3   Impulse Response Functions

(a) Benchmark Specification

(b) Level Specification

Figure 3: The figure illustrates the impulse responses to a neutral technology shock.
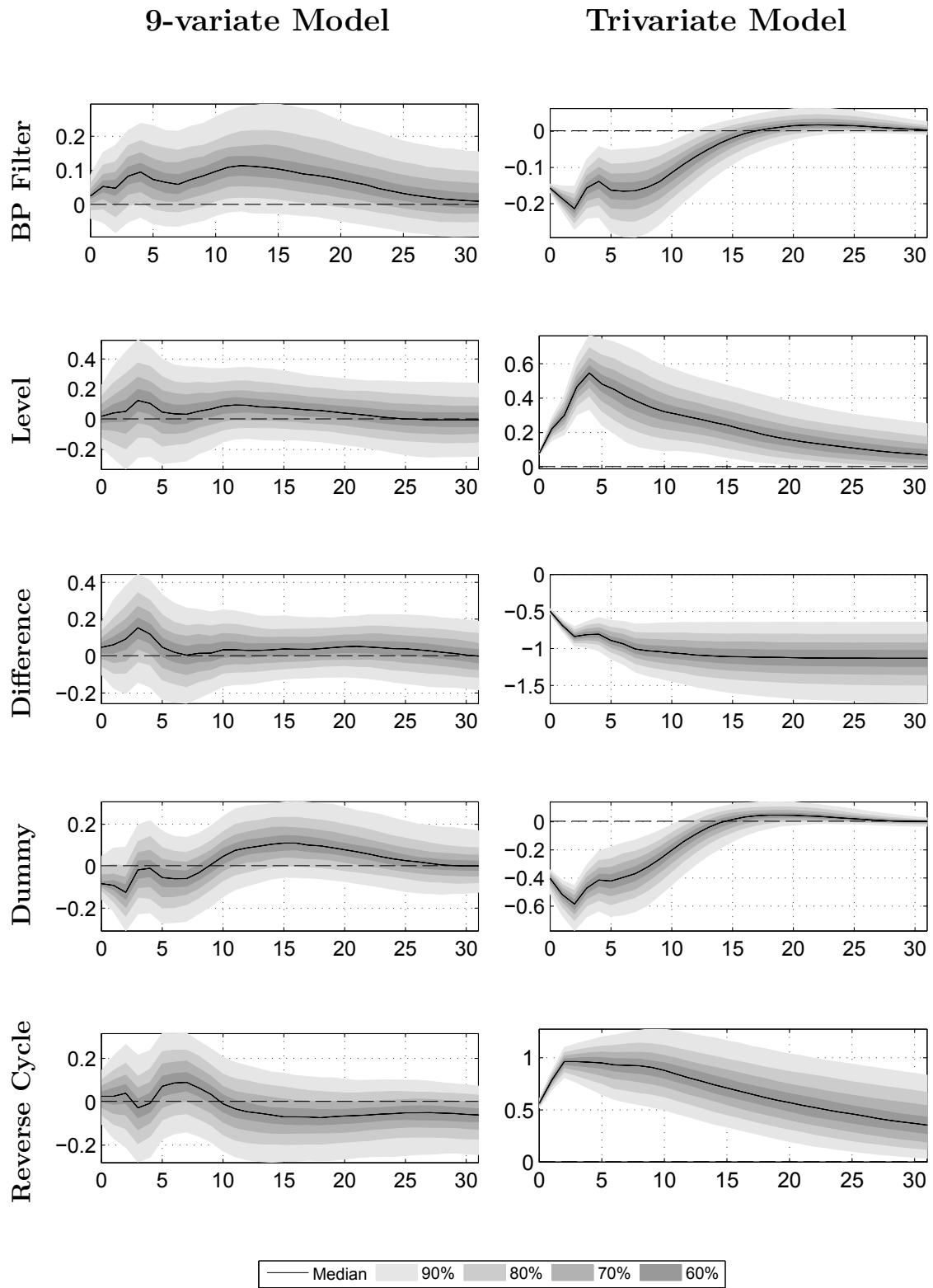
Figure 4: The figure illustrates the low-frequency bias by the means of the per-capita hours response to a neutral technology shock.
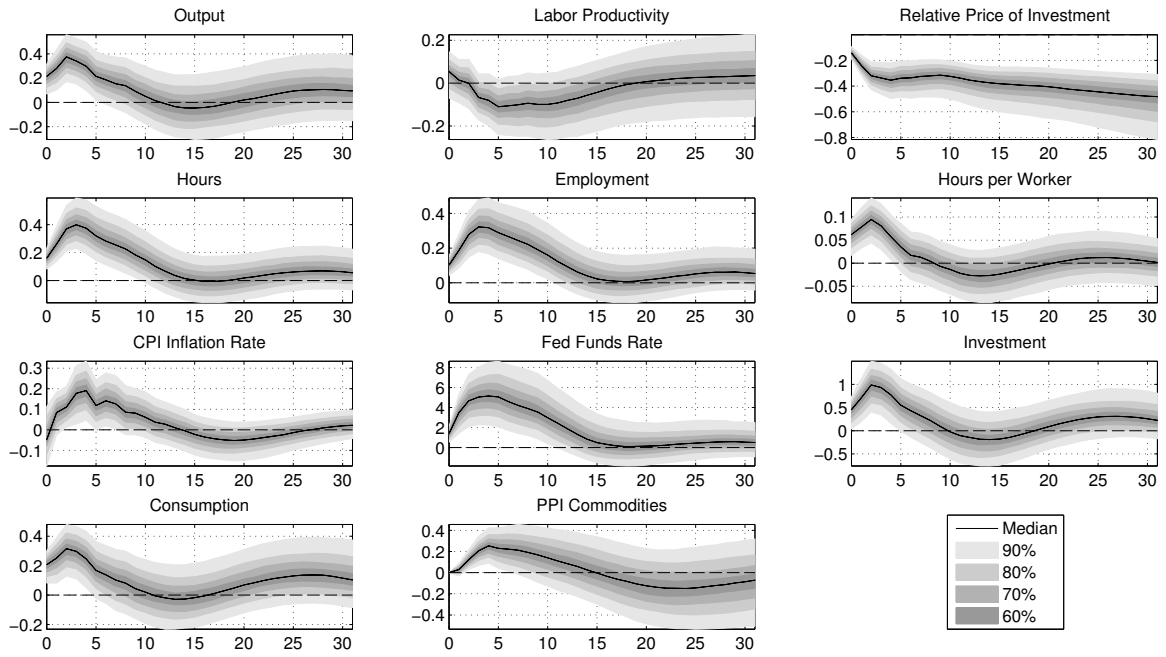
(a) Benchmark Specification
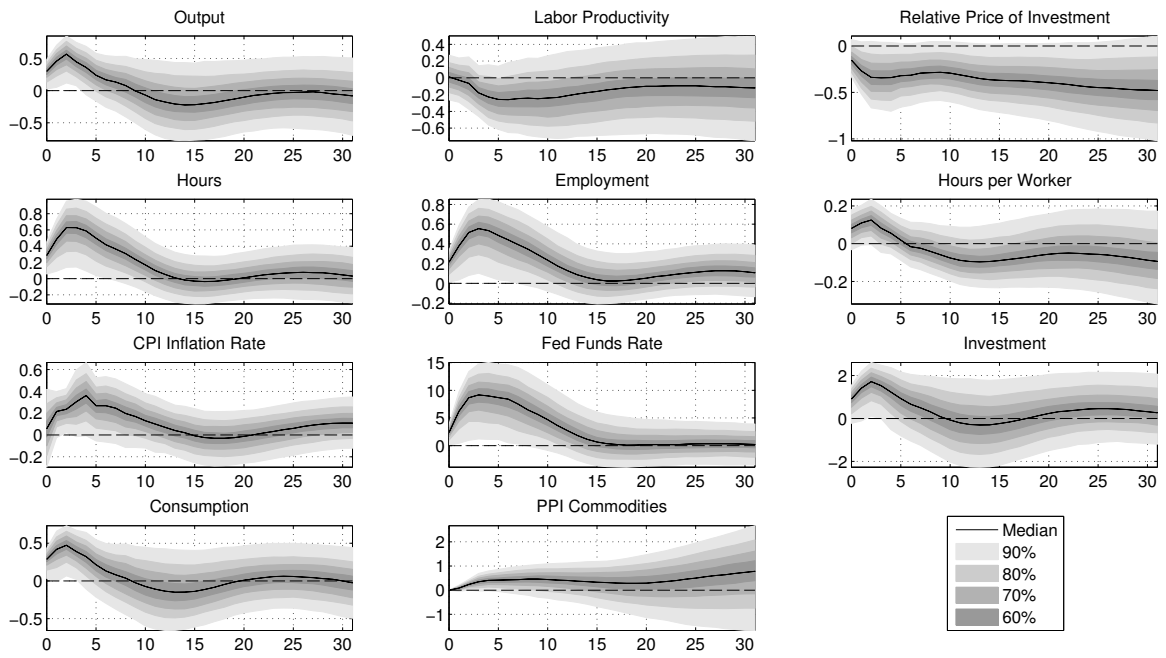
(b) Level Specification

Figure 5: The figure illustrates the impulse responses to an investment-specific technology shock.
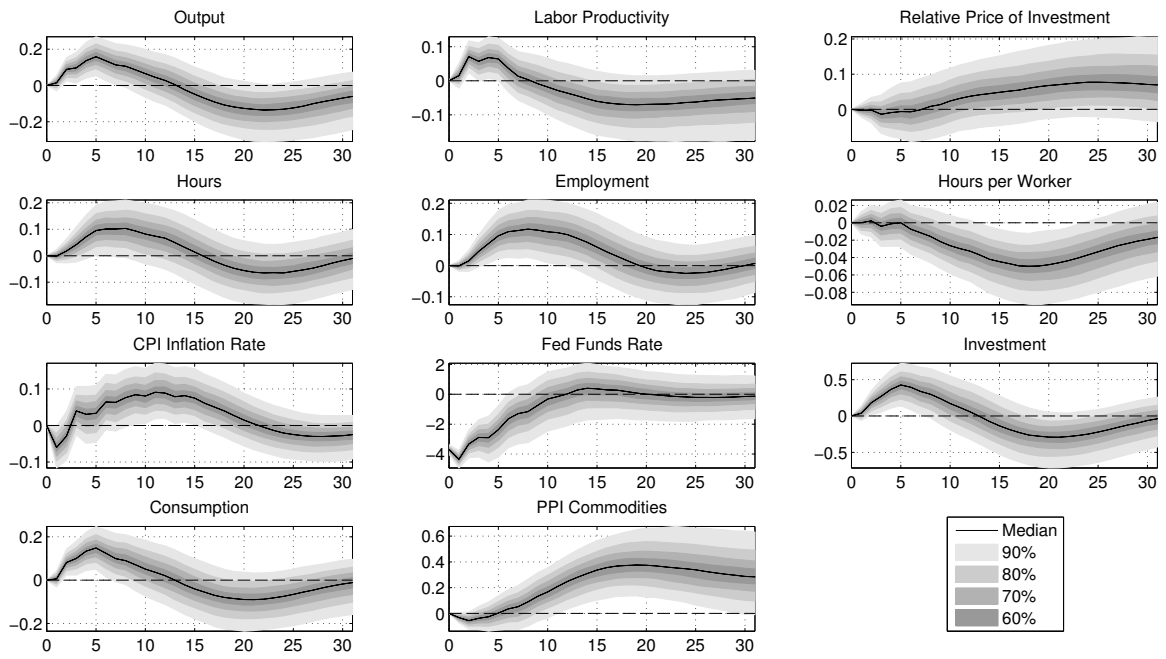
(a) Benchmark Specification
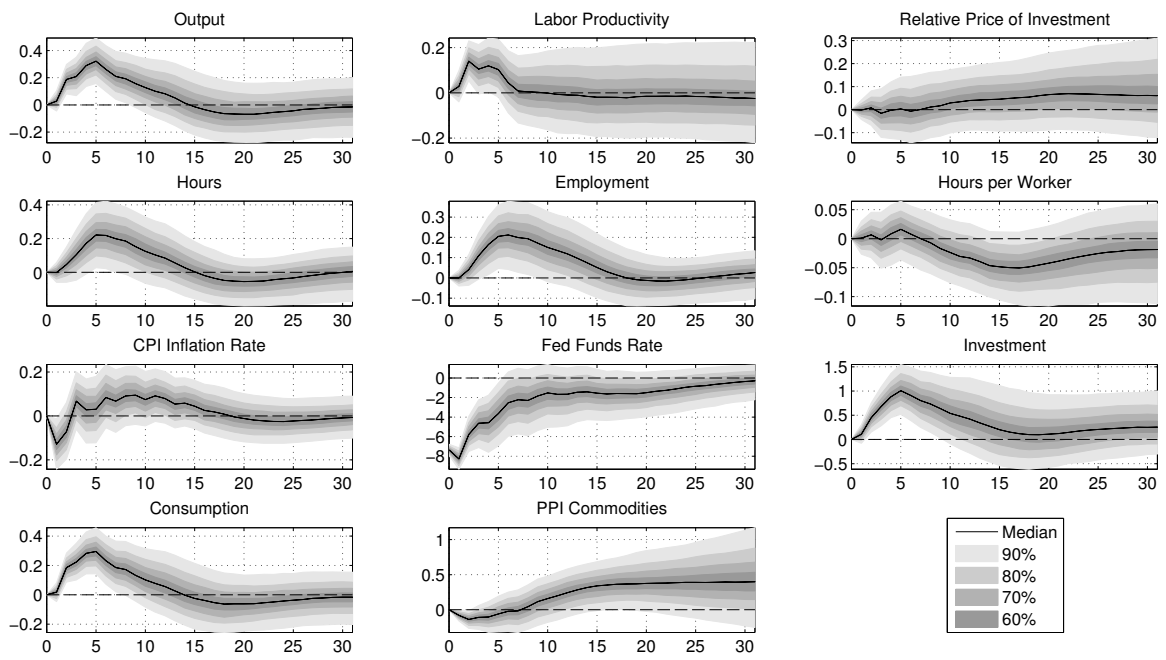
(b) Level Specification

Figure 6: The figure illustrates the impulse responses to a monetary policy shock.

35
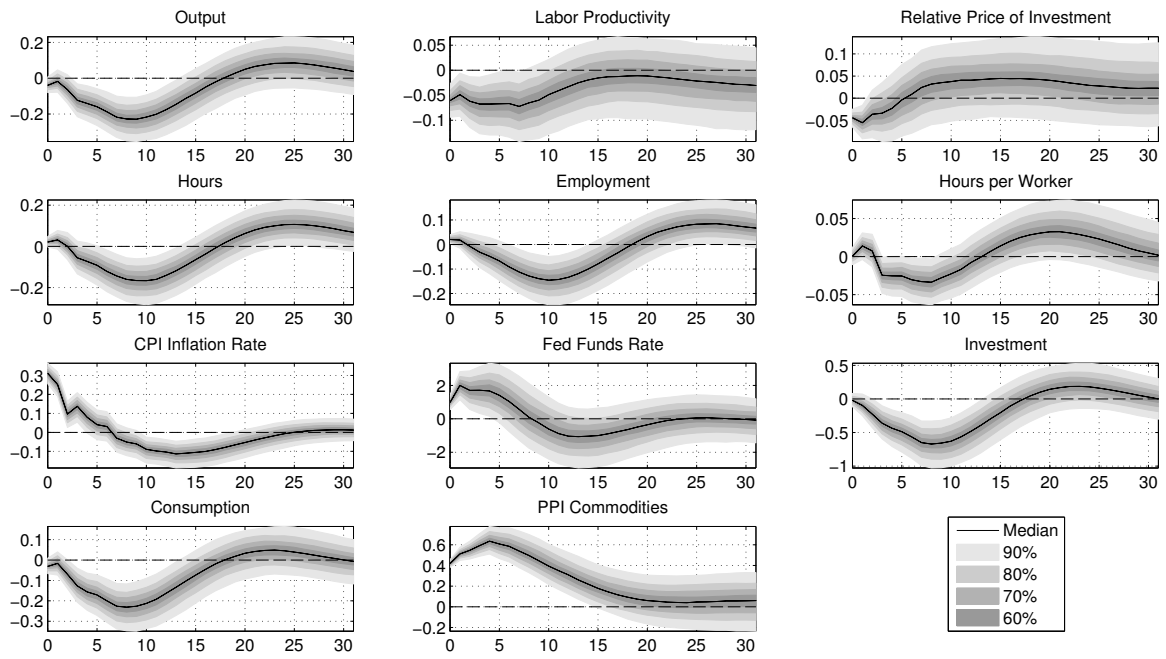
(a) Benchmark Specification
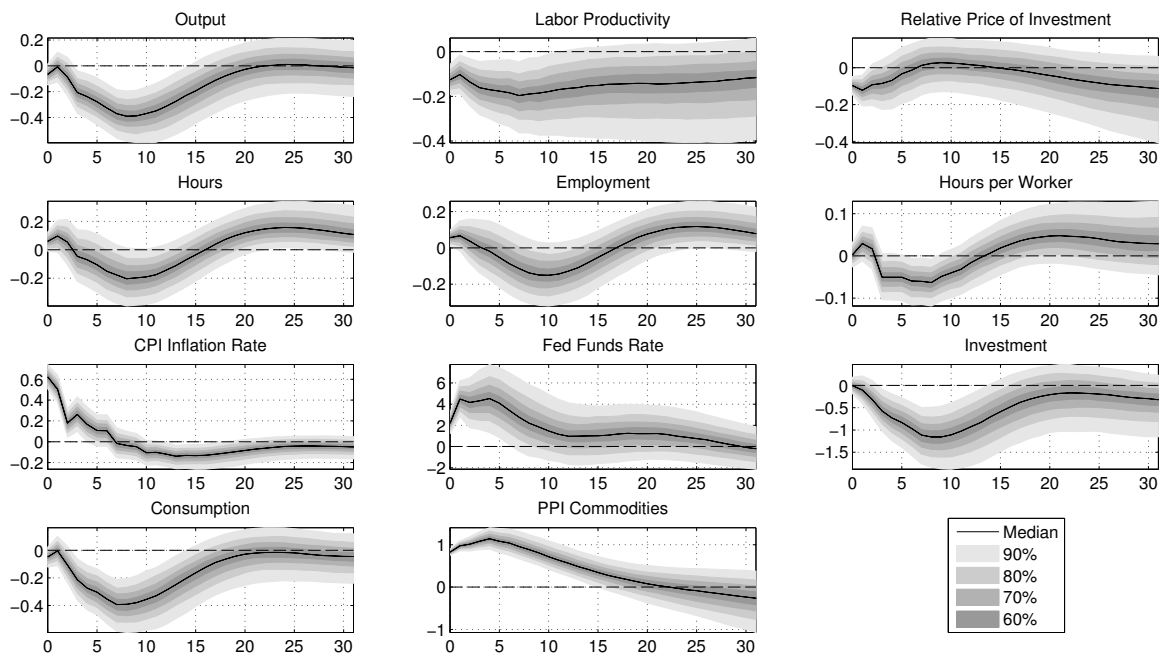
(b) Level Specification

Figure 7: The figure illustrates the impulse responses to a commodity price shock.

B.4 Counterfactual Exercise
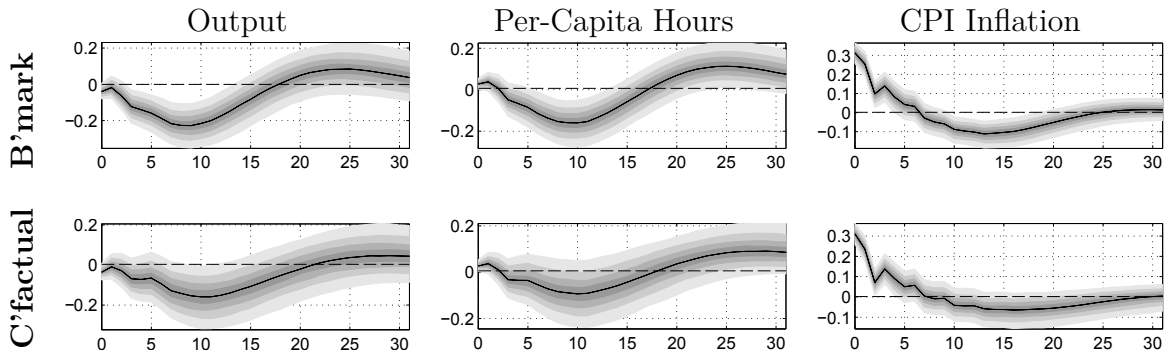
Figure 8: The top panel illustrates the responses of output, per-capita hours, and inflation to the estimated commodity price shock. The bottom panel illustrates the same responses when the Federal Funds rate — counterfactually — is assumed to be constant.

B.5 The Response of the Core Inflation Rate
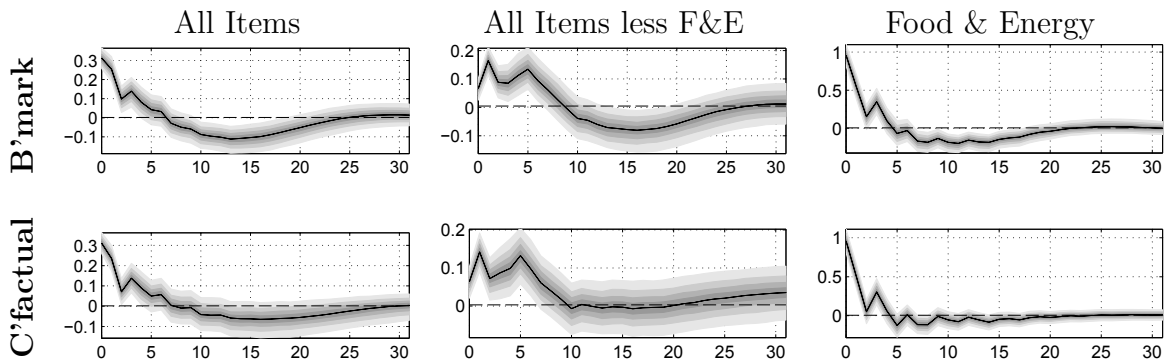
Figure 9: The figure illustrates the impulse responses of three CPI inflation measures to the identified commodity price shock; i.e., the "headline" inflation rate (all items), the "core" inflation rate (all items less food and energy), and the "food and energy" inflation rate. Due to limited data availability, the latter two responses are estimated using a slightly reduced sample period (1958Q2-2007Q4). The CPI "food and energy" is a weighted average of its components, using time varying weights (based on own calculations). All data are taken from FRED.

B.6 Historical Decomposition of Shocks
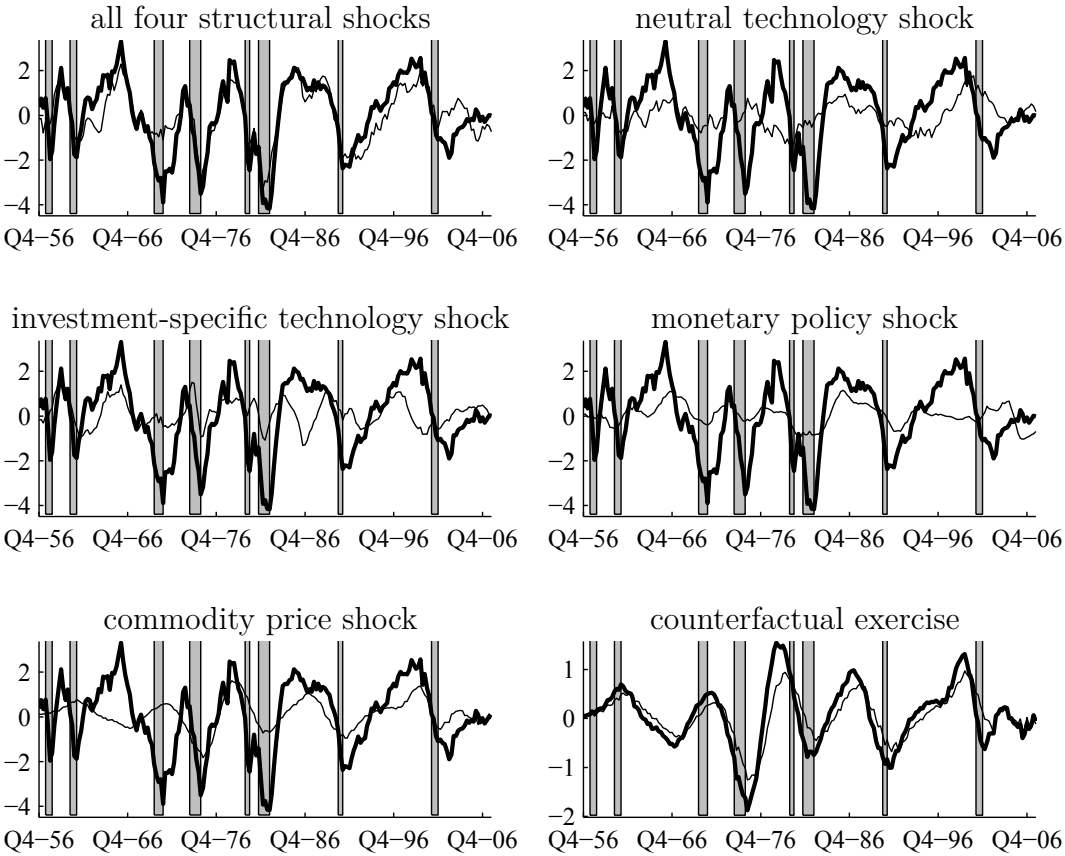
Figure 10: The figure illustrates the historical decomposition of the four structural shocks for output. The bold line represents the bandpass filtered data, the thin line represents the time series predicted by the respective shock(s). In addition, the counterfactual exercise contrast the output series predicted by the commodity price shock (bold line) with the output series predicted by the commodity price shock in the absence of the monetary policy feedback rule (thin line).

B.7 Forecast Error Variance Decomposition
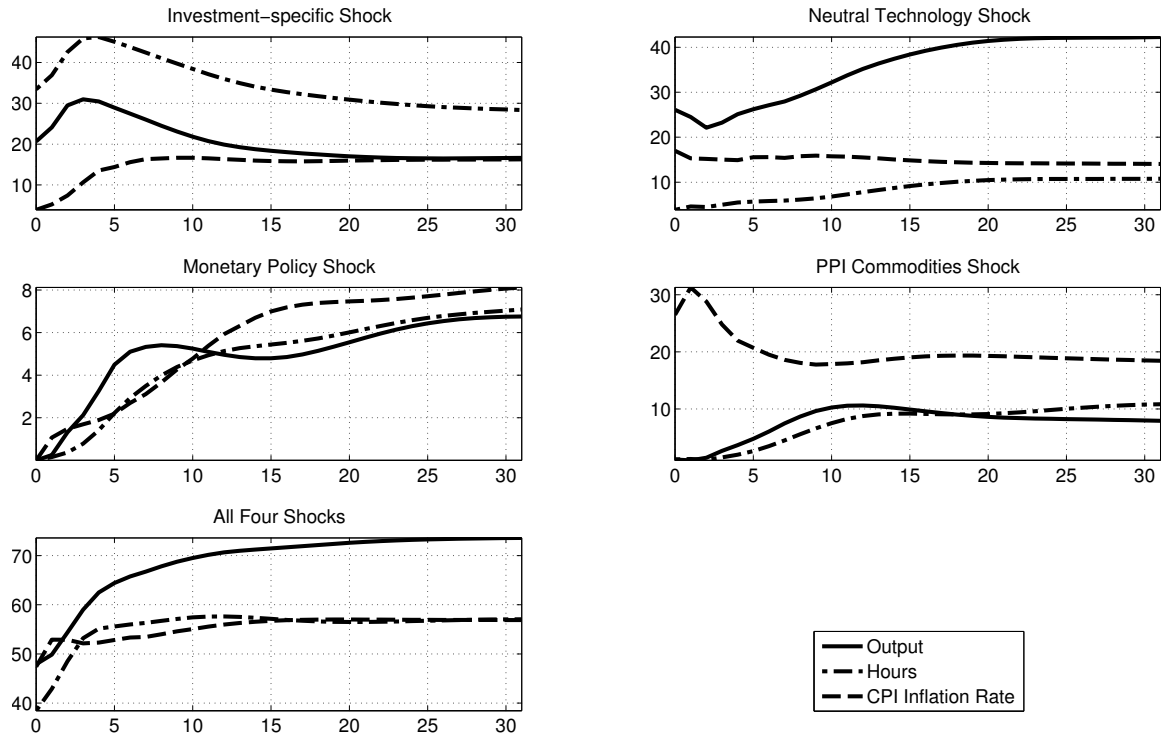
Figure 11: The figure illustrates the forecast error variance decomposition in our benchmark specification.

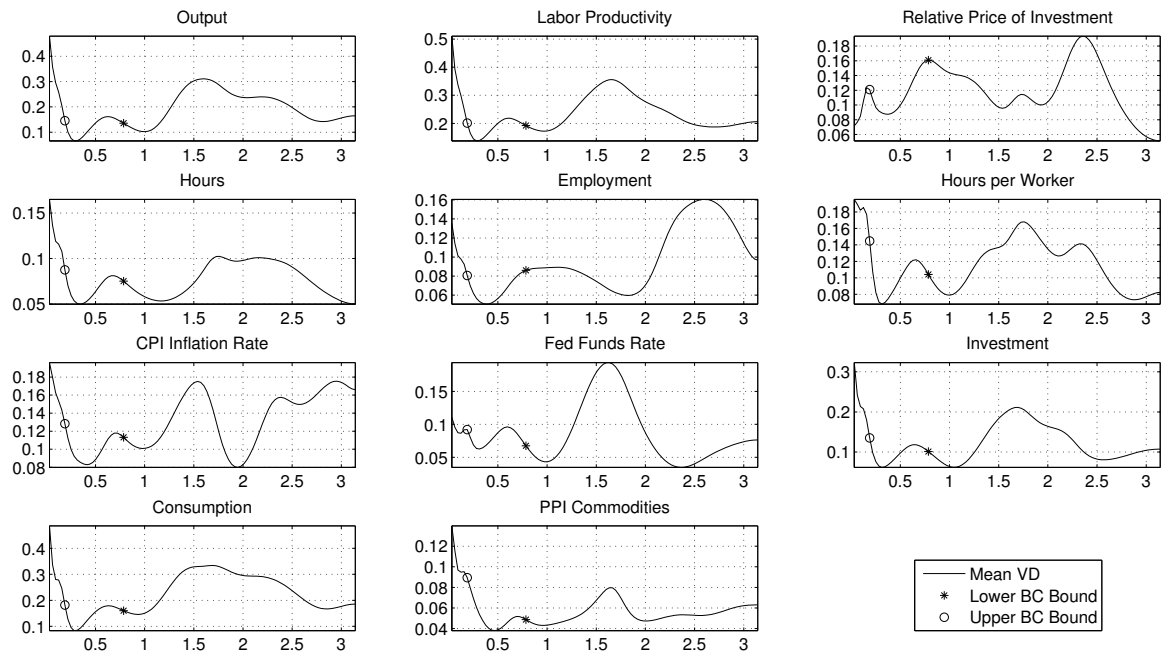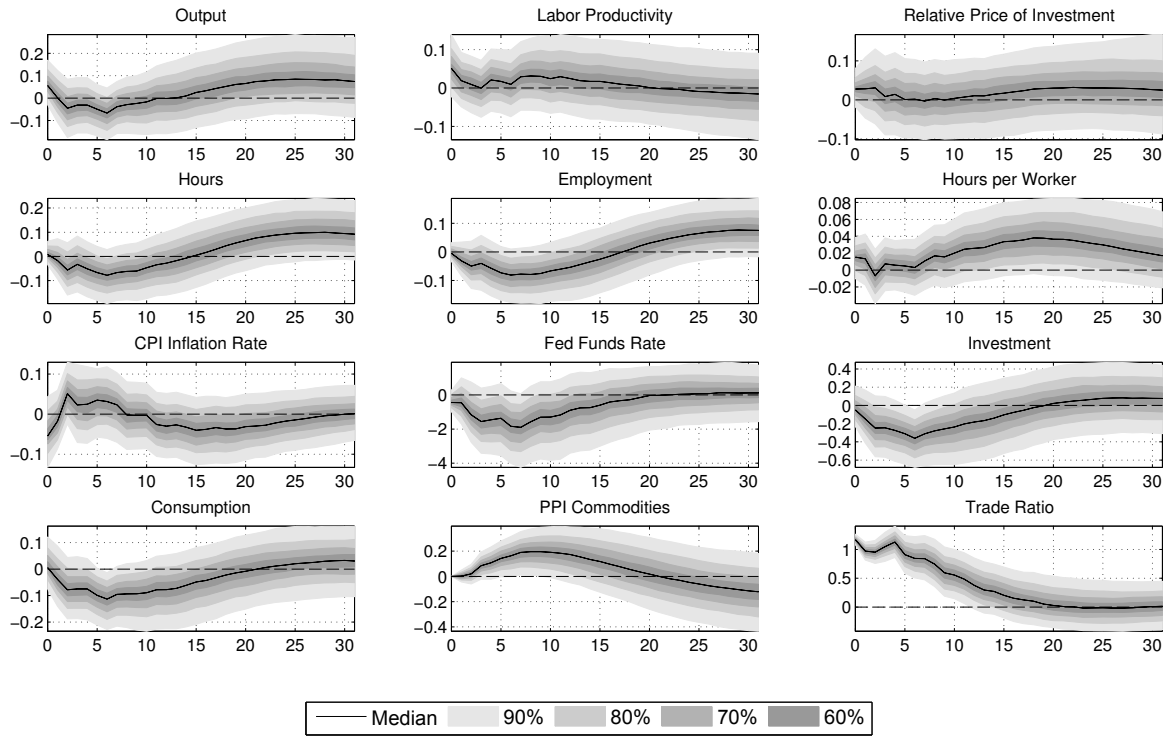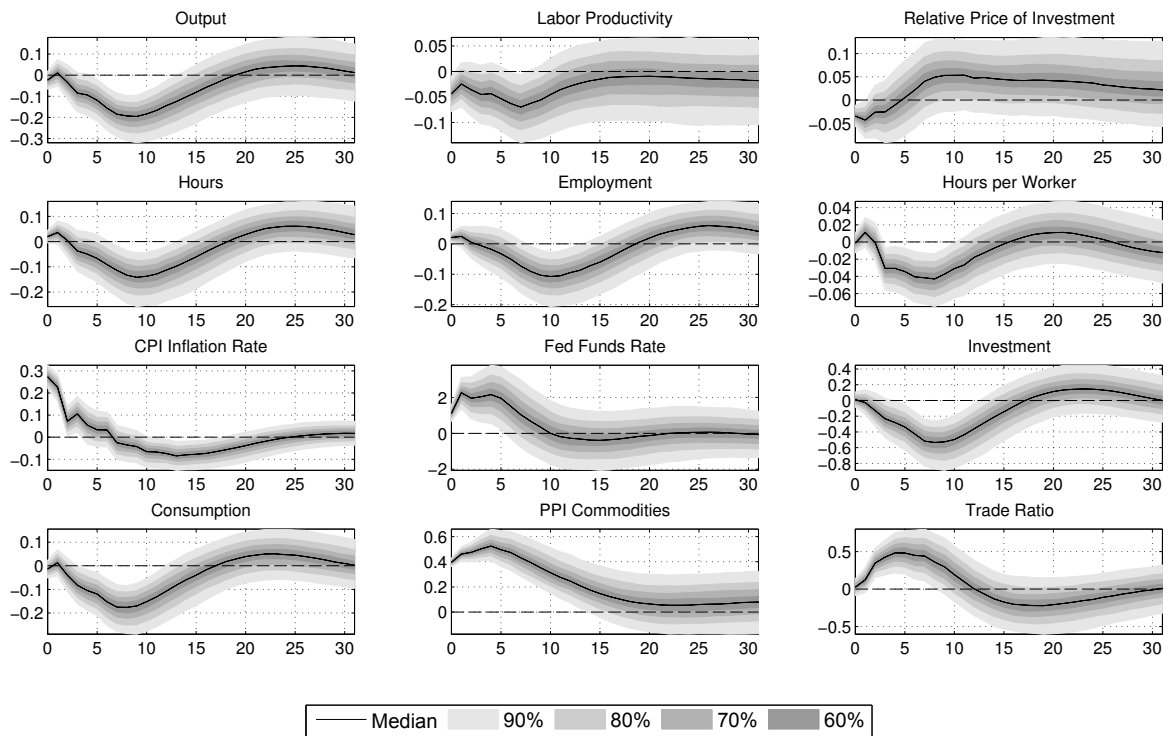## B.8 Variance Decomposition at the Frequency Domain

Figure 12: The figure illustrates the explanatory power of neutral technology shocks across the whole spectrum in our benchmark specification.

B.9 External Demand

(a) External Demand Shock

(b) Commodity Price Shock

Figure 13: The figure illustrates the impulse responses to an external demand shock.
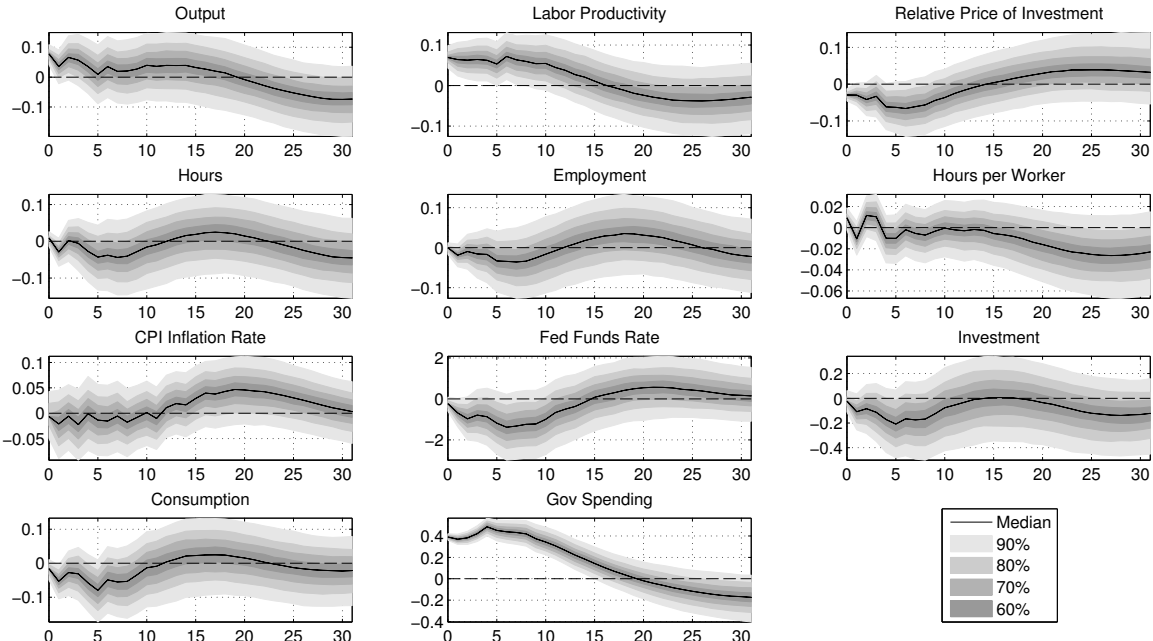
B.10   Government Spending

Figure 14: The figure illustrates the impulse responses to an expansionary government spending shock.