News Shocks and Business Cycles*

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Abstract

We propose and implement a novel approach for the identification of “news shocks” about changes in future technology. In a VAR featuring a measure of observed aggregate technology, forward-looking variables, and macroeconomic aggregates, we identify the news shock as the shock orthogonal to observed technology innovations that best explains variation in future observed technology. We find that news shocks account for the bulk of low frequency variation in technology; in contrast surprise technology shocks appear largely transitory. A favorable news shock is associated with an increase in aggregate consumption and decreases in output, hours, and investment on impact. After the impact effects, aggregate variables largely track predicted movements in observed technology. These are roughly the predictions of a simple neoclassical model augmented with news shocks. In addition, favorable news shocks lead to increases in stock prices and consumer confidence and decreases in inflation. While an important source of output fluctuations at medium frequencies, an historical decomposition reveals that news shocks fail to account for output declines in four out of six of the most recent US recessions.

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1 Introduction

Most modern theories assume that economic fluctuations are driven by changes in current fundamentals, such as aggregate productivity. The last several years have witnessed a resuscitation of a much older theory in which business cycles can arise without any change in fundamentals at all. The expectations driven business cycle hypothesis – originally advanced by Pigou (1927) and reincarnated in its modern form chiefly in Beaudry and Portier (2004) – posits that business cycles might arise on the basis of expectations of future fundamentals.¹ Often referred to as the news driven business cycle, theories of this sort are appealing for a number of reasons.² If favorable news about future productivity can set off a boom today, then a realization of productivity which is worse than expected can induce a recession without any actual reduction in productivity itself ever occurring. As such, this theory of business cycles immediately addresses several of the concerns with conventional theories of the cycle – booms and busts can happen absent large changes in fundamentals and no technological regress is required to generate recessions.

It has, however, proven challenging to make news shocks about future fundamentals work in the context of relatively standard business cycle models, a point first recognized by Barro and King (1984) and later emphasized in Cochrane (1994). In a standard neoclassical setting, the wealth effect of good news about future productivity causes households to desire more consumption of both goods and leisure. With no change in labor demand, the inward shift in labor supply leads to a reduction in equilibrium employment and output. Falling output and rising consumption necessitate a fall in investment. Not only does good news about the future tend to cause a recession today, the implied negative comovement among macroeconomic aggregates is difficult to reconcile with the strong positive unconditional comovement of these series in the data.

In sharp contrast to the predictions of standard neoclassical models, recent empirical evidence suggests that news shocks about future productivity do induce positive comovement among the major macroeconomic aggregates. In particular, Beaudry and Portier (2006), Beaudry, Dupaigne, and Portier (2008), and Beaudry and Lucke (2009) propose two alternative VAR-based schemes for identifying news shocks. In one, these authors associate stock price innovations orthogonalized with respect to total factor productivity (TFP) with the

¹This theory of business cycles is not to be confused with “sunspot” theories (e.g. Farmer (1998)) in which non-fundamental shocks can induce fluctuations. Expectations driven business cycle models generally presume rational expectations and a unique equilibrium in which agents receive stochastic signals of future fundamentals which are, in expectation, correct.

²This terminology differs from the literature on the effect on macroeconomic news on economic aggregates (Anderson, Bollerslev, Diebold, and Vega (2003)). We will follow the terminology introduced by Beaudry and Portier in referring to signals about changes in future productivity as news shocks.
news shock. In the other, they combine short and long run restrictions, identifying the news shock as the structural shock orthogonal to TFP innovations which has a long run effect on TFP. Under either orthogonalization scheme, their identified shocks are associated with a large, broad-based economic expansion occurring in anticipation of future TFP improvement.

In this paper we reassess the empirical evidence in favor of the news driven business cycle. In particular, we propose and implement a novel approach for the identification of news shocks about future technology. In a VAR featuring a cyclically-adjusted measure of aggregate TFP and several forward-looking variables, we identify a conventional surprise technology shock as the reduced form innovation in TFP.\(^3\) We then identify the news shock as the shock orthogonal to the TFP innovation that best explains future variation in measured TFP. This identification strategy is an application of principal components. It identifies the news shock as the linear combination of reduced form innovations orthogonal to the TFP innovation which maximizes the sum of contributions to TFP’s forecast error variance over a finite horizon.

Our empirical approach is highly flexible and has a number of potential advantages over alternative methodologies. Relative to the estimation and specification of a fully-developed DSGE model, our approach imposes a minimum of theoretical restrictions and allows the data to speak for itself. We nevertheless provide simulation evidence from a popular DSGE model that our empirical methodology is likely to perform well in practice. Our key identifying assumption is that a limited number of structural shocks account for movements in observed TFP. This is a ubiquitous feature of all papers in this literature of which we are aware. We do not impose that news shocks (nor surprise technology shocks) necessarily have permanent effects on observed TFP and other macroeconomic variables. Nor do we have to make explicit assumptions about common trends – since our identification is not based on the zero frequency, it can be conducted on VAR systems estimated in levels or as stationary vector error correction models (VECMs). Because it is a partial identification strategy, our approach can be conducted on relatively large systems without having to impose additional (and potentially invalid) assumptions on other shocks.

We apply our approach to post-war US data in Section 3 of the paper. A key result is that a favorable news shock (i.e. one which portends future increases in observed TFP) is associated with an impact increase in consumption and modest declines in output, investment, and hours of work. After the impact effects, these aggregate variables largely track, rather than anticipate, movements in TFP. In addition, we show that positive news shocks are associated with disinflation and with increases in stock prices, consumer confidence, real

\(^3\)In particular, we use a quarterly version of the Basu, Fernald, and Kimball (2006) utilization-adjusted measure. See Section 3.1 for details.
wages, and real interest rates. We find that news shocks appear to capture much of the low frequency movements in TFP and other aggregate variables. In contrast, the surprise technology shock leads to largely transitory impulse responses of TFP, output, consumption, investment, and hours. While important at medium to low frequencies, an historical decomposition reveals that news shocks alone fail to account for output declines in four out of six US recessions between 1961 and 2007.\(^4\)

In Section 3.4 we discuss the differences between our results and those in the existing literature. While we do find that stock prices rise in anticipation of good news, there appear to be important movements in stock prices unrelated to technology shocks altogether. This finding is incompatible with the pure recursive identification of news shocks in Beaudry and Portier (2006) and Beaudry, Dupaigne, and Portier (2008). As noted above, we find that the reduced form innovation in TFP appears to have largely transitory effects,\(^5\) which is at odds with the assumptions made in Beaudry and Portier (2006) and Beaudry and Lucke (2009) that both news and surprise technology shocks permanently impact the level of TFP. We also document an important practical difference between our results and theirs. Whereas our two identified technology shocks explain upwards of 90 percent of the forecast error variance of measured TFP at business cycle frequencies, theirs leave as much as 35 percent of the variance of measured TFP unexplained. Concretely, this means that an unnamed shock orthogonal to TFP’s innovation accounts for about as much variation in TFP over business cycle frequencies as does the shock they interpret as being news. We find this problematic.

In Section 4 we place our results in the broader literature and point out some implications for macroeconomic modeling. While a large literature has developed seeking to generate models capable of generating positive impact comovement in response to news, our estimated impulse responses are consistent with the predictions of a wide class of existing DSGE models, including the most basic neoclassical ones. To make the point stark, we take an off-the-shelf real business cycle model and show that it is capable of generating conditional responses of aggregate variables to a news shock that align closely with our empirical impulse responses. We show that the model driven only by news shocks does a poor job of matching the unconditional moments of the data, but that the inclusion of news shocks into the model along with conventional surprise technology helps to improve the fit along some dimensions.\(^6\) To be clear, we do not take this as evidence that a simple neoclassical model

\(^4\)We currently do not have access to TFP data which would allow us to extend the sample to include the most recent recession.

\(^5\)Note that, in a univariate context, our preferred measure of TFP (indeed virtually any measure of TFP) is well-characterized as following a random walk. Only in a multivariate context does the transitory nature of TFP’s own innovation manifest itself.

\(^6\)See also Kurmann and Otrok (2010) and Mertens (2010) for additional channels through which news
is an adequate structural description of the economy. Rather, we use it to make the point that the conditional responses of aggregate variables to a news shock do not reveal a fatal flaw in conventional DSGE models which trace their ancestry to a stochastic neoclassical growth model.

The remainder of the paper is organized as follows. Section 2 lays out our empirical strategy. Section 3 presents the main empirical results. Section 4 provides a detailed discussion of these results and points out some avenues for future research. The final section concludes.

2 Empirical Strategy

We assume that aggregate technology is well-characterized as following a stochastic process driven by two shocks. The first is the traditional surprise technology shock of the real business cycle literature, which impacts the level of technology in the same period in which agents see it. The second is the news shock, which is differentiated from the first in that agents observe the news shock in advance.

Letting $A_t$ denote technology, this identifying assumption can be expressed in terms of the univariate moving average representation:

$$\ln A_t = \left[ B_{11}(L) \quad B_{12}(L) \right] \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$$

$\varepsilon_{1,t}$ is the conventional surprise technology shock while $\varepsilon_{2,t}$ is the news shock. The only restriction on the moving representation is that $B_{12}(0) = 0$, so that news shocks have no contemporaneous effect on technology.\(^7\)

The following is an example process satisfying this assumption:

$$\ln A_t = g + \ln A_{t-1} + \varepsilon_{1,t} + \varepsilon_{2,t-j}$$

(1)

Here log technology follows a random walk with drift, with $g$ describing the drift term. $\varepsilon_1$ is the conventional surprise technology shock. Given the timing assumption, $\varepsilon_2$ has no immediate impact on the level of technology but portends a change in technology $j$ periods into the future.

In a univariate context, it would not be possible to separately identify $\varepsilon_1$ and $\varepsilon_2$. The identification of news shocks must come from surprise movements in variables other than shocks help explain the data.

\(^7\)More generally, the two shocks may be correlated. If so, our orthogonalization assigns the common component to the surprise technology shock.
technology. As such, estimation of a vector autoregression (VAR) seems sensible in this context. In a system featuring an empirical measure of aggregate technology and several forward-looking variables, we identify the surprise technology shock as the reduced-form innovation in technology. The news shock is then identified as the shock that best explains future movements in technology not accounted for by its own innovation. Our identification follows directly from our assumption that two shocks characterize the stochastic process for technology. This identification strategy is closely related to Francis, Owyang, and Roush’s (2007) maximum forecast error variance approach, which builds on Faust (1998) and Uhlig (2003, 2004). Section 2.1 provides formal details on the identifying strategy. Section 2.2. considers the suitability of this identification approach, and provides simulation evidence that our approach is likely to perform well in practice.

2.1 Identifying News Shocks

Let $y_t$ be a $k \times 1$ vector of observables of length $T$. One can form the reduced form moving average representation in the levels of the observables either by estimating a stationary vector error correction model (VECM) or an unrestricted VAR in levels:

$$y_t = B(L)u_t$$  (2)

Assume there exists a linear mapping between innovations and structural shocks:

$$u_t = A_0 \varepsilon_t$$  (3)

This implies the following structural moving average representation:

$$y_t = C(L) \varepsilon_t$$  (4)

Where $C(L) = B(L)A_0$ and $\varepsilon_t = A_0^{-1}u_t$. The impact matrix must satisfy $A_0 A_0' = \Sigma$, where $\Sigma$ is the variance-covariance matrix of innovations, but it is not unique. For some arbitrary orthogonalization, $\tilde{A}_0$ (e.g. a Choleski decomposition), the entire space of permissible impact matrices can be written as $\tilde{A}_0 D$, where $D$ is a $k \times k$ orthonormal matrix ($DD' = I$).

The $h$ step ahead forecast error is:

$$y_{t+h} - E_{t-1}y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A}_0 D \varepsilon_{t+h-\tau}$$

The share of the forecast error variance of variable $i$ attributable to structural shock $j$ at horizon $h$ is then:
\[ \Omega_{i,j}(h) = \frac{e_i' \left( \sum_{\tau=0}^h B_{i,\tau} A_0 D e_j' D' A_0' B_{i,\tau}' \right) e_i}{e_i' \left( \sum_{\tau=0}^h B_{i,\tau} \Sigma B_{i,\tau}' \right) e_i} = \frac{\sum_{\tau=0}^h B_{i,\tau} A_0 \gamma' \bar{A}_0' B_{i,\tau}'}{\sum_{\tau=0}^h B_{i,\tau} \Sigma B_{i,\tau}'} \]

The \( e_i \) denote selection vectors with one in the \( i \)th place and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the \( j \)th column of \( D \), which we will denote by \( \gamma \). \( \bar{A}_0 \gamma \) is a \( k \times 1 \) vector corresponding with the \( j \)th column of a possible orthogonalization. The selection vectors outside the parentheses in both numerator and denominator pick out the \( i \)th row of the matrix of moving average coefficients, which we denote by \( B_{i,\tau} \).

Let observed technology occupy the first position in the system, and let the unanticipated shock be indexed by 1 and the news shock by 2. Our identifying assumption implies that these two shocks account for all variation in technology at all horizons:

\[ \Omega_{1,1}(h) + \Omega_{1,2}(h) = 1 \quad \forall \ h \]

It is general not possible to force this restriction to hold at all horizons. Instead, we propose picking parts of the impact matrix to come as close as possible to making this expression hold over a finite subset of horizons. With the surprise shock identified as the innovation in observed technology, \( \Omega_{1,1}(h) \) will be invariant at all \( h \) to alternative identifications of the other \( k-1 \) structural shocks. As such, choosing elements of \( A_0 \) to come as close as possible to making the above expression hold is equivalent to choosing the impact matrix to maximize contributions to \( \Omega_{1,2}(h) \) over \( h \). Since the contribution to the forecast error variance depends only on a single column of the impact matrix, this suggests choosing the second column of the impact matrix to solve the following optimization problem:

\[ \gamma^* = \arg \max \sum_{h=0}^H \Omega_{1,2}(h) = \frac{\sum_{\tau=0}^h B_{i,\tau} A_0 \gamma' \bar{A}_0' B_{i,\tau}'}{\sum_{\tau=0}^h B_{i,\tau} \Sigma B_{i,\tau}'} \]

s.t.
\[ \tilde{A}_0(1, j) = 0 \quad \forall \ j > 1 \]
\[ \gamma(1, 1) = 0 \]
\[ \gamma'\gamma = 1 \]

So as to ensure that the resulting identification belongs to the space of possible orthogonalizations of the reduced form, the problem is expressed in terms of choosing \( \gamma \) conditional on an arbitrary orthogonalization, \( \tilde{A}_0 \). \( H \) is some finite truncation horizon. The first two constraints impose that the news shock has no contemporaneous effect on the level of technology. The third restriction (that \( \gamma \) have unit length) ensures that \( \gamma \) is a column vector belonging to an orthonormal matrix. Uhlig (2003) shows that this maximization problem can be rewritten as a quadratic form in which the non-zero portion of \( \gamma \) is the eigenvector associated with the maximum eigenvalue of a weighted sum of the lower \((k - 1) \times (k - 1)\) submatrices of \( (\mathbf{B}_1, \tilde{A}_0)' (\mathbf{B}_1, \tilde{A}_0) \) over \( \tau \). In other words, this procedure essentially identifies the news shock as the first principal component of observed technology orthogonalized with respect to its own innovation.

The common assumption in the news shock literature is that a limited number of shocks lead to movements in aggregate technology. Our identification strategy is based solely on this assumption, and does not rely upon (potentially invalid) auxiliary assumptions about other shocks or on the persistence of variables. Our approach is a partial identification strategy, only identifying the two technology shocks. As such, it can be conducted on a system with any number of variables without having to impose additional assumptions.

Our identification strategy encompasses the existing identifying assumptions in the empirical literature on news shocks. Beaudry and Portier (2006) and Beaudry, Dupaigne, and Portier (2008) propose identifying news shocks with the innovation in stock prices orthogonalized with respect to technology innovations. Were the conditions required for this identification to be valid satisfied, our approach would identify (asymptotically) exactly the same shock. Beaudry and Lucke (2009) propose using a combination of short and long run restrictions to identify news shocks. In particular, in systems featuring technology, stock prices, and other variables, they use two long run restrictions to identify the two technology shocks, and differentiate the news shock from the surprise technology shock with an orthogonality restriction. This identification is similar to ours as the truncation horizon gets arbitrarily large (i.e. as \( H \to \infty \)). The long run identification is problematic for two reasons. First, in practice it identifies a news shock and a surprise technology shock that together leave a large share of the variance of observed technology unexplained at business
cycle frequencies. Second, our analysis (which does not impose any assumptions about the permanence of shocks) reveals that surprise innovations to measured technology are highly transitory. The existing long run identifications assume that both kinds of technology shocks are permanent, suggesting that these results may suffer from misspecification.

Our approach has at least two other practical advantages over long run identification. Identification at frequency zero is based on sums of VAR coefficients, which are biased in finite samples. Summing up biased coefficients exacerbates the bias, and the resulting identification and estimation are often highly unreliable (Faust and Leeper (1997)). Francis, Owyang, and Roush (2007) show that medium run identification similar to that proposed here performs better in finite samples than does long run identification. Secondly, because identification is not based on the zero frequency, we need not take an explicit stance on the order of integration of variables or on the cointegrating relationships among them. As noted by Fisher (2010), vector error correction models paint very different pictures concerning the importance of news shocks depending on the number of assumed common trends. Estimation of a VAR in levels will produce consistent estimates of the VAR impulse responses and is robust to cointegration of unknown form.\(^8\)

### 2.2 Suitability

Recent work has questioned the ability of structural VARs to adequately recover shocks from economic models. Following the recommendation of Chari, Kehoe, and McGrattan (2008), we simulate data from a dynamic stochastic general equilibrium (DSGE) model to examine the performance of our empirical approach. We consider a neoclassical model with real frictions (habit formation in consumption and investment adjustment costs), augmented with both news and surprise technology shocks of the form specified in (1) above. The full description of the model and the calibration is contained in the Appendix.

We simulate 2000 different data sets with 191 observations each, which corresponds to the sample size in our benchmark estimation. We estimate VARs featuring technology, consumption, output and hours, which coincides with the benchmark empirical VAR in Section 3. We estimate the system in levels and include three lags of each variable. This is the same specification that we use in our benchmark empirical VAR.

Figure 1 depicts both theoretical and estimated impulse responses averaged over the simulations to a news shock that technology will be permanently higher. The theoretical responses are solid black and the average estimated responses over the simulations are depicted by the dashed line. The shaded gray areas are the +/- one standard deviation confidence

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\(^8\)Indeed, when there is uncertainty concerning the nature of common trends in the data, estimating the VAR in levels is the “conservative” approach as advocated by, for example, Hamilton (1994).
bands from the simulations. Although investment does not appear directly in the system, we impute its response as the output response less the share-weighted consumption response. A number of features from the simulations stand out. The estimated empirical impulse responses are roughly unbiased on impact and for most horizons thereafter. A favorable news shock leads to rising consumption but falling output, hours, and investment on impact in the model. After impact, the aggregate variables track movements in technology. Our empirical identification captures these features quite well. The estimated responses to a news shock are only slightly downward biased at long horizons, and the estimated dynamics are very close to the true dynamics at all horizons.

The average correlation between the identified news shock and the true news shock across simulations is 0.73, with the median correlation 0.81 and the 10th and 90th percentile correlations 0.55 and 0.88, respectively. The average correlation between the identified and true surprise technology shock (identified as the reduced form innovation in technology) is even higher at 0.92. The results improve even further as we let the size of the simulated samples become arbitrarily large. The simulations are of similar high quality under alternative specifications of the model and over a variety of different parameterizations.\footnote{In particular, the quality of the simulations is roughly invariant to alternative parameterizations of the variance of non-technology shocks. This differs from the conclusions in Chari, Kehoe, and McGrattan (2008), who find that the small sample performance of long run restrictions to identify technology shocks depends heavily on the contribution of non-technology shocks in the model. One reason we do not reach the same conclusion is because the measure of technology is not influenced by non-technology shocks, whereas average labor productivity (which is what enters their VARs) is.}

We close this section of the paper by addressing the implications of news shocks for VAR invertibility. Fernandez-Villaverde, Rubio-Ramirez, Sargent, and Watson (2007) discuss the conditions under which DSGE models produce moving average representations in the observables which can be inverted into a VAR representation in which the VAR innovations correspond to economic shocks. Invertibility problems potentially arise when there are unobserved state variables which do not enter the estimated VAR (Watson (1994)). If the observables do not fully reveal the values of the unobserved states, then the VAR innovations will be linear combinations of structural shocks and measurement errors, potentially invalidating conclusions drawn from structural impulse response analysis. Leeper, Walker, and Yang (2008) stress that anticipated shocks to future state variables are potentially pernicious for VAR invertibility. The essential difficulty is that when shocks are anticipated by agents several periods in advance, the shocks themselves become unobserved states.

It is straightforward to verify that the condition for invertibility in Fernandez-Villaverde,
et al (2007) is not strictly satisfied in the model with a process for technology characterized by (1). The intuition for the failure of invertibility is that the news shock is both a shock and a state variable in the model – agents must keep track of its value for several periods until it loads onto the level of technology. In contrast, if we specify a “smooth” diffusion process for technology with only a one period anticipation lag, as we do in Section 4 (and which fits the data better), then invertibility obtains. Nevertheless, as noted by Sims and Zha (2006) and Sims (2009), non-invertibility is not an either/or proposition, and structural VAR techniques applied to data generated from a model with a non-invertibility may nonetheless perform quite well. The simulation results here indicate our VAR-based procedure does well in practice, even though the non-invertibility leads to small asymptotic biases. As stressed by Watson (1994) and Sims (2009), the inclusion of forward-looking variables in the system helps to forecast the missing state variables, and mitigates the role of any non-invertibility in practice.

Blanchard, L’Hullier, and Lorenzoni (2009) study the implications for structural VAR analysis of agents facing signal extraction problems. In particular, they consider a framework in which agents receive news about productivity that is contaminated with noise. The essential point of their paper is that it is not possible to employ long run restrictions to separately identify the noise shock. The intuition for this finding is straightforward – if the news is about the permanent component of productivity, and the agents in the model cannot separate out news from noise, then there can be no ex-ante reversion to a noise disturbance, and a long run restriction is rendered invalid. Nevertheless, it is possible to identify the news shock from the perspective of the agents in their model even when the news is contaminated with noise. The variance of the noise essentially becomes a structural parameter – the more noisy the signal, the less agents respond to it. Drawing conclusions about the explicit role of noise requires imposing more structure on the problem than does a VAR, but the VAR methodology is nonetheless capable of identifying the structural impulse responses to news shocks.

As noted in the Introduction, much of the appeal of the news driven business cycle hypothesis is that it can potentially generate booms followed by busts absent any ex-post change in underlying fundamentals. Impulse response analysis, be it based on estimated time series models or structural DSGE models, is an ex-ante exercise – an impulse response function is defined as the change in the expectation of future values of a variable conditional on the revelation of information at a particular point in time. Therefore, by definition an impulse response cannot show a bust brought upon by an ex-post realization that news turned out to be wrong. This does not mean that estimated impulse responses are not informative about the possibility of such boom-bust episodes. Indeed, a necessary precondition of
the boom-bust hypothesis is that there be a boom in anticipation of the change in future fundamentals. Our impulse response analysis identifies the high frequency impacts of news about future productivity, and therefore informs us on whether or not the boom-bust promise of the news literature is an important feature of the data.

3 Empirical Evidence

In this section we present the main results of the paper. We begin with a brief discussion of the data.

3.1 Data

The most critical data series needed to proceed is an empirical measure of technology. The Solow residual is not particularly appealing, primarily due to the fact that standard growth accounting techniques make no attempt to control for unobserved input variation (labor hoarding and capital utilization). Since identification of the news shock requires orthogonalization with respect to observed technology, it is important that the empirical measure of technology adequately control for unobserved input variation. To address these issues, we employ a quarterly version of the Basu, Fernald, and Kimball (2006) total factor productivity (TFP) series, which arguably represents the state of the art in growth accounting. Their essential insight is to exploit the first order condition which says that firms should vary intensity of inputs along all margins simultaneously. As such, they propose measuring unobserved input variation as a function of observed variation in hours per worker. They also make use of industry level data to allow for non-constant returns to scale in the production function. As the industry level data is only available at an annual frequency, it is not possible to construct a quarterly technology series with both the unobserved input and returns to scale corrections. What we use in this paper is a quarterly measure using only the utilization correction.\footnote{This series was constructed and given to us directly by John Fernald.}

Formally, the quarterly version of this TFP series presumes a constant returns to scale production function of the form: $Y = AF(ZK, EQH)$, where $Z$ is capital utilization, $E$ is labor effort, $H$ is total labor hours, and $Q$ is a labor quality adjustment. The traditional uncorrected Solow Residual is then $\Delta A = \Delta Y - \theta \Delta K - (1-\theta)\Delta QH$, where $\theta$ is capital’s share. The utilization correction subtracts from this $\Delta U = \theta \Delta Z + (1-\theta)\Delta E$, where observed labor variation is used as a proxy for unobserved variation in both labor and capital. The standard Solow residual is both more volatile and procyclical than the resulting corrected
TFP measure. In particular, the standard deviation of the HP detrended Solow residual is roughly 33 percent larger than for the adjusted series. The correlation between HP detrended output and the Solow residual is roughly 0.8, while the output correlation with corrected TFP is about half that at 0.4.

The output measure we use is the log of real output in the non-farm business sector at a quarterly frequency. The consumption series is the log of real non-durables and services. The hours series is total hours worked in the non-farm business sector. We convert these series to per capita terms by dividing by the civilian non-institutionalized population aged sixteen and over. The results are not sensitive to this transformation. The consumption data are from the BEA; the output, hours, and population data are from the BLS. The population series in raw form is at a monthly frequency. We convert it to a quarterly frequency using the last monthly observation of each quarter.

The measure of stock prices which we use is the log of the real S&P 500 Index, taken from Robert Shiller’s website. The measure of inflation is the percentage change in the CPI for all urban consumers. Use of alternative price indexes produces similar results. Both the stock price and inflation series are at a monthly frequency. As with the population data, we convert to a quarterly frequency by taking the last monthly observation from each quarter. The consumer confidence data are from the Michigan Survey of Consumers, and summarize responses to a forward-looking question concerning aggregate expectations over a five year horizon. For more on the confidence data, see Barsky and Sims (2008).\footnote{The specific survey question is: “Looking ahead, which would you say is more likely – that in the country as a whole we’ll have continuous good times during the next five years, or that we’ll have periods of widespread unemployment or depression, or what?” The series is constructed as the percentage of respondents giving a favorable answer less the percentage giving an unfavorable answer plus 100.} Our benchmark data series spans the period 1960-2007, which is when the available TFP series ends.

3.2 Results

We include four variables in the benchmark system: the corrected TFP series, non-durables and services consumption, real output, and hours worked per capita. These are the same series used in the model-based simulations of Section 2.2. We estimate the system in the levels of all variables. While several of these series appear to be $I(1)$, estimating the system in levels will produce consistent estimates of impulse responses and is robust to cointegration of unknown form. Our results are very similar when either imposing cointegrating relationships on the data or when estimating a vector error correction model (VECM). We include three lags of each series in the VAR, in accord with the selection of the Schwartz Information Criterion. We set the truncation horizon in the identification problem at $H = 40$. In
words, we identify the news shock as the shock orthogonal to TFP innovations which best accounts for unexplained movements in TFP over a ten year horizon.

Figure 2 shows the estimated impulse responses to the identified news shock. The shaded gray areas are +/- one standard error confidence bands from the bias-corrected bootstrap procedure of Kilian (1998). TFP rises rather rapidly, reaching a peak response of slightly more than 0.2 percentage points some five years subsequent to the shock. Consistent with simple permanent income intuition, consumption jumps up about 0.2 percentage points on impact, rising further over time. Output and hours both decline on impact. Only after measured TFP beings to increase do these series begin to rise. Investment also jumps down on impact before recovering after a few quarters. As will be argued in Section 4, these responses are at least broadly consistent with the implications of conventional neoclassical models. In particular, there is no large output “boom” in anticipation of increases in TFP.

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In Figure 3 we show the estimated responses to the surprise technology shock, identified as the reduced form innovation in TFP. Quite strikingly, TFP’s response to its own innovation appears largely transitory. Output, consumption, hours, and investment all rise on impact before reverting. Given the transitory nature of the TFP response, the consumption response is quite naturally small. In contrast, the output and investment increases on impact are large before reverting to their pre-shock values.

We next identify news and surprise technology shocks in a larger system. In addition to the four variables in the benchmark system, we also include a measure of stock prices, consumer confidence, and inflation (see Section 3.1 for data descriptions). There are several reasons for including these additional variables. Stock prices and consumer confidence are naturally forward-looking, and previous research has shown them to be prognostic of future movements in economic activity in general and TFP in particular (e.g. Beaudry and Portier (2006) and Barsky and Sims (2010)). Inflation is forward-looking in the standard monetary models of the business cycle that are now popular among central banks (e.g. Smets and Wouters (2007)). As such, including these additional variables in the system will help in the identification of the news shock, as well as serving to ameliorate any potential invertibility issues (see Watson (1994) or Section 2.2). Further, it is of interest in and of itself to examine the responses of these forward-looking variables to news shocks.

Figure 4 shows the estimated responses of TFP, consumption, output, hours, and invest-

12 As in Section 2.2, the investment response is imputed as output less the share-weighted consumption response, where it is assumed that consumption is 70 percent of output, which is in line with the data.

13 Note that care must be taken when discussing permanent vs. transitory responses from a system estimated in levels. Re-estimating the system as a VECM leads to a very similar response of TFP to its own innovation, which gives us comfort in characterizing the response to a surprise technology shock as “largely transitory”.

13
ment to the identified news shock. These responses are similar to those shown from the smaller system in Figure 2. Output, hours, and investment all decline on impact followed by relatively quick reversals; consumption rises. The dynamic paths of these variables largely track—as opposed to anticipate—the estimated time path of TFP. With the inclusion of the additional variables in the system there is somewhat more predictability in the time path of TFP, so that its response is larger here than in Figure 2. Figure 6 shows the responses of these variables to the surprise technology shock. These are very similar to what is estimated in the smaller system. In particular, TFP’s response is largely transitory.

Figure 5 shows the responses of stock prices, inflation, and consumer confidence to a news shock. Consistent with the results in Beaudry and Portier (2006), stock prices rise significantly on impact. There is some evidence of reversion at longer horizons, though that stock prices are an exact random walk cannot be rejected in a statistical sense. Inflation is estimated to fall significantly and persistently on impact in response to good news. This response is at least broadly consistent with the New Keynesian framework in which current inflation equals an expected present discounted value of future marginal costs. Consumer confidence rises on impact, which is consistent with the empirical findings in Barsky and Sims (2010).

Table 1 depicts the share of the forecast error variance of the variables in the seven variable VAR attributable to the news shock at various horizons. The numbers in parentheses are the standard errors from the bootstrap replications used to construct the confidence bands for the impulse responses. News shocks account for more than one quarter of the variance of TFP at a horizon of four years and more than 40 percent at a horizon of ten years. The second to last row of the table shows the total contribution to TFP’s forecast error variance of the news shock and the surprise technology shock. These two shocks combine to explain roughly 95 percent of the variation in TFP at frequencies up to ten years. That so little of TFP’s forecast error variance remains unexplained at most horizons validates the assumption underlying identification that most of the movements in measured technology can be attributed to just two shocks. This suggests that our approach has done a good job of identifying the news shock.

News shocks account for a relatively small share of the forecast error variances of consumption at short horizons, and a somewhat larger share of the forecast error variance of output. The shock contributes more significantly to the variance decomposition of hours at high frequencies and much less so at lower frequencies. At longer horizons the news shock contributes more significantly to the variance decomposition of the aggregate variables excluding hours, explaining between ten and forty of the variance of output at business cycle frequencies. Relative to much of the identified VAR literature, these contributions to the
forecast error variance of output are large. This suggests that news shocks are a potentially important component behind economic fluctuations, though not necessarily in the way that the extant literature has suggested. The final row of the table shows the total fraction of the forecast variance of output explained by the news and surprise technology shocks combined. At business cycle frequencies, these two shocks combine to leave more than 50 percent of the variance of output unexplained. This means that non-technology shocks (i.e. “demand” shocks) are an important driving force behind fluctuations, a result which is backed up in both the identified VAR literature and in estimated DSGE models.

Figure 7 plots the time series of identified news shocks from the seven variable VAR. So as to make the figure more readable, what is shown is the four quarter centered moving average of the shock series. The shaded areas in the figure correspond to recession dates as defined by the NBER business cycle dating committee. There is no visually discernible relationship among the smoothed shock series and the timing of recessions. The only recession for which large, negative news shocks preceded is the 1973-1975 recession. The correlation between the shock series and HP filtered output is negative contemporaneously and positive when output is led several quarters. This correlation structure is broadly consistent with the patterns observed in the estimated impulse responses. Switching to a lower frequency, the 1970s are characterized by a predominance of negative news shocks, which loosely corresponds with the productivity slowdown. In contrast, the late 1990s were a period of largely positive news shock realizations.

In order to get a better sense for how important news shocks have been in explaining particular episodes, Figure 8 plots an historical decomposition of real output. The subplots focus in on a one year centered window around the NBER defined recession dates, treating the 1980 and 1981-1982 recessions as one event. The dashed lines show the simulated value of output from the seven variable VAR as if news shocks were the only stochastic disturbance. The solid line shows the time path of actual output. In four out of six recessions (not counting the current one, for which we do not have data), the simulated time path of output in response to news shocks is increasing during recessions, not decreasing. The two exceptions are the 1973-1975 recession and the 1980 recession. In neither of these events, however, do news shocks explain a large share of the output decline. On the basis of these simulations, it is difficult to conclude that news shocks have been a major driving force behind post-war US recessions.

As will be discussed more in Section 4, most theoretical models typically have strong testable predictions concerning the behavior of equilibrium prices in response to news shocks. In particular, both real wages and real interest rates should rise following a good news shock. The rise in the wage comes from a reduction in labor supply and the rise in the interest rate
comes from a reduction in savings supply, both resulting from the positive wealth effect associated with good news. To see whether this prediction is borne out in the data, we include measures of both series in our empirical VAR. We measure the real wage as the log of real hourly compensation in the non-farm business sector, and the real interest rate as the Baa corporate bond yield less expected inflation, where we get the expected inflation number from the Michigan Survey of Consumers. We include these measures in our seven variable VAR, replacing the consumer confidence and inflation measures. The impulse responses of the quantity variables and of stock prices to the news shock are very similar. Figure 9 shows the estimated responses of the real wage and the real interest rate. Consistent with our predictions, both rise on impact. The real wage is estimated to be significantly higher for a number of periods and its long horizon response of similar magnitude to the response of output. While statistically insignificant, the interest rate response is economically large and positive for a number of periods after impact.

3.3 Sensitivity

Our main result that news shocks induce negative impact comovement among aggregate variables is robust to alternative lag structures in the reduced form system as well as to various different assumptions and/or specifications concerning the long run relationships among the series.\footnote{Our results are also qualitatively robust with alternative measures of observed TFP. Application of our identification to a system with the Solow residual in place of the utilization-adjusted TFP measure again finds negative impact comovement, with output, hours, and investment all declining in anticipation of good news. The main difference is that the response of the Solow residual itself to the news shock appears far more transitory than is the response of the BFK TFP measure in Figures 2 and 4. Similar results obtain with alternative utilization corrections to the Solow residual – see Footnote 16.} In the interest of space, we only describe these results qualitatively here.

At all tested lag lengths, output, investment, and hours decline on impact in response to a favorable news shock, while consumption rises. With more lags in the reduced form system the impulse responses are less smooth and there is more evidence of reversion in all series at longer horizons, but the basic qualitative nature of the responses is unchanged. The results are also similar with fewer lags. We have experimented with estimating VECM models with either assumed or estimated common trends. We prefer the levels specification because invalid assumptions concerning common trends can yield misleading results (Fisher (2010)). Nevertheless, our results about the effects of news shocks are qualitatively similar when estimating VECMs. The main differences in the VECM specifications concern the quantitative contribution of news shocks to the variance decomposition of the variables at medium and low frequencies. The impact effects of news on aggregate variables are always

\begin{align*}
\text{output} \quad & \text{decline} \\
\text{investment} \quad & \text{decline} \\
\text{hours} \quad & \text{decline} \\
\text{consumption} \quad & \text{rise}
\end{align*}
very similar, and the reverting behavior of TFP, as well other aggregate variables, to the surprise technology shock continues to manifest itself. Qualitatively, the results are also very similar across sub-samples (e.g. estimating the model only post 1984).

One might be concerned that our identification confuses genuine news about neutral technology with investment specific technology shocks.\footnote{Fisher (2006), for example, finds that investment specific technology shocks account for important business cycle frequency movements in hours. This result is completely compatible with ours, as we find that neither news nor surprise technology shocks account for much of the movements of hours at horizons between six and thirty-two quarters. As noted in our discussion of the variance decomposition in Section 3.2, news shocks and technology shocks also leave a large share of output fluctuations unexplained at business cycle frequencies. This is also consistent with an important role for investment specific shocks.} If vintages of capital are not adequately measured, then fluctuations in the relative price of investment will show up as movements in TFP, particular over long periods of time. This would mean that what we identify as news may actually reflect investment specific technical change. To address this issue, we experimented with including various different metrics of the relative price of investment. As in Fisher (2006), we construct the relative price of investment using different measures of the investment price deflator from the NIPA accounts divided by different measures of consumption price deflators. In none of these specifications is our identified news shocks strongly correlated with the relative price of investment, and the basic patterns of our identified impulse responses do not change. We also tried a specification in which we restrict the news shock to affect neither TFP nor the relative price of investment on impact. This yields very similar results to our benchmark. In the interest of space, we omit these figures from the paper.

While the utilization-adjusted technology series we use in this paper arguably represents the state of the art in growth accounting, one may nevertheless object to the notion that the resulting series accurately reflects true technology. To the extent to which it is a poor measure of true technology, the analysis conducted thus far may be invalid. Indeed, most of the work in the structural VAR literature assumes that technology is unobservable, and attempts to identify technology shocks off of the time series properties of observed labor productivity.

As a final robustness check, as well as to provide a closer link to some of the existing VAR literature, we estimate a system with output per hour of work in place of the TFP series. As this necessitates dropping the measure of output, the resulting system features output per hour, stock prices, consumption, hours, inflation, and consumer confidence. In most DSGE models news shocks will lead to movements in output per hour on impact and non-technology shocks will affect labor productivity in the short run. As such, the identifying restrictions that the news shock is orthogonal to the measure of productivity and that surprise and news...
shocks completely explain variation in productivity are no longer theoretically valid when output per hour is used in place of a measure of TFP. A different orthogonalization strategy to identify news shocks is therefore required.

We employ a shape restriction to identify a set of candidate impulse responses to a news shock in the system with labor productivity. In particular, we impose that a favorable news shock results in a “small” impact effect on labor productivity followed by sustained growth. While most DSGE models would have the implication that a favorable news shock raises labor productivity on impact (because hours fall and real wages rise), we do not explicitly impose this. The only restriction on the data is that the response of labor productivity be growing – in particular that the response is larger after ten quarters than it is on impact, and in turn that the response is larger after twenty-four quarters than it is at ten.

The shape restriction methodology has much to recommend it in this context. As noted, it does not rely upon an explicit and potentially controversial measure of technology. Furthermore, it is valid under less restrictive assumptions than is our benchmark identification. In particular, it does not assume that the news shock is contemporaneously orthogonal to true technology, nor does it assume that the stochastic process for true technology is driven only by two shocks. It merely imposes that news shocks lead to increases in measured labor productivity over time. The details of the shape restriction identification are in Appendix 6.2. See also Faust (1998).

The impulse responses of aggregate variables for this identification are in Figure 10. The solid line shows the median response, while the dashed lines depict the +/- one standard deviation of the distribution of candidate responses. These responses are both qualitatively and quantitatively in line with the responses in earlier figures. Labor productivity moves little on impact, followed by rapid growth for the first several quarters, and slower, prolonged growth thereafter, with a long run response slightly below 0.5 percent. Consumption rises slightly on impact, followed by sustained growth. As in Figures 2 and 4, output, hours, and investment all fall on impact and then track movements in productivity. The impact declines in both output and investment are virtually identical to the benchmark estimates; the impact decline in hours is somewhat smaller here than in the system with TFP. The overall qualitative nature of the responses is very similar to our baseline estimates. This suggests that our results are not driven by our preferred measure of technology or our identification approach.

\[\text{Output does not enter the system directly, but is imputed as the output per hour response plus the hours response. As before, the investment response is then calculated as the output response less the share-weighted consumption response.}\]
3.4 Relation with Earlier Work

The most well-known empirical work in the news shock literature are papers are by Beaudry and Portier (2006), Beaudry, Dupaigne, and Portier (2008), and Beaudry and Lucke (2009). These authors estimate two to five variable systems featuring measures of TFP, stock prices, and other macroeconomic aggregates. They propose two alternative orthogonalization schemes aimed at isolating news shocks – the first is to associate the news shock with the stock price innovation orthogonalized with respect to TFP, and the second combines short and long run restrictions to identify the news shock. These authors argue that both orthogonalization schemes yield very similar results. They find that news shocks lead to positive conditional comovement among macroeconomic aggregates on impact, that aggregate variables strongly anticipate movements in technology, and that news shocks account for the bulk of the variance of aggregate variables at business cycle frequencies.

The conditions under which either of these orthogonalization schemes are valid are encompassed by our identification strategy. In particular, were the conditions required for the pure recursive identification satisfied, our identification would (asymptotically) identify the same shock and impulse responses. Likewise, their long run identifying assumption in the second orthogonalization scheme rests on the same implicit assumption underlying our identification – that a limited number of shocks account for variation in measured technology. It is, however, more restrictive in the sense that it imposes that both kind of technology shocks permanently impact the level of TFP. Ours, in contrast, only imposes that the two technology shocks together explain the bulk of movements in TFP, without taking a stand on whether both permanently impact TFP. In practice, we observe that there is a significant transitory component to TFP, however measured. If one interprets observed TFP as a true measure of aggregate technology, as is required for the news shock interpretation of their results, then the transitory component of TFP is incompatible with their identifying assumption that there are two, permanent technology shocks. This suggests that their results likely suffer from a misspecification bias.

In practice, there is a large quantitative and qualitative difference between our results and theirs in the estimated effects of news shocks on TFP itself. The shock identified by these authors typically does not have any noticeable effect on TFP for several years.\footnote{Discrepancies in our results do not result from different data, and in particular from different measures of TFP. We have conducted my empirical analysis using Beaudry and Portier’s (2006) TFP data (available from the American Economic Review website) and obtain very similar results.} Indeed, Beaudry and Portier (2006) note that “growth beyond its [TFP’s] initial level takes somewhere between 12 and 16 quarters” (p. 1303) following a news shock, while in Beaudry, Dupaigne, and Portier (2008), they state “it [news shock] has almost no impact on TFP.
during the first five years” (p. 3). In contrast, the news shock we identify begins to affect TFP soon after impact, and explains TFP movements well at both short and long horizons. That these authors’ identified shock has such a delayed effect on TFP makes its interpretation as a news shock problematic. To make this point clear, we estimate the seven variable system of Section 3.2 using a truncation horizon of $H = 1000$ instead of $H = 40$. This is approximately equivalent to identifying the news shock with a combined short and long run restriction, without necessarily imposing that the surprise technology shock has permanent effects. We continue to find negative impact comovement under this specification, though it is less drastic than in our benchmark specification. In addition, the shock identified using this approach accounts for a larger share of the forecast error variance of aggregate variables at business cycle frequencies.

Table 2 shows the fraction of the forecast error variance of TFP attributable to this shock at various horizons as well as the total variance in TFP accounted for by this shock along with the surprise technology shock. A comparison with the corresponding rows in Table 1 is instructive. Whereas the news shock identified using our empirical strategy explains between 20 and 50 percent of the variance of TFP at business cycle frequencies, the shock identified using the long run restriction explains only 5 to 25 percent of the TFP variance at horizons from one to ten years. Importantly, the long run identification leaves up to 40 percent of the variance of TFP unexplained at business cycle frequencies. In other words, some other structural shock orthogonal to TFP’s innovation potentially accounts for twice as much variation in TFP at these frequencies than does what these authors deem the news shock. In comparison, our identification leaves less than 5 percent of TFP’s variance unaccounted for at business cycle frequencies.

That the shock identified by these authors leaves so much of the variance of TFP unexplained at business cycle frequencies is troubling for a couple of reasons. Most obviously, it leaves unanswered the question of what the business cycle implications are of the shock orthogonal to TFP’s innovation which explains the remaining variance in TFP at these frequencies. Another more fundamental problem with their results concerns a potential role for research and development. One might imagine that “booms” (particularly in stock prices) lead to increased R&D, which are in turn manifested as higher TFP several periods later. The long delays in the transmission of their identified shock into TFP are consistent with this hypothesis, and suggest that the direction of causation may be reversed – rather than news about TFP causing economic activity, the economic activity may be causing TFP. Our identification approach is potentially subject to the same criticism, but we think much less

18 Note that, unlike concerns with the relative price of investment and investment specific shocks, this could be the case even if TFP perfectly measures true technology.
so. The development of new technologies is a slow process, and aggregate activity-driven R&D is unlikely to manifest itself in changes in observed TFP for a number of years. By focusing our identification of news shocks on movements in observed TFP at medium frequencies (as opposed to the zero frequency), we are much more likely to pick up exogenous news. Furthermore, our identification strategy is more consistent with the nascent theoretical literature on news shocks, which generally assumes delays between arrival of news and adoption of less than two years.

An alternative approach to the VAR-based methodology of estimating the implications of news shocks for aggregate variables would be the estimation of a fully specified DSGE model. This is the approach taken by Schmitt-Grohe and Uribe (2008), who argue that news shocks about future technology are quantitatively important for understanding fluctuations (though they also find that favorable news shocks lead to an immediate reduction in hours), and Kahn and Tsoukalas (2009), who reach conclusions more in line with ours. Kahn and Tsoukalas show that Schmitt-Grohe and Uribe’s results are highly sensitive to model structure, and in particular to the range of potential shocks taken into consideration. The advantage of the VAR methodology pursued here is that it is highly flexible, and reliably identifies news shocks from a variety of different model structures, including those in which news shocks are a quantitatively important feature of the data generating process. In practice, estimation of a fully specified model in this context is problematic, as there is no consensus on what the appropriate theoretical structure is in which news shocks have a chance to be an important component of the data generating process. Used properly, results from VAR analysis should help inform and improve structural economic models. VARs are most useful in situations where it is not clear what the appropriate DSGE model is. We think that the news literature is one situation where this is precisely the case.

4 Discussion

In this section we discuss our results, place them in the context of the existing literature, point out some unresolved issues, and suggest avenues for future research.

A large literature has developed that seeks develop theoretical models which generate positive impact comovement in response to good news. This has not proven to be a particularly easy task. Among papers in this growing literature are Beaudry and Portier (2004), Den Haan and Kaltenbrunner (2006), Christiano, Ilut, Motto, and Rostagno (2007), Jaimovich and Rebelo (2009), and Dupor and Mehkari (2009). Our empirical results suggest that this excessive focus on the impact effects of news shocks has been somewhat misplaced. A similar point is made by Leeper and Walker (2009).
To make this point concrete, we show here that a simple, textbook neoclassical growth model augmented with news shocks is capable of generating impulse responses which are very similar to those that we estimate in the data. The model is a variant of the Hansen (1985) indivisible labor model and can be expressed as the solution to a social planner’s problem:

$$\max E_0 \sum_{t=0}^{\infty} \beta^t (\ln C_t - \psi N_t)$$

s.t.

$$C_t + K_{t+1} = A_t K_t^\theta N_t^{1-\theta} + (1 - \delta) K_t$$

(5)

$$\ln A_t = g_{t-1} + \ln A_{t-1}$$

$$g_t = \rho g_{t-1} + u_t$$

(6) is simply a “smooth” version of the news process shown in (1) above. Given the timing assumption, $u_t$ can be interpreted as a news shock since it has no contemporaneous effect on the level of technology. Since we are here only interested in matching the conditional responses to a news shock, we do not specify a process for the surprise technology shock. It would be straightforward to include it, either as a permanent or as a transitory disturbance to the level of $A_t$.

We choose the parameters of this simple model so as to fit the estimated impulse responses of TFP, consumption, output and hours to the news shock from the seven variable VAR (i.e. the impulse responses in Figure 4). The best-fitting parameter configuration is $\beta = 0.997$, $\theta = 0.41$, $\rho = 0.83$, and a standard deviation of the news shock of 0.009 (the parameter $\psi$ does not influence the dynamics; we set it to 3.49 to fix steady state labor hours at 0.2). Note that we do not interpret these parameters or this model as an actual description of the US economy, but rather as an illustrative exercise.

The impulse responses from this parameterized model are shown as the dashed line in Figure 11, along with the empirical impulse responses (solid line) and confidence regions (shaded gray) from Figure 4. The model’s impulse responses lie very close to those estimated in the data at all horizons and are completely contained by the shaded confidence regions. In short, this simple model appears to provide a very good fit to the data, at least along
this dimension. The various “fixes” that have been proposed to deal with negative impact comovement in response to news appear unnecessary.

Given that positive comovement among aggregate variables is a ubiquitous feature of the data, news shocks as estimated here cannot be the sole driving force behind fluctuations. The first interior row of Table 3 shows selected correlations among HP filtered aggregate variables for the period 1960-2007 (using smoothing parameter 1600). These correlations are all positive and strong, but many are far from one. The second interior row of the table shows the correlations that would obtain if the news shock were the only stochastic disturbance in the simple mode as presented above (parameterized as described). While the correlations between output and investment and output and hours are reasonably close to those in the data, the correlations involving consumption and other aggregates are negative. This is clearly at odds with the data.

The next row of the table shows the resulting moments if a surprise technology shock were the only stochastic disturbance in the model. The shock is assumed to follow a stationary AR(1) process with autoregressive coefficient 0.98 and standard deviation of 0.75 percent. This calibration produces an impulse response of technology that matches the observed response of TFP to its own innovation in our VARs. Here the resulting correlations are all nearly one, which is too high relative to the data. The final row shows the correlations that result if we include both the permanent news shock and the transitory surprise technology shock in the simple neoclassical model. Relative to the one shock model, the two shock version fits better on many dimensions – the correlations are all positive but not too close to one.

The above exercise is meant to be illustrative. We do not claim that this simple model is an adequate characterization of the complex US economy. Rather, this exercise makes two related points. First, conventional business cycle models are capable of qualitatively matching the dynamic, conditional responses of aggregate variables to news about future technology. Second, even if news shocks do not induce positive comovement on impact, they can nevertheless be an important part of the data generating process and can help explain some features of the data. In particular, the presence of news shocks can work to lower the correlations among aggregate variables that obtain in a simple one shock RBC model, in much the same way that, for example, government spending or distortionary tax shocks do (Christiano and Eichenbaum (1992) and McGrattan (1994)). New research points out several additional channels by which news shocks help to better fit the data. Kurmann and Otrok (2010), using a similar methodology to that pursued here, argue that news shocks help explain the slope of the term structure of interest rates. Mertens (2010) shows how news shocks can help account for the comovement between output and interest rates that
has puzzled economists since King and Watson (1996). Further, news shocks (or more generally slow technological diffusion) can be an important propagation mechanism, even if news shocks do not induce high frequency comovement (Andolfatto and MacDonald (1998) and Leeper and Walker (2009)).

While it seems intuitive that stock prices should rise in anticipation of good news, conventional models have difficulty generating stock market booms in advance of good news. This is true even in theoretical models that can generate positive impact comovement among aggregate quantity variables. Christiano, Ilut, Motto, and Rostagno (2008) document this phenomenon in detail. Walentin (2009) proposes that limited enforcement of financial contracts can potentially help generate stock price appreciations in anticipation of higher future productivity. In addition to stock price increases, our empirical analysis suggests that favorable news shocks are disinflationary. Our empirical results along these dimensions should help inform researchers building detailed DSGE models.

Finally, our results have implications reaching beyond the news literature. Many VAR identifications based on long run restrictions find that the shock responsible for the unit root in labor productivity leads to an impact reduction in hours (Shapiro and Watson (1988) and Gali (1999)). Some authors have argued that this finding lends credence to sticky price models (Gali (1999) and Basu, Fernald, and Kimball (2006)). Our result that the low frequency component of observed TFP is mainly driven by news shocks offers a potential reconciliation of these results without relying upon nominal frictions. As shown above, a negative conditional correlation between hours and “technology shocks” obtained from a long run restriction is exactly the qualitative prediction of a simple flexible price model when the long run component of productivity is mainly attributable to news.

5 Conclusion

The news driven business cycle hypothesis offers the tantalizing possibility that business cycles could emerge absent any (ex-post) change in fundamentals. If good news about the future can set off a boom today, then a realization worse than anticipated can set off a bust. For this story to work, however, good news about the future must induce broad-based comovement, which is not the prediction of standard macro models. Existing empirical evidence suggesting that news shocks do lead to broad-based comovement has spawned a new literature searching for theoretical frameworks capable of delivering business cycle-like behavior when driven by news shocks about future technology.

This paper has taken a closer look at the empirical evidence in favor of this theory of fluctuations. We implemented a new empirical approach of identifying news shocks
that is directly based on the implications of theoretical models of news driven business cycles. In contrast to the existing literature, we find that good news is associated with an increase in consumption and impact declines in output, hours, and investment. After impact, aggregate variables largely track, as opposed to anticipate, predicted movements in measured technology. The impulse responses we estimate are broadly consistent with the implications of standard macro models. While important at medium to low frequencies, an historical decomposition reveals that news shocks have not been a major source of post-war US recessions. News shocks nevertheless do help to explain several features of the data. While we find no evidence to support the “boom-bust” story advanced by the literature, incorporating news shocks into existing models seems like a promising avenue for future research.
6 Appendix

6.1 Simulations

The simulations discussed in Section 2 are from a neoclassical model with real frictions and augmented with news shocks. The model can be expressed as a planner’s problem:

$$\max \sum_{t=0}^{\infty} \beta^t E_0 \left( \ln (C_t - bC_{t-1}) - \psi_t \frac{N_t^{1+1/\eta}}{1 + 1/\eta} \right)$$

s.t.

$$K_{t+1} = (1 - \delta)K_t + \left(1 - \phi \left( \frac{I_t}{I_{t-1}} \right) \right) I_t$$

$$Y_t = A_t K_t^{\theta} N_t^{1-\theta}$$

$$Y_t = C_t + I_t + G_t$$

$$G_t = g_t Y_t$$

$$\ln A_t = g_A + \ln A_{t-1} + \varepsilon_{1,t} + \varepsilon_{2,t-j}$$

$$\ln g_t = (1 - \rho) \ln \bar{g} + \rho \ln g_{t-1} + \varepsilon_{3,t}$$

$$\ln \psi_t = \nu \ln \psi_{t-1} + \varepsilon_{4,t}$$

$C$ is consumption, $N$ is employment, $Y$ is output, $K$ is capital, $A$ is the level of technology, and $G$ is government spending. $\beta$ is the subjective discount factor, $b$ is the degree of habit persistence, $\eta$ is the Frisch labor supply elasticity, $\theta$ is capital’s share of income, and $\delta$ is the depreciation rate on capital. $\psi_t$ is a time-varying preference parameter with mean one and autoregressive coefficient $\nu$. We assume that the government consumes a stochastic fraction of output, $g_t$. The log government share of output follows a stationary autoregressive process, with autoregressive parameter $\rho$. The government spending and preference shocks are included so as to introduce sufficient variation to be able to estimate a VAR with more than a few variables. $\phi(\cdot)$ is a convex function describing costs associated with adjusting investment. We assume that it has the following properties: $\phi(1) = 0$, $\phi'(1) = 0$, and $\phi''(\cdot) = \gamma \geq 0$. Log technology follows a random walk with drift with both an unanticipated shock and a news shock, with $j$ describing the number of periods of anticipation in the news process. This specification of the process for technology is consistent with the more general specification in the text of Section 2.

The model as presented has the desirable property that there exist parameterizations in which news shocks induce positive comovement among aggregate variables on impact.
In particular, for sufficiently high degrees of habit persistence and adjustment costs to investment, output, consumption, hours, and investment can all rise upon news of future technological improvement. In the case with $b = \gamma = 0$, the model converges to the simple real business cycle model in which good news about the future leads to falling output, hours, and investment on impact.

The model is solved by log-linearizing the first order conditions about the balanced growth path. As a baseline, we calibrate the parameters as follows: $\beta = 0.99$, $b = 0.8$, $\psi = 1$, $\eta = 1$, $\delta = 0.025$, $\theta = 0.33$, $\gamma = 0.3$, $\bar{g} = 0.2$, $g_A = 0.25$, $\nu = 0.8$, and $\rho = 0.95$. This calibration implies that, along the balanced growth path, government consumption is 20 percent of output, private consumption is 56.5 percent of output, and investment is 23.5 percent of output. These numbers are in line with US data when durable consumption is included as a component of investment. Technology grows at the annualized rate of one percent per year, with output, consumption, and investment per capita growing at 1.5 percent per year. We assume three periods of anticipation for news shocks (i.e. $j = 3$). We set the standard deviation of the unanticipated technology shock to 0.66 percent and the standard deviation of the news shock at 0.33 percent. We calibrate the standard deviations of the remaining two shocks at 0.15. Similar results obtain for alternative calibrations of the non-technology shocks.

6.2 Shape Restrictions

For the shape restriction results in Section 3.3, the vector of observables, $y_t$, contains output per hour, stock prices, consumption, hours, inflation, and consumer confidence. After estimating either a VAR in levels or a VECM, the reduced form moving average representation can be formed as in equation (4). The structural impulse response function over the entire space of possible orthogonalizations is:

$$y_t = B(L)\tilde{A}_0D\epsilon_t$$  \hspace{1cm} (A.6)

$\tilde{A}_0$ is an arbitrary orthogonalization of the reduced form and $D$ is an orthonormal matrix. The impulse response to a particular structural shock depends only on a column of $D$, again denoted by $\varsigma$, which must be unit length.

We compute an arbitrary Choleski decomposition of the reduced form, $\tilde{A}_0$. We then draw 100,000 unit length vectors of conformable size (i.e. 100,000 candidate $\varsigma$) from a normal distribution. These random vectors are then rescaled to be of unit length. For each of these vectors, we compute the implied impulse response of output per hour to the shock defined by the impulse vector $\tilde{A}_0\varsigma$. We keep all candidate $\varsigma$ which produce an impulse response of
output per hour that satisfies the shape restriction described in the text. In particular, we impose that the candidate $\zeta$ yield an impact effect on output per hour which is less than 0.25 percent in absolute value, for which the impulse response at a horizon of 10 quarters is greater than the impact response, and for which the impulse response at 24 quarters is greater than the impulse response at 10 quarters. This procedure identifies a set of candidate impulse response functions to a shock which leads to a small impact effect on labor productivity but a growing response over time. Of the 100,000 candidate $\zeta$, roughly 30 percent produce impulse responses satisfying the shape restriction. The results in Figure 10 are presented where the solid line is the median response over the candidate $\zeta$, while the the dashed lines are the 16th and 84th percentiles of the distribution of candidate responses.
References


Table 1
Share of Forecast Error Variance Attributable to News Shock: Seven Variable VAR

<table>
<thead>
<tr>
<th></th>
<th>$h=0$</th>
<th>$h=4$</th>
<th>$h=8$</th>
<th>$h=16$</th>
<th>$h=24$</th>
<th>$h=40$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>0.000</td>
<td>0.062</td>
<td>0.126</td>
<td>0.269</td>
<td>0.366</td>
<td>0.454</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.06)</td>
<td>(0.11)</td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.050</td>
<td>0.234</td>
<td>0.377</td>
<td>0.493</td>
<td>0.524</td>
<td>0.507</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.18)</td>
<td>(0.24)</td>
<td>(0.27)</td>
<td>(0.27)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Output</td>
<td>0.111</td>
<td>0.091</td>
<td>0.242</td>
<td>0.382</td>
<td>0.429</td>
<td>0.431</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.10)</td>
<td>(0.18)</td>
<td>(0.23)</td>
<td>(0.24)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Hours</td>
<td>0.622</td>
<td>0.200</td>
<td>0.105</td>
<td>0.092</td>
<td>0.094</td>
<td>0.089</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.16)</td>
<td>(0.13)</td>
<td>(0.15)</td>
<td>(0.16)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Stock Price</td>
<td>0.140</td>
<td>0.200</td>
<td>0.185</td>
<td>0.189</td>
<td>0.193</td>
<td>0.181</td>
</tr>
<tr>
<td></td>
<td>(0.17)</td>
<td>(0.20)</td>
<td>(0.20)</td>
<td>(0.21)</td>
<td>(0.22)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Confidence</td>
<td>0.245</td>
<td>0.343</td>
<td>0.353</td>
<td>0.333</td>
<td>0.310</td>
<td>0.286</td>
</tr>
<tr>
<td></td>
<td>(0.21)</td>
<td>(0.22)</td>
<td>(0.22)</td>
<td>(0.22)</td>
<td>(0.20)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Inflation</td>
<td>0.138</td>
<td>0.220</td>
<td>0.226</td>
<td>0.205</td>
<td>0.191</td>
<td>0.180</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.18)</td>
<td>(0.15)</td>
<td>(0.15)</td>
<td>(0.14)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>Total TFP</td>
<td>1.000</td>
<td>0.948</td>
<td>0.943</td>
<td>0.951</td>
<td>0.948</td>
<td>0.910</td>
</tr>
<tr>
<td>Total Output</td>
<td>0.731</td>
<td>0.282</td>
<td>0.364</td>
<td>0.451</td>
<td>0.491</td>
<td>0.520</td>
</tr>
</tbody>
</table>

The letter $h$ refers to the forecast horizon. The numbers denote the fraction of the total forecast error variance of each variable assigned to the identified news shock. The numbers in parentheses are the standard deviation of a bias-corrected bootstrap simulation. The row titled “Total TFP” shows the total forecast error variance of measured TFP explained by the news shock and the TFP innovation. The row titled “Total Output” show the total forecast error variance of output explained by the news shock and the TFP innovation.

Table 2
Share of Forecast Error Variance Attributable to News Shock
“Long Run” Identification

<table>
<thead>
<tr>
<th></th>
<th>$h=0$</th>
<th>$h=4$</th>
<th>$h=8$</th>
<th>$h=16$</th>
<th>$h=24$</th>
<th>$h=40$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TFP</td>
<td>0.000</td>
<td>0.053</td>
<td>0.099</td>
<td>0.186</td>
<td>0.213</td>
<td>0.279</td>
</tr>
<tr>
<td>Total TFP</td>
<td>1.000</td>
<td>0.913</td>
<td>0.879</td>
<td>0.792</td>
<td>0.705</td>
<td>0.626</td>
</tr>
</tbody>
</table>

The first row shows the fraction of the TFP forecast error variance attributable to the news shock under the “long run” identifying restriction, as described in Section 3.4. The final row shows the total fraction of the forecast error variance of TFP explained by the news shock under this identifying restriction as well as the reduced form TFP innovation.

Table 3
Unconditional Business Cycle Moments

<table>
<thead>
<tr>
<th></th>
<th>corr($y,c$)</th>
<th>corr($y,i$)</th>
<th>corr($y,n$)</th>
<th>corr($y,y/n$)</th>
<th>corr($c,i$)</th>
<th>corr($c,n$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>US Data</td>
<td>0.82</td>
<td>0.78</td>
<td>0.86</td>
<td>0.49</td>
<td>0.61</td>
<td>0.69</td>
</tr>
<tr>
<td>Only news</td>
<td>-0.35</td>
<td>0.94</td>
<td>0.91</td>
<td>0.08</td>
<td>-0.63</td>
<td>-0.70</td>
</tr>
<tr>
<td>Only surprise</td>
<td>0.97</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.96</td>
<td>0.95</td>
</tr>
<tr>
<td>Both shocks</td>
<td>0.50</td>
<td>0.97</td>
<td>0.95</td>
<td>0.82</td>
<td>0.29</td>
<td>0.20</td>
</tr>
</tbody>
</table>

This table shows selected business cycle moments (HP filtered with smoothing parameter 1600) for (i) US data 1960-2007; (ii) the model of Section 4 with only news shocks; (iii) the model of Section 4 with only surprise technology shocks; and (iv) the model of Section 4 with both news and surprise technology shocks.
The solid line shows the theoretical impulse response to a news shock from the model presented in the Appendix. The dashed line is the average estimated impulse responses from a Monte Carlo simulation with 2000 repetitions and 191 observations per repetition. The estimated VAR includes TFP, consumption, output, and hours, all in levels. The investment response is imputed as the output response less the share-weighted consumption response. The shaded gray areas are the one +/- one standard deviation confidence bands from the 2000 Monte Carlo repetitions.
The solid lines are the estimated impulse responses to a news shock from a four variable VAR featuring TFP, consumption, output, and hours. The investment impulse response is imputed as output minus the share-weighted consumption response. The shaded gray areas are the +/- one standard deviation confidence band from 2000 bias-corrected bootstrap replications of the reduced form VAR.
Figure 3
Empirical Impulse Responses to Surprise Technology Shock: Four Variable VAR

The solid lines are the estimated impulse responses to the surprise technology shock, which is simply the reduced form innovation in the VAR. See also the note accompanying Figure 2.
Figure 4
Empirical Impulse Responses to News Shock: Seven Variable VAR

The solid line is the estimated impulse response to a news shock from a seven variable VAR featuring TFP, consumption, output, hours, stock prices, consumer confidence, and inflation. See also the note to Figure 2.
These are impulse responses of the “information variables” from the seven variable VAR described in Section 3. See also the notes to Figures 2 and 3.
Empirical Impulse Responses to Surprise Technology Shock: Seven Variable VAR

The solid lines are the impulse responses of the variables to the contemporaneous innovation in TFP from the seven variable system. See also the note to Figure 2.
This figure plots the four quarter centered moving average of the identified news shock series from the seven variable system described in Section 3.
In these figures the solid line is the actual level of log real output. The dashed line is the simulated log level if news shocks were the only stochastic disturbance. The shaded areas correspond to recession dates as defined by the NBER.
Figure 9
Empirical Impulse Responses of Real Wages and Real Interest Rates to News Shock: Seven Variable VAR

These are impulse responses of real wages (real hourly compensation in the non-farm business sector) and real interest rates (nominal Baa bond yield minus Michigan Survey of Consumers expected inflation). These series are included in the seven variable VAR, replacing inflation and consumer confidence. See also notes to Figure 2.

Figure 10
Empirical Impulse Responses to News Shock: Shape Restriction with Output per Hour

These are results from a six variable VAR featuring labor productivity, stock prices, consumption, hours, confidence, and inflation. The news shock is identified using a shape restriction on output per hour, as described in the text. Shaded areas are +/- one standard error confidence bands.
Figure 11
Empirical Impulse Responses vs. RBC Model Impulse Responses

The solid lines are the estimation empirical responses, identical to those shown in Figure 4. The shaded gray areas are the +/- one standard error bootstrap confidence bands. The dashed lines are the theoretical responses from the best-fitting parameterization of the simple RBC model.