News and Economic Fluctuations
Motivating Question

Can news about the future drive economic fluctuations?

• **Pigou (1927) and Keynes (1936):** Anticipation effects may be important drivers of business cycles.

• **Obstfeld-Rogoff (1995), Corsetti-Konstantinou (2012):** Changing expectations about future growth can lead to current account fluctuations.

• **Cochrane (1994):** News shocks about future TFP cannot drive business cycles in a standard model.

  Wealth effect leads to a party: ↑ consumption, but ↓ hours.

Abstract

What are the shocks that drive economic fluctuations? I examine technology and money shocks in some detail, and briefly review the evidence on oil price and credit shocks. I conclude that none of these popular candidates accounts for the bulk of economic fluctuations. I then examine whether "consumption shocks," reflecting news that agents see but we do not, can account for fluctuations. I find that it may be possible to construct models with this feature, though it is more difficult than is commonly realized. If this view is correct, we will forever remain ignorant of the fundamental causes of economic fluctuations.
The potential information in consumption:

One might doubt that agents in the economy can forecast so much better than economists. We too are consumers, and we spend more time reading the paper and poring over the data than most. But this argument forgets aggregation. Each person has information about his own prospects, most of which is idiosyncratic. Total consumption aggregates all this information about aggregate activity. Ask a consumer about next year’s GDP and he will answer “I don’t know.” But he may know that his factory is closing, and hence he is consuming less. This idiosyncratic shock is correlated with future GDP. Summing over consumers, aggregate consumption can reveal information about future aggregate activity, although neither consumers in the economy nor economists who study it can name what the crucial pieces of information are.
Response to news of 1% technology shock

FIGURE 23
Response of King/Plosser/Rebello model to news of a 1 percent technology shock.
To be specific, Figure 23 plots the response of the King, Plosser, Rebelo model to news that a 1% permanent technology shock will happen in one year. Consumption rises instantly, and then varies slowly due to intertemporal substitution effects. Labor declines. There is no current technology shock, and capital has not changed, so there is no wage-rate increase to induce more labor supply. At higher consumption levels, consumers choose to work less. Since labor diminishes, and technology and capital are unchanged, current output \((Y - (AN)^\alpha K^{1-\alpha})\) also goes down. Investment, the residual between declining output and rising consumption, declines so much I could not fit it on the graph. The boom only comes when the technology shock actually happens.

Thus, news of a future improvement in technology sets off a recession (or, perhaps more appropriately, a binge and a vacation) in the standard real business-cycle model. This behavior is robust to parameterization and to variations on the model, including adjustment costs to investment, varying labor effort, and varying capital utilization (I tried all three). In the remain-
Empirical evidence in favor of news-driven business cycles


- **Schmitt-Grohe and Uribe (2012):** Estimate a DSGE model with various types of news shocks (including non-TFP).

- These papers find that news about the future:
  - leads to an ↑ in output, consumption, investment, hours
  - can explain 50% of business cycle fluctuations
Theoretical models with news-driven business cycles

Examples:

- **Beaudry and Portier (2004):** 3-sector model, capital adjustment, complementarities.

- **Den Haan and Kaltenbrunner (2005):** model with matching frictions.

- **Jaimovich and Rebelo (2008, 2009):** Investment adjustment costs and preferences with little wealth effect on labor supply in the short-run.
Empirical evidence against news-driven business cycles

• Barsky and Sims (2011), Barsky, Basu, and Lee (2014),

- Use time series identification similar to Francis et al. (2014) to identify shocks.
- Find that a news shock ↑ consumption, but ↓ hours, ↓ output, and ↓ investment on impact.
- Find that news contributes little to our understanding of recessions, but does have some explanatory power for medium and long-run.
Empirical evidence against news-driven business cycles

• Forni, Gambetti, Sala (2014)
  
  Use a FAVAR to show that news shocks have only a small role in business cycles.

• Kurmann and Mertens (2014)
  
  Demonstrate a fundamental identification problem with the Beaudry-Portier (2006) method, suggesting that they did not identify news shocks.
A common view of the business cycle gives a central role to anticipations. Consumers and firms continuously receive information about the future, which is sometimes news and sometimes just noise. Based on this information, consumers and firms choose spending and, because of nominal rigidities, spending affects output in the short run. If ex post the information turns out to be news, the economy adjusts gradually to a new level of activity. If it turns out to be just noise, the economy returns to its initial state. Therefore, the dynamics of news and noise generate both short-run and long-run changes in aggregate activity.

This view appears to capture many of the aspects often ascribed to fluctuations: the role of animal spirits in affecting demand—spirits coming here from a rational reaction to information about the future—the role of demand in affecting output in the short run, together with the notion that in the long run output follows a natural path determined by fundamentals.
Other issues


In this paper, we examine whether this view is consistent with the data. We reach three main conclusions, the first two methodological, the third substantive.

Structural VARs typically cannot recover news and noise shocks. The reason is straightforward: if agents face a signal extraction problem, and are unable to separate news from noise, then the econometrician, faced with either the same data as the agents or a subset of these data, cannot do it either.

While structural estimation methods cannot recover the actual time series for news and noise shocks either, they can recover underlying structural parameters, and thus the relative role and dynamic effects of news and noise shocks.

Estimation of both a simple model, and then of a more elaborate DSGE model suggest that agents indeed solve such a signal extraction problem, and that noise shocks play an important role in determining short-run dynamics.
Summary of Key Papers in the News Literature
Beaudry-Portier AER 2006

(Econometric model exposited on the whiteboard in class)
Beaudry-Portier AER 2006

• Estimate the role of news in driving business cycles.

• Use an SVAR that includes stock prices to identify news to TFP.

The two disturbances we isolate with our procedure are: a disturbance that represents innovations in stock prices, which are orthogonal to innovations in TFP; and a disturbance that drives long-run movements in TFP. The main intriguing observation we uncover is that these two disturbances—when isolated separately without imposing orthogonality—are found to be almost perfectly colinear and to induce the same dynamics. We also show that these colinear shock series cause standard business cycle comovements and explain a large fraction of business cycle fluctuations. Moreover, when we use measures of TFP which control for variable rates of factor utilization, as, for example, when we use the series constructed by Basu et al. (2002), we find that our shock series anticipates TFP growth by several years.
A. Two Orthogonalization Schemes

Let us begin our discussion from a situation where we already have an estimate of the reduced form moving average (Wold) representation for the bivariate system \((TFP_t, SP_t)\) (for ease of presentation we neglect any drift terms):

\[
\begin{pmatrix}
\Delta TFP_t \\
\Delta SP_t
\end{pmatrix} = C(L) \begin{pmatrix}
\mu_{1,t} \\
\mu_{2,t}
\end{pmatrix},
\]
We want to consider two of these possibilities, one that imposes an impact restriction on the representation and one that imposes a long-run restriction. In order to see this clearly, let us denote these two alternative representations by

\[
\begin{align*}
\begin{pmatrix}
\Delta TFP_t \\
\Delta SP_t
\end{pmatrix}
&= \Gamma(L)
\begin{pmatrix}
\varepsilon_{1,t} \\
\varepsilon_{2,t}
\end{pmatrix}, \\
\begin{pmatrix}
\Delta TFP_t \\
\Delta SP_t
\end{pmatrix}
&= \tilde{\Gamma}(L)
\begin{pmatrix}
\tilde{\varepsilon}_{1,t} \\
\tilde{\varepsilon}_{2,t}
\end{pmatrix},
\end{align*}
\]

Since this system has one more variable than equations, however, it is necessary to add a restriction to pin down a particular solution. In case (1), we do this by imposing that the 1, 2 element of $\Gamma_0$ is equal to zero; that is, we choose an orthogonalization where the second disturbance $\varepsilon_2$ has no contemporaneous impact on $TFP_t$. In case (2), we impose that the 1, 2 element of the long-run matrix $\tilde{\Gamma}(1) = \sum_{i=0}^{\infty} \tilde{\Gamma}_i$ equals zero; that is, we choose an orthogonalization where the disturbance $\tilde{\varepsilon}_2$ has no long-run impact on $TFP_t$ (the use of this type of orthogonalization was first proposed by Olivier Jean Blanchard and Danny Quah, 1989). We use the two different orthogonalizations for empirical illustration.
An easy way to impose long-run restrictions (we will discuss the easier case with no cointegration)

• Suppose we have a bivariate system with TFP growth and stock price growth and we want to identify the technology shock as the only shock that affects the level of TFP in the long-run.

• It is important that all variables in the system be stationary.

• Write the first structural equation:

\[ \Delta TFP_t = \sum_{j=1}^{p} \omega_{11,j} \Delta TFP_{t-j} + \sum_{j=0}^{p} \omega_{12,j} \Delta SP_{t-j} + \varepsilon_{tech,t} \]

Technology shock not identified because of simultaneity from second structural equation. To impose the long-run restriction, estimate the following:

\[ \Delta TFP_t = \sum_{j=1}^{p} \omega_{11,j} \Delta TFP_{t-j} + \sum_{j=0}^{p-1} \theta_{12,j} \Delta^2 SP_{t-j} + \tilde{\varepsilon}_{1t} \]

By IV using lags 1 through p of ΔSP_t as instruments for the Δ^2SP_t.
FIGURE 1. IMPULSE RESPONSES TO SHOCKS $\varepsilon_2$ AND $\varepsilon_1$ IN THE ($TFP$, $SP$) VECM

Notes: In both panels of this figure, the bold line represents the point estimate of the responses to a unit $\varepsilon_2$ shock (the shock that does not have instantaneous impact of $TFP$ in the short-run identification). The line with circles represents the point estimate of the responses to a unit $\varepsilon_1$ shock (the shock that has a permanent impact on TFP in the long-run identification). Both identifications are done in the baseline bivariate specification (five lags and one cointegrating relation). The unit of the vertical axis is percentage deviation from the situation without shock. Dotted lines represent the 10-percent and 90-percent quantiles of the distribution of the impulse response functions (IRFs) in the case of the short-run identification, this distribution being the Bayesian simulated distribution obtained by Monte-Carlo integration with 2,500 replications, using the approach for just-identified systems discussed in Thomas J. Doan (1992).
Figure 2. Plot of $\varepsilon_2$ against $\tilde{\varepsilon}_1$ in the (TFP, SP) VECM

Notes: This figure plots $\varepsilon_2$ against $\tilde{\varepsilon}_1$. Both shocks are obtained from the baseline bivariate specification (five lags and one cointegrating relation). The straight line is the 45-degree line.
**Figure 4. Impulse Responses to Shocks $\varepsilon_2$ and $\tilde{\varepsilon}_1$ in the (TFP, SP) VECM, Using Basu et al. (2002) Measure of TFP (Annual, 1949–1989)**

*Notes:* In both panels of this figure, the bold line represents the point estimate of the responses to a unit $\varepsilon_2$ shock (the shock that does not have instantaneous impact on TFP in the short-run identification). The line with circles represents the point estimate of the responses to a unit $\tilde{\varepsilon}_1$ shock (the shock that has a permanent impact on TFP in the long-run identification). Both identifications are done in the baseline annual specification (two lags and one cointegrating relation). The unit of the vertical axis is percentage deviation from the situation without shock. Dotted lines represent the 10-percent and 90-percent quantiles of the distribution of the IRF in the case of the short-run identification, this distribution being the Bayesian simulated distribution obtained by Monte-Carlo integration with 2,500 replications, using the approach for just-identified systems discussed in Doan (1992).
Figure 9. Impulse Responses to $\varepsilon_2$ and $\tilde{\varepsilon}_1$ in the (TFP, SP, C, H) VECM, without (upper panels) or with (lower panels) Adjusting TFP for Capacity Utilization

Notes: In each panel of this figure, the bold line represents the point estimate of the responses to a unit $\varepsilon_2$ shock (the shock that does not have instantaneous impact on TFP in the short-run identification). The line with circles represents the point estimate of the responses to a unit $\tilde{\varepsilon}_1$ shock (the shock that has a permanent impact on TFP in the long-run identification). In this system with hours, both identifications are done in a specification with five lags and three cointegrating relations, i.e., a VAR in levels. The unit of the vertical axis is percentage deviation from the situation without shock. Dotted lines represent the 10-percent and 90-percent quantiles of the distribution of the IRF in the case of the short-run identification, this distribution being the Bayesian simulated distribution obtained by Monte-Carlo integration with 2,500 replications, using the approach for just-identified systems discussed in Doan (1992).
Figure 10. Share of the Forecast Error Variance (F.E.V.) of Consumption (C), Investment I, Output (C + I), and Hours (H) attributable to $\varepsilon_2$ (left panels) and to $\varepsilon_1$ (right panels) in VECMs, with nonadjusted TFP (top panels) or adjusted TFP (bottom panels).

Notes: This figure has four panels. The left panels display the share of the forecast variance of consumption and investment that is attributable to $\varepsilon_2$ (short-run identification) in the (TFP, SP, C, I) VECM (five lags and three cointegrating relations), of output (C + I) in the (TFP, SP, C, I) VECM (five lags and three cointegrating relations), and of hours (H) in the (TFP, SP, C, H) VECM (five lags and four cointegrating relations, i.e., a VAR in levels). The right panels display the same information in the case of the shock $\varepsilon_1$ (long-run identification). The top row uses a nonadjusted measure of TFP, while TFP is adjusted for variable capacity utilization in the bottom row.
Stock Prices, News, and Economic Fluctuations: Comment

By André Kurmann and Elmar Mertens*

Beaudry and Portier (2006) propose an identification scheme to study the effects of news shocks about future productivity in vector error correction models (VECMs). This comment shows that, when applied to their VECMs with more than two variables, the identification scheme does not have a unique solution. The problem arises from a particular interplay of cointegration assumptions and long-run restrictions.
This comment shows that, in the VECMs with more than two variables estimated by Beaudry and Portier (2006), their identification scheme fails to determine $TFP$ news. Yet these higher-dimension systems are crucial to quantify the business-cycle effects of $TFP$ news. The identification problem arises from the interplay of two assumptions. First, the Beaudry-Portier identification scheme, called BP restrictions from here on, requires that one of the non-news shocks has no permanent impact on either $TFP$ or consumption. Second, the VECMs estimated by Beaudry and Portier (2006) impose that $TFP$ and consumption are cointegrated. This cointegration means that $TFP$ and consumption have the same permanent component, which makes one of the two long-run restrictions redundant and leaves an infinity of candidate solutions. The results reported in Beaudry and Portier (2006) represent just one arbitrary choice among these solutions. The BP restrictions fail to identify $TFP$ news. The identification scheme and results presented in Beaudry and Portier (2006) therefore do not shed light on the importance of $TFP$ news shocks for business cycles.
Jaimovich-Rebelo AER 2009

They construct a model in which news about technology leads to business cycle comovements.

In their model, there is no “Cochrane Party Problem.”
Our model economy is populated by identical agents who maximize their lifetime utility \((U)\) defined over sequences of consumption \((C_t)\) and hours worked \((N_t)\):

\[
U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t - \psi N_t^\theta X_t)^{1-\sigma} - 1}{1 - \sigma},
\]

where

\[
X_t = C_t^{\gamma} X_{t-1}^{1-\gamma},
\]

and \(E_0\) denotes the expectation conditional on the information available at time zero. We assume that \(0 < \beta < 1, \theta > 1, \psi > 0,\) and \(\sigma > 0\). Agents internalize the dynamics of \(X_t\) in their maximization problem. The presence of \(X_t\) makes preferences non–time-separable in consumption and hours worked. These preferences nest as special cases the two classes of utility functions most widely used in the business cycle literature. When \(\gamma = 1\) we obtain preferences of the class discussed in King, Plosser, and Rebelo (1988), which we refer to as KPR. When \(\gamma = 0\) we obtain the preferences proposed by Greenwood, Hercowitz, and Huffman (1988), which we refer to as GHH.
Figure 3. Wealth Effects on the Labor Supply of a 1 Percent Permanent Real Wage Increase
We choose the following parameter values for our benchmark model. We set $\sigma = 1$, which corresponds to the case of logarithmic utility. We set $\theta$ to 1.4, which corresponds to an elasticity of labor supply of 2.5 when preferences take the GHH form. We set the discount factor $\beta$ to 0.985, implying a quarterly steady-state real interest rate of 1.5 percent. The share of labor in the production function, $\alpha$, is set to 0.64. We set the value of $\gamma$ to 0.001, so preferences are close to a GHH specification. We choose the second derivative of the adjustment-cost functions eval-

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{One-Sector Model, Response to News Shocks (Percentage deviation from steady state)}
\end{figure}
<table>
<thead>
<tr>
<th>One-sector model</th>
<th>News A</th>
<th>News z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum $\gamma$</td>
<td>0.650</td>
<td>0.400</td>
</tr>
<tr>
<td>Minimum adjustment costs, $\varphi''(1)$</td>
<td>0.370</td>
<td>0.400</td>
</tr>
<tr>
<td>Minimum elasticity of labor supply $\frac{1}{(\theta-1)}$</td>
<td>0.111</td>
<td>0.111</td>
</tr>
<tr>
<td>Maximum elasticity of utilization</td>
<td>2.500</td>
<td>5.000</td>
</tr>
</tbody>
</table>
“News Shocks and Business Cycles”
JME 2011
By Robert B. Barsky and Eric R. Sims

(Econometric details presented in class on whiteboard.)
Fig. 1. Model and Monte Carlo estimated impulse responses to news shocks. The solid line shows the theoretical impulse response to a news shock from the model presented in Section 2.2. 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 $\pm$ one standard deviation confidence bands from the 2000 Monte Carlo repetitions. The horizontal axes refer to forecast horizons and the units of the vertical axes are percentage deviations (times 100).
Fig. 2. Empirical impulse responses to news shock: four variable VAR. The solid lines are the estimated impulse responses to our 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. The horizontal axes refer to forecast horizons and the units of the vertical axes are percentage deviations.
Fig. 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. The shaded gray areas are the ± one standard deviation confidence band from 2000 bias-corrected bootstrap replications of the reduced form VAR. The horizontal axes refer to forecast horizons and the units of the vertical axes are in percentage deviations.
Fig. 5. Empirical impulse responses to news shock: seven variable VAR ("information variables"). These are impulse responses of the "information variables" from the seven variable VAR described in Section 3. The shaded gray areas are the ± one standard deviation confidence band from 2000 bias-corrected bootstrap replications of the reduced form VAR.
<table>
<thead>
<tr>
<th>Variable</th>
<th>$h=1$</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 forecast error variance of each variable at various forecast horizons to our identified news shock. Standard errors, from a bootstrap simulation, are in parentheses. “Total TFP” shows the total variance of TFP explained by our news shock and the TFP innovation combined. “Total output” shows the total variance of output explained by the news shock and the TFP innovation combined.
“News-Driven Business Cycles: Insights and Challenges”

Journal of Economic Literature 2014

By Paul Beaudry and Franck Portier
In their analysis, Barsky and Sims (2011) choose a horizon of forty quarters when maximizing $\sum_{j=1}^{h} \Omega_2(j)$. We follow this identification strategy with a first four-variable VARs ($TFP, Y, C, H$) estimated in levels over the period 1960:I–2007:IV, as in Barsky and Sims (2011). Impulse response functions are displayed on figure 15 with plain lines. The identified news shock is very different from the ones obtained using the combination of impact and long run restrictions suggested in subsection 3.3.2.1. In this figure, we see that hours fall in response to the identified news shock and stay for at least twenty quarters below their preshock level. Output does not increase much while $TFP$ increases very quickly following the news. This pattern is the one emphasized in Barsky and Sims (2011) and suggests that the effects of news shocks may actually be to create a recession—as would be consistent with a RBC model, as opposed to creating a boom.

![Figure 15. IRF to a News, Barsky and Sims's (2011) identification in the $(TFP, C, Y, H)$ VAR and in the $(TFP, SP, Y, H, \text{or } C)$ ones](image)

*Notes: This figure displays impulse responses to the news shock $\varepsilon_1$ in the log $(TFP, C, Y, H)$ VAR (plain lines) and in the $(TFP, SP, Y, H, \text{or } C)$ ones (dashed lines). The news shock is identified following Barsky and Sims (2011) as the shock that does not affect $TFP$ on impact and that maximizes $\sum_{j=1}^{h} \Omega_2(j)$, where $\Omega_2(j)$ is the forecast error variance at horizon $j$ that is attributed to that shock. The VAR is estimated in levels with four lags. The unit of the vertical axis is percentage deviation from the situation without shock. Grey areas correspond to the 68 percent confidence band for the $(TFP, C, Y, H)$ VAR. The distribution of IRF is the Bayesian simulated distribution obtained by Monte Carlo integration with 10,000 replications, using the approach for just-identified systems discussed in Doan (1992). The sample is 1960:I–2007:IV for the $(TFP, C, Y, H)$ VAR and 1947:1–2012:1H for the $(TFP, SP, Y, H, \text{or } C)$ ones. See the online appendix for a description of the data.*
Since this view is drastically different from the one obtained in Beaudry and Portier (2006), we estimate a second VAR over the full sample 1947:I–2012:III (to be comparable with the estimates of subsection 3.3.1) that is composed of $\{TFP, SP, Y, H\}$ of $\{TFP, SP, Y, C\}$. The main difference with the previous VAR we have estimated is that those ones include the stock prices index $SP$.

In figure 15, we report with dashed lines the impulse obtained using the method proposed by Barsky and Sims (2011), but with the stock prices index. As can be seen from the figure, the impulse responses to the identified news shock now look very similar to those presented in subsection 3.3.2.1, with both hours and consumption increasing after the arrival of news, and $TFP$ taking several quarters before starting to increase. These results highlight once again that the identification of news shocks may be sensitive to the choice of variables included in the VAR. In
What we do

We use new data on an observable news shock - giant oil discoveries – to analyze the effects of news on macroeconomic variables.

• We actually mean oil and natural gas discoveries.

• “Giant” means at least 500 million ultimately recoverable barrels.
Typical Oilfield Investment and Production Pattern

Draugen, Norway

- Investment
- Oil production

Year


Investment: 0 50 100 150 200
Oil production: 0

2000 4000 6000 8000
0 50 100 150 200

$50,000,000$
Model: Extension of Jaimovich-Rebelo OEM

- **Jaimovich-Rebelo Open Economy Model features**
  - JR preferences – shuts down most of the wealth effect on labor supply.
  - Investment adjustment costs
  - Labor adjustment costs

- **Our extensions**
  - Two-sector model
  - News is about oil sector, with 5 year lag
  - Oil sector has higher capital share, lower labor share
Oil News Shock

Baseline Model, 5 year lag of news
Econometric Specification

Dynamic panel: \( i = \text{country}, \ t = \text{year} \)

\[
y_{it} = A(L)y_{it} + B(L)\text{Disc}_{it} + \alpha_i + \alpha_t + \gamma_1'Z_{it} + \epsilon_{it}
\]

- Variable of interest
- Lags
- Current and lagged values of oil discovery news
- Country and year fixed effects
- Other control variables
- Error term
Empirical Results: Current Account (% of GDP)

Percentage response to oil discovery news. Shaded areas are 68% and 90% confidence intervals.
Percentage response to oil discovery news. Shaded areas are 68% and 90% confidence intervals.
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Some of the latest “news” results:

• Kurmann and (Eric) Sims show that different vintages of Fernald’s utilization-adjusted TFP series give different results.

• They show that the type of medium horizon restrictions Barsky-Sims used is very sensitive to measurement error.

• They use the Francis et al. version of medium horizon restrictions and find results similar to the original Barsky-Sims paper.