Three Essays on Structural Macroeconomics

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A Dissertation presented to the Graduate Faculty
of the University of Virginia in Candidacy for the Degree of
Doctor of Philosophy

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University of Virginia
July, 2013

Technology News in the Labor Market*

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Dissertation Essay 1
July 15, 2013

Abstract

I analyze the effect of an anticipated change to the level of technology (news shocks) on the aggregate labor market. I isolate the news shock associated with technology (capacity utilization adjusted measure of Total Factor Productivity) using a Structural Vector Auto Regression (SVAR) model. I find a significant response along both the intensive and extensive margins of employment. Specifically, I find that vacancies posted and hours worked jump up at the impact of a positive shock and that they stay bounded away from zero at a horizon of 10 years. In contrast, I find that the unemployment rate jumps down at impact and also remains bounded away from zero. Similarly, I find that the labor force participation rate jumps down at impact though the response is insignificant at longer horizons. Anticipation of a 1 percent increase in technology in 1 year causes an immediate jump in vacancies of 1.1 percent, of .058 percent in hours worked, a reduction of 1.45 percent in the unemployment rate and a reduction of .039 percent in the participation rate. Finally, I use the identified technology news time series to study its connection to an important part of the labor market: new business creation. I find that the index of new business is granger-causal for positive news shocks indicating that the standard assumption of exogenous technological advancement in empirical and theoretical macro modeling needs reworking.

JEL Classification: C32, E17, E24

Keywords: business cycles, unemployment, SVAR models

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*I thank Chris Otrok, Toshi Mukoyama, and Eric Young for their guidance. I also thank seminar participants at the University of Virginia and the Federal Reserve Board of Governors for their helpful comments. I received support from the Bankard Fund for Political Economy for this paper. All errors are mine.

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1 Introduction

Can news about upcoming changes to macroeconomic fundamentals contribute to the comovement between major aggregate variables? Such an expectations-driven business cycle has received increased attention recently[1] because it presents a view of business cycles that is in contrast to the real business cycles literature that started with Kydland and Prescott (1982). Instead of relying upon on large technological shocks or other changes in fundamentals to explain the observed comovement, proponents of a news driven cycle state that good news about the future is enough to generate a boom today and a realization of a fundamental variable that is poorer than expected is sufficient to bring about a downturn. In other words, a recession need not be the result of actual changes in any observable variable but the rational response to bad news about the future.

In this paper, I consider the possibility that a news shock that reveals the level of technology in the future drives the labor market. I define technology as the capacity utilization adjusted measure of Total Factor Productivity[2] (TFP from here on) and TFP news as a *noise-free* signal received today of the level of technology at some point in the future. Such a signal is by its nature different from other types of news shocks studied in the literature,[3] like shocks to fiscal policy. This is because changes to fiscal policy are observable in a way that changes to technology are not. Despite this characteristic of technology news shocks, the literature has repeatedly confirmed their existence and to a lesser degree, their relevance for predicting movements in macroeconomic variables. In this essay, I study the significance of TFP news shocks in driving the dynamics of the following labor market variables: unemployment, vacancy postings, participation rate and hours worked.

Technology news can have an effect on worker and firm decisions to enter the labor market for a couple of a priori reasons. In response to good news firms may try to secure labor now in anticipation of an increasingly crowded labor market while unemployed/out-of-the-labor-force workers may enter the labor market to capitalize on their increased marginal productivity in the future. Similarly, as a response to bad news firms may begin downsizing their workforce in anticipation of unfavorable market conditions.

In line with the literature, I test these hypotheses of the labor market using post-War US

[1]See Barsky and Sims (2011), Beaudry and Portier (2004, 2006, 2007), Den Haan and Kaltenbrunner (2009), Jaimovich and Rebelo (2009), Kurmann and Otrok (forthcoming), Krusell and Mckay (2010).

[2]See Basu, Fernald and Kimball (2006).

[3]See Leeper, Walker, Yang (forthcoming).

time series data on a suitably modified Structural Vector Auto Regression (SVAR) model. I identify TFP news in the SVAR model with the following variables: TFP, stock prices, investment, consumption, unemployment, vacancy postings, hours worked, and labor force participation rate. The key assumption that underlies my method is that two orthogonal shocks (a contemporaneous shock and a news shock) drive technology. The former is a surprise change to the level of technology in the current period while the latter contains information on upcoming changes to technology. Under this assumption, the TFP news shock is the structural shock orthogonal to the contemporaneous TFP shock that best explains the variation in TFP at a long finite horizon.[4]

I find that TFP news has a significant bearing on the labor market. Vacancies posted and hours worked jump on impact, temper their gains in the short-run but are bounded away from zero at a horizon of 40 quarters. Further, the unemployment rate jumps down when a TFP news shock hits, tempers its losses in the short-run and once again is bounded away from zero at a horizon of 40 quarters. And finally, I find that the participation rate jumps down at impact though the response is insignificant at longer horizons. A 1 percent TFP news shock (that will increase TFP by 1 percent in 1 year) increases vacancies by 1.1 percent, hours worked by 0.058 and reduces unemployment by about 1.45 percent and participation by .039 percent on impact.

The primary identification scheme used in this essay is a partial one. It cannot identify all the structural shocks that exist in the system but only those that satisfy the narrow criteria specified. The identified shocks may be classified as belonging to the set of supply shocks hitting the economy. I show below that these shocks explain between a third and a half of the variation in most of the labor market variables at a horizon of 40 quarters. The remaining variation may the result of demand shocks, other types of supply shocks, or shocks to regulation.

This paper contributes to the literature started by Gali (1999) looking at the effects of technology shocks on the labor market. Though, much of that work looks at the effects of a contemporaneous but permanent shock to technology on hours worked. This particular focus is the result of the relative prevalence of RBC type models since Kydland and Prescott (1982). The consistent conclusion from much of the literature starting with Gali (1999), however, is

[4]As in Francis, Owyang and Roush (2005) I find that my empirical estimates are dependent on the actual horizon chosen. However, I do not find a large difference in results over 12, 24, 40 quarter horizons (more on this in a later section). So, to maintain comparability with the literature I highlight results for 40 quarters.

that standard technology shocks alone cannot account for much of the variation we see in the labor market, a point made by this essay as well. The results presented here suggest that a model of the economy must incorporate the sensitivity of unemployment, vacancies, hours worked and the participation rate to shocks that are not of the contemporaneous, permanent variety. This 'other' kind of shock, a news shock, in fact, is a much bigger contributor to the variation in aggregates of the labor market and thus, needs an account in models of the economy.

The results of the empirical model discussed above and the implications they generate are closely tied to the definition of 'news shock' employed and the identification restrictions used (e.g.choice of horizon). I argue below that my primary identification scheme is well suited to study the question at hand, but nevertheless, it does not enjoy unanimity in the literature. As a consequence, to maintain comparability and as robustness check I provide results for an alternative identification scheme.

The other dominant approach uses a sequential scheme to identify the news shock instead of medium term restrictions.[5] I run a VAR on the same data but I follow a two-step identification approach. I first identify the structural shock associated with stock prices in the contemporaneous identification and the structural shock associated with TFP in the long-run identification. I find that these two seemingly disparate approaches identify the same shock. This shock has no affect on TFP in the current period but it does affect stock prices now and increases TFP in the long run. Given these characteristics, I label the identified shock as TFP news and observe a qualitatively similar labor market response to the shock (more on the quantitative differences below). Once again vacancy postings and hours worked jump up on impact, temper gains and remain bounded away from zero while unemployment jumps down, tempers losses and also remains bounded away from zero. The participation rate again jumps down at impact but reacts insignificantly over the longer run.

The two schemes implemented here, however, disagree at some horizons for a subset of variables. As in both Barsky and Sims (2011) and Francis, Owyang and Roush (2005), the approach preferred by this essay encompasses the other as the horizon over which forecast error variance is maximized grows without bound. Correspondingly, I find a stronger response in TFP to a news shock with the latter approach and marginally different responses in the labor market.

[5] See Beaudry and Portier (2006), Beaudry, Dupaigne and Portier (2011).

In sum, my results suggest that the labor market responds along both the intensive and extensive margins of employment as a reaction to technology news. Existing workers tend to work harder while existing firms tend to expand their labor force. But the market for labor is only partially characterized by the variables utilized in the baseline model. Of particular interest for the US economy, given its long-standing tradition of encouraging entrepreneurship, is the connection between new business creation and technology news.

A time series exists for this variable[6] though it is limited in duration and granularity in relation to the rest of my data. Consequently, I cannot use a SVAR to identify the effect of any structural shock on the formation of new business. Nevertheless, the less involved test of granger-causality is revealing. I find that new business creation is a significant predictor of positive technology news. The results cast doubt on the often made assumption that all structural shocks related to technology are exogenous.

The rest of the paper is as follows: the next section goes through the relevant empirical and theoretical papers. Section 3 begins with a description of the data, derives some basic properties of VAR models and goes through the baseline identification procedure. Section 4 discusses the results. Section 5 contains the robustness checks performed along with a comparison of the two identification approaches used in this paper. Section 6 provides some discussion of the findings. Section 7 looks at the implications for models. Section 8 discusses the connection between technology news and new business creation. The last section provides some concluding remarks.

2 Literature Review

This essay contributes to the following two strands of literature in the study of Business Cycles: the role of technology shocks in influencing aggregate fluctuations, and the effect of anticipating a change in a variable (technology) fundamental to the economy. Below I discuss relevant works in these areas.

2.1 Related Empirical Work

Much of the recent empirical work looking at the effect of technology shocks on the labor market begins with Gali (1999), which looks at the effect of a contemporaneous but per-

[6]The Kauffman Foundation has produced an annual index of entrepreneurship for the US since 1996.

manent shock to technology on hours worked.[7] The author concludes that such technology shocks lead to a decline in hours and a rise in unemployment. So, this shock alone cannot account for the cyclical movements in the economy. Similarly, Francis and Ramey (2005) extends the analysis by augmenting the empirical model in Gali (1999) with a capital tax rate. The identified technology shock has a permanent effect on real wages and no permanent effect on hours worked. The authors confirm that, once again, technology shocks lead to a drop in hours on impact. In contrast, Christiano, Eichenbaum, and Vigfusson (2003) find a rise hours as a response to a technology shock using the restrictions imposed by Gali (1999). The authors show the difference in conclusions rests on how hours enter the empirical model (log-levels vs. log-differences).

Canova, Lopez-Salido, and Michelacci (2010) extends the question and looks at the effect of technology shocks on the extensive margin of employment, and characterizes the response of both the job separation rate and the job finding rate. They find that a contemporaneous but permanent shock to technology leads to an increase in the number of employed workers, a decrease in the unemployment rate, and an increase in the job separation rate (which drives most of the variation in unemployment). They also find a contemporaneous but permanent shock to the marginal efficiency of investment leads to a rise in hours worked and to a lesser degree, in employment. They conclude (in contrast to the aforementioned literature) that standard technology shocks (contemporaneous permanent changes to TFP) are important for explaining the volatility of unemployment (extensive margin) while investment specific technology shocks are important for the variation in the intensive margin.

This set of papers considers the effect of a contemporaneous and permanent shock to technology. A related strand of literature argues that the expectation of a change in the variable is enough to bring about a change in real quantities. In recent work, this idea received support from Beadury and Portier (2006). They use a SVAR model on post-War US data on technology, stock prices, consumption, investment, and hours worked. Their scheme rests on the idea that stock prices can behave as a proxy for the information set of the economic agent. If technology news exists, upon receiving it the representative agent will use this information in the stock market causing the price to reflect or be a proxy for the unobservable technology shock. This intuition is embedded in a sequential identification scheme. They extract the structural shock that affects technology only in the long run but

[7] This focus is a result of the emphasis on the current level of technology in driving the representative agent's level of labor supplied in the standard RBC model.

may affect stock prices right now (long-run identification). They then extract the structural shock that affects stock prices contemporaneously (short-run identification). They compare these structural shocks and find that the effects on the other variables in the system are qualitatively and quantitatively similar. They conclude the shock they have extracted is unique and fits the description of a news shock. The authors use a similar methodology in Beaudry and Lucke (2010) and Beaudry, Dupaigne and Portier (2011). But here they identify five shocks, unanticipated TFP, anticipated TFP (news), unanticipated investment, preference, and monetary. In each, the authors find strong conditional comovement among major macroeconomic aggregates as a response to news.

The aforementioned strand of literature relies on long-run restrictions for its results. But as we know from Faust and Leeper (1997) and as summarized in Francis, Owyang, and Roush (2005), such restrictions produce impulse responses that are biased in sign or in magnitude. As a response to that criticism, Barsky and Sims (2011) studies this question using medium term restrictions and post-War US data on technology, stock prices, hours, output, inflation and consumer confidence. In the paper, the authors impose the restriction that the technology news shock be the structural shock that maximizes the contribution to the forecast-error variance of technology over a long finite horizon. The authors confirm that the news shock exists but leads to an increase in consumption and a decline in hours worked, investment, and output. Further, the shock leads to disinflation, increases in stock prices, consumer confidence, real wages, and real interest rates.

Barsky and Sims (2012) show that consumer confidence can be a useful predictor of changes in the economy. They reason that either the consumer confidence variable directly brings about the change in the future or that it essentially reflects that economic agents have early information of upcoming changes to the economy. Using a VAR analysis, the authors conclude that positive shocks to confidence are correlated only with long-run changes in output implying that agents have superior information about the economy.

The disagreement between Beaudry and Portier (2006) and Barsky and Sims (2011) (most notably when it comes to investment) highlights the role that the chosen identification scheme plays in providing empirical estimates of impulse responses. As a result, I show the results for both approaches applied to my data while controlling for the disputed variable in the empirical model.

2.2 Related Theoretical work

Schmitt Grohe and Uribe (2012) study the importance of news shocks using a structural model. Here, the authors create a DSGE model with anticipated and unanticipated shocks to technology, investment-specific productivity, and government spending. The model features real rigidities in investment adjustment costs, variable capacity utilization, habit formation in consumption, and leisure. The representative agent may receive information on each of these variables up to three quarters in advance (shocks may hit unexpectedly as well). They find that, in sum, news shocks drive most of the variance in output, consumption, and investment.

Khan and Tsoukalas (2012) estimate a model featuring both real and nominal rigidities and find that TFP news shocks are quantitatively unimportant in comparison to Schmitt-Grohe and Uribe (2012). They find that the amount of variation explained by technology news for output, consumption, investment growth, and hours is below 4 percent. Further, they find that it is the unanticipated shocks which drive most of the movements in these variables. The differences between the findings in Khan and Tsoukalas (2012) and Schmitt Grohe and Uribe (2012) point to the role that nominal rigidities play in the estimated models. The former paper shows that nominal frictions allow counter-cyclicality in both wage and price markups leading to a higher employment demand and supply than otherwise. As a result, they show that unanticipated shocks lead to strong responses in investment, output, and consumption and that the amount of the variation explained by the sum of unanticipated shocks far outweighs the amount explained by technology news.

Similarly, Fujiwara et al. (2011) estimate a New Keynesian DSGE model augmented with unanticipated and anticipated shocks to TFP to evaluate the performance and importance of technology news in driving aggregate fluctuations. Expectedly, in a model featuring nominal frictions, the authors do not find a large role for news with a maximum of 15 percent of the variation in output, hours, investment, and consumption resulting from news in the baseline specification.

3 Empirical Model

This sections contains a description of the data used, a brief primer on the basics of VAR modeling, the details of the empirical model and the identification scheme used.

3.1 The Data

The data used in this paper is public and is available in a quarterly frequency from the period 1957-2011. TFP is the capacity adjusted Total Factor Productivity series from Basu, Fernald and Kimball (2006) available on Fernald's website. The stock market index is the quarterly S&P 500 stock price index deflated by the Consumer Price Index. Consumption and Investment are the real per capita values of personal consumption expenditures and private domestic investment, respectively, available from the St. Louis Fed. The participation and unemployment rates are seasonally adjusted measures available from the BLS. The measure of the intensive margin of employment, average hours worked, is the seasonally adjusted measure for the non-farm business sector also from the BLS.

The data on vacancies has 2 sources: from 1957-1995, the series is the Conference Board's newspaper help-wanted index available on Wouter Den Haan's website and from 1995 to 2011 the series is the composite help wanted index of Barnichon (2010) which is available on his website. The need for this measure of vacancies arises because of the introduction of online vacancy postings starting in the mid-90s and the relative decline of newspaper advertising since that period.

3.2 VAR Basics

I begin by discussing the fundamentals of VAR models followed by the specifics of the identification scheme. A reduced form model in p lags is written in the following way:

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + B_3 Y_{t-3} + \cdots + B_p Y_{t-p} + u_t$$

In the equation above, Y_t is vector of observables of size mx1 and u_t is vector of unobservables of size mx1 with variance-covariance matrix Σ. In this form of the Vector Auto Regression model, no endogenous left-hand side variable has any simultaneous impact on any other endogenous variable (hence the term 'reduced-form'). The model, as written[8] faces an identification problem. To see this, rewrite the model in its MA(∞) form:

$$Y_t = [B(L)]^{-1} u_t = C(L) u_t \tag{1}$$

[8]assuming stationarity.

where $B(L) = I - B_1L - B_2L^2 - \cdots - B_pL^p$ and $C(L) = I + C_1L + C_2L^2 + \ldots$

Pick one of the multitude of square-roots of $\Sigma = AA'$ and define $v_t = A\xi_t$ where ξ_t is a vector of structural shocks and its variance-covariance matrix is I_m. The new series of estimated impulse responses

$$Y_t = C(L)v_t \tag{2}$$

is observationally equivalent to the old series. Additionally, we may also rewrite the series as:

$$Y_t = C(L)\eta_t \tag{3}$$

where $\eta_t = \bar{A}\xi_t$ and $\bar{A}$ is the **Cholesky** decomposition of Σ.

Yet another identification scheme follows:

$$Y_t = C(L)\epsilon_t \tag{4}$$

where $\epsilon_t = \bar{A}S\xi_t$ and $SS' = I_m$.

This last formulation proves to be the most convenient as it spans the full m-dimensional set of possible identification schemes as S varies. To choose among these we need to impose identification restrictions. The next sections discuss the specifics of the problem studied in this essay and the restrictions imposed.

3.3 Definition of Technology News

Most empirical work studying the effect of technology considers only the contemporaneous and unanticipated shock. While such technology shocks are important in our understanding of the economy, I test the idea that advance information of changes to technology is significant as well. I assume that economic agents receive two kinds of information regarding technology: contemporaneous and news.

With Y_t defined as the vector containing TFP, stock prices, consumption, investment, and the labor market variables, respectively, the stochastic process for TFP (with $S = I_m$ in (4) above) is:

$$TFP_t = C_{(1,1)}(1)\epsilon_t(1,1) + C_{(1,2)}(2)\epsilon_{t-1}(2,1) + C_{(1,2)}(3)\epsilon_{t-2}(2,1) + \ldots \tag{5}$$

This equation shows that technology in period t is affected by only the contemporaneous shock in period t ($C_{(1,1)}(1)\epsilon_t(1,1)$) or by a news shock emanating from any previous period ($C_{(1,2)}(2)\epsilon_{t-1}(2,1) + C_{(1,2)}(3)\epsilon_{t-2}(2,1) + \ldots$).

Implicit in this definition is that technology is entirely unaffected by the other structural shocks in the system. The remaining $m-2$ structural shocks can perturb any of the other $m-1$ variables while the two identified structural shocks affect every variable. Further, given that the aim of this paper is to study only the effect of technology news, a full account of identification scheme (a matrix S that defines each structural shock) is unnecessary. Consequently, the scheme employed is a partial one.

The particular identification I employ is most closely related to Barsky and Sims (2011) which builds on Francis, Owyang, and Roush (2005), Faust (1998) and Uhlig (2003, 2004). In a nutshell, I estimate a reduced form VAR in these variables and isolate the contemporaneous TFP shock. I extract a TFP news shock as the structural shock orthogonal to the contemporaneous TFP shock that best explains the variation in TFP over a 10 year horizon. In practice, this amounts to finding a linear combination of the other reduced form shocks that maximizes the contribution to the variance decomposition of TFP. The next section describes this procedure in greater detail.

3.4 Identification

I first define the contribution made by a structural shock to a variable's total variation in the VAR system for a fixed identification and then allow the identification scheme to vary to pick the one that maximizes this contribution. Using (4) above as a starting point, the forecast error over the next h periods is:

$$Y_{t+h} - E_{t-1}Y_{t+h} = \sum\nolimits_{\tau=0}^{h} C_\tau \bar{A} S \epsilon_{t+h-\tau} \tag{6}$$

The share of the forecast error variance of variable i attributable to shock j at horizon h is given by:

$$\Omega_{i,j}(h) = \frac{e_i'\left(\sum_{\tau=0}^{h} C_\tau \bar{A} S e_j e_j' S' \bar{A}' C_\tau'\right) e_i}{e_i'\left(\sum_{\tau=0}^{h} C_\tau \Sigma C_\tau'\right) e_i} \tag{7}$$

where e_i is mx1 with a 1 in the ith place and zeros elsewhere. The numerator of this equation shows the variance contributed by shock j to variable i over the next h periods for a chosen identification scheme while the denominator shows the total variation produced by all shocks to variable i over the next h periods. Their quotient produces the desired variation contribution. This expression is simplified a bit to leave only the mx1 vector γ that entirely defines the identification scheme:

$$\Omega_{i,j}(h) = \frac{\sum_{\tau=0}^{h} C_{i,\tau}\bar{A}\gamma\gamma'\bar{A}'C'_{i,\tau}}{\sum_{\tau=0}^{h} C_{i,\tau}\Sigma C'_{i,\tau}} \tag{8}$$

In the numerator of equation above, the term $C_{i,\tau}\bar{A}$ is a 1xm vector showing the 'unweighted' effect of each structural shock on only variable i at horizon h, while its product with the mx1 vector γ produces the weighted effect. The denominator shows the total variation that exists in the i-th variable.

Given the ordering of the VAR system described above, the process of estimating the structural shock amounts to properly choosing the weighting vector γ so that the total contribution to the variance is as large as can be over some chosen horizon H. This is a grid search problem where the effect of structural shock 2 (news) on variable 1(TFP) is maximized:

$$\begin{aligned} \underset{\gamma}{\text{maximize}} \sum_{\tau=0}^{H} \Omega_{1,2}(h) \\ \text{subject to} \\ \gamma(1,1) = 0 \\ \gamma\gamma' = 1 \end{aligned}$$

The first constraint reiterates the definition of technology news provided in (5) so that news can affect TFP only in the future and the only shock that affects technology contemporaneously is the first structural shock. The second constraint ensures that the chosen vector is essentially a weighting vector and that it is a column of some square root of the Identity. These two constraints combine to estimate the structural news shock as the shock resulting from a particular linear combination (weighting) of the other (non-TFP) contemporaneous shocks.

4 Results

Though many model variables appear to not be stationary, I follow Hamilton (1994) by estimating the system in levels under both identification schemes. The text argues that the resulting estimates of impulse responses are consistent and are robust to co-integrating relationships of unknown degree.

The empirical model features 2 lags as dictated by the Akaike Information Criterion. I show one standard deviation bootstrapped standard errors. Below, I discuss results for the baseline Barsky and Sims (2011) (BS) identification.

Figure 1 displays the results for vacancies and unemployment. Figure 2 displays the results for hours and stock prices while Figure 3 displays the impulse response in TFP and the labor force participation rate. The figures indicate that a future increase in TFP causes an increase in vacancies, participation rate and hours and a reduction in unemployment and participation upon impact. Each labor market variable except the participation rate is indicated to be bounded away from zero over a 10 year horizon.

Note that, we see an immediate increase in the forward looking stock price variable at the impact of the identified shock. This response suggests that as investors receive technology news, they adjust their expectation of present-discounted value of profits for US firms and as a result, we see a sustained jump in the variable.

Tables 1 and 2 reveal the magnitude of the effects of a 1 percent TFP news shock in 1 year and at impact, respectively. At impact I find a 1.1 percent increase in vacancies, 0.058 percent increase in hours, .039 percent decline in the participation rate and a 1.45 percent decline in unemployment. One year later, I find 5.56 percent increase in vacancies, 0.172 percent increase in hours, .042 percent decline in the participation rate and a 6.30 percent decline in unemployment.[9] Tables 1 and 2 also state the effects of the TFP news shock as estimated by the Beaudry and Portier (2006) (BP) identification, which are discussed in a later section.

For the baseline BS identification I also estimate the contribution of the identified shocks[10] in explaining the variation in these variables. Figure 4 displays the contribution of the contemporaneous TFP shock along with the TFP news shock to vacancies, Figure 5 displays the contribution of the identified shocks to the unemployment rate, Figure 6 displays the

[9] The Beveridge ratio is estimated to be approximately 2.5 at impact and 12 at a period of 1 year.

[10] Note that since the identification scheme used is only a partial one, I cannot provide the contributions of the other structural shocks.

contribution to hours worked, Figure 7 displays the contribution to stock prices, Figure 8 for LFP and lastly, Figure 9 displays the contribution to TFP. I find that TFP news explains between a fifth and a third of the variation in most labor market variables while both shocks taken together account for anywhere between a third and a half of the variation.[11] I find that TFP news is considerably more significant in explaining the movements in these variables when compared to the contemporaneous shock.

5 Robustness Checks

As a robustness check, I employ the Beaudry and Portier (2006) identification scheme. The primary motive for this exercise is to note any divergence in the qualitative nature of the response to news shocks for any of the labor market variables. The responses in investment and to lesser degree, consumption, for example, are dependent on the identification scheme used as pointed out by Barsky and Sims (2011). As a result, I include both variables as controls and identify the effect of a news shock using this alternative method.

5.1 Alternative Identification - Beaudry and Portier Approach

Using equation (1), an observationally equivalent series may be produced as follows:

$$Y_t = [B(L)]^{-1}u_t = C(L)u_t = C(L)A\epsilon_t \tag{9}$$

where $AA' = \Sigma$, ϵ_t is a vector of structural shocks, the variance-covariance matrix of ϵ_t is I_m, and $C(L) = I + C_1L + C_2L^2 + \dots$

Note that A may be *any* square root of Σ and not just the Cholesky as was assumed in an earlier section. The Beaudry and Portier (2006) approach proceeds sequentially:

- In the first step, a restriction is placed on only the contemporaneous impact matrix A that it be the Cholesky decomposition of Σ.
- In the second step, a restriction is placed imposing lower-diagonality on the product: $C(1)A$. Note that $C(1) = I + C_1 + C_2 + \dots$ is the reduced-form long-run impact matrix while $C(1)A$ is the structural long-run impact matrix. While both schemes are

[11] The lone exception is the labor force participation rate.

essentially imposing structure on the impact matrix A, only the latter scheme does not restrict it to be lower diagonal.

As before, the VAR is ordered with TFP first followed by Stock Prices, Consumption, Investment, and the labor market variables, respectively. Imposing lower diagonality on the impact matrix for the first part of the identification procedure amounts to forcing Stock Prices to respond only to a contemporaneous (first structural) and news shock (second structural) to technology. Similarly, imposing lower diagonality on the structural long-run impact matrix forces the first structural shock to be the sole cause of movements in TFP in the long run though it may affect Stock Prices at any time horizon.

The sequential scheme used here is different from the scheme used in the baseline specification in that this one is complete. The full space of structural shocks is able to be identified under this scheme though the focus is primarily on the first structural shock in the long-run identification and the second structural shock in the short run identification. The other structural shocks identified, while informative, are irrelevant to the question studied in this essay and are discarded.

5.2 Alternative Results

Figure 10 indicates the impulse responses for TFP under the sequential BP identification scheme. The top panel shows the impulse response that results from the structural shock associated with TFP in the long run identification while the bottom panel shows the impulse response associated with stock prices in the contemporaneous identification. Figure 11 follows the same pattern for stock prices, Figure 12 for the unemployment rate, Figure 13 for vacancies, Figure 14 for the participation rate and Figure 15 for hours worked.

The overarching theme in these figures is that the top and bottom panels are quantitatively similar and thus, the sequential scheme identifies the same shock. The shock does not affect TFP now, does affect TFP in the future and affects stock prices now. So, the identified shock fits the bill to be classified as a news shock. The implied mechanism is captured by the efficient markets hypothesis: investors receive technology news and correspondingly revise their expectations for the present discounted value of US firm profits which causes a change in the stock price index.

5.3 Comparison

How does the Beaudry and Portier (2006) approach compare to the identification scheme used in the baseline specification? Recall that the former identification requires the technology news shock be such that it affects technology only in the long run but may affect stock prices in the current period. The intuition behind the approach is that good news, if it exists, is reflected quickly in the information variable of Stock Prices. In practice, this shock is extracted by imposing lower diagonality on the contemporaneous and long-run impact matrices.

The key differences between this approach and the one favored in this paper are the former's reliance on long-run restrictions and its imposition of enough identification restrictions to extract the entire structural shock vector.

From (3) above we see that imposing a long-run restriction amounts to imposing a restriction on an infinite sum of polynomial matrices. As shown using Monte Carlo methods by Erceg, Guerrieri, and Gust (2004), and Chari, Kehoe, and McGrattan (2003) these restrictions may face a small sample problem. The authors argue that finite datasets produce imprecise estimates at long horizons and so, identification schemes based on these imprecise estimates may be misleading.

Apart from the possible imprecision in estimates at the very long horizon, the Beaudry and Portier (2006) approach is imposing more restrictions on the data than are needed. In keeping with the terminology above, the entire S matrix in (5) is estimated instead of only a single row as in the primary identification scheme of this essay. The other identified vectors, though informative, are irrelevant to the study at hand and do not lend themselves to an obvious economic interpretation.

Finally, as shown by Barsky and Sims (2011), their approach leaves unexplained smaller fractions of the forecast error variance at business cycle frequencies than the Beaudry and Portier (2006) approach. The latter approach may leave up to one third of the variance of TFP unexplained while former method cannot account for only about 5 percent.

5.4 The Role of Alternative Horizons

The results in the baseline model are for an exogenously chosen horizon of 40 quarters. Since there is no theory-driven reason for choosing this value, I present other results as well. Figures 16 and 17 show the contribution of the two identified shocks in explaining TFP under different definitions of news shocks.

Figure 16 identifies technology news as the structural shock that maximizes the contribution at a horizon of 24 quarters while Figure 17 identifies technology news as the structural shock that maximizes contribution at a horizon of 12 quarters. The figures show that as the horizon used in the definition decreases, the scheme leaves unexplained a smaller percentage of the variation over that new horizon while leaving a greater percentage unexplained over other horizons. For example, if technology news is as in Figure 9, we see that the shock explains a larger portion of the variation over 40 quarters than in the other two figures. This result is consistent with both Francis, Owyang, and Roush (2005) and Barsky and Sims (2011).[12] Though the significance of news shocks changes slightly, it still true that contemporaneous shocks to technology drive most of the variation and that the impulse effects on the other variables in the system are close.

6 Discussion

The lesson from the results is that technology news leads to a response in employment along both the intensive and extensive margins. As agents get good news regarding an upcoming change to technology, we observe matched firms and workers choosing to work harder (longer hours) and unmatched firms and workers doing their best to get in a match. Further, we see an immediate increase (though not necessarily in the short to medium term) in the participation rate as previously discouraged workers choose to enter the market for labor. And finally, we observe a consistent decline in the unemployment rate.

The variance decomposition of each of these variables to the two identified shocks shows that even though technology news explains a comparatively small amount of the variation in technology, it is much more significant in our understanding of the labor market. The contemporaneous shock explains more than twice as much of the variation in technology (much more at most horizons) while explaining as little as a fifth (much less at most horizons) of the variation in the important labor market variables.

Though technology news is more significant to the labor market than the contemporaneous shock, it need not be that news is the most important structural shock. The identification strategy used above is only a partial one. It leaves open the possibility that another uniden-

[12] In fact, these papers shows that the Beaudry and Portier (2006) scheme is a special case of their identification as the horizon grows without bound, though the bias gets increasingly worse.

tified shock is more important in explaining the labor market than are the identified shocks.

Note that the shocks identified in this essay are from the supply side (though they are not the only shocks that can meet this definition). It may be argued that shocks from the demand side are as important for some of these variables. A shock to preferences, for example, may lead to a strong response along both the intensive and extensive margins of employment. This question is left for future research.

Another area ripe for more study is the divergence in the estimated impulse responses for a set of variables over the two identification schemes. Though the immediate responses for each variable are relatively close over the two identification schemes it is not necessarily so for longer terms. In the short and medium term we see a difference in the impulse response of LFP and TFP. In the former variable, we observe a temporary rise followed by an eventual return to zero predicted by the BS approach while the point estimate given by the BP approach is stronger. Similarly, the response in TFP is much weaker over 40 quarters for the BS approach. These differences are mildly reminiscent of the different responses in investment given by Beaudry and Portier (2006) and Barsky and Sims (2011) though, there is no large qualitative difference.

7 Implications for Models

This essay contributes to the literature started by Gali (1999) looking at the effects of technology shocks on the labor market. The consistent conclusion from that paper and the ones that have followed it has been that the standard RBC model gives too much significance to the contemporaneous and permanent technology shock. In a broad sense, this is a conclusion made by this essay as well. More specifically, the results presented here suggest that models dealing with aggregate fluctuations need to incorporate the effects of the anticipation of changes to technology. Though the contemporaneous shock to technology explains a great amount of the variation in itself it does not explain most of the movements in the labor market variables studied here.

The results suggest that macro models must account for the sensitivity of employment (in all its dimensions) to a news shock. Not only do existing workers and firms operate more intensively, but we also see significant changes along the extensive margin as employers post vacancies and new workers join the labor force. The resulting persistent change in the unemployment rate, consequently, is driven without significant contribution by the contemporaneous shock to technology.

In addition, the findings suggest that average weekly hours worked by an employee is a relatively stable variable when compared to the unemployment rate.[13] This reflects that a firm-worker pair is able to change its employment status much quicker than it can change the intensity with which it operates, a finding that is partly a result of the soft-cap on hours worked imposed by Federal regulation. Models that treat total hours worked homogenously (characteristic of RBC modeling) may miss the importance of adjustments along the extensive margin of employment.

The adjustments that may occur along either the intensive or extensive margins for matched firms constitute an incomplete list of all of the reactions in the labor market. In the next section, I study the connection between news and the formation of new businesses. This particular reaction along the extensive margin turns out to be important not because of how it is affected by the identified shock but because of its significance in predicting good news.

8 News and Entrepreneurship

I discuss first the relevant paper and the data used, followed by a brief description of granger causality and its associated tests. I then discuss the results of several such tests and their implications for modeling.

8.1 Background

Lucke (2013) tests the idea that the identified news shock in Beaudry and Lucke (2010) contains information[14] about upcoming technological advances. Instead of relying on the non-intuitive definition of technology as used by mainstream macro (and in particular, by Basu, Fernald and Kimball (2006)), Lucke (2013) considers the effect of news shocks on the number of patents granted in the US.[15] If the interpretation proposed by Beaudry and Lucke (2010) is correct that the identified shock contains information about changes to technology,

[13]Andolfatto (1996) reports that in an accounting of the variation in total hours worked, the amount contributed by changes in employment is twice the amount contributed by changes in average hours worked.

[14]The identification scheme utilized here is closely related to that of Beaudry and Portier (2006). Essentially, the news shock affects TFP only in the long-run while increasing Stock Prices today.

[15]The methodology used in Lucke (2013) is particularly imaginative given the use of annual patent data. The author is able to identify the technology news shock using quarterly data (over a longer time period) and then aggregate to an annual frequency for empirical tests.

then it should also be predictive for its proxies, namely, the number of patents granted. Indeed, this intuition is confirmed by tests for granger causality.

Using similar intuition and the aforementioned results, I test for the presence of a relationship between the news shock identified by the baseline model and the index of new business creation. If technology news is relevant for understanding the labor market, then it must also be predictive for this index. I test this reasoning using the identified news shock along with data from the Kauffman Foundation on the Index of Entrepreneurial Activity which is available annually from 1996-2011. The time series uses matched CPS microdata to identify the number of individuals who start new businesses.

Note that the index of entrepreneurship may be a part of the data on vacancies used above. New business owners might post vacancies that become a part of vacancy measure created by Barnichon (2010) though the overlap is likely to be insignificant.

8.2 Granger-Causality

One variable is granger-causal for another if an unexpected change in one later leads to a change in the other. More specifically, assuming stationarity, a variable x granger-causes variable y if and only if any lagged values of x have predictive power for y over and above its own lagged values. Let

where we fail to reject the null that $b_1 = b_2 = \cdots = b_q = 0$ for all admissible q.[16]

8.3 Results and Implications

I estimate several bivariate VARs in the two identified news shocks from the baseline model along with the entrepreneurship index. To maintain comparability with Lucke (2013) I also use publicly available annual data on patents granted from the US Patent Office. The model features a constant, a linear trend and one lag as chosen by the Akaike criterion.

My findings once again suggest that news is a predictor of patents granted confirming the view that the identified news shock is technological in nature. Unlike in Lucke (2013), however, I find that the number of patents is a predictor of news as well. So, I find two-way granger causality between the variables which suggests that there is an unidentified

[16] It is important to note that the term 'granger-causal' is not synonymous with 'causal.' It is wholly possible that a third unidentified variable is directly responsible for one or both of the variables in question.

third variable (or possibly a set of variables) with greater explanatory power. Lastly and unexpectedly, my findings suggest that new business formation is granger-causal for TFP news and not vice versa.

Taken together, these results show that TFP news has statistically significant predictors, a conclusion that is in contrast to the assumed exogeneity of all shocks related to technology in modern macro modeling. The caveat here is that the data on entrepreneurship is much coarser and of a lesser horizon than the rest of the data used in this essay. So, while suggestive, these results require confirmation from a larger dataset.

9 Conclusion

This essay looks at the empirical effect of technology news on the labor market. While the existence of such shocks has been confirmed by many papers, its relevance for employers and workers is hardly studied. Using post-war US data in a Structural Vector Auto Regression, I find robust evidence that the intensive and extensive margins of employment react significantly to such information. Good news leads to an expansion of employment and greater entry into the labor market as agents try to take advantage of favorable economic conditions. These results also suggest that news shocks explain more of the variation in the labor market and should play a role in macro modeling. Further, tests of granger causality using the identified news shock and data on new business creation show that the latter variable is predictive (though, not necessarily causal) for the former and suggest that the often made assumption that technology is exogenous needs to be reconsidered.

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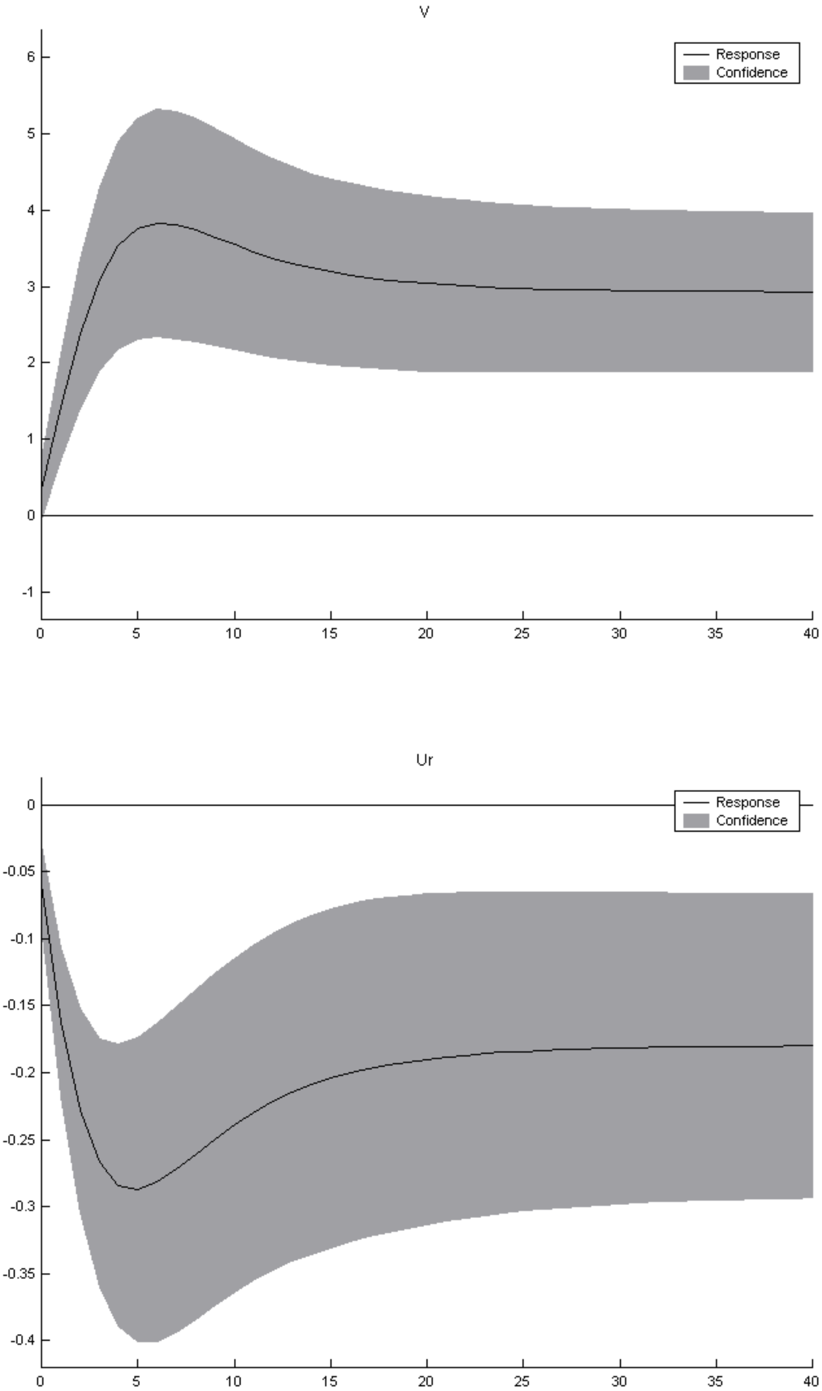


Figure 1: Responses in vacancies and unemployment rate to TFP news under Barsky and Sims (2011) identification scheme in a VAR with TFP, stock prices, consumption, investment, and labor market variables.

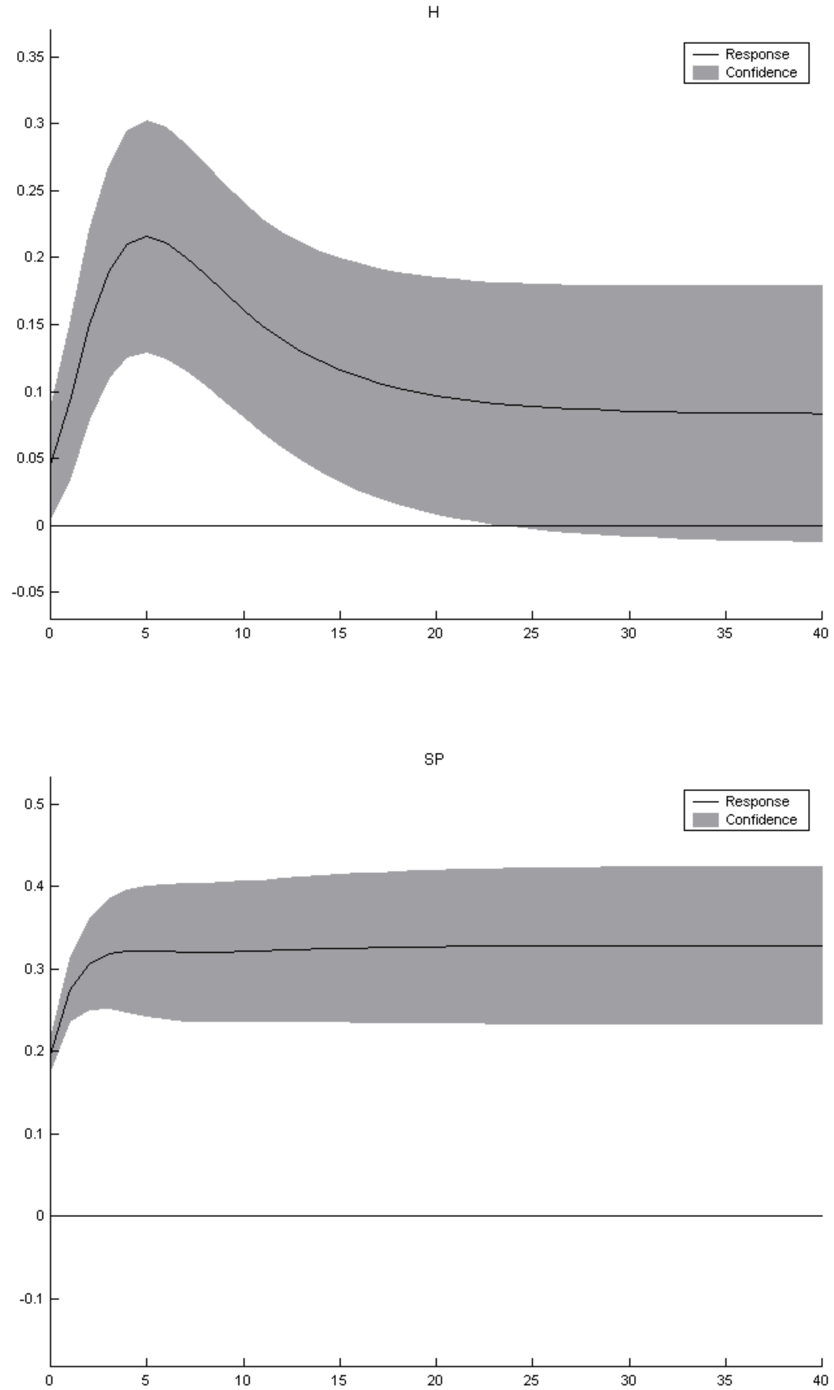


Figure 2: Responses in hours and stock prices to TFP news under Barsky and Sims (2011) identification scheme in a VAR with TFP, stock prices, consumption, investment, and labor market variables.

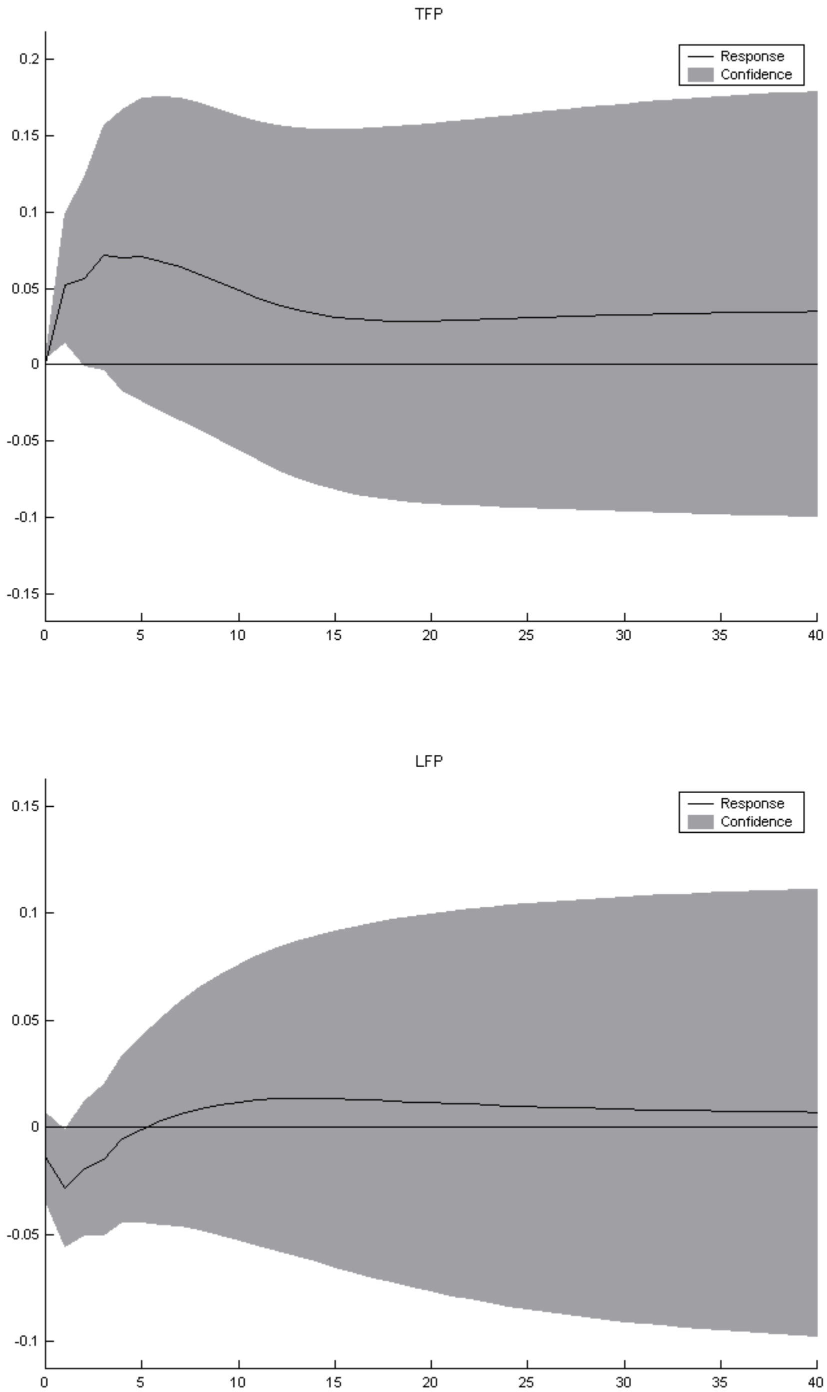


Figure 3: Responses in TFP and labor force participation to TFP news under Barsky and Sims (2011) identification scheme in a VAR with TFP, stock prices, consumption, investment, and labor market variables.

Effects (in 1 year) of a 1% TFP News Shock (TFP increases by 1% in 1 year)

	Vacancies	Unemployment Rate	Hours Worked	Stock Prices	LFP
BS approach	5.56	-6.30	.172	11.83	-.046
BP approach	5.46	-7.26	.179	11.83	-.046

Table 1: This table shows the impact (in 1 year) in percent changes caused by receiving news that TFP will be 1% higher than expected in 1 year. The 1st approach is defined as the identification scheme where TFP news is viewed as the structural shock orthogonal to contemporaneous TFP shock that maximizes the contribution to FEVD over 40 quarters. BP approach refers to the identification scheme proposed by Beaudry and Portier (2006).

Impact Effects of a 1% TFP News Shock (TFP increases by 1% in 1 year)

	Vacancies	Unemployment Rate	Hours Worked	Stock Prices	LFP
BS approach	1.1	-1.45	.058	7.92	-.039
BP approach	1.09	-1.73	.058	7.92	-.040

Table 2: This table shows the impact effects of receiving news that TFP will be 1% higher than expected in 1 year. The 1st approach is defined as the identification scheme where TFP news is viewed as the structural shock orthogonal to contemporaneous TFP shock that maximizes the contribution to FEVD over 40 quarters. BP approach refers to the identification scheme proposed by Beaudry and Portier (2006).

Note: A **F**orecast **E**rror **V**ariance **D**ecomposition gives the contribution of each identified structural shock to the total forecast error variance of each variable in the empirical VAR.

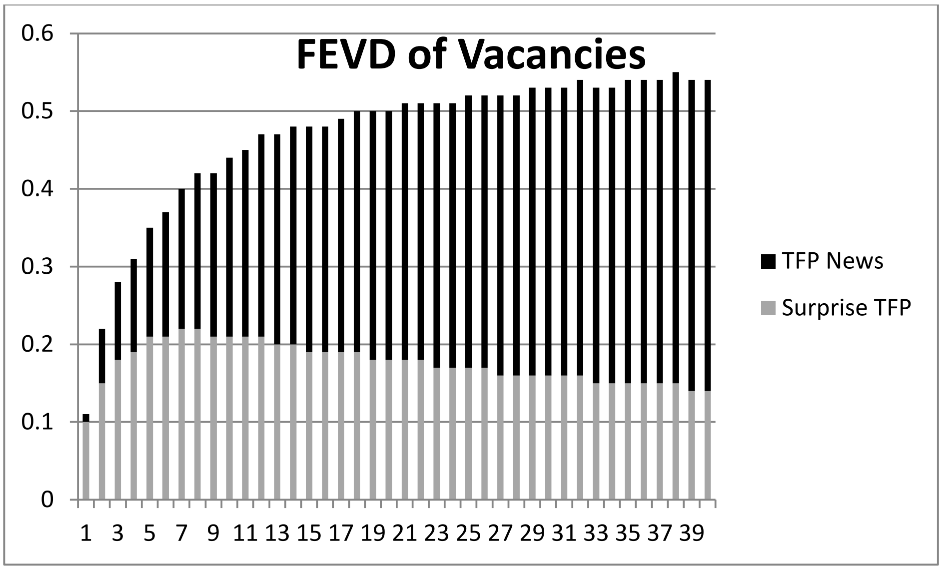


Figure 4: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of vacancies for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over 40 quarters.

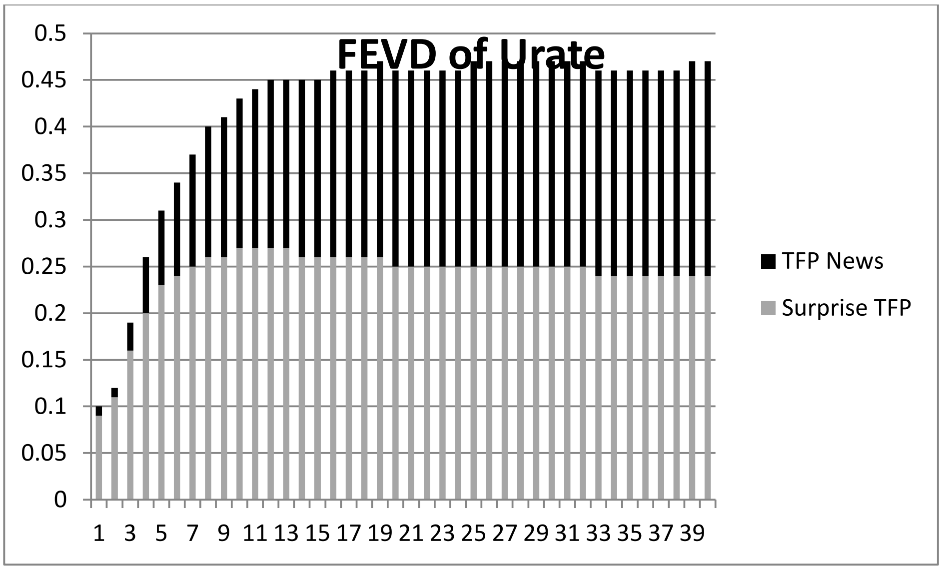


Figure 5: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of the unemployment rate for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over 40 quarters.

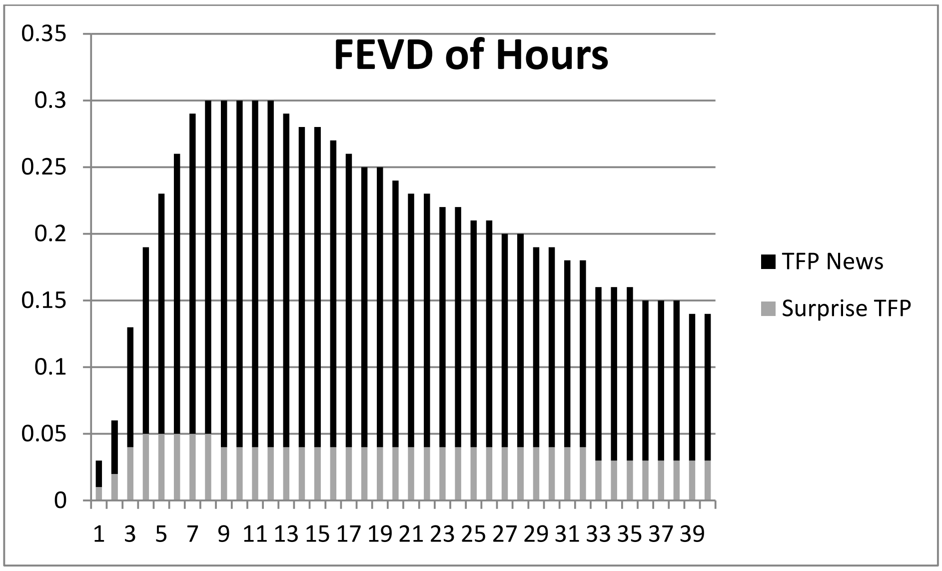


Figure 6: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of Stock average hours worked for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over 40 quarters.

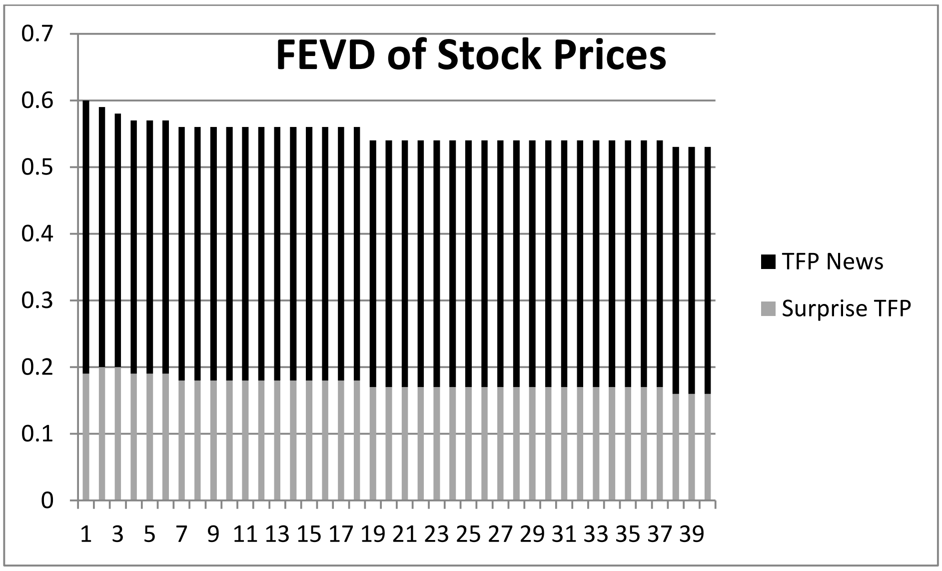


Figure 7: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of the Stock Prices for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over 40 quarters.

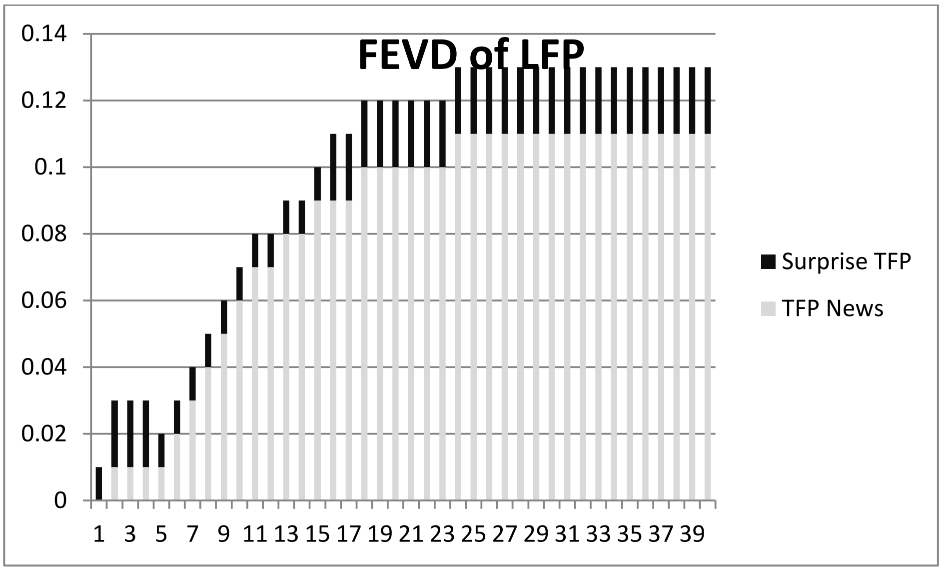


Figure 8: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of the utilization adjusted TFP for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over 40quarters.

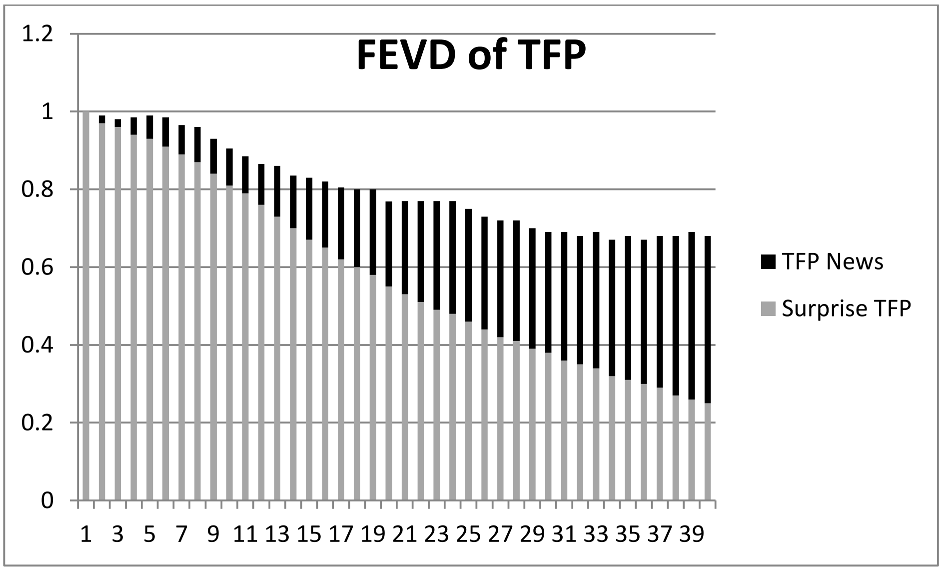


Figure 9: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of the utilization adjusted TFP for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over 40quarters.

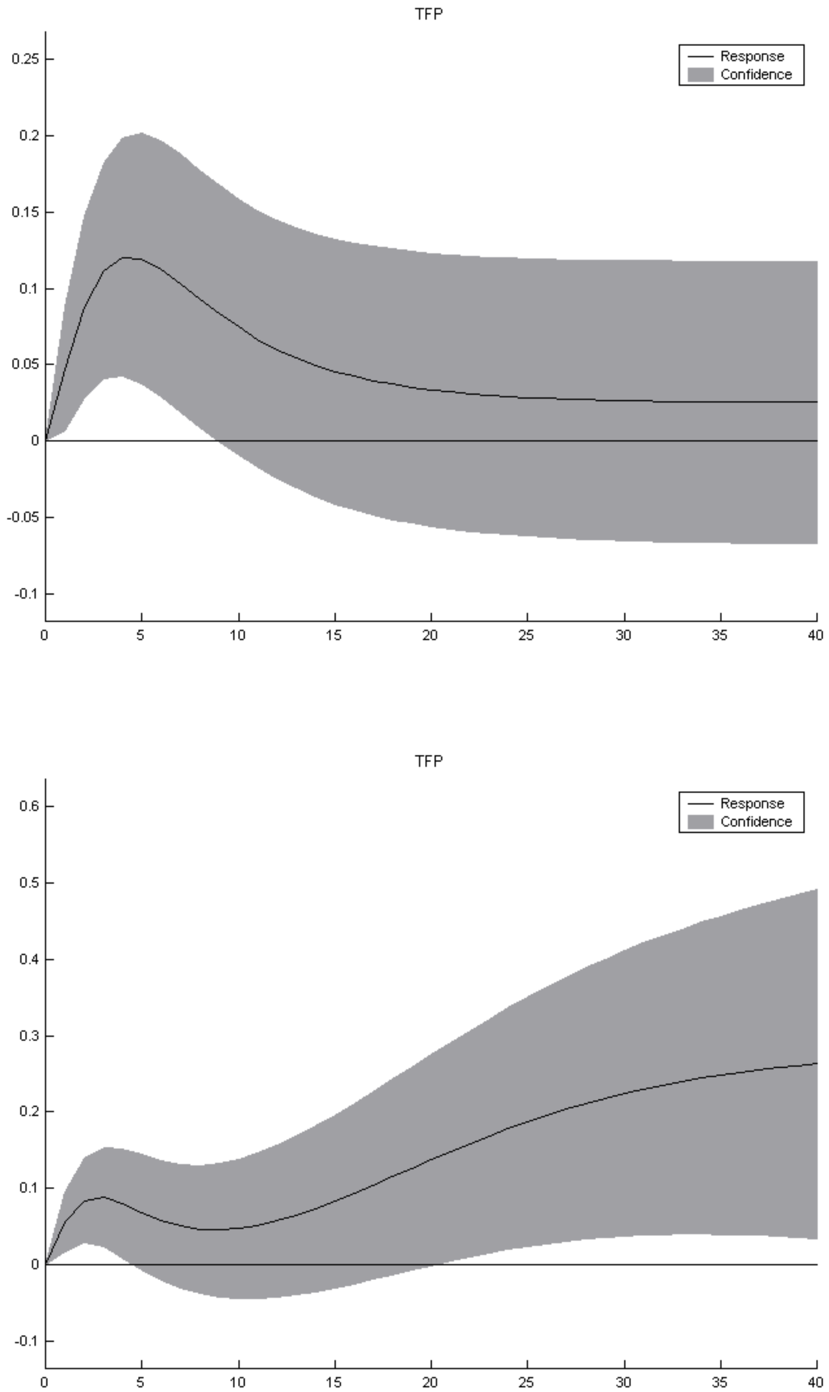


Figure 10: Responses in TFP under Beaudry and Portier (2006) identification scheme. Top panel represents the structural shock associated with TFP in the long-run identification. Bottom panel represents the structural shock associated with SP in the contemporaneous identification.

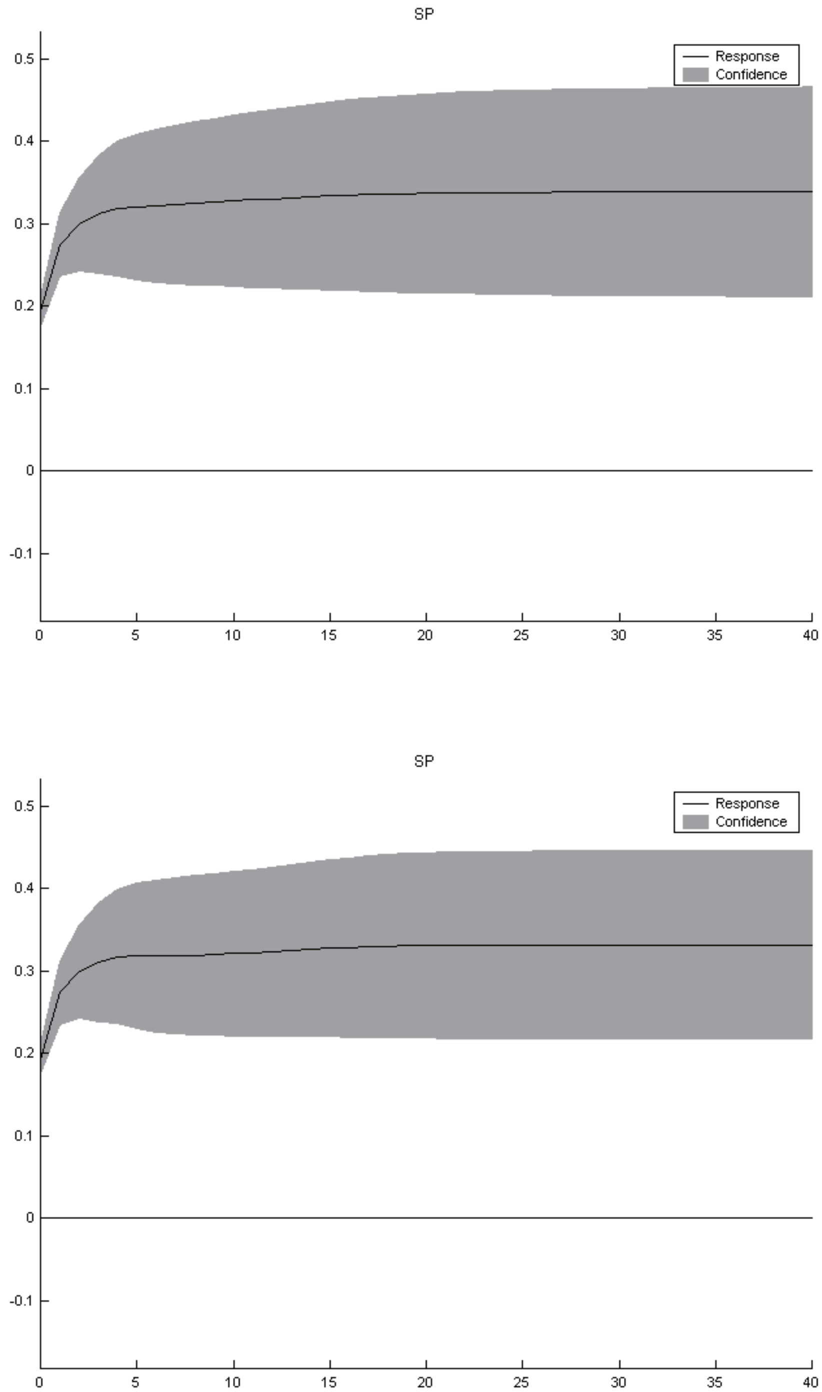


Figure 11: Responses in SP under Beaudry and Portier (2006) identification scheme. Top panel represents the structural shock associated with TFP in the long-run identification. Bottom panel represents the structural shock associated with SP in the contemporaneous identification.

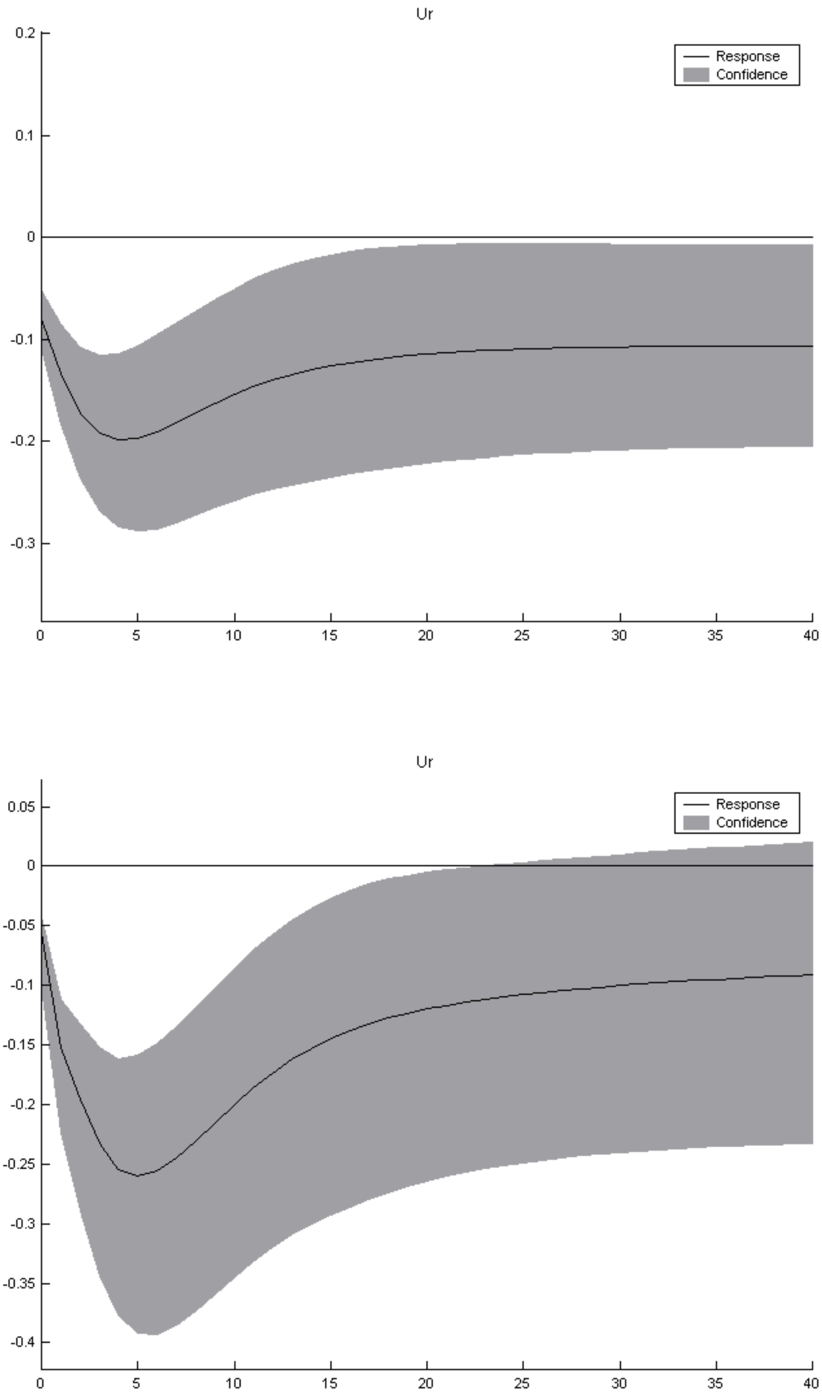


Figure 12: Responses in unemployment rate under Beaudry and Portier (2006) identification scheme. Top panel represents the structural shock associated with TFP in the long-run identification. Bottom panel represents the structural shock associated with SP in the contemporaneous identification.

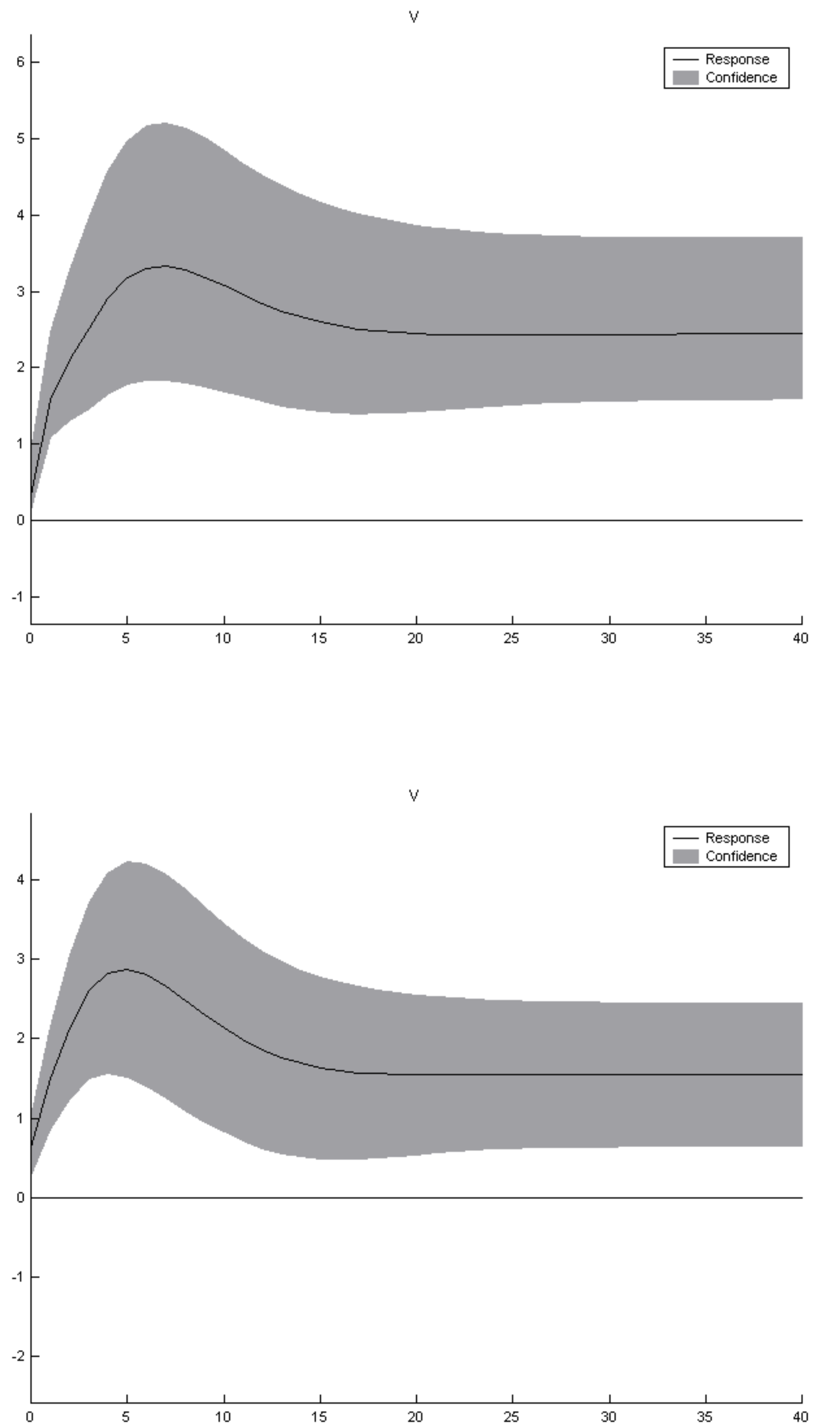
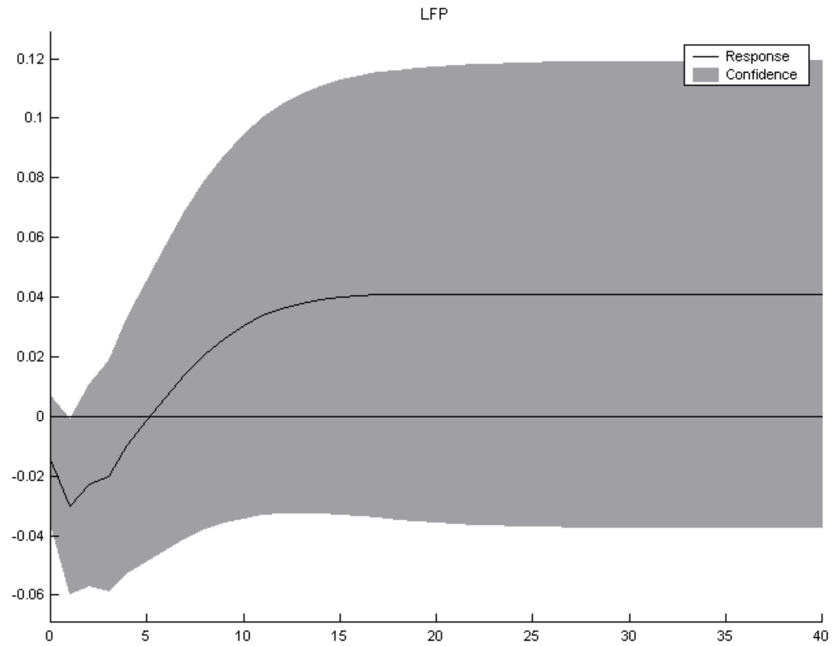


Figure 13: Responses in vacancies under Beaudry and Portier (2006) identification scheme. Top panel represents the structural shock associated with TFP in the long-run identification. Bottom panel represents the structural shock associated with SP in the contemporaneous identification.



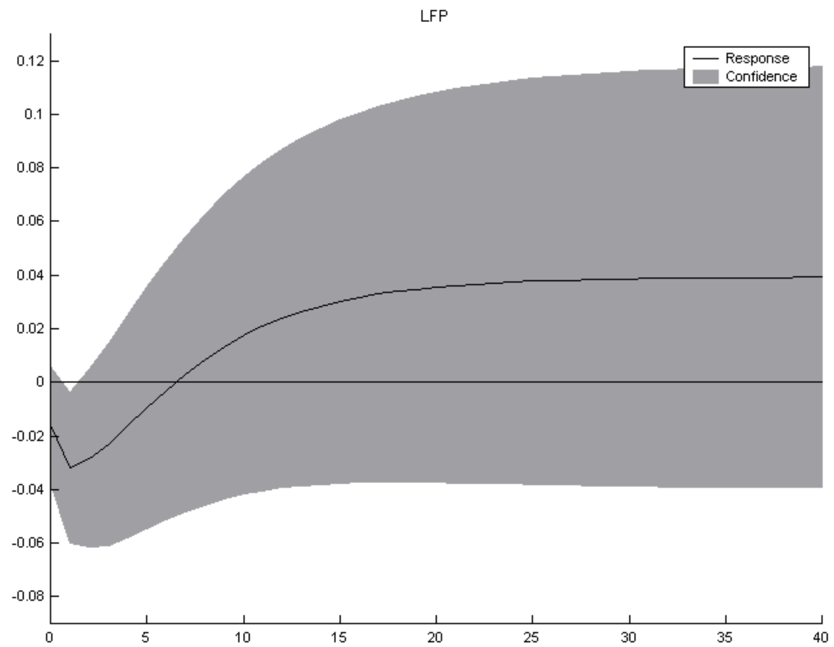


Figure 14: Responses in labor force participation under Beaudry and Portier (2006) identification scheme. Top panel represents the structural shock associated with TFP in the long-run identification. Bottom panel represents the structural shock associated with SP in the contemporaneous identification.

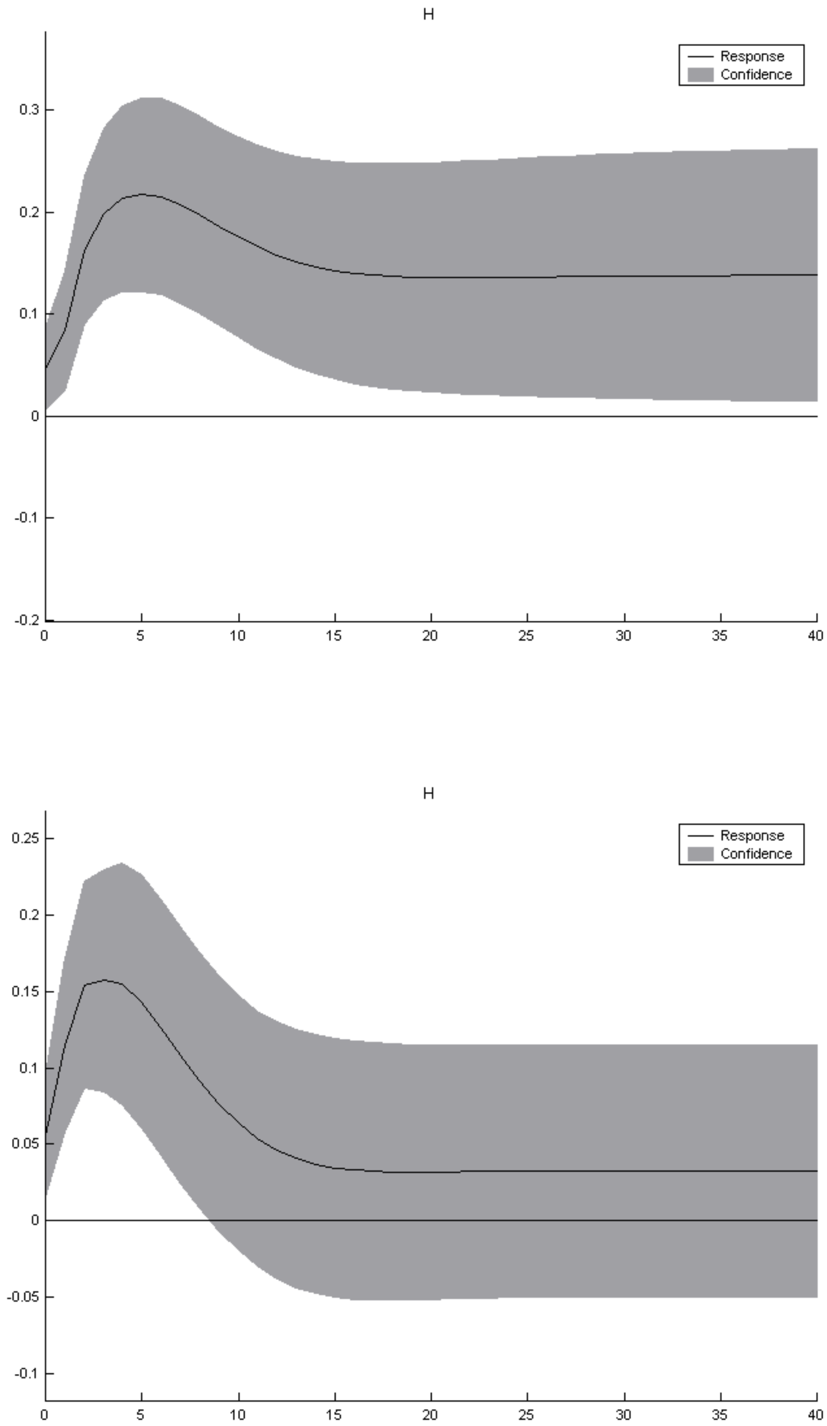


Figure 15: Responses in hours under Beaudry and Portier (2006) identification scheme. Top panel represents the structural shock associated with TFP in the long-run identification. Bottom panel represents the structural shock associated with SP in the contemporaneous identification.

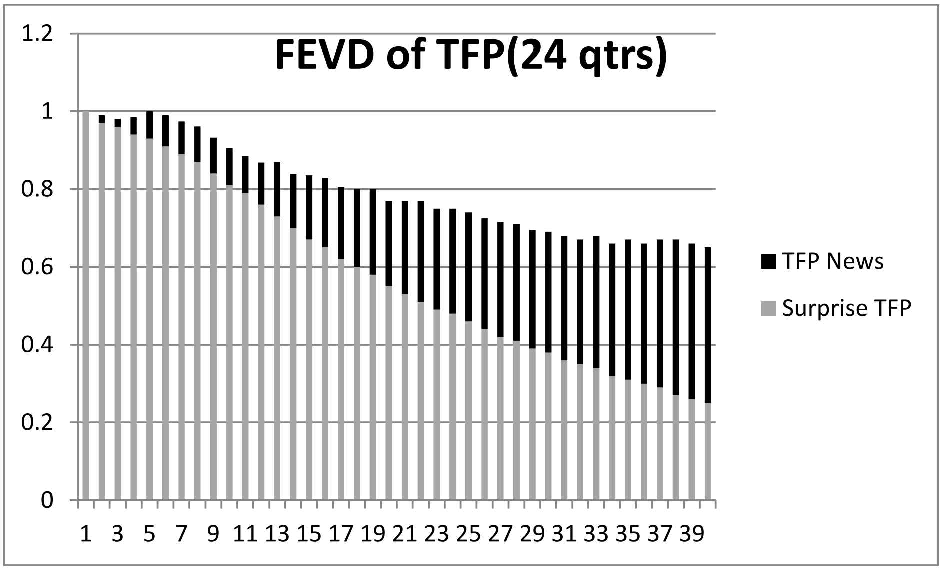


Figure 16: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of the utilization adjusted TFP for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over **24** quarters.

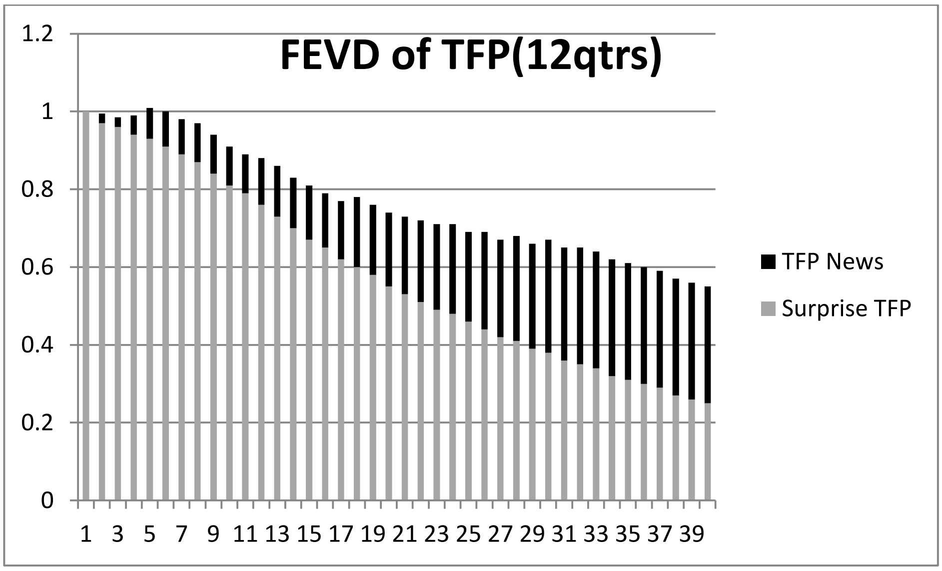


Figure 17: Empirical contribution of the TFP news shock and the contemporaneous TFP shock on Forecast Error variance of the utilization adjusted TFP for 40 quarters. TFP news is identified as the structural shock that maximizes the contribution to the FEVD over **12** quarters.

Granger Causality in Bivariate VARs

	Surprise TFP	TFP News	Kauffman Index Patents Granted
Surprise TFP			0.0488 0.3215
TFP News			0.6632 0.0308
Kauffman Index Patents Granted	0.2461 0.5249	0.0031 0.0493	

Table 3: Does the row variable Granger-Cause the column variable? This table shows p-values for this question in several bivariate VARs with the only two structural shocks identified in the baseline model along with a measure of Entrepreneurship and the number of patents granted.

Labor Market Dynamics under an Anticipated Change in Technology*

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University of Virginia

Dissertation Essay 2
July 15, 2013

Abstract

Can the anticipation of an upcoming change to the level of technology (news shocks) drive employment decisions? Using a Diamond-Mortensen-Pissarides type search and match model, I show that the intensive and extensive margins of employment are sensitive to news shocks. The model utilizes Moen's competitive search framework and features a finite-length contract between risk-neutral entrepreneurs and risk-averse workers. The model outcome is qualitatively consistent with the empirical results from my first essay, but the quantitative response turns out to be much smaller. I find that the length of the contract has an important effect on the labor market responses to news shocks, implying that commonly made assumptions, such as infinite-length contracts and period-by-period bargaining, are not innocuous in analyzing the effect of news shocks.

JEL Classification: C32, E17, E24

Keywords: business cycles, unemployment, labor contract theory

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*I thank Chris Otrok, Toshi Mukoyama, and Eric Young for their guidance. I also thank seminar participants at the University of Virginia and the Federal Reserve Board of Governors for their helpful comments. I received support from the Bankard Fund for Political Economy for this paper. All errors are mine.

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1 Introduction

Much of the modern business cycle literature, which began with Kydland and Prescott (1982), appeals to contemporaneous shocks to fundamental variables in an economy to explain the empirically observed comovement among major aggregate variables. Usually these shocks affect consumer preferences, fiscal or monetary policy variables, or technology. But, a surprise change to one or more of these variables is not necessary to explain the observed comovement.

In this essay, I study whether news shocks that contain information about upcoming changes to fundamentals can be drivers of the business cycle. That news regarding changes to policy is a driver of the financial markets, and to a lesser extent the general Macroeconomy is an accepted idea. Recently, though the literature studying the causes of the business cycle has seen the emergence of a new explanatory variable: news regarding upcoming changes to technology. I add to this literature by studying the sensitivity of employment to technology news in a modified model of the labor market.

The definition of technology used in this essay is not confined to advances in consumer electronics (e.g. iPhones) and other devices but is taken to be the capacity-utilization adjusted measure of the Solow Residual. This measure includes advances not only in consumer electronics but also any changes to policy or the production process that serve to increase aggregate US productivity. The existence of such news shocks has been established[1] though there is less of a consensus in the empirical literature that news shocks can lead to comovement among major aggregate variables.

There is theoretical work[2] which argues that news shocks can drive the business cycle. In line with this last strand of literature, I show that news shocks can play a role in driving the business cycle and more specifically, in labor market outcomes. Good news of technology leads to a response along both the extensive (firm entry, vacancy posting) and intensive (hours worked) margins of employment as both workers and firms try to position themselves to take advantage of the upcoming technology boom.

These are the results of a model where workers and firms enter the market for labor contracts after receiving news about future productivity and search for an employment match. Workers look to contracts as insurance vehicles against uncertain future consumption while

[1]See Barsky and Sims (2011), Beaudry and Portier (2004, 2006, 2007), Kurmann and Otrok (forthcoming).
[2]See Den Haan and Kaltenbrunner (2009), Jaimovich and Rebelo (2009), Krusell and Mckay (2010).

firms use contracts to secure labor in anticipation of increased productive capacity. Good news increases the value of being unemployed and the ex-ante profit for prospective entrepreneurs. The equilibrium contract features both these increases by promising higher wages to new workers and higher expected profits to matched entrepreneurs.

The need to introduce contracts in this paper is not apparent and requires justification. I take it that negotiations between a firm and its workers are not adequately characterized by the spot market in every period in which the two parties work together. If this were false, we should observe continual renegotiation on a large scale in the US and we should not observe macroeconomic conditions at the time of hiring having a greater impact on wages than conditions in subsequent periods.[3] In addition, we observe firm-worker pairs operating with explicit contracts (unionized auto workers, college professors) and we also observe worker-firm pairs operating *as if* they were under a contract (Azariadis and Stiglitz (1983)). For these reasons, I abandon the spot price framework of labor market negotiations and adopt a labor contract framework.[4]

I find that good news affects prospective and existing entrepreneurs in different ways. A positive TFP (Total Factor Productivity or technology) news shock increases the value of unemployment and consequently lessens the burden on an entrepreneur of an existing firm as contracts specify only the level of utility that must be delivered to the laborer. As this responsibility is reduced the entrepreneur has an increased incentive to 'invest' [5] and produce which leads to an increase in aggregate output. The prospective entrepreneur behaves differently. Good news leads to additional entry by entrepreneurs to the labor market in order to take advantage of increased profit opportunities. Newly employed entrepreneurs sign contracts that are different that those contracts signed just a period earlier. Good news implies that new contracts must promise a higher expected utility to laborers as expected production over the life of the contract has now increased. An increase in the contracted utility leads to comparatively higher wages paid and fewer hours worked than those workers who signed contracts before good news was received. In other words, the dynamics of newly formed firms reduce to the dynamics that are characteristic of standard neoclassical models. These subclass of firms experience a decline in labor hours and an increase in wages, a

[3] See Bils (1985) and Pissarides (2009) which show that wages of workers hired during an economic boom are higher than those of workers hired before the boom began.

[4] See Rudanko (2009, 2011).

[5] Labor is used more intensively in the match.

prediction that is in line with predictions made by representative agent models.[6]

Other work that studies the connection between TFP news and the labor market[7] also concludes that a news shock can drive the movements observed in these variables. This paper, however, argues that a key driving force behind these movements is the presence of contracts that allow trade in a service that other papers do not: consumption insurance. I work with the assumption that entrepreneurs are risk-neutral while laborers are risk-averse[8] which allows entrepreneurs to profit by selling insurance through contracts to laborers looking to smooth their otherwise jagged consumption patterns. This profit motive is strengthened with the duration of the contract. Longer contracts allow more insurance to be sold and so increase the profit potential. As a consequence, the incentive to post vacancies (prospective entrepreneur's desire to enter the labor market) is also increased. I argue that this mitigates some of the unemployment volatility problem that is characteristic of search modeling.

Quantitatively, I find that the longer-term contracts along with a greater degree of risk aversion on the part of laborers generate a response in vacancy postings as a reaction to TFP news at a much higher level than in a search model without such features. Further, I find that this model setup reduces the need to set unemployment compensation to be too high a proportion of employment income.[9]

The rest of the paper is as follows: The next section discusses the literature. Section 3 details the theoretical model. Section 4 describes the equilibrium and the solution method. Section 5 details the model solution and quantitative results. Section 6 provides a discussion of the results and the last section provides some concluding remarks.

2 Literature Review

I discuss first the relevant empirical papers and then the relevant theoretical and quantitative papers.

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[6]See the discussion on Beaudry and Portier (2007) below.

[7]See Den Haan and Kaltenbrunner (2009) and Krusell and McKay (2010).

[8]Qualitatively, the results would not be markedly different as long as entrepreneurs were *less* risk-averse than the laborers. I justify the neutrality assumption by noting that entrepreneurs have greater access to credit markets and thus, can smooth their own consumption streams.

[9]Hagedorn and Manovskii (2008) argue that unemployment compensation that pays roughly 80 percent of compensation when employed may be necessary to generate a sufficient response in vacancy postings as a reaction to shocks.

2.1 Related Empirical Work

Beaudry and Portier (2006) revives the idea first discussed in Pigou (1927) that news can drive the business cycle. The authors use a Structural Vector Auto Regression (SVAR) with TFP and stock prices to identify anticipated shocks to technology. In particular, they use a sequential identification scheme. First, they extract the structural shock associated with TFP in the long run identification then they extract the structural shock associated with stock prices that is orthogonal to the contemporaneous TFP shock. They find that the identified shocks are highly correlated which indicates that the shock is unique and they classify it as technology news. The intuition behind the approach comes from the efficient markets hypothesis: Good news regarding productivity increases investor perception of the present discounted value of profits for US firms and the change is reflected through stock prices. The authors find that technology news shocks lead to significant increases in consumption, investment and hours worked over the business cycle. This method is also used in Beaudry and Lucke (2009) and Beaudry, Dupaigne and Portier (2011). Here they identify five shocks, unanticipated TFP, anticipated TFP (news), unanticipated investment, preference, and monetary. Once again the authors find strong conditional comovement among major macroeconomic aggregates as a response to news.

Barsky and Sims (2012) look at another forward-looking variable in the context of SVARs: consumer confidence. They show that shocks to consumer confidence are strongly correlated to production in the long-run but at the same time are not correlated to temporary changes in output. Barsky and Sims (2011) impose medium-term restrictions on a VAR with TFP, output, hours, stock prices, inflation and consumer confidence. The restrictions identify the news shock as the structural shock orthogonal to the reduced form shock associated with TFP that best maximizes the contribution to the Forecast Error Variance at business cycle frequencies. With this approach, they find that a news shock leads to an increase in consumption but a decline in hours worked, investment and output. The shock also leads to disinflation, increases in stock prices, consumer confidence, real wages, and real interest rates.

Note that the two approaches discussed above differ significantly in the effects of TFP news on TFP itself over a forecast horizon of 10 years. The former set of papers do not find any noticeable change in the level of technology for up to 4 years after the news shock while the latter papers identify a TFP news shock that affects TFP soon after impact. Further, the former set leave about one-third of TFP forecast error variance unexplained over the same horizon while the latter leave only about 5 percent unaccounted for at business cycle frequencies.

Finally, in my first essay I carry out an empirical analysis on the effect of technology news shocks on the labor market variables of hours worked, unemployment rate and vacancies posted (along with other controls). Using both of the identification schemes prevalent in the literature, I find that the labor market responds along both the intensive and extensive margins of employment as a reaction to technology news. Positive information leads to an immediate jump up in vacancies, hours worked, and a jump down in the unemployment rate. These responses are significant at impact and remain that way for the next 10 years. I conclude that the anticipation of a boom in technology leads not only to matched worker-firm pairs working harder (more labor hours) but to workforce expansion in existing firms and to new entrants in the labor market.

2.2 Related Theoretical work

Beaudry and Portier (2007) attempt to build a representative agent model where output, consumption, investment and hours worked move together in response to a news shock. They find that in such models good news increases the incentive to invest but also increases the representative agent's wealth[10] and so, the increase in investment is paid for by a reduction in the representative agent's supply of hours. This leads to an increase in leisure and a decrease in output.

Jaimovich and Rebelo (2009) use a standard business cycle model with a special class of preferences and convex labor and investment adjustment costs to show that news can be a driver of the business cycle. The preference specification is such that it reduces the wealth effect of good news as in Greenwood, Hercowitz, and Huffman (1988). The labor and investment adjustment cost work in conjunction with this assumption in the following way: an expected increase in TFP produces a wealth effect that makes the households work less but it makes them anticipate an increase in marginal productivity of capital and labor at the time the productivity changes. With convex adjustment costs, it is beneficial for these workers to start increasing investment and labor hours now.

Schmitt Grohe and Uribe (2012) use a similar labor adjustment cost to estimate the

[10] The wealth effect dominates the substitution effect.

quantitative importance of TFP news shocks. They estimate a large DSGE model with real frictions and structural (anticipated and unanticipated) shocks. The shocks studied are to TFP, investment-specific productivity and government spending. The shocks may either be totally unanticipated or anticipated at up to a horizon of 3 quarters. The authors conduct a Bayesian estimation of the parameters to measure the impact of news and find that the anticipated shocks explain most of the variation in output growth and that anticipated shocks to TFP are the largest driver of the business cycle.

Den Haan and Kaltenbrunner (2009) and Krusell and McKay (2010) study a search model augmented with TFP news. Both papers conclude that a suitably parameterized search model can induce a simultaneous increase in vacancy postings, consumption, employment and output because of the presence of search frictions. These frictions prompt entrepreneurs to enter the labor market well in advance of the actual realization of technological advancement.

Blanchard, L'Huillier and Lorenzoni (2011) study the effects of noisy news in model where agents face a signal extraction problem. They find that a SVAR model cannot separately identify news and noise shocks. Lorenzoni (2009) builds a model with heterogeneous productivity shocks and private information which lead to expectational errors relative to a full information model. Noisy news leads to dynamics that are similar to demand shocks: they increase output, employment and inflation in the short run and have no effects in the long run.

3 The Model

The model studied here is based on the Diamond-Mortensen-Pissarides search and match model augmented with the optimal fixed duration contract under news. There is a continuum of measure one workers with preferences $E_0 \sum_{\tau=0}^{\infty} \beta^\tau u(c_\tau, l_\tau)$,where c represents consumption and l represents hours worked, E_0 represents expectations formed at time 0 and β is the rate of discounting. Workers consume their income each period, so consumption equals wage w_t if employed and unemployment compensation b if unemployed. Each entrepreneur has preferences $E_0 \sum_{\tau=0}^{\infty} \beta^\tau \pi_\tau$, where π_τ represents period τ profits. Entrepreneurs have access to a constant returns to scale production technology using only worker hours as input: $y_t = a_t l_t$,where a_t is the level of TFP.

TFP follows a 3-state Markov Chain. Each period agents receive news, I about the level of technology tomorrow: $I_t = a_{t+1}$. Agents use this news to forecast the time path of technology and enter the market for j-period labor contracts. Note that in this simple setup TFP news is *noise-free.* Both types of agents know with certainty the level of TFP for only the following period. They forecast the path of TFP beyond next period using the Markov matrix.

Workers can search without cost while entrepreneurs must pay a fixed cost, p to enter the labor market. Workers will accept a contract that provides at least as much utility as remaining unemployed while entrepreneurs will enter the market until free entry eats up their expected profits. Each entrepreneur-worker firm has a probability δ of being hit by a separation shock in a given period. At that time the match is terminated, the worker becomes unemployed and the firm dissolves.

3.1 Job Search

Entrepreneurs post labor contracts by paying p, and workers choose a contract to apply for considering its value and their likelihood of getting the job. Let N_u denote the measure of applicants and N_v denote the measure of vacancies for a particular contract. The measure of matches that take place this period is determined by a Cobb-Douglas matching function $m(N_v, N_u) = KN_u^{\alpha}N_v^{1-\alpha}$, with $0 < K < 1$ and $0 < \alpha < 1$. Defining $\theta = N_v/N_u$ as the vacancy-unemployment ratio, the probability that a worker finds a job is $\mu(\theta) = m(N_v, N_u)/N_u$ and the probability that an entrepreneur finds a worker is $q(\theta) = m(N_v, N_u)/N_v$.

3.2 Contracts

The entrepreneur enters the labor market by paying the fixed cost and posts a contract that specifies worker hours and wages in **all** future states of the world for the entire duration. A contract then, is a set of functions that are conditional on current TFP and news and for all continuation histories of these state variables over the life of the contract.

A match history of shocks for a production unit that starts in state $S_0 = (a, I)$ and is still producing τ periods later is $S^{\tau} = (S_0, S_1, ..., S_{\tau})$. A wage contract is a set of functions:

$$\sigma(S_0) = \{w_{\tau}(S^{\tau}), l_{\tau}(S^{\tau})\} \; for \; \tau = 0...j$$

3.3 Value Of A Contract To Workers

Each unemployed worker looks at the posted contract, evaluates the value of that contract and then makes the decision to apply. The worker valuation of a posted contract is:

$$V_\sigma(S) = u(w,l) + E_S \sum_{i=1}^{j-1} \beta^i [(1-\delta)^i u(w_i, l_i) + \delta(1-\delta)^{i-1} V_u(S_i)] + E_S \beta^j (1-\delta)^j V_u(S_j)$$

The value of being unemployed is:

$$V_u(S) = u(b,0) + \beta E_S[\mu(\theta) V_\sigma(S_{i+1}) + (1-\mu(\theta)) V_u(S_{i+1})].$$

The first equation states that the value of a posted contract is simply the utility value of the specified hours and wages plus the expected utility from contract specified wages and hours for all periods in which the match operates. The value of unemployment is derived similarly. It is the utility value of unemployment compensation along with expected benefits from being employed in the next period.

3.4 Value Of A Contract To Entrepreneurs

The entrepreneur's valuation of a given contract depends only on the expected path of TFP. By free entry (listed in the equilibrium conditions below), we do not have to worry about the entrepreneur's values of being vacant at different points in time.

$$W_\sigma(S,k) = al - w + E_S \sum_{i=1}^{j-1} \beta^i (1-\delta)^i [a_i l_i - w_i]$$

3.5 Pareto Frontier of Efficient Contracts

Given V, V_u, S, the Pareto frontier of efficient j-period contracts is:

$$C_j(V, S, V_u) = sup_{\sigma \in \Sigma(S,V_u)} \{W_\sigma(S) \Big| V_\sigma(S) = V\}$$

where $\Sigma(S, V_u) = \{\sigma | V_\sigma(S) \geq V_u(S)\}$

By definition, a contract on this frontier cannot be Pareto dominated after any history. So C_j must satisfy the following functional equation:

$C_j(V, S, V_u) = max_{w,l,\{V(S')\}}\ al - w + \beta(1-\delta) E_S C_{j-1}(V(S'), S', V_u)$

subject to $V = u(w,l) + \beta E_S[(1-\delta)V(S') + \delta V_u(S')]$

Note: The 'prime' notation above refers to next-period quantities.

4 Equilibrium

Following Moen (1997), a competitive search equilibrium for a given S is described by a triplet $\{V_u, \theta, \sigma\}$ so that:

1. Search gives zero profit to an entrepreneur: $q(\theta)W_\sigma(S) = p$

2. No Pareto improving market is possible: $\neg\exists\{V_u^*, \theta^*, \sigma^*\}$ so that both the worker and the entrepreneur have a higher ex-ante expected utility.

4.1 Equilibrium Properties

I derive first some properties of the Pareto frontier and then show that the equilibrium features a unique contract.

Proposition 1: C_j is decreasing, concave and continuously differentiable in V $\forall j$.

Proof: With the assumption of concave and continuously differentiable utility for the laborers in consumption and leisure, C_1 is concave, decreasing and continuously differentiable. By induction, C_j satisfies these properties as well.

Of all the possible contracts that may be signed, one that satisfies both of the equilibrium conditions. It is found by solving the following problem:

$$max_{V,\theta}\ \mu(\theta)(V - V_u(S)) \tag{1}$$

subject to q(θ)$C_j(V, S, V_u) = p$

Proposition 2: A unique contract offered in the labor market each period.

Proof: Use the maximization problem above that characterizes the equilibrium. The constraint implicitly defines θ as a function of V. Using the implicit function theorem, the derivative of the maximand is:

$$\mu(\theta)[1 - \frac{\mu'(\theta)}{q'(\theta)\theta}\frac{C_{jV}(V, S, V_u)}{C_j(V, S, V_u)}(V - V_u(S))] \tag{2}$$

where C_{jV} is a partial derivative. Since C_j is decreasing in V, $\exists V$:C$_j(V, a, V_u) = 0$. The term in brackets is decreasing from $V_u(S)$ to V since C is concave in V. Since the derivative above is positive at $V_u(S)$ there is exactly one point in the middle where the derivative is 0. So, the contract exists and is unique.

The first proposition above shows that C_j is a 'nice' function and its properties easily lead to the existence and uniqueness of labor contracts in this model economy. I use these propositions to lay out my model solution strategy next.

4.2 Solution Method

Solving the model amounts to finding the solution to a fixed point problem. I start with a guess for V_u, solve for C_j and finally produce a new guess for V_u. I stop when the guess and the terminal quantity are close enough.

Step 1: Solve for C_j. Solve for C_1 first and then for C_j using the recursive definition provided above. To solve for this functional I need to assume the function V_u. C_1 is defined as follows:

$$C_1(V, S, V_u) = max_{w,l}\ al - w \tag{3}$$

subject to $V = u(w, l) + \beta E_S V_u(S')$

To derive the efficient j-th period contract, C_j, requires only a bit of algebra. Note: The prime notation refers to the next period. Since technology is a 3-state Markov process, the state variable can take any of 9 possible values. Let $S = S_1, S_2, ...S_n$

Step 2: Solve for V_σ, V_u by fixing C_j. Given C_j we can derive the values of $V_\sigma(S)$ and $V_u(S)$ for $S = S_1, S_2, S_3...S_n$ by solving the following 2n equations:

$$\frac{1-\alpha}{\alpha}\frac{C_{jV}(V, S, V_u)}{C_j(V, S, V_u)}(V - V_u(S)) = 1 \tag{4}$$

$$V_u(S) = u(b, 0) + \beta\Sigma\pi(S'|S)[V_u(S') + K^{\frac{1}{\alpha}}p^{\frac{\alpha-1}{\alpha}}C_{j-1}(V_\sigma(S'), S', V_u)^{\frac{1-\alpha}{\alpha}}(V_\sigma(S') - V_u(s'))] \tag{5}$$

where π is the distribution of tomorrow's state variables, K is the matching parameter, and p is the fixed cost that an entrepreneur must pay to enter the labor market. Equation 4 is just the FOC from the maximization problem given above. Equation 5 is the definition of V_u where $\mu(\theta)$ has been substituted out using the free entry condition. Equations 4 and 5 produce 2n equations in 2n unknowns.

5 Model Solution

I discuss first how the parameters of the model were chosen then, the different model setups considered followed by the results.

5.1 Parameters

Table 1 lists the parameters used in simulating each of the models in this section. Most of the parameters are set to be consistent with Rudanko (2009) and those for which no counterpart exists, I have chosen multiple candidates to show the effect of varying the parameter. Finally, the worker's utility function in the last model is chosen to be consistent with Andolfatto (1996).

As stated above, I use a Cobb-Douglas matching function for the labor market. This choice necessitates that the simulation interval is kept short to allow workers to stay unemployed for at least one period. Empirical studies on vacancies and unemployment dictate the elasticity of the matching function be set at 0.72. The technology process is set to match the standard deviation, and the AR(1) coefficient of productivity and the transition matrix is chosen so that at the intermediate productivity level, the process is equally likely to move in either direction and to return to the intermediate value if it is at the extremes. The discount factor is chosen to give a 1.2 percent quarterly return. The separation rate and vacancy cost are set to be consistent with Shimer (2005). The unemployment compensation is set at 0.4 in contrast to the value recommended by Hagedorn and Manovskii (2008) to be about 0.8 of the average wage when employed. Finally, the vacancy cost is set so that average job-finding probability is 0.15 each period. This ensures that the model is consistent with the average level of unemployment calculated from post-war US data.

5.2 Results

Using these parameters, I vary the model along 3 dimensions: contract length, risk aversion, and inclusion of hours. For each model, I present results for aggregates of model simulations.

The model simulation proceeds in the following way. After having solved for C_j and V_u using the method described above, I simulate the technology process and form the associated news vector. The model begins with full employment and I simulate each subsequent period by solving the maximization problem in (1). The solution provides the value of new contracts along with labor market tightness. Since an exogenous share of jobs is destroyed each period, I may calculate the triplet that characterizes the model equilibrium. I continue in this manner until I have approximately 20 years of model data (I discard the first 1000 periods). I form model aggregates by taking the average of the equilibrium triplet series over 100 different simulations. The data on technology, vacancy postings, and unemployment is transformed to quarterly and I turn to empirical methods to extract model generated impulse responses.

Figure 1 displays the impulse responses to TFP news for technology, vacancy postings and unemployment. This model (call it model 1) was solved by assuming that worker's utility was independent of hours worked, workers had risk aversion parameter equal to 0.5 and contracts were for 20 periods only. We see TFP react only in the periods following the impact of the TFP news shock while vacancies and unemployment jump at impact and remain above 0 at a horizon of 10 years.

Figure 2 displays the impulse responses to TFP news for vacancies and unemployment for the second model simulation.[11] Here, the only difference is that contracts are for 30 periods (model 2). We see once again the two variables jump when the shock hits. It should be noted though, both variables respond in a much stronger way to the news shock at impact. Finally, unemployment seems to return to zero in the long run unlike in the previous model simulation.

Figure 3 displays the last set of impulse responses. Here we see the reactions of vacancies, unemployment and hours worked to a TFP news shock. The simulated model is different from the one before in that it includes worker hours, greater degree of risk aversion for the workers and an extended contract length of 30 periods (model 3). Once again impact effects are stronger than before and unemployment seems to regress to its original level. In addition, hours worked decrease in the long run.

Table 2 displays the impact effects of a 1 percent TFP shock on vacancies, unemployment, and hours worked. A clear pattern emerges of more amplified labor market dynamics as entrepreneurs are able to offer greater consumption insurance to their workers. Though, the model generated dynamics still fall short of the VAR estimates. This might be an indication that not enough insurance is being transacted and that contracts should be lengthened to facilitate this transfer. Alternatively, we may conclude that the unemployment compensation parameter should be closer to the value recommended by Hagedorn and Manovskii (2008)

The results discussed here lead to the conclusion, as in Den Haan and Kaltenbrunner (2009) and Krusell and McKay (2010) that a positive TFP news shock can affect the decisions made by entrepreneurs and laborers well before the actual change in technology is realized. Workers' value of being unemployed and entrepreneur's profits increase in anticipation which leads to more valuable contracts and higher wages paid.

[11]The response in TFP is omitted since it is almost identical to that shown in Figure 1.

The model presented here is different in a few ways from existing theoretical work. First, the insurance mechanism is important in incentivizing new vacancies. Greater risk aversion by workers and longer contracts allow entrepreneurs to sell more insurance and thus increase their profits. Including hours in the worker's utility function has a similar result on the incentive to enter markets. Since entrepreneurs have greater freedom in delivering the promised utility to their workers, they are able to choose the path that is most profitable. Once again this leads to an increased desire to enter the labor market in response to a positive TFP news shock. These channels through which TFP news can affect the labor market were not considered in other papers. Second, Krusell and McKay (2010) consider an environment where news shocks are zero probability events. Neither the entrepreneur nor the worker is able make decisions contingent on future news. In my model, the state space explicitly contains the news variable and so both parties are able to adjust their economic behavior in anticipation. Finally, my model features the Pareto frontier of efficient contracts which reveals that existing and new matches behave in different ways after a news shock. New matches tend to feature higher wages paid to laborers and lesser hours worked than existing matches. The intuition behind this result is that contracts specify the level of utility that must be delivered by the entrepreneur to the laborer. A positive shock increases the value of unemployment and so reduces the need to provide utility through high wages and fewer working hours.

6 Discussion

The search model solved above is suited to study questions that a representative agent model augmented with TFP news shocks cannot. This single-agent framework cannot exploit the dynamics that result from changes in the value of being unemployed. Positive news shocks in these models lead to an increase in the representative agent's wealth and therefore an increase in his choices of consumption and leisure and a reduction in output. This is in marked contrast to the aggregate data where the aggregate variables move together. As I mentioned above, other work has overcome this difficulty by imposing a special class of utility functions that elicits a weak labor supply reaction to good news about technology. In contrast, the current setup tries to provide an explanation for this comovement by exploiting changes in the value of being unemployed. The contract that is agreed to by both parties stipulates only what *expected utility* must be delivered to the laborer. Good news about the future increases the value of being unemployed and so reduces the utility the entrepreneur must provide through wages and hours worked.

As the utility that the entrepreneur must provide to the laborer through wages and hours worked decreases, the entrepreneur can afford to use more labor hours. One expects that a sufficiently modified model that includes capital would also see an increased incentive to invest. Prospective entrepreneurs now have higher expected profits and so decide to enter the labor market in larger numbers. This model predicts changes in aggregate capital at both the intensive and extensive margin. In addition, as more entrepreneurs decide to enter the market, the measure of employment matches that take place increases as well leading to a decrease in the rate of unemployment. Here again we have a change in employment at both the intensive and extensive margin. In fact, an extension of the argument above quickly shows that this model predicts changes at the intensive and extensive margin of the following variables: employment, wages, investment and capital.

The different response of wages for new and existing laborers points to a new analysis of the weak cyclicality that is characteristic of the aggregate wage. As I have argued above, new workers will contract a higher wage than their predecessors (a result similar to the neoclassical models) because of the increase in the value of being unemployed. Existing workers, in contrast, will see less wage growth and an increase in labor hours as a result of good news. In aggregate, these conflicting effects can lead to a weak response of the aggregate wage to good news. This model feature is in line with Pissarides (2009) which shows that wages of new workers are generally more cyclical than are wages of existing workers.

It is important to note the different reactions good news elicits from existing entrepreneurs in comparison to new entrepreneurs. Old entrepreneurs realize that good news lessens their obligations to the worker because of an increase in the value of being unemployed. This weakened burden allows them to increase labor hours and decrease the wage. New entrepreneurs on the other hand, face a situation that is analogous to that faced by the representative agent models mentioned above. Since the value of being unemployed has now increased, each new contract must promise a greater level of lifetime utility. So, the new entrepreneurs' choice of labor hours and wages stands in stark contrast to the choice made by old entrepreneurs. In fact, the choices made by new entrepreneurs mirrors the choices made in representative agent models. This model then, has a special case neoclassical models where each entrepreneur has a contract that lasts only for a period.

7 Conclusion

Can TFP news drive the business cycle? Standard models have trouble making such a story work as good news leads to an increase in the representative agent's wealth and thus, to a reduction in labor supply. Good news about the future leads to a recession today. These models miss the connection between the value of being unemployed and news. As the value increases in response to good news, matched entrepreneurs need to provide lesser utility through wages and leisure hours. This provides an incentive to the entrepreneurs to raise investment and production. In contrast, the behavior of the unemployed laborers and entrepreneurs is similar to the reactions of the representative agent in standard models. An increase in the value of being unemployed leads to a contract signed that is worth more to the laborers and leads to comparatively less number of hours worked and higher wages paid. The different responses to good news generated here cannot be studied in representative agent models.

The model may be extended by including capital formation. The new model can study investment decisions at both the intensive and extensive margins. Further, the model can also look at the responses in the level of aggregate capital as a response to news shocks. This model can study the difference between how the representative agent models treat the level of aggregate capital and its role in the model presented here. In previous work, aggregate capital has a structural connection to each aggregate variable while here it has only a 'reduced form' connection. More specifically, the level of aggregate capital was used in previous studies to make the choice of aggregate hours, aggregate investment and aggregate consumption (some FOC was satisfied). There is no such equation that connects aggregate capital and any other aggregate variable on a structural level in this model. A positive news shock leads to an increase in aggregate capital because of changes in the intensive and extensive margin. Each existing entrepreneur decides to build up the existing capital stock and new entrepreneurs enter the labor market to capitalize on their expectations of higher profits. Since the level of aggregate capital increases with the decisions made by each entrepreneur, there is no structural connection between the aggregate variables but only a reduced form correlation.

Study of news revisions under this model may provide an explanation for the boom period of the 1990s followed by the subsequent dotcom crash. The 90s were a period which saw higher than normal number entrants into industries that benefited from widespread use of the Internet (web service startups). Further, the period also saw existing firms investing and accumulating capital at a higher rate. The model presents a possible explanation for the expansion and subsequent 'crash': agents' expectations were too high about the productivity gains and so, the 'crash' was actually an adjustment period after years of over investment. Firms realized the true capacity of this technological growth and adjusted their investment and employment accordingly. The explanation is appealing in that it does not rely upon technological regress nor some other large change in fundamentals. An additional implication of this model is that expansionary fiscal or monetary policies in periods of adjustment (recession) may not address the problem since they only temporarily increase output and employment and ultimately, delay the needed adjustment in the economy.

Finally, it would be instructive to study the effect of limited commitment contracts in place of full commitment contracts in this model. I expect this change to dampen the effects of a positive news shock. Under a limited commitment contract, old entrepreneurs cannot take advantage of their existing contracts in the same way. With the possibility of an outside option, laborers are not locked into contracts if the expected utility of being unemployed exceeds the utility of staying with the entrepreneur.

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Model Parameters

Description	Variable	Value
Simulation Interval	n/a	10 days
Technology	a	{.96885,1,1.03115}
Transition Matrix	$\prod = \lambda * I_{3x3} + (1-\lambda)*Q$	Q = [0 1 0;.5 0 .5;0 1 0] and λ = 0.98805
Discount	β	0.9987 (1.2% quarterly return)
Job Separation	δ	.01
Matching function	$\mu(\theta)$	$0.15*\theta^{0.28}$
Unemp. Comp.	B	0.4
Contract Length	j	{20,30}
U (utility w/o hrs)	$C^{(1-\Upsilon)}/ (1-\Upsilon)$	ϒ ={.25,.5}
H (utility w/hrs)	$U + 2*(1-\eta)^{-1}*(1-l)^\wedge(1-\eta)$	η =2

Table 1: Most of the parameters are set to be consistent with Rudanko (2009). For those parameters for which no counterpart exists in Rudanko (2009), I have chosen multiple candidates to show the effect of varying this parameter. H is chosen to be consistent with Andolfatto (1996).

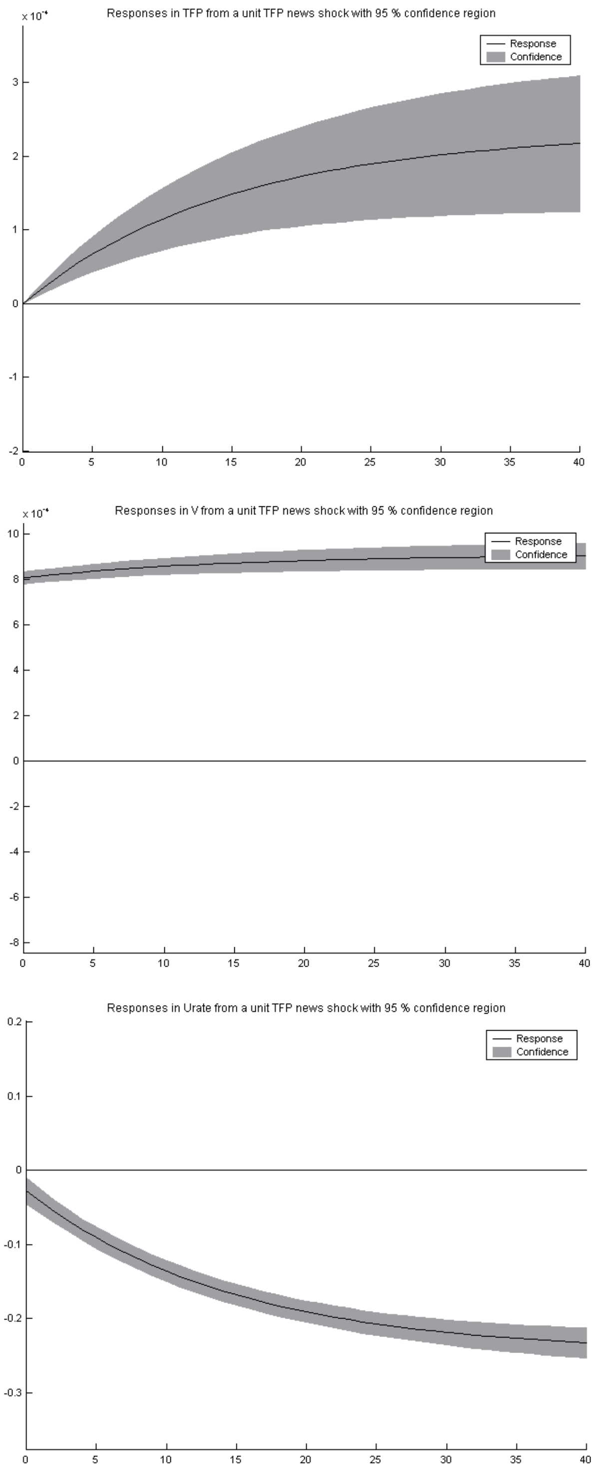

Figure 1: Model generated impulse responses to a TFP news shock for TFP, vacancies, and unemployment. The model solved featured a contract length of 20 periods, risk aversion parameter equal to 0.5 and hours were not included (model 1).

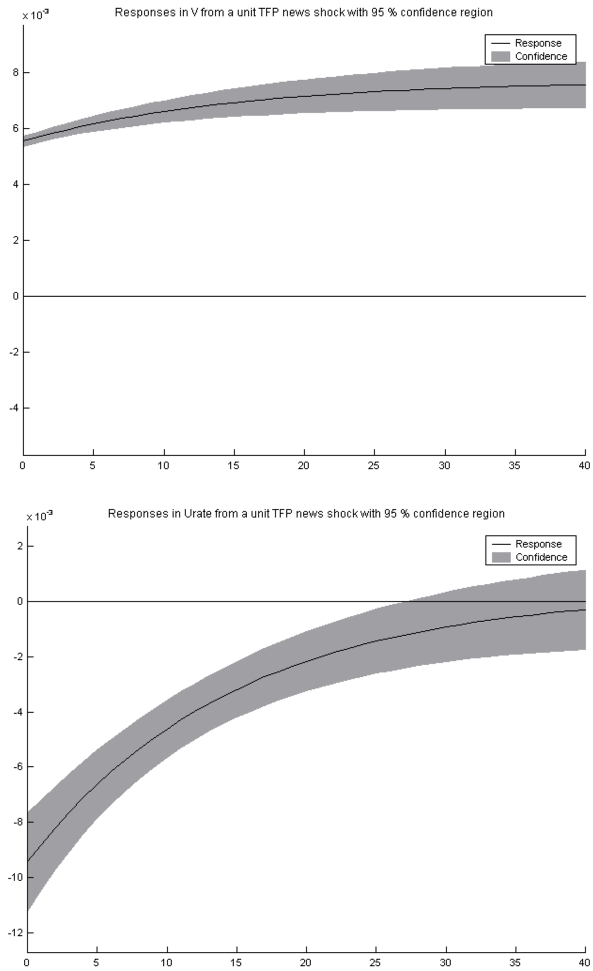

Figure 2: Model generated impulse responses to a TFP news shock for vacancies, and unemployment. The model solved featured a contract length of 30 periods, risk aversion parameter equal to 0.5 and hours were not included (model 2).

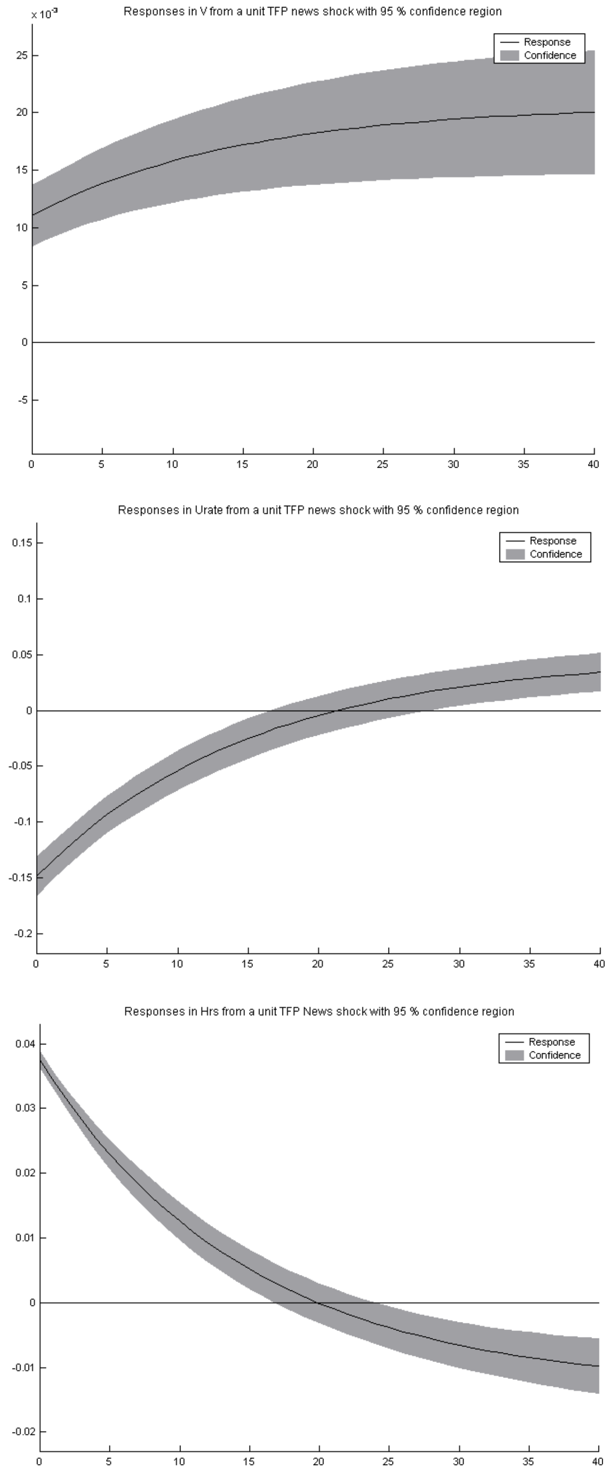

Figure 3: Model generated impulse responses to a TFP news shock for vacancies, unemployment, and hours worked. The model solved featured a contract length of 30 periods, risk aversion parameter equal to 0.25 and hours were included (model 3).

Effects (in 1 year) of a 1% TFP News Shock (TFP increases by 1% in 1 year)

	Vacancies	Unemployment Rate	Hours Worked
Model 1	1.25	-0.85	-
Model 2	1.62	-2.77	-
Model 3	3.10	-4.91	.157

Table 2: This table shows the model generated impact percent changes caused by receiving news that TFP will be 1% higher than expected in 1 year.

Identifying Tax News in the Presence of Fiscal Foresight*

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Dissertation Essay 3
July 15, 2013

Abstract

The legislative process and the corresponding implementation lags provide agents with signals about future tax rates. This phenomenon, commonly known as fiscal foresight, produces a law of motion for capital that contains a non-invertible moving average component in a standard Real Business Cycle model. So, standard backward-looking tools of the macro literature dealing with the identification of shocks, like Vector Auto Regressive Moving Average modeling and the Kalman filter, are not applicable. I show that Kalman smoothing, a forward looking approach, is able to produce consistent estimates for this model economy. Finally, I show that the smoother is able to produce consistent estimates for the model only because of a characteristic of tax news: tax news is transmitted without noise/distortion to the representative agent today and to the econometrician at some point in the future.

JEL Classification: C20, C32, E13

Keywords: fiscal foresight, real business cycle models, identifying shocks

*I thank Chris Otrok, Toshi Mukoyama, and Eric Young for their guidance. I also thank seminar participants at the University of Virginia and the Graduate Student Conference at the University of Maryland for their helpful comments. I received support from the Bankard Fund for Political Economy for this paper. All errors are mine.

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1 Introduction

People routinely receive news about upcoming changes in the macroeconomic climate. In response, they adjust their economic behavior well before the change takes place. Since such news need not be observable to the econometrician, implementation of the change is incorrectly classified as a shock to the economy.

This paper focuses on the econometric implications of tax news, or fiscal foresight. Evidence for its presence abounds. The Tax Reform Act of 1986 repealed the capital gains exclusion from income, which raised the maximum capital gains tax rate. The lag between enactment and enforcement saw a massive jump in capital gains realizations from 172 billion USD to about 328 billion USD. Similarly, House and Shapiro (2006) argue that workers and firms delayed production in response to President Bush's phased-in tax cuts of 2001.[1]

The presence of fiscal foresight poses a problem for standard tools of the macroeconomics literature dealing with the identification of shocks. Using a standard RBC model with fiscal foresight as in Leeper, Walker, and Yang (forthcoming), I show that the Vector Auto Regressive Moving Average (VARMA) method [2] and the Kalman filter must yield inconsistent estimates of tax news.

Kalman smoothing, in contrast, can produce consistent estimates in an environment with foresight. I show that this is partly due to the method's reliance on both past and future observables. Consistency, however, depends on an identification assumption regarding the *lesser* weight given to more recent news shocks since they contain information about tax rates *further* in the future.

2 The Model

I use a standard RBC model augmented with two periods of fiscal foresight as in Leeper, Walker, Yang (forthcoming). This simple model is sufficient in highlighting the reason behind the inconsistency of backward looking approaches and the reason behind the consistency of the Kalman smoother.

Consumers have log preferences, the supply of labor is inelastic and there is complete

[1] See also Jaimovich and Rebelo (2009). They show that productivity news can have a significant impact on business cycle fluctuations.

[2] The condition specified in Fernandez-Villaverde, Rubio-Ramirez, Sargent and Watson (2009) for the impulse responses from a VAR to match those of the economic model is not met.

depreciation of capital. Output is produced using a Cobb-Douglas technology. The government imposes a proportional income tax and then adjusts lump sum transfers to balance its budget each period.

The equilibrium conditions are standard. The model solution is characterized by the law of motion for capital.

$$k_t = \alpha k_{t-1} + a_t - (1-\theta)\left(\frac{\tau}{1-\tau}\right)\sum_{i=0}^{\infty}\theta^i E_t \tau_{t+i+1} \tag{1}$$

where k_t denotes capital, α is the share of capital in the Cobb-Douglas production function, a_t is the TFP shock, τ is the steady state tax rate, β is the discount factor, and $\theta = \alpha\beta(1-\tau)$. Note that agents internalize their expectations of future tax rates when making their economic choices.

Let the process for taxes be white noise normal and endow the agents with two periods of tax foresight. In other words, agents receive a perfect signal each period about the taxes they face two periods later. The law of motion for capital now becomes:

$$k_t = \alpha k_{t-1} + a_t - (1-\theta)\left(\frac{\tau}{1-\tau}\right)(\epsilon_{\tau,t-1} + \theta\epsilon_{\tau,t}) \tag{2}$$

where $\epsilon_{\tau,t}$ represents the *tax news* and not the *tax shock* received in period t.

3 Backward Looking Approaches And The Invertibility Problem

Since $\theta = \alpha\beta(1-\tau) < 1$, the root of the lag polynomial (L+θ) lies inside the unit circle. So (2) contains a non-invertible moving average component. I show below that this parameterization creates a positive lower bound for the MSE of the tax shock estimates for each approach.

Proposition: MSE_t of the VARMA estimates of tax shocks is $2 - 2\theta$.

Proof: Assume for simplicity that the TFP shock a_t is observed. Further, W.L.O.G I set $(1-\theta)\left(\frac{\tau}{1-\tau}\right)$=1. From (2) it follows that the VARMA representation is

$$\begin{bmatrix} a_t \\ k_t \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{(L+\theta)}{(1-\alpha L)} & \frac{1}{1-\alpha L} \end{bmatrix} \begin{bmatrix} \epsilon_{\tau,t} \\ \epsilon_{a,t} \end{bmatrix}$$

Since the root of the determinant of the square matrix above lies inside the unit circle, VARMA actually identifies an observationally equivalent invertible process instead of the true non-invertible process. To see this, modify the representation above as follows:

$$\begin{bmatrix} a_t \\ k_t \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{(L+\theta)}{(1-\alpha L)} & \frac{1}{1-\alpha L} \end{bmatrix} \begin{bmatrix} \frac{1+\theta L}{L+\theta} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{L+\theta}{1+\theta L} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_{\tau,t} \\ \epsilon_{a,t} \end{bmatrix}$$

We can now write the VARMA so that the root of the determinant of the square matrix lies outside the unit circle.

$$\begin{bmatrix} a_t \\ k_t \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{(1+\theta L)}{(1-\alpha L)} & \frac{1}{1-\alpha L} \end{bmatrix} \begin{bmatrix} \epsilon^*_{\tau,t} \\ \epsilon^*_{a,t} \end{bmatrix}$$

where

$$\begin{bmatrix} \epsilon^*_{\tau,t} \\ \epsilon^*_{a,t} \end{bmatrix} = \begin{bmatrix} \frac{L+\theta}{1+\theta L} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_{\tau,t} \\ \epsilon_{a,t} \end{bmatrix}$$

So, the identified tax shock is the following function of the true shock.

$$\epsilon^*_{\tau,t} = \theta\epsilon_{\tau,t} + (1-\theta^2)\epsilon_{\tau,t-1} + \theta(1-\theta^2)\epsilon_{\tau,t-2} + \theta^2(1-\theta^2)\epsilon_{\tau,t-2} + ... \tag{3}$$

To arrive at the MSE we need to calculate $E_t(\epsilon_{\tau,t} - \epsilon^*_{\tau,t})^2$. Using the derivation above we see that the MSE is 2-2θ.

Applying the formulas from Hamilton (1994) the MSE_t of the Kalman filter is

$$p_{t+1} = \frac{1}{1+\theta^2+\theta^4+\theta^6+...\theta^{2t+2}}. \tag{4}$$

To highlight these results, I simulate a model economy and then use the VARMA and the Kalman filter to extract the tax news received by agents in each period. Figures 1 and 2 are scatter plots of the true tax news against estimates produced by each approach. Note the clear deterioration in estimation accuracy as θ moves closer to the origin.

4 Kalman Smoothing

It is a well-known fact in the study of time series data that a non-invertible moving average process is invertible in future observables. With this as motivation, I apply the Kalman smoother to the problem considered here. Kalman smoothing is used to form an inference about the unobserved states (tax news) using *all* available information. It works backwards by using the regular Kalman filter to obtain estimates of the state vector for the last time period and uses this estimate in the linear projection for estimates of earlier state vectors.

Let $\epsilon^*_{a/b}$ denote the estimate of the tax news received in period a given information till period b. To arrive at $\epsilon^*_{t/T}$, the Kalman Smoother equation is (using the derivations in

Hamilton (1994)):

$$\epsilon^*_{t/T} = \epsilon^*_{t/t+1} + J_t[\epsilon^*_{t+1/T} - \epsilon^*_{t+1/t+1}] \tag{5}$$

where $J_t = \frac{p_t}{\theta}$ is the slope of a regression by $\epsilon^*_{t/t}$ on $\epsilon^*_{t/t+1}$.

Since we work backwards, we already know $\epsilon^*_{t+1/T}$. The other two terms in (5) are:

$$\epsilon^*_{t/t} = \frac{\theta}{\theta^2 + p_t}[k_t - \epsilon^*_{t-1/t-1}] \tag{6}$$

$$\epsilon^*_{t-1/t} = \epsilon^*_{t-1/t-1} + \frac{p_{t-1}}{\theta}\epsilon^*_{t/t} \tag{7}$$

So, $J_t[\epsilon^*_{t+1/T} - \epsilon^*_{t+1/t+1}]$ reflects the use of $\epsilon^*_{t+1/t+1}$ for approximating $\epsilon^*_{t/t+1}$ and also reflects its subsequent removal by the smoothing algorithm in favor of the 'smoothed' version, $\epsilon^*_{t+1/T}$.

Figure 3 shows the estimation accuracy of the Kalman smoother as θ moves closer to the origin. We observe a marked difference from the other approaches. Even though we have that the smoothing algorithm is *in principle* more accurate than both the Kalman filter and the VARMA method, other problems remain.

Foresight introduces unusual discounting in the law of motion for capital. More recent news receives less weight since it provides information about a more distant time period (see (2)). The maximum likelihood equations produced by the Kalman filter quickly show that the variance of the tax shock and the weights given to the news shocks are not identified separately. Consistent estimation of the state vectors is *impossible* without knowledge of at least one of these three parameters.

5 What Is Special About Tax News? Can We Extract Other Types Of news?

In the paragraphs above I show that the econometrician can identify tax news as long as she has access to information from the future. In other words, the econometrician is able to extract tax news received at time period $t - a$ using information from periods $t - a + 1$ till period t. But can this method apply to other forms of news? If economic agents receive information about other fundamental variables in an economy (e.g. government spending, technology) can we use the Kalman smoother to extract this information as well? If the method is not generalizable, what is peculiar about this model and problem?

If economic agents receive news about a variable that affects their decision today and that variable is observable to the agent today without any noise and to the econometrician sometime in the future also without any noise then Kalman smoothing can extract the relevant news. In fact, these assumptions are implicit in the sections above. If either the economic agent acted after receiving noisy tax news (true tax rate along with noise) or the econometrician observed a noisy tax rate at some point in the future, then the method does not work. In (2) above, it is apparent that receiving noisy tax news produces a stark identification problem. If such noise existed, signal extraction cannot be performed. I forgo this possibility because tax news is different from other kinds of news signals. Both the economic agent (at time period $t - a$) and the econometrician (at time period t) receive tax information without any sort of associated noise component. The nature of the legislative and implementation lags makes this so. This need not happen with other sorts of signals that exist in the US economy.

Consider, for example, news received regarding upcoming changes in technology. Recent work concludes that technology news exists.[3] But by its nature, when doing VAR analysis we assume that economic agents are receiving such news mixed with a noise component and their economic decisions are based on this imperfect measure of US aggregate productivity in the future. To compound the problem, it is also implicit in that work that the econometrician's measure of technology is not without noise. As a result, the methods described here *cannot* extract the news information received by economic agents. This finding is apparent after redoing the Kalman smoothing calculations above when tax news is noisy.

This finding is consistent with that of Blanchard, L'huillier, and Lorenzoni (2011) who study technology news in a model where agents receive noisy information about productivity. Here, this variable is affected by both a permanent component shock (one that builds over time) and a transitory shock. Agents are not able to observe the two components individually but instead can only observe a noisy signal regarding the permanent component. This signal can contain information about a permanently higher level of productivity in the future (news) or can be composed entirely of noise. The agents then face a signal extraction problem. The authors show that a VAR applied to model generated data on productivity, productivity signals, and fundamentals cannot produce consistent estimates of the permanent component of productivity. Further, the paper also shows that using future realizations of these variables is not enough to identify the permanent component of productivity. The problem reduces to the invertibility condition discussed by Fernandez-Villaverde, Rubio-Ramirez, Sargent,

[3]See Barsky and Sims (2011), Beaudry and Portier (2004, 2006), Kurmann and Otrok (forthcoming).

Watson (2009). Since some state variables (noise) are hidden for all time periods from both the agent and the econometrician it is no longer possible to distinguish a shock to the statistical model as coming from a shock to the observable state variables or from a discrepancy between expectation of an unobserved state variable and its true realization. The paper shows that even with a large amount of data from the future, the econometrician must remain unsure of the true state vector and thus, both VARMA and Kalman smoothing analysis are of no use.

The model studied above imposes considerably more structure. I assume that economic agents receive tax news today without any distortion and that the econometrician is able to observe this realization at some point in the future also without any distortion. This assumption is a result of the essential nature of tax news. The lags that are inherent in the legislative and enforcement process make clear (i.e. noiseless) exactly what tax rate the representative agent will face. As a result of this peculiarity, I am able to use information from the future to extract tax news received at any point in time.

6 Conclusion

Foresight presents a two-pronged problem to researchers. First, it introduces a non-invertible MA component in the process for capital. And second, it introduces unusual discounting for the tax news process. Neither the Kalman filter nor the VARMA approach can overcome these difficulties due to their reliance on only past information. In contrast, Kalman smoothing, with its projection on tomorrow's state vector, is able to overcome the non-invertibility problem. The second problem, however, affects each approach similarly. Without knowledge of the unusual weights given to tax shocks, consistent estimates are not possible.

Questions remain. So far I have tried only to show that the smoothing algorithm is better in principle at estimating the unobserved states. During actual estimation, researchers face the considerable problem of model selection, and the choice of the size of their state space. In other words, they must decide whether the data exhibits 2 or 3 or some other degree of foresight. The trade off between better model fit and a greater number of free parameters deserves study. Looking at a state space AIC information criterion similar to the one proposed by Cavanaugh and Shumway (2006) might be a good start.

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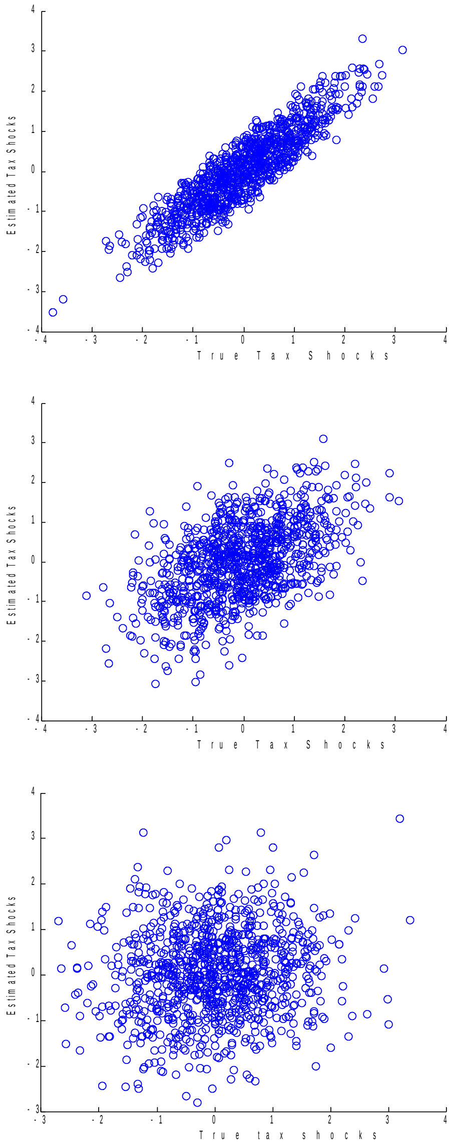

Figure 1: This figure shows the VARMA estimates of the tax shocks(y-axis) against the true tax shocks(x-axis) for $\theta = .9, .5, .05$, respectively in the law of motion for capital [2]. I simulate 1000 draws using the following parametrization: $k_t = \frac{1}{2}k_{t-1} + a_t - (\epsilon_{\tau,t-1} + \theta\epsilon_{\tau,t})$ where a_t and ϵ_t are standard white noise processes.

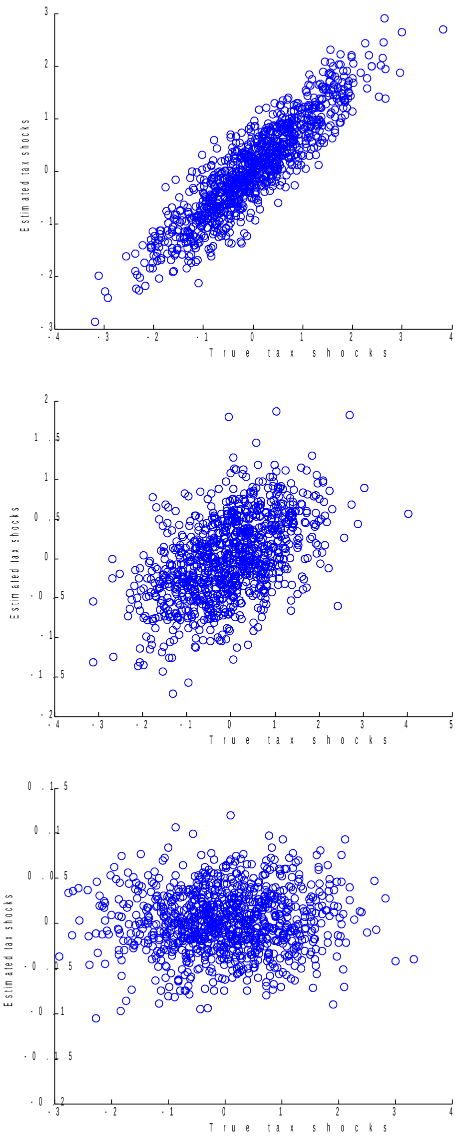

Figure 2: This figure shows the standard Kalman filter estimates of the tax shocks(y-axis) against the true tax shocks(x-axis) for $\theta = .9, .5, .05$, respectively in the law of motion for capital [2]. I simulate 1000 draws using the following parametrization: $k_t = \frac{1}{2}k_{t-1} + a_t - (\epsilon_{\tau,t-1} + \theta\epsilon_{\tau,t})$ where a_t and ϵ_t are standard white noise processes.

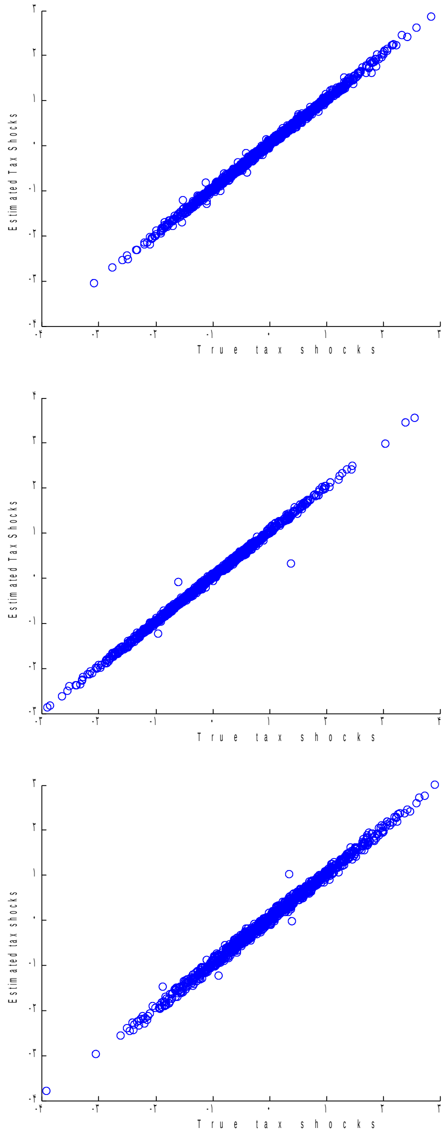

Figure 3: This figure shows the Kalman smoother estimates of the tax shocks(y-axis) against the true tax shocks(x-axis) for $\theta = .9, .5, .05$, respectively in the law of motion for capital [2]. I simulate 1000 draws using the following parametrization: $k_t = \frac{1}{2}k_{t-1} + a_t - (\epsilon_{\tau,t-1} + \theta\epsilon_{\tau,t})$ where a_t and ϵ_t are standard white noise processes.