News Shocks about Future Investment Specific Technology and Business Cycles

Nadav Ben Zeev*

Department of Economics, The Hebrew University of Jerusalem, Jerusalem 91905, Israel

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Abstract

Which shocks drive the business cycle? This paper provides robust evidence that news shocks about future investment specific technology (IST) constitute a significant force behind the business cycle. Extending a recent empirical approach to identifying news shocks, I find robust evidence that IST news shocks induce positive comovement, i.e., raise output, consumption, investment, and hours of work, explain 70% of their business cycle variation, and have played an important part in nine of the last ten U.S recessions.

Keywords: IST, News Shocks, Business Cycle, VAR, DSGE

JEL Classifications: E0, E00, E1, E10, E2, E20, E3, E30, E31, E32

* *Address for correspondence*: Department of Economics, The Hebrew University of Jerusalem, 91905, Israel. Phone: 972-54-4807448. E-mail: nadav.benzeev@mail.huji.ac.il.

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1. Introduction

The quest for understanding the driving forces behind business cycles has been a prominent feature of modern macroeconomic research. The role of several candidate shocks as business cycle drivers has been studied, leaving much debate and lack of consensus on the types of shocks that drive business cycles. Such candidate shocks include total factor productivity (TFP) shocks (e.g. Gali (1999) and Basu, Fernald, and Kimball (2006; Henceforth BFK)), investment specific technology (IST) shocks (e.g. Greenwood, Hercowitz, and Krusell (2000; Henceforth GHK), Fisher (2006), Justiniano et al. (2010a, 2010b), and Khan and Tsoukalas (2011)), and news shocks about future TFP, i.e. shocks that portend future changes in TFP (e.g. Beaudry and Portier (2006), Beaudry and Lucke (2009), and Barsky and Sims (2010a)). This paper belongs to the relatively small literature that has examined the role of news shocks about future IST in the business cycle. It contributes to both the vast literature that strives to comprehend which forces drive business cycles and the small literature on IST news shocks by providing robust evidence that IST news shocks are a significant force behind business cycles.

The few papers that have tried to assess the role of IST news shocks in the business cycle did so using estimated dynamic stochastic general equilibrium (DSGE) models (i.e. Davis (2007), Schmitt-Grohé and Uríbe (2008), and Khan and Tsoukalas (2010)). The main advantage of the DSGE approach is that it provides a structural interpretation of the mechanisms transmitting the shocks. The disadvantage, however, is that model based inferences often depend upon the assumed structure which could be different from the true one. Therefore, imposing a certain structure on the data could lead to incorrect inferences. Davis (2007) introduces news shocks in the Christiano et al. (2005) model and finds that IST news shocks account for about 52% of the variation in output growth.[1] By contrast, Schmitt-Grohé and Uríbe (2008)

[1] Nevertheless, it is unclear whether or not IST news shocks produce business cycle comovement in his paper as the impulse responses are not shown.

estimate a flexible price-wage DSGE model with TFP and IST news shocks and find a strong role for TFP news compared to a negligible role for IST news. Lastly, Khan and Tsoukalas (2010) estimate a DSGE model with both real and nominal frictions, including TFP and IST news shocks, and find a relatively weak role for news shocks as drivers of the business cycle. That the above DSGE literature arrived at different conclusions about the relative importance of each type of news shock suggests that some features of the model structure may themselves have an effect on the quantitative assessments. Overall, the empirical DSGE literature has not found robust evidence in support of a strong role for IST news shocks as business cycle drivers.

This paper takes a different approach than the above DSGE literature and closely examines the role of IST news shocks as business cycle drivers by extending the VAR based method for the identification of news shocks that was recently proposed by Barsky and Sims (2010a),[2] which in turn builds upon the maximum forecast error variance (MFEV) identification approach developed by Uhlig (2003). Whereas the former identified TFP news shocks as the shocks that maximally explain future variation in TFP over a finite horizon orthogonalized with respect to unanticipated TFP shocks, thus adding one identifying restriction to the MFEV optimization problem, I add *two* identifying restrictions for the identification of IST news shocks. In particular, the IST news shock is identified as the linear combination of reduced form innovations orthogonal to both unanticipated TFP and IST shocks which maximizes the sum of contributions to IST forecast error variance over a finite horizon.[3] As discussed in section 2.2, the main reason for including TFP and the

[2] They focus on TFP news shocks and find the latter to be associated with an increase in consumption and decrease in output, investment and hours worked on impact thus suggesting an unimportant role of these shocks in the business cycle.

[3] It's important to note here that TFP is a measure of exogenous neutral technology, as opposed to labor productivity, and it is therefore appropriate to impose on IST news shocks to be orthogonal to it contemporaneously.

corresponding additional orthogonality restriction is that the monte carlo simulation results, using DSGE model generated data, showed that it significantly improves the identification of IST news shocks. The main virtue of this identification approach to IST news shocks is that it does not impose a specific model structure on the data as in the empirical DSGE literature but rather exploits two common assumptions in IST news driven DSGE models that (*i*) only a limited number of shocks ever affect IST and (*ii*) IST news shocks do not affect IST contemporaneously but rather portend future changes in it. After it is shown that this identification procedure performs well on DSGE model generated data in terms of identifying IST news shocks and their business cycle effects, it is applied it on postwar U.S data.[4] I find robust evidence that IST news shocks induce positive business cycle comovement, i.e., raise output, consumption, investment, and hours of work, explain 70% of their forecast error variance at business cycle frequencies, and have played an important part in nine of the last ten U.S recessions. Overall, it can be deduced that IST news shocks are not only capable of generating business cycles but also that they have played an important role as drivers of U.S business cycles over the last sixty years.

The above findings stand in contrast to the findings of the DSGE literature on IST news shocks. While the results from this literature depend on the type of structure of the model, my results are derived from a model free identification approach that does not impose any structure on the data but is still capable of identifying IST news shocks and their business cycle effects from a variety of model structures. Nevertheless, it's important to understand what type of model structure is needed in order for IST news shocks to be at the very least capable of generating business cycles. In the next section, which provides monte carlo simulation evidence that confirms that the proposed identification approach works fairly well on DSGE model

[4] I follow GHK (1997, 2000), Fisher (2006), Schmitt-Grohé and Uríbe (2008), Beaudry and Lucke (2009), and Liu et al. (2011) and use a real investment price measure to gauge IST (see section 3.1 for data descriptions).

generated data, I present a state-of-the-art DSGE model that is capable of providing the structure that is needed for IST news shocks to be drivers of business cycles. The model is a standard New-Keynesian DSGE model (e.g. Smets and Wouters (2007)) augmented with the recently popularized Jaimovich and Rebelo (2009) preference structure and a specification of the cost of utilization in terms of increased depreciation of capital, as originally proposed by Greenwood, Hercowitz and Huffman (1988; Henceforth GHH) in a neoclassical setting. The model essentially contains the three elements that are needed for IST news shocks to be capable of generating business cycles, as shown by Jaimovich and Rebelo (2009): preferences with a small wealth effect on labor supply, investment adjustment costs, and variable capital utilization.

The remainder of the paper is organized as follows. In the next section the details of the empirical strategy are laid out and simulation evidence that the identification procedure performs well on data generated from a state-of-the-art DSGE model is provided. Section 3 begins with a description of the data, after which it presents the main empirical evidence and provides a sensitivity analysis of the results as well as a discussion on their relation to earlier work. The final section concludes.

2. Empirical Strategy

It is assumed that IST is well-characterized as following a stochastic process driven by two shocks. The first is the traditional unanticipated IST shock of the IST literature, first introduced in the pioneering work of GHH (1988), which impacts the level of IST in the same period in which agents observe it. The second is the news shock, which is differentiated from the first shock in that agents observe the news shock in advance and it portends future changes in IST. The following is an example process that incorporates both unanticipated and IST news shocks:

$$\varepsilon_t^{is} = \varepsilon_{t-1}^{is} + g_{t-1}^{is} + \eta_t^{is} \tag{1}$$

$$g_t^{is} = \kappa g_{t-1}^{is} + e_t^{is} \tag{2}$$

Here log IST, denoted by ε_t^{is} , follows a unit root process where the drift term itself g_{t-1}^{is} follows an AR(1) process. Parameter κ describes the persistence of the drift term. η_t^{is} is the conventional unanticipated IST shock. Given the timing assumption, e_t^{is} has no immediate impact on the level of IST but portends future changes in it. Hence, it can be defined as an IST news shock. In a VAR including empirical measures of TFP, IST and several macroeconomic aggregates, the IST news shock is identified as the shock that best explains future movements in IST over a horizon of fifteen years and that is orthogonal to both TFP and IST unanticipated shocks. The restriction with respect to IST is important for identification as it imposes on the identified shock to have no contemporaneous effect on IST, which complies with the definition of a news shock. I include TFP in the VAR and impose the corresponding additional orthogonality restriction because monte carlo simulation evidence indicated that doing so significantly improves identification. In practice, this identification strategy involves finding the linear combination of VAR innovations contemporaneously uncorrelated with TFP and IST innovations which maximally contributes to IST's future forecast error variance.

The remainder of this section is organized as follows. Section 2.1 introduces terminology and lays out the identification strategy more formally. This paper follows recent work which used monte carlo simulations based on DSGE models to check the suitability of a given identification method (e.g. Francis et al. (2007), Chari et al. (2008), and Barsky and Sims (2010a)). Thus, it is verified in Section 2.2 that the identification strategy is capable of recovering the IST news shock and its dynamic effects from data simulated from DSGE models. On the basis of simulations from a state-of-the-art DSGE model, it is shown that the identification method is likely to perform well at identifying IST news shocks in practice.

2.1 Identification Strategy

The identification method pursued in the paper will now be presented in detail. Let y_t be a k x1 vector of observables of length T. Estimating a stationary vector error correction model (VECM) or an unrestricted VAR in levels can generate the reduced form moving average representation in the levels of the observables:

$$y_t = B(L)u_t \tag{3}$$

It is assumed there exists a linear mapping between innovations and structural shocks:

$$u_t = A\varepsilon_t \tag{4}$$

This implies the following structural moving average representation:

$$y_t = C(L)\varepsilon_t \tag{5}$$

Where $C(L) = B(L)A$ and $\varepsilon_t = A^{-1}u_t$. The impact matrix A must satisfy $AA' = \Sigma$, where Σ is the variance-covariance matrix of innovations. However, there's an infinite number of impact matrices that solve the system $AA' = \Sigma$. In particular, for some arbitrary orthogonalization, $\widetilde{A}$ (e.g. a Choleski decomposition), the entire space of permissible impact matrices can be written as $\widetilde{A}D$, where D is a k x k orthonormal matrix ($DD' = I$).

The h step ahead forecast error is:

$$y_{t+h} - E_t y_{t+h} = \sum_{\tau=0}^{h} B_\tau \widetilde{A} D \varepsilon_{t+h-\tau} \tag{6}$$

The contribution to the forecast error variance of variable i attributable to structural shock j at horizon h is then:

$$\Omega_{i,j}(h) = \sum_{\tau=0}^{h} B_{i,\tau} \widetilde{A}\gamma\gamma' \widetilde{A}' B_{i,\tau}' \tag{7}$$

γ constitutes the *j*th column of D. $\widetilde{A}\gamma$ is then a k x 1 vector corresponding with the *j*th column of a possible orthogonalization and $B_{i,\tau}$ represents the *i*th row of the matrix of moving average coefficients at horizon τ. Let TFP and IST occupy the first and second positions in the system, respectively, and let the unanticipated TFP and IST shocks be indexed by 1 and 2, respectively. Finally, the news shock is indexed by 3 and is identified as the shock that is orthogonal to unanticipated TFP and IST shocks and that maximally explains movements in IST not accounted for by its own innovations and TFP innovations. In particular, the IST news shocks is identified by finding the γ which maximizes the sum of contribution to the forecast error variance of IST at horizons from 0 to H subject to the restriction that this shock have no contemporaneous effect on TFP and IST. This implies solving the following optimization problem:

$$\gamma^{*} = \arg\max \sum_{h=0}^{H} \Omega_{2,3}(h) = \sum_{h=0}^{H} \sum_{\tau=0}^{h} \mathrm{B}_{2,\tau} \widetilde{\mathrm{A}} \gamma \gamma' \widetilde{\mathrm{A}}' \mathrm{B}_{2,\tau}'$$

$$s.t \quad \begin{array}{l} \widetilde{\mathrm{A}}(1,j) = 0 \quad \forall\ j > 1 \\ \widetilde{\mathrm{A}}(2,j) = 0 \quad \forall\ j > 2 \\ \gamma(1,1) = 0 \\ \gamma(2,1) = 0 \\ \gamma'\gamma = 1 \end{array}$$

H is some finite truncation horizon. The first four constraints impose on the identified shock to have no contemporaneous effect on TFP and IST. The fifth restriction that imposes on γ to have unit length ensures that γ is a column vector belonging to an orthonormal matrix. Following Uhlig (2003), this maximization problem can be rewritten as a quadratic form in which the non-zero portion of γ is the eigenvector associated with the maximum eigenvalue of the lower (k-2) x (k-2) sub-matrix of the following matrix S:

$$\mathrm{S} = \sum_{\tau=0}^{H} (H + 1 - \tau) \left(\mathrm{B}_{2,\tau} \widetilde{\mathrm{A}}\right)' \left(\mathrm{B}_{2,\tau} \widetilde{\mathrm{A}}\right)$$

Hence, this procedure constitutes an application of principle components. Specifically, it identifies the IST news shock as the first principal component of the lower (k-2) x (k-2) sub-matrix of matrix S orthogonalized with respect to IST and TFP innovations.

2.2 Simulation Evidence

Simulation evidence which confirms that the above proposed empirical strategy is indeed capable of doing a good job of identifying IST news shocks will now be presented. I consider the by now classic Smets and Wouters (2007) model augmented with three elements, along the lines of Khan and Tsoukalas (2010, 2011): the recently popularized Jaimovich and Rebelo (2009) preferences that allow for an arbitrarily weak wealth effect on labor supply,[5] specification of the cost of utilization in terms of increased depreciation of capital, as originally proposed by GHH (1988) in a neoclassical setting,[6] and finally the model also includes TFP and IST news shocks. TFP news shocks are also included in the model in order to be consistent with the news shocks literature.

The equilibrium conditions of the model log-linearized about the balanced growth path, along with the definition of the variables, are presented in table 1 (for detailed derivation see Smets and Wouters (2007) and Khan and Tsoukalas (2010, 2011)). Equation (T.1) is the aggregate resource constraint; Eq. (T.2) is the Euler equation for consumption where the coefficients c_1 and c_2 depend on the underlying model parameters and the steady state level of hours worked;[7] Eq. (T.3) is the Euler equation for investment; Eq.(T.4) depicts the dynamics of Tobin's q; Eq.(T.5) is the aggregate production function; Capital services used in production are a function of capital installed in the previous period and capital utilization, as described by eq. (T.6); Eq. (T.7) expresses the optimal capital utilization rate as a function of the value of capital and rental rate on capital; Eq. (T.8) is the capital accumulation equation; The price mark up is defined by Eq. (T.9); Inflation dynamics are described by the New-Keynesian Phillips curve in Eq. (T.10); Cost minimization by firms implies that

[5] These preferences nest two polar specifications that have featured prominently in the business cycle literature: the one used in King et al. (1988) and the one introduced by GHH (1988).

[6] Traditionally, the cost of utilization is specified in terms of forgone consumption following Christiano et al. (2005), who studied the effects of monetary policy shocks. I follow Khan and Tsoukalas (2011) who use the capital depreciation specification and show that it has a superior fit with the data relative to the Christiano et.al (2005) specification. This specification is also used in Jaimovich and Rebelo (2009).

[7] The reader is referred to Khan and Tsoukalas (2010, 2011) for the exact expressions for these parameters.

the capital-labor ratio is inversely related to the rental rate of capital and positively related to the wage rate, as described by eq. (T.11); The wage markup is given by Eq. (T.12); The wage inflation dynamics are described by Eq. (T.13); Lastly, Eq. (T.14) describes the monetary policy rule.

The news processes, given by eq. (T.16) and (T.21), are simply a smooth version of the news process studied in Beaudry and Portier (2004) and Jaimovich and Rebelo (2009) where the news shock portends a future permanent change in technology j periods into the future. This smooth specification is consistent with the smooth gradual news processes employed in Leeper et.al (2009) and Leeper and Walker (2011). Identification also performs well when the more standard specification of Beaudry and Portier (2004) and Jaimovich and Reblelo (2009) is used. Nevertheless, I choose the smooth version specification because it seems to be more consistent with the data, as indicated by the empirical results in section 3.

Labels, definitions and benchmark values of the parameters are in Table 2. The benchmark values of the discount factor, intertemporal elasticity, capital share and capital utilization elasticity are set in accordance with Jaimovich and Rebelo (2009). The wealth elasticity parameter is set at 0.1.[8] The values for the news persistence parameters follow Barsky and Sims (2010b) while those of the monetary policy rule are consistent with the empirical estimates of Coibion and Gorodnichenko (2007), Fernandez-Villaverde and Rubio-Ramirez (2007), Erceg, Guerrieri, and Gust (2006), and Ireland (2004). The standard deviation of the news shocks is set in

[8] The value chosen here is bigger than the estimate of Schmitt-Grohé and Uríbe (2008) (0.007) though significantly smaller than the estimate of Khan and Tsoukalas (2011) (0.53) and Khan and Tsoukalas (2010) (0.85). While bigger values have no noticeable effect on the simulation results, I prefer to use a smaller value as it generates a robust increase in hours on impact in response to IST news shocks.

accordance with Khan and Tsoukalas (2010) while all remaining parameters' values by and large follow the estimates of Smets and Wouters (2007).[9]

I simulate 2000 sets of data with 240 observations each, drawing all eight exogenous shocks from normal distributions. The sample size of 240 observations matches in size the empirical postwar sample employed in section 3 which spans the period 1951:Q1-2010:Q4. So as to make the simulated data as close as possible to actual data, the simulated series are transformed by adding back in trend growth where applicable.[10] For each simulation, I estimate a four-lag VAR with a constant that includes the levels of TFP, IST, output, investment, consumption, hours, nominal interest rate, and inflation, which coincides with the benchmark empirical VAR in Section 3. The truncation horizon is set at H=60. In other words, the IST news shock is identified as that shock orthogonal to current TFP and IST which maximally explains IST over a horizon of fifteen years. A truncation horizon of fifteen years, which is also used for the empirical VAR in section 3, is both long enough to account for potentially strong long run effects of IST news shocks on IST and short enough to provide reliable results. Following the identification procedure outlined above the estimated impulse responses and identified time series of IST news shocks for each simulation are collected.

Figure 1 depicts both theoretical and estimated impulse responses of IST, output, consumption, investment, hours, and inflation averaged over the simulations

[9] I follow Fisher (2006), Schmitt-Grohé and Uríbe (2008), Fernandez-Villaverde (2009), and Jaimovich and Rebelo (2009) and assume that TFP and IST follow a unit root process (see eq. T.15 and eq. T.21 in table 1). This implies that TFP and IST news shocks have a permanent effect on TFP and IST, respectively. The identification results are robust to assuming stationary processes for TFP and IST as in Smets and Wouters (2007) and Khan and Tsoukalas (2010, 2011).

[10] Following Fernandez-Villaverde (2009), quarterly trend growth rates of 0.28% and 0.34% are added to TFP and IST, respectively, and in accordance with the balanced growth path 0.63% is added to output, investment and consumption.

to a favorable IST news shock. The theoretical responses are represented by the solid lines and the average estimated responses over the simulations are depicted by the dashed lines, with the dotted lines depicting the 10^{th} and 90^{th} percentiles of the distribution of estimated impulse responses. It is apparent that the business cycle effects of IST news shocks are well identified. In particular, the estimated empirical impulse responses are unbiased on impact and for a number of quarters thereafter while being downward biased at long horizons. Nevertheless, the unbiasedness of the estimated responses at short horizons coupled with the observation that the confidence intervals do not include zero are especially important since my focus is not on the long horizon implications of IST news shocks, but rather on their ability to generate business cycles. Figure 2 depicts the results for identification of unanticipated IST shocks. Overall, the identification performs well at short horizons while being downward biased at long horizons. The identification of the effects of TFP shocks (not shown) also performs well, in particular at short run horizons.

The average correlation between the identified IST news shock and the true IST news shock across simulations is 0.81, with the median correlation 0.82 and the 10th and 90th percentile correlations 0.71 and 0.88, respectively. The mean correlation between identified unanticipated TFP and IST shocks and their corresponding true shocks is higher reaching 0.90 and 0.91, respectively.

A similar simulation exercise in which TFP was not included in the VAR was conducted as well. The results from this simulation indicate that on top of a significantly lower mean correlation (48%), the confidence interval of the empirical distribution of the estimated impulse responses is considerably wider. For example, the confidence interval for the output, consumption, and investment responses is more than three and a half times as large on impact and more than twice as large for the six quarters thereafter when TFP is excluded compared to the benchmark case, after which the difference is also considerable. This implies that estimation is much more precise, as measured by the confidence bands, when TFP and the corresponding orthogonality restriction are included in the estimation procedure.[11] Therefore, it is found that excluding TFP from the VAR is inferior to the benchmark case.

My series of simulation results also indicate that the issue of VAR non-invertibility is not a major concern for my identification strategy. VAR invertiblity pertains to the case in which DSGE models produce moving average representations in the observables which can be inverted into a VAR representation in which the VAR innovations correspond to economic shocks (see Fernandez-Villaverde, Rubio-Ramirez, Sargent, and Watson (2007) for the conditions needed for VAR invertibility). Invertibility problems potentially arise when there are unobserved state variables which do not enter the estimated VAR (Watson (1986)). Hence, having news shocks in the model generates invertibility problems as the latter constitute both shocks and unobserved state variables. I also experimented with news specifications in which news shocks affect IST with a lag of several periods as opposed to one period as in the benchmark case, thus exacerbating VAR invertibility problems due to the introduction of additional unobserved state variables, and found that identification still performs well despite a slight decline in the mean correlation between identified shocks and true shocks. Nevertheless, the empirical results of the next section provide evidence in favor of a news process in which there is a gradual increase in future IST starting with a lag of one period.

It is also important to note that the identification method is robust to assuming signal extraction problems facing agents. Blanchard, L'Hullier, and Lorenzoni (2009) consider a framework in which agents receive news about productivity that is contaminated with noise and conclude that it is not possible to employ long run restrictions to separately identify the noise shock. Nevertheless, similarly to the Barsky and Sims (2010a) identification method, the identification strategy pursued in this paper is still capable of identifying news shocks in the presence of noise since the introduction of noise into the news signals merely weakens the effect of news shocks

[11] Similar results obtain when the standard deviations of the estimated responses are compared.

on agents' actions while not altering any of the identifying assumptions as the IST and news processes themselves remain unaffected.

The suitability of the identification strategy appears robust to alternative calibrations of the model. Since the identification algorithm mechanically picks out from all the shocks that are orthogonal to current IST and TFP the shock that maximally explains future variation in IST, the method naturally performs better in calibrations in which there is more variation in IST directly attributable to the IST news shock. It is therefore encouraging that the empirical results, which will be presented in the next section, indicated that IST news shocks drive a considerable share of IST variation accounting for 83% of the latter at the fifteen year horizon. Furthermore, taking into account that the estimated effects of IST news shocks on IST at long horizons most likely understate the true effects, as demonstrated in figure 1,[12] suggests that we can be fairly confident that the identification method has performed well in practice. Overall, the monte carlo simulations suggest that the identifying strategy is capable of doing a good job of identifying both IST news shocks and their business cycle effects on macroeconomic aggregates.

3 Empirical Evidence

In this section the main results of the paper are presented. The findings indicate that favorable IST news shocks generate a rise in output, investment, consumption, and hours worked, explain 70% of their business cycle variation, and have played an important role as drivers of U.S business cycles over the last sixty years. Before proceeding, a brief discussion of the data is given. Then, section 3.2 presents the main empirical results in detail followed by a sensitivity analysis section which will provide evidence that the above results are robust. Finally, section 3.4 compares this paper to previous work in the literature.

[12] It is apparent that there is a relatively big downward bias at long horizons for the effect of the IST news shock on IST, as manifested in the failure of the confidence bands to contain the true response.

3.1 Data

Proper identification of IST news shocks requires an appropriate gauge of IST. I follow GHK (1997, 2000), Fisher (2006), Schmitt-Grohé and Uríbe (2008), Beadry and Lucke (2009), and Liu (2011) and use a real investment price measure to gauge IST. This price is measured as a consumption deflator divided by an investment deflator. The consumption deflator corresponds to nondurable and service consumption, derived directly from the National Income and Product Accounts (NIPA). The investment deflator corresponds to equipment and software investment and durable consumption, also derived directly from the NIPA. Some authors, such as GHK (1997, 2000) and Fisher (2006), preferred to use Gordon's (1990) price series for producer durable equipment (henceforth the GCV deflator), as later updated by Cummins and Violante (2002), so as to better account for quality changes. More recently, Liu et al. (2011) used an updated GCV series constructed by Patrick Higgins at the Atlanta Fed that spans the period 1959:Q1:2010:Q4. I prefer to use the NIPA deflators since they allow for a larger sample size. Furthermore, as Justiniano et al. (2010b) note, the NIPA deflators include quality adjustments that generate price declines in accordance with other studies based on micro data (e.g. Landefeld and Grimm, 2000). Nonetheless, it is shown in section 3.3 that the results are robust to the use of the recently updated GCV deflator used by Liu et al. (2011).[13]

For the TFP series, I employ the real-time, quarterly series on total factor productivity (TFP) for the U.S. business sector, adjusted for variations in factor utilization - labor effort and capital's workweek, constructed by Fernald (2009) and available for downloading from his website. The utilization adjustment follows BFK (2006).

The output measure used is the log of real GDP at a quarterly frequency. The consumption series is the log of real non-durables and services. The hours series is log

[13] I thank Patrick Higgins at the Atlanta Fed for providing me with this series. The reader is referred to the appendix in Liu et al. (2011) for a description of the methods used to construct the series.

of total hours worked in the non-farm business sector. These series are converted to per capita terms by dividing by the civilian non-institutionalized population aged sixteen and over. The output, investment, and consumption data are taken from the BEA; hours and population data are taken from the BLS. The population series in raw form is at a monthly frequency. It is converted to a quarterly frequency using the last monthly observation of each quarter. The measure of inflation is the percentage change in the CPI for all urban consumers. Use of alternative price indexes generates similar results. The three month Treasury Bill is used as the measure of the interest rate. Similar results obtain when the federal funds rate is used instead. I prefer to use the former because it is a better gauge of the theoretical interest rate in standard DSGE models where the time period is quarterly. The inflation and interest rates series are at a monthly frequency. As with the population data, these series are converted to a quarterly frequency by taking the last monthly observation from each quarter. My benchmark data series span the period 1951:Q1-2010:Q4.[14]

3.2 Benchmark Results

Eight variables are included in the benchmark system: TFP, IST, interest rates, inflation, output, investment and durables, non-durables and services consumption, and total hours worked. As a benchmark, the system is estimated as a VAR in levels. This system is identical to the one that was used in section 2.2 for the monte carlo simulations. The levels specification is preferred over a VECM because it produces consistent estimates of the impulse responses while being robust to cointegration of unknown form. In particular, it avoids making potentially invalid assumptions concerning common trends which can yield misleading results (e.g. Fisher (2010)). Furthermore, as was noted in section 2.2, the benchmark identification method is also valid in the presence of unit roots. The Akaike, Hannan-Quinn information and

[14] Similar results obtain when the entire postwar sample is used. Nevertheless, I prefer to start the sample in 1951 due to the Treasury-Fed Accord announced on March 3, 1951which restored independence to the Fed and therefore constituted a potentially important structural shift.

Schwartz criteria favor two lags, while the likelihood ratio test statistic chooses eight lags. Given the large number of variables in the VAR, a middle ground of four lags is chosen. Robustness to the levels specification and to alternative lag lengths will be considered in section 3.3.

In terms of the identification strategy outlined in the previous section, the truncation horizon is set at H=60. In words, then, the IST news shock is identified as that shock orthogonal to current TFP and IST which maximally explains movements in IST over a fifteen year horizon. As with lag length, robustness along this dimension is discussed below.

Table 3 presents estimates of both unconditional and conditional correlations between the growth rate of output and the growth rates of consumption, investment, and hours. The conditional correlations estimates are based on the benchmark VAR model and computed in accordance with Gali's (1999) formula where the conditioning is made with respect to IST news shocks. These estimates can be used to infer the extent of the capability of IST news shocks to generate business cycles. As the first column of table 3 shows, the unconditional correlations, which are computed directly from the data, are high, as expected, reflecting the well known feature of the business cycle that output, consumption, investment, and hours move in tandem. As the second column of the table demonstrates, the conditional correlations of output with consumption, investment, and hours are very high at 91%, 97%, and 94%, respectively, all being statistically significant at the one percent level.[15] That the conditional correlations are at such high levels is an indication that IST news shocks are capable of generating business cycles.

Figure 3 shows the estimated impulse responses of IST, output, investment, consumption, hours, and inflation to a favorable IST news shock from the benchmark VAR, with the dashed lines representing 1st and 99th percentile confidence bands.

[15] The confidence bands (not shown) for the conditional correlation estimates were constructed from a residual based bootstrap procedure repeated 2000 times.

These bands are constructed from a residual based bootstrap procedure repeated 2000 times. I use the Hall confidence interval (see Hall (1992)) which attains the nominal confidence content at least asymptotically under general conditions and was also shown to have relatively good small sample properties by Kilian (1999). Following a favorable IST news shock, IST does not change on impact, by construction, after which it grows gradually and persistently increasing by 1.34 percent after ten years and eventually peaking after 27 years at 2.07 percent higher than its pre-shock value. Output, investment, consumption, and hours all jump up on impact, with the responses being both statistically and economically significant at 0.29, 0.27, and 0.26 percent for output, consumption, and hours, respectively, and 1.07 percent for investment, after which they all keep growing where output, investment, and hours reach their peak after six quarters while consumption peaks after thirteen years. The significant positive conditional comovement among aggregate variables on impact is compatible with IST news shocks being an important source of fluctuations. Moreover, the identified IST news shock series significantly raises the three month T-Bill rate with a lag of one period while it significantly reduces inflation on impact and has an insignificant effect on TFP. The responses of inflation, interest rate, and real macroeconomic aggregates are broadly consistent with the DSGE model presented in the previous section. As the primary focus of this paper is the business cycle relevance of IST news shocks, the impulse responses of TFP and interest rates are omitted.

Figure 4 depicts the share of the forecast error variance of several of the variables in the VAR attributable to the IST news shock and unanticipated IST and TFP shocks over a range of five years. IST news shocks account for 47 percent of the forecast error variance share of IST at the five years horizon and 72 percent at the ten year horizon (not shown). The IST news shock and the unanticipated IST innovation combine to account for 91 percent or more of the forecast error variance of IST at frequencies up to ten years. At the five year horizon, 91 percent of IST fluctuations are explained by the two shocks. That such a small portion of IST remains unexplained at both short and long horizons validates the assumption underlying identification that most of the movements in IST can be attributed to only two shocks, and suggests that the identification method has done a good job at identifying the IST news shock.

IST news shocks account for a large share of the forecast error variance of macroeconomic aggregates at business cycle frequencies. In particular, they explain 60 percent of output fluctuations at the one year horizon and 72 percent at the two year horizon. IST news shocks account for 74 percent of consumption and hours forecast error variance at the two year horizon, and 65 percent of investment forecast error variance. Overall, the results indicate that IST news shocks are a substantial source of the business cycle.

Figure 5 plots the time series of identified IST news shocks from the benchmark VAR. The shaded areas represent recession dates as defined by the NBER. So as to make the figure more readable, the one year moving average of the identified shock series is shown as opposed to the actual series. Negative IST news shocks are associated with nine of the last ten U.S recessions, the exception being the 1981-1982 recession. Furthermore, a series of positive IST news shocks is prevalent in the mid to late 1990's confirming the view that the ten year long 1990's expansion was in part induced by positive news about IST. The story that emerges from figure 5 is consistent with the results from the historical decomposition discussed below which indicate that IST news shocks were an important driver of U.S business cycles in the last sixty years.

Table 4 shows the historical contribution of IST news shocks to the ten NBER determined U.S recessions since 1951. In particular, for each recession the contribution of IST news to the percentage change in output per capital from peak to trough (in deviation from trend growth) is calculated. A 1.7% output per capita steady state annual growth is assumed, which is consistent with the average growth rate of output per capita over the sample. The results indicate that IST news were a driving force behind nine of the last ten U.S recessions, where the only recession in which

IST news had no role was the 1981-1982 recession. The recent recession, in which output loss was 7.8 percent, seems to have been driven in part by IST news shocks which contributed 3.8 percent of that accumulated decline. IST news shocks also contributed 1.6 percent and 5.1 percent of the accumulated 2.7 percent and 7.9 percent output per capita loss during the 1990-1991 and 1973-1975 recessions, respectively. Moreover, that 1.1 percent of the 1.5 percent output loss in the 2001 recession is attributed to IST news shocks is consistent with the view that a downward revision of expectations about future IST took place after the IST news driven boom of the mid to late 1990's. One may be concerned that the above results for the recent recession and some of the prior recessions (e.g. 1973-1975, 1980, 1990-1991) may be driven in part by credit market shocks and oil price shocks, respectively. Robustness along this dimension is discussed below in the next section where it is shown that these results, as well as the other results in the paper, are not driven by oil shocks or financial shocks. Overall, the historical decomposition results point to a central role of IST news shocks as a driving force of the business cycle.

Figure 6 shows the impulse responses of aggregate variables to the unanticipated IST shock. IST's response to its own innovation is large and significant on impact and also quite persistent. Output rises for the first three quarters following the shock, after which it starts to decline. Investment rises significantly for the first five quarters and then starts to fall though this negative response is insignificant. Hours follow a similar pattern as investment whereas consumption falls significantly on impact and thereafter as well. The negative response of consumption is consistent with a modified version of the DSGE model of the previous section in which the cost of utilization is specified in terms of forgone consumption as in Christiano et al. (2005) (see Khan and Tsoukalas (2011)). Taken as a whole, the results indicate that unanticipated IST shocks are not an important source of the business cycle, a finding that may appear surprising in light of a growing recent literature arguing that this type of shock represents an important driver of aggregate activity (e.g. Fisher (2006), Justiniano et al. (2010a), and Khan and Tsoukalas (2010)). Nevertheless, Schmitt-

Groh'e and Uribe (2008) include the real price of investment as an observable in their structural estimation procedure and find that unanticipated IST shocks have a negligible role as drivers of the business cycle. They argue that, at least in the context of structural DSGE models estimated using Bayesian methods, this discrepancy is explained to a large extent by whether the set of observables used for estimation includes or not the price of investment. Furthermore, Beaudry and Lucke (2009), who combine short and long run restrictions in an SVECM framework, also find that unanticipated IST shocks have a negligible role as business cycle drivers.

Lastly, the impulse responses of aggregate variables to the unanticipated TFP shock (not shown) indicate that positive TFP shocks generate an increase in output, investment, and consumption and a decline in hours. These results are consistent with the findings of Gali (1999) and BFK (2006) which indicate that TFP shocks are not important drivers of business cycle fluctuations.

3.3 Sensitivity Analysis

The main result that IST news shocks are an important force behind business cycles is robust to alternative lag structures, different truncation horizons for the maximization problem underlying identification, alternative real investment price measure, larger systems containing additional variables as well as estimation of a VECM which accounts for a potential long run relationship between non stationary variables in the model.

At all tested lag lengths, output, investment, consumption and hours rise on impact in response to a favorable IST news shock with the effect being similar both qualitatively and quantitatively. With more lags in the reduced form system there is more evidence of reversion in the series at long horizons, but the basic qualitative nature of the responses is unchanged. The qualitative and quantitative nature of the responses is also unaltered with different truncation horizons, both shorter ones such as H=40 and longer ones such as H=80. The results are also similar across sub-samples (e.g. estimating the VAR only post 1984). In the interest of space, these figures are omitted from the paper.

The main results are also robust to using a different measure of the real investment price. I estimated the benchmark system with the real price of investment measured by the GCV deflator instead of the NIPA deflators, as used by Liu et al. (2011). Figure 7 presents the impulse responses from this system. Both the quantitative and qualitative nature of the results remains unchanged as IST news shocks continue to induce business cycle comovement. Moreover, news shocks are deflationary as in the benchmark case.

Robustness to the levels specification was also considered. While estimation of a VAR in levels will in general produce consistent estimates of the impulse responses and variance decomposition, estimation of a vector error correction model (VECM) will result in an efficiency gain in finite samples if the non-stationary variables in the VAR share a common stochastic trend. Nevertheless, as discussed in Section 3.2, the levels specification is preferred because it produces consistent estimates of the impulse responses while being robust to cointegration of unknown form. In particular, it avoids making potentially invalid assumptions concerning common trends which can yield misleading results (e.g. Fisher (2010)). Impulse responses from an estimated VECM (not shown) in which I allowed for two cointegrating vectors between TFP, IST, consumption, output, and investment, while imposing that interest rates, inflation, and hours are stationary, indicate that the effects of IST news shocks are both quantitatively and qualitatively similar to the benchmark results. Similar results also obtain when a different number of cointegrating vectors is allowed for. The only difference lies in the estimated long-run responses, with more evidence of reversion evident in the levels specification.

Furthermore, the IST news shock was also identified in a larger system. In addition to the eight variables in the benchmark system, measures of stock prices and consumer confidence were also included. The measure of stock prices used is the log of the real S&P 500 Index, taken from Robert Shiller's website. This series is converted to a quarterly frequency by taking the last monthly observation from each quarter. The results are insensitive to dividing the stock price data by the population.

The consumer confidence data are from the Michigan Survey of Consumers, and summarize responses to a forward-looking question concerning aggregate expectations over a five year horizon. This series is available from 1960:Q1 hence dictating 36 fewer observations compared to the benchmark sample. There are several reasons for including these additional variables. Stock prices and consumer confidence are naturally forward-looking, and previous research has shown them to be prognostic of future movements in economic activity in general and TFP in particular (e.g. Beaudry and Portier (2006) and Barsky and Sims (2010b)). Thus, it is reasonable to presume that these variables also contain information about future IST. Moreover, as stressed by Watson (1986), the inclusion of forward-looking variables mitigates the impact of potential non-invertibilities even if these variables do not fully reveal the missing state(s). Furthermore, it is of interest in and of itself to examine the responses of these forward-looking variables to IST news shocks. Figure 8 depicts the responses of the six benchmark variables as well as stock prices and consumer confidence to a favorable IST news shock. It is apparent that the main results are left unchanged; favorable IST news shocks generate positive comovemnent and are deflationary. Moreover, IST news shocks are associated with a significant positive increase in both stock prices and consumer confidence, a finding which is consistent with the view that these variables contain important information about the future value of IST.

Finally, as noted in the previous section, it was also confirmed that the results in the paper are not driven by either financial shocks originating in credit markets or shocks to the real price of oil. In relation to the issue of a possible connection between the identified IST news shocks and credit market shocks, it was found that the results are robust to adding to the VAR a risk premium variable, measured by the spread between the expected return on medium-grade bonds and high-grade bonds (Moody's seasoned Baa corporate bond yield and Aaa corporate bond yield, respectively), and imposing on the identified IST news shock to be orthogonal to the risk premium innovation. This robustness is an indication that the results regarding IST news shocks reported in section 3.2 are not driven by pure financial shocks that originate in the financial system. Moreover, so as to verify that the results are not driven by oil shocks, an extended identification procedure was also applied to larger systems including the real price of oil where the identified IST news shock was imposed upon to be orthogonal to oil innovations. The results obtained were similar to the benchmark results, both qualitatively and quantitatively.

3.4 Relation with Previous Work

The robust evidence found in this paper that IST news shocks are important drivers of business cycles contrasts with the mixed evidence provided by the relatively small number of papers that estimated DSGE models which contain IST news shocks. Given that there is no clear agreement on what the true structure of the economy is, and that inferences regarding the role of IST news shocks based on different structural models differ, it seems worthwhile to use an identification method that does not impose any structural model on the data but rather imposes identifying assumptions that are common to different IST news driven DSGE models. This is precisely what is done in this paper, thus offering new insights regarding the business cycle implications of IST news shocks.

The results in this paper indicate that unanticipated IST shocks are not an important source of the business cycle as opposed to IST news shocks. Fisher (2006) identified unanticipated IST shocks in an SVAR framework with long run restrictions and found that IST shocks are important drivers of the business cycle. Since his identification procedure allows IST shocks to raise IST on impact while imposing that they are the only shocks to affect IST in the long run, it really identifies a combination of unanticipated IST shocks and IST news shocks, thus offering a potential reconciliation with the results presented here. So as to further shed light on the difference between my results and Fisher's, I applied both my identification method as well as Fisher's using the same variables he used in his paper and found that the correlations between my identified IST news shocks and unanticipated shocks and Fisher's identified unanticipated IST shocks are 0.8 and 0.25, respectively. This evidence indicates that Fisher's method identifies a combination of unanticipated IST shocks and IST news shocks, though his identified shock is more strongly associated with IST news shocks than unanticipated IST shocks.[16]

Even though there has not been an attempt in the literature to identify IST news shocks along the lines of the identification approach presented in this paper, Beaudry and Lucke (2009) employ a method that, at least to some extent, resembles the one used in this paper. They use a combination of short and long run restrictions in an SVECM framework for the identification of news shocks. In particular, in systems featuring TFP, IST and other variables their identified news shock is identified by postulating zero effects on both types of technology on impact, but allowing for unrestricted long-run effects. Thus, under their identification scheme news can be news about both TFP and IST. In contrast, the identification approach in this paper is aimed at identifying specific news shocks, namely IST news shocks. In fact, as was shown in section 2.2, my identification method performs well on data generated from a DSGE model that contains both TFP and IST news shocks, in which case the Beaudry and Lucke (2009) identification method would not be appropriate as it does not impose any restriction on the type of news shocks being identified. In particular, Schmitt-Grohé (2010) shows that their SVECM identification method fails to identify both IST news shocks and TFP news shocks once the true model contains both news shocks. Nevertheless, Beaudry and Lucke (2009) do report results in favor of news shocks being an important driver of business cycle while interpreting their identified news shock as TFP news because these shocks explain about 60% of TFP forecast error variance in the long run.

[16] It's interesting to note that this result is sensitive to whether hours enter the VAR in levels, as in Fisher's baseline specification, or in first differences in accordance with Fisher's alternative specification. In particular, when hours enter the VAR in first differences the correlations between my identified IST news shocks and unanticipated shocks and Fisher's identified IST shocks are 0.66 and 0.58, respectively.

Lastly, from a methodological standpoint, even though the identification method used in this paper builds on the one employed by Barsky and Sims (2010a), there is a difference worth noting. In their work, the identified TFP news shock is orthogonal only to the unanticipated TFP shock. I extend their identification method by imposing upon the IST news shock to be orthogonal to both IST and TFP shocks thus enabling me to identify both unanticipated IST and TFP shocks in addition to IST news shocks. As was reported in section 2.2, adding TFP to the system and imposing the corresponding orthogonality restriction improves the identification of IST news shocks. Furthermore, that the identified IST news shock has an insignificant and negligible effect on TFP confirms that the identified IST news shocks are not related to TFP news shocks.

4 Conclusion

This paper has closely examined the hypothesis that IST news shocks are important drivers of business cycles. While the few papers that have examined the role of IST news shocks employed fully specified estimated DSGE models to do so, this paper used a different identification approach that does not impose a structural model on the data but rather exploits identifying assumptions that are common to a variety of IST news driven DSGE models. Specifically, I extended the empirical VAR based approach to identifying news shocks that was recently proposed by Barsky and Sims (2010a), which is directly based on the implications of theoretical models of expectations driven business cycles, and showed that this approach performs well on model generated data in terms of identifying IST news shocks and their business cycle effects on macroeconomic aggregates.

Applying this empirical procedure on postwar U.S data, I found robust evidence that IST news shocks induce positive comovement, i.e., raise output, consumption, investment, and hours of work, and explain 70% of their forecast error variance at business cycle frequencies. Furthermore, the historical decomposition results indicate that IST news played an important part in nine of the last ten U.S recessions. Overall, it can be deduced that IST news shocks are not only capable of generating business cycles but also that they have played an important role as drivers of U.S business cycles over the last 50 years.

The empirical results of this paper with respect to IST news shocks are broadly consistent with the state-of-the-art DSGE model presented in section 2.2, which extends the by now classic Smets and Wouters (2007) model via the addition of two elements, along the lines of Khan and Tsoukalas (2011): the recently popularized Jaimovich and Rebelo preferences that allow for an arbitrarily weak wealth effect on labor supply and specification of the cost of utilization in terms of increased depreciation of capital, as originally proposed by GHH (1988) in a neoclassical setting. Nevertheless, this model does not match the empirical results found by Barsky and Sims (2010a) that TFP news shocks are associated with a contemporaneous decline in output, investment, and hours and an increase in consumption thus indicating an unimportant role for these shocks in the business cycle. Hence, it seems interesting and important for future research to focus on formulating a DSGE model that fits both Barsky and Sims' (2010a) results and this paper's results.

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Table 1

The Variables and Equations of the Model

(a) The variables of the model; (b) the equations of the model

a)

Label	Definition
y_t	Output
i_t	Investment
c_t	Consumption
l_t	Hours
k_t	Installed capital
k_t^s	Capital services
π_t	Inflation rate
q_t	Tobin's q
r_t^k	Real capital rental rate
r_t	Nominal rate
z_t	Utilization rate
u_t^p	Price mark-up
u_t^w	Wage mark-up

b)

$$\mathrm{y_t} = (1\text{-}\mathrm{i_y}\text{-}\mathrm{g}_y)\mathrm{c_t} + \mathrm{i_y i_t} + \varepsilon_t^g \tag{T.1}$$

$$\mathrm{c_t} = \mathrm{E_t c_{t+1}} + \mathrm{c_1}(\mathrm{r_t} - \mathrm{E_t}\pi_{t+1} + \varepsilon_t^b) + \mathrm{c_2 E_t}(\mathrm{l_{t+1}} - \mathrm{l_t}) + \mathrm{c_2}(1+\sigma_l)^{-1}\mathrm{E_t}(\mathrm{x_{t+1}} - \mathrm{x_t}) \tag{T.2}$$

$$\mathrm{i_t} = \frac{1}{1+\beta\gamma^{1-\sigma_c}}\left(\mathrm{i_{t-1}} + \beta\gamma^{1-\sigma_c}\mathrm{E_t i_{t+1}} + \frac{1}{\gamma^2\varphi}(\mathrm{q_t} + \varepsilon_t^{is})\right) \tag{T.3}$$

$$\mathrm{q_t} = -(\mathrm{r_t} - \mathrm{E_t}\pi_{t+1} + \varepsilon_t^b) + \frac{\mathrm{r}_*^k}{\mathrm{r}_*^k + (1-\delta)}\mathrm{E_t r_{t+1}^k} + \frac{(1-\delta)}{\mathrm{r}_*^k + (1-\delta)}\mathrm{E_t q_{t+1}} \tag{T.4}$$

$$\mathrm{y_t} = \phi_p(\alpha \mathrm{k}_t^s + (1\text{-}\alpha)\mathrm{l_t} + \varepsilon_t^a) \tag{T.5}$$

$$\mathrm{k}_t^s = \mathrm{k_{t-1}} + \mathrm{z_t} \tag{T.6}$$

$$\mathrm{z}_t = \psi(\mathrm{r}_t^k - q_t) \tag{T.7}$$

$$\mathrm{k_t} = \frac{(1\text{-}\delta)}{\nu}\mathrm{k_{t-1}} + \left(1\text{-}\frac{(1\text{-}\delta)}{\nu}\right)\mathrm{i_t} + \left(1\text{-}\frac{(1\text{-}\delta)}{\nu}\right)\varepsilon_t^{is} - \frac{\delta' Z_*}{\nu} z_t \tag{T.8}$$

$$u_t^p = \alpha(\mathrm{k}_t^s\text{-}\mathrm{l_t}) + \varepsilon_t^a - w_\mathrm{t} \tag{T.9}$$

$$\pi_\mathrm{t} = \frac{\iota_p}{1+\beta\gamma^{1-\sigma_c}\iota_p}\pi_{\mathrm{t-1}} + \frac{\beta\gamma^{1-\sigma_c}\iota_p}{1+\beta\gamma^{1-\sigma_c}\iota_p}\mathrm{E_t}\pi_{\mathrm{t+1}} - \frac{(1\text{-}\beta\gamma^{1-\sigma_c}\xi_p)(1-\xi_p)}{(1+\beta\gamma^{1-\sigma_c}\iota_p)(1+(\phi_p-1)\varepsilon_p)\xi_p}u_t^p \tag{T.10}$$

$$r_t^k = -(k_t^s - l_t) + w_t \qquad (T.11)$$

$$u_t^w = w_t - \{(1-\chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega})^{-1}\left((1-\chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega}\sigma_l + \chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega}\sigma_l)l_t\right)$$
$$+(1-\chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega})^{-1}\left((1-\chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega} + \chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega}\sigma_l)x_t\right) \qquad (T.12)$$
$$-(1-\chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega})^{-1}\left(\chi\omega L_*^{(1+\sigma_l)}\gamma^{(\omega-1)/\omega})c_t\right)\}$$

$$w_t = \frac{1}{1+\beta\gamma^{1-\sigma_c}}w_{t-1} + \left(1-\frac{1}{1+\beta\gamma^{1-\sigma_c}}\right)(E_t w_{t+1} + E_t\pi_{t+1}) - \frac{1+\beta\gamma^{1-\sigma_c}}{1+\beta\gamma^{1-\sigma_c}}\pi_t + \frac{\iota_w}{1+\beta\gamma^{1-\sigma_c}}\pi_{t-1}$$
$$-\frac{(1-\beta\gamma^{1-\sigma_c}\xi_w)(1-\xi_w)}{((1+\beta\gamma^{1-\sigma_c})\xi_w)((\phi_w-1)\varepsilon_w+1)}u_t^w + \varepsilon_t^w \qquad (T.13)$$

$$r_t = p_r r_{t-1} + (1-p_r)(\Theta_\pi \pi_t + \Theta_y \Delta y_t) + \varepsilon_t^r \qquad (T.14)$$

$$\varepsilon_t^a = \varepsilon_{t-1}^a + g_{t-1}^a + \eta_t^a \qquad (T.15)$$

$$g_t^a = \kappa g_{t-1}^a + e_t^a \qquad (T.16)$$

$$\varepsilon_t^b = \rho_b \varepsilon_{t-1}^b + \eta_t^b \qquad (T.17)$$

$$\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g \qquad (T.18)$$

$$\varepsilon_t^w = \rho_w \varepsilon_{t-1}^w + \eta_t^w - \kappa_w \eta_{t-1}^w \qquad (T.19)$$

$$\varepsilon_t^{is} = \varepsilon_{t-1}^{is} + g_{t-1}^{is} + \eta_t^{is} \qquad (T.20)$$

$$g_t^{is} = \kappa g_{t-1}^{is} + e_t^{is} \qquad (T.21)$$

Notes: This table presents the equations of the DSGE model of section 2.2. x_t is an index variable that makes preferences non-time-separable in consumption and hours worked (see Jaimovich and Rebelo (2009)). The eight disturbances are: TFP unanticipated shock ε_t^a; TFP news shock e_t^a; monetary policy shock ε_t^r; risk premium shock ε_t^b; government spending shock ε_t^g; wage mark-up shock ε_t^w;IST unanticipated shock ε_t^{is}; IST news shock e_t^{is}. In particular, news processes g_{t-1}^a and g_{t-1}^{is} are stochastic drift terms that follow AR(1) processes (T.16) and (T.21), respectively. Following Barsky and Sims (2010a, 2010b), the corresponding i.i.d shocks e_t^a and e_t^{is} in (T.16) and (T.21) are defined as TFP and IST news shocks as they portend future changes in TFP and IST, respectively.

Table 2

Description of the Parameters of the Model and Benchmark Values

Label	Definition	Benchmark Value
σ_c	Inverse intertemporal elasticity	1
ω	Wealth elasticity	0.1
ξ_w	Calvo wages	0.7
σ_l	Inverse labor elasticity	1.83
ξ_p	Calvo prices	0.66
ι_w	Wage indexation	0.58
ι_p	Price indexation	0.24
ψ	Capital utilization elasticity	0.15
ϕ_p	Fixed cost share	1.25
ϕ_w	Steady state labor market mark-up	1.25
ε_p	Goods market curvature	10
ε_w	Labor market curvature	10
Θ_π	Monetary Policy rule inflation	4.5
p_r	Monetary Policy rule inflation	0.75
Θ_y	Monetary Policy rule output growth	1
φ	Investment adjustment cost	5.88
γ	Deterministic output growth	0.0063
ν	Deterministic capital growth	0.0092
β	Discount factor	0.985
L^*	Steady state hours	0.53
α	Capital share	0.36
ρ_b	Risk premium persistence	0.22
ρ_g	Government spending persistence	0.9
ρ_w	Wage mark-up persistence	0.9
κ_w	Wage mark-up MA	0.9
κ	News shock persistence	0.8
σ_a	TFP shock st. dev.	0.0045
σ_e^a	TFP news shock st. dev.	0.0009
σ_b	Risk premium shock st. dev.	0.0023
σ_g	Government spending shock st. dev.	0.00016
σ_r	Monetary policy shock st. dev.	0.0023
σ_{is}	IST shock st. dev.	0.0045
σ_e^{is}	IST news shock st. dev.	0.0019

Notes: This table presents a description of the parameters of the DSGE model of section 2.2 as well as their benchmark values.

Table 3

Correlation Estimates

	Unconditional	Conditional
Output	1	1
Consumption	0.54	0.91
Investment	0.84	0.97
Hours	0.73	0.94

Notes: Table 3 reports estimates of both unconditional and conditional correlations between the growth rate of output and the growth rates of consumption, investment, and hours. The unconditional correlations are computed directly from the data whereas the conditional correlations estimates are based upon the benchmark VAR model where it is assumed that IST news shocks are the only shocks hitting the economy.

Table 4

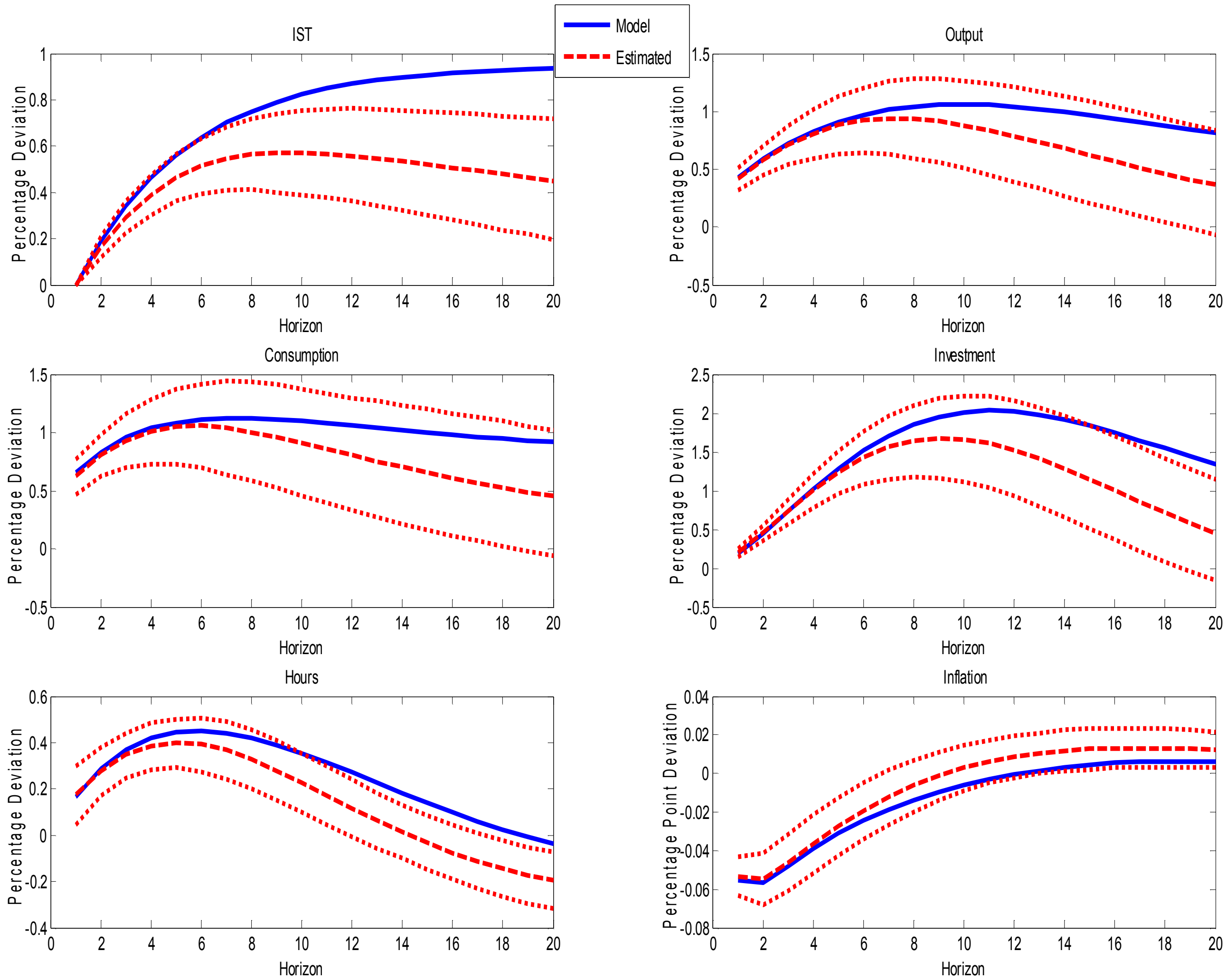
Historical Contribution of IST News Shocks to Output per Capita Loss in U.S Recessions

Recession	Percentage Change in Output per Capita (deviation from trend growth)	Contribution of IST News Shocks
1953:2-1954:2	-5.5	-1.9
1957:3-1958:2	-5.4	-1.9
1960:2-1961:1	-2.8	-1.2
1969:4-1970:4	-4.1	-1.2
1973:4-1975:1	-7.9	-5.1
1980:1-1980:3	-3.9	-1.4
1981:3-1982:4	-6.3	1.6
1990:3-1991:1	-2.7	-1.6
2001:1-2001:4	-1.5	-1.1
2007:4-2009:2	-7.8	-3.8

Notes: Table 4 reports estimates of the contribution of IST news shocks to each of the recessions in my sample period. The first column presents the percentage change from peak to trough of output per capita, relative to trend growth, in every recession. The second column reports the contribution of IST news shocks, based on the benchmark VAR model, to the corresponding output loss. A 1.7% output per capita annual trend growth is assumed, which is consistent with the average growth rate of output per capita over the sample.

Figure 1

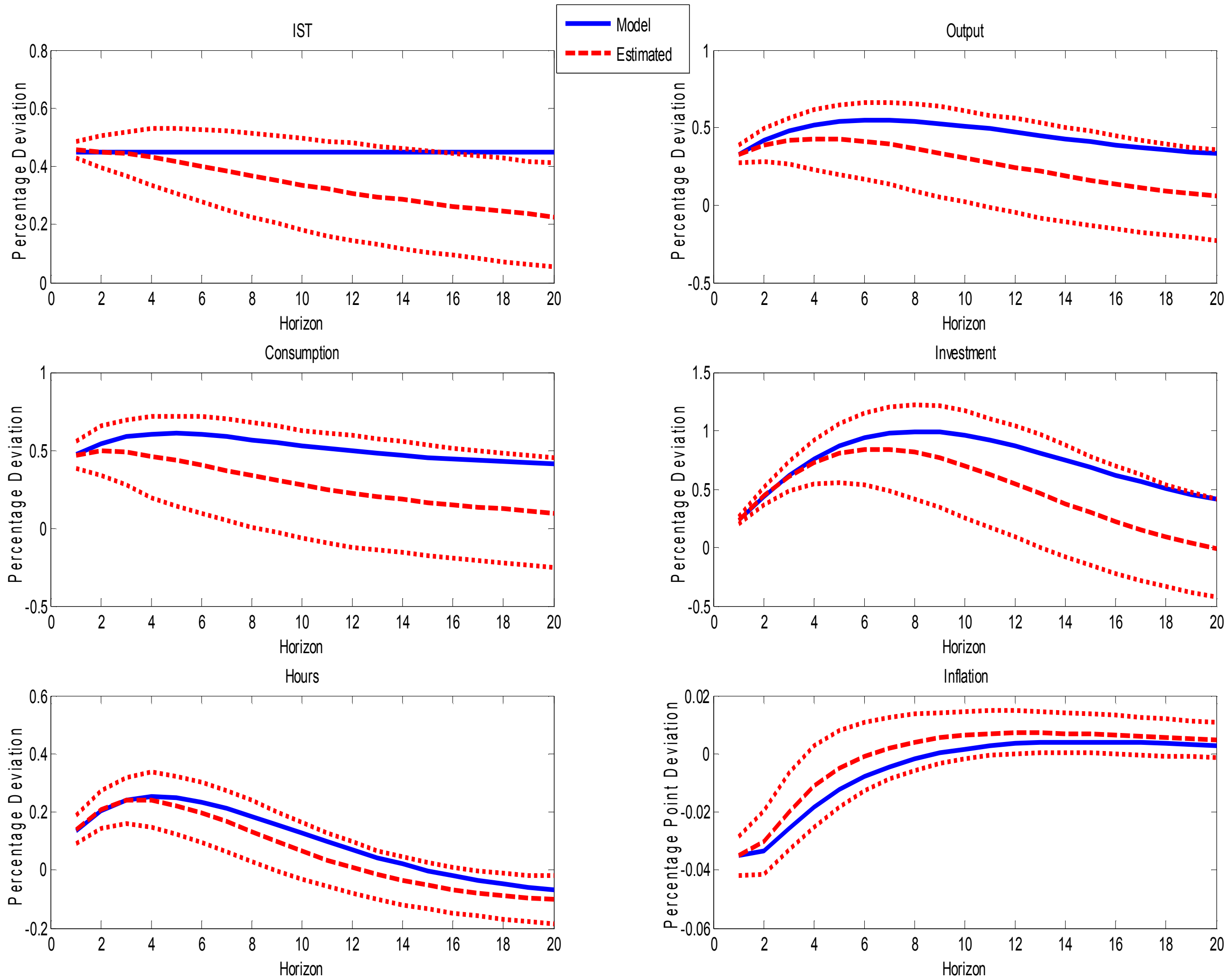
Model and Monte Carlo Estimated Impulse Responses to IST News Shock



The solid lines show the theoretical impulse response to an IST news shock from the model of section 2.2. The dashed lines depict the average estimated impulse responses over 2000 Monte Carlo simulations, with the dotted lines representing the 10th and 90th percentiles of the distribution of estimated impulse responses.

Figure 2

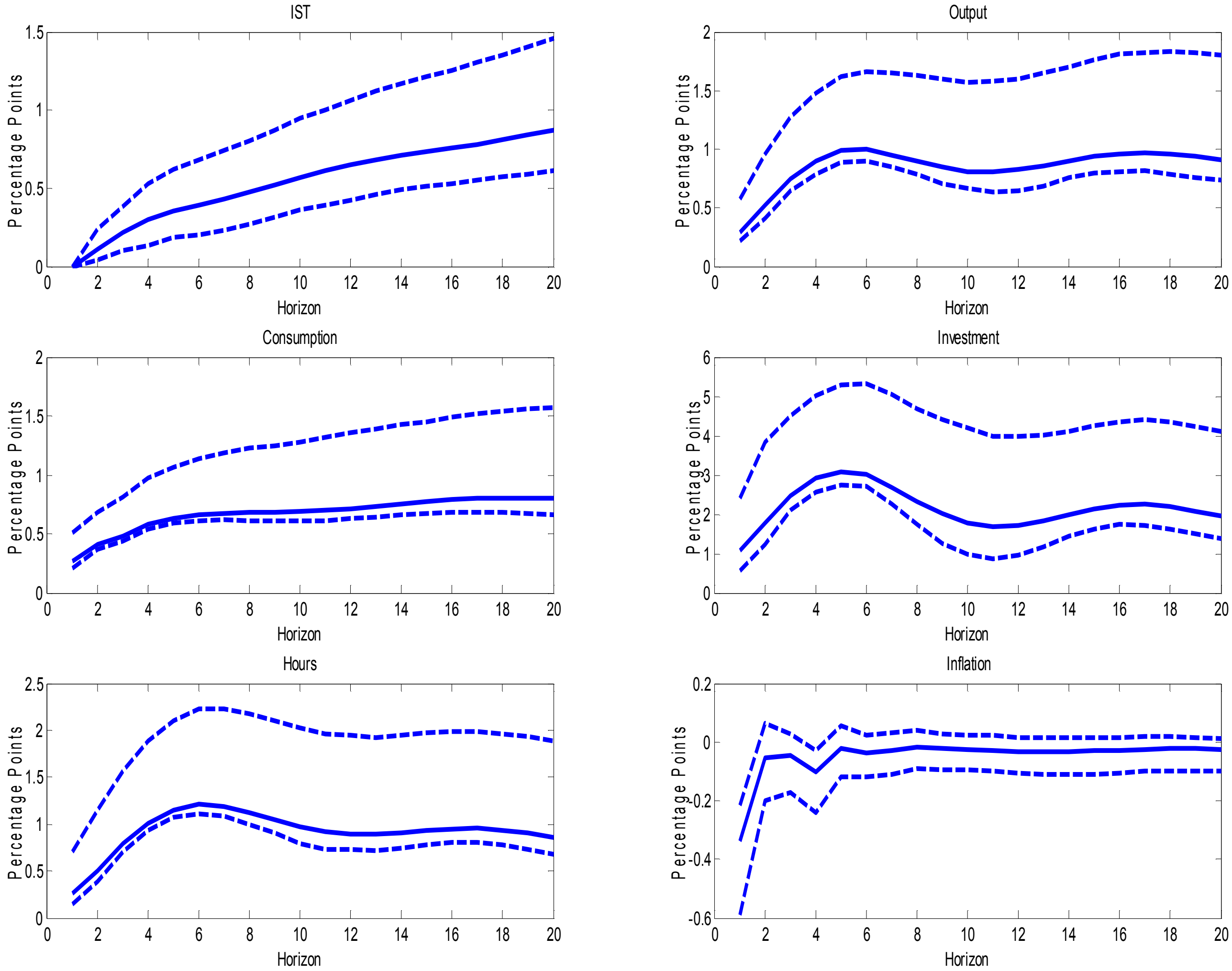
Model and Monte Carlo Estimated Impulse Responses to Unanticipated IST Shock



The solid lines show the theoretical impulse response to an unanticipated IST shock from the model of section 2.2. The dashed lines depict the average estimated impulse responses over 2000 Monte Carlo simulations, with the dotted lines representing the 10th and 90th percentiles of the distribution of estimated impulse responses.

Figure 3

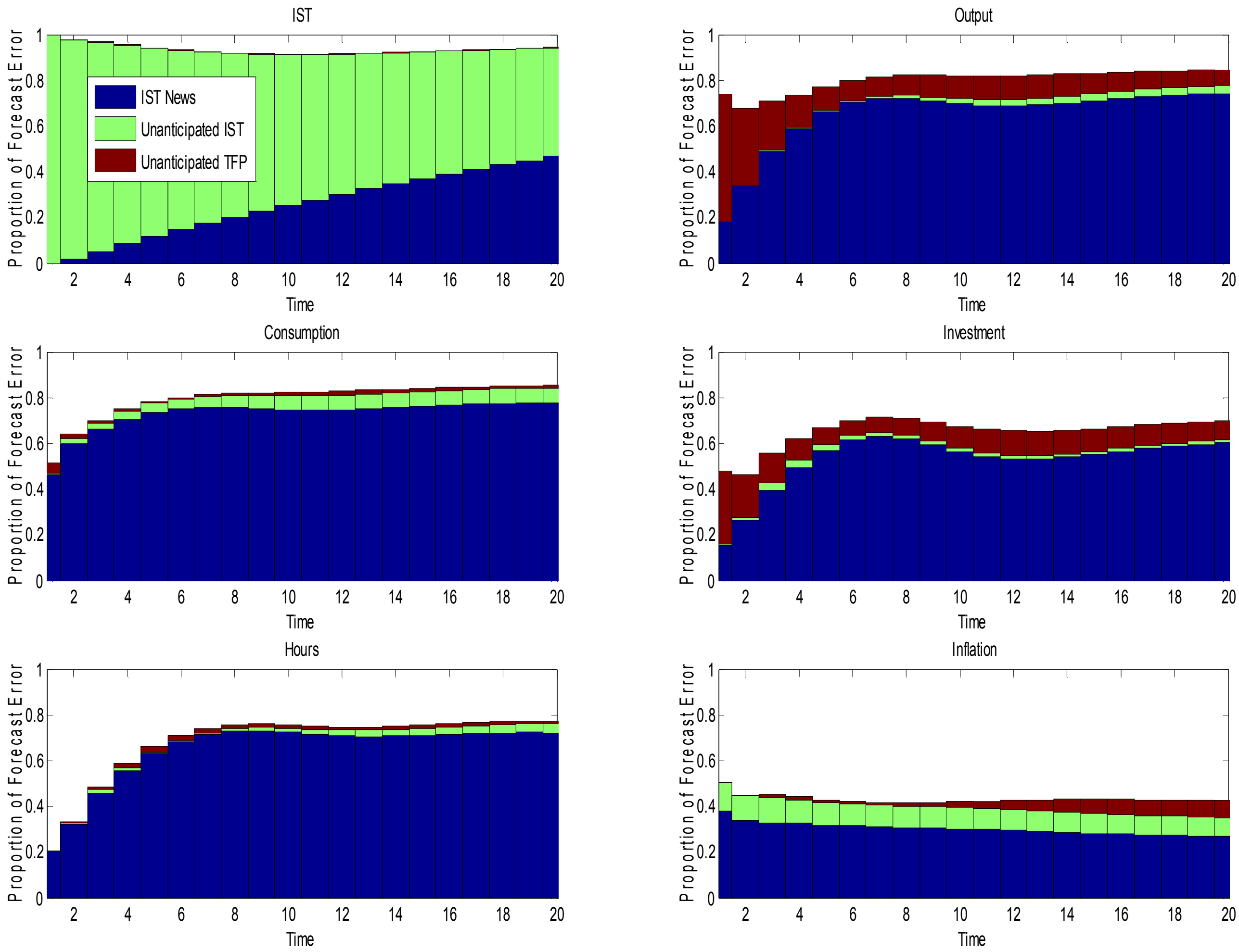
Empirical Impulse Responses to IST News Shock



The solid lines are the estimated impulse responses to the IST news shock from the benchmark VAR. Dashed lines represent 1st and 99th percentile Hall (1992) confidence bands generated from a residual based bootstrap procedure repeated 2000 times.

Figure 4

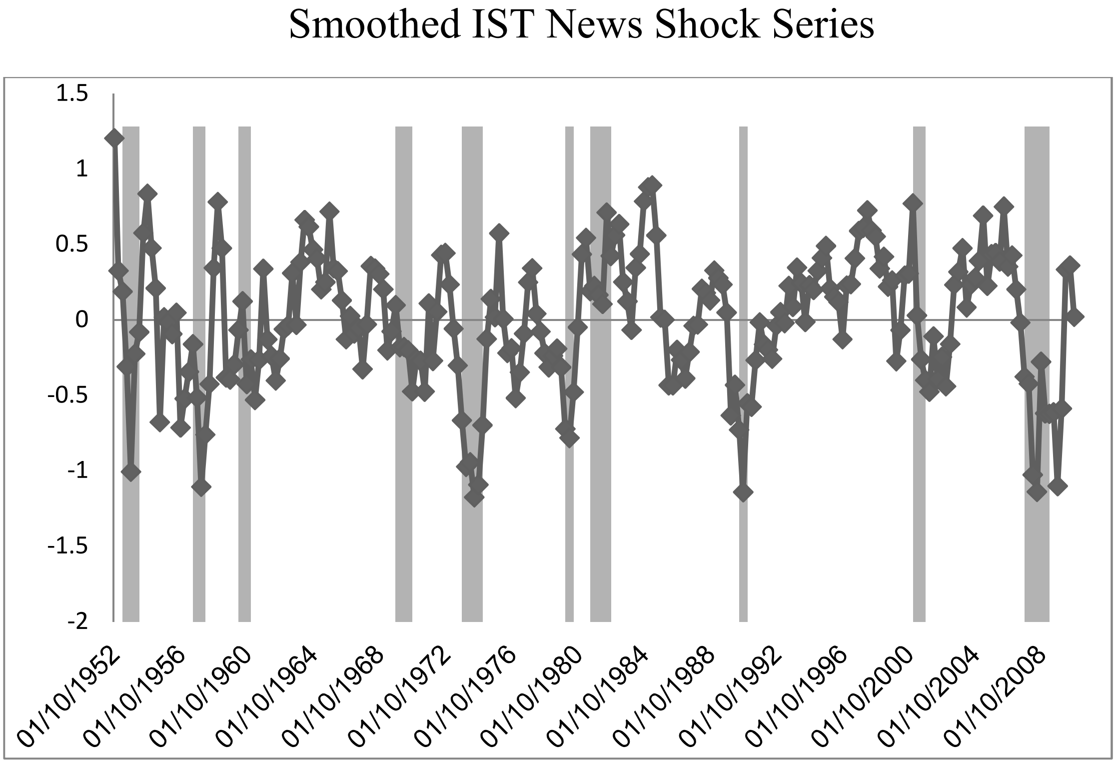
Share of Forecast Error Variance Attributable to Identified Shocks (IST News, Unanticipated IST and TFP)



The above bar diagrams show the share of forecast error variance of each variable attributable to the identified IST news, unanticipated IST and unanticipated TFP shocks from the benchmark VAR. As the identification pursued in the paper is a partial one, the sum of relative contributions of all three shocks do not necessarily add up to one as there are potentially additional unidentified shocks also accounting for part of the forecast error variance.

Figure 5

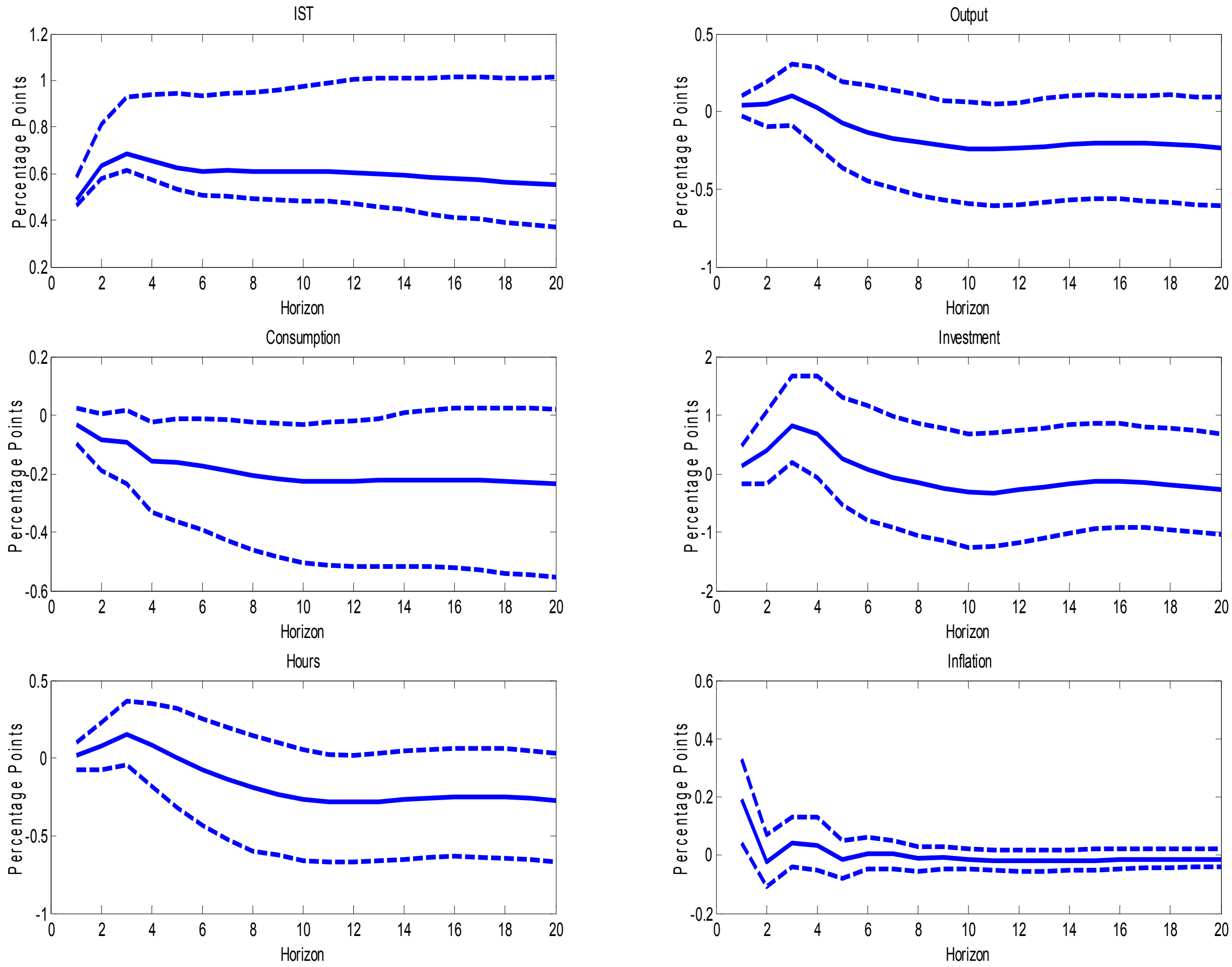
Identified News Shock Time Series and U.S Recessions



This figure plots the time series of identified IST news shocks from the benchmark VAR. U.S recession are represented by the shaded areas. So as to render the figure more readable, the plotted data is smoothed using a one year moving average. Specifically, it is calculated as $\varepsilon_t^s = (\varepsilon_{t-3} + \varepsilon_{t-2} + \varepsilon_{t-1} + \varepsilon_t)/4$. The series begins in 1952:4 and ends in 2010:4.

Figure 6

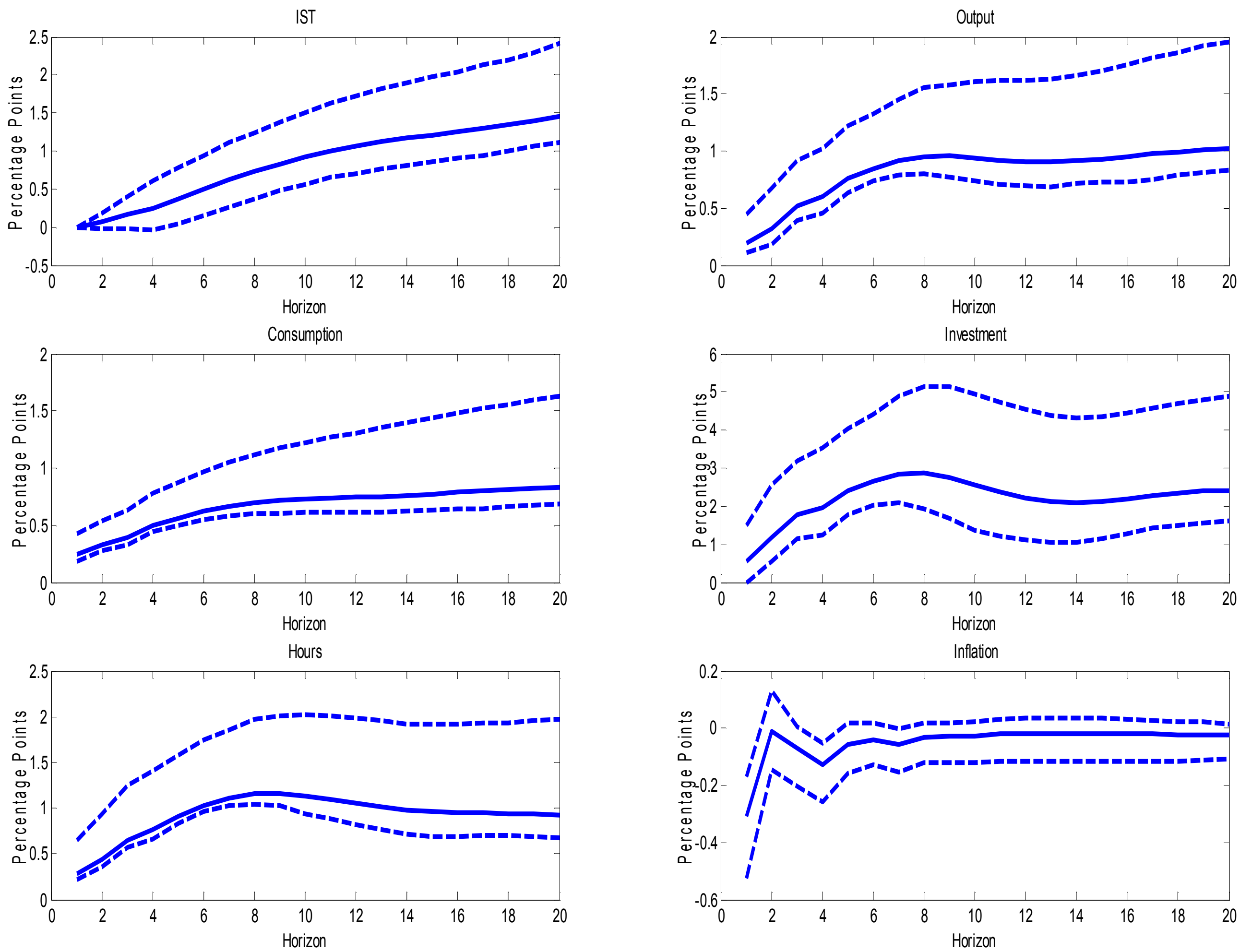
Empirical Impulse Responses to Unanticipated IST Shock



The solid lines are the estimated impulse responses to the unanticipated IST shock from the benchmark VAR. Dashed lines represent 1st and 99th percentile Hall (1992) confidence bands generated from a residual based bootstrap procedure repeated 2000 times.

Figure 7

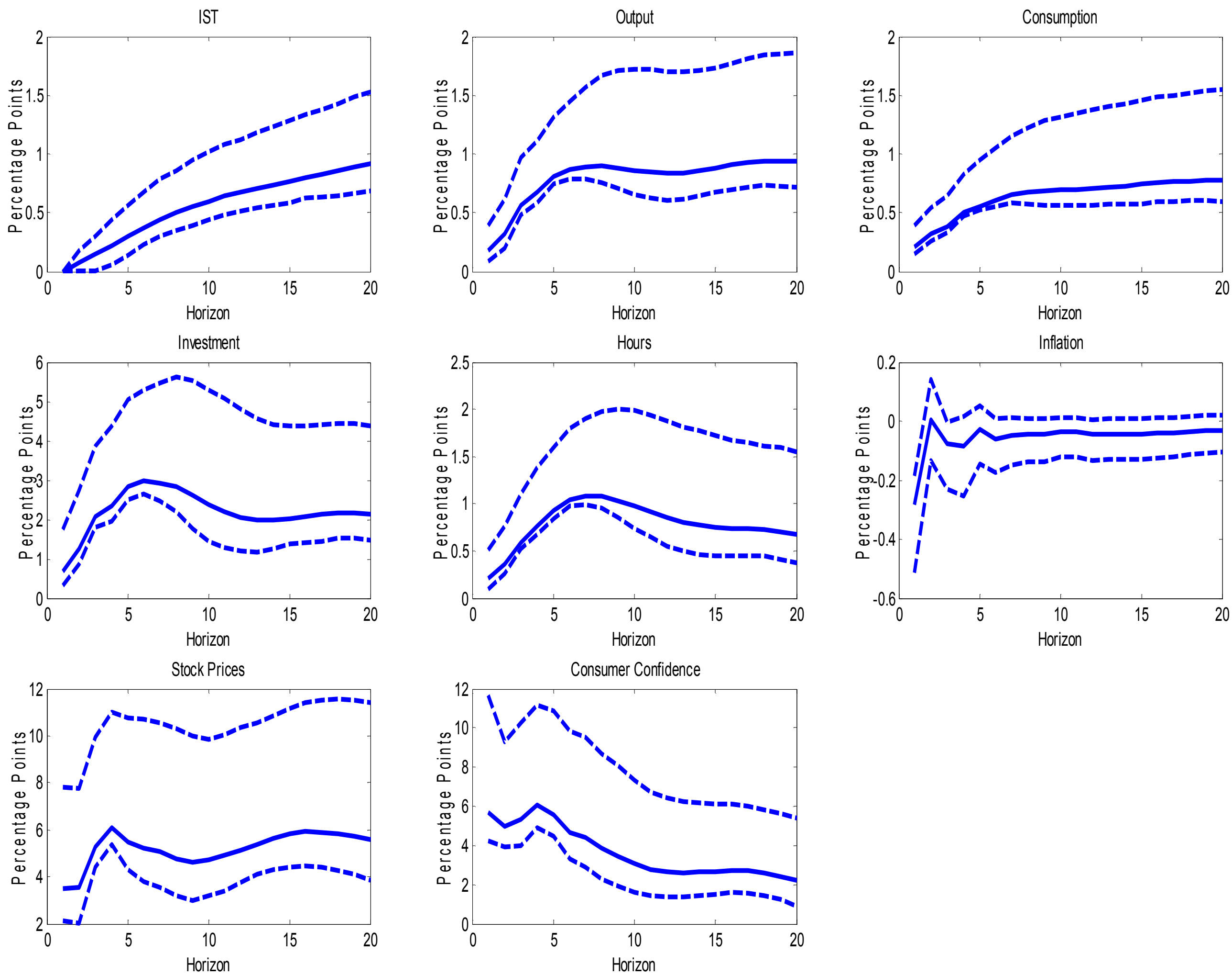
Empirical Impulse Responses to IST News Shock: Alternative Investment Price Measure



The solid lines are the estimated impulse responses to the IST news shock from the benchmark VAR with the real price of investment measured by the GCV deflator instead of the NIPA deflators, as used in Liu et al. (2011). Dashed lines represent 1st and 99th percentile Hall (1992) confidence bands generated from a residual based bootstrap procedure repeated 2000 times.

Figure 8

Empirical Impulse Responses to IST News Shock: Larger VAR



The solid lines are the estimated impulse responses to the IST news shock from a larger VAR that includes stock prices and consumer confidence in addition to the eight benchmark variables. The consumer confidence series starts in 1960:Q1, hence dictating 36 fewer observations for the larger system compared to the benchmark system. Dashed lines represent 1st and 99th percentile Hall (1992) confidence bands generated from a residual based bootstrap procedure repeated 2000 times.