A Sectoral Approach to News Shocks

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June, 2013

Abstract

In this paper, I explore the dynamic effects of aggregate news about future technology improvements on sectoral fundamentals. I document that the durable goods sector responds significantly more to news shocks than the nondurable goods sector. By looking at the behavior of various sectoral fundamentals and also inventories, which have been largely neglected in the news literature, I show that aggregate news propagates the business cycle mainly through the durable goods sector. My theoretical framework is a two-sector, two-factor, real business cycle model augmented with the following three real rigidities: habit persistence in consumption, variable capacity utilization, and investment adjustment costs in both sectors. In addition, I introduce inventories as a factor in the production of durable goods. The model is successful in replicating the empirical responses of the US economy to news shocks. It reproduces the stronger response of the durable goods sector and can perfectly match the responses of inventories.

Keywords: News Shocks, Durable and Nondurable Goods Sectors, Inventories

JEL Classification Codes: E32, D84, L60, C51

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1 Introduction

The idea that the expectations about future changes in productivity represent an important driving force of the business cycle has received a great deal of attention in the recent literature in economics, after being abandoned for more than half a century.[1] Beaudry and Portier (2004, 2006), Christiano et al. (2010), Jaimovich and Rebelo (2009), Beaudry and Lucke (2010), and Schmitt-Grohé and Uribe (2012), among others, provide compelling evidence that news about future technological developments accounts for the bulk of business-cycle fluctuations. A different stream of the literature investigates the role of the durable goods industries in the propagation of business cycles. In particular, Mankiw (1985) concludes that durable goods industries play an essential role in the business cycle and that explaining fluctuations in the durable goods sector is vital for understanding aggregate economic fluctuations. The purpose of this paper is to link these two ideas and analyze through which sectors news shocks propagate the business cycle.

Understanding the nature of the aggregate news shock is a crucial first step in my analysis since the effects of aggregate news on sectoral fundamentals obviously depend on whether aggregate news contains information about the nondurable, durable, or both sectors. For instance, consider the following three simple scenarios: aggregate news being news about only the nondurable sector, about only the durable sector, or about both sectors simultaneously. In the first situation, an aggregate news shock would represent a demand shock to the durable sector and a supply shock to the nondurable sector, since investment in capital in the nondurable sector increases as a result of higher productivity and higher consumer demand. In the second case, a news shock represents both a supply and a demand shock to the durable goods sector, and, presumably, would imply significantly different behavior on the part of durable goods producers in response to the shock. Finally, the third scenario represents a combination of the first two.

By examining the behavior of a variety of fundamentals at the sectoral level, I show that the second scenario is the dominant one. Aggregate news appears, mainly, to be news about productivity in the durable goods sector. Although the dynamics of all sectoral level fundamentals are altered in the three scenarios, the behavior of investment and inventories in the durable goods sector is helpful to revealing which of the three scenarios is most likely. In particular, my empirical

[1] Pigou (1927) was one of the first authors to propose that agents' expectations about the future are an important source of business cycle fluctuations.

analysis shows that the response of the inventories to a unit aggregate news shock is statistically significant; this would not be the case if the dominant scenario were the first one (aggregate news being news only about the nondurable sector), since, as I show, a demand shock to the durable goods sector would not affect inventories of the durable sector in a quantitatively significant way. My analysis, therefore, confirms that the behavior of inventories carries relevant information for understanding the propagation of news shocks and business cycles.

To identify news shocks, I use the two-step identification procedure proposed by Beaudry and Portier (2006). This identification procedure sequentially uses short-run and long-run identification schemes to recover news shocks. It assumes that news shocks are ones which are orthogonal to current total factor productivity (TFP) innovations but permanently raise TFP in the long run. On the other hand, news shocks represent innovations to the stock price index and therefore instantaneously affect it. Whereas Beaudry and Portier recover aggregate news shock, I recover, in addition, sector-specific news shocks. Specifically, I retrieve news shocks for the manufacturing sector, the durable goods sector, and the nondurable goods sector. In order to do so, I create a data set composed of quarterly TFP (corrected for variation in capacity utilization) and stock price indices at the level of these three sectors. To do so, I mimic the procedure utilized by Beaudry and Portier (2006), but implement it at the sectoral level.

After obtaining measures of aggregate and sectoral news shocks, I investigate how they affect the behavior of the following sectoral fundamentals: productivity, consumption, hours, output and investment. I show that there is a great deal of comovement among these variables at the sectoral levels. However, the data indicate that there are much higher percentage responses of relevant variables in the durable goods sector than in the nondurable goods sector. In particular, after a 1 percent aggregate news shock, durable sector productivity responds by approximately 3 percent after ten quarters, while the response of productivity in the nondurable goods sector is approximately 0.5 percent. The percentage responses of other durable goods sector fundamentals are also significantly higher than those of the same fundamentals in the nondurable goods sector. Furthermore, when I investigate the effects of sector-specific news on the same sectoral fundamentals this basic pattern prevails.

My results suggest that aggregate news shocks are propagated primarily through the durable goods sector. Within the durable goods sector, the percentage responses are the highest in the

following two-digit standard industrial classification code (SIC) industries: primary metals, industrial machinery, instruments, and electronic equipment. These are, in fact, the industries with the highest share in the value added of the manufacturing sector in the United States. The percentage responses of the nondurable goods sector variables are much less than those of the durable goods sector variables; among the nondurable goods sector industries, the industries that respond the most are those that produce goods having some level of durability, even though they are classified as nondurable industries.

My investigation of inventories is motivated by an obvious and key difference between the durable and nondurable sectors. Nearly a century ago, Pigou (1927) proposes that the possibility of holding stocks of inventories explained the fact that business cycle fluctuations are more pronounced in durables industries than in nondurables industries.[2] Early research in the real business cycle tradition (see Blinder (1986), Christiano and Eichenbaum (1987), Eichenbaum (1984), Ramey (1989)) focused considerable attention on the importance of explaining the behavior of inventories. Recent research has suggested that improved inventories management contributed to the great moderation (see Kahn (2008*a*,*b*)). I re-establish the role and importance of inventories with new empirical evidence concerning the response of inventories to news shocks. To do so, I use the two standard inventories indicators: the inventories-to-sales ratio and the change in the inventories-to-output ratio. Whereas the percentage responses of both inventories indicators to news are statistically significant in the durables sector, the percentage responses of inventories in the nondurables sector are statistically insignificant.

Finally, I design a theoretical model that is consistent with the empirical evidence on how the economy responds to news shocks. Specifically, I build a two-sector, two-factor, real business cycle model which follows Baxter (1996) in its basic structure. Sector 1 produces a pure consumption

[2] In his book *Industrial Fluctuations*, Pigou says the following: "When for any reason the aggregate demand is increased in commodities that are durable and are not destroyed in the act of use, the resultant extra production of these commodities in the years of high demand involves the existence of a correspondingly enlarged stock, and so gives rise to a smaller demand for new production of these commodities than it used to give rise to before. Thus, the upward fluctuation of industrial activity above the normal carries with it a subsequent downward fluctuation below the normal when the stimulus is removed, and not merely a subsequent return to the normal... The same thing holds good of those consumption goods which are destroyed in a single act of use, provided that they are durable in their own nature and are of such a sort that they can be held in store without great cost of risk: for dealers pile up stocks of them in booms, and in depressions are forced to offer them out of their stocks in competition with the current output of industry... Here, then, we have a second reason for expecting that instrumental industries will fluctuate more than others, even though it is in the others that the cause of fluctuations lies."

(nondurable) good, whereas sector 2 produces consumer durables and the capital good used in producing both goods. Both sectors use capital and labor as their factor inputs. The key difference between the two sectors is that a good produced in sector 2 can be stocked, whereas the output of sector 1 is perishable. I model this feature by adding inventories into the production function of sector 2, following Christiano (1988) and Kydland and Prescott (1982). These authors argue that the stock of inventories, as the stock of fixed capital, provides a flow of services to a firm.

My model is augmented by the following four real rigidities: habit persistence in consumption, investment adjustment costs in both sectors, as well as adjustment costs associated with changes in the stock of consumer durables, and variable capacity utilization. I introduce habit persistence in consumption in order to obtain a hump-shaped consumption response. Following Jaimovich and Rebelo (2009), I introduce investment adjustment costs in order to obtain comovement between hours, consumption, output and investment. Variable capacity utilization assures that the model-based and empirical measures of TFP coincide. Finally, news shocks are introduced by feeding the empirical responses of TFP in the two sectors into the model.

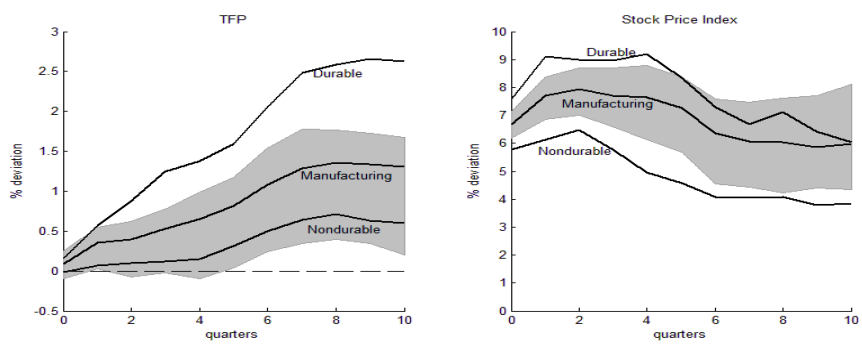
The model is successful in mimicking the empirical responses to news shocks at the sectoral level. First, the response of the inventories-to-sales ratio can be perfectly matched. Second, the model is able to reproduce the stronger overall response of the durable goods sector to news shocks. For example, responses of hours, consumption and output are all higher in the durable goods sector. Third, the model reproduces the comovements observed among sectoral level fundamentals. That is, the model reproduces comovement among hours, consumption, output and investment in both sectors. Even though it cannot perfectly match the responses of all the variables (for example, response of hours in the nondurable goods sector), overall the model fits the data rather well.

The remainder of the paper is structured as follows: In Section 2, I describe some of the main findings in more detail, the data used in the analysis, as well as all empirical findings. In particular, I first explain how I obtain measures of aggregate and sectoral news shocks and how I recover their effects on sectoral fundamentals. The two-sector model is presented in Section 3. Section 4 explains calibration and estimation of the model. Quantitative findings using the model are presented in Section 5. Section 6 concludes.

2 Empirical Evidence

In this paper, I investigate, analyze and define the nature of aggregate news shocks. I first explore the effects of aggregate news shocks on sectoral TFPs and stock price indices. Specifically, I analyze the manufacturing sector, the durable goods sector, and the nondurable goods sector (see responses in Figure 1). According to the analysis, whereas TFPs do not respond immediately to news, stock prices do in all sectors. This observation confirms that news is immediately reflected in the variables that express agents' expectations about the future, such as stock prices. Another striking observation is the different quantitative behavior of durable and nondurable goods sectors. Both the percentage responses of TFP and stock prices in the durable goods sector are significantly greater than in the nondurable goods sector. Specifically, after ten quarters, the response of durable sector TFP is almost five times greater than the response of nondurable sector TFP, whereas the impact response of the durable sector stock price index is 2 percent greater than the impact response of the nondurable sector stock price index. This might suggest that the information contained in an aggregate news shock is more about future productivity in the durable sector than about nondurable sector productivity.

Figure 1: Impulse responses of the sectoral TFPs and Stock Price Indices to a unit aggregate news shock

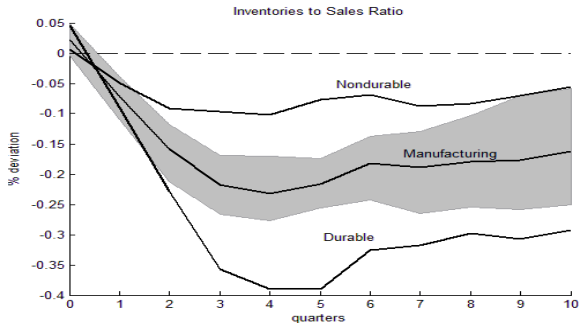


Note: Impulse responses of sectoral TFPs to a unit aggregate news shock are given in the left panel; the responses of sectoral stock price indices are given in the right panel. Shaded areas represent 5% and 95% confidence bands of the responses at the level of the manufacturing sector, which are obtained using the Monte-Carlo experiments with 1000 replications.

A key difference between durable and nondurable producers is that the former are more able

to respond quickly to demand shocks by running down stocks of inventories.[3] My exploration of the role of inventories, which have not previously been studied in the news literature, is motivated by this key difference between the producers of durable and nondurable goods. My empirical evidence suggests that the response of inventories-to-sales ratio to an aggregate news shock is almost nonexistent in the nondurable industries, whereas there is a noticeable and significant drop in the durable industries. The average responses of the inventories-to-sales ratio in the manufacturing, durable, and nondurable sectors are presented in Figure 2. Specifically, in the durables sector the ratio drops by 0.4 percent within one year of a news shock, whereas the average response in the nondurables sector is small and insignificant.

FIGURE 2: IMPULSE RESPONSE OF THE SECTORAL INVENTORIES TO SALES RATIO TO A UNIT AGGREGATE NEWS SHOCK



Note: Point estimates of the responses of manufacturing, durables and nondurables sector inventories to sales ratio to a unit aggregate news shock are displayed. Shaded areas represent 5% and 95% confidence bands of the responses at the level of the manufacturing sector, which are obtained using the Monte-Carlo experiments with 1000 replications.

In order to achieve a more complete analysis, I extend my investigation to other sectoral-level fundamentals, such as hours, output, investment, and consumption. A discussion of this follows a detailed explanation of how aggregate news shock and sectoral news shocks are identified.

[3] This is not to say that stocks of inventories cannot be held in the nondurable sector industries, but their volume is lower than in the durable sector industries. In particular, more than 60 percent of manufacturing sector inventories are carried by the durable sector. Also, the inventories of durable producers can be held for a longer periods of time.

2.1 Identification of News Shocks

When the effects of a particular shock are discussed in macroeconomics, an important first step is to clearly communicate the validity of the identification scheme. News shocks are typically defined as the arrival of new information about future productivity growth that ends up being reflected instantaneously in forward-looking variables, but does not have an instantaneous impact on the current TFP.[4] Rather, the effects on TFP are realized only after a certain number of quarters. Although it is relatively straightforward to think about this phenomenon in the theoretical framework, recovering its empirical analog is more challenging. In this paper, I will use the identification scheme proposed by Beaudry and Portier (2006). There are other identification schemes proposed in the literature as well. For example, Barsky and Sims (2011) identify news shock as a shock orthogonal to the TFP innovation that best explains future variation in measured TFP. Although news identified using this identification scheme does not reproduce comovement among consumption, hours, output and investment, it still leads to larger responses in the durable sector. However, the purpose of this paper is not to propose a new identification scheme, and therefore I choose one identification strategy to carry out my analysis.

The identification procedure of Beaudry and Portier takes, as a starting point, the definition of a news shock given above. The most natural choice of variables on which to base the procedure are a measure of productivity and some forward-looking variable that contains information about future developments. Like Beaudry and Portier, I use TFP as the measure of productivity, and a stock price index as the forward-looking variable. I start with a bivariate time series model for these variables. In order to recover news shocks, I sequentially impose two separate identification restrictions, described as the short-run and long-run, on the model.

To describe the short-run restriction, I assume that the two variables can be represented in log first differences, by the Wold representation:

$$\begin{bmatrix} \Delta TFP_t \\ \Delta SP_t \end{bmatrix} = \Gamma(L) \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

where $\Gamma(L) = \sum_{i=0}^{\infty} \Gamma_i L^i$, and the two shocks, ε_{1t} and ε_{2t}, are mutually orthogonal and have unit

[4] See, for example Beaudry and Portier (2006), Christiano et al. (2010), Jaimovich and Rebelo (2009).

variance. The short-run restriction imposes that ε_2, has no short-run effect on TFP. More formally, this restriction is imposed by setting the $1,2$ element of the matrix Γ_0 to zero.

The long-run restriction is based on an alternative Wold representation

$$\begin{bmatrix} \Delta TFP_t \\ \Delta SP_t \end{bmatrix} = \widetilde{\Gamma}(L) \begin{bmatrix} \widetilde{\varepsilon}_{1t} \\ \widetilde{\varepsilon}_{2t} \end{bmatrix}$$

where $\widetilde{\Gamma}(L) = \sum_{i=0}^{\infty} \widetilde{\Gamma}_i L^i$, and the two shocks, $\widetilde{\varepsilon}_{1t}$ and $\widetilde{\varepsilon}_{2t}$, are mutually orthogonal and have unit variance. The long-run restriction is that only $\widetilde{\varepsilon}_{1t}$, has a long-run effect on TFP. This restriction is imposed by setting the $1,2$ element of the matrix $\widetilde{\Gamma}(L) = \sum_{i=0}^{\infty} \widetilde{\Gamma}_i L^i$ to zero.[5]

As such these two identification schemes are purely ad-hoc. However, suppose that it happens to be the case that the two recovered disturbances, ε_2 and $\widetilde{\varepsilon}_1$, are extremely highly correlated, or effectively the same. This suggests that the procedure has recovered a single shock that, since it satisfies the short-run restriction, does not have an immediate effect on the productivity and affects it only with a delay, and, since it satisfies the long-run restriction, captures all important long-run information about productivity. Given these characteristics, the shock satisfies the two characteristics of news described above. Of course, the procedure only delivers plausible measures of news if the two shocks happen to be highly correlated.

2.2 Data

The data used in this paper can be broadly divided into aggregate and sectoral-level series. Specifically, I use data from the manufacturing which allow me to distinguish between the durable and nondurable goods sectors. As a further level of disaggregation, I also use data on nineteen two-digit SIC code manufacturing industries. Data for the manufacturing, durable goods, and nondurable goods sectors are available at the quarterly frequency for the sample period 1972:I - 2007:IV. Data for the two-digit industries are also available at the quarterly frequency, but for a shorter sample

[5] If the two series are found to be cointegrated, all elements in the second column equal zero, i.e. $\widetilde{\varepsilon}_1$ is the only permanent shock. This is because the rank of the matrix is one in the presence of the one cointegrating relation. Hence, in this case, a simple Cholesky decomposition cannot be used to recuperate the structural news shock, as in Blanchard and Quah (1989). In fact, to recover disturbance $\widetilde{\varepsilon}_1$, I follow the procedure proposed by King et al. (1991). This procedure allows one to impose the long-run restrictions using the fact of the existence of the cointegrating relations.

period, 1972:I - 1997:III.[6] Finally, aggregate data, for the entire US economy, are available at the quarterly frequency for the period 1949:I - 2007:IV.

In order to recover news shocks at all levels of aggregation, I create a data set composed of TFP and stock prices for these three sectors and nineteen two-digit industries. I construct TFP following Burnside, Eichenbaum and Rebelo (1995). Rather than considering their three different technology specifications, I use the model that allows me to measure TFP at the two-digit level, despite the absence of observations on material inputs. Specifically, I assume that time t gross output is produced using a Leontief production function

$$Y_t = \min\left(M_t, V_t\right),$$

where M_t denotes time t materials and V_t denotes value-added at time t, which, itself, is produced using hours of work (N_t), the stock of capital (K_t), and time varying capital utilization, measured by electricity use (E_t). As Burnside, Eichenbaum and Rebelo show, this specification allows gross output in sector i to be written as

$$Y_t^i = A_t^i F\left(N_t^i, \frac{E_t^i}{\phi}\right),$$

where ϕ represents the assumed fixed proportion between electricity consumption and capital services, with the latter being the product of the capital stock and its work week. I further assume that the function $F(\cdot)$ takes the Cobb-Douglas form.

After assuming that the labor and electricity markets are perfectly competitive, the expression for TFP in a sector or industry i can be obtained using a first-order log-linear approximation of the production function:

$$\Delta Y_t^i = (1-\alpha_1)\,\Delta N_t^i + \alpha_1 \Delta E_t^i + \Delta A_t^i, \tag{TFP}$$

where ΔA_t^i is assumed to be the growth rate of TFP, ΔY_t^i the growth rate of output, ΔN_t^i the

[6] In 1997 the SIC was replaced by the North American Industry Classification System (NAICS), and it is not possible to extend the two-digit SIC series further than 1997. Also, historical data have not been transformed to match NAICS.

growth rate of labor input and ΔE_t^i the growth rate of electricity use in sector or industry i.[7] Data on output (measured using the relevant indices of industrial production) and electricity consumption (my proxy for capital services) at the sectoral level are obtained from the Federal Reserve Board. As emphasized by Beaudry and Portier (2006) and Barsky and Sims (2011), TFP measures that are adjusted for capacity utilization are preferable since they lead to more realistic, substantially delayed, productivity responses to news shock. As a sectoral labor measure, I use the quarterly averages of monthly production workers, which is constructed as the product of the following two time series: average weekly hours of production workers and the number of production workers, both obtained from the Bureau of Labor Statistics. Finally, my assumption of a constant returns to scale Cobb-Douglas technology allows me to calibrate the parameter $1-\alpha_1$, using labor's share of income.[8] I compute labor's share as the ratio of labor compensation and nominal income in each sector or industry. Both series needed for this calculation are obtained from the Bureau of Economic Analysis.

Sectoral stock price data are extracted from Kenneth French's website.[9] Data on S&P500 were obtained from Robert Shiller's website.[10] Using the consumer price index (CPI) as the inflation measure and the civilian noninstitutional population over 16, I convert these data to real per capita measures. Besides using TFP and stock price indices data in my empirical analysis, I also use data on real per capita consumption, hours, investment, output and several inventories indicators, at the aggregate and sectoral level. Detailed explanations of these data and all other data used in the paper, as well as their sources, are provided in the online Appendix A.

[7] Since in my model I consider inventories to be a factor of the production in the durable goods sector, the durable sector measure of TFP will be slightly altered in order to account for this: $\Delta A_t^{dur} = \Delta Y_t^{dur} - \left(1-\alpha^{dur}\right)\Delta N_t^{dur}$ $-\alpha^{dur}\left(1-\rho\right)\Delta E_t^{dur} - \alpha^{dur}\rho\Delta I_t^{dur}$, where ρ controls for the role of inventories I_t in the production function of the durable goods sector.

[8] Burnside (1996) concludes that "the typical U.S. manufacturing industry displays constant returns with no external effects."

[9] The data are available for download at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_lInibrary.html. The data are constructed from The Center for Research in Security Prices (CRSP) database. The particular series used here are the stock price indices of the manufacturing sector, durable goods sector, nondurable goods sector, as well as stock price indices of all two-digit SIC manufacturing industries.

[10] Available at http://www.econ.yale.edu/~shiller/data.htm

2.3 Sectoral News

The news literature has focused primarily on aggregate news and its effects on aggregate variables, and has remained largely silent concerning the effects of news on sectoral fundamentals, and concerning the possibility that some shocks are in fact news specific to a particular sector of the economy. In order to understand these sectoral aspects of news shocks, in this section I describe news shocks recovered at the sectoral level, and I explore the dynamic responses of sectoral fundamentals to aggregate and sector-specific news.

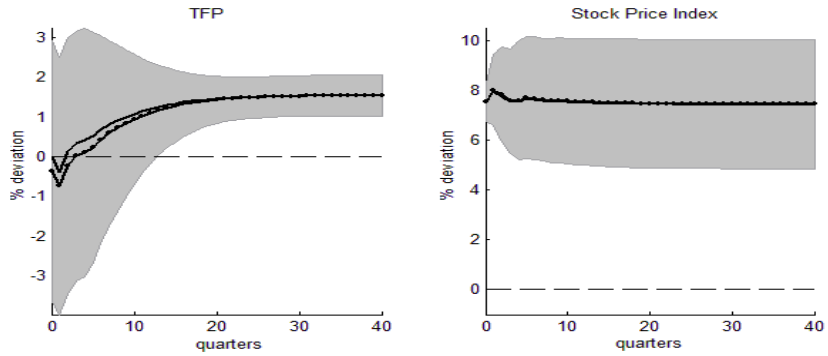
Beaudry and Portier (2006) show that, for the aggregate US economy, the two disturbances, ε_{2t} and $\widetilde{\varepsilon}_{1t}$, obtained from the short-run and long-run identification schemes are highly correlated, and induce nearly identical dynamic responses of TFP and stock prices. This feature of the identified shocks is preserved when a third variable, such as consumption, output, investment, or hours is added to the system. More importantly for my analysis, the correlation between the two disturbances is very high also when sectoral data is used. In particular, I identify news shocks in the manufacturing, durable goods and nondurable goods sectors and compare these recovered sectoral level shocks to the aggregate news shocks. Manufacturing news shock is identified using a two-variable vector autoregressive system in the log first differences of TFP and stock price index for the manufacturing sector. According to a Likelihood Ratio Test, the hypothesis of cointegration between TFP and the stock price index cannot be rejected at the 5% level.[11] Therefore, a vector error correction model (VECM) is the appropriate specification. In the case of the manufacturing sector, the correlation between the two identified disturbances, ε_2 (short-run) and $\widetilde{\varepsilon}_1$ (long-run), is very high, 0.994.

The responses of the manufacturing sector TFP and stock price index to a 1 percent increase in ε_2 and $\widetilde{\varepsilon}_1$ are displayed in Figure 3. As in the aggregate economy, the dynamics induced by the two disturbances are very similar. In particular, the short-run disturbance, ε_2, permanently affects TFP while the long-run disturbance, $\widetilde{\varepsilon}_1$, has nearly no impact effect on TFP. These two facts suggest that the identification procedure has correctly isolated news shocks in the manufacturing sector. The impulse response functions for TFP have a somewhat different shape in the manufacturing sector than they do for the full economy. In the aggregate case, TFP increases soon after the shock, and does so sharply, whereas manufacturing sector TFP increases slowly after an

[11] See (Hamilton, 1994, p. 648).

initial (statistically insignificant) drop in the first two quarters after the shock.[12] The response of the manufacturing stock price index is very similar to the response of its aggregate counterpart to aggregate news. It increases on impact by 7.5 percent and remains at roughly the same level indefinitely.

FIGURE 3: IMPULSE RESPONSES TO SHOCKS ε_2 AND $\widetilde{\varepsilon}_1$ IN THE (TFP, SP) VAR AT THE MANUFACTURING SECTOR LEVEL



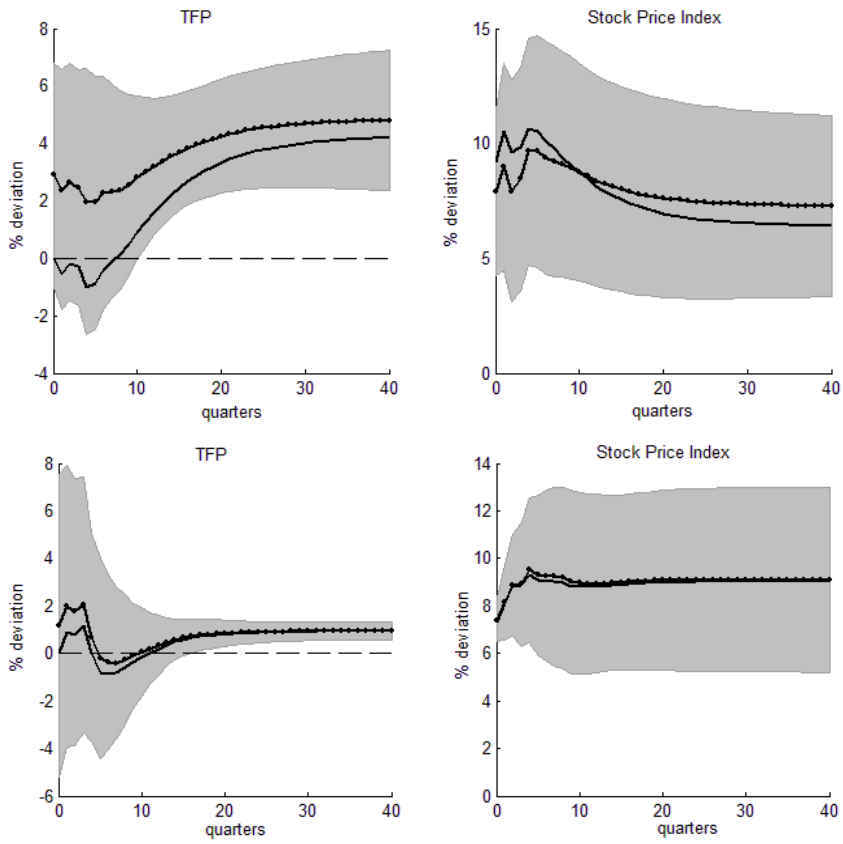
Note: Left panel represents the response of the manufacturing TFP to the two disturbances; the response of the manufacturing stock price index to these disturbances is given on the right panel. Dotted lines represent point estimates of the responses to a unit ε_2 shock, solid lines represent the responses to a unit $\widetilde{\varepsilon}_1$ shock, whereas the borders of the shaded area represent 5% and 95% confidence bands of the impulse response functions in the case of long-run identification. Confidence bands are obtained using the Monte-Carlo experiments with 5000 replications.

I also identify durable-sector-specific news shocks and nondurable-sector-specific news shocks by adopting the same identification procedure. I use a two-variable VECM in the log first differences of sectoral TFP and stock prices for the durable and nondurable goods sectors respectively.[13] Figure 4 displays the impulse response functions of sectoral TFPs and stock prices.

[12]Nevertheless, when aggregate TFP is corrected for capacity utilization, its qualitative response more closely resembles the response of the manufacturing TFP response. In particular, aggregate TFP does not increase for several years; the diffusion process appears to be slower than when unadjusted measure of TFP is used.

[13]In both sectors, a Likelihood Ratio Test suggests the presence of one cointegrating vector.

Figure 4: Impulse responses to shocks ε_2 and $\widetilde{\varepsilon}_1$ in the (TFP, SP) VAR at the durables sector level (the upper panel) and nondurables sector level (the lower panel)



Note: The top panel represents the responses of the durable goods sector TFP and stock price index, whereas the lower-panel represents the responses of the nondurable goods sector TFP and stock price index. On both panels, left graph represents the responses of TFPs to the two disturbances, whereas the right graph represents the responses of SP to these disturbances. Dotted lines represent point estimates of the responses to a unit ε_2 shock, solid lines represent the responses to a unit $\widetilde{\varepsilon}_1$ shock, whereas the borders of the shaded area represent 5% and 95% confidence bands of the impulse response functions in the case of long-run identification. Confidence bands are obtained using the Monte-Carlo experiments with 5000 replications.

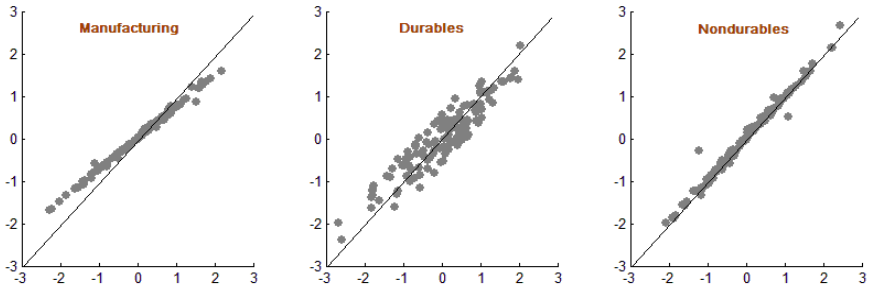
As in the case of the aggregate economy and manufacturing sector, the disturbances originating from the short-run and long-run identification procedures induce quite similar dynamics. However, in both sectors, the long-run shock, $\widetilde{\varepsilon}_1$, has an immediate effect on TFP; in the durable sector it rises by approximately 2 percent, whereas in the nondurable sector it rises by 1 percent. But, as the time horizon expands, the two responses almost converge in both sectors. Furthermore, the

two responses lie within the 95% long-run confidence bands, suggesting statistical similarity.

Evidently, the long-run response of durable sector TFP is considerably greater than that of nondurable goods sector TFP; after 40 quarters, the effect of a 1 percent durable sector news shock on durables TFP is approximately 4 percent, whereas the effect of a 1 percent nondurable sector news shock on nondurables TFP is less than 1 percent. This greater response of durables TFP suggests that the relatively large 1.5 percent response of manufacturing TFP to a news shock is mostly driven by the behavior of the durable sector. In addition, the response of durables TFP to durables news qualitatively resembles the response of its manufacturing counterpart to manufacturing news. Both the higher durables TFP response and its resemblance to the manufacturing TFP response suggest that manufacturing news is mainly about the future growth of durables TFP, rather than about the future growth of nondurables TFP.

Even though the long-run disturbances have an immediate effect on sectoral TFPs, the correlations between the two disturbances in both sectors are still high (0.934 in the durable goods sector and 0.989 in the nondurable goods sector). Scatter plots of the two disturbances, ε_2 and $\widetilde{\varepsilon}_1$, at the manufacturing, durables, and nondurables levels are plotted in Figure 5.

Figure 5: Correlation between ε_2 and $\widetilde{\varepsilon}_1$ in the Manufacturing, Durable and Nondurable Goods Sectors



Note: Two disturbances, ε_2 and $\widetilde{\varepsilon}_1$, are plotted against each other at the level of the manufacturing sector, durable goods sector and nondurable goods sector.

In order to understand how these aggregate and sectoral news shocks are related, I calculated correlations between aggregate news shocks and sectoral news shocks. The correlation between the aggregate and nondurable news shocks (0.738), is lower that the correlation between the aggregate and durable news shocks (0.758). This result also holds when manufacturing news is

compared to durable and nondurable news; the correlation between the durables and manufacturing news is 0.885, whereas the correlation between the nondurable and manufacturing news shocks is 0.837. These facts indicate that aggregate and manufacturing news shocks carry more information concerning the durable sector developments, than they do concerning the nondurable sector.

In order to investigate whether the higher durable sector responses are due only to some aggregation effect, in the next section I extend the analysis to a more disaggregated level. I consider two-digit SIC industries and their responses to various types of news shocks.

2.3.1 Two-digit SIC Level

The same identification procedure is performed at the level of nineteen two-digit SIC manufacturing industries.[14] Specifically, ten of these industries are classified as durable goods industries, and the remaining nine as nondurable goods industries. For each two-digit SIC industry, I construct a vector autoregressive system composed of the TFP and stock price index of that particular industry, sequentially performing short-run and the long-run identifications. However, at the more disaggregated level, impulse response functions implied by the two disturbances follow rather different dynamics, contrary to the aggregate or sectoral levels. Thus, the correlation between the two recovered shocks is rather small, on average. This evidence suggests that the identification scheme fails to recover news shocks that are specific to the two-digit SIC industries. One plausible explanation is that classifying firms according to two-digit SIC codes is somewhat difficult. In particular, SIC classifies establishments by their primary type of activity - the activity that contributes the most to the value added of the establishment. Since firms often operate in more than one industry, the information that is contained in their TFP or stock price index is not necessarily tied to only one two-digit SIC industry. Hence, as the level of disaggregation deepens, it becomes more difficult to extract industry-specific news shocks from the data.

Even though I am not able to identify news specific to the two-digit SIC industries, the behavior of the two-digit SIC productivity, stock prices, and other fundamentals in response to recovered aggregate or sectoral news may carry important information. Conditional upon the recovered

[14] SIC represents a numerical system developed by the Federal Government for classifying all types of economic activity within the United States economy.

shocks representing news shocks, one can run the following regression:

$$\Delta X_t = \sum_{j=0}^{J} \psi_j \varepsilon_{2,t-j} + \mu_t, \tag{1}$$

in order to infer the effects of news shocks on a variable X_t. Here, ε_{2t} represents the recovered structural news shock at time t coming from the short-run identification procedure.[15] Specifically, it can represent either the aggregate news shock or one of the three recovered sectoral news shocks. The point estimate impulse response of variable X_t to a particular news shock after a horizon n is measured as the cumulative sum of the regression coefficients $\psi_j's : \sum_{j=1}^{n} \psi_j$.

I first investigate the effects of an aggregate news shock on the productivity of the nineteen two-digit SIC industries. Figure 6 displays the responses of durables and nondurables industries to a unit aggregate news shock. First, the impact response of productivity is statistically equal to zero in all industries, satisfying the condition that news shocks do not affect productivity immediately. Second, durables industries are, on average, more responsive to aggregate news in the long-run than nondurable industries. Within the durable goods sector, industries with the highest percentage responses are the following: primary metals, industrial machinery, instruments and electronic equipment. These industries have the highest shares in the total value added of the durable goods sector. On average, the responses in the nondurable sector industries are much smaller. Industries that consistently respond the most, among the nondurable goods industries, are chemicals, petroleum, and textile mills, which are industries whose output has a somewhat durable character.[16]

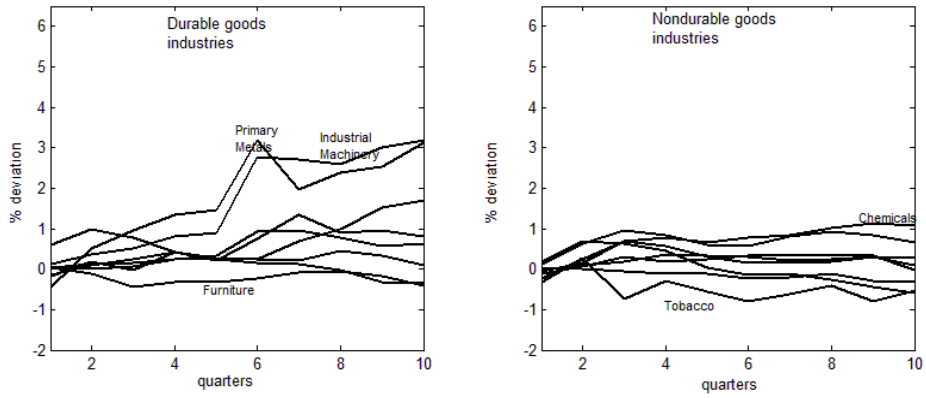
When I repeat a similar exercise - recovering industry responses to sectoral news - I obtain similar conclusions. First, durable goods industries respond more to all types of news shocks. Second, the response of each two-digit SIC industry is the highest to a news shock specific to the sector to which the industry belongs (according to the SIC). For instance, nondurable goods industries respond more to nondurable news shocks than to durable news shocks, whereas durable

[15] Since I showed that the correlations between the long-run and short-run shocks are very high (both at the aggregate and sectoral levels), the effects of $\tilde{\varepsilon}_1$ and ε_2 on X_t are nearly identical.

[16] Beaudry and Portier (2005) use annual Multifactor Productivity Trends sectoral data in order to analyze the effects of aggregate news shocks on two-digit SIC industries. They also find higher responses in the durables sector. In particular, they find that the industries with the highest growth rate among the durable sector industries are those with the highest long-run responses to the aggregate news.

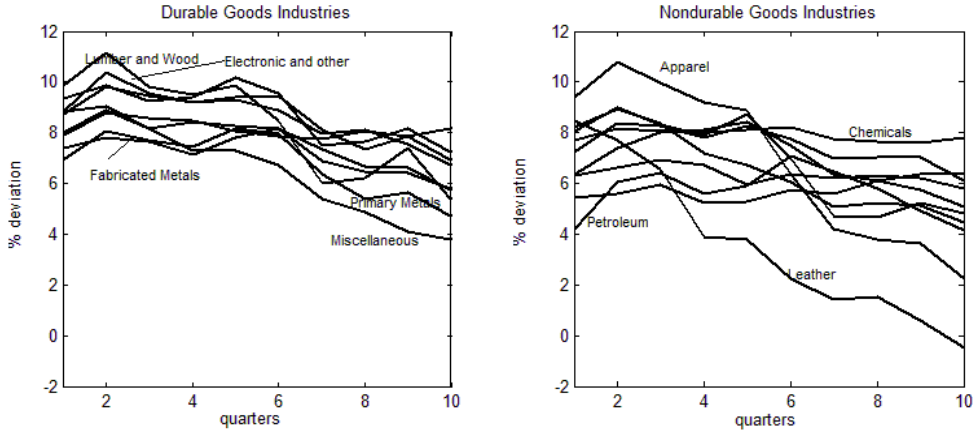
goods industries respond more to durable news shocks than to nondurable news shocks. This result is somewhat expected, since the sector-specific news carries more information about the TFP in that particular sector than, for example, aggregate news.

Figure 6: Responses of Two-Digit SIC Durables (left panel) and Nondurables Industries′ (right panel) TFPs to a Unit Aggregate News Shock



After documenting that aggregate and sectoral news do not have an impact effect on TFP in the two-digit industries, I also examine the responses of the two-digit SIC stock price indices. If the price indices rise on impact this supports the view that the recovered shocks represent news. The responses of stock prices in the nineteen two-digit manufacturing industries to a 1 percent aggregate news shock are shown in Figure 7. Stock prices respond significantly on impact in each industry, confirming that news shocks are immediately reflected in forward-looking variables. The average response of the stock price indices in the durable goods sector is higher than that of the stock price indices in the nondurable goods sector. Specifically, stock prices of each durable sector two-digit industry respond by more than 7 percent to an aggregate news shock, whereas the response in four nondurable goods industries is less than 7 percent. The initial large response of stock prices is followed by decreases during the following ten quarters. To explain this decline, Haertel and Lucke (2008) argue that by the time new technology is diffused, competition reduces profits and stock prices adjust to a lower level.

Figure 7: Responses of Two-Digit SIC Durables (left panel) and Nondurables Industries′ (right panel) Stock Prices to a Unit Aggregate News Shock



2.4 Effects of News on Other Sectoral Fundamentals

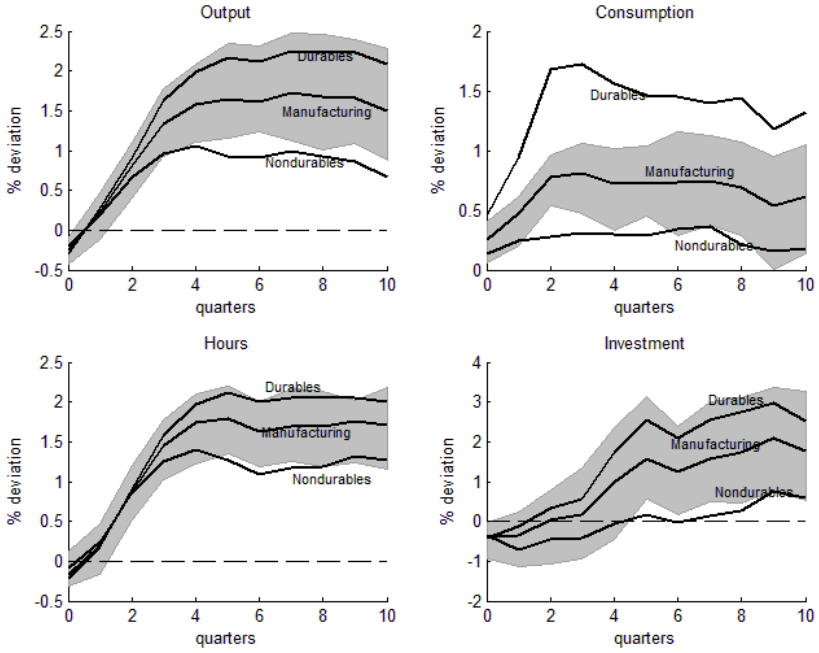
As previously shown, the percentage response of durable goods sector TFP to news is significantly larger than that of nondurable goods sector TFP. In particular, the long-run durable sector TFP response is almost five times greater than the response of the nondurable sector TFP. In order to complete the empirical analysis, I explore whether this result is also present in the case of other sectoral fundamentals. Specifically, I examine the responses of sectoral output, consumption, hours, and investment.

Figure 8 displays the responses of sectoral fundamentals to a 1 percent aggregate news shock. The shaded area represents 90% confidence bands of the manufacturing sector responses. There are several features worth noticing. First, there is evidence of the comovement among the sectoral fundamentals. Second, the responses of all durable sector fundamentals are significantly greater than the responses of nondurable sector fundamentals. Specifically, after ten quarters, the percentage response of durable sector output is four times higher than that of nondurable sector output. Also, the responses of durable consumption, hours and investment are higher than those of the same variables in the nondurable goods sector. Third, only consumption responses are statistically positive on impact, whereas the impact responses of other fundamentals are not statistically different from zero. After ten periods, all durable sector fundamentals remain above their initial levels and these responses are statistically different from zero. In contrast, in the nondurable

goods sector only the responses of hours and output are significantly different from zero after 10 quarters; the responses of consumption and investment are not statistically significant over this time horizon.

I also examine the effects of sectoral news on the same sectoral fundamentals. In line with the previous results for TFP, the effects of sectoral news on sectoral fundamentals are larger than the effects of aggregate news. In particular, durable goods sector fundamentals respond most to the durable news shock, while nondurable goods sector fundamentals respond most to the nondurable news shock.

Figure 8: Responses of the sectoral fundamentals to a unit aggregate news shock

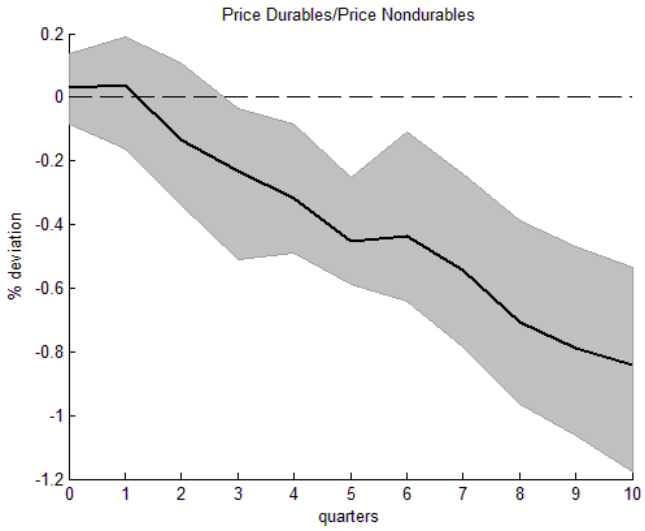


Note: Solid lines represent point estimates of the sectoral responses to a unit aggregate news shock. Shaded areas represent 5% and 95% confidence bands of the responses at the level of manufacturing sector.

Finally, since I document an overall larger response of durable sector TFP to aggregate news shock, there is an implied increase in the relative productivity of the durable and nondurable goods sectors. Hence one would expect a decline in the relative price of durables goods in response to an aggregate news shock. Furthermore, if consumption for both types of goods occurs on impact, due

to a positive wealth effect, the lack of inventories of nondurables could create a scarcity effect that would reinforce the decline in the relative price of durables. When I analyze the response of the relative price of durable goods (the ratio between durable sector and nondurable sector consumer price indices) to an aggregate news shock, the above intuition turns out to be correct. As Figure 9 displays, the relative price of durable goods decreases by 0.8 percent after ten quarters.

Figure 9: Impulse responses of the inventories-to-sales ratio to a unit sectoral news shock



Note: Solid lines represent point estimates of the relative price of durable goods to a unit aggregate news shock. Shaded areas represent 5% and 95% confidence bands.

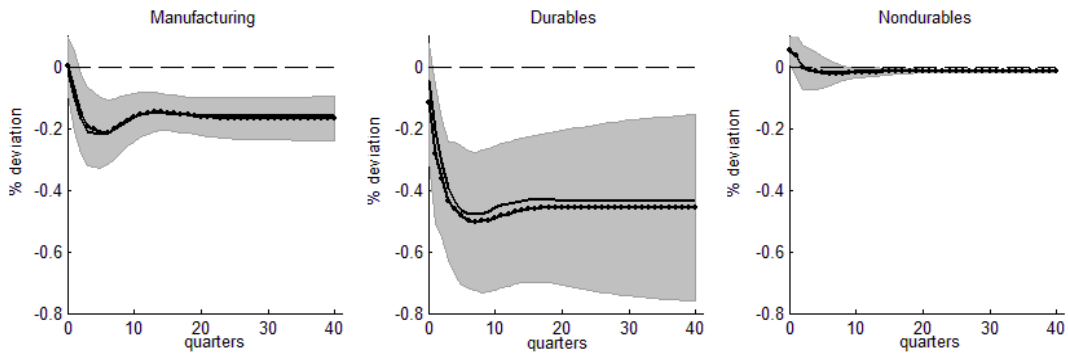
Overall, the evidence presented in this section further supports the idea that durable goods sector fundamentals are more responsive to news shocks, and that aggregate news shocks propagate business cycles mainly through the durable goods sector.

2.5 Inventories

A key difference between durable and nondurable goods is that producers of durables can stock inventories and use them as a buffer to news shocks. This feature of durable goods has potentially important implications for how the sector responds to news shocks. For this reason, I devote this section to examining the behavior of the two most commonly used inventories indicators: the

inventories-to-sales ratio and the change in the inventories-to-output ratio (see Blinder and Fischer (1981) and Lovell (1961)). To obtain the responses of these variables to news shocks, I add the inventories indicator to the benchmark two-variable system. When the third variable is added, the identification process becomes more involved.[17]

Figure 10: Impulse responses of the inventories-to-sales ratio to a unit sectoral news shock



Note: Left panel represents the response of the manufacturing inventories-to-sales ratio to the two disturbances coming from the three-variable (TFP, stock price index, inventories-to-sales ratio) VECM at the manufacturing sector level. Middle panel represents the response of the durables inventories-to-sales ratio to the two durable sector disturbances originating from the three-variable VECM at the durable goods sector level. Right panel represents the response of the nondurable inventories-to-sales ratio to the two nondurable sector disturbances originating from the three-variable VECM at the nondurable sector level. In all three panels the dotted lines represent the point estimates of the response to the short-run sectoral disturbance, whereas the solid lines represent the point estimates of the responses to the long-run sectoral disturbance. Finally, shaded areas represent 5% and 95% confidence bands of the long-run sectoral responses. Confidence bands are obtained using the Monte-Carlo experiments with 5000 replications.

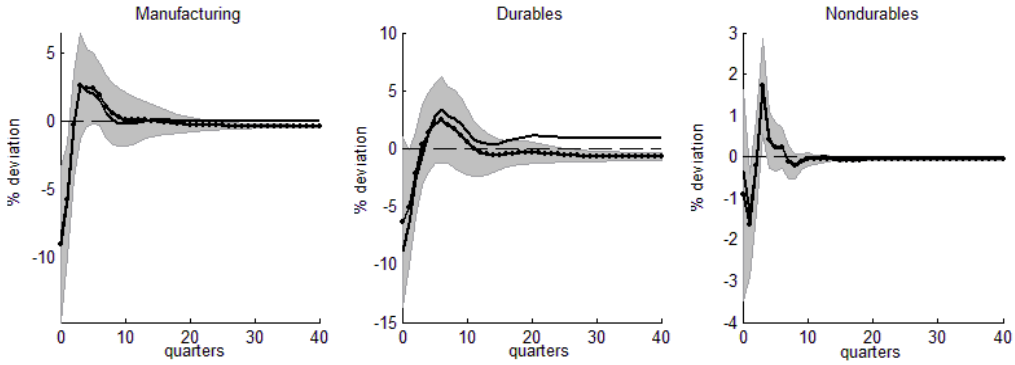
Figure 10 displays the responses of inventories-to-sales ratio in three sectors (manufacturing, durables, and nondurables) to the sectoral level news shocks in those sectors (identified with either the short-run or long-run restriction). The view commonly accepted in the literature is that inventories-to-sales ratio is countercyclical.[18] Firms accumulate their inventories when demand is weak, and liquidate them when demand is high. Also, if there is uncertainty about the sales in the future, firms may hold inventories against the contingency that demand will be unexpectedly

[17] A detailed explanation is provided in the online Appendix C.

[18] For example, Blinder (1981) argues: "The most commonly used indicator of the state of inventory equilibrium or disequilibrium is the ratio of inventories to sales in manufacturing and trade. This ratio moves countercyclically, rising in recessions."

high. Therefore, one would expect the inventories-to-sales ratio to decrease when good news about future productivity arrives. My analysis confirms this view. Specifically, the inventories-to-sales ratio in manufacturing decreases by 0.25 percent over six quarters, remaining at that level in the longer run. As expected, the response of inventories in the durables sector is twice as large as that in the manufacturing sector (a decline of almost 0.6 percent), whereas the response of the inventories-to-sales ratio in the nondurables sector is statistically insignificant over the whole time horizon

FIGURE 11: RESPONSE OF THE CHANGE IN THE INVENTORIES-TO-OUTPUT RATIO TO A UNIT SECTORAL NEWS SHOCK



Note: Left panel represents the response of the change in inventories-to-output ratio in the manufacturing sector to the two disturbances originating from the three-variable (TFP, stock price index, change in inventories-to-output ratio) VECM at the manufacturing sector level. Middle panel represents the response of the durables change in inventories-to-output ratio to the two durable sector disturbances (originating from the three-variable VECM at the durable goods sector level). Right panel represents the response of the nondurable change in inventories-to-output ratio to the two nondurable sector disturbances (originating from the three-variable VECM at the nondurable goods sector level). In all three panels the dotted lines represent the point estimates of the response to the short-run sectoral disturbance, whereas the solid lines represent the point estimates of the responses to the long-run sectoral disturbance. Finally, shaded areas represent 5% and 95% confidence bands of the long-run sectoral responses. Confidence bands are obtained using the Monte-Carlo experiments with 5000 replications.

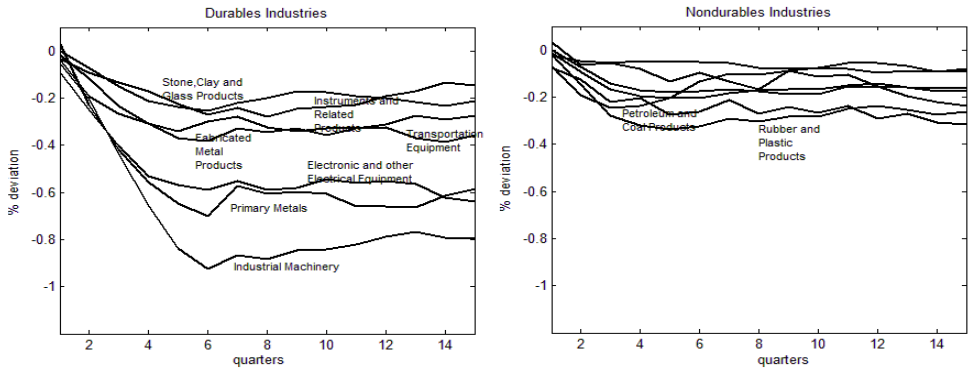
Figure 11 displays the corresponding responses of the change in the inventories-to-output ratio. After an initial decrease, this indicator increases, reaching a peak after five to six quarters. Although the response is significant at the level of manufacturing and durable sector, there is, again, no statistically significant response in the nondurable sector. The rationale behind this qualitative response is as follows: as the good news about the future productivity is realized, producers

decrease the inventories levels in order to meet increased demand. However, as time passes, they increase production and inventories levels return to some optimally determined, long-run level of inventories. This indicator is not permanently affected by the news, but this is explained by the fact that it measures the change in inventories (scaled by output) as opposed to the level.

2.5.1 Inventories at the two-digit SIC level

After documenting that inventories respond much more in the durables sector than in the non-durables sector, I investigate in which two-digit industries inventories respond the most to news shocks, and explore whether these coincide with the industries whose productivities respond most to news shocks. In Figure 12, I present the responses of the inventories-to-sales ratio at the two-digit SIC level, to a unit aggregate news shock. The responses of both durable and nondurable sector industries are presented.

FIGURE 12: Response of Inventories-to-Sales Ratios to a unit Aggregate News Shock at the Level of 2-Digit SIC Industries



The percentage responses of the inventories-to-sales ratios of durable sector industries are much larger than those of nondurable sector industries. Results are robust when sectoral news shocks are used instead of aggregate news shocks. Again, durable goods industries are more responsive than the nondurable goods industries. The responses of durables industries are largest with respect to durable news, just as the responses of nondurables industries are greatest with respect to nondurable news. Responses of all industries, on average, are larger in the case of a unit manufacturing news shock than in that of a unit aggregate news shock. Additionally, the

percentage responses of durable sector inventories are higher, on average, in the case of a unit durable news shock than in the case of a unit manufacturing news shock. Nondurable goods inventories do not respond significantly to any of the news shock, with one exception: petroleum inventories respond significantly to nondurable news shock. On the other hand, the responses of several durable goods industries are statistically significant. Finally, the durable industries with biggest declines in inventories are the same as those with the largest responses of productivity to news. At first, this result might seem surprising. If the increased demand for goods, as a result of the wealth effect, were distributed evenly across industries, then one might expect the sectors with the biggest TFP responses to be more able to meet demand without running down inventories. But there are two important considerations that work against this argument. First, the different responses of TFP in the different sectors imply changes in relative prices. Industries with larger TFP responses will have falling relative prices and there will be substitution towards their products. Second, news about productivity leads to an increase in investment demand that, in the short run, should put additional pressure on inventories in the durables sector but not in the nondurables sector.

3 The Model

I use a two-sector, two-factor, real business cycle model as a theoretical framework to study sectoral business cycles. As in Baxter (1996), sector 1 produces a nondurable consumption good, and sector 2 produces a consumer durable good and the capital good used as an input in the production of both sectors. The main difference between the two sectors is that a good produced in sector 2 can be stocked. In the model, the reason that durable goods are held as stocked inventories, is that inventories are an argument of the production function of sector 2, following Christiano (1988) and Kydland and Prescott (1982). These authors argue that the stock of inventories, as the stock of fixed capital, provides a flow of services to a firm.

3.1 Households

The economy is populated by a large number of identical, infinitely-lived agents who derive utility from the consumption of the nondurable consumption good, the service flow from the durable

consumption good, and leisure. The agent's lifetime utility is

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(\left(C_t^* - hC_{t-1}^*\right) v\left(1 - N_t\right)\right)^{1-\sigma} - 1}{1-\sigma},$$

where β represents a subjective discount factor, h is the coefficient of habit persistence in consumption, σ is the inverse of the elasticity of intertemporal substitution defined in terms of $\left(C_t^* - hC_{t-1}^*\right) v\left(1 - N_t\right)$, and where N_t represents hours worked at time t. Two types of preferences are considered: preferences proposed by Greenwood, Hercowitz and Huffman (1988), which I refer to as GHH, and preferences proposed by King, Plosser and Rebelo (1988), which I refer to as KPR.[19] In the case of GHH preferences, utility function is separable in consumption and leisure, taking the following form:

$$U^{GHH} = E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(\left(C_t^* - hC_{t-1}^*\right) - \psi N_t^{\theta}\right)^{1-\sigma} - 1}{1-\sigma}.$$

In the case of KPR preferences, utility is given by

$$U^{KPR} = E_0 \sum_{t=0}^{\infty} \beta^t \frac{\left(\left(C_t^* - hC_{t-1}^*\right)\left(1 - \psi N_t^{\theta}\right)\right)^{1-\sigma} - 1}{1-\sigma}.$$

The composite consumption good (C_t^*) is given by the constant elasticity of substitution function:

$$C_t^* = \left[\chi_1 C_{1t}^{\mu} + \chi_2 C_{2t}^{\mu}\right]^{\frac{1}{\mu}},$$

where C_{1t} and C_{2t} represent period t consumption of the nondurable consumption good and consumption of the service flow from the durable consumption good, respectively, and parameters χ_1 and χ_2 determine the weight of these two goods in the composite consumption good. The parameter μ is equal to $(1 - 1/\varrho)$, where ϱ is the constant elasticity of substitution between C_{1t}

[19] Jaimovich and Rebelo (2009) show that these two types of preferences induce qualitatively different responses of the main macroeconomic variables, most importantly hours, to news about future TFP increase. The main characteristic of GHH preferences is that the optimal number of hours worked depends only on the contemporaneous real wage, and therefore news about a future TFP increase produces neither substitution effect, nor a wealth effect on hours. Consequently, hours do not decrease on impact as the result of news. This is not the case with KPR preferences where the optimal number of hours worked responds to changes in lifetime income as well as the current wage. Given good news about future changes in TFP, agents reduce today's supply of labor, because they perceive a higher level of lifetime income, and therefore want to enjoy more leisure.

and C_{2t}. If the elasticity of substitution is greater than 1 in absolute value, goods are substitutes, whereas, if the elasticity of substitution is less than 1 in absolute value, goods are complements. Finally, I assume that the service flow from the durable consumption good is proportional to the stock of the durable consumption good S_t:

$$C_{2t} = \gamma S_t, \ \gamma > 0.$$

3.2 Producers

Two final goods are produced in the economy: a perishable consumption good, produced in sector 1, and a capital good, produced in sector 2. A good produced in sector 2 can be used either as an investment good in both sectors or as a consumer durable. Production processes in both sectors require the use of labor and capital. In addition, the production function of sector 2 has inventories as an argument.[20] In both sectors, I model capital services as the product of the capital stock and the level of capital utilization. The cost of increasing utilization is additional depreciation of the capital stock. This feature is introduced through the depreciation rate that depends on the rate of capacity utilization, and takes the form $\delta^j(u_{jt}) = \delta_0^j + \delta_1^j(u_{jt} - 1) + \frac{\delta_2^j}{2}(u_{jt} - 1)^2$, where $\delta_0^j, \delta_1^j, \delta_2^j > 0$ and $j = 1, 2$ corresponding to the two sectors. Parameter δ_0^j represents the steady state depreciation rate of the $j - th$ sector, since δ_1^j is calibrated such that, in the steady state, the utilization rate in both sectors is equal to one. Sector 1's production technology is a standard Cobb-Douglas function:

$$Y_{1t} = F_{1t}(K_{1t}, N_{1t}) = A_{1t}(N_{1t})^{1-\alpha_1}(u_{1t}K_{1t})^{\alpha_1},$$

where N_{1t} and K_{1t} represent labor and capital input at time t, u_{1t} represents the rate of capacity utilization in sector 1, A_{1t} represents the technology process in sector 1, and $0 < 1 - \alpha_1 < 1$ is labor's share in sector 1. Sector 2's production function is assumed to have the form:

[20] As Christiano (1988) argues: that "all other things being equal, larger inventory stocks probably do augment society's ability to produce goods. For example, spatial separation of the stages of production and distribution, together with economies of scales in transportation, implies that labor inputs can be conserved by transporting goods in bulk and holding inventories." Also, Kydland and Prescott (1982) suggest that "with larger inventories, stores can economize on labor resources allocated to restocking." Therefore, adding inventories into the production function does not seem unreasonable.

$$Y_{2t} = F_{2t}\left(K_{2t}, N_{2t}, I_t\right) = A_{2t}\left(N_{2t}\right)^{1-\alpha_2}\left[(1-\rho)\left(u_{2t}K_{2t}\right)^{-\nu} + \rho I_t^{-\nu}\right]^{-\frac{\alpha_2}{\nu}},$$

where N_{2t} and K_{2t} represent labor and capital used in the production of sector 2 output at time t, u_{2t} is the capacity utilization rate in sector 2, I_t denotes stock of inventories at time t, and $0 < 1-\alpha_2 < 1$ is labor's share in sector 2. The parameter ρ controls the role of inventories in the production function of sector 2. If $\rho = 0$ we are back to the standard Cobb-Douglas production function case. Finally, the elasticity of substitution between capital and inventories is $\frac{1}{1+\nu}$; this elasticity is arguably less than one which is why ν is required to be positive.[21]

Households are assumed to own the physical capital used in both sectors. Labor is assumed to be mobile across sectors; at the same time, I assume that the adjustment cost is incurred when the level of investment changes over time. In addition, changing stocks of consumer durables is also subject to an adjustment cost.[22] The capital stocks in both sectors, K_{1t} and K_{2t}, and the stock of consumer durables S_t evolve over time following laws of motion:

$$\begin{aligned}
K_{1,t+1} &= \left(1-\delta^1\left(u_{1t}\right)\right)K_{1t} + X_{1t}\left(1-\phi_1\left(\frac{X_{1t}}{X_{1t-1}}\right)\right), \\
K_{2,t+1} &= \left(1-\delta^2\left(u_{2t}\right)\right)K_{2t} + X_{2t}\left(1-\phi_2\left(\frac{X_{2t}}{X_{2t-1}}\right)\right), \\
S_{t+1} &= \left(1-\delta_S\right)S_t + D_t\left(1-\phi_3\left(\frac{D_t}{D_{t-1}}\right)\right),
\end{aligned}$$

where X_{1t} and X_{2t} denote gross investment in sectors 1 and 2 at time t, while D_t denotes purchases of new consumer durables. Function $\phi_j(\cdot)$ represents the adjustment cost function, which is chosen so that it satisfies the condition of no adjustment costs in the steady state; i.e. $\phi_j(1) = \phi_j'(1) = 0$, $(j = 1, 2, 3)$. Also, $\phi_j'(\cdot), \phi_j''(\cdot) > 0$. This function does not necessarily need to be identical across the sectors, and, therefore, can take different forms.[23]

[21] See Kydland and Prescott (1982).

[22] I follow Bernanke (1985), Startz (1989), and Baxter (1996) in assuming that the stock of consumer durables is subject to the adjustment cost, although my specification is different from theirs.

[23] See onliine Appendix C for the exact forms used.

3.3 Resource Constraints

Since an individual's allocation of time is normalized to 1, the hours in both sectors cannot exceed the total available hours N_t that are equal to $1 - L_t$, where L_t denotes time allocated to leisure at time t. Therefore, a unit of time is allocated as follows:

$$N_{1t} + N_{2t} + L_t \leq 1.$$

The resource constraint for the sector producing the pure consumption good is

$$C_{1t} \leq Y_{1t}.$$

For the sector producing the capital good the resource constraint is

$$D_t + X_{1t} + X_{2t} + \Delta I_t \leq Y_{2t}.$$

3.4 Introducing News Shocks Into the Model

To analyze the theoretical effects of news, I introduce news shocks into the model by making reference to my estimates in Section 2. In particular, I assume that the news shock corresponds to an aggregate news shock as identified by my estimation procedure. I assume that the response of TFP in model sector 1 corresponds to the response of TFP in the nondurables sector to an aggregate news shock in the data. I assume that the response of TFP in model sector 2 corresponds to the response of TFP in the durables sector to an aggregate news shock in the data. I first estimate the regression coefficients $\psi_j' s$ in (1) ; in this case, X_t represents the productivity of sector k $(k = 1, 2)$. The sequence $\sum_{i=0}^{n} \psi_i^k$ represents a point estimate of the impulse response function of sector $k's$ TFP to a news shock (aggregate or sectoral), after n periods. In the regressions I set $J = 8$ so that the implied impulse response functions of the levels of TFP in the two sectors are constant for $n > J = 8$.

These estimated productivity responses are then introduced into the model. Figure 1 shows the responses of sectoral TFPs to an aggregate news shock; the responses are smoother than productivity processes commonly used in the theoretical news literature, where news about future

technology developments is often introduced as follows. The economy is assumed to be in the steady state in period 0, when a signal arrives suggesting that in s periods a positive technology shock will occur.[24] In this case, the productivity process remains at its steady-state level until period s, when the productivity increase is realized. TFP then rises by 1 percent and follows its exogenous law of motion afterwards.[25]

In my analysis, the productivity process is at its steady state level in period 0, after which it starts to increase, with TFP increasing by 1 percent in the long-run. In both approaches, in period 0 households learn the expected future path of the technology process. The key difference is that in my analysis the productivity increase begins in period 1 and occurs smoothly over time, whereas in the typical theoretical analysis it is delayed (s periods) and abrupt.

4 Calibration and the Estimation

Before obtaining quantitative predictions from the model, I assign numerical values to its parameters. I calibrate some of the structural parameters of the model in a standard fashion; the rest of the parameters are estimated. Table 1 summarizes values of the calibrated parameters.

The time unit is defined to be a quarter. I assign a value of 0.9902 to the subjective discount factor β, which is consistent with an annual real interest rate of 4 percent. I calibrate utility parameters, χ_1 and χ_2, such that the steady-state shares of nondurable goods and durable goods in composite consumption equal the average over the sample period ($C_1/C^* = 0.723$ and $C_2/C^* = 1 - 0.723$). The preference parameter ψ is chosen so that the agents allocate one-third of their time-endowment to work. Following Bernanke (1985) and Baxter (1996), annual capital depreciation rates in the two sectors are 7.1 percent, which leads to the quarterly depreciation rates, δ_0^1 and δ_0^2, being 1.73 percent. The annual depreciation rate of the stock of durables is 15.6 percent (following Baxter(1996)). I calibrate the parameters δ_1^1 and δ_1^2 to ensure that steady-state capital utilizations in both sectors, u_1 and u_2, equals unity. The labor share coefficients, $1-\alpha_1$ and $1-\alpha_2$, are chosen to match the mean of labor's share over the sample period. The parameter ρ, which determines the

[24] Christiano et al. (2010) and Jaimovich and Rebelo (2009), among others, allow for the possibility of this signal to be false or noisy. That is, after s periods the expected increase in technology does not happen, or is smaller than previously expected.

[25] See, for example Christiano et al. (2010), Beaudry and Portier (2004), Beaudry and Portier (2005), Jaimovich and Rebelo (2009), and Schmitt-Grohé and Uribe (2012).

role of inventories in the production function of sector 2, is chosen to match the share of inventories in output. Finally, I choose the parameter ν so that the elasticity of substitution between capital services and inventories matches the value used by Christiano (1988).

TABLE 1: CALIBRATED PARAMETERS

Parameter	Value	Description
β	$1.04^{-1/4}$	Subjective discount factor
γ	0.7	Service flow from durables
$1-\alpha_1$	0.74	Labor share in the nondurable goods sector
$1-\alpha_2$	0.60	Labor share in the durable goods sector
δ_0^1	0.0173	Steady-state depreciation rate in the nondurable goods sector
δ_0^2	0.0173	Steady-state depreciation rate in the durable goods sector
δ_0^S	0.0358	Depreciation rate of the stock of durables
ρ	0.0003	Determines the role of inventories in the production function
χ_1	1.185	Composite consumption good parameter with sector 1
χ_2	0.053	Composite consumption good parameter with sector 2
δ_1^1	0.0303	Nondurable goods sector depreciation rate parameter
δ_1^2	0.0247	Durable goods sector depreciation rate parameter
ν	3.671	Elasticity of substitution between inventories and capital

I use impulse response function matching to estimate the remaining parameters: σ (the inverse of the elasticity of intertemporal substitution), h (the habit persistence parameter), ϱ (the elasticity of substitution between C_{1t} and C_{2t}), the three coefficients of the investment adjustment cost functions (κ_1, κ_2, and κ_S), and the two coefficients of the rate of capacity utilization functions (δ_2^1 and δ_2^2). Let ζ denote parameters that I estimate, $\Phi(\zeta)$ denote the model impulse responses that are functions of the structural parameters ζ, and $\hat{\Phi}$ denote the corresponding estimated empirical impulse responses. The estimator for ζ is the solution to the following minimization problem:

$$\hat{\zeta} = \arg\min_{\zeta} \left(\hat{\Phi} - \Phi(\zeta)\right)' W^{-1} \left(\hat{\Phi} - \Phi(\zeta)\right),$$

where W is the diagonal matrix with the sample variances of the $\hat{\Phi}'s$ along the diagonal.[26] I match

[26] I follow Altig et al. (2011) who argue that with this choice of the weighting matrix W, $\hat{\zeta}$ is the value of ζ which

the following impulse response functions: composite consumption, aggregate hours, output, and investment in the durable goods sector. The point estimates of the parameters are given in Table 2. In the following section, I discuss the predictions of the model.

TABLE 2: ESTIMATED PARAMETERS

Parameter	Estimated Value	Description
κ_1	9.48	Sector 1 investment adjustment cost function parameter
κ_2	5.31	Sector 2 investment adjustment cost function parameter
κ_S	8.73	Stock of durables adjustment cost function parameter
σ	1.64	Intertemporal elasticity of substitution
h	0.78	Habit persistence in consumption parameter
ϱ	0.91	Elasticity of substitution
δ_2^1	0.17	Parameter of the depreciation rate in the nondurable sector
δ_2^2	0.14	Parameter of the depreciation rate in the durable sector

5 Predictions of the Estimated Model

One of the main challenges the news literature has faced is building a model that can generate Pigou cycles, a comovement between consumption, hours, output, and investment, in response to news about higher future TFP. Beaudry and Portier (2004) were the first authors to recognize that the standard real business cycle model, with KPR preferences, fails to meet this challenge. In particular, good news increases consumption and leisure on impact through the wealth effect. Since leisure increases, hours worked and output decrease. The only way for consumption and hours (or output) to move in opposite directions is through a decrease of investment. To solve this problem, Beaudry and Portier propose a three-sector model, in which consumption is given as a composite of nondurable and durable goods. Both of these goods are produced with labor and a fixed production factor. The model is capable of generating Pigou cycles. However, in a more recent paper, Jaimovich and Rebelo (2009) formulate a one-sector model that is able to generate Pigou cycles. This is a standard real business cycle model, augmented with the investment adjustment costs and variable capital utilization. Furthermore, the model features a new type of

ensures that theoretical IRFs lie as much as possible inside the confidence bands of estimated IRFs.

preferences that do not induce a wealth effect on leisure/labor when news is received. Therefore, hours does not decrease on impact and the desired comovement between output, consumption and investment can be obtained. Several other authors have been able to obtain the desired comovement between these variables using a one-sector model (see Den Haan and Kaltenbrunner (2009), Christiano et al. (2010), Schmitt-Grohé and Uribe (2012). In most of these papers news is introduced as described above: in period t agents learn that there will be a one-percent permanent increase in TFP beginning in period $t+j$, where $0 < j \leq n$. Therefore, the productivity process features a kink in period $t+j$.

In my empirical analysis I make a distinction between the durable and nondurable goods sectors. One obvious difference between the producers in these two sectors is the possibility of the durable sector producers holding stocks of inventories. This channel can help my model replicate comovement between consumption and investment, since holding stocks of inventories is one way that the durable goods sector producers can meet higher consumer demand without necessarily having to decrease investment.

Finally, there are two main distinctions between my approach and the approaches taken in the aforementioned papers. First, as indicated before, I introduce news shocks by feeding the empirical responses of TFPs in the two sectors into the model. Thus, the productivity process in this case does not feature a kink, but is rather a much smoother process. Second, the focus of my analysis is not only on obtaining the right qualitative comovement between the main macroeconomic variables (hours, consumption, output and investment), but also on obtaining quantitatively good fit of the model impulse response functions to those in the data, while considering additional implications of the model for the behavior of inventories, and behavior of sectoral level data. In order to make progress on these quantitative dimensions, it was necessary to use a richer model than the ones found in the literature.

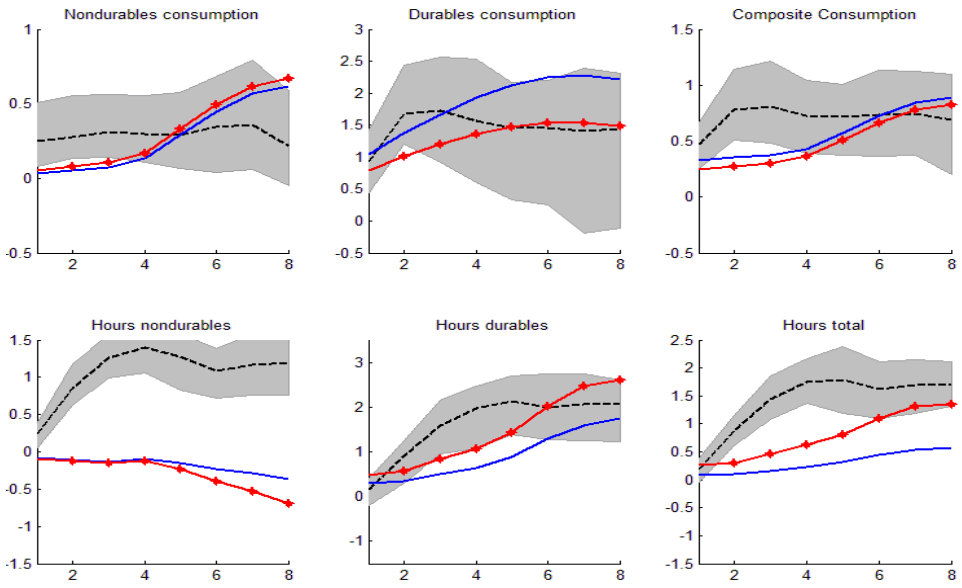
5.1 Benchmark Model

Figures 13 and 14 display the theoretical and empirical responses of five macroeconomic time series (consumption, hours, investment, output and inventories-to-sales ratio) to a unit aggregate news shock. Theoretical responses are computed using the benchmark model described in Section 3. The shaded areas represent 90% confidence intervals of the empirical responses, and the dashed

lines represent point estimates of the empirical impulse responses. The solid lines represent theoretical responses under GHH preferences, and the starred lines represent responses under KPR preferences. There is no significant difference between the model responses when preferences take the KPR or GHH form. This result is not surprising, considering the nature of the technology process. In particular, the technology process does not feature the kink as it does in the most of the rest of the theoretical literature on news shocks; instead, it starts increasing slowly from period 1. This representation of technology is more consistent with the notion that the technology process diffuses slowly over time, and, therefore, the main distinction between KPR and GHH preferences described above is almost eliminated.

FIGURE 13: Model and Empirical Responses to a unit Aggregate News Shock

Consumption and Hours Responses



Note: The shaded areas represent 90% confidence intervals of the empirical responses, and the dashed lines represent point estimates of the empirical impulse responses. The solid lines represent theoretical responses under GHH preferences, and the starred lines represent responses under KPR preferences.

Comovement between total hours, consumption, output, and investment is evident. Aggregate hours worked increase; at the same time, the benchmark model is not able to match the response of hours worked in the nondurable sector. In particular, the benchmark model wrongly predicts

a decrease of nondurable hours. My intuition is as follows: hours can move freely between the sectors, and, therefore, hours worked tend to increase in the sector in which the productivity is higher, which is the durable sector. In order to solve this problem, in one variant of the model I introduce adjustment costs in labor in the nondurable sector. Adding this feature improves the model fit in this dimension; the model can generate an increase of hours in the nondurable goods sector.[27] Moreover, the model matches the response of hours in the durable goods sector quite well. Since this increase is larger than the decrease of hours in the nondurables sector, the benchmark model is still able to obtain increase of the total hours. However, the model needs a labor adjustment cost in order to be able to generate more realistic responses of the nondurable sector hours.

The model does a good job in replicating the consumption responses. It can generate positive initial responses of consumption in the durable goods sector and in composite consumption, whereas the initial response of nondurable consumption is below the confidence bands for several periods. The response of durable goods consumption lies inside the confidence bands in all periods. The estimate of the parameter of the elasticity of substitution suggests some degree of complementarity between durable and nondurable goods in consumption, which helps obtaining comovement between consumptions in the two sectors.

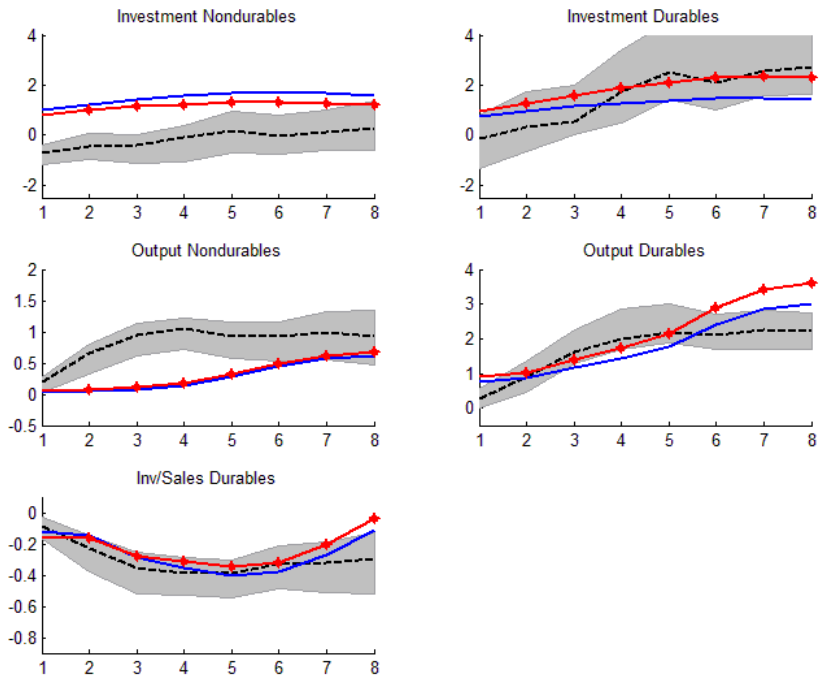
The model cannot generate a negative initial response of investment in the nondurable goods sector, which is observed in the data. In order to drive down investment in the nondurable sector, a high value of the coefficient in the investment adjustment cost function is needed. This is also true in the case of durable goods sector investment; the estimated investment adjustment cost must be quite large. Had these adjustment costs not been introduced, the responses would be much larger and occur more quickly, because changing the level of investment would not be costly for producers. The response of output in the durable goods sector is matched very well; the model response of durables sector output lies within the 90% confidence bands of the empirical response almost all the time, whereas nondurables sector output is inside the confidence bands only in the longer run. That is, the hump- shaped response of output in the nondurable goods sector cannot be obtained, which is primarily the result of the qualitative response of output following the shape of the productivity process in the nondurable sector. Rather than being hump-shaped,

[27] Also Jaimovich and Rebelo (2009) introduce this cost in order to obtain better response of the total hours.

the response of nondurable goods sector output is very small over the first four quarters, after which it starts slowly to increase, reaching the confidence band of the empirical response after six quarters.

Finally, the model is able to replicate the response of the inventories-to-sales ratio, which is not one of the responses that is being matched in the estimation. That my model works well in this dimension is very encouraging, particularly since it is able to replicate the response of the variable which, as mentioned above, is relevant for understanding differing extent to which news shocks are propagated in durable and nondurable goods sectors.

FIGURE 14: Model and Empirical Responses to a unit Aggregate News Shock



Note: The shaded areas represent 90% confidence intervals of the empirical responses, and the dashed lines represents point estimates of the empirical impulse responses. The solid lines represent theoretical responses under GHH preferences, and the starred lines represent responses under KPR preferences.

I conclude by arguing that by examining a model with distinct durable and nondurable goods sectors, with an explicit role for inventories, and by modeling news shocks using an approach that departs from most of the theoretical literature, I am able to replicate some of the key characteristics of the empirical responses of the economy to news about future productivity. The benchmark model performs relatively poorly in explaining the behavior of the nondurable goods sector hours,

but is quite successful in explaining the behavior of the durable goods sector and some aggregate variables.

6 Conclusions

In this paper, I present evidence that the responses to news shocks of the fundamentals in the durable goods sector are different from the responses of these fundamentals in the nondurable goods sector. In particular, the responses of durable goods sector fundamentals are significantly greater than the responses of nondurable goods sector fundamentals. After a 1 percent aggregate news shock, durable sector productivity rises by approximately 3 percent after ten quarters, whereas the response of productivity in the nondurable goods sector is approximately 0.5 percent. The percentage responses of other durable goods sector fundamentals are also significantly higher than those of the same fundamentals in the nondurable goods sector. This empirical evidence suggests that aggregate news shocks are propagated through the durable goods sector of the economy. In order to explain these different behaviors of the durable and nondurable goods sectors, I introduce inventories into the analysis. By looking at the behavior of this variable, which has been largely neglected in the news literature, I am able to conclude that inventories play an important role in how aggregate news shocks are propagated through the durable goods sector.

As a theoretical framework, I use a two-sector, two-factor, real business cycle model. I also introduce inventories into the production function of durable goods producers. My model is consistent with the empirical evidence on how the economy responds to news shocks. Specifically, the model is successful in mimicking the empirical responses to news shocks at the sectoral level. First, the model reproduces the comovement among hours, consumption, output and investment in both sectors. Second, the model is able to reproduce the stronger overall response of the durable goods sector to news shocks. Finally, the model is able to perfectly match inventories responses.

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