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The Response of Capital Goods Shipments to Demand over the Business Cycle

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Abstract

This paper studies the behavior of producers of capital goods, examining how they set shipments in response to fluctuations in new orders. The paper establishes a stylized fact: the response of shipments to orders is more pronounced when the level of new orders is low relative to the level of shipments, usually after orders plunge in recessions. This cyclical change in firm behavior is quantitatively important, accounting for a large portion of the steep decline in equipment investment in the 2001 and 2007-9 recessions. We examine economic interpretations of this stylized fact using a model where firms smooth production with a target delivery lag for new orders. Heightened persistence in orders growth may explain part of the greater responsiveness of shipments to orders, as may increases in firms' target buffer stocks of unfilled orders relative to shipments.

(JEL: E22, E23, E32)

Keywords: Shipments, Orders, Business Investment, Business Cycles, Threshold Cointegration, Markov Switching Models

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1 Introduction

Equipment investment is an important part of the US business cycle, accounting for about a quarter of the variance of annual real GDP growth since 1985.[1] The data produced by the US Census Bureau on shipments of non-defense capital goods are the primary source data used by the US Bureau of Economic Analysis (BEA) to produce estimates of equipment investment, and the Census Bureau also produces data on net new orders and backlogs of unfilled orders for most of these capital goods industries. Since these industries generally take orders before producing and shipping the capital goods, the orders data are followed closely as an indicator of where shipments, equipment investment, and the business cycle are headed.

Most papers in the investment literature study the behavior of firms who employ capital equipment to produce goods for final consumption. Relatively few papers study the behavior of the firms who provide the capital equipment to those firms making consumption goods, as we do here. For these capital-goods-supplying firms, demand is other firms' demand for capital, as reflected in the orders data. The data on capital goods orders and shipments afford us the opportunity to study how these firms respond to fluctuations in demand, and this paper documents and studies some interesting changes in firm response patterns over the business cycle. Using different types of variation and different econometric specifications, including threshold cointegration and Markov switching models, we show that shipments of capital goods producers exhibit stronger responses to fluctuations in orders when the level of new orders is low relative to the level of shipments, typically in and around recessions. Furthermore, we demonstrate that the change in the response of shipments to orders accounts for much of the steep decline in shipments (and thus equipment investment) seen in the last two recessions (i.e. the 2001 and 2007-9 recessions).

We interpret these empirical results through the lens of a production smoothing model with a target delivery lag for new orders, expressed as a ratio of unfilled orders to shipments. Backlogs of unfilled orders are used by firms as a buffer between demand and production, in much the same way as finished goods inventory stocks are used to absorb demand shocks, so this model resembles closely the theoretical machinery that has been developed over the years to study inventories.[2] Since order backlogs are usually associated with production-to-order industries, which encompass most of the non-defense capital goods we analyze, while finished goods inventories are more prominent in production-to-stock industries, we assume that

[1]The contribution of equipment investment to the variance of GDP growth is measured as the covariance of its contribution to GDP growth with GDP growth itself, a method that ensures the variance contributions of the components of GDP sum to one.

[2]Blinder and Maccini (1991) and Ramey and West (1999) provide surveys of existing models on inventory dynamics.

firms do not hold finished goods inventories (Abramowitz 1950, Besley 1969).[3]

Similar to Blanchard and Fischer (1989), the production smoothing model predicts greater responsiveness of shipments to orders when the effects of shocks to orders persist longer. Using threshold autoregressions and Markov switching specifications, we show that the orders growth process exhibits significant time-varying persistence. For limited periods of time (generally a few quarters or less), the short run dynamics of orders growth are governed by extreme persistence, such that the best estimate of orders growth next period is close to current orders growth.[4] And, in line with the implications of the theory, these periods of heightened orders growth persistence tend to coincide with the periods of increased responsiveness of shipments to orders.

While the changing persistence of the orders process provides a plausible explanation for some of the time variation in the responsiveness of shipments to orders that we observe, it probably does not explain all of it. The model shows that the persistence of the orders process should affect only a subset of the coefficients in our empirical specifications, not the case in a number of our specifications. We consider other explanations for these changes in the responsiveness of shipments to orders, including cyclical changes in other parameters of the production smoothing model. Interestingly, the ratio of unfilled orders to shipments tends to shoot above its trend in recessions and then fall back afterwards, suggesting cyclical changes in the target delivery lag. Perhaps firms desire larger buffer stocks of unfilled orders in bad economic times, amplifying downturns. We also discuss briefly whether features of other models, such as (S, s) models may help explain these empirical results.

Some of the literature related to our paper is the following. As in Kahn (2010), we analyze how the behavior of firms in production-to-order industries helps explain certain features of the business cycle. Our finding that the sensitivity of shipments to orders is higher when shocks to orders are more persistent is similar to the result in Tevlin and Whelan (2003), where more persistent changes in fundamentals lead to higher investment elasticities. The business cycle asymmetries in the dynamics of orders and shipments that we uncover are also related to the literature on asymmetric business cycles, such as French and Sichel (1993). And the increased persistence in recessionary episodes may be related to the effect of uncertainty shocks on investment demand, as in Bloom (2009). However, our paper suggests that these shocks

[3]Similar to West (1989), we could have implemented a model with both inventory and backlog stocks by treating unfilled orders as stocks of negative inventories, but the evidence in Besley (1969), Reagan and Sheehan (1985), and Haltiwanger and Maccini (1989) argues against such a specification. Kahn (2010) analyzes a model without a production smoothing motive where firms produce to order but hold inventories as work in process.

[4]Note that this is not a unit root in growth rates, because the extreme persistence is itself temporary, usually lasting only a few quarters. Our specifications are geared towards capturing the short-run dynamics of orders rather than characterizing their long-run properties, a distinction made in Cochrane (1988).

may be significantly amplified by the endogenous response of producers of capital goods.

2 Data

We use monthly data on orders and shipments from the Census Manufacturers' Shipments, Inventories, and Orders (M3) survey. This survey includes data on monthly flows of shipments and new orders and end-of-month stocks of inventories and unfilled orders for several manufacturing industry groupings. The M3 survey asks respondents directly about shipments, inventories, and unfilled orders, and new orders are backed out as shipments plus the change in unfilled orders.

Although not mandatory, the M3 survey is regularly benchmarked to the more comprehensive Annual Survey of Manufacturers (ASM) and Quinquennial Economic Census (EC). However, neither the ASM nor the EC contain any information on unfilled orders, which raises some questions about the quality of the unfilled and new orders data in the M3 survey, especially at low frequencies. To address this problem, the Census conducted comprehensive unfilled orders surveys in 1976, 1986, 2000, and 2008. Starting in 2009, a new annual unfilled orders survey was created.

To analyze the response of shipments to demand over the business cycle, we focus on industries producing non-defense capital goods excluding aircraft, industries that mostly produce to order and accumulate non-trivial backlogs of unfilled orders recorded by the Census Bureau.[5] We exclude defense-related industries because shipments in these industries are not very sensitive to the business cycle.[6] Finally, we exclude the aircraft industry because it is characterized by extremely long lags between new orders and final shipments.[7] Note that our selected aggregate includes most of the M3 equipment categories that the BEA uses to estimate private equipment investment in the quarterly National Income and Product Accounts.

The M3 data is available on a NAICS industry classification from January 1992 to present. However, we use the historical data on a SIC industry classification to extend the aggregate data on non-defense capital goods excluding aircraft back to January 1968. In the empirical analysis, we use both the shorter, NAICS-based time-series and the longer, SIC-extended time-series. These data are nominal, so we construct real data as a chain-weighted aggregate of the relevant M3 categories. As

[5] Note that although other industries with unfilled orders can be found in the broader durable goods aggregate, unfilled orders to shipments ratios are much higher in capital goods than in other durable goods industries. For 2010 as a whole, capital goods industries accounted for about three-fourths of total unfilled orders in manufacturing, and had an unfilled orders to shipments ratio about five times higher than in other durable goods industries.

[6] For 2010 as a whole, defense-related industries accounted for a bit less than 15 percent of shipments and about one-quarter of total unfilled orders in capital goods industries.

[7] For 2010 as a whole, after trending up since the early 2000s, the aircraft industry reached an unfilled orders to shipments ratio nearly ten times higher than in other capital goods industries.

described in appendix A, we use the US Bureau of Labor Statistics (BLS) data on Producer Price Indexes (PPI) to construct price deflators at the M3 category level and then chain-aggregate the M3 categories included in non-defense capital goods excluding aircraft. Figure 1 plots the logarithms of real orders and shipments (the thin and thick lines, respectively), using the SIC-extended time-series, from 1968 to 2011. The chart shows that both series are highly pro-cyclical and that orders are generally more volatile than shipments. Moreover, during expansions orders tend to run above shipments, while in recessions orders tend to plunge below shipments.[8]

3 Empirical Results

In this section we report a wide array of results showing that shipments respond more strongly to orders at certain times, most typically in or around recessions. We emphasize that we are not particularly wedded to any of these econometric specifications: for example, we do not necessarily believe we have identified a precise cutoff for the level of orders relative to shipments where all of the increased sensitivity of orders to shipments is activated. Rather, the different specifications are simply different ways of illustrating the same stylized fact, broadly speaking.

3.1 Threshold Cointegration Evidence

3.1.1 Monthly Shipments Growth Specifications

We begin our econometric examination of the monthly shipments data with regressions of the log difference of real shipments, Δs_t, on six of its lags, Δs_{t-k}, six lags of the log difference of real orders, Δo_{t-k}, and an error correction term equal to the first lag of log real orders minus real shipments, $o_{t-1} - s_{t-1}$, where x_t is defined as $100 \times \log(X_t)$. The lag length of six is the optimal lag length according to the Akaike information criterion. Columns one and three of Table 1 show estimation results using the long sample extending from January 1969 to June 2011 and the shorter January 1993 to June 2011 sample using NAICS-based data only.[9] Shipments are

[8] In constructing the chain-aggregated series shown in Figure 1, we use the same price deflator for orders and shipments for each M3 category. However, in production-to-order industries, there is usually a lag between when an order is received and when such order is produced and shipped. We constructed new orders price deflators that are adjusted for this production and shipping lag (see appendix A for a description of the adjustment method), producing a real new orders series that was similar to the standard new orders series shown in Figure 1, except from the early 1970s to the early 1980s when the gap between orders and shipments tends to be smaller in expansions and new orders tend to fall more below shipments in recessions. Regression results using this adjusted time series were similar to those reported.

[9] Using augmented Dickey-Fuller tests, we find in both samples that log orders and log shipments are non-stationary I(1) variables and that the error correction term defined as log orders minus log shipments is stationary, indicating an error-correction cointegration relationship.

quite noisy, so shipments growth exhibits substantial negative serial correlation at the first and second lags. Many of the coefficients on lagged orders growth are significant, so shipments do respond to lagged orders, but the error correction terms are not statistically significant.[10]

This result is somewhat puzzling, because Figure 1 shows that in periods such as 1982, 2001, and from late 2008 to early 2009, when orders plunged, shipments followed orders down, suggesting error correction of shipments towards orders. As a first pass at examining potential non-linearities in the response of shipments to orders, we add to the regression the error correction term multiplied by a dummy variable equal to one when orders fall below shipments. Columns two and four of Table 1 show results: the error correction coefficient is negative (but small and insignificant) when orders are above shipments, but shifts to positive when orders are below shipments. The increase is sizable using the 1993 to 2011 sample, with log shipments correcting to close about a third of the gap between log orders and shipments each month when orders are below shipments.

With a known break point, these standard errors would be valid, but since the break point is unknown, the OLS standard errors here should be interpreted with some caution: see Balke and Fombe (1997) and Hansen and Seo (2002), who discuss these threshold cointegration models, as well as the earlier literature on threshold autoregression starting with Tong (1983, 1990). Table 1a reports results from a fully general threshold cointegration model allowing all parameters to break when the error correction term falls below a certain value κ (i.e. we include interactions of all variables with an indicator variable $\mathbf{1}_{o_{t-1}-s_{t-1}<\kappa}$). The value κ is estimated using the search procedure described in Hansen and Seo (2002).

The optimized value of κ is 1.73 (in percentage points) using the longer sample, and -0.13 using the shorter sample, the latter activating the dummy when orders are more than slightly below shipments. Both specifications show increased responsiveness of shipments to orders when the dummy is activated, with the coefficients on the interactions with the lagged orders growth terms and the error correction all positive.

Since the standard errors here are somewhat suspect, we use the heteroskedasticity-robust sup-LM statistic of Hansen and Seo (2002) to test the significance of the non-linearities, computing asymptotic p-values for this statistic with the fixed regressor bootstrap described in that paper.[11] The p-value of the test statistic is 0.48 using the 1969-2011 sample, but only 0.04 using the 1993-2011 sample.

[10] When regressing the log difference of orders (Δo_t) on the same set of explanatory variables, the error correction term is statistically significant, with a coefficient implying log orders corrects to close about a quarter of the gap between log orders and shipments each month.

[11] In computing the supremum, we restrict the range of cutoff values considered for $(o_{t-1} - s_{t-1})$ to exclude the highest and lowest 15 percent of its observations.

3.1.2 Quarterly Shipments Growth Specifications

Before examining these non-linearities further, we convert the data from monthly to quarterly to wipe out much of the high-frequency noise in the data leading to the negative serial correlation in shipments growth in Tables 1 and 1a. Similar to those monthly specifications, we explain the log difference of quarterly shipments with two of its lags, two lags of the log difference of quarterly orders, the quarterly error correction term, and some interactions of these terms with a dummy variable. The first row of each panel of Table 2 reports results without interactions, and similar to Table 1, we find some responsiveness of shipments growth to lagged orders growth and no evidence of error correction of shipments towards orders, but now we see no significant negative serial correlation in shipments growth.

We experimented with specifications that allow for interactions with all six of the parameters in this quarterly specification, but the coefficients on the dummy-interacted constant and lagged shipments terms were not particular large, and the presence of these additional terms did not affect the coefficients on the dummy-interacted orders terms very much. In light of this, we settled on the more parsimonious specification reported in Table 2, which allows the coefficients on the orders variables (the error correction term and the lagged orders growth terms) to shift when the error correction term falls below the critical threshold κ. The optimal value of κ (again estimated as in Hansen and Seo (2002)) activates the dummy when orders fall below a threshold of a little less than one percent above shipments, with the coefficient on the first lag of orders growth increasing considerably when orders fall below this threshold. Testing the joint significance of the non-linearities using the sup-LM statistic, we find a p-value of 0.11 using the 1969-2011 sample, and 0.06 using the 1993-2011 sample.

The coefficient changes in Table 2 show that shipments react more quickly to changes in orders when $o_{t-1} - s_{t-1} < \kappa$. After one quarter, shipments decline 0.6 percent for every 1 percent decline in orders, compared to a decline of less than 0.1 percent when $o_{t-1} - s_{t-1} > \kappa$. To show how this increased responsiveness below the threshold allows the model to fit cyclical declines in shipments, Figure 2 plots NAICS-based quarterly shipments growth, the heavy solid line, from 1993Q1 to 2011Q2, along with two sets of predicted values from the short-sample specification in Table 2. The first set of predicted values, the lighter solid line, uses the full specification with interactions, while the second set of predicted values, the dashed line, sets the coefficients on the dummy interactions to zero, imposing the above-cutoff coefficients on the entire sample. In the periods where the error correction is above the cutoff, the two sets of predicted values coincide, and periods where it is below the cutoff are shaded. The error correction term is below the cutoff on and off through the mid-to-late 1990s, but stays below the cutoff for more than several consecutive quarters only in recessions and their aftermath. In these periods, the predicted values using the above-cutoff parameters do not come close to capturing the depth of the decline in shipments. Therefore, the increased responsiveness of shipments to orders below the cutoff is critical to explaining the severity of the shipments declines in and around recessions.[12]

3.1.3 Quarterly Orders Growth Specifications

Table 3 examines the properties of the orders growth process. The first row of each panel reports results from a standard autoregression, while the second shows results from a threshold autoregression.[13] In addition to allowing the coefficients on the lagged orders terms to change, this specification also allows the variance of the shocks to the orders process to change when orders are below the cutoff; the change in the variance is the ${\sigma^2}^{\kappa}$ parameter. In the longer sample, the cutoff κ is quite a bit higher than the cutoff in Table 2, and the variance declines when orders fall below this threshold. In the shorter sample, the cutoff is exactly the same as the cutoff in Table 2, and the shock variance increases when orders fall below this threshold.

In both samples, we see virtually no persistence in orders growth when orders are above the cutoff, with $\gamma_{o1} + \gamma_{o2} \approx 0$. However, when orders are below the cutoff, orders growth is quite persistent, with $\gamma_{o1} + \gamma_{o2}$ about 0.6 in the long sample and 0.8 in the short sample. While this heightened persistence is itself temporary, the degree of persistence is a noteworthy for a growth rate process. When orders are below the cutoff, as they typically were in recent recessions, a rapid orders decline in the current quarter generally signals a continued rapid decline next quarter.[14]

The evidence for non-linearity in the orders growth autoregressions in Table 3 is strong, with the p-value for the sup-LM statistic equal to 0.04 using the long sample and 0.001 using the short sample. The more than doubling of the regression $\overline{R}^2$ when we allow for the non-linearity, from 0.17 to 0.40, is particularly striking in the short sample. We conclude that the short-run dynamics of orders growth exhibit significantly more persistence in periods where orders fall below the critical threshold κ.

3.2 Markov Switching Model Evidence

3.2.1 Shipments Growth Specifications

The specifications employed so far assume that the dummy variable is activated when the error correction term falls below a certain critical value, but the next set of results, reported in Table 4, relaxes that assumption. The activation of the dummy variable can be thought of as a regime switch, and Table 4 reports results

[12]We obtained a similar result, slightly less stark, using results from the 1969 to 2011 sample.

[13]Similar results were obtained when we included lags of shipments growth and the error correction term in the regression as well as lags of orders growth.

[14]In contrast, when orders are above the cutoff, a rapid decline in orders in the current quarter signals nothing about the direction of change in orders next quarter.

from a two-state Markov switching model where the coefficients on the lagged orders growth terms $\gamma_{o1}^{\psi_t}$ and $\gamma_{o2}^{\psi_t}$ and the error correction term β^{ψ_t} switch with the state ψ_t. The estimates maximize the likelihood by jointly estimating the state-dependent coefficients and the probability the economy is in state 1 or state 2 in each quarter. The probabilities in quarter t influence the probabilities in quarter $t+1$ through a Markov transition matrix, where p_{ii} is the probability the economy remains in state i in period $t+1$ conditional on the economy being in state i in period t. Using this structure, the model chooses the probabilities to provide the best fit of shipments growth, so the probabilities are not tied directly to the level of the error correction term in any way.

Table 4 shows that shipments respond more to fluctuations in orders in state 2. If the economy stays in state 2 with 100 percent probability, the level of shipments declines by more than 1 percent for each 1 percent decline in orders, compared to changes in the level of shipments of less than 0.25 percent if the economy is in state 1. Consequently, we call state 2 the "high response state". The coefficient on the first lag of orders growth increases markedly in this high-response state, and, as in the threshold specifications, the response of shipments to orders comes more quickly. Notably, the coefficient on the error correction term also shifts from small and negative to large and positive in the high response state.

Smoothed probabilities that the economy is in the high response state, computed from the 1969 to 2011 sample, are shown in Figure 3; for comparison, periods where the error correction term is below the optimal threshold $\kappa = 0.95$ from Table 2 are shaded gray. Most of the spikes up in the probability of the high response state are in the shaded areas where the error correction term is below the threshold, although we do see two spikes up in the high-response probabilities outside of the shaded areas, in 1972 and 1978. However, starting with the 1981-2 recession, the largest spikes up in the probabilities of the high-response state occur in the shaded areas, and, indeed, during recessions.

These probabilities look somewhat ragged, because the model estimates a very low value for p_{22}, 17 percent, implying that the high response state is not at all persistent. This probability p_{22} is higher using the shorter sample, and smoothed probabilities from this sample are shown in Figure 4, with gray shading where the error correction term is below the optimal $\kappa = 0.87$ threshold from Table 2. These smoothed probabilities are elevated from late 2000 through the end of the 2001 recession, in the pause in the recovery from late 2002 to early 2003, at the height of the 2007-9 recession, and in the first quarter of recovery from that recession. Except for late 2000, these periods are all shaded, with orders having dropped precipitously so the error correction term was below the critical threshold. The Markov-switching model could have estimated elevated probabilities of the high-response state at other times, for example, in booms with orders running well above shipments, and the fact that it generally does not do so provides some validation for the use of the simplified threshold specifications in section 3.1.

3.2.2 Orders Growth Specifications

Table 5 reports from a Markov-switching autoregression in orders growth, using the 1993 to present sample, allowing the variance to change with the state as well as the autoregressive parameters.[15] While orders growth exhibits virtually no persistence in state 1, we see very high persistence in the orders growth process in state 2. Indeed, if state 2 were permanent, orders growth would be non-stationary, but the average duration of state 2 is only a couple of quarters, with a probability of continuation into next quarter of 56 percent. Still, these parameters imply that if orders are plunging and the economy is in state 2, orders will continue to plunge until either a large positive shock to orders or the economy transitions out of state 2.

In addition to the relatively high persistence in state 2, the model also estimates a relatively high variance. Since state 2 tends to occur in and around recessions, the variance finding is consistent with the earlier literature on asymmetric business cycles, such as French and Sichel (1993) and Beaudry and Koop (1993), who characterize recessions as periods of relatively large shocks concentrated over a short period of time. Our finding of increased persistence in the orders process over short periods of time in recessionary episodes is a new result, but not necessarily inconsistent with those earlier findings.[16]

We call state 2 the "high persistence state", and Figure 4a plots smoothed probabilities of this state along with smoothed probabilities of the high response state for shipments from Figure 4. These states largely coincide, so periods were orders growth exhibits high persistence tend to be periods where shipments growth responds strongly to orders growth. We also see elevated smoothed probabilities of the high persistence state again tending to occur in periods shaded gray, where the error correction term is below the optimal threshold $\kappa = 0.87$ from Table 3, providing more support for the simplified threshold specifications in section 3.1.

Figure 5 plots quarterly shipments growth and the predicted values from the Markov-switching model, computed using smoothed probabilities, so the probabilities in each quarter are estimated using information from all quarters in the sample. The model tracks very well the declines in shipments in the 2001 recession and its

[15]Using the 1969 to present sample, we found results that were not particularly useful, with the model defining states so that one state was an extremely high variance state, with elevated probabilities of that state for only a few data points in the sample.

[16]Beaudry and Koop (1993) find that positive shocks tend to have more persistent effects on the level of output over the medium-term than negative shocks. Our results focus more on the short-term dynamics of orders growth, and so are not strictly comparable. Furthermore, while we find that orders do tend to exhibit heightened persistence in periods of large negative shocks, that heightened persistence tends to carry over into the early stages of recoveries when shocks can be large and positive, such as in early 2010. So, the general statement of Beaudry and Koop (1993) that in recessions negative shocks cause an inverse hump-shaped effect on output does not seem contrary to our finding that over periods where orders are below the cutoff all shocks tend to have a sharper and more persistent effect on orders growth.

aftermath, and in the 2007-9 recession. The other line in the figure shows predicted values if the economy had stayed in state 1 (with 100 percent probability) throughout the sample. Shipments would have fallen much less in these recessions had this been the case, indicating that most of the decline in shipments (and equipment investment) in those recessions was due to changes in the responsiveness of shipments to orders. These results are very similar to those in Figure 2, again highlighting the broad similarities between the threshold cointegrations and Markov switching specifications.

3.3 Evidence Using Across-Industry Variation

Since our NAICS-based sample is somewhat short, we bring additional variation to bear in our final cut at the data. Using twenty industry categories, we ran cross-sectional regressions for each quarter from 1993Q1 to 2011Q2 of industry-level shipments growth on a constant, the industry-level error correction term, and one lag each of industry-level shipments growth and orders growth.[17] The time series of cross-sectional $\widehat{\beta^{XS}}$s on the error correction term shows interesting cyclical patterns, and these are plotted in Figure 6, with recessions shaded gray.[18] Note that including a constant in the regression for each quarter purges the data of aggregate effects, as the inclusion of a set of time dummies would in a panel regression, so these time-varying coefficients are estimated using variation that is orthogonal to the aggregate variation we have exploited thus far.

Figure 6 shows that while the $\widehat{\beta^{XS}}$s reach some elevated values in the mid-1990s, they are most elevated for extended periods during the 2001 and 2007-9 recessions, peaking at a value close to 0.8 at the height of the Great Recession. On average, the $\widehat{\beta^{XS}}$ average 0.43 in recessions and only 0.13 in expansions, providing across-industry evidence that shipments respond more to orders in bad economic times.

Table 6 shows aggregate regression results including the time series of $\widehat{\beta^{XS}}$ lagged one quarter, both directly and interacted with the aggregate error correction term

[17]The twenty categories of non-defense capital good we use are: 1. small arms and ordnance; 2. construction machinery; 3. mining, oil, and gas field machinery; 4. industrial machinery; 5. vending, laundry, and other machinery; 6. photographic equipment; 7. metalworking machinery; 8. turbines and generators and other power transmission equipment; 9. pumps and compressors; 10. material handling equipment; 11. all other machinery; 12. electronic computers; 13. communications equipment; 14. search and navigation equipment; 15. electromedical, measuring, and control instruments; 16. electrical equipment; 17. other electrical equipment, appliances, and components; 18. office and institutional furniture; 19. railroad rolling stock; and 20. ships and boats. We exclude the following categories of non-defense capital goods from the regression, because Census does not record unfilled orders for those categories, instead setting orders equal to shipments: heavy duty trucks; computer storage devices; other computer peripheral equipment; farm machinery and equipment; and medical equipment and supplies.

[18]The time series of coefficients on lagged orders growth and lagged shipments growth looked much noisier, not displaying any clear cyclical patterns.

$o_{t-1} - s_{t-1}$ and the orders growth terms Δo_{t-k}. The adjusted R-square of the regression increases from 0.40 to 0.42 when lagged $\widehat{\beta^{XS}}$ is added to the regression, but it increases more, to 0.45, when lagged $\widehat{\beta^{XS}}$ interacted with the aggregate error correction term is added instead, and it increases to 0.50 when both terms are added. Further, the coefficient on the aggregate error correction term interacted with lagged $\widehat{\beta^{XS}}$ is highly statistically significant. With $\widehat{\beta^{XS}}$ averaging about 0.13 in expansions and 0.43 in recessions, the second to last specification tells us that the time-varying coefficient on the error correction term is close to zero in expansions and about 0.35 in recessions.

In the last specification in Table 6, we interact the $\widehat{\beta^{XS}}$ with the lagged orders growth terms as well as the error correction term. While the interesting time variation in the cross sectional regression coefficients appears in the error correction term, when these cross sectional error correction coefficients are interacted with all the aggregate orders terms, it is the interaction with the second lag of orders growth that is largest and statistically significant. So, at the aggregate level, we have strong evidence of increased sensitivity of shipments to orders during downturns, but whether that increased sensitivity appears through the error correction term or the lagged orders growth terms is less clear.

4 Theoretical Explanations

Our goal in this section is not to write down and estimate a fully structural model. Rather, it is to derive implications from a simple stylized model, with an eye towards organizing our thoughts about firm behavior, and providing some basic insights into the factors that might or might not explain our empirical results.

4.1 A Framework: Production Smoothing with a Target Delivery Lag

In this model, firms produce a complex good with customizable specifications, making holding inventories of the finished good extremely costly as it is very unlikely that a customer will request the particular set of specifications in a good that has been already produced. Because all firms face the same constraint, customers are willing to wait a certain time until the ordered good is delivered. This type of good is naturally a produced-to-order good, where the firm holds unfilled orders but no finished goods inventories. Unfilled orders are accumulated according to:

$$U_t = U_{t-1} + O_t - S_t.$$

The ratio of unfilled orders to shipments U/S is expressed in units of time, measuring the average amount of time the firm takes to produce and deliver an ordered good.

The technological constraints related to the degree of customization in the product and how fast it can be built pose natural limits on how low U/S can fall. It may be costly for the firm to operate with a small U/S for other reasons as well, as speeding up production may entail additional costs such as overtime for labor and additional wear and tear on equipment. We assume it is costly for the firm to operate with a large U/S as well, as customers may need to be compensated when firms delay delivery, or they may switch to another firm and cancel the order altogether. We model these different costs by assuming a quadratic cost for firms to deviate from a certain target ratio of unfilled orders to shipments, c.

The target c is an important parameter in the model, helping pin down the degree to which shipments respond to orders. To see this, note that:

$$\frac{U_t}{S_t} = \frac{U_{t-1} + O_t - S_t}{S_t} = \frac{\frac{U_{t-1}}{S_{t-1}} + \frac{O_{t-1}+\Delta O_t}{S_{t-1}} - \frac{S_{t-1}+\Delta S_t}{S_{t-1}}}{\frac{S_{t-1}+\Delta S_t}{S_{t-1}}}.$$

Rearranging yields:

$$gr_{s_t} = \frac{\left(\frac{U_{t-1}}{S_{t-1}} - \frac{U_t}{S_t}\right) + \left(\frac{O_{t-1}}{S_{t-1}} - 1\right)}{1 + \frac{U_t}{S_t}} + \frac{\frac{O_{t-1}}{S_{t-1}}}{1 + \frac{U_t}{S_t}} gr_{o_t}, \tag{1}$$

where $gr_{x_t} \equiv \left(X_t - X_{t-1}\right)/X_{t-1}$. As an example, assume that $S_{t-1} = O_{t-1}$ and the firm is at its target ratio so $\frac{U_{t-1}}{S_{t-1}} = c$. Then if the firm stays at the target in period t, for any change in orders, gr_{o_t}, (1) implies:

$$gr_{s_t} = \frac{1}{1+c} gr_{o_t}. \tag{1'}$$

With the stock of unfilled orders equal to three months worth of shipments, for example, monthly shipments need to change by only a quarter as much as orders to keep U/S constant, and $\frac{1}{1+c}$ of the remaining gap between orders and shipments is eliminated each month. The response of shipments to changes in orders is drawn out over a number of periods if the firm stays at the target, with the speed of convergence of shipments to orders determined by the target c.

Layered on top of the cost of deviating from the target c is an increasing marginal cost of production, modelled as a quadratic function of current shipments, which leads firms to smooth production by using unfilled orders as a buffer between shipments and stochastic demand. Firms take the price of their product, p, as given. At the beginning of each period, once new orders are received, firms decide how much to produce and sell of total orders in stock (including current new orders and backlogged orders). The optimization problem of the firm is given by:[19]

$$V\left(U_{t-1}\right)=\max_{S_\tau}\left\{pS_t-\left(a_1S_t+\frac{a_2}{2}S_t^2\right)-\frac{b}{2}\left(U_t-cS_t\right)^2+\beta E_\tau V\left(U_t\right)\right\}. \quad (2)$$

The first-order condition for this problem leads to the difference equation[20]

$$p-a_1-a_2S_t+b\left(1+c\right)\left(U_t-cS_t\right)=\beta E_t\left\{p-a_1-a_2S_{t+1}+bc\left(U_{t+1}-cS_{t+1}\right)\right\}. \quad (3)$$

This condition says that the marginal benefit of selling one additional unit in the current period must equal the expected marginal benefit of selling this unit next period. Assuming that unfilled orders are above its target, selling the unit in the current period both raises S_t and lowers U_t, while selling it only next period only raises S_{t+1}. We then solve the difference equation for U_t and apply the unfilled orders accumulation equation to get (not including constants)

$$S_t=\left(1-\lambda_1\right)U_{t-1}+\left(1-\lambda_1\right)O_t+\left(\left(1-\lambda_1\right)-\frac{1}{\left(1+\alpha\right)\left(1+c\right)}\right)\sum_{i=1}^{\infty}\left(\beta\lambda_1\right)^iE_tO_{t+i}, \quad (4)$$

where $\alpha\equiv a_2/\left[bc\left(1+c\right)\right]$, $\left(1-\lambda_1\right)>1/\left[\left(1+\alpha\right)\left(1+c\right)\right]$, and $\lambda_1\in(0,1)$ is the stationary root of the characteristic equation associated with the difference equation.

For simplicity, assume that aggregate orders growth follows an autoregressive process:

$$\Delta O_t=d\left(1-\rho\right)+\rho\Delta O_{t-1}+u_t,\ u_t\sim iid(0,\sigma^2\left(1-\rho^2\right)) \quad (5)$$

where d and σ^2 are the long-run mean and variance of new orders growth and ρ is the autocorrelation parameter. Aggregating (4), taking first differences, and using $E_{t-1}\Delta O_{t+i}=d+\rho^{i+1}\left(\Delta O_{t-1}-d\right)$, for $i\geq0$, produces (not including constants):[21]

$$E_{t-1}\left(\Delta S_t\right)=\left(1-\lambda_1\right)\left(O_{t-1}-S_{t-1}\right)+\left(1-\lambda_1\right)\left(1+\delta\left(\rho\right)\right)\rho\Delta O_{t-1}, \quad (4')$$

where

$$\delta\left(\rho\right)\equiv\left(1-\frac{1}{\left(1+\alpha\right)\left(1+c\right)\left(1-\lambda_1\right)}\right)\frac{\beta\lambda_1\rho}{1-\beta\lambda_1\rho}\geq0,\text{ if }\rho\geq0. \quad (6)$$

The last term in equation (4), which is associated with the parameter δ in (4'), reflects the effect of the production smoothing motive; when the cost function in (2)

[19] Our model assumptions allow an expression for aggregate shipments growth that is linear and resembles the baseline specifications we use in the empirical section. Assuming that firms do not observe orders received during the period and set shipments based on the stock of unfilled orders at the end of last period would not significantly change our results below.

[20] For the sake of brevity, we assume that unfilled orders are always non-negative.

[21] Given the upward drift in aggregate new orders, we assume that perfectly competitive firms enter the market to satisfy an increasing demand over time.

is linear in output, i.e., $a_2 = 0$, this last term is absent in (4) ($\delta = 0$ in 4') and unfilled orders are kept at a constant distance from their target, with $1 - \lambda_1 = 1/(1+c)$ as in (1'). With a production smoothing motive the coefficient of the error correction term gets smaller, as $1 - \lambda_1 < 1/(1+c)$ if $a_2 > 0$. In addition, if new orders growth exhibits high positive persistence we may get a higher coefficient on new orders growth than on the error correction term. This likely explains the findings in most of our empirical specifications of higher coefficients on new orders growth than on the error correction term when orders become highly persistent, such as in Table 4.

4.2 Time-Varying Persistence of Demand Shocks

According to (4'), both with and without a production smoothing motive, i.e., $\delta \geq 0$, the sensitivity of shipments growth to new orders growth increases with the persistent in the new orders process:[22]

$$\frac{\partial^2 E_{t-1}\Delta S_t}{\partial \Delta O_{t-1}\partial \rho} = \frac{1}{(1-\beta\lambda_1\rho)^2}\left[(1-\lambda_1) - \frac{1}{(1+\alpha)(1+c)}\right] + \frac{1}{(1+\alpha)(1+c)} > 0. \quad (7)$$

This shows that the target unfilled orders ratio plays an important role in the response of producers to increased persistence in new orders growth. If new orders growth becomes more persistent, producers will take more signal from new orders shocks in order to avoid large deviations from their orders backlog target.[23]

Unlike the other model parameters (a_2, b, and c), which affect the sensitivity of shipments growth to both the error correction term and lagged new orders growth, the parameter governing the persistence of demand shocks, ρ, affects only the coefficient on lagged new orders growth. The hypothesis that increased persistence of orders shocks explains some of the increased responsiveness of shipments to orders at certain times then provides two testable implications: first, the increased persistence of orders shocks should coincide with the increased sensitivity of shipments to orders, and second, the increased sensitivity of orders to shipments should appear as larger coefficients on lagged new orders growth, not as a larger coefficient on the error correction term.

Regarding the first testable implication, for the 1993 to 2011 sample, the evidence in Tables 2 and 3 and in Figure 4a is clearly favorable. Periods where orders growth exhibits high persistence do tend to be periods where shipments growth responds strongly to orders growth. Regarding the second testable implication, in all the

[22] We assume that firms expect the persistence of orders growth to be permanently higher. However, even if firms expect the persistence to be temporarily higher, our result of an increased sensitivity of shipments growth to orders growth would still hold.

[23] However, in the presence of a production smoothing motive the expression in (7) is higher than $1 - \lambda_1$, suggesting that in this case the sensitivity of shipments to new orders growth will likely increase proportionately more in response to an increase in the persistence of the new orders process.

specifications we examine in section 3, the increased sensitivity of shipments to orders does appear, at least in part, as larger coefficients on lagged new orders growth. With the empirical results confirming both of our testable implications, we conclude that changes in the persistence of the orders growth process are likely driving part of the changing responsiveness of shipments to orders over the business cycle.

However, in many of the specifications in section 3, we also observe an increase in the coefficient on the error correction term. In the threshold specifications, the increase in the error correction coefficient below the threshold appears in the monthly specifications, although not in the quarterly ones. In the Markov switching results, a sizable increase in the error correction coefficient in the high-response state does appear. And time variation in the error correction coefficient appears in the cross-sectional regression coefficients reported in Figure 6. Changing orders persistence cannot explain these results, so it falls short of providing a full and complete explanation for the time varying responsiveness of shipments to orders that we document. Simulations of the model, both with and without a production smoothing motive and using a non-linear aggregate orders process similar to that estimated in Table 3 (except that changes in volatility are not allowed), confirm this prediction. In addition, these simulations show that the higher persistence of new orders cannot account for all of the increase in the sensitivity of shipments to new orders growth when new orders become more persistent. We conclude that capital goods producers must be changing their behavior for other reasons, possibly reacting to other changes in the business environment.

4.3 Other Explanations

Next we consider time variation in the target ratio of unfilled orders to shipments. While this target c is unobserved, it probably tracks actual U/S fairly closely over long periods of time. Figure 7 shows that U/S shows a strong downward trend between the mid-1970s and the late 1990s, similar to the results in Kahn (2010), who argues that technological advances allowing for shorter delivery lags for produced-to-order goods can help explain the Great Moderation. Our 1993 to 2011 specifications generally show larger responses of shipments to orders than our 1969 to 2011 specifications, in line with the model prediction if the equilibrium target c is lower in the latter part of the sample.

The business cycle frequency movements in this ratio are interesting as well. To emphasize these fluctuations, we plot the detrended logarithm of this ratio, along with the log ratio of new orders to shipments. At business cycle frequencies, when orders are below shipments, U/S tends to increase noticeably. Although shipments tend to fall less than new orders in recessions, firms cut shipments more aggressively than needed to leave U/S unchanged, perhaps revealing an increase in the target c during recessions. Lack of access to credit and heightened pessimism or higher uncertainty could be leading firms to build up relatively large buffer stocks of unfilled orders in bad economic times, similar to how some firms hoard cash. In addition, customers may be willing to accept longer delivery lags in bad economic times, reducing the cost to producers of running a large orders backlog, thus increasing the target c.[24] In the early stages of a recovery, when demand rebounds, the costs of a long delivery lag could increase again, bringing c back down.

Regarding a_2 and b, the following expression shows that the lower the cost of production fluctuations and the higher the cost of deviations from the unfilled orders target, the higher the sensitivity of shipments to both new orders growth and the error correction term. We have:

$$\frac{\partial\left(1-\lambda_1\right)}{\partial x}=-\frac{\frac{1}{(1+\alpha)^2\beta}\left(\frac{1}{c}-\beta\frac{1}{1+c}\right)\lambda_1}{\frac{1+\beta}{\beta}+\frac{1}{(1+\alpha)\beta}\left(\frac{1}{c}-\beta\frac{1}{1+c}\right)-2\lambda_1}\frac{\partial\alpha}{\partial x}, \tag{8}$$

where x is either a_2 or b; so $\partial\left(1-\lambda_1\right)/\partial a_2<0$ and $\partial\left(1-\lambda_1\right)/\partial b>0$.[25] Then the relatively large error correction coefficients around recessions may reflect firms giving more importance to bringing unfilled orders closer to target than smoothing production when shocks are large and negative.

Finally, other economic mechanisms not built into our framework may help explain part of our empirical results. In particular, if firms face non-convex adjustment costs, leading to (S,s) decision rules where firms only change production if unfilled orders deviate substantially from target, then the fraction of adjusting firms could increase disproportionately in periods with large negative demand shocks, increasing the responsiveness of shipments to orders in such periods.[26] Simulating such a model, we found it largely insufficient to explain our main empirical findings, but a more flexible specification might be more successful. In particular, we assumed a symmetric shock process in our simulations, and employing an asymmetric shock process, with larger or more volatile shocks in recessions, may imply higher sensitiv-

[24] These explanations may seem to run contrary to equation (1'), since an increase in c would tend to reduce the sensitivity $\frac{1}{1+c}$ of shipments growth to orders growth. However, when the increase in the target coincides with a drop in orders, the sensitivity of shipments to orders could increase temporarily during the transition to the new target. The decline in orders reduces the numerator of $\frac{U_t}{S_t}$, and if c rises, firms must reduce the denominator, shipments, by more than would be necessary if c remained constant. Conversely, if the target c falls as orders rebound coming out of a recession, shipments will have to temporarily surge to bring down $\frac{U_t}{S_t}$, again temporarily boosting the sensitivity of shipments to orders. Explicitly modelling these dynamics, by endogenously determining of the optimal U/S and how it changes over the business cycle, would be an interesting area for future research.

[25] We can also show that these parameters have effects with the same sign on the coefficient on new orders growth.

[26] Other (S,s) models have been studied in the related context of retail and wholesale inventories (Blinder 1981, Caplin 1985, Fisher and Hornstein 2000) and manufacturing material and supply inventories (Khan and Thomas 2007).

ity of shipments to orders in recessions (see Caballero 1992, Bloom 2009).[27] French and Sichel (1993) find evidence for such asymmetric shocks, and our results here suggest some asymmetry as well. Alternatively, an extreme form of an (S, s) model where firms only adjust production by changing the number of shifts may also have some success at explaining both the higher sensitivity of shipments to orders in recessions and the counter-cyclical unfilled orders to shipments ratio.

5 Conclusion

Using a variety of approaches and statistical techniques, we have demonstrated that shipments of capital goods producers exhibit stronger responses to fluctuations in their new orders when the level of orders is low relative to the level of shipments, typically in and around recessions. This change in the response of shipments to orders is quantitatively important, accounting for much of the steep decline in shipments (and thus equipment investment) in the 2001 and 2007-9 recessions, and those declines in equipment investment accounted for a sizable portion of the deceleration in overall economic output in those recessions. Our results show how changes in time series processes and firm behavior amplify shocks in recessionary episodes, contributing to an understanding of how recessions are different from expansions and why they are more severe than standard linear economic models predict.

We provide interpretations for our empirical finding using a production smoothing model where firms receive orders and then set production and shipments using a target delivery lag, expressed as the ratio of unfilled orders to shipments. In the model, the sensitivity of shipments to new orders increases with the persistence of shocks to the orders process, which our results show varies over time. Consistent with the model, the heightened sensitivity of shipments to orders tends to occur when shocks to the orders process display heightened persistence, often in and around recessions. At such times, the short run dynamics of the orders process are highly persistent in growth rates, so that a decline in orders (perhaps in the early stages of a recession) signals that orders are likely to continue to decline, and a stabilization of orders (perhaps in the late stages of a recession or the early stages of a recovery) signals that orders are likely to remain stable.

Understanding why the orders process becomes so persistent in recessionary episodes likely would necessitate returning to the traditional domain of investment research—studying the behavior of the firms providing the demand for capital. That is beyond the scope of this paper, which studies the behavior of firms supplying the capital, but we can offer some speculative hypotheses. Clearly recent recessions have

[27] Simulations assuming an asymmetric new orders process as estimated in Table 3 (except that changes in volatility are not allowed), show that adding a fixed production adjustment cost to the model in section 4.1 does not change significantly our findings of an increase in the sensitivity of shipments to orders in periods of high persistence in new orders growth.

entailed large negative shocks. At issue is why firms (in the aggregate) do not adjust to the shock instantaneously, but instead react in such a way that capital goods orders fall over a number of quarters, generating positive persistence in growth rates. Some models generate such slow adjustment—the production smoothing model with a target delivery lag we study in this paper, for example; similar models may be governing other firms' production decisions and thus their demand for capital. Or firms may make adjustments to their capital expansion plans only periodically, and it may be costly to cancel orders and projects already in the pipeline, so that plans made before a recession provide some support to capital demand in the early stages of the recession. In addition, firms may be uncertain about the magnitude of the negative demand shock, which may reveal itself only slowly over the course of a recession, leading firms to ratchet back their capital goods orders gradually. Finally, causal feedback loops may be at play—negative feedback loops in recessions and positive feedback loops in the early stages of expansions—helping generate the extreme persistence we observe in orders growth at certain times.

Time-varying persistence of the orders process likely explains only part of the time-varying sensitivity of shipments to orders we observe, however. We consider other complementary explanations, including changes over the business cycle in other parameters of the production smoothing model such as the target delivery lag. Interestingly, the ratio of unfilled orders to shipments is counter-cyclical, suggesting firms may be slashing shipments in recessions to hold larger buffer stocks of unfilled orders (relative to shipments), perhaps for precautionary reasons. Further investigation of this aspect of firm behavior might be another worthwhile goal for future research.

A Appendix: Constructing Real M3 Data

We construct the real data for non-defense capital goods excluding aircraft by chain-weigthing the real data of the M3 equipment categories included in that aggregate. We obtain the real data at the M3 category level in two steps. First, we use PPIs to create price deflators for the detailed SIC / NAICS industry codes included in each M3 category. Whenever a matching industry PPI is incomplete or unavailable, we use the closest commodity or industry PPI. Second, we use these price deflators together with the ASM and EC data on annual nominal shipments for each detailed SIC / NAICS code to create a chain-weighted price deflator for each M3 category. Employing the shipments data from the ASM and EC for this purpose seems sensible because they serve as annual benchmarks for the M3 data.

According to the BLS, the PPIs are a measure of price changes in the monthly shipments data. Our baseline assumption is that these price changes apply equally to the orders data, in which case the price deflators for shipments, new orders, and unfilled orders are identical. However, the current stock of unfilled orders reflects future monthly shipments, implying that new and unfilled orders are not valued at current shipments prices. We create a current-price measure of the backlog of unfilled orders as the deflated flow of future nominal monthly shipments that exhausts such backlog, from which a similar current-price measure of new orders can be derived. Finally, we use the shipments price deflator to create the alternative real data on new and unfilled orders. Although our empirical analysis is done with the standard reals, the results are not very sensitive to using one or the other measure of the real orders data.

B Appendix: Proofs on section 4

In this appendix we show how to derive equations (4), (4'), (7), and (8). From the first order condition (3), we get the difference equation

$$E_tU_{t+1} - \left[\frac{1+\beta}{\beta} + \frac{1}{(1+\alpha)\beta}\left(\frac{1}{c} - \beta\frac{1}{1+c}\right)\right]U_t + \frac{1}{\beta}U_{t-1} = \frac{(1-\beta)\,p}{\beta bc\,(1+c)\,(1+\alpha)} - \frac{1}{\beta}O_t + \frac{1}{1+\alpha}\left(\frac{c}{1+c} + \alpha\right)E_tO_{t+1}, \quad (9)$$

where $\alpha \equiv \frac{a_2}{bc(1+c)}$. The characteristic equation of the LHS homogeneous equation in (9) can be written as

$$f(\lambda) = \lambda^2 + h_1\lambda + h_2 = 0,$$

Since $h_1^2 - 4h_2 > 0$, the characteristic equation has two real and distinct roots, λ_1 and λ_2. Moreover, because $h_1 < 0$ and $h_2 > 0$, the two roots must be positive. Furthermore, since $f(1) < 0$, one root is stationary, $\lambda_1 \in (0,1)$, while the other root is nonstationary $\lambda_2 > 1$. Using the lag, L, and forward, F, operators, we can rewrite the LHS of (9) as

$$E_t\left[\left(1 + h_1L + h_2L^2\right)U_{t+1}\right] = -\frac{1}{\beta\lambda_1}E_t\left[(1-\lambda_1L)(1-\beta\lambda_1F)\,U_t\right],$$

where we use $\lambda_1\lambda_2 = \frac{1}{\beta}$. We then get (not including constants)

$$U_t = \lambda_1U_{t-1} + \lambda_1O_t - \left[(1-\lambda_1) - \frac{1}{(1+\alpha)(1+c)}\right]\sum_{i=1}^{\infty}(\beta\lambda_1)^i\,E_tO_{t+i}.$$

From the unfilled orders accumulation equation we finally obtain (4). Note that,

$$f\left(1 - \frac{1}{(1+\alpha)(1+c)}\right) < 0 \Rightarrow (1-\lambda_1) - \frac{1}{(1+\alpha)(1+b)} > 0.$$

Taking first differences of (4) and using $E_{t-1}\Delta O_{t+i} = d + \rho^{i+1}(\Delta O_{t-1} - d)$ we obtain (4'). We use the expression for δ in (6) to obtain (7). Finally, to derive (8), we take partial derivatives from the characteristic equation to get

$$(2\lambda_1 + h_1)\frac{\partial \lambda_1}{\partial x} = -\frac{1}{(1+\alpha)^2 \beta}\left(\frac{1}{c} - \beta\frac{1}{1+c}\right)\lambda_1 \frac{\partial \alpha}{\partial x},$$

where $2\lambda_1 + h_1 < 0$. Therefore, $\partial(1-\lambda_1)/\partial b > 0$ and $\partial(1-\lambda_1)/\partial a_2 < 0$ because $\partial\alpha/\partial b < 0$ and $\partial\alpha/\partial a_2 > 0$.

References

Abramowitz, M., 1950, *Inventories and Business Cycles*, National Bureau of Economic Research, New York.

Balke, N.S., Fomby, T.B., 1997, "Threshold cointegration," *International Economic Review* 38, 627-45.

Beaudry, P., Koop, G., 1993, "Do recessions permanently change output?," *Journal of Monetary Economics* 31, 149-63.

Besley, D.A., 1969, *Industry Production Behavior: The Order-Stock Distinction*, North-Holland, Amsterdam.

Blanchard, O.J., Fischer, S., 1989, *Lectures on Macroeconomics*, MIT Press, Cambridge.

Blinder, A.S., 1981, "Retail inventory behavior and business fluctuations," *Brookings Papers on Economic Activity* 2, 443-505.

Blinder, A.S., Maccini, L.J., 1991, "Taking stock: a critical assessment of recent research on inventories," *Journal of Economic Perspectives* 5, 73-96.

Bloom, N., 2009, "The Impact of Uncertainty Shocks," *Econometrica* 77, 623-85.

Caballero, R.J., 1992, "A fallacy of composition," *The American Economic Review* 82, 1279-92

Caplin, A.S., 1985, "The variability of aggregate demand with (S, s) inventory policies," *Econometrica* 53, 1395-1409.

Cochrane, J.H., 1988, "How Big is the Random Walk in GNP?" *The Journal of Political Economy* 96, 893-920.

Fisher, J.D.M., Hornstein, A., 2000, "(S, s) inventory policies in general equilibrium," *Review of Economic Studies* 67, 117-45.

French, M.W., Sichel, D.E., 1993, "Cyclical patterns in the variance of economic activity," *Journal of Business and Economic Statistics* 11, 113-19.

Haltiwanger, J.C., Maccini, L.J., 1989. "Inventories, orders, temporary and permanent layoffs: an econometric analysis," *Carnegie-Rochester Conference Series on Public Policy* 30, 301-66.

Hansen, B.E., Seo, B., 2002, "Testing for two-regine threshold cointegration in vector error-correction models," *Journal of Econometrics* 110, 293-318.

Kahn, J.A., 2010, "The Great Moderation and the Great Recession," Economics Department, Yeshiva University, New York, working paper.

Khan, A., Thomas, J.K., 2007, "Inventories and the business cycle: an equilibrium analysis of (S, s) policies," *American Economic Review* 97, 1165-88.

Ramey, V.A., West, K.D., 1999, "Inventories," *Handbook of Macroeconomics*, vol 15. Elsevier Science, New York, 863-923.

Reagan, P., Sheehan, D.P., 1985, "The stylized facts about the behavior of manufacturers' inventories and backorders over the business cycle: 1959 - 1980," *Journal of Monetary Economics* 15, 217-46.

Tevlin, S., Whelan, K., 2003, "Explaining the Investment Boom of the 1990s," *Journal of Money, Credit, and Banking* 35, 1-22.

Tong, H., 1983, *Threshold Models in Nonlinear Time Series Analasis: Lecture Notes in Statistics*, 21. Springer, New York.

Tong, H., 1990, *Non-Linear Time Series: A Dynamical System Approach*, Oxford University Press, Oxford.

West, K.D. 1989, "Order Backlogs and Production Smoothing," *Lecture notes in economics and mathematical systems*, vol. 322. (New York: Springer, 1989), New York, NY. 246-69.

Table 1: Regressions Explaining Monthly Shipments Growth

$$\Delta s_t = \alpha + \sum_{i=1}^{6} \gamma_{si} \Delta s_{t-i} + \sum_{i=1}^{6} \gamma_{oi} \Delta o_{t-i} + \beta \left(o_{t-1} - s_{t-1} \right) \ldots$$
$$+ \mathbf{1}_{o_{t-1}-s_{t-1}<0} \left(\beta^0 \left(o_{t-1} - s_{t-1} \right) \right) + u_t$$

	1969M1 to 2011M6		1993M1 to 2011M6	
α	0.20 (0.09)	0.51 (0.12)	0.13 (0.12)	0.75 (0.21)
γ_{s1}	−0.42 (0.05)	−0.43 (0.05)	−0.57 (0.10)	−0.63 (0.10)
γ_{s2}	−0.19 (0.06)	−0.20 (0.06)	−0.19 (0.10)	−0.23 (0.10)
γ_{s3}	0.14 (0.06)	0.10 (0.06)	0.16 (0.10)	0.09 (0.10)
γ_{s4}	0.09 (0.06)	0.06 (0.06)	−0.03 (0.10)	−0.04 (0.10)
γ_{s5}	0.04 (0.05)	0.02 (0.05)	−0.19 (0.10)	−0.19 (0.09)
γ_{s6}	0.13 (0.05)	0.11 (0.05)	0.03 (0.08)	0.02 (0.08)
γ_{o1}	0.09 (0.03)	0.07 (0.03)	0.18 (0.07)	0.20 (0.07)
γ_{o2}	0.11 (0.03)	0.09 (0.03)	0.13 (0.07)	0.12 (0.07)
γ_{o3}	0.13 (0.03)	0.13 (0.03)	0.16 (0.07)	0.15 (0.07)
γ_{o4}	0.10 (0.03)	0.09 (0.03)	0.18 (0.07)	0.14 (0.07)
γ_{o5}	0.07 (0.03)	0.06 (0.03)	0.19 (0.06)	0.15 (0.06)
γ_{o6}	0.04 (0.02)	0.04 (0.02)	0.15 (0.05)	0.13 (0.05)
β	0.00 (0.02)	−0.04 (0.03)	0.05 (0.07)	−0.14 (0.09)
β^0		0.19 (0.05)		0.46 (0.13)
$\overline{R}^2$	0.23	0.25	0.38	0.41

Note: $s \equiv 100 \times \ln(S)$, $o \equiv 100 \times \ln(O)$, where O and S are real orders and shipments of nondefense capital goods excluding aircraft, respectively. Standard errors of estimates are in parenthesis.

Table 1a: Regressions Explaining Monthly Shipments Growth

$$\Delta s_t = \alpha + \sum_{i=1}^{6} \gamma_{si} \Delta s_{t-i} + \sum_{i=1}^{6} \gamma_{oi} \Delta o_{t-i} + \beta \left(o_{t-1} - s_{t-1}\right) \ldots$$
$$+ \mathbf{1}_{o_{t-1} - s_{t-1} < \kappa} \left(\alpha^{\kappa} + \sum_{i=1}^{6} \gamma_{si}^{\kappa} \Delta s_{t-i} + \sum_{i=1}^{6} \gamma_{oi}^{\kappa} \Delta o_{t-i} + \beta^{\kappa} \left(o_{t-1} - s_{t-1}\right)\right) + u_t$$

1969M1 to 2011M6				1993M1 to 2011M6			
α	0.51 (0.22)	α^{κ}	−0.09 (0.25)	α	1.12 (0.32)	α^{κ}	−0.97 (0.44)
γ_{s1}	−0.44 (0.09)	γ_{s1}^{κ}	0.01 (0.11)	γ_{s1}	−0.68 (0.13)	γ_{s1}^{κ}	−0.02 (0.20)
γ_{s2}	−0.34 (0.10)	γ_{s2}^{κ}	0.24 (0.12)	γ_{s2}	−0.42 (0.13)	γ_{s2}^{κ}	0.48 (0.23)
γ_{s3}	0.08 (0.09)	γ_{s3}^{κ}	0.05 (0.12)	γ_{s3}	0.11 (0.13)	γ_{s3}^{κ}	−0.10 (0.22)
γ_{s4}	0.13 (0.09)	γ_{s4}^{κ}	−0.11 (0.12)	γ_{s4}	0.11 (0.13)	γ_{s4}^{κ}	−0.38 (0.21)
γ_{s5}	0.18 (0.10)	γ_{s5}^{κ}	−0.26 (0.12)	γ_{s5}	−0.12 (0.12)	γ_{s5}^{κ}	0.06 (0.19)
γ_{s6}	0.19 (0.09)	γ_{s6}^{κ}	−0.11 (0.11)	γ_{s6}	0.16 (0.10)	γ_{s6}^{κ}	−0.33 (0.17)
γ_{o1}	0.05 (0.04)	γ_{o1}^{κ}	0.03 (0.06)	γ_{o1}	0.21 (0.10)	γ_{o1}^{κ}	0.10 (0.15)
γ_{o2}	0.08 (0.05)	γ_{o2}^{κ}	0.01 (0.06)	γ_{o2}	0.09 (0.10)	γ_{o2}^{κ}	0.03 (0.15)
γ_{o3}	0.07 (0.05)	γ_{o3}^{κ}	0.07 (0.06)	γ_{o3}	0.00 (0.09)	γ_{o3}^{κ}	0.20 (0.15)
γ_{o4}	0.04 (0.05)	γ_{o4}^{κ}	0.07 (0.06)	γ_{o4}	−0.03 (0.09)	γ_{o4}^{κ}	0.42 (0.15)
γ_{o5}	0.01 (0.04)	γ_{o5}^{κ}	0.08 (0.06)	γ_{o5}	0.07 (0.08)	γ_{o5}^{κ}	0.03 (0.13)
γ_{o6}	−0.01 (0.04)	γ_{o6}^{κ}	0.07 (0.05)	γ_{o6}	0.11 (0.06)	γ_{o6}^{κ}	0.03 (0.11)
β	−0.02 (0.03)	β^{κ}	0.14 (0.06)	β	−0.20 (0.11)	β^{κ}	0.33 (0.18)
		κ	1.73			κ	−0.13
$\overline{R}^2$			0.25				0.48

Note: See Table 1.

Table 2: Regressions Explaining Quarterly Shipments Growth

$$\Delta s_t = \alpha + \gamma_{s1}\Delta s_{t-1} + \gamma_{s2}\Delta s_{t-2} + \gamma_{o1}\Delta o_{t-1} + \gamma_{o2}\Delta o_{t-2} + \beta\left(o_{t-1} - s_{t-1}\right)\ldots$$
$$+\mathbf{1}_{o_{t-1}-s_{t-1}<\kappa}\left(\gamma_{o1}^{\kappa}\Delta o_{t-1} + \gamma_{o2}^{\kappa}\Delta o_{t-2} + \beta^{\kappa}\left(o_{t-1} - s_{t-1}\right)\right) + u_t$$

1969Q1 to 2011Q2

α	γ_{s1}	γ_{s2}	γ_{o1}	γ_{o2}	β	κ	γ_{o1}^{κ}	γ_{o2}^{κ}	β^{κ}	$\overline{R}^2$
0.45	**0.09**	**0.09**	**0.28**	**0.13**	**-0.06**					0.40
(0.18)	(0.12)	(0.10)	(0.06)	(0.06)	(0.05)					
0.77	**0.10**	**0.10**	**0.15**	**0.13**	**-0.07**	**0.950**	**0.20**	**-0.09**	**0.15**	0.42
(0.24)	(0.11)	(0.10)	(0.08)	(0.07)	(0.06)		(0.09)	(0.08)	(0.14)	

1993Q1 to 2011Q2

α	γ_{s1}	γ_{s2}	γ_{o1}	γ_{o2}	β	κ	γ_{o1}^{κ}	γ_{o2}^{κ}	β^{κ}	$\overline{R}^2$
0.37	**0.01**	**-0.25**	**0.38**	**0.38**	**-0.05**					0.40
(0.27)	(0.23)	(0.21)	(0.16)	(0.15)	(0.17)					
0.39	**0.01**	**0.15**	**-0.10**	**0.15**	**0.18**	**0.870**	**0.86**	**-0.27**	**-0.33**	0.56
(0.42)	(0.20)	(0.19)	(0.17)	(0.16)	(0.23)		(0.19)	(0.17)	(0.41)	

Note: See Table 1.

Table 3: Regressions Explaining Quarterly Orders Growth

$$\Delta o_t = \alpha + \gamma_{o1}\Delta o_{t-1} + \gamma_{o2}\Delta o_{t-2} + \mathbf{1}_{o_{t-1}-s_{t-1}<\kappa}\left(\gamma_{o1}^{\kappa}\Delta o_{t-1} + \gamma_{o2}^{\kappa}\Delta o_{t-2}\right) + u_t$$

1969Q1 to 2011Q2

α	γ_{o1}	γ_{o2}	σ^2	κ	γ_{o1}^{κ}	γ_{o2}^{κ}	$\sigma^{2\,\kappa}$	$\overline{R}^2$
0.53	**0.23**	**0.18**						0.10
(0.37)	(0.12)	(0.12)						
1.17	**-0.10**	**0.10**	**24.87**	**2.400**	**0.50**	**0.08**	**-12.04**	0.14
(0.33)	(0.14)	(0.14)	(4.58)		(0.17)	(0.16)	(4.90)	

1993Q1 to 2011Q2

α	γ_{o1}	γ_{o2}	σ^2	κ	γ_{o1}^{κ}	γ_{o2}^{κ}	$\sigma^{2\,\kappa}$	$\overline{R}^2$
0.40	**0.39**	**0.11**						0.17
(0.44)	(0.16)	(0.16)						
1.18	**-0.24**	**0.12**	**4.76**	**0.870**	**1.20**	**-0.37**	**8.03**	0.40
(0.44)	(0.13)	(0.13)	(1.03)		(0.23)	(0.24)	(3.58)	

Note: See Table 1.

Table 4: Markov-Switching Model Explaining Quarterly Shipments Growth

$$\Delta s_t = \alpha + \gamma_{s1}\Delta s_{t-1} + \gamma_{s2}\Delta s_{t-2} + \gamma_{o1}^{\psi_t}\Delta o_{t-1} + \gamma_{o2}^{\psi_t}\Delta o_{t-2} + \beta^{\psi_t}\left(o_{t-1} - s_{t-1}\right)$$

1969Q1 to 2011Q2

α	γ_{s1}	γ_{s2}	$\gamma_{o1}^{\psi_t=1}$	$\gamma_{o2}^{\psi_t=1}$	$\beta^{\psi_t=1}$	$\gamma_{o1}^{\psi_t=2}$	$\gamma_{o2}^{\psi_t=2}$	$\beta^{\psi_t=2}$	p_{11}	p_{22}
0.64	**0.05**	**0.08**	**0.26**	**0.13**	**-0.10**	**0.86**	**-0.23**	**0.48**	0.88	0.16
(0.18)	(0.11)	(0.09)	(0.06)	(0.06)	(0.05)	(0.17)	(0.21)	(0.21)	(0.07)	(0.17)

1993Q1 to 2011Q2

α	γ_{s1}	γ_{s2}	$\gamma_{o1}^{\psi_t=1}$	$\gamma_{o2}^{\psi_t=1}$	$\beta^{\psi_t=1}$	$\gamma_{o1}^{\psi_t=2}$	$\gamma_{o2}^{\psi_t=2}$	$\beta^{\psi_t=2}$	p_{11}	p_{22}
0.82	**0.21**	**-0.03**	**-0.02**	**0.35**	**-0.17**	**0.83**	**-0.26**	**0.42**	0.82	0.46
(0.24)	(0.12)	(0.19)	(0.11)	(0.15)	(0.15)	(0.13)	(0.17)	(0.26)	(0.04)	(0.03)

Note: See Table 1.

Table 5: Markov-Switching Model Explaining Quarterly Orders Growth

$$\Delta o_t = \alpha + \gamma_{o1}^{\psi_t}\Delta o_{t-1} + \gamma_{o2}^{\psi_t}\Delta o_{t-2} + u_t$$

1993Q1 to 2011Q2

α	$\gamma_{o1}^{\psi_t=1}$	$\gamma_{o2}^{\psi_t=1}$	$\sigma^{2\ \psi_t=1}$	$\gamma_{o1}^{\psi_t=2}$	$\gamma_{o2}^{\psi_t=2}$	$\sigma^{2\ \psi_t=2}$	p_{11}	p_{22}
1.19	**-0.15**	**0.22**	**4.23**	**1.46**	**-0.34**	**8.78**	0.85	0.56
(0.38)	(0.10)	(0.14)	(1.41)	(0.24)	(0.19)	(5.33)	(0.11)	(0.20)

Note: See Table 1.

Table 6: Regressions Using Cross Sectional Estimates $\widehat{\beta_{t-1}^{XS}}$

$$\Delta s_t = \alpha + \gamma_{s1}\Delta s_{t-1} + \gamma_{s2}\Delta s_{t-2} + \gamma_{o1}\Delta o_{t-1} + \gamma_{o2}\Delta o_{t-2} \ldots$$
$$+\beta\left(o_{t-1} - s_{t-1}\right) + \beta^c\widehat{\beta_{t-1}^{XS}} + \beta^{os}\widehat{\beta_{t-1}^{XS}}\left(o_{t-1} - s_{t-1}\right) + \beta^{o1}\widehat{\beta_{t-1}^{XS}}\Delta o_{t-1} + \beta^{o2}\widehat{\beta_{t-1}^{XS}}\Delta o_{t-2} + u_t$$

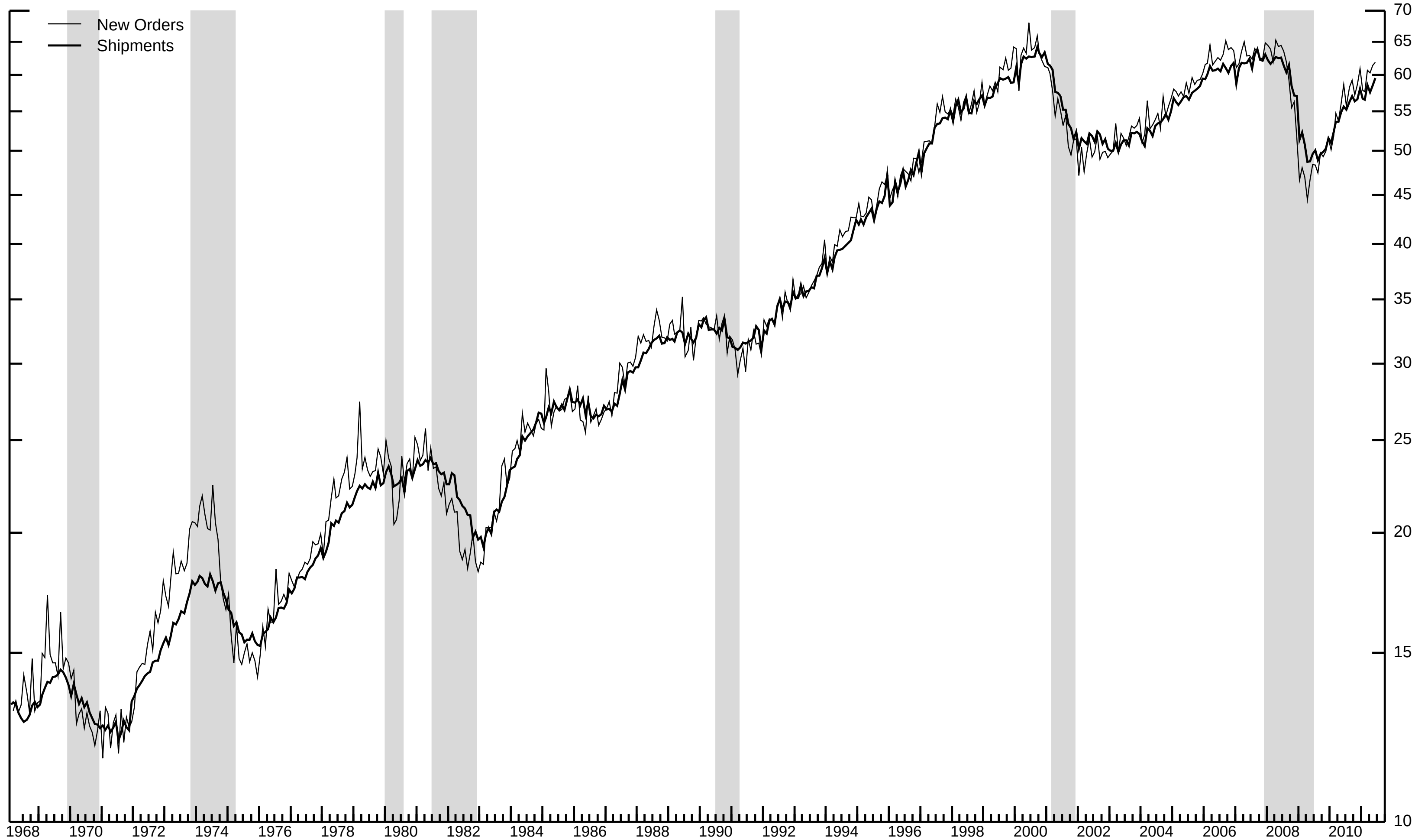
1993Q1 to 2011Q2

γ_1^s	γ_2^s	γ_1^o	γ_2^o	β	β^c	β^{os}	β^{o1}	β^{o2}	$\overline{R}^2$
0.01	**-0.25**	**0.38**	**0.38**	**-0.05**					0.40
(0.23)	(0.21)	(0.16)	(0.15)	(0.17)					
-0.01	**-0.24**	**0.33**	**0.35**	**0.00**	**-2.08**				0.42
(0.23)	(0.21)	(0.17)	(0.15)	(0.17)	(1.14)				
-0.00	**-0.17**	**0.33**	**0.31**	**-0.22**		**0.99**			0.45
(0.23)	(0.22)	(0.16)	(0.16)	(0.19)		(0.41)			
-0.03	**-0.13**	**0.24**	**0.25**	**-0.20**	**-3.12**	**1.30**			0.50
(0.23)	(0.24)	(0.17)	(0.18)	(0.19)	(1.26)	(0.47)			
0.01	**-0.23**	**0.15**	**0.15**	**0.00**	**-2.80**	**-0.39**	**0.46**	**1.11**	0.54
(0.23)	(0.27)	(0.20)	(0.20)	(0.20)	(1.35)	(0.89)	(0.54)	(0.49)	

Note: See Table 1. $\widehat{\beta_{t-1}^{XS}}$ represents the time-series of coefficient estimates on regressions of industry-level shipments growth on the industry-level error-correction term across 20 M3 industry categories.

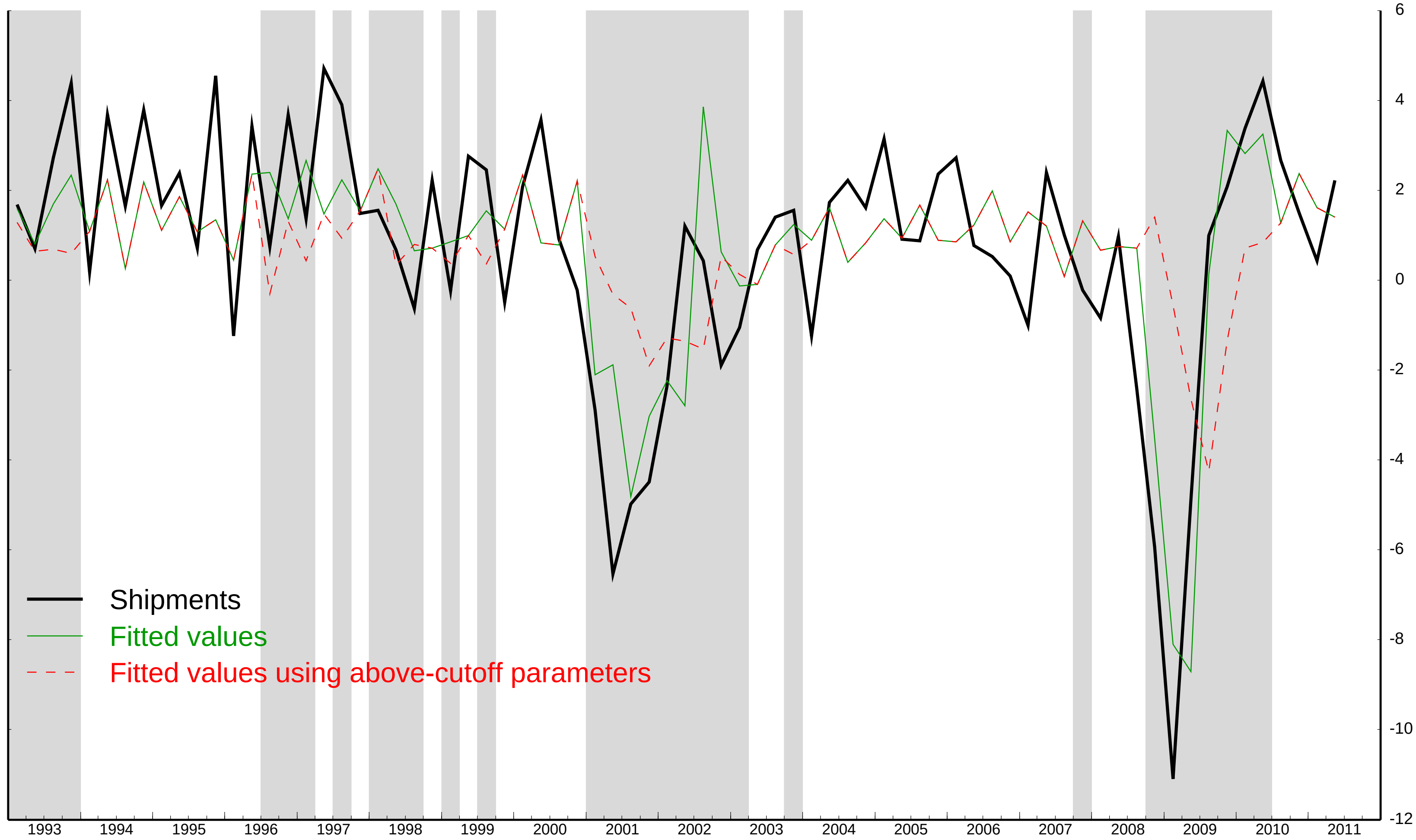
Figure 1: Real Orders and Shipments of Nondefense Capital Goods Excluding Aircraft

Billions of chained (2005) dollars; logarithmic scale



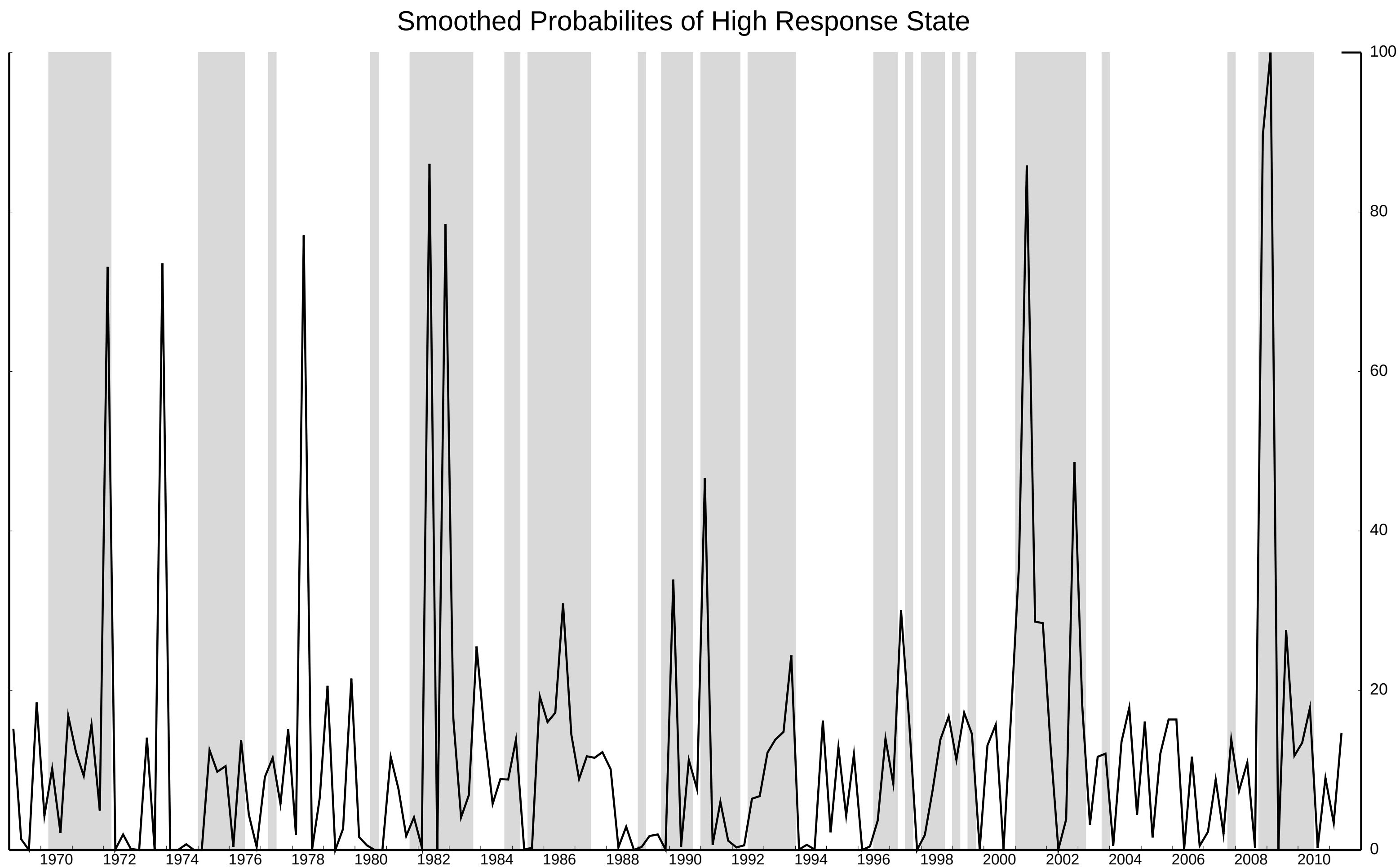
Note: Shaded bars indicate recessions as defined by the NBER.

Figure 2: Shipments Growth and Fitted Values from Threshold Cointegration Models



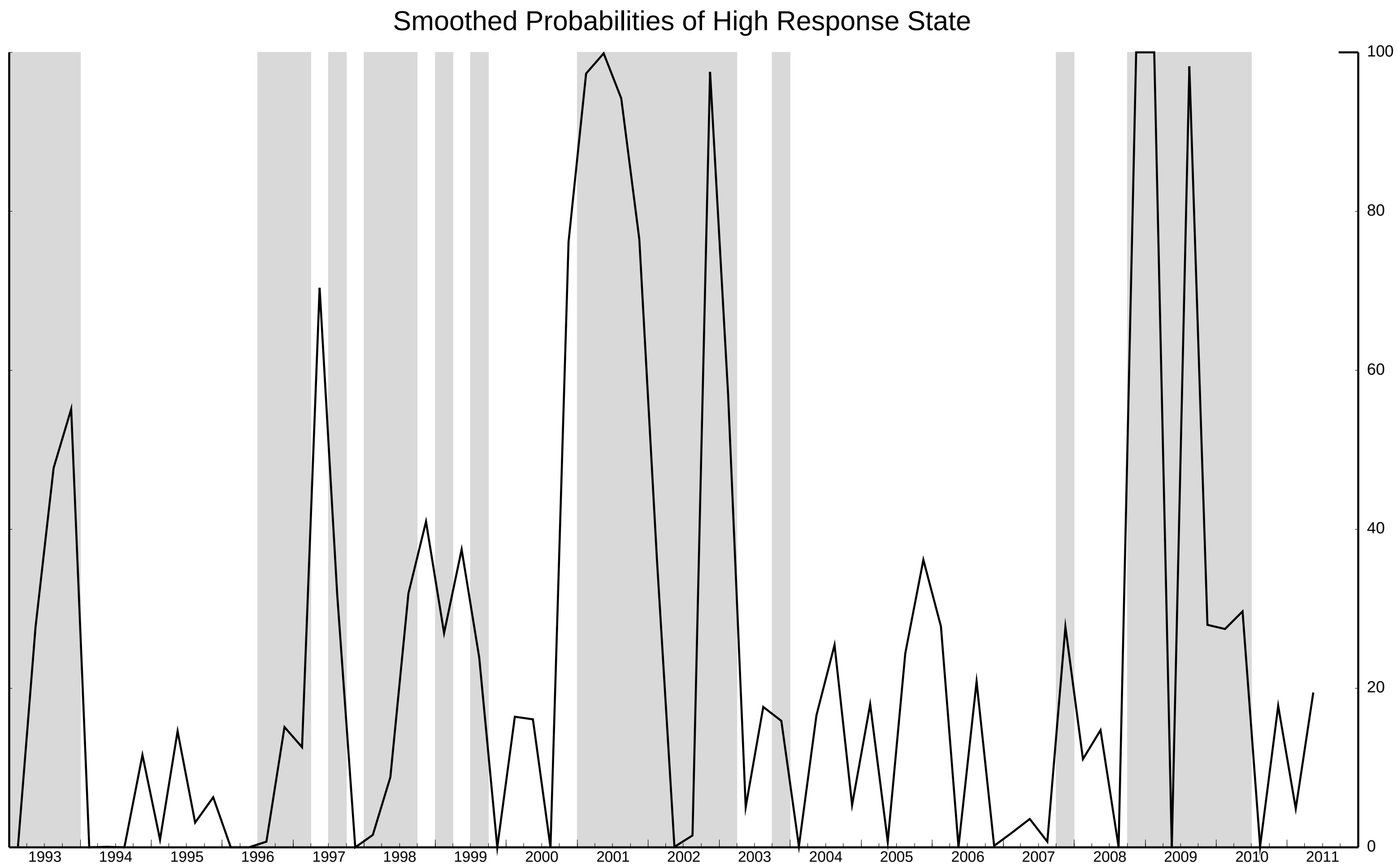
Note: Real shipments of nondefense capital goods excluding aircraft. Shaded bars indicate periods where the error correction term is below the threshold estimated in Table 2.

Figure 3: Markov Switching Models for Shipments



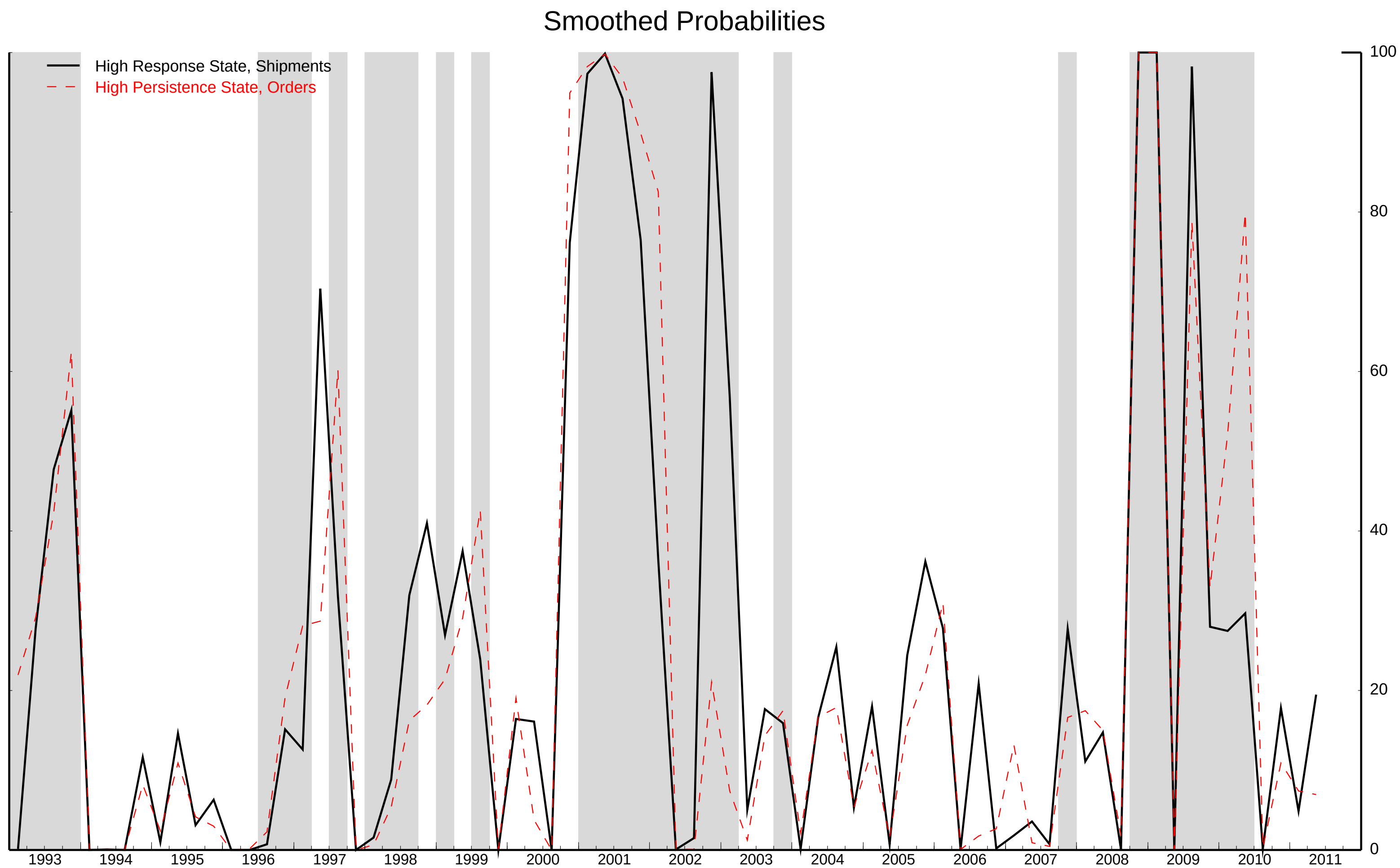
Note: Real shipments of nondefense capital goods excluding aircraft. Shaded bars indicate periods where the error correction term is below the threshold estimated in Table 2.

Figure 4: Markov Switching Model for Shipments



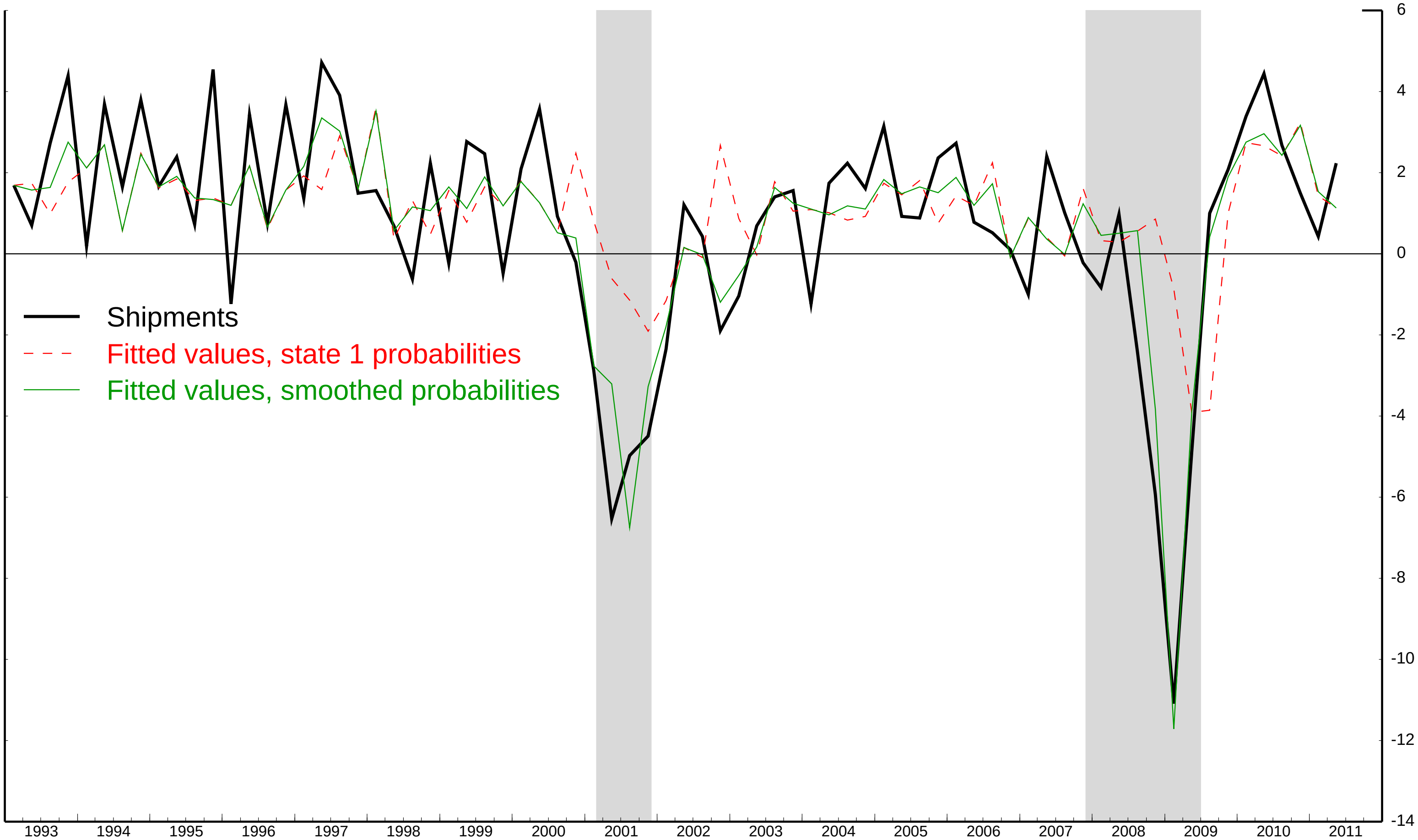
Note: Real shipments of nondefense capital goods excluding aircraft. Shaded bars indicate periods where the error correction term is below the threshold estimated in Table 2.

Figure 4a: Markov Switching Model



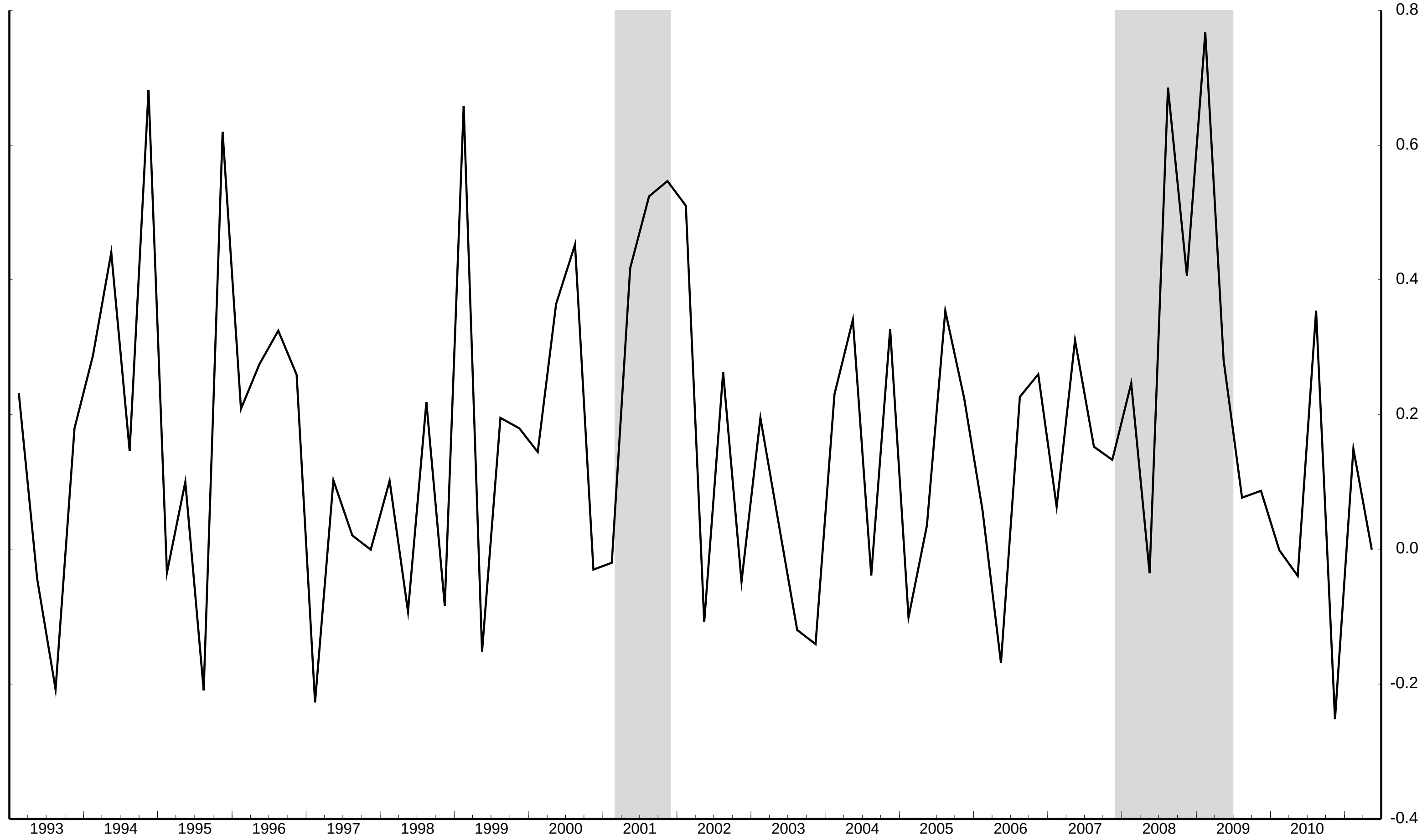
Note: Real orders and shipments of nondefense capital goods excluding aircraft. Shaded bars indicate periods where the error correction term is below the threshold estimated in Table 2.

Figure 5: Shipments Growth and Fitted Values from Markov Switching Models



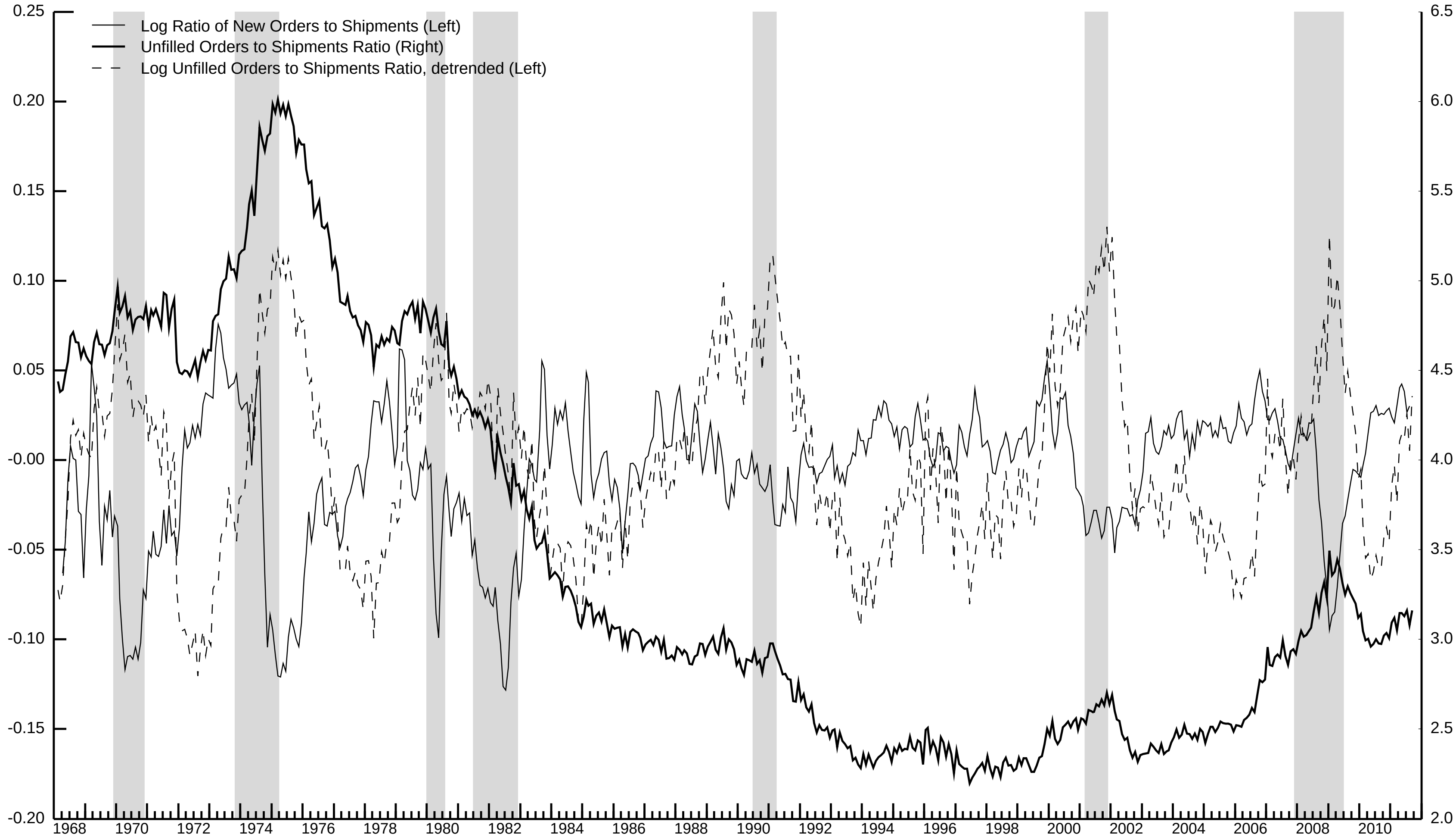
Note: Real shipments of nondefense capital goods excluding aircraft. Shaded bars indicate recessions as defined by the NBER.

Figure 6: Cross Sectional Betas,
Regressions of Quarterly Shipments Growth on Lagged
Log(Orders/Shipments)



Note: Time series of coefficient estimates on regressions of industry-level shipments growth on the industry-level error-correction term across 20 M3 industry categories. Shaded bars indicate recessions as defined by the NBER.

Figure 7: Orders, Shipments and Unfilled Orders to Shipments Ratio



Note: Real orders and shipments of nondefense capital goods excluding aircraft in chained (2005) dollars, using a price deflator for orders at each M3 category that reflects current and future prices of shipments. The log ratio of new orders to shipments is a centered 3 month moving average. The log unfilled orders to shipments ratio line is detrended using an eighth-degree polynomial time trend. Shaded bars indicate recessions as defined by the NBER.