Seasonality and the production-smoothing model

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Abstract

The debate over whether firms smooth production relative to demand continues. In this paper we find that results obtained in Blinder (Quarterly Journal of Economics 101 (3) (1986) 431–453) and Blinder and Maccini (Journal of Economic Surveys 5 (4) (1991) 293–328), indicating that firms do not smooth production, are greatly influenced by the seasonal adjustment of the Census data for US manufacturing. Using seasonally adjusted data, we find significant evidence of production smoothing in 10 of 14 manufacturing industries for the years 1982–1997. Further, the prevalence of production smoothing has increased over time, which we attribute either to fundamental changes in the collection of the data or to the advent of improved methods of inventory management. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

The main goal of the production-smoothing literature has been to discern the extent to which firms use inventories to smooth production levels in the face of fluctuating demand. Whether firms smooth or bunch production over time is not merely an academic question; it has broad implications for the business cycle, inventory demand and even seasonal and frictional unemployment.

Others have shown that seasonally unadjusted data are preferable to seasonally adjusted data when doing dynamic production studies [1–3]. Nevertheless, studies have typically used seasonally adjusted data to characterize dynamic firm behavior [4,5]. Through a direct comparison of seasonally adjusted and unadjusted Census data, we show that seasonally unadjusted data manifest the production-smoothing behavior of firms more accurately than seasonally adjusted data.

When measuring the extent of production smoothing, seasonally unadjusted data have two advantages. First, seasonal fluctuations comprise the largest source of the fluctuations in inventory, production and shipments series, so seasonal adjustment reduces the ability to estimate the extent of the production smoothing effect of inventories.

Second, seasonal fluctuations are regular, anticipated and short-lived, the type of fluctuation over which a firm is most likely to use inventories to smooth production. Business cycle fluctuations...
have a much more uncertain length and depth and produce inventory changes that cannot be sustained indefinitely; production adjustments follow and inventories fail to act as a buffer.

Our results show that the seasonal adjustment of data alters the perceived relationship between the production, shipments and finished goods inventory variables and produces misleading results in tests of production smoothing. We find that while seasonally adjusted data indicates production is more variable than shipments, indicating no production smoothing, seasonally unadjusted data shows that production is less variable than shipments in 10 of 14 manufacturing industries. We conclude that only seasonally unadjusted data should be used for studies of dynamic production behavior.

2. Literature review

Blinder [4] and Blinder and Maccini [6] find little evidence to support the production-smoothing hypothesis. Using monthly, seasonally adjusted data for durable and nondurable manufacturing from the Census Bureau, the two studies find the ratio of the variance of production to the variance of shipments falls between 1.03 and 1.20 for the two sectors and the covariance of shipments and change in inventories to be positive. For two-digit SIC industries, the ratio ranges from 0.93 to 1.38, with 17 out of 20 industries having a ratio greater than one. A ratio of the variances of production and shipments less than one strongly supports the production-smoothing hypothesis.

In light of the paucity of evidence supporting production smoothing, researchers responded by attempting to refute the very idea of production smoothing. Production smoothing may not exist, it has been suggested, due to the stochastic behavior of demand, concavity of costs and the existence of significant supply shocks in manufacturing.

Researchers have also tried to find new ways of testing the production-smoothing hypothesis, focusing on the properties of the data used to test the hypothesis. For instance, there might be a positive correlation between inventories and sales due to the behavior of demand shocks and the development of expectations. Blinder [4] suggests that if a motivation for inventories is to avoid unfilled orders, then desired inventories are a positive function of current and future expected sales. In adjustment to expectations, firms accumulate inventories even in the face of increased sales.

Ramey [7] argues that manufacturers face concave costs, owing to firms’ incentive to build excess capacity and hoard labor during low production periods. Further, Ramey suggests that concave costs of adjustment contribute to the explanation of production-bunching behavior. The problems of rebalancing assembly lines when changing output levels in capital-intensive production industries may lead to large shifts in output rather than gradual transitions from one level to the next.

Alternatively, cost shocks through time could cause firms to over-produce during low-cost periods and under-produce in high-cost periods. Blinder [4] and West [8] note that if cost shocks play a larger role in production decisions than demand shocks, then firms could optimally bunch production. Blinder [4] doubts that cost shocks dominate demand shocks in the macroeconomy, but combined with the serial correlation of demand shocks, the two effects could produce production bunching.


Ghali [3] shows seasonal adjustment affects production-smoothing results. His data from the Portland cement industry supports production smoothing only in data that are not seasonally adjusted; after seasonal adjustment, he obtains results similar to Blinder’s. Miron and Zeldes [2] also recognizes the importance of using seasonally unadjusted data and finds widely varying estimates
of production smoothing of seasonal and non-seasonal fluctuations for various two-digit SIC industries.

Ghali and Dimelis [11], using data for six highly disaggregated industries from 1950 to 1960, find significant evidence of production smoothing either using the variance bounds test or estimating a reduced form equation. They suggest that the failure of previous models to detect production smoothing is either due to the level of aggregation or the test used.

3. Data

We have monthly, seasonally adjusted and unadjusted data on production, inventory, shipments and new orders from 1959 to 1997 for 14 2-digit SIC industries in both durable and nondurable manufacturing. We also have the same aggregate data for durable, nondurable and total manufacturing. All but the production series comes from data files supplied by the Census Bureau; production numbers were created from the identity

\[ P_t = S_t + (F_t - F_{t-1}) \]

where \( P_t \) is the production in period \( t \), \( S_t \) the shipments in period \( t \), and \( F_t \) the inventory at the end of period \( t \).

Because of their intertemporal nature, inventories cannot be properly deflated by a simple index. We calculate real values by considering both current and lagged price levels, as well as the age composition of the goods held in inventory. To deflate nominal seasonally unadjusted data we calculated the implied deflator of the BEA for seasonally adjusted inventories from the ratio of nominal and real seasonally adjusted inventory numbers [2]. As in West [8], inventory numbers are converted from cost to market values by an industry-specific factor in order to adjust for the ratio of shipments to cost of goods sold.

Due to a change in inventory recording methods by the Census bureau in 1982, the inventory numbers from before and after that time are not consistent. Thus, we separate our data analysis into pre-1982 and post-1982 results, placing more weight on the latter simply because the revision in the data collection appears to have significantly improved the reliability of the data.\(^2\)

4. Seasonally adjusted vs. unadjusted data comparisons

Our first task is to demonstrate that seasonality is indeed important in the behavior of variables relevant to production smoothing. This is easily achieved by examining Table 1, taken from the 1998 Current Industrial Reports, M3-1 (95). Table 1 compiles data from Appendix E (M3-1 [95]) of the report, which details the monthly fluctuations in inventories and shipments, the variables that sum to production. It reports the maximum and minimum proportion of the monthly fluctuations attributable to seasonal factors for 14 2-digit SIC variables. It shows that seasonal fluctuations are almost always the major source of variance in every single variable we examine, sometimes causing as much as 98% of the total variability in inventory or shipments. Table 1 succinctly illustrates our point that using seasonally adjusted data when testing for production-smoothing behavior obscures the most important cause of demand fluctuations.

Figs. 1 and 2 also demonstrate the importance of seasonality as a source of fluctuations. Figs. 1 and 2 show the fluctuations in durable goods shipments and inventories for the 1990s for both seasonally adjusted and unadjusted data; both show that seasonally unadjusted data are much more volatile.

\(^2\)Until 1982, firms were asked to report their inventories at book values, according to whatever method they used for tax purposes (LIFO, FIFO, and so forth). Because of this, the value of aggregate inventories for an industry was not precise. Effective with the 1982 Census of Manufactures, instructions for reporting inventories changed. LIFO users were asked to report inventories prior to the LIFO adjustment, as well as the LIFO reserve and the LIFO value after adjustment for the reserve. (From the Manufacturers' Shipments, Inventories, and Orders (M3) Survey.)
Consistent with Blinder [4] and Blinder and Maccini [5], we measure the extent of production smoothing by examining the ratio of the variance of production to the variance of shipments for a firm or industry. Table 2 provides the variance ratios for 14 2-digit SIC manufacturing industries and for total, durable, and non-durable manufacturing, calculated for both seasonally adjusted and unadjusted data. This method is intuitively appealing: a ratio less than one indicates that output changes less than shipments and hence inventories are being used to smooth production.

Neither Blinder nor Blinder and Maccini find much evidence of production smoothing using seasonally adjusted data; Blinder estimated a variance ratio of 1.20 for DUR and 1.05 for NDUR; Blinder and Maccini obtained 1.03 for both sectors with a slightly larger data set. We find similar results for seasonally adjusted data regardless of the industry, aggregation, or time frame, with only 1 industry (primary metals) showing any evidence of production smoothing. Of course, as we argued before, there is no reason for there to be significant production smoothing outside of the seasonal demand fluctuations.

However, using seasonally unadjusted data, we find abundant evidence of production smoothing. Using the more reliable post-1982 data we find the variance ratios to be below 1 in 10 of the 14 industries, as well as in aggregate non-durable, durable, and total manufacturing. Correcting for the imprecise pre-1982 numbers and the seasonal adjustment, the data give the unmistakable impression that production smoothing occurs to some degree in most manufacturing industries. It is not surprising that Blinder did not detect evidence of production smoothing in his data; as we point out, seasonal fluctuations are the source of most of the variability in demand.

In general, seasonally unadjusted data and seasonally adjusted data provide significantly different answers to the question of production smoothing. We find strong support for the production-smoothing hypothesis using seasonally unadjusted data, particularly in post-1982 data.

5. Conclusion

This paper supports the production-smoothing hypothesis. While Blinder’s seminal work in the area fails to detect any evidence of production smoothing, merely using seasonally unadjusted data and updating the data set reverses his finding. Since we show that seasonal factors are the primary source of fluctuations in output, we argue that ignoring such factors by using seasonally adjusted data is inappropriate.

Our results complement Ghali [3] and Dimelis and Ghali [11], which find evidence of production smoothing for a small number of highly disaggregated industries in an earlier time period. Thus, our work suggests that production smoothing is a somewhat robust result that is solely dependent upon using seasonally unadjusted data.

The results have implications for any study of dynamics; seasonal fluctuations have significant and unique impacts on intertemporal behavior and should not be disregarded.
When there are short term, fairly predictable changes in output demand, as we find in seasonal cycles, it is only natural for firms to respond by using inventories as a buffer. For less predictable output demand fluctuations, firms may be less apt to respond with inventory, but may simply choose not to fill all orders.

A more highly disaggregated data set covering more industries might allow the researcher to discern the extent to which inventories and unfilled orders serve as buffers to output demand.

Table 2
Var(production)/Var(shipments) for seasonally adjusted (SA) and seasonally unadjusted (NSA) data 1958–1998

<table>
<thead>
<tr>
<th>Industry</th>
<th>Pre-1982</th>
<th>Post-1982</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SA</td>
<td>NSA</td>
</tr>
<tr>
<td>Total manufacturing</td>
<td>1.05</td>
<td>1.02</td>
</tr>
<tr>
<td>Nondurable manufacturing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rubber and plastics</td>
<td>1.34</td>
<td>1.08</td>
</tr>
<tr>
<td>Petroleum</td>
<td>1.38</td>
<td>1.40</td>
</tr>
<tr>
<td>Chemicals</td>
<td>1.39</td>
<td>0.82</td>
</tr>
<tr>
<td>Paper</td>
<td>1.37</td>
<td>1.01</td>
</tr>
<tr>
<td>Textile</td>
<td>1.40</td>
<td>1.10</td>
</tr>
<tr>
<td>Tobacco</td>
<td>4.10</td>
<td>14.93</td>
</tr>
<tr>
<td>Food</td>
<td>1.35</td>
<td>1.15</td>
</tr>
<tr>
<td>Durable manufacturing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instruments</td>
<td>2.43</td>
<td>1.08</td>
</tr>
<tr>
<td>Transportation equipment</td>
<td>1.04</td>
<td>0.93</td>
</tr>
<tr>
<td>Electronics</td>
<td>1.55</td>
<td>1.14</td>
</tr>
<tr>
<td>Industrial and mach. equip.</td>
<td>1.43</td>
<td>1.11</td>
</tr>
<tr>
<td>Fabricated metals</td>
<td>1.57</td>
<td>1.21</td>
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<tr>
<td>Primary metals</td>
<td>0.83</td>
<td>0.90</td>
</tr>
<tr>
<td>Stone, clay and glass</td>
<td>1.52</td>
<td>0.84</td>
</tr>
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References


