Beyond Inventory Management: The Bullwhip Effect and the Great Moderation

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Abstract

We resurrect the question of whether improved business practices contributed to increased macroeconomic stability since the 1980s (the so-called Great Moderation). While previous studies on the issue are limited to examining inventory management, we analyse the role of better supply chain management on enhancing firms' ability to coordinate their production. By investigating ordering and backordering behaviour in the durables manufacturing sector, we find that the improved business practices have significantly dampened order volatility to the sector (the 'bullwhip effect'), by around 40-50%. Using the stylised fact that the durables manufacturing sector is responsible for half of the overall Great Moderation, we determine that the contribution of better business practices is quantitatively significant, at 20-25% of the overall Great Moderation.

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1. Introduction

Despite the Great Recession, understanding the causes of the period of prolonged macroeconomic stability that preceded it (known as the Great Moderation) remain important. This is because if that period was driven mostly by good luck, as suggested in Stock and Watson (2003), Ahmed, Levin, and Wilson (2004), Kim, Nelson, and Piger (2004) and Herrera and Pesavento (2005), then there is no reason to expect such stability to resume. Studies that estimate the changes in the reaction function of the Federal Reserve like Clarida, Galí, and Gertler (2000), Cogley and Sargent (2001), Orphanides (2004) and Boivin and Giannoni (2006) are proponents that better monetary policy was a main driver. Stability induced by better monetary policy is more likely to be continued.

New business practices, often taken to mean better inventory management techniques, is a third suggested cause for the Great Moderation and are also likely to be a more persistant driver of lower volatility. McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Kahn, McConnell, and Perez-Quiros (2002) suggested there was a substantial role for inventory management. However others, such as Stock and Watson (2003), consider the role for inventory management and dismiss it. McCarthy and Zakrajšek (2007) using a VAR analysis of the Great Moderation concluded that inventory management played, at most, a supporting role. The reason earlier papers tend to dismiss a role for new business practices is related to the focus on inventories and is summed up nicely by Taylor (2013):

> *"Firms cut inventories when sales weaken and rebuild inventories when sales strengthen. Better inventory control could thus explain the improved stability. But this explanation also had problems. When one looked at final sales – GDP less inventories – one saw the same amount of improvement in economic stability."*

Our main contribution in this paper is to extend the concept of business practices to include supply chain management and backordering behaviour in addition to inventory management. Importantly, we will argue that changes in business practices can endogenously dampen sales volatility. As such, the reduction in sales volatility is not sufficient to reject a central role for new business practices. Davis and Kahn (2008) considered the potential contribution of supply chain management in the Great Moderation, but leaves how it connects with sales volatility as an open question.

We focus on the durables manufacturing sector. We do this for a number of reasons. First, despite accounting for only about 20% of GDP, durables production is one of the biggest contributors to output volatility.[1] Second, it is also one of the biggest contributors to output moderation as a result of a large fall in within-sector volatility (Stock and Watson, 2003); a back-of-the-envelope calculation from the results in Stock and Watson (2003) suggests that it accounts for around half of the overall Great Moderation (see Table 7 in the appendix). Third, McConnell and Perez-Quiros (2000) and Davis and Kahn (2008) show the timing of durables output volatility falls, impeccably matches the observed break in GDP volatility. Finally, manufacturing industries are placed upstream of the supply chain, and therefore, has the most to benefit from the new business practices; for example, backorder books are sizeable in durables manufacturing.

We make two specific empirical contributions. First, motivated by the finding of Zarnowitz (1962) that firms respond to demand shocks by accumulation/depletion of backorders first (changing lead times), we document how the Great Moderation was not just a period of lower inventory investment volatility but can also be characterised by quicker delivery, shorter lead times and reduced use of backordering in the durable goods manufacturing sector. To explore what these developments mean for the analysis of the effects of new business practices, rather than focus on the production identity that states production (Y) is equal to the sum of sales (S) and inventory investment (ΔI), we further disaggregate sales into its components

[1] About 2-2.5 times more volatile than non-durables, and 6-10 times more than services (Table 7 in Stock and Watson (2003)).

of new orders O and adjustments to backorders ΔU:

$$\begin{aligned} Y &= \quad S \quad &+\Delta I \\ &= (O - \Delta U) &+\Delta I. \end{aligned} \tag{1}$$

We find that reduced volatility of new orders accounts for the majority of sales and production volatility falls. Given that the previous literature claims that the decline in sales volatility is most likely driven by background macro factors (good luck or good policy), a similar argument would likely be adopted to explain declining new order volatility. They would consider this as similar evidence that we need to look at alternative explanations to new business practices. However, given that most orders in the manufacturing sector are placed by intermediate goods producers, rather than consumers, supply chain management can be an important determinant of order volatility. We argue that improved business practices can endogenously dampen order volatility; upstream suppliers meeting new orders consistently more quickly can give rise to a reduction in the volatility of sales. This is unlike the analysis in standard macroeconomic models of inventories.

The second empirical contribution is to show that improved business practices contributed substantially more to the Great Moderation than previously thought. While still not the dominant contributor, this channel can account for 20-25% of the output volatility declines. This finding comes from our application of the empirical approach of McCarthy and Zakrajšek (2007) (MZ hereafter) to our broader concept of business practices in the durabless manufacturing sector. We estimate a separate structural VAR for the pre-1979 (High Volatility, HV) and post-1984 (Low Volatility, LV) period. Using forecast standard errors as a measure of volatility, we ask the question if volatility reductions emanate from luck and macroeconomic changes, better business practices (identified as sector-level structural changes), or a combination of both.

Counterfactuals between the two SVARs suggest that sector-level structural changes have contributed to approximately half of the fall of new orders volatility. We interpret this as the result of a dampening of the *'bullwhip effect'* (Lee, Padmanabhan, and Whang, 2004)– the well-documented phenomenon where demand shocks from downstream consumers are amplified through the supply chain to upstream producers. New business practices, such as the adoption of Electronic Data Interchange ICT systems which led to better communication along supply chains, would diminish the amplification of new orders volatility and stabilise production.

We also find evidence of changes in backordering behaviour. The successful adoption of lean production and just-in-time techniques reduces the need for backorders to smooth out demand shocks and, as a consequence, delivery times would lower and more consistent. Finally, we find that implied inventory volatility (as a proportion of inventory stocks) in the durables sector actually increases.[2] This is suggestive of the adoption of flexible production processes (as predicted by most macroeconomic models of inventories and production flexibility such as Alessandria, Kaboski, and Midrigan (2013) and McMahon (2012).

The rest of the paper is organised as follows. Section 2 describes the data used and establishes some motivating stylised facts. Section 3 details the bullwhip effect that the empirical evidence we present in this paper supports. Section 4 introduces the structural vector autoregression, and the counterfactual methodology. Section 5 analyses the results and implications for the role of business practices on the Great Moderation. Section 6 concludes.

2. New Business Practices: Technologies and Stylised Facts

Anyone reading the management and operations research literature will be left in no doubt that business practices have evolved a great deal since the 1960s. New technologies allow firms much greater control over their production, sales and distribution processes. In this section we first review the broad types of technological improvements that many practicitioners consider as driving forces for improved

[2]The MZ result that inventory volatility has fallen holds in the non-durables manufacturing SVAR (reported in the appendix). This indicates that particular result was driven by the much larger non-durables sector.

management of inventories and distribution. We then examine developments in the durables manufacturing sector to see how production and distribution, back-ordering, and inventories (disaggregated into stages of production – materials and supplies, work-in-process and finished goods inventories) evolved before and during the Great Moderation.

Our analysis uses industry-level monthly data is from the United States Census Bureau. The historic time series for *Manufacturers Shipments, Inventories & Orders* covers January 1967 to December 1996. All variables are in current dollars (by net selling values) and seasonally adjusted. To deflate the variables, we use the implicit sales price deflators from the Bureau of Economic Analysis.[3]

2.1. *Back-ordering and the Bullwhip Effect*

Before we turn to an analysis of the new technologies that have affected (in particular) the manufacturing sector, we describe two important related characteristics of manufacturing supply chains. We believe that these characteristics are key to understanding the Great Moderation but are generally under-researched areas of macroeconomics.

The first concept is backordering. Zarnowitz (1962) documented that firms respond to demand shocks by accumulation/depletion of backorders first (changing lead times), then adjusting inventories, and eventually changing production and/or prices. The role of backorders is particularly relevant in durables manufacturing where backorder books are sizeable and backorder adjustments account for substantial variance of production and sales growth.

The second concept is the bullwhip effect. This supply-chain phenomenon, dating back to Forrester (1961), is well-documented in the management science literature. It captures the situation whereby demand shocks from downstream consumers are amplified through the supply chain to upstream producers. Lee,

[3]Deflating the nominal variables using these price deflators makes the implicit assumption that the intra-sector composition of inventory investment, backorders and new orders are the same as sales.

Padmanabhan, and Whang (2004) group the causes into four categories: demand signal processing, shortages and rationing gaming, order batching, and price variations. Let us look in more detail at how each of these causes to see how they give rise to extra volatility in the manufacturing sector (and to make clear how some are directly related to the use of backordering).

Firstly, demand signal processing results from the need of producers to forecast future demand by using their immediate customer's orders. If there are lead-times in production and delivery of raw materials, positive autocorrelation of demand, and each member of the supply chain processes the order signals from below, shocks are amplified as they go upwards through the supply chain.

Secondly, shortages are a period of more extensive use of backordering. This contributes to the bullwhip effect when customers attempt to manipulate their supplier's rationing. If the producer fulfils orders of a good that is short in supply on the basis of order size in proportion to total orders, customers will place extra 'phantom orders' in order to get more of the good. When the supply shortage eventually clears, they cancel their phantom orders and, thus, the producer sees amplified fluctuations in their order book.

Thirdly, order batching by downstream firms creates volatility of order inflows for the manufacturing. This occurs when a firm's own demand comes in, depleting inventory, but they may not place an order immediately with its supplier. This may be due to the fact that material requirement planning (MRP) systems are run only monthly, or due to firms attempting to get economies of scale from delivery and order processing costs (including management time to process the order).

Finally, price variations may lead a customer to attempt to build inventory (high orders) during times of low prices, and the opposite when prices are high. This leads to large, irregular orders. Such periods of low nad high prices may follow from over-reactive production which results in periods of large excess supply and periods of severely limited supply. This means price variation is both a result of, and contributor to, the bullwhip phenomenon.

Improvements of supply chain management are based on the introduction of ICT-based systems and lean production. To understand why these might have a stabilising effect on the production of durables, we now discuss some of the main developments and link them to our two important channels. We stress three broad developments (which are also related):

1. *Electronic Data Interchanges (EDIs)*
2. *Vendor Management Inventory (VMI)*
3. *Just-in-Time Production (JIT)*

The adoption of ICT systems by manufacturers, and all along the supply chain, allowed for widespread use of EDI. That is, computers from one firm in the supply chain could send information to another firm in a standardized format and with little need for human intervention. This has led to better communication, and vitally better information, along supply chains.

VMI makes the (upstream) manufacturer responsible for maintaining appropriate inventory levels at downstream links in the supply chain (such as a wholesaler). The downstream firm agrees to provide detailed and timely information on sales and inventory levels. The manufacturer can then optimally fulfill orders across each of the (potentially many) downstream firms.

JIT, or lean manufacturing, is an approach to manufacturing which originated in Japan and is associated with Toyota. It made its way to the West in 1977. It involves reduced waste and shorter lead times in production which in turn facilitates greater flexibility in the manufacturing. A simplistic view of flexible manufacturing is that it leads to more volatile production. However, flexibility to meet demands in a more responsive fashion (for example by changing production from focusd on one product to focused on another) may actually give rise to greater stability. As we will argue, reduced and more consistent lead times by the manufacturer may endogenously change ordering behaviour by downstream firms.

These three new business practices are inter-related. For example, while VMI was an impetus for widespread adoption of EDI (in exchange for information the downstream firm no longer had to manage the inventory), it is also the case that VMI could only work because of EDI. Causality similarly runs both ways when we consider JIT and EDI, or JIT and VMI; VMI/EDI led to faster delivery response times, and computerised flow production allowed firms to more easily adjust production.

2.3. *The Evolution of Durables Manufacturing: Some Stylized Facts*

Regardless of the extent to which these new practices caused each other, it should be clear that they, at least potentially, could give rise to profound effects on the use of backordering and the bullwhip effect. In this subsection, we establish some stylized facts on the evolution of key variables in the durables manufacturing sector over time and particularly in the Great Moderation. These facts can shed light on the aforementioned channels by demonstrating the effects of the adoption of improved supply chain management techniques and flexible production processes. These stylised facts can be grouped into the following:

1. *Reductions in production materials lead times*
2. *Reductions in lead time volatility*
3. *Reductions in backorders-sales ratios*
4. *Reductions in inventories-sales ratios*

Since firms respond faster by adjusting production, delivery times became lower and more consistent. Figure 1 shows that there have been large falls in production materials delivery lead times. There was a sharp reduction in lead times between pre-1980 and post-1984 (mean of 72 and 49 days, respectively). These declines began in the early-1980s and coincide with a rapid increase in firms achieving JIT ordering; Figure 2 shows that the proportion of manufacturing firms with JIT ordering (defined as receiving orders in less than five days) more than tripled from before the 1980s to the Great Moderation period.

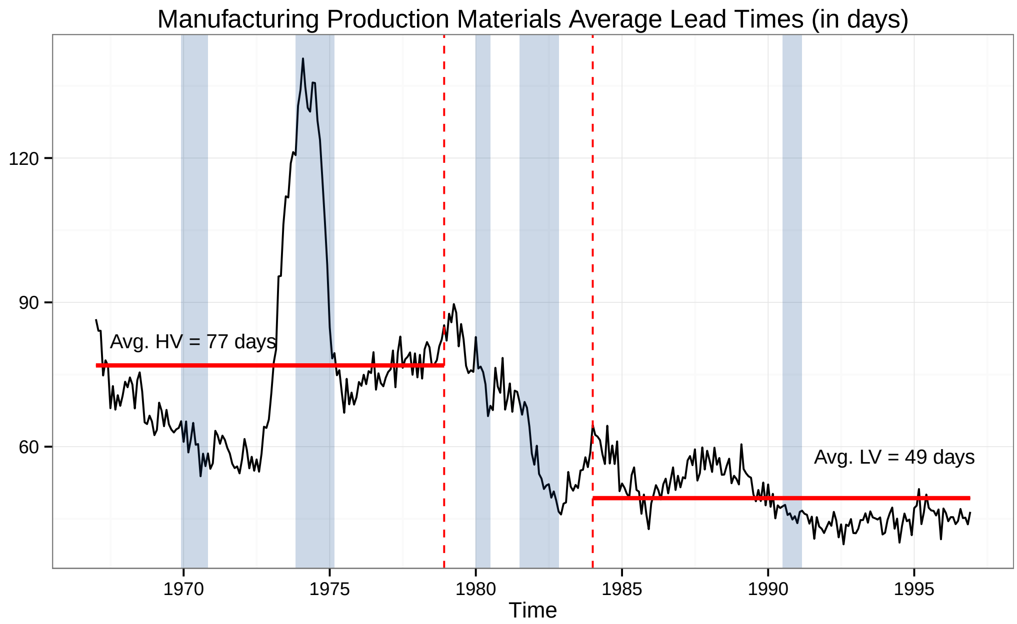

Figure 1: Average Manufacturing Production Materials Lead Times

Notes: Insitute for Supply Management data. Shaded areas are NBER-dated recessions.

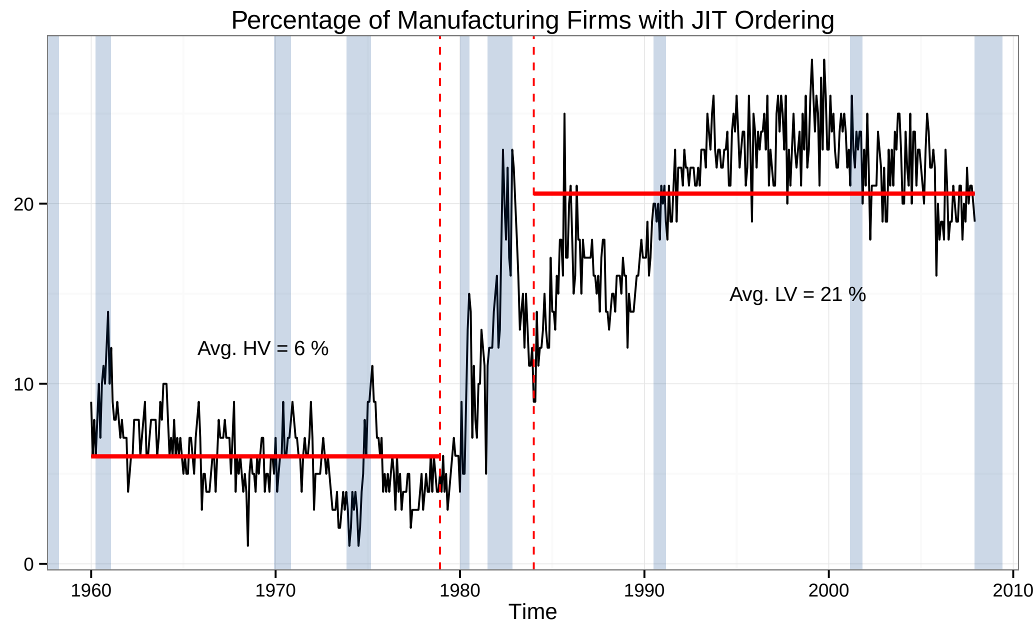

Figure 2: Percentage of Manufacturing Firms with Just-in-Time ordering

Notes: JIT defined as receiving orders in less than five days. Shaded areas are NBER-dated recessions.

As we will argue below, it is not only the first moment that affects ordering behaviour, but also the variance of lead times. This relates to the reduction in the backorder adjustment margin and consistency of delivery times. As a proxy for leadtime disruptions, we calculate rolling volatilities of the Institute for Supply Management's Manufacturing Supplier Deliveries Index.[4] We use this index, rather than raw delivery times, as it is calculated like the Purchasing Managers' Index – it emphasises *changes* to delivery times, which is the crucial factor in determining disruptions to production scheduling. Figure 3 shows a sharp decline in volatility from the early 1980s. Increased delivery consistency allows manufacturers to improve production scheduling, and implement just-in-time practices to respond to demand shocks faster.

[4]The volatilities are calculated by the Q_n estimator of scale.

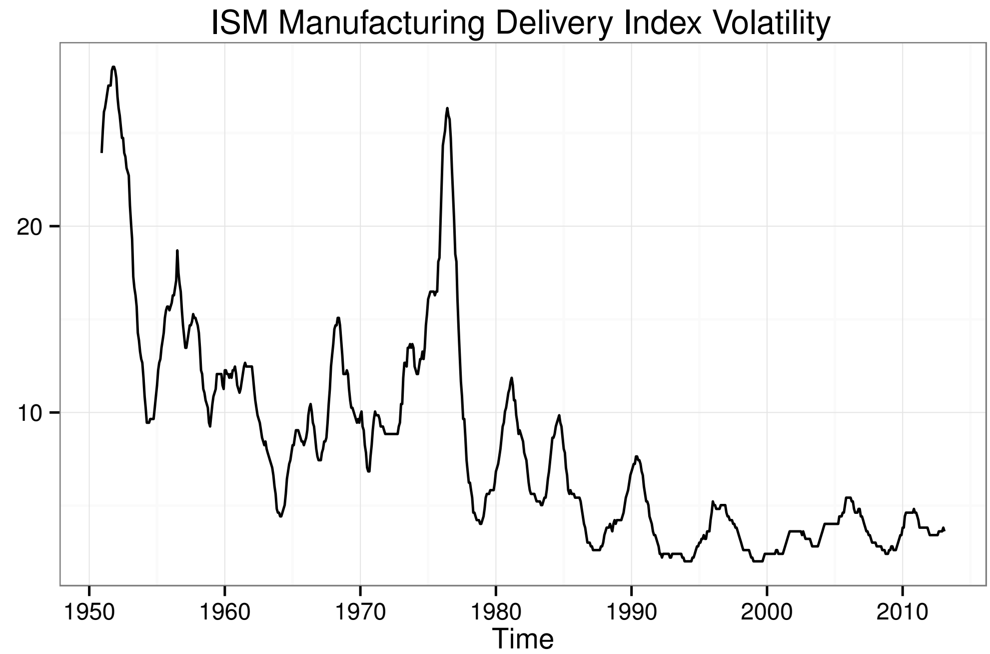

Figure 3: Volatility of ISM Manufacturing Deliveries Index.

Notes: Authors' own calculations. Calculated as the 36-month Backward-Looking rolling standard deviation of the ISM Manufacturing Deliveries Index.

JIT allows producers to respond faster to demand fluctuations and so allows firms to reduce backorder books. There is also less need to use backordering because, through VMI, the manufacturer can essentially reduce desired inventory across downstream firms while they adjust production smoothly. We see there is a large fall in durables sector backorders (relative to sales) in the early 1980s (figure 4).[5] However, this decline occurred only gradually and is not as stark as the previous stylized facts. This might be expected given it is a stock variable and so may take somewhat longer to adjust. It is worth noting that while the backorder-book size has declined, the higher frequency volatility remains relatively high. This is important as it is the change in backorder books, and not the size of them, that affects production volatility.

[5]We exclude the Transportation sector due to its special characteristic of extremely long lead times, which would not be informative on the state of supply chain management. The total durables manufacturing and disaggregated data is available in the appendices.

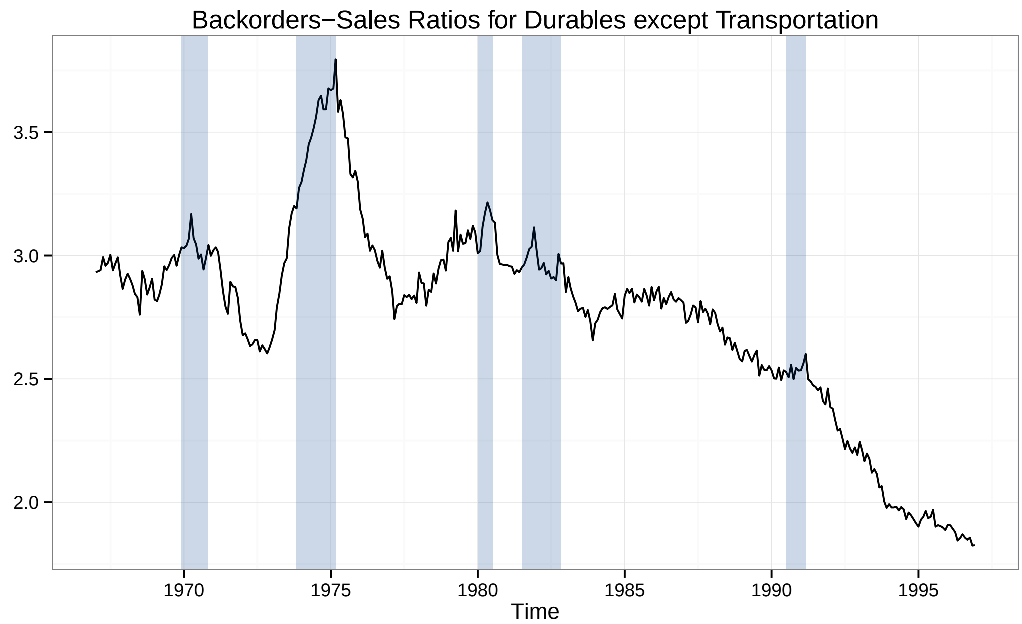

Figure 4: Backorders to Shipments Ratio (excluding Transportation sector)

Notes: We exclude the Transportation sector due to its special characteristic of extremely long lead times, which would not be informative on the state of supply chain management. Shaded areas are NBER-dated recessions.

Finally we turn to the evolution of inventories – the focus of most of the previous literature. Inventories-sales ratios for the durables sector have also fallen since the early 1980s (figure 5). This was driven mostly by materials and supplies inventories first in the late 1970s (and to a lesser extent, final goods inventories). It was only in the 1990s that holdings of work-in-progress inventories fell strongly. This suggests steady improvements in inventory control but perhaps not as starkly occurring at the time associated with the start of the Great Moderation.

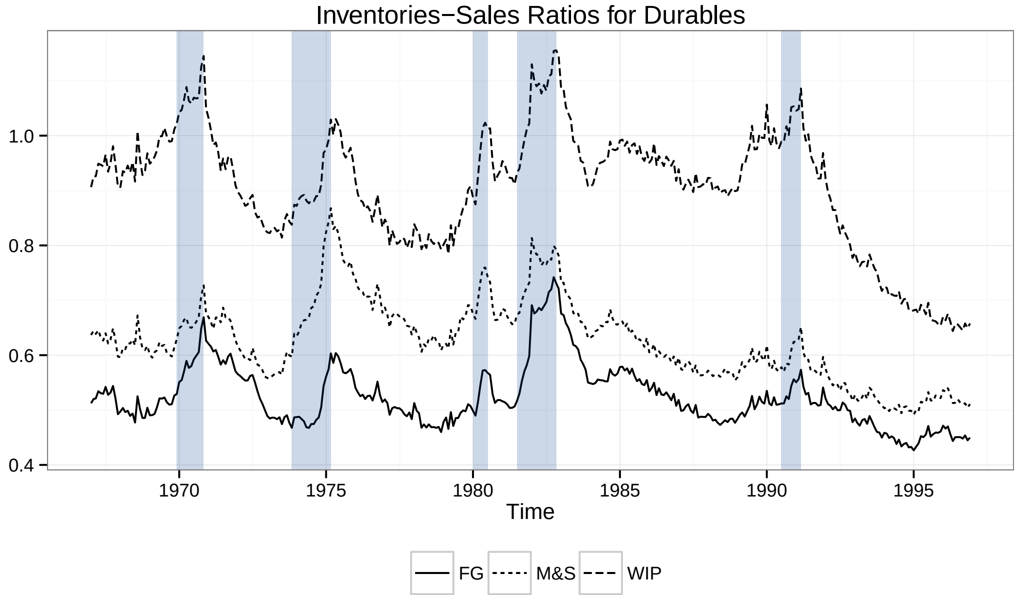

Figure 5: Inventories to Shipments Ratio

Notes: We exclude the Transportation sector due to its special characteristic of extremely long lead times, which would not be informative on the state of supply chain management. Shaded areas are NBER-dated recessions.

3. Analysis of Volatility: Role of New Business Practices

The previous section presents evidence of the effects of new business practices in durables manufacturing. Importantly given the exisiting literature, the evidence pointed to effects outside of simply changes in how inventories are managed. We also suggest that these changes should affect volatility. We therefore now turn our attention to the behaviour of volatility in the durables manufacturing industry.

We will focus on the comparison of two twelve-year periods to try to capture the 'steady state' volatility in each period. The first period covers January 1967 to December 1978 and we call it the High Volatility (HV) period (as MZ do). The second is the Low Volatility (LV) period covering January 1984 to December 1996.[6] This split follows MZ and allows for a transition period from 1979 to 1983 during which the exceptional volatility of the Volcker disinflation and extensive

[6]We stop in December 1996 to ensure comparable data across the HV and LV periods.

manufacturing restructuring may contaminate the results. (Some of the figures we presented of inventories and backorder behaviour clearly show that this interval was indeed a transition period.)

3.1. *Volatility Decomposition*

In this subsection we document a volatility decomposition of durable manufacturing production volatility. We use (1) applied to quarterly growth rates (meaning that the RHS terms are quarterly growth contributions) and then examine the following volatility decomposition (where V(x) denotes the variance of x and Cov(x,z) denotes the covariance of x and z):

$$V(Y) = (V(O) + V(\Delta U) - 2Cov(O, \Delta U)) + V(\Delta I) + 2Cov(S, \Delta I). \tag{2}$$

In table 1 we present this decomposition in the form of standard deviations for the HV and LV periods. The advantage of using standard deviations is that it allows us to express everything in terms of five core drivng parameters:

1. $\sigma_{\Delta I} \equiv \sqrt{V(\Delta I)}$ is the standard deviation of the change in inventories
2. $\sigma_O \equiv \sqrt{V(O)}$ is the standard deviation of new orders
3. $\sigma_{\Delta U} \equiv \sqrt{V(\Delta U)}$ is the standard deviation of the change in backorders
4. $\rho_{S,\Delta I}$ is the correlation coefficient between S and ΔI
5. $\rho_{O,\Delta U}$ is the correlation coefficient between O and ΔU

The other terms of equation (2) can be expressed as functions of these five parameters. For example, $Cov(O, \Delta U) = \rho_{O,\Delta U}(\sigma_O)(\sigma_{\Delta U})$ and $V(S) = (\sigma_O^2 + \sigma_{\Delta U}^2 - 2\rho_{O,\Delta U}(\sigma_O)(\sigma_{\Delta U})$.

Table 1: Volatility decomposition of durable manufacturing production

		HV	LV	$\frac{X^{HV}-X^{LV}}{X^{HV}}$
Core Parameters	$\sigma_{\Delta I}$	1.1	1.0	-9%
	σ_O	5.6	3.9	-30%
	$\sigma_{\Delta U}$	3.6	3.1	-14%
	$\rho_{S,\Delta I}$	0.04	0.12	+200%
	$\rho_{O,\Delta U}$	0.77	0.79	+3%
Resulting Volatility	σ_Y	3.8	2.7	-29%
	σ_S	3.6	2.4	-33%

Notes: Quarterly growth contributions in percentage points. High volatility period (HV) covers 1967:1-1978:12; Low volatility (LV) period covers 1984:1-1996:12. Identity used is $Y = S + \Delta I = (O - \Delta U) + \Delta I$.

This decomposition reveals that the three core standard deviation terms all declined between the periods. In particular, the standard deviation of new order quarterly growth contributions fell by 30% after 1984. The volatility of inventory investment fell 9% but the correlation between sales and inventory investment actually increased markedly. The correlation between new orders and backordering was broadly stable. The standard deviation of changes in backorder books declind 14%. Taken together, these changes give rise to a 33% fall in sales volatility and a 29% decline in the volatility of production growth.

Unlike the findings in McConnell and Perez-Quiros (2000) for the aggregate economy, there is little evidence that changes in inventory investment volatility, nor the cyclicality (correlation) of inventory investment, contribute to the stabilisation of durable manufacturing. Almost all stability arises from the fall in sales volatility and particularly new order volatility declines.

To be more precise, we perform a counterfactual exercise asking how much would production volatility have declined if *only* $\sigma_{\Delta I}$ fell to its LV level (with other parameters remaining at HV levels). Using the decomposition in table 1, this is an easy exercise:

$$V(Y)^{Alt} = (\sigma_O^{HV})^2 + (\sigma_{\Delta U}^{HV})^2 - 2\rho_{O,\Delta U}^{HV}(\sigma_O^{HV})(\sigma_{\Delta U}^{HV}) + \sigma_{\Delta I}^{LV} + 2\rho_{S,\Delta I}^{HV}(\sigma_S^{HV})(\sigma_{\Delta I}^{LV}) \quad (3)$$

We then repeat the exercise changing the appropriate parameters to ascertain what would have happened to production volatility if only σ_O or $\sigma_{\Delta U}$ changed.

If only the inventory investment term, changed production volatility would have declined a very small amount. In fact, the decline makes up less than 3% of the actual decline in volatility that took place. By changing new orders volatility, the implied production volatility makes up around 90% of the actual decline we observe. In contrast, changing backorders volatility actually increases volatility slightly. This is because the fall in backorder variance does not compensate enough for the less-negative covariance term.

3.2. *The Role of New Technologies in Reduced Order Volatility*

Although only an illustrative decomposition, this analysis essentially produces the same result that led earlier studies to conclude that changes in inventory management practices did not drive the volatility reduction associated with the Great Moderation. We agree with the previous literature that to explain the fall in production volatility, one has to explain the moderation of sales volatilty. In fact, we push this finding further and show that it is really new orders volatility that needs to be explained. However, we do not conclude that this analysis rules out a role for new business practices.

Given the types of new business practices we have discussed, we need to think more carefully about where would expect changes in the decompostion table. For example, while we saw that backorder books have declined in size, it is the volatility of quarterly growth contribution that matters most for the decomposition exercise. The effects of less backordering may actually show up as reduced volatility of new orders; with less backordering, there is less use of phantom orders which reduces volatility in orders and would mute the bullwhip effect.

In a similar vein, by allowing upstream producers access to downstream demand data, EDI should alleviate demand signal processing difficulties and contribute to less amplification of volatility up the supply chain. The better information means that manufacturers are less likely to be surprised by changes in orders, or can better identify purely transitory movements in downstream demand. JIT allows producers to respond faster to demand fluctuations and therefore intermediate goods producers know they will receive extra orders speedily if they themselves experience a demand shock. In response to shorter and more consistent delivery times, intermediate goods producers stop making large, irregular orders when lead times are low (previously necessary to build up materials inventories and avoid costly materials stockouts).

We believe that new business practices can endogenously change the volatility orders; other researchers have interpreted orders or sales as exogenous processes (to new business practices). Our interpretation leaves open a clearer role for new business practices, and in particular the dimensions of supply chain management discussed above.

Such endogenous demand processes are not standard in typical models of business cycles and inventories. For example in the RBC model of Alessandria, Kaboski, and Midrigan (2013), retailers buy an input subject to both idiosyncratic demand uncertainty and re-order uncertainty. A new business practice that reduces the inventory-sales ratio 15% (a figure from Khan and Thomas (2007)) would increase output volatility slightly. Similarly, in McMahon (2012), more flexible distribution technology leads to greater (not lesser) volatility of production for given other exogenous processes.

However, in the operations research literature such endogeneity is more common. In fact, in that literature the dependence of new order volatility on backordering behaviour and lead times variability is well-established. For example, Song and Zipkin (1996) shows that consistent lead times on a firms own orders affects inventory and ordering behaviour. Song, Zhang, Hou, and Wang (2010) show that in response to stochastically shorter lead times, customers will optimally reduce the amount of safety inventory that they hold and reduce the size of orders. The response to less-variable lead times is, however, ambiguous.

Of course, the overall effect of new business practices is an empirical question. Our decomposition, while interesting, does not allow us to conclude that there was or was not a crucial role for new business practices. However it does convince us that any role should manifest itself through reduced new orders volatility onto increased stability of durable goods production. Of course, nothing precludes the macroeconomic factors from driving these changes; reduced downstream aggregate demand volatility as a result of good luck or good policy could also lead to lower upstream order volatility. We have merely argued that new business practices may be an adequate explanation.

We now want to push our analysis further, and especially to establish more clearly the direction of causality. To disentangle between the three effects and establish causality, we now adopt a multivariate approach. This VAR analysis will allow us, subject to our identification scheme, to formalise the links between aggregate and the sector-level variables.

4. Separating Out Business Practices and Macro Effects

This section explores new order, inventory and backorder dynamics in the durables manufacturing sector, within a structural VAR framework. Building on the methodology of MZ, we examine possible structural changes in the economy by estimating separate SVAR models for the pre-1979 (*High Volatility*) period and the post-1984 (*Low Volatility*) period. We then apply a counterfactuals decomposition methodology that follows Stock and Watson (2003) as well as Simon (2001), to analyse the structural contribution of each variable to overall forecast error variance. In this section we will make clear the specific approach we use and the identification assumptions we make.

4.1. *The SVAR Model*

The defining feature of the MZ approach is the separation between the *aggregate* and *industrial* block of variables. The reduced-form VAR is as follows:

$$\begin{bmatrix} \mathbf{x}_t \\ \mathbf{y}_t \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11}(L) & \mathbf{A}_{12}(L) \\ \mathbf{0} & \mathbf{A}_{22}(L) \end{bmatrix} \cdot \begin{bmatrix} \mathbf{x}_{t-1} \\ \mathbf{y}_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_t \\ \mathbf{u}_t \end{bmatrix} \tag{4}$$

where $\mathbf{x}_t$ and $\mathbf{y}_t$ denotes the industry and aggregate block, respectively. The submatrix of zeros in the lower left shows the block exogeneity assumption.

This approach is similar the pseudo-panel VAR methodology of Barth and Ramey (2002) and Davis and Haltiwanger (2001). The coefficients within the aggregate block are constant for each industry that the VAR is estimated for; obviously each industry block has its own set of coefficients as well as industry-specific coefficients transmitting aggregate activity to the industry block. The main motivation of this pseudo-panel VAR approach is to achieve 'more efficient estimation' (a nine-variable VAR has many coefficients to estimate) and 'consistent identification of the monetary policy shock' (Barth and Ramey, 2002). The approach essentially relies on the dynamics of aggregate variables being well explained within the aggregate block (as is the case in standard VARs with aggregate only variables, for example, Bernanke and Gertler (1995)).

This means that, when we do the decomposition exercise, we can use changes in the aggregate block's parameters to capture macro level changes across the two periods. We will also examine whether there have been changes in the transmission of aggregate demand shocks (captured by a monetary policy shock identified in the spirit of Bernanke and Gertler (1995)) to industry-level variables.

Unlike the pseudo-panel VAR approach, in this paper we focus on the effects on only one industry – durables manufacturing (for reasons already discussed). The methodology can easily be extended to other sectors. We present the results for the non-durables manufacturing sector in the appendix.[7]

Relative to MZ, we follow our earlier analysis and include extra variables in our industry block: $\mathbf{x}_t = [o_t \ u_t \ \overline{p}_t \ m_t \ h_t]'$. New orders are deonted o_t and u_t is backorders. The relative price level, $\overline{p}_t$, is defined as the deviation of the log implicit sales price deflator from the log aggregate price level ($p_{it} - p_t$). Input inventories are m_t (materials and supplies, M&S). For the sake of parsimony h_t captures the sum of final goods and work-in-progress inventories as they are both production outputs (incomplete and complete).

The aggregate block $\mathbf{y}_t = [e_t \ p_t \ p_t^c \ r_t]'$ consists of the aggregate economic activity measure e_t (we use private non-farm payroll employment since GDP is not available monthly), aggregate price level (PCE deflator) p_t, industrial commodities price index (commodities PPI) p_t^c and the Federal Funds rate r_t.

We transform each series apart from the Federal Funds rate r_t by taking the logarithm and removing a stochastic trend using a one-sided exponential smoother filter.[8] There are two distinct advantages to using the one-sided exponential smoother filter. Firstly, since it is one-sided, there would be no end-of-sample issues as would be found with more common two-sided filters. Secondly, as Watson (1986) pointed out, since the filter uses past data to determine trends, this may mitigate issues associated with correlation between the filtered data and the residuals leading to inconsistent estimates.

The sample is separated into the two periods as we used for the volatility decomposition in Section 3: *HV* (1967:1 to 1978:12) and *LV* periods (1984:1 to 1996:12). As previously mentioned, the sample choice allows for a transition interval between the *HV* and *LV* periods. During this transition interval, average lead times falling dramatically (Figure 1) and the percentage of firms ordering just-in-time tripled, while it was fairly steady both before and after the transition (Figure 2). This ap-

[7]Non-durables manufacturing had a smaller role in the overall Great Moderation, so it was not analysed in detail here. Nevertheless, the main results are broadly similar to durables.

[8]As in Gourieroux and Monfort (1997), the smoothed series from the ES filter is $\hat{x}_t = gx_t + (1 - g)\hat{x}_{t-1}$ where x_t is the actual data. Following MZ, the gain parameter g is set to 0.2. The main results were checked to be robust to $g = 0.1$ and $g = 0.3$.

proach enhances the ability to detect the effect of changes in business practices as well as monetary policy regimes.[9]

4.2. *Identification of the SVAR model*

The impulse responses and variance decomposition require an identification of the structural VAR. The intuitive restrictions on the contemporaneous relationships between the reduced-form VAR innovations imposed largely follows MZ, with some modifications to take into account of the split of sales into new orders and backorders. The vector of structural shocks are defined as:

$$\mathbf{A}_0 \cdot \begin{bmatrix} \mathbf{e}_t \\ \mathbf{u}_t \end{bmatrix} = \mathbf{B} \begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix}; \quad \begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix} \sim \mathrm{MVN}(\mathbf{0}, \mathbf{I}_9) \tag{5}$$

where $\mathbf{B} = diag(\sigma_o, \ldots, \sigma_r)$ is a diagonal matrix of the standard deviations of the structural innovations. The contemporaneous relationships matrix $\mathbf{A}_0$ is:

$$\mathbf{A}_0 = \begin{array}{c} \\ o_t \\ u_t \\ \overline{p}_t \\ m_t \\ h_t \\ e_t \\ p_t \\ p_t^c \\ r_t \end{array} \begin{array}{c} \begin{array}{ccccc|cccc} o_t & u_t & \overline{p}_t & m_t & h_t & e_t & p_t & p_t^c & r_t \end{array} \\ \left[\begin{array}{ccccc|cccc} 1 & a_{12} & a_{13} & 0 & 0 & a_{16} & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & a_{25} & a_{26} & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & a_{36} & a_{37} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & a_{45} & 0 & 0 & a_{48} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & a_{56} & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{76} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{86} & a_{87} & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{96} & a_{97} & a_{98} & 1 \end{array}\right] \end{array} \tag{6}$$

The zero restrictions on the lower left part of the matrix reflect the block exogeneity assumption. The lower right part of the matrix exhibit the recursive

[9]The transition could be endogenised by adopting a Markov-switching framework, but there would likely be very little value-added since it is already well-known that 1984 is the crucial period.

ordering between the aggregate variables as in Bernanke and Gertler (1995). The ordering is such that the Fed Funds Rate responds to all aggregate variables contemporaneously (like a Taylor rule), and employment does not respond to any aggregate variable contemporaneously.

The upper left quadrant portrays the contemporaneous interaction between the industrial variables. As MZ describe it, the restrictions 'reflect the stickiness of price and production plans that are reasonable given the monthly frequency'. We adopt a similar identification scheme like MZ, where there is a recursive ordering similar to the aggregate block, with a few additions in the upper triangular. In particular, new orders o_t and backorders u_t may affect all industrial variables (a_{21} to a_{51}, and a_{12} to a_{52}). Relative prices $\bar{p}_t$ can influence new orders (a_{13}), as well as inventory stages (a_{43} and a_{53}). M&S inventories m_t can affect FG + WIP inventories h_t, while FG + WIP inventories can influence M&S inventories as well as backorders.

Inventories at the high frequencies are often used as adjustment margins, hence a flexible relationship with the sector-level variables is allowed. However, at this frequency, it is unlikely that relative prices would be affected contemporaneously by anything other than new orders and backorders. Similarly, it is doubtful that backorders are affected by other than new orders, or FG inventories (which is a substitute for backorders). Relative prices has an effect on backorders only through new orders (which is allowed), and M&S inventories are purely an input to production. Finally, new orders are only affected by backorders (indicator of lead times) and relative prices (the price adjustment margin) as the orders within a given month should only reflect the activity of the downstream producers, but also react to lead times of the durables manufacturers.

The upper right of the matrix shows how the aggregate variables are connected to the industrial block contemporaneously. We follow MZ again, but with shipments split up into new orders and backorders. Aggregate economic activity e_t can influence all variables, except M&S inventories (parameters a_{16} to a_{56}). This is the crucial variable that transmits demand into the sector. It is unlikely to affect M&S inventories as it is an input to production which is likely to be sticky within one month. The aggregate price level p_t can affect the relative price level (a_{37}) and commodity prices p_t^c can alter the M&S inventories (a_{48}). The aggregate price level is a component of the relative price level, thus allowing a contemporaneous relationship is sensible. The commodity price index proxies the acquisition cost of M&S inventories, hence permitting contemporaneous correlation for the pair. The zeros in this quadrant is reflective of the simple intuition that the aggregate block drives the demand for durables (ie. new orders) only through economic activity, while the variables within the aggregate block can affect each other through the recursive ordering.

The lag order for this monthly VAR is chosen by AIC (Ivanov and Kilian, 2005). Searching on a grid of asymmetric lags on the industry-level and aggregate variables results in two lags each for the *HV* period, and an asymmetric two and three lags for industry and aggregate blocks, respectively, in the *LV* period. Thus, we estimate the SVARs with the latter's asymmetric lag structure (2 lags on industry, 3 on the aggregate block). MZ has more asymmetry in the lags (four on industry, and seven on the aggregate). The reason that the lags suggested by AIC is smaller could be due to the large increase of the parameters to be estimated from adding one variable, into a nine-variable VAR. Using other (harsher) criteria such as Hannan-Quinn or Schwarz-Bayes results in a much shorter lag structure, which would be unlikely to capture the true data-generating process given the monthly frequency. Nevertheless, the main results are robust to a variety of other lag structures.[10]

4.3. *Counterfactuals Methodology*

The counterfactuals method as in Stock and Watson (2003) can disentangle if industry-level structure (affected by new business practices), or macro effects,

[10]The results were checked to be robust under symmetric VARs with 2, 3, 4 and 6 lags.

produces the fall in volatilities. For this exercise we will measure the decline in volatility using the forecast root mean squared errors (RMSE).[11]

Better business practices

$$\begin{bmatrix} \mathbf{x}_t \\ \mathbf{y}_t \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11}(L) & \mathbf{A}_{12}(L) \\ \mathbf{0} & \mathbf{A}_{22}(L) \end{bmatrix} \cdot \begin{bmatrix} \mathbf{x}_{t-1} \\ \mathbf{y}_{t-1} \end{bmatrix} + \mathbf{A}_0^{-1}\mathbf{B} \begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix}$$

Better policy (macro)

Good luck (macro)

Figure 6: Effects of the hypotheses on the SVAR (structural version of Equation 4)

Figure 6 shows schematically how the three hypotheses parse into changes in the SVAR. We will measure the *business practices* effect in each period $j \in \{HV, LV\}$ using the upper two quadrants of the lagged coefficients $\{\mathbf{A}_{11,j}(L), \mathbf{A}_{12,j}(L)\}$, and upper two quadrants of the contemporaneous matrix $\mathbf{A}_{0,j}$). The upper right quadrant contains the bullwhip effect – the transmission and amplification of downstream demand to upstream orders. The upper left quadrant encompasses the flexible production and effects of reduced delivery times. We donate all the industry level parameters that capture the business practices effects as $\mathbf{\Gamma}_j$.

The *macro* effects are composed of the aggregate level parameters ($\mathbf{A}_{22,j}(L)$ and the lower right quadrant of $\mathbf{A}_{0,j}$), as well as the shocks. The lower right quadrant parameters incorporate how monetary policy has changed. For the main results, we are agnostic of the composition of the macro effects between good luck and good policy, as we are mainly interested in the amount of volatility reduction that can be allocated to new business practices as opposed to one of the macro hypotheses. We will collect all the coefficients associated with the macro effects in $\mathbf{\Lambda}_j$.

We use our estimated SVAR for two different counterfactual exercises. First, we

[11] Following MZ, the horizon used is 60 months ahead. This is long enough such that the forecast error variances approach the unconditional volatility of the variable, which is what we are interested in. The results are robust to longer horizons (90 and 120 months).

perform a counterfactual analysis. Our two sets of estimated SVAR coefficients (one for each period) yield two sets of business practices effects, $[\mathbf{\Gamma}_{HV},\mathbf{\Lambda}_{HV}]$, and two sets of macro effects (policy and shocks), $[\mathbf{\Gamma}_{LV},\mathbf{\Lambda}_{LV}]$.The LV combination gives lower volatility compared to the HV for most variables. With particular attention on new orders, we mix between the business practices and macro factors to see whether practices, or general macroeconomic developments in monetary policy and shocks, produce the lower volatility.

The second analysis is a more traditional counterfactual between structure and shocks. This involves grouping the parameters $(\mathbf{A}_j, \mathbf{A}_j(L))$ into $\mathbf{\Theta}_j$, to denote the industry and macroeconomic structure at period j and the structural shocks are grouped into $\mathbf{\Sigma}_j = \mathbf{B}_j'\mathbf{B}_j$. We can then perform the counterfactual exercises of what happens if, for example, only the shocks changed and the structures did not.

Additionally, we examine more standard forecast error variance decomposition (FEVD) and impulse response analysis. Specifically, to narrow down the mechanisms that drive the results of the counterfactuals, we examine the impulse responses (defined as log-point deviation) of the sector-level variables (Figure 7), as well as aggregate variables (Figure 8) to a 100 bps Federal Funds Rate increase.[12]

5. Results

5.1. *Evidence of a role for new business practices*

This subsection examines to what extent there is evidence of the new business practices that we have discussed. We explore the existence of the channels posited through which better business practices can reduce new orders volatility as well as other supportive evidence in the behaviour of other variables. This section uses all the analytical tools we just described.

[12] IRFs to a 1% commodities price increase can be found in the appendices (Figures 11).

Counterfactuals	*Relative RMSE* $[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{HV}]$ Practices	$[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{LV}]$ Macro	$[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{LV}]$ Total
New Orders o_t	0.72	0.79	0.59
Backorders u_t	0.83	1.14	0.70
Relative price $\overline{p}_t$	1.34	0.54	0.78
M&S Inventory m_t	1.77	1.07	1.21
FG Inventory h_t	1.33	2.10	1.21

Table 2: 60-month RMSE counterfactuals of business practices and macro effects
Notes: The RMSEs are relative to the HV *micro and macro parameters/shocks, ie.* $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$.

The counterfactual RMSEs, shown relative to the *HV* period $[\mathbf{\Gamma}_{HV},\mathbf{\Lambda}_{HV}]$, are shown in Table 2. As described before, we mix the coefficients that change to highlight which gave rise to the greater decrease in volatility. For example, if the combination of $[\mathbf{\Gamma}_{LV},\mathbf{\Lambda}_{HV}]$ (*LV* period business practices, and *HV* macro structure and shocks) produces similar volatility reductions as the overall *LV* SVAR system, then we conclude that business practices has been driving the volatility moderation. Similarly, macro factors would be attributed as the cause of the moderation if $[\mathbf{\Gamma}_{HV},\mathbf{\Lambda}_{LV}]$ is able to reduce enough volatility. If there are complementarities between parameters and shocks, then the volatility reduction would not be additive (although they usually are).

For new orders volatility, the counterfactuals indicate that new business practices contributed $1 - 0.72 = 28\%$ and macro factors $1 - 0.79 = 21\%$ out of the total reduction in volatility of $1 - 0.59 = 41\%$. Therefore, both practices and macro factors account for the stabilisation, contributing around half each.[13]

Further evidence is shown in the FEVD (absolute numbers for RMSEs) of industry-level variables found in Table 3. The FEVD suggests that more of new orders volatility is now explained by industry (rather than aggregate) variables. Table 4 shows that the 'sensitivity' of new orders relative to employment shocks have been reduced by 27%. This is consistent with a dampening of the bullwhip effect – the transmission between downstream demand to upstream orders.

[13]Note that the counterfactuals do not necessarily add up, but here they get close to doing so: $0.72 \times 0.79 = 0.57 \approx 0.59$.

One may worry that the macro factors somehow influence the transmission of aggregate variables to the sector-level variables (the top right quadrant of parameters). To address this, we can perform another counterfactual of changing the upper-left quadrant of parameters only (Table 8 in appendices) – or in other words, changing specifically the sector-level interactions between the sector variables. This leaves out a part of the bullwhip effect (the transmission between aggregate demand to new orders), and emphasises the flexible production and just-in-time techniques. This alone achieves a $1 - 0.82 = 18\%$ reduction in new orders volatility, demonstrating the strong influence of the within-sector structure on new orders volatility.

There is also evidence of backordering behaviour change. In the *HV* period, the IRFs support the Zarnowitz idea of shipments and production smoothing using the backorder margin. For a contractionary demand shock (a 100 bps increase in the Fed Funds Rate), backorders are being run down until new orders start to recover. This is consistent with large variations in delivery times. However, in the *LV* period, backorder levels remain largely stable. In other words, delivery times become more consistent. More lean production enables faster reaction times to order disturbances, and customers are more certain they would receive goods faster and on time. This leads to the dampening of new order volatility.

The evidence of changes in inventory behaviour is, as the earlier analysis suggested, more complicated. The behaviour of M&S inventories and FG + WIP inventories are very similar. With the negative demand shock, all types of inventory stocks rise in the short term more in the LV period, before falling to suit the lower level of orders. However, the interpretation of this result is fundamentally different, as M&S inventories are inputs to the production stage, and FG + WIP are production outputs.

	RMSE	Forecast Variance Decomposition (%) Own	o_t	u_t	Other Industry	Aggregate
High Volatility						
New Orders o_t	1.6		0.4	1.5	4.0	94.1
Backorders u_t	1.3		0.4	18.0	5.9	75.7
Relative price $\overline{p}_t$	0.5	6.1	0.1	0.2	0.0	93.6
M&S Inventory m_t	0.6	3.0	0.2	14.2	5.9	76.7
FG Inventory h_t	0.7	12.2	0.2	0.4	10.0	77.1
Low Volatility						
New Orders o_t	0.9		1.2	1.8	11.8	85.3
Backorders u_t	0.9		0.1	4.6	8.6	86.8
Relative price $\overline{p}_t$	0.4	34.1	0.2	0.7	0.3	64.7
M&S Inventory m_t	0.7	6.6	0.1	0.8	20.0	72.4
FG Inventory h_t	0.8	2.0	0.1	0.0	8.1	89.8

Table 3: Forecast Error Variance Decomposition

	Industry					Aggregate			
	o_t	u_t	$\overline{p}_t$	m_t	h_t	e_t	p_t	p_t^C	r_t
New Orders o_t	1.11	0.46	1.12	2.33	0.35	0.73	0.72	0.02	0.12
Backorders u_t	0.06	0.19	1.50	2.36	0.04	1.04	1.64	0.03	0.15
Relative price $\overline{p}_t$	1.37	2.16	2.40	1.67	15.81	0.2	2.2	0.01	0.72
M&S Inventory m_t	1.26	0.09	39.4	1.18	0.09	5.62	1.58	0.11	3.33
FG Inventory h_t	0.53	0.23	1.07	2.88	0.41	7.84	1.65	0.11	0.75

Table 4: 60-month horizon relative sensitivity to structural shocks
Notes: The sensitivity measures how the volatility of one variable (rows) is driven by a standardised shock of a particular variable (columns). See Simon (2001) for details on the calculation. The table reports the ratio of the sensitivity between the *LV* and *HV* periods: a ratio less than one indicates that the variable is less sensitive in the *LV* period.

For M&S inventories, there could be two channels operating. Firstly, with better supply chain management, as well as reduced and consistent lead times, lead to more stable M&S inventory stocks as firms' suppliers can vary shipments faster as necessary. The second channel could be that flexible production leads to to manufacturers' consuming inputs with greater fluctuations, leading to more volatile inventories.[14] Given that M&S inventories are more volatile in the *LV* period, this suggests that the latter channel is dominant. The IRFs show that there is an accumulation of M&S inventories as new orders fall, suggesting that firms are cut-

[14] A prediction of McMahon (2012) is when inventories become more flexible, they are more volatile.

ting production faster (and symmetrically, are able to increase production quickly when there is a positive demand shock). Furthermore, despite the increase in structural shock variance, the counterfactuals indicate that overwhelmingly micro factors are responsible for the higher volatility (in contrast to FG + WIP inventories). This hints that flexible production techniques are operating in the *LV* period.

On the other hand, FG + WIP inventory dynamics play a role in stabilising production. However, the channel is somewhat different from MZ. The similarity is that we also find that FG + WIP inventories become more countercyclical with respect to new orders in the *LV* period. That is, inventories rise initially with the fall in new orders, before eventually declining when new orders start recovering. In contrast to MZ, all inventory type stocks become more volatile. The counterfactuals suggest that for FG + WIP inventories, this mostly comes from the macro factors (and from the conventional counterfactuals, aggregate structure) – hence this supports MZ's assertion that firms expect less persistent sales shocks, the perceived benefits of maintaining stable production increases. Combine the four facts that: the RMSEs (which approximates unconditional volatility) of inventories are much smaller than the RMSE for new orders; that inventories IRF rose by 0.2% while new orders fell by 0.5% in the *LV* period, in contrast to a negligible response of inventories with a 1% fall in new orders in the *HV* period; it is inventory investment that enters the production identity; and finally, inventory-sales ratios for durables hover around two. It is likely that the net effect of FG + WIP inventory dynamics to be more production smoothing.

As also found in MZ's IRFs, the *HV* period impulse responses behave almost cyclical (especially for new orders), although they decay back to zero after some periods. IRFs to sector-level variable shocks do not show this behaviour, thus this feature is driven from the aggregate block. In particular, the economic activity indicator exhibit the same wave as new orders, as well as aggregate and commodity prices with congruent timing of the troughs and peaks. However, could this be caused by fluctuating economic activity driving the swings in prices, or is the vari-

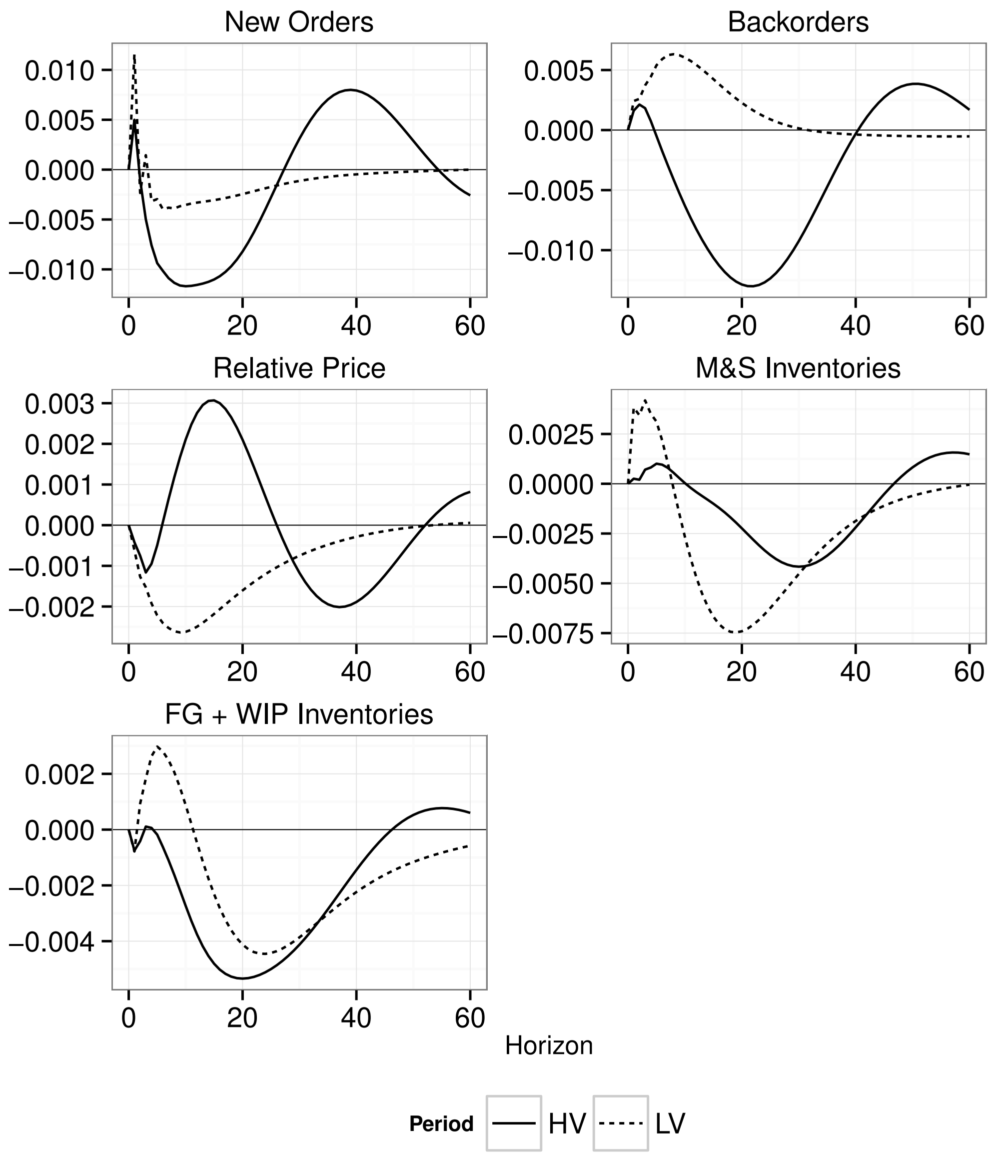

Figure 7: Durables impulse response to a 100 bps Fed Funds Rate increase

ability in prices inducing fluctuations in economic activity? The literature suggests a possible channel for the latter – the indeterminacy of the monetary policy rule in the *HV* period (the pre-Volcker era). For example, Lubik and Schorfheide (2004), Sims and Zha (2006) and others have documented that during the *HV* period the Federal Reserve did not increase nominal rates aggressively enough in response to a rise in inflation. This induces business-cycle fluctuations in output and inflation that would not occur if determinacy was satisfied. The IRFs to a commodity price shock (Figure 11) is consistent with this story. A 1% increase in commodity prices induces a large increase in aggregate prices, and also large fluctuations in economic activity, in the *HV* period. Meanwhile, in the *LV* period, a credible and aggressive Federal Reserve anchored inflation expectations such that the impact on aggregate prices and economic activity was negligible.

Taken overall, the main conclusion is that there is evidence for lean production and micro structural changes lead to more stable orders. Firms are more inclined to use FG inventories rather than backorders to stabilise production in the *LV* period. Greater flexibility in production processes and supply chain management leads to these dynamics, and in turn, this changes ordering behaviour such that it stabilises production. The results in Stock and Watson (2003) suggest that the durables good sector contributed to approximately half the overall output volatility moderation, despite its small relatively size.[15] Extending business practices to include supply chain management, our results suggest that business practices is responsible for approximately 40-50%. Combining the two, business practices have contributed to at least 20-25% of the overall Great Moderation. Better practices could have contributed more, through other sectors, or in other ways. Defining business practices as the changes in the sector-level parameters may or may not pick up the effects of better cash flow management, better hedging and others.

[15] See appendices for calculations.

5.2. *Evidence for macro effects*

The previous subsection has highlighted that not only business practices contributed to the Great Moderation, but also the decline in aggregate demand volatility. We present evidence that supports both the narrative-based literature (that the Great Moderation emanates from better monetary policy), as well as the VAR-based literature (that it was good luck).

The counterfactuals and IRFs suggest that the underlying macroeconomic background that feeds demand shocks into the industry-level variables has changed. The first point is that there is a large reduction in shocks. The structural variances of Table 5 indicates that the standard deviation of employment shocks fell by 38% in the *LV* period, and commodities price shocks by 25%. Like most VAR-based studies, this particular result is reconcilable with the good luck hypothesis.

Durables SVAR

Industry Block		Aggregate Block	
Shock to	*Ratio*	*Shock to*	*Ratio*
New Orders o_t	0.83	Employment e_t	0.62
Backorders u_t	0.80	Aggregate price p_t	1.01
Relative price $\overline{p}_t$	1.01	Commodities price p_t^c	0.75
M&S Inventory m_t	2.47	Fed Funds Rate r_t	0.97
FG Inventory h_t	0.60		

Table 5: Relative size of structural shocks, where Ratio = $\sigma(LV)/\sigma(HV)$

However, it must be remarked that employment is an imperfect indicator of overall economic activity – greater labour market flexibility may induce greater employment volatility. The focus of the paper instead is on the components of sector-level durable goods production, which we know to be a large contributor of the Great Moderation.

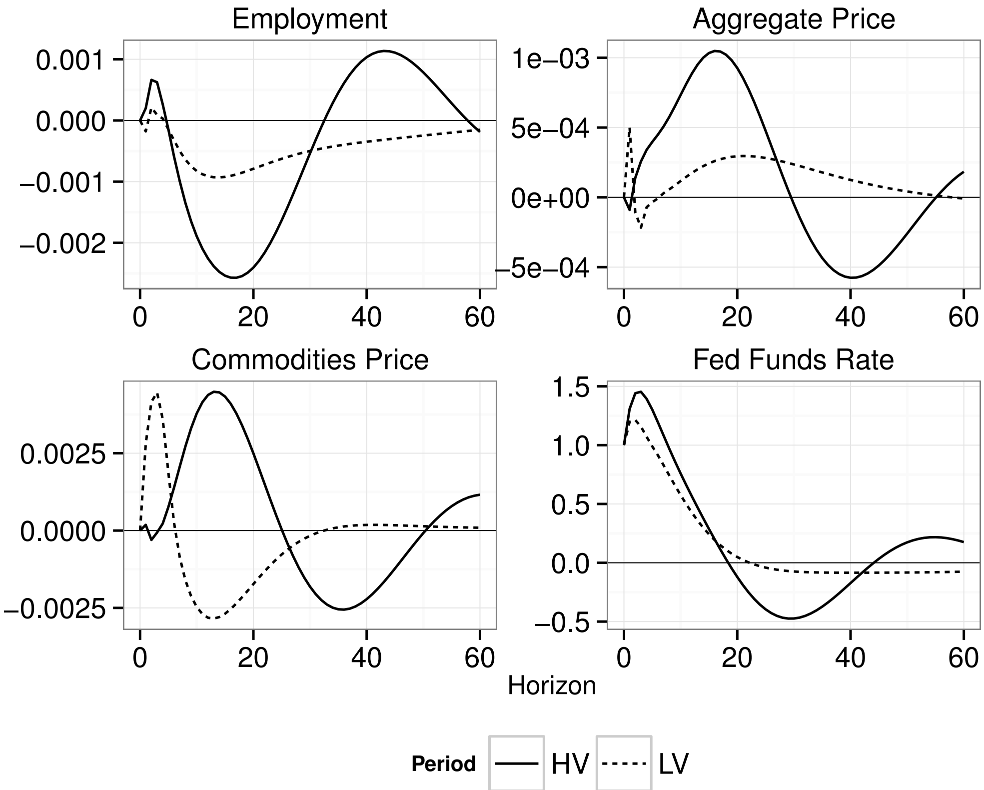

Figure 8: Aggregates impulse response to a 100 bps Fed Funds Rate increase

	Relative RMSE		
	$[\Theta_{HV}, \Sigma_{LV}]$	$[\Theta_{LV}, \Sigma_{HV}]$	$[\Theta_{LV}, \Sigma_{LV}]$
Counterfactuals	Shocks	Structure	Total
Industrial Block			
New Orders o_t	0.78	0.73	0.59
Backorders u_t	0.77	0.84	0.7
Relative price $\overline{p}_t$	0.80	0.79	0.78
M&S Inventory m_t	0.86	1.54	1.21
FG Inventory h_t	0.82	1.69	1.21
Aggregate Block			
Employment e_t	0.80	1.24	0.92
Aggregate price p_t	0.96	0.91	0.88
Commodities price p_t^c	0.78	0.67	0.57
Fed Funds Rate r_t	0.84	1.80	1.33

Table 6: 60-month RMSE counterfactuals of structure and shocks

Notes: The RMSEs are relative to the HV shocks and parameters, ie. $[\Theta_{HV}, \Sigma_{HV}]$.

On the other hand, unlike VAR-based evidence and similar to narrative-based evidence, we find significant aggregate structural changes. Firstly, the response of economic activity to monetary policy shocks in the *LV* period is much more muted. Secondly, the response of economic activity to a commodities price shock (Figure 11) reveals how better monetary policy affects the economy differently. Commodity price shocks no longer cause economic activity fluctuations (or aggregate price level). This offers evidence that the macro structure has changed to stabilise exogenous shocks better. Noting the counterfactual (Table 6) that macroeconomic structure *increases* Federal Funds Rate volatility, this suggests that the Federal Reserve became more responsive to movements in output and inflation. This is consistent with past literature – for example, Clarida, Galí, and Gertler (2000), Boivin and Giannoni (2002), Lubik and Schorfheide (2004) – that suggests the Federal Reserve's reaction function parameter to inflation have increased, and also Watson (1999) that the Federal Funds Rate became more persistent. Greater response and persistence induces more variability in the Federal Funds Rate. Thus, the isolation of the macroeconomic system from exogenous shocks appears to resulted from the Federal Reserve's credibility in fighting inflation.

This is also supported by the counterfactuals of commodity price forecast errors. Shocks contribute to some reduction in volatility, but it is mostly from the sensitivity of the system (see Table 4). This explains why *LV* period impulse responses of all variables are much more muted, as well as returning to zero faster. Credible monetary policy anchored inflation expectations and price shocks do not become persistent. This is consistent with the results in McCarthy and Zakrajšek (2003) and Bernanke and Gertler (1995), where they found that aggregate output and prices responded less to oil price shocks post-1985.

Therefore, the results are consistent with the hypothesis that an aggressive Federal Reserve stance stabilised the macroeconomic system, deriving from reducing the impact of exogenous price shocks on real variables, rather than directly smoothing output.

6. Conclusion

In this paper, we revisit the important question of what gave rise to the Great Moderation. In particular, our main contribution is to extend the definition of new business practices to include aspects of supply chain management that fit much more closely with actual changes in practice than simply better inventory management practices.

Our empirical work analysis supports a much greater role for new business practices in attenuating sales volatility in the durable manufacturing sector than most of the earlier literature. Our evidence is consistent with a reduction of the bullwhip effect and the effects of flexible production.

Most of the Great Moderation is still caused by the main macro factors – good luck and monetary policy. We present evidence that both play a role. Nevertheless, our results bring a case for optimism – around a quarter of the volatility reduction is due to better business practices (20-25%). Unlike the good luck result from most VAR-based studies, we can expect that this volatility will not easily return as the new technologies have changed supply chain management, and parts of our macroeconomic structures, forever.

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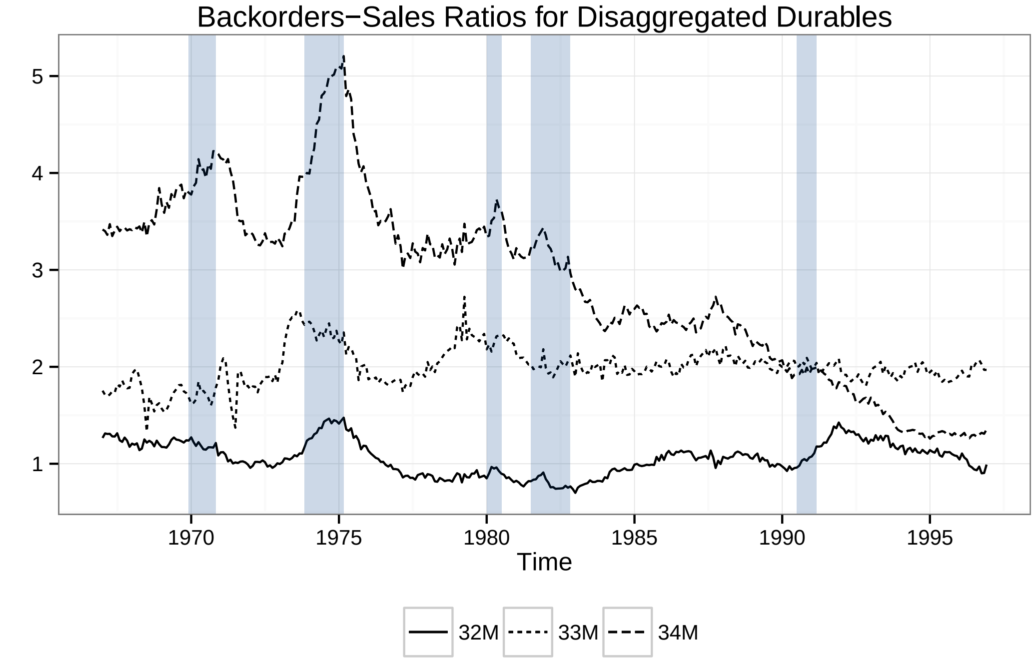
A. Appendix



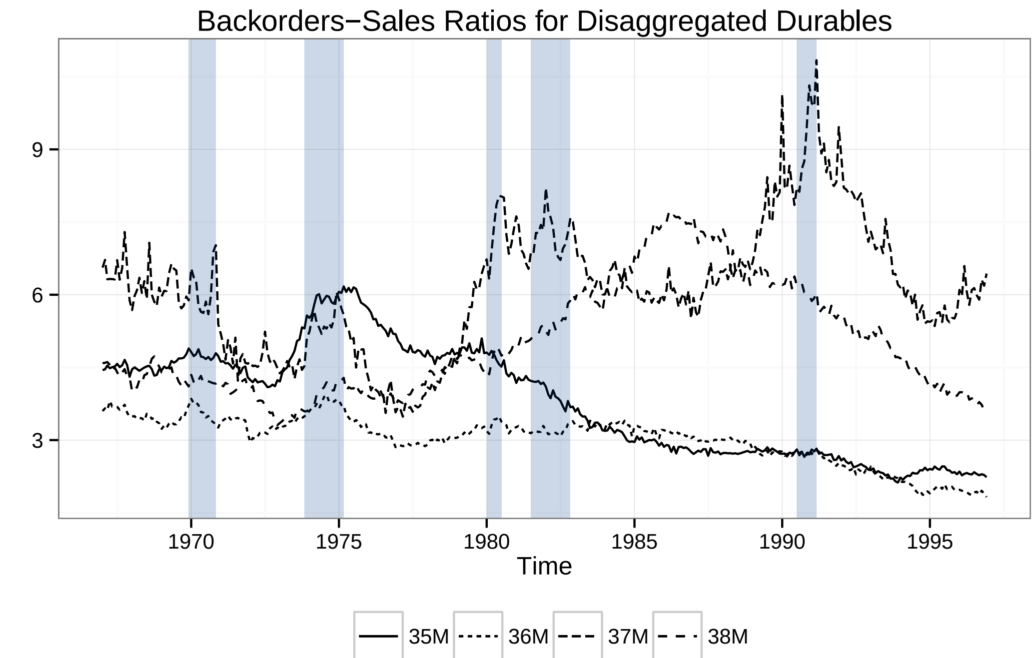


Figure 9: Disaggregated Backorders to Shipments Ratio
SIC codes: 32M – Stone, Clay and Glass, 33M – Primary metals, 34M – Fabricated metals, 35M – Industrial machinery and equipment, 36M – Electronic and other electrical equipment, 37M – Transportation equipment, 38M – Instruments and related products.

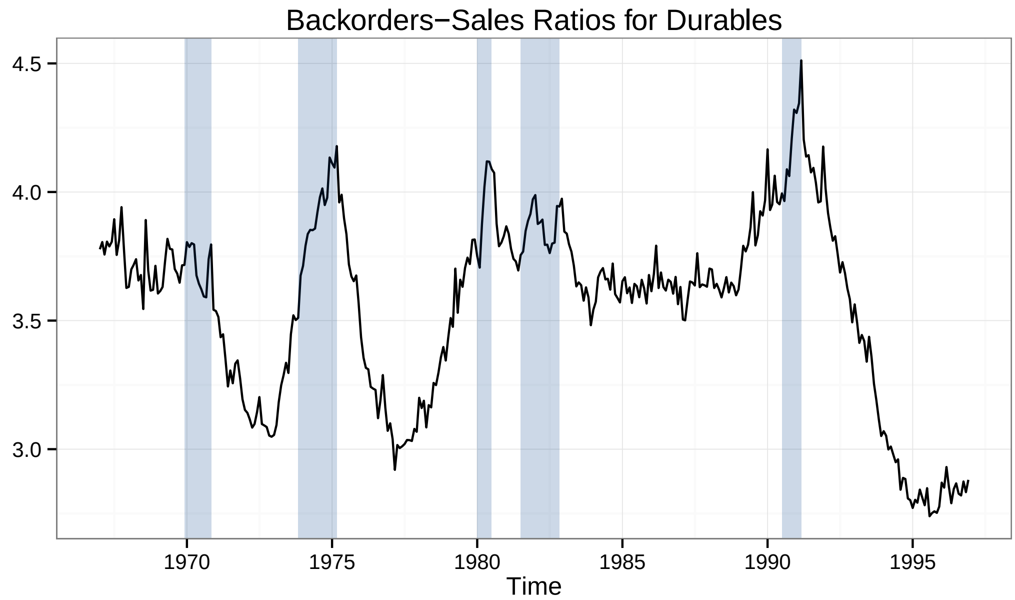


Figure 10: Backorders to Shipments Ratio for All Durables Industries
Shaded areas are NBER-dated recessions

	Std. Dev		Shares	
	1960-1983	1984-2001	1960	2001
GDP (actual)	0.027	0.016		
Durables	0.084	0.053	0.18	0.18
Nondurables	0.030	0.018	0.31	0.19
Services	0.012	0.008	0.39	0.53
Structures	0.072	0.048	0.11	0.09

Table 7: Stock and Watson (2003, Table 6) Counterfactuals

The counterfactual to approximate the role of durables in the overall Great Moderation is based on the following. Calculate the implied volatility of GDP by using the volatility and weight of each sector s, but omit the covariance terms. $\sqrt{\sum_s \omega_{s,HV}^2 \sigma_{s,HV}^2} = 0.020$ and $\sqrt{\sum_s \omega_{s,LV}^2 \sigma_{s,LV}^2} = 0.0118$. This results in a ratio $0.0118/0.020 = 0.59$, or a 40% reduction in volatility. Coincidentally, the ratio of *actual* GDP volatilities is also $0.016/0.027 = 0.59$, meaning that the effects of the covariances cancel out. Or equivalently, the ratio between the actual and implied volatility is constant for the two periods ($0.027/0.020 = 1.35$ and $0.16/0.118 = 1.35$).

To get an approximation of the effect of durables, substitute the *LV* volatility of durables, while keeping all other industries in the *HV* period, resulting in an implied volatility of 0.0166. The ratio from the implied volatility in the *HV* period is $(0.0162/0.020 = 0.81)$. Thus we conclude that durables account for approximately half of the Great Moderation. In comparison, if a similar counterfactual is performed on nondurables (a much bigger sector) implies a volatility of 0.018, or only a 10% reduction in overall volatility, as opposed to the 20% of durables.

		Relative RMSE	
Counterfactuals	Within Industry LV	All other parameters LV	All parameters LV
New Orders o_t	0.82	0.80	0.73
Backorders u_t	2.07	0.91	0.84
Relative price $\overline{p}_t$	3.09	0.36	0.79
M&S Inventory m_t	5.02	1.41	1.54
FG Inventory h_t	1.95	3.18	1.69

Table 8: 60-month counterfactuals of the within industry parameters, given Σ_{HV}

Notes: The RMSEs are relative to the HV *variances and parameters, ie.* $[\Theta_{HV}, \Sigma_{HV}]$.

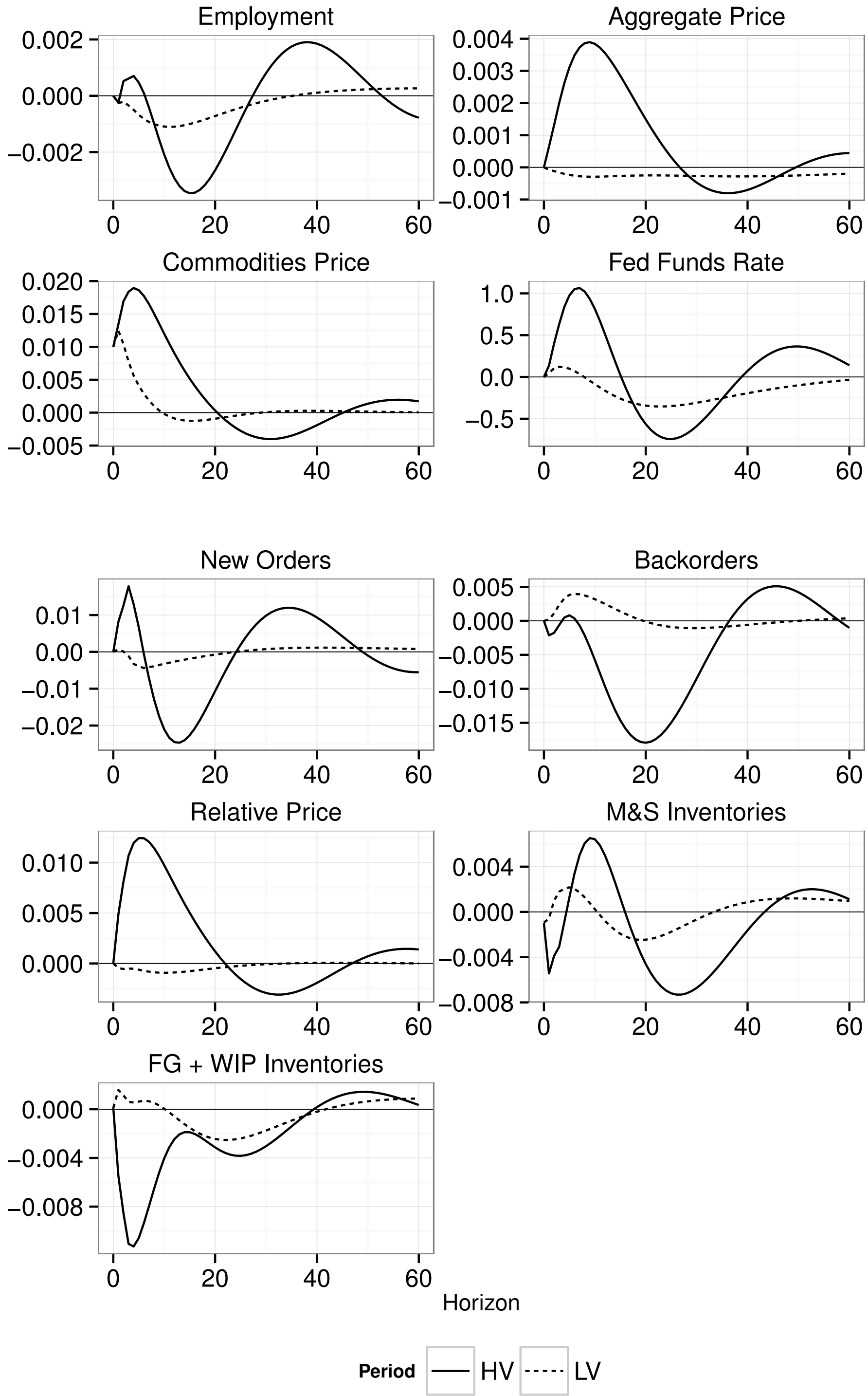


Figure 11: Impulse Responses to a 1% increase in commodities prices

B. Non-Durables Results

Counterfactuals	$[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{HV}]$ Practices	*Relative RMSE* $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{LV}]$ Macro	$[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{LV}]$ Total
New Orders o_t	0.81	0.87	0.57
Backorders u_t	1.01	0.90	0.80
Relative price $\overline{p}_t$	1.58	0.65	1.13
M&S Inventory m_t	0.66	0.92	0.70
FG Inventory h_t	0.56	0.72	0.50

Table 9: 60-month RMSE counterfactuals of business practices vs. macro effects

Notes: The RMSEs are relative to the HV *practoces and macro parameters/shocks, ie.* $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$.

Counterfactuals	$[\Theta_i^{HV}, \Sigma_i^{LV}]$ Shocks	*Relative RMSE* $[\Theta_i^{LV}, \Sigma_i^{HV}]$ Structure	$[\Theta_i^{LV}, \Sigma_i^{LV}]$ Total
Industrial Block			
New Orders o_t	0.86	0.60	0.57
Backorders u_t	0.89	0.92	0.80
Relative price $\overline{p}_t$	0.97	1.30	1.13
M&S Inventory m_t	0.99	0.84	0.70
FG Inventory h_t	1.01	0.52	0.50

Table 10: 60-month RMSE counterfactuals of structure and shocks

Notes: The RMSEs are relative to the HV shocks and parameters, ie. $[\Theta_i^{HV}, \Sigma_i^{HV}]$.

		Forecast Variance Decomposition (%)				
	RMSE	Own	o_{it}	u_{it}	Other Industry	Aggregate
High Volatility						
New Orders o_{it}	0.52		4.68	0.46	1.43	93.43
Backorders u_{it}	1.99		0.02	2.02	1.74	96.23
Relative price $\overline{p}_{it}$	0.51	5.81	0.61	0.09	1.40	92.08
M&S Inventory m_{it}	0.57	2.35	0.27	0.67	5.62	91.08
FG Inventory h_{it}	0.56	11.59	0.17	0.53	1.22	86.49
Low Volatility						
New Orders o_{it}	0.30		8.67	0.16	2.30	88.87
Backorders u_{it}	1.60		0.16	1.67	17.10	81.07
Relative price $\overline{p}_{it}$	0.57	21.11	0.04	0.43	2.41	76.02
M&S Inventory m_{it}	0.40	7.74	0.29	0.21	7.65	84.10
FG Inventory h_{it}	0.28	16.90	0.18	0.22	8.61	74.09

Table 11: Forecast Error Variance Decomposition

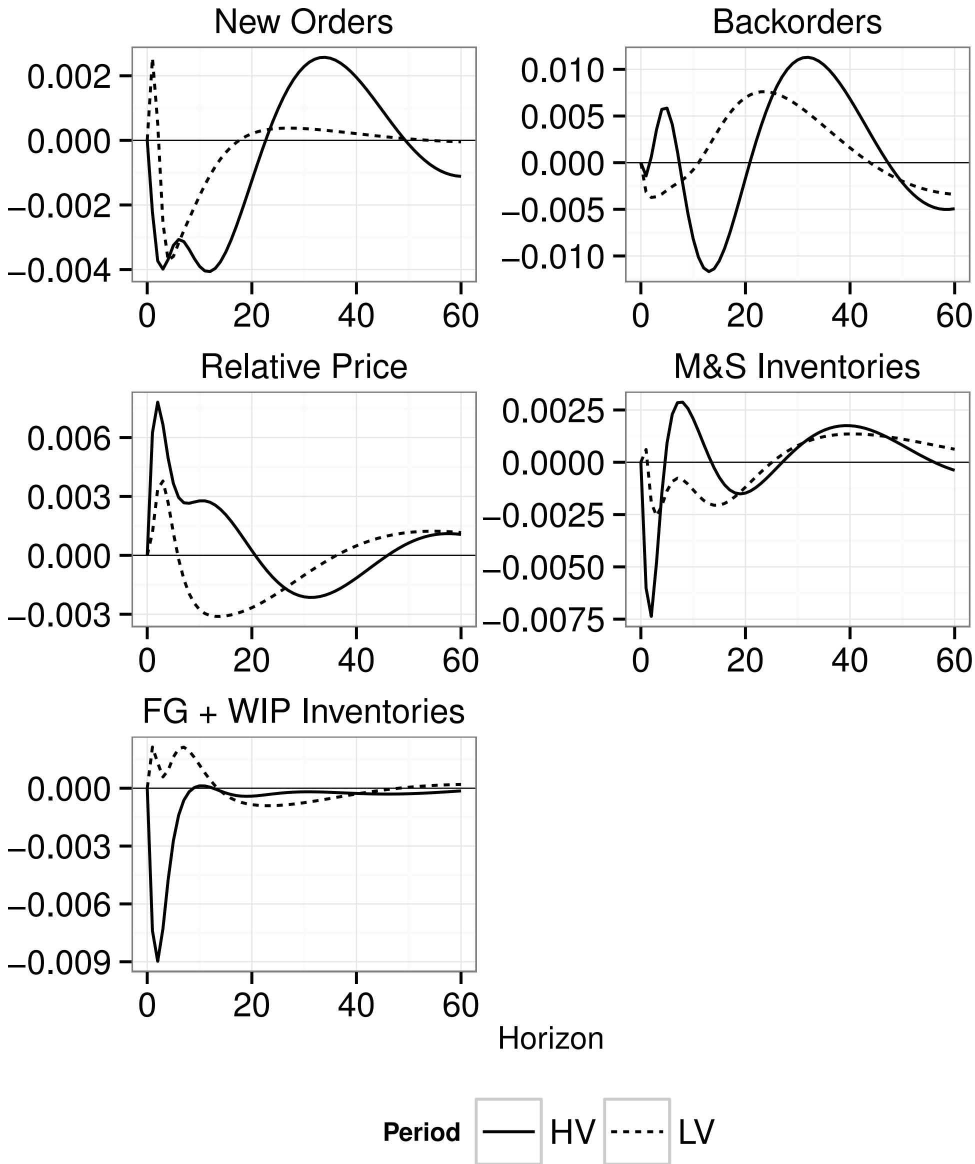


Figure 12: Non-durables Impulse Responses to a 100 bps Fed Funds Rate Increase