Beyond Inventory Management: The Bullwhip Effect and the Great Moderation

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Abstract

We resurrect the question if improved business practices contributed to increased macroeconomic stability since the 1980s – the 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

In addition to good luck and better policy, it has been suggested that new business practices may have contributed to the period of prolonged macroeconomic stability since the mid-1980s (known as the Great Moderation). We revisit the question of how much new business practices contributed to the Great Moderation. Previous attempts at answering this question, such as Stock and Watson (2003), Ahmed, Levin, and Wilson (2004), Kim, Nelson, and Piger (2004) and Herrera and Pesavento (2005), have considered the idea of better inventory management and focus their analysis on the production identity: $Y = S + \Delta I$, denoting production, sales and inventory investment, respectively. These analyses generally concluded that there was little effect from inventory management because the decline in output is driven by reduced sales volatility. We extend the concept of business practices and supply chain management to include backordering behaviour as well as inventory management. We show that reduced use of backordering and shorter lead times, as we document happened in the data, can cause a reduction in the volatility of sales. Following the approach of McCarthy and Zakrajšek (2007) (MZ hereafter), but applied to the broader concept of business practices, we find 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.

Supply chain management is an important determinant of order volatility because most orders to the manufacturing sector are placed by intermediate goods producers, rather than consumers. The role of order volatility on sales and production volatility is clearly seen through the decomposition of sales into its constituents:

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

where in the latter identity, O denotes new orders and ΔU changes in backorders.

While previous literature claim that sales volatility only change to background macro factors (good luck or good policy), we argue that improved business practices have dampened ordering volatility. A calculation in Section 2 demonstrates that the fall in new orders volatility is key to the reduction in production volatility, hence we emphasise the analysis on the sources of new orders volatility. We show evidence that is consistent with two channels of how better practices can achieve such an effect.

The main theme is a reduction of the 'bullwhip effect'. Well-documented in the management science literature, it is a phenomenon where demand shocks from downstream consumers are amplified through the supply chain to upstream producers. This is caused by a systematic distortion of demand information through the supply chain, when the manufacturers only observe its immediate order data (and not further down the supply chain), and there are lead times and ordering lags.[1] This causes order volatility to be amplified through the supply chain. The first channel into the reduction of the bullwhip effect is the adoption of ICT systems by manufacturers, which led to better communication along supply chains. This diminished the amplification of new orders volatility, and thus, stabilised production.

The second channel of the bullwhip effect reduction relates to the role of backorders, especially in durables manufacturing where backorder books are sizeable. 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. However, the adoption of lean production and just-in-time techniques reduces the need for backorders to smooth out demand shocks. Firms respond faster by adjusting production or with better inventory control. Consequently, delivery times became lower and more consistent, and therefore, intermediate goods producers know they will receive extra raw materials speedily if they themselves experience a demand shock. In

[1] Lee, Padmanabhan, and Whang (2004) have grouped the causes into four categories: demand signal processing, shortages and rationing gaming, order batching, and price variations.

response, 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).

Despite their small share of GDP (approximately 18%), durables production is one of the biggest contributors to output moderation – due to its high volatility[2] as well as experiencing large falls 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 **??** in appendices). Davis and Kahn (2008) also show the timing of durables output volatility falls, impeccably matches the observed break in GDP volatility. Furthermore, manufacturing industries are placed upstream of the supply chain (especially durables), and therefore, has the most to benefit from an attenuation of the bullwhip effect.

The approach of this paper largely follows McCarthy and Zakrajšek (2007) (hereinafter, MZ). A structural VAR is estimated for each period, pre-1979 and post-1984. Using forecast standard errors as a measure of volatility, we ask the question if volatility reductions emanate from luck and macroeconomic changes (shocks or better policy), structural microeconomic changes (better business practices), or a combination of both. This is answered by counterfactuals between the two SVARs from the two periods. Conventional impulse response analysis, and decomposing forecast error variances into its structural shocks versus sensitivity of the system, are also used to narrow down the sources of the volatility reduction.

The results suggest that sector-level structural changes has contributed to approximately half of the fall of new orders volatility – which we interpret as the dampening of the bullwhip effect. There is also evidence of changes in backordering behaviour, one of the key mechanisms posited. In addition, implied inventory volatility (as a proportion of inventory stocks) in the durables sector actually in-

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

creases,[3] suggesting the effects of the flexible production processes being implemented. Nevertheless, some new orders moderation stems from macro factors. The role of monetary policy is indirect – it is due to enhanced stabilisation of commodity and aggregate price shocks from a more credible Federal Reserve, which in turn stabilised overall economic activity.

There are already many studies attempting to determine which are the correct explanation(s). For instance, Stock and Watson (2003), Ahmed, Levin, and Wilson (2004), Kim, Nelson, and Piger (2004) and Herrera and Pesavento (2005) suggest that it was mainly shocks. Narrative studies that estimate 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 responsible. Earlier papers on the Great Moderation attributed a very important role to inventory management, such as McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Kahn, McConnell, and Perez-Quiros (2002). However, later papers such as McCarthy and Zakrajšek (2007) concluded that inventory management played at most, a supporting role instead. We focus on the effects on sales volatility by business practices improvements as a whole, rather than solely inventory management. Davis and Kahn (2008) mention the potential contribution of supply chain management in the Great Moderation, but leaves out how it connects with sales volatility as an open question.

The contribution of this paper is three-fold. Firstly, by disaggregating sales into its components (new orders and backorders), we demonstrate that new orders volatility accounts for the majority of sales and production volatility falls. Secondly, we show that approximately half the new orders volatility attenuation is caused by within-sector structural changes, or 20-25% of the overall Great Moderation. Thirdly, we give evidence that support specific channels on how better business practices can cause such a reduction in order volatility, through improve-

[3] The MZ result that inventory volatility has fallen holds in the non-durables manufacturing SVAR (not reported), indicating that particular result was driven by the much larger non-durables sector.

ments in supply chain management and flexible production processes.

The rest of the paper is organised as follows. Section 2 describes the data used and establishes some motivating stylised facts. Section 3 illustrates in a standard partial equilibrium framework how business practices can endogenously affect new order volatility. Section 4 introduces the structural vector autoregression, and the counterfactual methodology to answer the research question. Section 5 analyses the results and implications for the role of business practices on the Great Moderation. Section 6 concludes.

2. Evolution of Backorders, Inventories and Volatilities

2.1. *Data*

The industry-level monthly data is from the United States Census Bureau – the historic time series for *Manufacturers Shipments, Inventories & Orders*, from 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.[4] Inventories are disaggregated into stages of production – materials and supplies, work-in-process and finished goods inventories.

2.2. *Volatility Decomposition*

In this subsection, we document a volatility decomposition of durables production and sales. The exercise reveals that the reduction in production volatility during the Great Moderation is driven by increased stability of new orders.

As with MZ, we denote the sample 1967:1-1978:12 as the *High Volatility (HV)* period, and 1984:1-1996:12 as the *Low Volatility (LV)* period. This allows for a transition period from 1979 to 1983, where the exceptional volatility of the Volcker

[4] 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.

disinflation and extensive manufacturing restructuring may contaminate the results. The aim is that the decomposition splits the 'steady state' volatility instead. Some of the charts in the next subsection clearly show that this interval was indeed a transition period.

Std. Dev.	HV	LV	$\sigma^{HV} - \sigma^{LV}$	$\frac{\sigma^{HV}-\sigma^{LV}}{\sigma^{HV}}$
Y	3.8	2.7	1.1	29%
ΔI	1.1	1.0	0.1	2%
S	3.6	2.4	1.3	34%
O	5.6	3.9	1.7	31%
ΔU	3.6	3.1	0.5	15%
$\text{corr}(S, \Delta I)$	0.04	0.12		
$\text{corr}(O, \Delta U)$	0.77	0.79		

Table 1: Volatility decomposition of production

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

HV: 1967:1-1978:12, LV: 1984:1-1996:12
Quarterly growth contributions in percentage points

The decomposition show for the 29% reduction in production volatility, almost all arise from the fall in sales volatility. Neither changes in inventory investment volatility, nor the cyclicality (correlation) of inventory investment contribute to the stabilisation. This is the same result as many previous studies. This led them to conclude that business practices, or more accurately, inventory management, did not contribute to the Great Moderation.

However, we can go one step further and decompose the sources of sales volatility, using the identity $S = O - \Delta U$. This reveals that most of the fall of sales volatility derive from a reduction in new orders volatility. To be more precise, we perform a counterfactual exercise, by combining the HV and LV new orders and backorders volatilities. The implied sales volatility by changing new orders volatility $\{\sigma_O^{LV}, \sigma_{\Delta U}^{HV}, \rho^{HV}\}$ is 2.6%, a 29% reduction, roughly matching the overall fall in sales and production volatility.[5] In contrast, the opposite counterfactual

[5]This counterfactual variance is calculated: $V(S_{imp}) = (\sigma_O^{LV})^2 + (\sigma_{\Delta U}^{HV})^2 - 2\rho^{HV}(\sigma_O^{LV})(\sigma_{\Delta U}^{HV})$. Thus, $\sigma_{S,imp} = \sqrt{0.039^2 + 0.036^2 - 2(0.77)(0.039)(0.036)} = 0.026$

of changing backorders volatility $\{\sigma_O^{HV}, \sigma_{\Delta U}^{LV}, \rho^{HV}\}$ actually increases volatility to 3.84%.[6] Thus, we conclude that to explain the fall in production and sales volatility, one has to explain the moderation of new orders volatility. Having a new interpretation of 'orders', leads to a clearer possible role of business practices, and in particular, supply chain management.

2.3. *Stylised Facts on the Evolution of Durables Manufacturing*

In this subsection, we show developments of the durables manufacturing sector over time. They can shed light on the the aforementioned channels through which better practices can lead to lower order volatility, 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 backorders-sales ratios*
2. *Reductions in inventories-sales ratios*
3. *Reductions in production materials lead times*
4. *Reductions in lead time volatility*

The first stylised fact is that there is a large fall in durables sector backorders (relative to sales) in the early 1980s (Figure 1).[7] Better business practices – in particular, lean production and just-in-time techniques – is likely to produce this result by allowing firms to react faster to demand shocks, requiring less use of the backorder margin.

The second stylised fact is that inventories-sales ratios for the durables sector have also fallen since the early 1980s (Figure 2). This was driven mostly by materials and supplies inventories first in the late 1970s (and to a lesser extent, final

[6]This is caused by the fall in backorder variance not compensating enough for the less-negative covariance term.

[7]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.

goods inventories), and then strongly afterwards in the 1990s by work-in-progress inventories. This suggests steady improvements in inventory control.

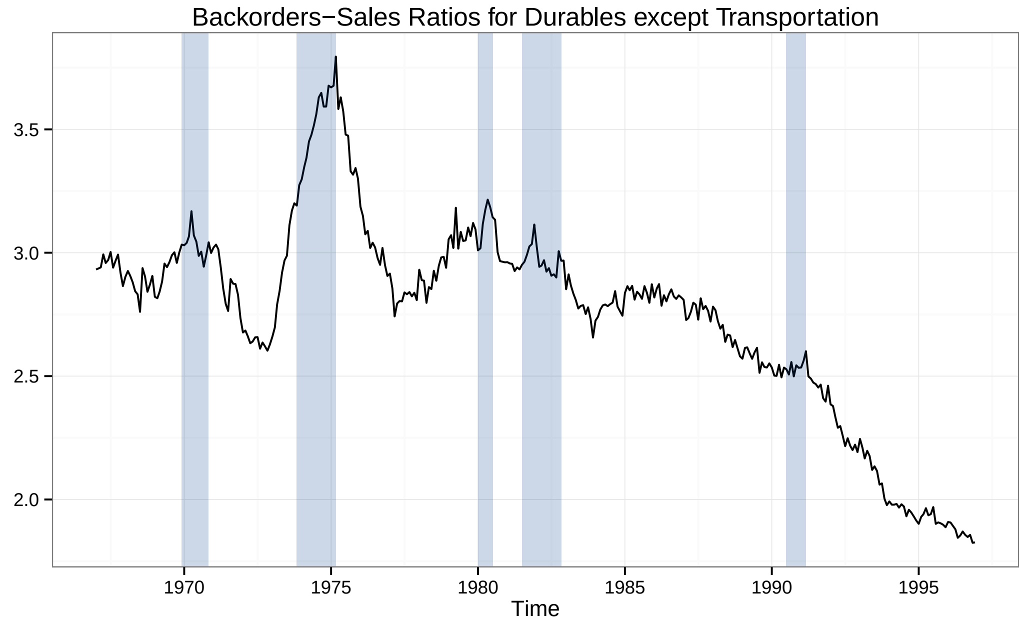


Figure 1: Backorders to Shipments Ratio (excluding Transportation sector)
Shaded areas are NBER-dated recessions

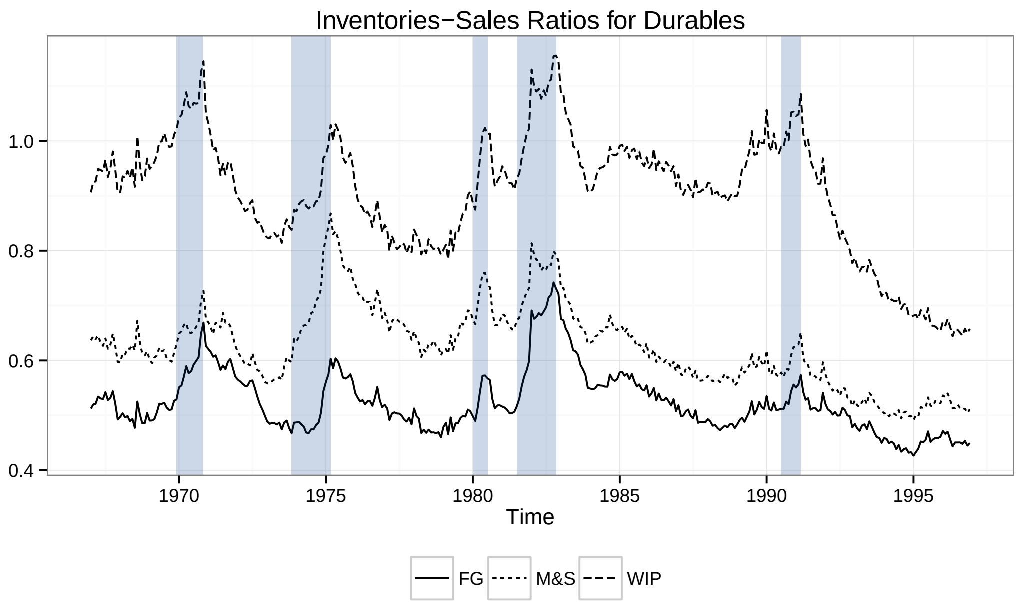


Figure 2: Inventories to Shipments Ratio
Shaded areas are NBER-dated recessions

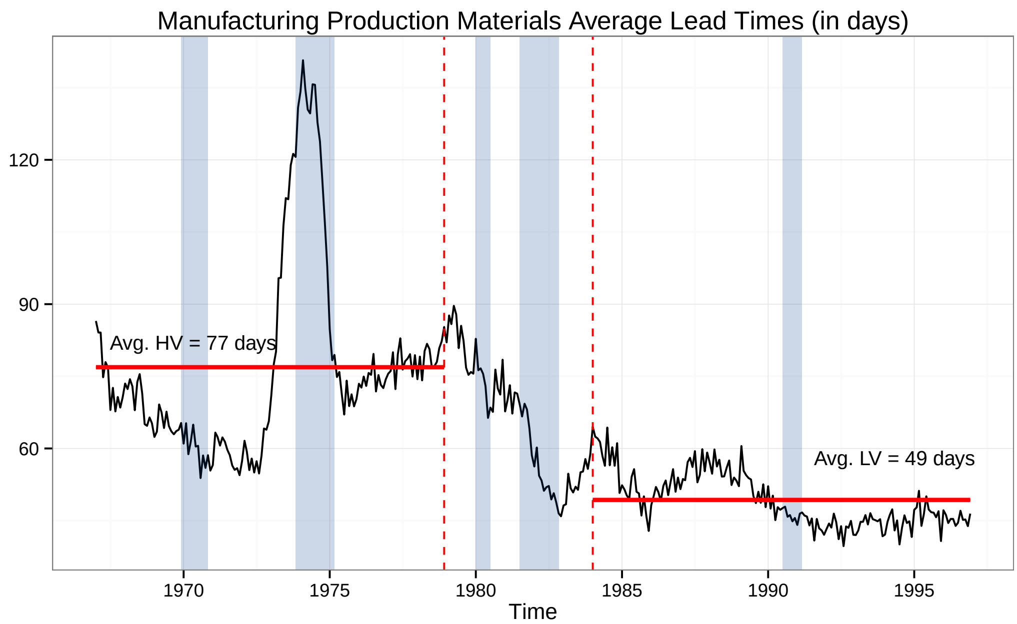


Figure 3: Average Manufacturing Production Materials Lead Times
Source: Insitute for Supply Management
Shaded areas are NBER-dated recessions

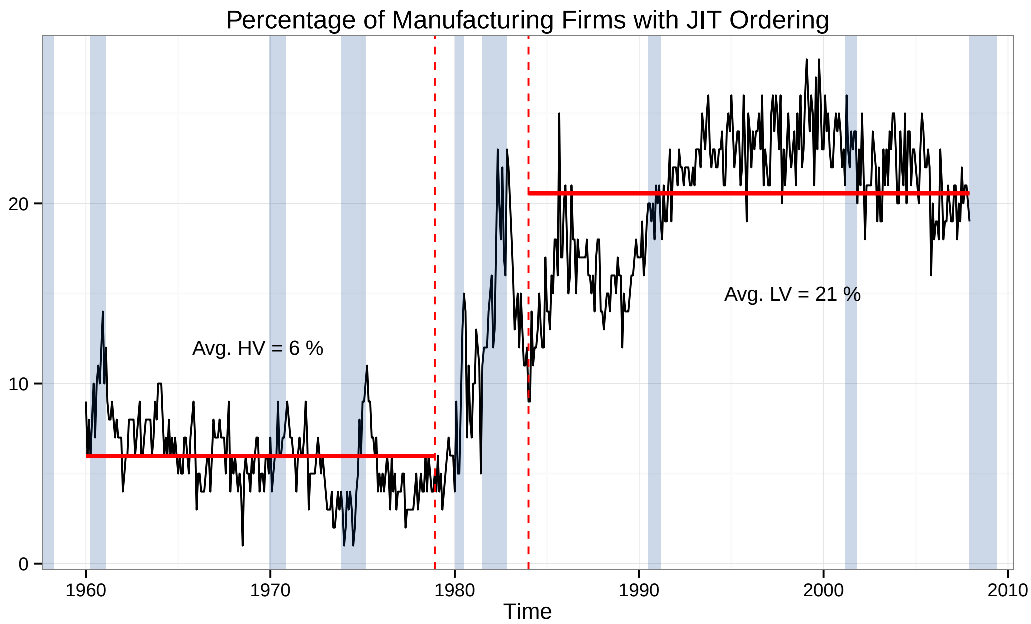


Figure 4: Percentage of Manufacturing Firms with Just-in-Time ordering
JIT defined as receiving orders in less than five days.
Shaded areas are NBER-dated recessions

Figure 5: 36-month Backward Looking Volatility of ISM Manufacturing Deliveries Index. Source: Authors' own calculations.

The falls in backorder book sizes and inventories seem to coincide with the falls in production materials delivery lead times, where there was also a sharp reduction in lead times from pre-1980s, and post-mid-1980s (mean of 72 and 49 days, respectively). Declines began in the early-1980s along with a rapid increase in firms achieving JIT ordering. Figure 4 shows that the proportion of manufacturing firms with JIT ordering (defined as receiving orders in less than five days) more than tripled from the *HV* to *LV* periods.

In addition, it is not only the first moment that affects ordering behaviour, but also the variance of lead times.[8] This relates to the reduction in the backorder adjustment margin and consistency of delivery times. As a proxy for leadtime

[8]See Song and Zipkin (1996) for an operational research view into the importance of steady lead times.

disruptions, we calculate rolling volatilities of the Institute for Supply Management's Manufacturing Supplier Deliveries Index[9] (Figure 5). 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. This also 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.

These two exercises highlight the crucial role new orders volatility takes in the increased stability of durable goods production, as well as underscoring the potential channels how improved business practices may cause this decline in order volatility. However, all three competing hypotheses are can still yield such a result. Reduced downstream aggregate demand volatility from good luck or good policy can lead to lower upstream order volatility. Furthermore, direction of causality is not yet demonstrated. For instance, a more stable economy may lead to reduced volatility of delivery times. To disentangle between the three effects and establish causality, we now adopt a multivariate approach, which allows us to formalise the links between aggregate and the sector-level variables.

3. Lead times, backordering and new order volatility

WORK IN PROGRESS

The objective of this section is to illustrate how new order volatility is affected by backordering behaviour and lead times variability.

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 McCarthy and Zakrajšek (2007), the model takes into account possible

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

structural changes in the economy, by estimating the SVAR pre-1979 (the *High Volatility* period) and post-1984 (the *Low Volatility* period).

4.1. *The SVAR Model*

The counterfactuals decomposition methodology largely follows Stock and Watson (2003), as well as Simon (2001) for analysing the structural contribution of each variable to overall forecast error variance. The defining feature of the MZ approach is the separation between the *aggregate* and *industrial* block of variables. This approach is reminiscent of the pseudo-panel VAR methodology of Barth and Ramey (2002) and Davis and Haltiwanger (2001). That is, while the coefficients within the aggregate block do not change across industries, but obviously each industry block has its own set of coefficients (as well as the 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). This assumes that the aggregate variables are explained well enough by variables within the aggregate block, like VARs with aggregate only variables, for example, Bernanke and Gertler (1995). This implies that all of the dynamics of aggregate demand is contained within the aggregate block's parameters. We will use a contractionary monetary policy shock to model the effect of an adverse aggregate demand shock, and inspect the transmission from the aggregate block to industry-level variables.

We show results on one sector as we focus on the effects of durables manufacturing. The methodology can easily be extended to other sectors.[10] The recursive identification and structure of the aggregate block is derived from Bernanke and Gertler (1995). The reduced-form VAR is as follows:

[10] The results for the non-durables manufacturing sector are in the appendix. 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.

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

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.

The industry block is described by the vector $\mathbf{x}_t = [o_t\ u_t\ \overline{p}_t\ m_t\ h_t]'$, of new orders o_t, backorders u_t, relative price level $\overline{p}_t$, materials and supplies (M&S) inventories m_t and the sum of final goods and work-in-progress inventories h_t.[11] The relative price level is defined as the deviation of the log implicit sales price deflator from the log aggregate price level, $\overline{p}_t \equiv p_{it} - p_t$.

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

In each series (apart from the Federal Funds rate r_t), the logarithm is taken and a stochastic trend is removed by a one-sided exponential smoother filter.[12] There are two distinct advantages. 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.

As with the volatility decomposition in Section 2, the sample is separated into *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*

[11] WIP and FG inventories are summed for parsimony, as they are both production outputs (incomplete and complete), while M&S inventories are inputs to production.

[12] 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 $g = 0.3$.

periods. Since the Great Moderation is a long-run volatility reduction, we are interested in the change monetary policy regimes and business practices, not the transition per se. During this transition interval, average lead times falling dramatically (Figure 3) and the percentage of firms ordering just-in-time tripled, while it was fairly steady both before and after the transition (Figure 4). This approach enhances the ability to detect the effect of changes in business practices as well as monetary policy regimes.[13]

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:

$$\mathbf{A}_0 \cdot \begin{bmatrix} \mathbf{e}_t \\ \mathbf{u}_t \end{bmatrix} = \mathbf{B} \begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix}; \quad \begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix} \sim \mathrm{MVN}(\mathbf{0}, \mathbf{I}_9) \tag{2}$$

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:

[13]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.

$$
\mathbf{A}_0 = \begin{array}{c|ccccc|cccc}
 & o_t & u_t & \overline{p}_t & m_t & h_t & e_t & p_t & p_t^c & r_t \\
\hline
o_t & 1 & a_{12} & a_{13} & 0 & 0 & a_{16} & 0 & 0 & 0 \\
u_t & a_{21} & 1 & 0 & 0 & a_{25} & a_{26} & 0 & 0 & 0 \\
\overline{p}_t & a_{31} & a_{32} & 1 & 0 & 0 & a_{36} & a_{37} & 0 & 0 \\
m_t & a_{41} & a_{42} & a_{43} & 1 & a_{45} & 0 & 0 & a_{48} & 0 \\
h_t & a_{51} & a_{52} & a_{53} & a_{54} & 1 & a_{56} & 0 & 0 & 0 \\
\hline
e_t & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
p_t & 0 & 0 & 0 & 0 & 0 & a_{76} & 1 & 0 & 0 \\
p_t^c & 0 & 0 & 0 & 0 & 0 & a_{86} & a_{87} & 1 & 0 \\
r_t & 0 & 0 & 0 & 0 & 0 & a_{96} & a_{97} & a_{98} & 1
\end{array} \tag{3}
$$

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 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.

As advised by Ivanov and Kilian (2005), the lag order for this monthly VAR is chosen by AIC. 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 much 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.[14]

4.2. *Counterfactuals Methodology*

The counterfactuals method as in Stock and Watson (2003) can disentangle if industry-level structure, or macro effects, produces the fall in volatilities, measured in forecast root mean squared errors (RMSE).[15]

The following diagram shows how the three hypotheses parse into changes in the SVAR.

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 1)

For each period $j \in \{HV, LV\}$, denote the industry level parameters (the upper two quadrants of the lagged coefficients $\{\mathbf{A}_{11,j}(L), \mathbf{A}_{12,j}(L)\}$, and upper two

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

[15]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).

quadrants of the contemporaneous matrix $\mathbf{A}_{0,j}$), as the *business practices* effect $\mathbf{\Gamma}_j$. 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.

The *macro* effects $\mathbf{\Lambda}_j$ 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, as we are interested in the micro effects on the variables.

Therefore, by estimating the SVARs at the two periods, we gain two sets of business practices effects and macro effects (policy and shocks), $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$ and $[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{LV}]$ respectively.

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. 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).

In addition, we can also perform the more traditional counterfactual between structure and shocks, by grouping the parameters ($\mathbf{A}_j, \mathbf{A}_j(L)$) into $\mathbf{\Theta}_j$, to denote the industry and macroeconomic structure at period j. Similarly, the structural shocks are grouped into $\mathbf{\Sigma}_j = \mathbf{B}_j'\mathbf{B}_j$.

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.[16]

5. Results

5.1. *Durables Manufacturing*

This subsection examine to what extent the different hypotheses explain the decline in new orders volatility. Moreover, we explore the existence of the channels posited through which better business practices can reduce new orders volatility. The RMSEs relative to the HV period $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$ is shown in Table 2. The absolute numbers for RMSEs of industry-level variables can be found on Table 3.

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.* $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$.

Firstly, the counterfactuals in Table 2 for new orders volatility indicate 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.[17]

Furthermore, the forecast error variance decomposition (FEVD) (Table 3) of new orders volatility has shifted some of the explanatory power from aggregate to the industry variables and the 'sensitivity' of new orders relative to employment

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

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

shocks have been reduced by 27%, consistent with a dampening of the bullwhip effect – the transmission between downstream demand to upstream orders.

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 7 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.

Secondly, there is 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 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.

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

		Forecast Variance Decomposition (%)				
	RMSE	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

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

necessary. The second channel could be that flexible production leads to to manufacturers' consuming inputs with greater fluctuations, leading to more volatile inventories.[18] 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 cutting 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.

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

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 variability 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.

Combining these results, 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.[19] 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.

5.2. *Aggregate*

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 8 indicates that the standard deviation of employment shocks fell by 38%

[19] See appendices for calculations.

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.

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.

	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.

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

Counterfactuals	*Relative RMSE* $[\Theta_{HV}, \Sigma_{LV}]$ Shocks	$[\Theta_{LV}, \Sigma_{HV}]$ Structure	$[\Theta_{LV}, \Sigma_{LV}]$ 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 5: 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 5) 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 is 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 examine more closely the role of business practices in attenuating sales volatility in manufacturing sectors. Changes in within-sector dynamics has a more prominent role in the volatility moderation through the reduction of the bullwhip effect and the effects of flexible production, relative to changes in the macroeconomic environment. We find that about 20-25% of the overall Great Moderation is caused by improvements in business and manufacturing practices, a quantitatively significant amount.

However, most of the Great Moderation is still caused by macro factors – either good luck and monetary policy. We present evidence that both practices and the Great Moderation contribute towards output stabilisation, although we remain agnostic on the exact composition of the macro factors between shocks and policy. Monetary policy's importance lies in stabilising external price shocks, as well as working together with industry-level changes in the non-durables sector for stabilising new orders. The 'good luck' hypothesis also play at least some part in the Great Moderation. Nevertheless, the results bring a case for optimism – unlike the good luck result from most VAR-based studies, at least a large minority of the volatility (20-25%) will not return as managers do not forget how to manage businesses or supply chains.

References

Ahmed, S., A. Levin, and B. A. Wilson (2004): "Recent US Macroeconomic Stability: Good Policies, Good Practices, or Good Luck?," *Review of Economics and Statistics*, 86(3), 824–832.

Barth, M. J., and V. A. Ramey (2002): "The cost channel of monetary transmission," in *NBER Macroeconomics Annual 2001*, ed. by B. S. Bernanke, and K. Rogoff, pp. 199–256. MIT Press, MIT Press.

Bernanke, B. S., and M. Gertler (1995): "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, 9, 24–48.

Blanchard, O. J., and J. Simon (2001): "The Long and Large Decline in US Output Volatility," *Brookings Papers on Economic Activity*, 2001(1), 135–174.

Boivin, J., and M. P. Giannoni (2002): "Has Monetary Policy Become Less Powerful?," *Federal Reserve Bank of New York Staff Report*, (144).

——— (2006): "Has monetary policy become more effective?," *Review of Economics and Statistics*, 88(3), 445–462.

Clarida, R., J. Galí, and M. Gertler (2000): "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115(1), 147–180.

Cogley, T., and T. J. Sargent (2001): "Evolving Post-World War II US Inflation Dynamics," in *NBER Macroeconomics Annual*, ed. by B. S. Bernanke, and K. Rogoff, pp. 331–388. MIT Press.

Davis, S. J., and J. Haltiwanger (2001): "Sectoral job creation and destruction responses to oil price changes," *Journal of Monetary Economics*, 48(3), 465–512.

Davis, S. J., and J. A. Kahn (2008): "Interpreting the great moderation: Changes in the volatility of economic activity at the macro and micro levels," *Journal of Economic Perspectives*, 22, 155–180.

Gourieroux, C., and A. Monfort (1997): *Time Series and Dynamic Models*, Themes in Modern Econometrics. Cambridge University Press.

Herrera, A. M., and E. Pesavento (2005): "The Decline in U.S. Output Volatility," *Journal of Business & Economic Statistics*, 23(4), 462–472.

Ivanov, V., and L. Kilian (2005): "A Practitioner's Guide to Lag Order Selection for VAR Impulse Response Analysis," *Studies in Nonlinear Dynamics & Econometrics*, 9(1).

Kahn, J. A., M. McConnell, and G. Perez-Quiros (2002): "On the Causes of the Increased Stability of the US Economy," *Federal Reserve Bank of New York, Economic Policy Review*, 8(1), 183–202.

Kim, C.-J., C. R. Nelson, and J. Piger (2004): "The Less-Volatile US Economy: a Bayesian Investigation of Timing, Breadth, and Potential Explanations," *Journal of Business & Economic Statistics*, 22(1), 80–93.

Lee, H. L., V. Padmanabhan, and S. Whang (2004): "Information Distortion in a Supply Chain: The Bullwhip Effect," *Management Science*, 50(12 Supplement), 1875–1886.

Lubik, T. A., and F. Schorfheide (2004): "Testing for indeterminacy: An application to US monetary policy," *American Economic Review*, pp. 190–217.

McCarthy, J., and E. Zakrajšek (2003): "Inventory Dynamics and Business Cycles: What Has Changed?," *Board of Governors of the Federal Reserve System Finance and Economics Discussion Series*, 26.

McCarthy, J., and E. Zakrajšek (2007): "Inventory Dynamics and Business Cycles: What Has Changed?," *Journal of Money, Credit and Banking*, 39(2), 591–613.

McConnell, M., and G. Perez-Quiros (2000): "Output Fluctuations in the United States: What Has Changed Since the Early 1980'S?," *American Economic Review*, 90(5), 1464–1476.

McMahon, M. (2012): "Inventories in Motion: A New Approach To Inventories Over The Business Cycle," .

Orphanides, A. (2004): "Monetary Policy Rules, Macroeconomic Stability, and Inflation: a View From the Trenches," *Journal of Money, Credit and Banking*, 36(2), 151–175.

Simon, J. (2001): "The Decline in Australian Output Volatility," *Reserve Bank of Australia Research Discussion Paper*, 1.

Sims, C. A., and T. Zha (2006): "Were there regime switches in US monetary policy?," *American Economic Review*, pp. 54–81.

Song, J.-S., and P. H. Zipkin (1996): "The Joint Effect of Leadtime Variance and Lot Size in a Parallel Processing Environment," *Management Science*, 42(9), 1352–1363.

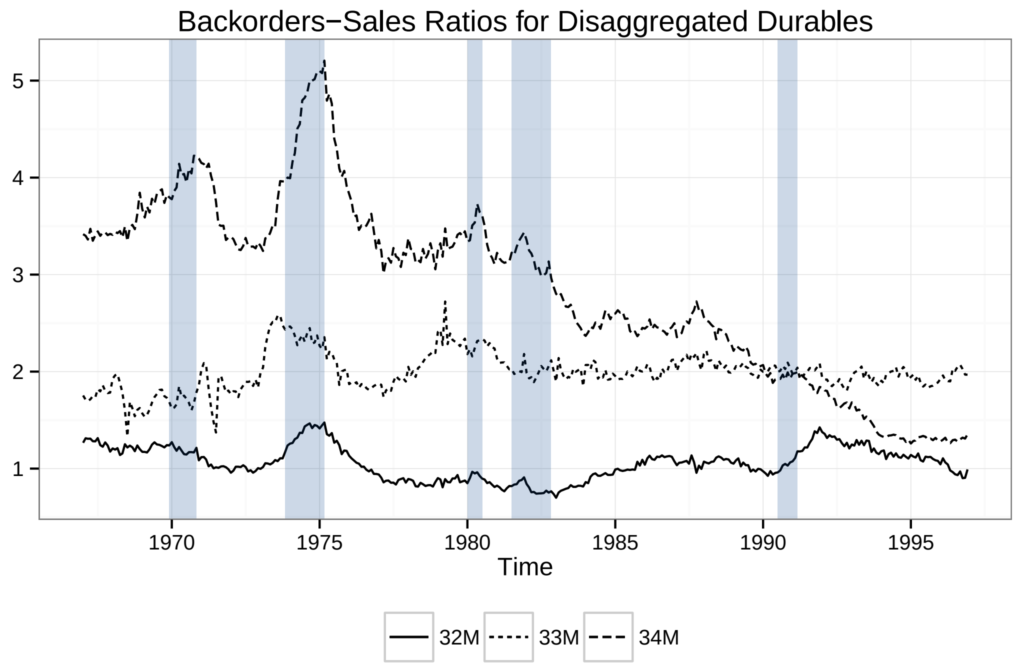
Stock, J. H., and M. W. Watson (2003): "Has the Business Cycle Changed and Why?," in *NBER Macroeconomics Annual 2002, Volume 17*, ed. by M. Gertler, and K. Rogoff, pp. 159–230. MIT press.

Watson, M. W. (1986): "Univariate Detrending Methods with Stochastic Trends," *Journal of Monetary Economics*, 18(1), 49–75.

——— (1999): "Explaining the Increased Variability in Long-Term Interest Rates," *FRB Richmond Economic Quarterly*, 85(4), 71–96.

Zarnowitz, V. (1962): "Unfilled Orders, Price Changes, and Business Fluctuations," *Review of Economics and Statistics*, 44(4), 367–394.

A. Appendix



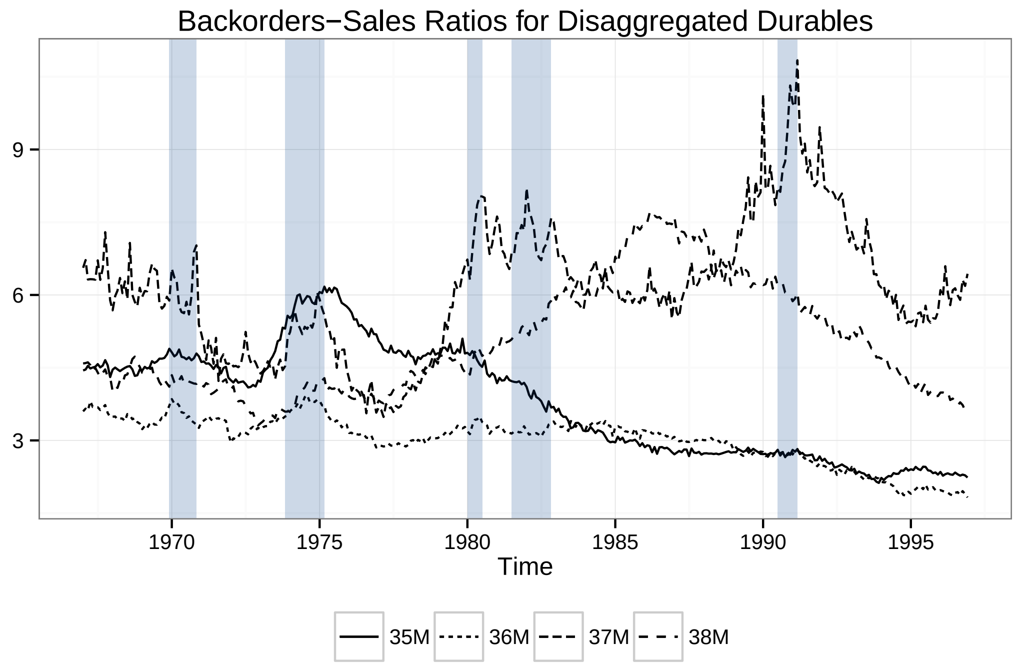


Figure 9: Disaggregated Backorders to Shipments Ratio
SIC codes: 32M – Stone, Clay and Glass, 33M – Primary metals, 34M – Fabricated metals, 35M – Industrial machinery and equipment, 36M – Electronic and other electrical equipment, 37M – Transportation equipment, 38M – Instruments and related products.

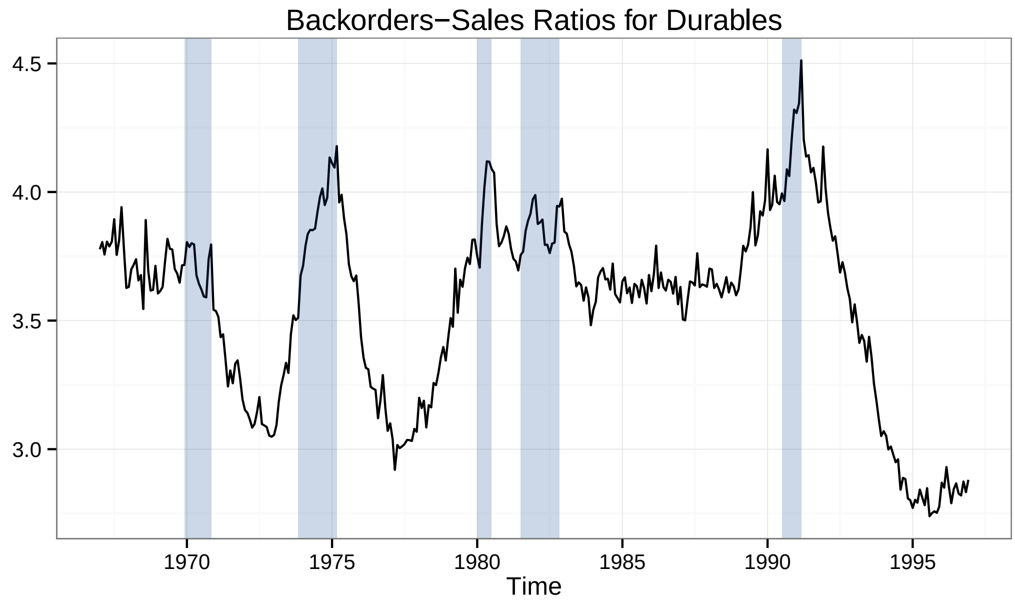


Figure 10: Backorders to Shipments Ratio for All Durables Industries
Shaded areas are NBER-dated recessions

	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 6: 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.

Counterfactuals	Within Industry LV	*Relative RMSE* 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 7: 60-month counterfactuals of the within industry parameters, given Σ_{HV}
Notes: The RMSEs are relative to the HV *variances and parameters, ie.* $[\Theta_{HV}, \Sigma_{HV}]$.

Durables SVAR

Industry Block *Shock to*	*Ratio*	Aggregate Block *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 8: Relative size of structural shocks, where Ratio = $\sigma(LV)/\sigma(HV)$

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