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On the Causes of the Increased Stability of the U.S. Economy

1. Introduction

The volatility of real GDP growth in the United States has fallen by half since the early 1980s relative to the prior postwar experience.[1] Inflation also stabilized around then (although only when compared with a shorter period of volatility in the 1970s). Some studies have argued that an improvement in U.S. monetary policy around that time can explain both the lower output and inflation volatility; others have attributed the decreased volatility of GDP to a reduction in the size of the shocks hitting the U.S. economy—essentially "good luck"—and have attributed the improvement on the inflation front to better policy.[2]

In this paper, we argue that changes in inventory behavior stemming from improvements in information technology (IT) have played a direct role in reducing real output volatility. Our rationale is that even if the magnitude of the exogenous shocks hitting the economy has not changed, the role of inventory investment in magnifying or propagating those shocks has moderated significantly. Thus, even a large swing in final demand would be expected to produce a smaller swing in production now than it would have twenty or thirty years ago. We argue further that this implies a more modest role for both luck and improved monetary policy in stabilizing output, although policy remains the likely source of reduced inflation volatility.

Our view that technical progress is primarily responsible for the reduced volatility of output is formed largely by two important features of the data. First, in a growth-accounting sense, most of the reduction in aggregate variability can be explained by a corresponding reduction in the variability of output in the durable goods sector. The nondurables, services, and structures sectors of the economy do not contribute importantly to the increased aggregate stability, nor are these sectors themselves significantly more stable.[3] Second, the dramatic decline in the volatility of durables production is not accompanied by a similar reduction in the variability of durables final sales. In fact, the ratio of output variability to sales variability in that sector drops sharply after the early 1980s. The view that policy alone brought about the increased stability would have to explain why policy affected the volatility of production so much more than final sales, and why the phenomenon of increased stability has been concentrated in the durable goods sector. In other words, policy (or good luck) would have to explain why the impact was felt primarily in durable goods inventories.

After providing a detailed look at the changing volatility of macro data, we present a model in which improved information about final demand leads to less volatile output, both absolutely and relative to final demand. We then show how changes in monetary policy alone are unlikely to have important effects on the volatility of production relative to final sales. Finally, we suggest that monetary policy played the primary role in the reduction of inflation volatility.

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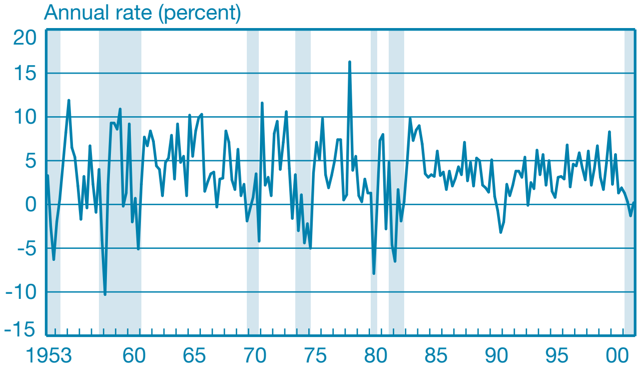
2. The Changing Macroeconomic Environment

In this section, we provide an overview of the changing volatility of the U.S. macroeconomy over the postwar period 1952:3 to 2000:2. We begin by comparing the behavior of inflation and output volatility over three subsamples and conclude that while the stability of output growth over the past fifteen or so years is unprecedented, the current stability of inflation is similar to the stability that prevailed in the 1950s and 1960s. Turning then to disaggregate output data, we point out the importance of the durable goods sector in explaining the decline in aggregate volatility. We then look at the changing relative volatilities of output and final sales throughout the goods sector and highlight the role of inventory behavior in stabilizing output.

2.1 Inflation and Output

Chart 1 presents U.S. real GDP growth from 1953:2 to 2000:2; Chart 2 depicts the consumer price index (CPI) over the same period. It is easy to see that both inflation and output have been less volatile in the most recent two decades than in the turbulent 1970s. When viewed in comparison with the 1950s and 1960s, however, the stability of the recent period is considerably more striking for output growth than it is for inflation.

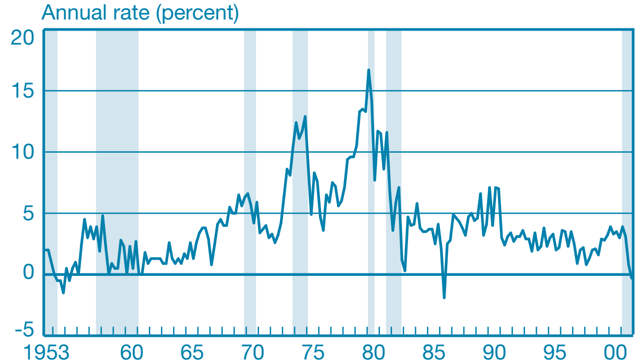
Chart 1
U.S. Real GDP Growth: 1953:2-2000:2



Source: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts.

Note: The shaded areas indicate periods designated national recessions by the National Bureau of Economic Research.

Chart 2
U.S. Inflation: 1953:2-2000:2



Source: U.S. Department of Labor, Bureau of Labor Statistics.

Note: The shaded areas indicate periods designated national recessions by the National Bureau of Economic Research.

To demonstrate more clearly how the volatility of these macroeconomic aggregates has evolved over time, we compute point estimates for the standard deviation of various measures of nominal and real activity over three subsamples within our larger sample period 1953:2 to 2000:2. The first is 1953:2 to 1968:4, corresponding to the first fifteen years of the postwar sample; the second is the fifteen-year period from 1969:1 to 1983:4, with the end date corresponding to the date McConnell and Perez-Quiros (2000) find for the break in the volatility of output growth; the last is 1984:1 to 2000:2.[4]

Table 1 reports the standard deviation of the CPI, the GDP deflator, and the core CPI for each sample period. In all cases, the standard deviation of inflation is around twice as large in the 1969:1-1983:4 period as it is in either the 1953:2-1968:4 or the 1984:1-2000:2 periods. Thus, the current stability of inflation is not unprecedented—in the fifteen or so years following the Korean War, the U.S. economy achieved inflation outcomes similar to those we are currently experiencing.

Turning now to the real side of the economy, we find that the volatility of output since the early 1980s is significantly lower than it is in either of the earlier subperiods. Table 2 reports the standard deviation of GDP growth and its components for our three sample periods.[5] Focusing first on aggregate GDP, we see that the unconditional standard deviation of real growth in the 1970s is not markedly different from that of the 1950s and 1960s and that the most recent period is more stable than either of the earlier two.[6]

An analysis of the components of real GDP growth reveals that the behavior of durables volatility most closely mimics the behavior of aggregate volatility. In particular, the magnitudes

Table 1
The Changing Variability of Inflation

	Inflation		
Variable	1953:2-1968:4	1969:1-1983:4	1984:1-2000:2
Consumer price index (CPI)	1.6	3.6	1.5
GDP deflator	1.4	2.3	1.0
Core CPI	1.4	3.3	1.1

Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; U.S. Department of Labor, Bureau of Labor Statistics.

Notes: The figures reported are the standard deviation of the variable in the left column. Inflation is measured as the percentage change in the price level at an annual rate. The first subsample in the "Core CPI" row is 1957:2 to 1968:4 because of limited data availability.

Table 2
The Changing Variability of Real Activity

	Output Growth		
Variable	1953:2-1968:4	1969:1-1983:4	1984:1-2000:2
Aggregate	4.5	4.8	2.2
Durables	18.1	17.9	8.0
Nondurables	5.9	7.9	4.8
Services	3.4	1.5	1.4
Structures	7.0	13.6	8.6

Source: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts.

Notes: The figures reported are the standard deviation of the variable in the left column. Output growth is measured as the percentage change in chain-weighted 1996 dollars at an annual rate.

of the standard deviations in each of the two early periods are similar and are more than twice as high as the standard deviation in the later period. This is precisely the pattern observed in the aggregate data, and it is matched in no sector other than durables. The volatility in the nondurables and structures sectors more closely follows the pattern of inflation volatility, being high in the middle period but presenting similar magnitudes in the earlier and later periods. Finally, there is sizable reduction in services volatility in the two later periods relative to the early period.[7]

Thus, we see that a 50 percent decline in the standard deviation of durables growth occurred at the same time that the volatility of overall GDP growth contracted. The durables sector accounts for only about 20 percent of GDP, however, so it does not necessarily follow that its impact on aggregate volatility would be large. To gauge the potential role of the durables sector in accounting for the behavior of aggregate volatility, we undertake an experiment like the one presented in McConnell and Perez-Quiros (2000). Drawing on the study's finding of a structural break in the residual variance of an AR(1) specification for durables growth in 1985:1, we generate an artificial series for durable goods growth under the counterfactual assumption that the residual variance post-1985 is equal to its average value in the pre-1985 period. We then aggregate to construct an artificial GDP series under this counterfactual assumption and compare the volatility of this series with the actual (Table 3). The table shows that the volatility reduction in the durables sector is large enough to account for more than two-thirds of the decline in aggregate volatility.

2.2 Output, Final Sales, and Inventories

Having established that the magnitude of the durables sector's decline in volatility is sufficient to account for much of the decline in aggregate volatility since the early 1980s, we ask what factor within durables—and perhaps within nondurables as well—has contributed to stabilizing output. As a starting point, one might ask whether or not the dramatic increase in output stability simply reflects greater stability in aggregate final demand. In other words, does it appear that producers are simply facing more stable demand and consequently are able to stabilize output? Alternatively, have there been changes in production behavior (and thus inventory behavior) that appear not to have been induced by a change in the volatility of

Table 3
Explaining the Changing Variability of Real Activity

Variable	1953:2-1984:4	1985:1-2000:2
Actual	4.7	2.2
Durables experiment	4.7	3.9

Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; authors' calculations.

Notes: The figures reported are the standard deviation of the variable in the left column. "Durables experiment" refers to an artificial GDP series constructed under the counterfactual assumption that the volatility of output in the durable goods sector did not decline after 1985:1. Output growth is measured as the percentage change in chain-weighted 1996 dollars at an annual rate.

final demand? Sorting through these two possibilities seems crucial to understanding whether the current stability of the real economy can be attributed mainly to technologically induced changes in inventory behavior or instead to policy- or even luck-induced stability in final demand.

In this section, we use only data from the goods sector because the distinction between production, final sales, and inventories is meaningful only in that sector. Aggregate GDP and final sales both include the services and structures sectors of the economy. Since virtually no inventories are held in these sectors, it is not meaningful to examine changes in inventory behavior in response to movements in these components of aggregate final sales.

Table 4 provides a summary of the data from the goods sector, splitting the sample according to the McConnell and Perez-Quiros (2000) break date, 1984:1. We see that the unconditional standard deviation of output and final sales has fallen in both the overall goods sector and each of the durables and nondurables sectors, although the decline is most dramatic for durable goods output. We also see, however, that while the ratio of output to final sales variability is uniformly greater than 1 in the early sample, the ratio for the durables sector in the later sample has fallen to a value approximately equal to 1.[8] Thus, the durables sector (and the overall goods sector) has experienced a contraction not only in overall output volatility, but also in output volatility relative to final sales volatility. The contraction in this ratio points to a change in inventory behavior.

To illustrate the role of inventory behavior in explaining output volatility in a simple growth-accounting framework, Table 5 decomposes the variance of output growth in the goods sector into the variance of the growth contributions of sales and inventory investment along with their covariance. In the goods sector as a whole (top panel), as well as in the durables and nondurables sectors separately (bottom two panels), the percentage of the decline in output volatility *not* accounted for by a reduction in sales volatility (reported in the last column) is large—78.3 percent in the overall goods sector and 86.8 percent in the durables sector. Thus, particularly in durables, we find an important role for the variance of the growth contribution of inventory investment, as well as for the decline in the covariance between the growth contributions of inventories and sales, in explaining the reduction in output volatility.[9] The decomposition in the table suggests that a change in inventory behavior has contributed substantially to the drop in output

Table 4

Output and Final Sales Growth in the Goods Sector: 1953:2-2001:1

Variable	1953:2-1983:4	1984:1-2001:1
Goods		
Output	8.2	4.6
Final sales	5.7	4.3
Ratio	1.4	1.1
Durables		
Output	17.9	8.1
Final sales	10.7	8.4
Ratio	1.7	1.0
Nondurables		
Output	6.9	4.8
Final sales	4.7	3.0
Ratio	1.5	1.6

Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; authors' calculations.

Notes: The figures reported are the standard deviation of the annualized quarterly growth rate (chain-weighted 1996) of the variable in the left column. "Ratio" is the ratio of the standard deviation of output growth to final sales growth.

Table 5

The Role of Inventories in Lower Output Volatility

Component	1959:1-1983:4	1984:1-2000:2	Percentage of $\Delta \mathrm{var}(\hat{y})$
Goods			
$\mathrm{var}(\hat{y})$	3.73	1.14	100
$\mathrm{var}(\hat{s})$	1.58	1.02	21.7
$\mathrm{var}(\widehat{\Delta I})$	2.26	1.15	43.4
$2\mathrm{cov}(\widehat{\Delta I}, \hat{s})$	-0.12	-1.02	35.0
Durable goods			
$\mathrm{var}(\hat{y})$	17.46	3.70	100
$\mathrm{var}(\hat{s})$	5.68	3.91	13.2
$\mathrm{var}(\widehat{\Delta I})$	9.11	3.92	38.2
$2\mathrm{cov}(\widehat{\Delta I}, \hat{s})$	2.68	-4.12	48.5
Nondurable goods			
$\mathrm{var}(\hat{y})$	2.97	1.39	100
$\mathrm{var}(\hat{s})$	1.12	0.52	38.1
$\mathrm{var}(\widehat{\Delta I})$	2.37	0.99	87.7
$2\mathrm{cov}(\widehat{\Delta I}, \hat{s})$	-0.56	-0.12	-25.8

Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; authors' calculations.

Notes: We use growth contributions because the data are chain-weighted. $\hat{y}$ refers to the quarterly (not annualized) growth rate of output, while $\hat{s}$ is the quarterly growth contribution of sales and $\widehat{\Delta I}$ is the quarterly growth contribution of inventory investment. We approximate the growth contribution of sales by its lagged nominal share multiplied by its growth rate. The growth contribution of inventory investment is defined as a residual, such that $\hat{y} = \hat{s} + \widehat{\Delta I}$.

volatility, although it does not rule out the possibility that some exogenous change in the sales process (beyond its volatility) has played some role.

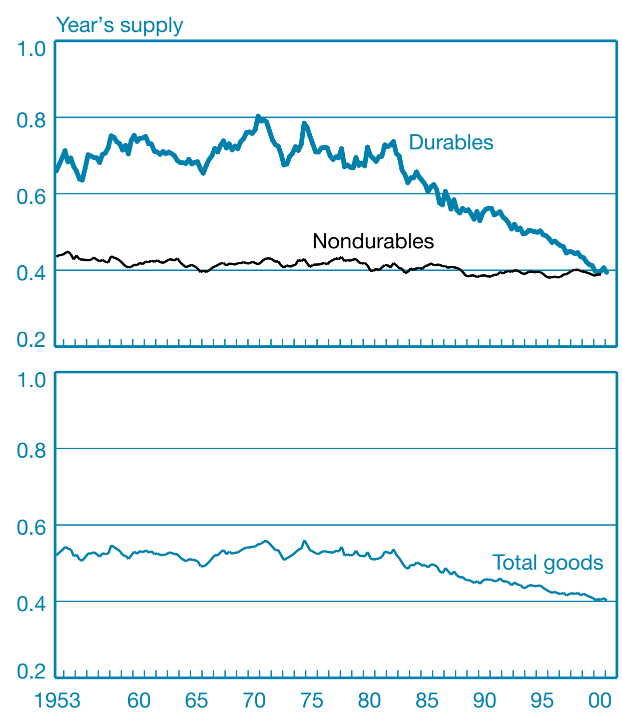
2.3 Other Evidence on Changing Inventory Behavior

The behavior of inventory-to-sales (I-S) ratios in the goods-producing sectors of the economy suggests that firms are economizing increasingly on their inventory holdings as well as staying closer to their desired (or "target") I-S ratios. The bottom panel of Chart 3 plots the ratio of real nonfarm inventories to final sales of goods starting in 1953.[10] It reveals that there is little drift in this ratio until the early 1980s, when it begins to trend downward. The top panel plots the ratios separately for durables and nondurables. The durables ratio has no discernible drift through the early 1980s, but then begins to drop precipitously, down roughly 30 percent by the end of the sample during a time span of less than twenty years. In nondurables, meanwhile, the ratio has only a slight downward drift over the entire sample period, on the order of a 10 percent total decline over a span of more than fifty years.

To add slightly more structure to the problem, we extract a smooth trend from the durables I-S ratios and interpret this trend as the target, or desired, I-S ratio for the durables sector.[11] Thus, movements away from trend are deviations from the target. The results of this exercise appear in Chart 4. The top panel plots the actual ratio along with the target ratio; the bottom panel plots deviations from the trend, along with bands indicating two standard deviations. These plots reveal two important aspects of the behavior of the I-S ratio. First, our measure of the target declined almost steadily after the early 1980s.[12] This decline in the target ratio provides circumstantial evidence of a structural change in the durable goods sector around the same time as the decline in volatility. Second, there is a significant reduction in the size of the deviations from the target after the early 1980s.[13] We interpret this as evidence that firms are making smaller mistakes now than before, a phenomenon that could plausibly be linked to improvements in information technology.

Chart 3

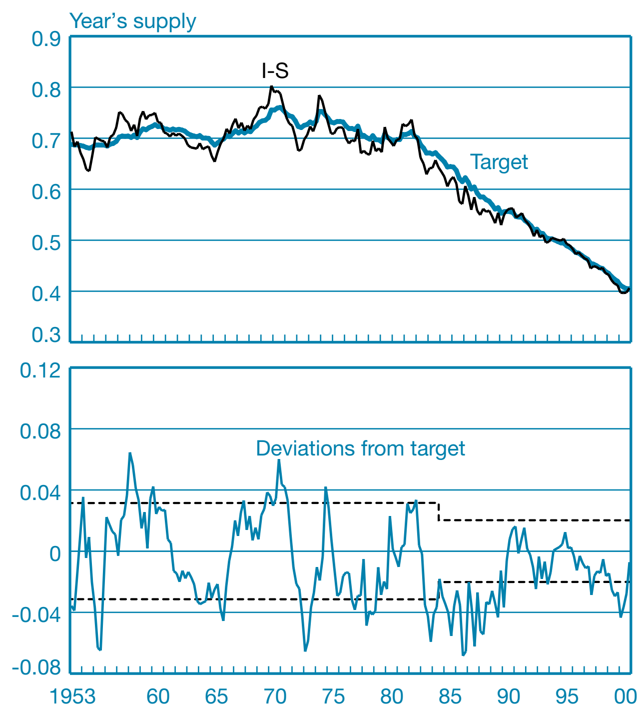
Postwar Inventory-to-Sales Ratios



Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; authors' calculations.

Chart 4

Durables I-S, Target I-S, and Deviations from Target



Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; authors' calculations.

Note: I-S is inventory-to-sales.

Additional evidence can be found from a simple vector autoregression on the growth rates of final sales and inventories. Table 6 presents results from the durable goods sector for the pre- and post-1984 sample periods (real 1996 chain-weighed dollars, in growth rates). Although a modest decline occurs in the volatility of the dependent variables, what is striking is the increase in the R^2 for the sales equation, apparently due to the increased explanatory role of lagged inventories. As seen in the bottom panel of the table, inventories explain only 5 percent of the variance in sales in the early period, but 15 percent in the later period. At the same time, lagged sales play *less* of a role in explaining inventory investment. Both of these findings are consistent with the theory that inventory investment incorporates better information—and is therefore better able to anticipate sales—in the later sample period. Finally, we note that the stronger evidence of technological change in the durable goods sector may be an artifact of differences in the speed at which IT has been disseminated across sectors. An examination of manufacturing, wholesale, and retail trade publications from the mid-to-late 1980s on such topics as flexible manufacturing, "just-in-time" inventory management, and computer numerically controlled machine tools reveals numerous references to dramatic changes in production techniques in the late 1970s and early 1980s in the durable goods sector. There is particular emphasis on new techniques in the motor vehicles, aerospace, primary metals, and electrical and industrial equipment industries, although there are also examples from industries such as lumber and furniture. Virtually all of these references emphasize the fact that these manufacturing techniques have the desired effect of reducing the inventory-to-sales ratios across all stages of fabrication.[14] In addition, data on investment in IT capital indicate that the durables sector invested twice as much per worker (in nominal terms) as the nondurables sector over the 1965-85 period.[15]

Table 6
The Durable Goods Sector

	1953:1-1983:4		1984:1-2000:2	
	Sales_t	Inventories_t	Sales_t	Inventories_t
VAR estimates				
Sales_{t-1}	0.152	0.142	-0.212	0.132
	(0.089)	(0.041)	(0.129)	(0.054)
Sales_{t-2}	0.138	0.116	-0.138	0.173
	(0.089)	(0.041)	(0.112)	(0.047)
Inventories_{t-1}	0.445	0.390	1.007	0.446
	(0.206)	(0.094)	(0.286)	(0.121)
Inventories_{t-2}	-0.551	-0.030	0.082	-0.038
	(0.190)	(0.087)	(0.319)	(0.135)
R^2	0.132	0.442	0.275	0.410
Standard deviation dependent	0.025	0.015	0.020	0.010
Variance decomposition (percent)				
Sales	94.6	37.8	84.1	18.2
Inventories	5.4	62.2	14.9	81.8

Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; authors' calculations.

Notes: The figures reported in the top panel are the results of a vector autoregression (VAR) on the growth rates (change in the log, not annualized) of final sales and inventories for the durable goods sector. The bottom panel reports the results of a variance decomposition after ten periods, with sales placed first in the ordering.

3. A General Equilibrium Model of Output, Sales, and Inventories

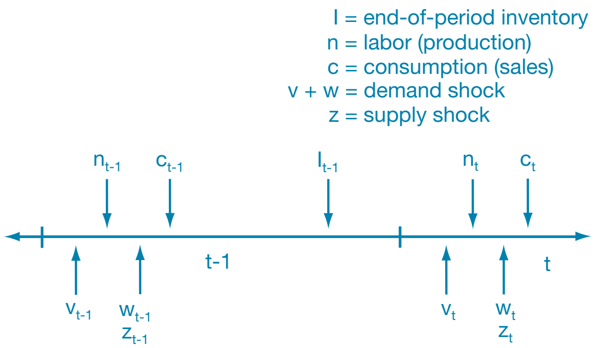
In this section, we explore the implications of better technology and increased anti-inflationary monetary policy using a model of the macroeconomy. Our results illustrate how increased information on the part of the firm can reduce output volatility with no change in the underlying volatility of the shocks hitting the economy. The effect of this is to lower the ratio of output volatility to sales volatility. We then incorporate monetary policy into the model to show that while a more anti-inflationary policy will have the effect of reducing inflation volatility, it will tend to leave the ratio of output to sales volatility unchanged.

3.1 Technology and Preferences

We describe a model that illustrates the effect of increasing the amount of information that producers have about final demand at the moment they make their production decisions. We merely outline the model's main characteristics here; the model's actual structural equations are presented in Appendix A. The key feature of the model is that firms make decisions regarding production before they know final demand for the period. Exhibit 1 illustrates the timing of decision making and information flows in the model. Producers choose labor n_t, observing only part (v_t) of the demand shock $w_t + v_t$ in period *t*. To the extent that sales deviate from their expectations (that is, $w_t \neq 0$), there will be unintended inventory accumulation or

Exhibit 1

The Time Structure of Decisions and Information



decumulation. If we assume that firms have a desired, or target, inventory-to-sales ratio, then these movements in inventories push firms away from their target and force them to alter production in the following period to accommodate both the change in demand and the recovery of inventories toward their target. (We illustrate this effect in more detail in the next section.)

The consumer side of the model provides the underlying motive for the target inventory-to-sales ratio. The stock of inventories enters the consumer's utility function, under the assumption that inventories are complementary to consumption expenditures. The motivation for this is that inventories provide a service to consumers, either in reducing transaction or transportation costs, or in more precisely matching consumers' demands. This would also be true for inventories at other stages of the production process, though we do not model those explicitly.

The other important feature of the model is that consumers have demand shocks, modeled as shocks to the preference between consumption and leisure. Such shocks are frequently a feature of macroeconomic models involving policy decisions (for example, Clarida, Galí, and Gertler [2000] and Woodford [1999]). Here they play a key role in driving inventory investment dynamics as well as in the changes in information technology.

Otherwise, the model has standard assumptions that give rise to "permanent income" behavior: consumers are forward-looking and alter their expenditures according to real interest rates and expectations about future income. A positive demand shock typically drives up the equilibrium real interest rate, increases expenditures, and reduces inventories to the extent that the shock was unanticipated.

The model has two other potentially important simplifications. First, the steady-state I-S ratio is essentially determined by a parameter of the utility function θ, which is the weight of consumption relative to inventories in utility. (A higher value of θ corresponds to a lower steady-state I-S ratio.) Consequently, the improvements in IT do not translate into a lower I-S ratio in the model, even though they appear to do so in the data. When we simulate our model below, we include a lower inventory-to-sales ratio as part of technological progress.[16]

The second simplification is that the produced good is modeled as a nondurable good in terms of how it enters into consumer utility. While the qualitative implications of the model are unlikely to be affected, quantitative issues arise in calibrating the model to real-world data, as we discuss below.

3.2 Progress in Information Technology: An Illustration

Because of the nature of the inventory problem, in which forecast errors carry over into current production decisions, improvements in IT or inventory management can reduce output volatility. There has been a wealth of anecdotal and case study evidence to suggest that information about final sales travels upstream much more quickly than it used to because of advances in information technology.

Exhibit 2 illustrates this basic point. Firms enter period 1 with sales of 50 units and a target I-S ratio of 2, that is, 100 units of inventories. To demonstrate the effect of firms having to commit to their production levels before knowing demand in the period, we trace out the effects of an unanticipated permanent increase in final demand. This scenario is reported on the left side of the exhibit. Since the firm does not know the level of demand in the period before it commits to production, it will choose to produce the expected value of final demand (in this example, 50 units). Later in the period, a permanent increase in demand to 75 units is revealed to the firm. To meet this demand, the firm initially draws down its inventories, leaving it with 75 units of inventories at the end of the period. The increase in the expected value of demand in future periods causes the firm to raise its target level of inventories from 100 to 150, in order to maintain the I-S ratio at 2. In period 2, then, the firm must produce 150 units—75 to meet the new higher demand in that period and 75 to get the firm back to its desired I-S target. Finally, in period 3, the firm enters the period with desired inventories equal to its target and simply produces the expected value of inventories in that period.

To show how better information works to reduce output volatility in our model, we now suppose that rather than waiting until after it has committed to production, the firm gets a signal about the upcoming demand shock prior to making its

Exhibit 2

The Impact of Information on Production Decisions

Period 0: Sales = 50

Production = 50
Target I-S = 2
Inventories = 100
Target inventories = 100

Period 1: Permanent increase in sales from 50 to 75

Low information	High information
Production based only on Period 0 information Sales forecast = 50	Production based only on current sales information Sales forecast = 75
Production = 50 Inventories = 75 Target inventories = 150 Actual < Target	Production = 125 Inventories = 150 Target inventories = 150 Actual = Target

Period 2: Sales = 75

Low information	High information
Production = 150 Inventories = 150 Target inventories = 150	Production = 75 Inventories = 150 Target inventories = 150

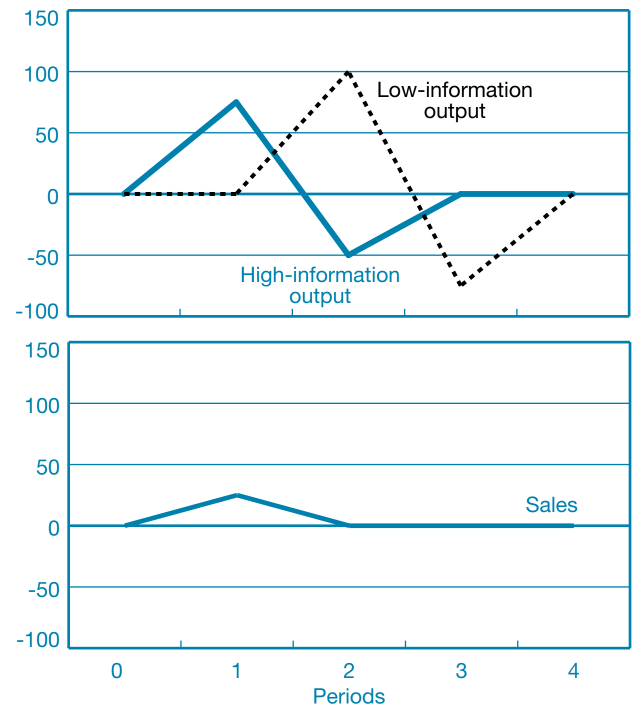
Period 3: Sales = 75

Low information	High information
Production = 75 Inventories = 150 Target inventories = 150	Production = 75 Inventories = 150 Target inventories = 150

Note: I-S is inventory-to-sales.

Chart 5

The Impact of Information on Volatility



Source: Authors' calculations.

production decision. An extreme example of this scenario, one in which the firm knows the exact demand shock, is shown on the right side of Exhibit 2. In this example, we assume that the firm finds out the magnitude of the demand shock in advance of making its production decision, and hence it chooses to produce 125 units of the good—75 of which will meet current demand and 50 of which will be added to inventories, raising the stock to 150 and keeping the firm at its target ratio of 2.

To see the effect of better information on the volatility of production, compare the movements in output under our two scenarios. As shown in the top panel of Chart 5, for the same underlying demand shock (shown in the bottom panel), production jumps by 100 units under the low-information scenario, but only by 75 units under the high-information scenario (Chart 5 depicts the first differences of the movements described in Exhibit 2). The demand increase is identical in both cases, so the reduction in volatility is entirely a consequence of the change in the propagation mechanism. The change in the propagation of the demand shock in turn stems from the improved information that allows firms to know more in advance about the likely realization of demand for that period.

It should be noted that this simple example makes the extreme assumption that the firm adjusts its inventories to target within one period upon learning of the demand change. The full general equilibrium model described above and detailed in Appendix A allows for the more realistic case in which the response is optimally spread out over time. But the essential results concerning volatility carry over to that case.

It is also important to note that better information at the time production decisions are made can also be thought of as greater *flexibility* in production scheduling rather than a change in the timing of information flows per se. For example, if production decisions (or hiring decisions, materials orders, or other decisions) can be made with shorter lead time, then presumably they can be made with more up-to-date information, even if the flow of information itself is unchanged.[17]

3.3 The Full Story: Adding Monetary Policy to the Model

Up to this point, the technological view can explain the stabilization of output without any role for monetary policy. At the same time, the model has nothing to say about inflation.

We now introduce inflation into the picture, along with a role for discretionary policy. To do this, we adopt a variant of the simple log-linear accelerationist framework employed by a number of contributors to the literature on policy research.[18] According to this view, not all producers change prices at all times, but ultimately prices respond to changes in marginal cost. Consequently, inflation accelerates to the extent that the marginal cost of production increases. In implementing this idea, we presume that the policymaker can effectively manipulate real interest rates in the short run (a feature that is common to sticky price models of monetary policy) and thereby influence "demand" and marginal cost.

The three assumptions that we add to the general equilibrium model, described in the previous section and detailed in Appendix A, are as follows:

1. Inflation is driven by changes in marginal cost.
2. The monetary policy authority can temporarily set real interest rates, and does so according to a rule that depends on lagged inflation.
3. The short-run quantity of labor is determined by the production decision, with the wage adjusting to keep labor on its supply curve.

The Phillips curve associated with assumption 1 above is

$$(1)\quad \pi_t = (1-\omega)\pi_{t-1} + \omega\beta E_t\pi_{t+1} + \gamma[(\alpha+\delta)n_t - z_t] + \varepsilon_t,$$

where π_t is inflation in period *t* and *n* is the quantity of labor. The quantity $(\alpha+\delta)n_t - z_t$ captures movements in the marginal cost of production (see Appendix A). Here, α is capital's share in production and δ is the inverse of the elasticity of labor supply. The parameter ω determines the extent to which the inflation process is forward- as opposed to backward-looking, while γ determines the sensitivity of inflation to marginal cost. (In sticky price models, γ is related to the speed or frequency of price adjustments.)

The policy rule corresponding to assumption 2 is

$$(2)\quad r_t = \psi\pi_{t-1},$$

where r_t is the real interest rate and ψ determines the policymaker's response to lagged inflation. Thus, a larger value of ψ implies a more aggressive anti-inflationary policy stance. The simplicity of this equation is intended to capture the idea that the policymaker has limited information, and in particular cannot observe the actual shocks that would permit a rule with a richer set of contingencies.

4. Assessing the Impact of Information and Policy

The first task in applying the model is to choose parameters. Ideally, as many of the parameters as possible would be "calibrated," that is, chosen based on prior information such as estimates from econometric studies, or factor shares or other ratios that appear to be stable over long periods of time. The details of our parameter choices are provided in Appendix A, with the exception of our choice of ψ, the policy response to inflation, which we discuss here.

As mentioned earlier, our guide for choosing the policy rule parameter is simply that it gives rise to realistic outcomes, and that the rule is not obviously inferior to another rule of the same form. Underlying this is a presumption that policymakers are doing the best they can given whatever informational and institutional constraints they face.

We suppose that the policymaker trades off the distortions generated by having a real rate different from the equilibrium value against the desire to reduce inflation volatility.[19] For the parameters in this example, the analysis suggests that a choice of ψ less than 0.02 would not be sensible, because below 0.02, both inflation volatility and the distortion are diminishing. How far above 0.02 is desirable would depend on the policymaker's distaste for inflation, although presumably the inflation benefits of increasing ψ farther and farther above 0.02 would be diminishing while the cost of the distortion would be increasing.

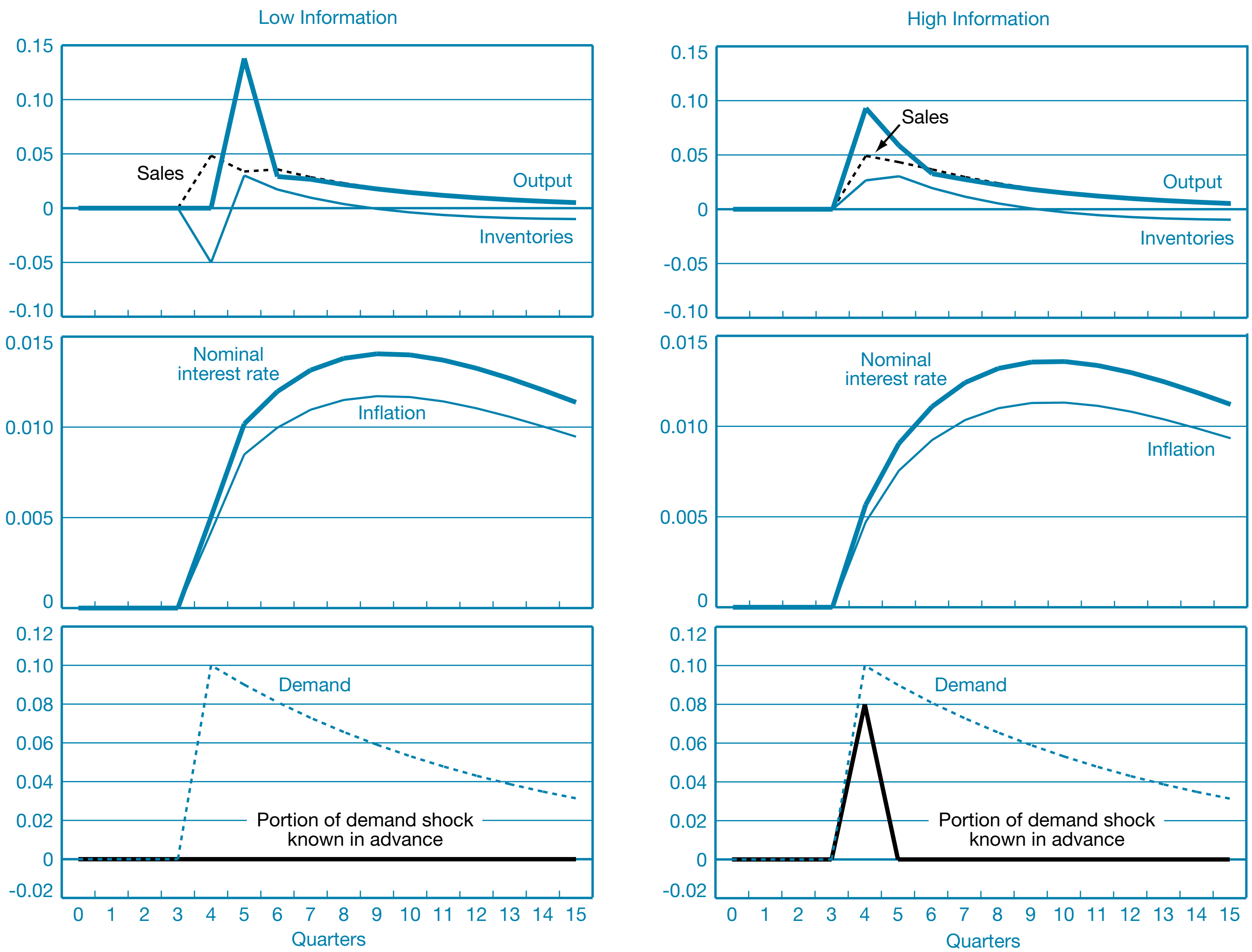
To demonstrate the basic workings of the model, we now trace out the effects of a transitory (though serially correlated) increase in demand on output, sales, inventories, inflation, and nominal interest rates under different assumptions about IT (Chart 6) and policy aggressiveness (Chart 7). Starting with Chart 6, we consider two cases: "low information," in which producers know only the previous period's sales and inventories, and "high information," in which producers also know 80 percent of the current demand shock (that is, a signal-to-noise ratio of 4) before committing to production.[20] The top two panels plot the responses of the economic variables while the bottom panel illustrates the increase in the portion of the total demand shock known in advance of the production decision. (The total demand shock is given by the dashed line; the portion of the shock known in advance is given by the solid line.) Note that both charts assume that the unobserved part of the demand shock is the same sign as the observed part, though in practice they are independent. The total demand shift is the same in both cases (0.10), but the percentage of the demand shock known at the time the production decision is made goes from 0 to 80 moving from left to right.

Turning first to the low-information case, we see that when the shock hits, production does not respond immediately and inventories are depleted. In subsequent periods, output is increased, both to accommodate the increase in demand and to replenish the inventory stock. In the high-information panels, the firm has advance knowledge of most of the demand shock. In this case, output is increased both to meet the increase in demand and to keep inventories near their target. The important aspect of this is that the overall increase in output needed to accommodate the shock is smaller in the second case than in the first because the firm is not caught entirely by surprise.

These simulations confirm the basic intuition of the simple example considered above: the primary impact of better information is to moderate the output response relative to sales, because of the smaller inventory imbalance. In other words, the more the demand increase is anticipated, the sooner the increase in production can begin (and be spread over more

Chart 6

The Impact of Demand Shocks under Alternative Information Technology Scenarios



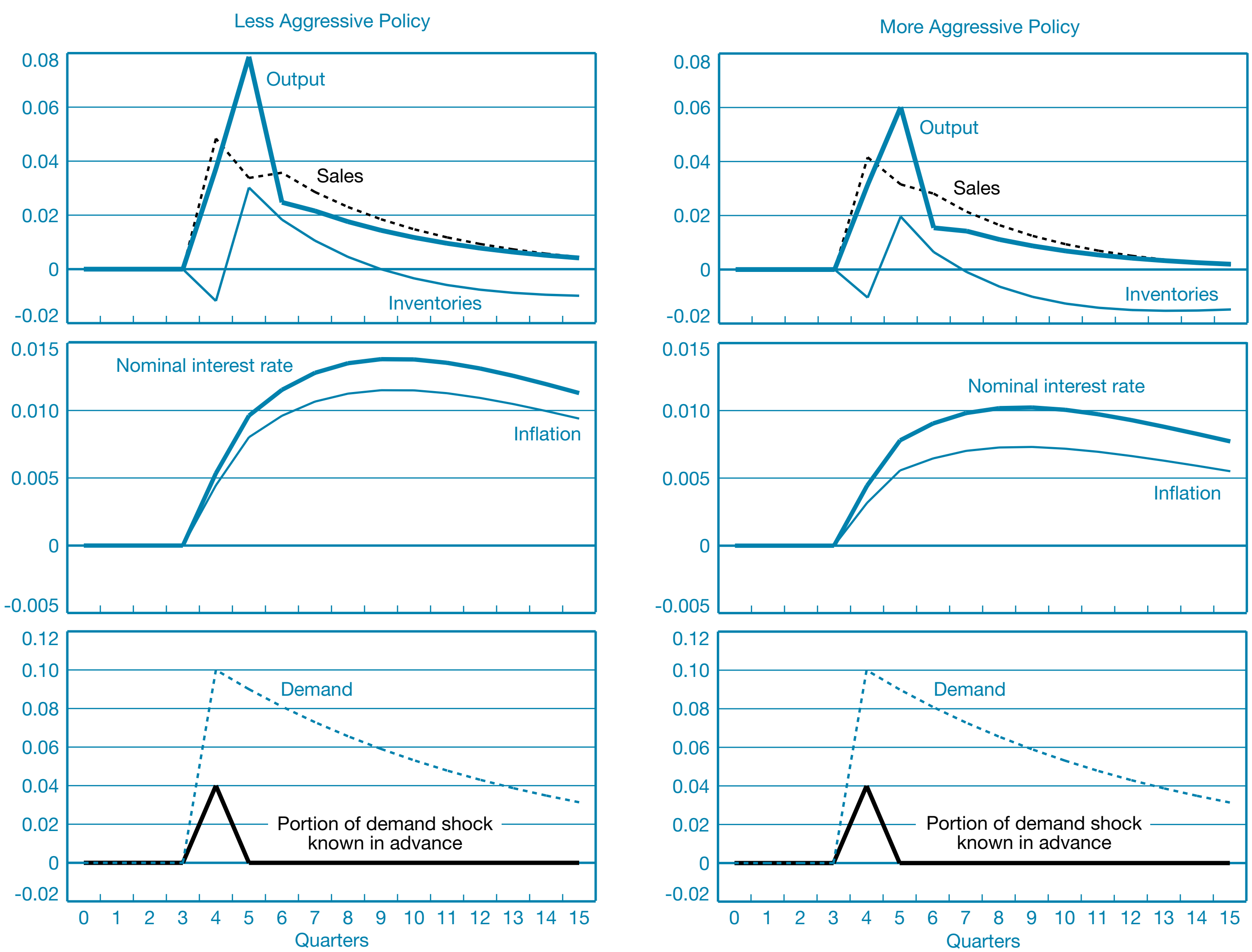
Source: Authors' calculations.

time), so that the inventory-to-sales ratio gets less out of line. It should be noted that the reduced output response to a given demand shock does not translate into noticeably lower inflation. This is somewhat surprising, given that a smaller output response implies a smaller increase in marginal cost. Thus, it seems unlikely that the benefits of better inventory management, at least as modeled here, can help to account for lower inflation volatility.

Turning now to the effects of more anti-inflationary monetary policy, depicted in Chart 7, we note that the variables represented are identical to those in Chart 6. Now, however, as we move from left to right, the experiment is one in which the anti-inflation parameter ψ is raised from 0.2 to 0.4 (in other words, policy becomes more aggressive against inflation). Here, we see that while policy does indeed dampen the effects of demand shocks on output, it also dampens their effects on sales, and hence we do not appear to have as dramatic a reduction in the relative effects on output and sales as we did in Chart 6. Looking at the middle panels of Chart 7, however, we can see that as we move from less aggressive to more aggressive policy, the impact of the demand shock on inflation is nearly half as large. Hence, policy seems to have important effects on the propagation of a demand shock to inflation, as would be expected.

Chart 7

The Impact of Demand Shocks under Alternative Policy Rules



Source: Authors' calculations.

4.1 Simulation Results

In reality, economies are hit by a variety of shocks, and policy decisions may have different effects depending on which types of shocks have occurred. For this reason, and to help quantify the effects of policy and progress on volatility, we turn to a simulation of the model that includes both supply and demand shocks. For this exercise, we made supply and demand shocks of roughly comparable magnitude, based on a variety of results in the empirical literature suggesting this to be the case.[21]

The goal of the simulations is to compare how changes in policy and changes in information technology, as we have modeled them, affect volatility both qualitatively and quantitatively. To do this, we simulate the model economy and compute standard deviations of output growth, sales growth, and inflation for low and high values of ψ, holding IT fixed, and for low and high values of information, holding ψ fixed.

The results of the simulations are shown in Table 7. In the column labeled "Base," we report the standard deviation of the variables of interest for the baseline parameter values of $\psi = 0.2$, "low information" (meaning no information exists about the current demand shock). The shock volatilities are scaled to match the pre-1984 volatility of goods sector output. The column labeled "Policy" pertains to a simulation of the model in which the parameter ψ is increased from 0.2 to 0.4, but information and average I-S ratios are held at their base values. The "Progress" column gives the outcomes for the case in which $\psi = 0.2$, but information is high (80 percent of the shock is known in advance) and the average I-S ratio is lowered by 20 percent. The next-to-last column reports the case in which $\psi = 0.4$, information is high, and average I-S ratios are low.

The results are qualitatively similar to the impulse response figures: a more anti-inflationary policy rule has a strong effect on inflation volatility, a moderate effect on output and sales volatility, but little effect on the ratio of output to sales volatility (shown in the last row of the table). Technological progress, however, reduces output volatility but has little impact on sales volatility; thus, we get a larger reduction in the ratio in this case. It also has virtually no impact on inflation volatility. Note also that technology has the effect of reducing the size of deviations from the inventory-to-sales target. The final case, where we allow both for more anti-inflation policy and better IT, shows an economy with lower output volatility—both absolutely and relative to the volatility of final sales, lower inflation volatility, and a very slight reduction in the size of deviations from the target ratio.

The quantitative magnitudes of our results suggest that perhaps more than one factor has been at work, since no single factor appears able to match the data quantitatively. Even our combinations of policy and better information cannot easily account for the 50 percent decline in volatility that occurred after 1983.

However, a number of simplifications in the model may limit its ability to match the data quantitatively. First, information improves in a very limited way—only information about the current shock is enhanced. In another paper (Kahn, McConnell, and Perez-Quiros 2001), we explore other channels of improved information and find that they may help to account for the magnitude of the observed volatility reductions as well as the more negative covariance between inventory investment and sales found in Table 5. Second, we do not model durability explicitly, even though the durable goods sector is the focus of the change in inventory behavior. This may help to explain why the model implies relatively low sales volatilities compared with the data. Adding durability might also alter the response of sales to monetary policy, since durable goods demand is likely to be more sensitive to interest rates. Third, while supply shocks were included, we do not give them

Table 7
Simulation Results

Standard deviation of	Data 1953-83	Base	Policy	Progress	Policy and Progress	Data 1984-2000
Output	8.2	8.2	7.3	6.5	6.1	4.6
Final sales	5.7	3.3	3.1	3.4	3.1	4.3
Inflation	2.1	2.3	1.5	2.3	1.4	1.5
Deviations from target (I-S)	3.1	6.2	6.0	5.2	5.3	2.4
Output/final sales	1.4	2.5	2.4	1.9	2.0	1.1

Sources: U.S. Department of Commerce, Bureau of Economic Analysis, National Income and Product Accounts; authors' calculations.

Notes: The simulations are based on 50,000 Monte Carlo observations. The same realizations were used for all of the parameterizations. Data are standard deviations of annualized quarterly growth rates. I-S is inventory-to-sales.

an explicit role in accounting for structural change, although many economists believe that the volatility of supply shocks increased in the 1970s and played a role in the higher inflation of that decade. That scenario would require a more complicated model of policy that includes incomplete information, confusion, or mistakes by the policymaker. In our model, supply shock volatility primarily affects (both) output and sales volatility, with little spillover onto inflation. We should add, however, that without evidence of increased *real* volatility in the 1970s, it seems unlikely that supply shocks during that period could account for increased inflation, unless policy could neutralize the impact on output and force it all onto inflation.

Thus, although the model does not match the data quantitatively, it does capture the key qualitative features, namely, the reduced volatility of output relative to sales, the reduced volatility of the I-S ratio, and (with the help of policy) lower inflation volatility.

5. Summary

In this paper, we document the increased stability of both inflation and output in the U.S. economy since 1984, and argue that inventory investment, particularly in the durable goods sector, has played a key role in reducing volatility. Specifically, output has stabilized much more than final sales. We argue, first heuristically and then through a model, that an explanation relying solely on monetary policy is unlikely to account for these facts by itself. We also provide circumstantial and anecdotal evidence of improvements in IT and inventory management in the durables sector.

Our structural model, incorporating both inventories and information technology, illustrates how improved information about demand leads to lower output volatility without a comparable decrease in the volatility of sales. It also confirms the intuition that more aggressive monetary policy is likely to lower volatility of output and sales to the same degree, and is therefore unlikely to be the primary source of increased stability since 1984, although it—along with "luck" (smaller supply and demand shocks)—may have played a supporting role. Conversely, improved inventory management, with the resulting reduction in output volatility, does not translate into significantly lower inflation volatility, notwithstanding the presence of a Phillips curve in which changes in marginal cost are the driving force behind changes in inflation. Thus, in the final analysis, the paper suggests a rather "classical" interpretation of the increased stability since 1984: technological factors played the primary role on the output side, while monetary policy gets the credit for more stable inflation.

Appendix A: The Model

We solve for the equilibrium by examining a planner's problem. The planner solves

$$\max_{\{c,n\}} E_0\left\{\sum_{t=0}^{\infty}\beta^t U(\tilde{c}_t, n_t; \tilde{I}_{t-1}, \zeta_t)\right\}$$

subject to

$$\text{(A1)} \qquad \tilde{I}_t = \tilde{I}_{t-1} + A_t f(n_t) - \tilde{c}_t,$$

where n_t is work effort at t, $\tilde{c}_t$ is consumption, $\tilde{I}_t$ is the stock of inventories at the end of period t, A_t is a technology shock, and ζ_t is a taste shock (in the form of a shock to the marginal rate of substitution between leisure and goods).

We assume that U and f take the following forms:

$$U(\tilde{c}_t, n_t; \hat{I}_{t-1}, \zeta_t) = log[\theta\tilde{c}_t^{1-\rho} + (1-\theta)\tilde{I}_{t-1}^{1-\rho}]^{\frac{1}{1-\rho}} - \zeta_t b n_t^{1+\delta}$$

$$f(n_t) = n_t^{1-\alpha}$$

and that

$$A_t = (1+g)A_{t-1}\xi_t\tau_t/\tau_{t-1}$$

$$\zeta_t = \zeta_{t-1}^{\phi}v_t w_t,$$

where $E_{t-1}\{\xi_t\} = E_{t-1}\{v_t\} = E_{t-1}\{w_t\} = 1$. The first term in U captures the idea that a larger inventory stock increases the marginal utility of any given purchase c_t, either by reducing transaction costs (such as shopping time) or by better matching the consumer's tastes. The parameter ρ is the inverse of an elasticity of substitution, which will dictate the degree to which consumption and inventories are linked. The second term is a standard disutility of labor, with $\delta > 0$. The technology shock comprises a permanent shock, ξ_t, and a transitory shock, τ_t, while ζ_t is a preference shifter. The combined taste shock $v_t w_t$ is iid, only part of which (the v_t) is observable when n_t is chosen. Thus, in effect, n_t is chosen as of period $t-1$, except for the ability to anticipate part of the total preference shock $v_t + w_t$.

If we define $c_t \equiv \tilde{c}_t/A_{t-1}$ and $I_{t-1} \equiv \tilde{I}_{t-1}/A_{t-1}$, then we have

$$U(\tilde{c}_t, n_t; \tilde{I}_{t-1}, \zeta_t) = A_{t-1} + U(c_t, n_t; I_{t-1}, \zeta_t).$$

The resource constraint becomes

$$A_t I_t = A_{t-1}I_{t-1} + A_t n_t^{1-\alpha} - A_{t-1}c_t$$

$$(I_t - n_t^{1-\alpha})(1+g)z_t - I_{t-1} + c_t = 0,$$

where $z_t \equiv \xi_t\tau_t/\tau_{t-1}$. With this normalization, I, c, and n will be constant in steady state.

We can express the first-order conditions as

$$\text{(A2)} \qquad [\theta c_t^{1-\rho} + (1-\theta)I_{t-1}^{1-\rho}]^{-1}\theta c_t^{-\rho}\zeta_t - q_t = 0$$

$$\text{(A3)} \qquad b(1-\delta)n_t^{\delta} - n_t^{-\alpha}(1+g)^{-1}E_{t-1}\{q_t z_t | v_t\} = 0$$

$$\text{(A4)} \qquad E_t\{\beta[\theta c_{t+1}^{1-\rho} + (1-\theta)I_t^{1-\rho}]^{-1}(1-\theta)I_t^{-\rho}\zeta_{t+1} - q_t(1+g) + \beta q_{t+1}\} = 0,$$

where q_t is the normalized shadow price of consumption goods at date t and $E_{t-1}\{q_t z_t | v_t\}$ refers to the expectation given period $t-1$ information plus v_t.

The solution method involves linearizing the first-order conditions around the steady state, then using the methods described in Uhlig (1999) to solve for the equilibrium.

Inflation and Monetary Policy

To the above model, we append the Phillips curve introduced in the text,

$$\text{(A5)} \qquad \pi_t = (1-\omega)\pi_{t-1} + \omega\beta E_t\pi_{t+1} + \gamma[(\alpha+\delta)n_t - z_t] + \varepsilon_t,$$

and a policy rule that sets real interest rates, also described earlier. Since rates are set, we have to relax one of the first-order conditions. We make the standard assumption that equation A3 does not hold, and instead n_t is determined by inverting the production function and the real wage w_t is determined by the "supply curve" $b(1+\delta)n_t^{\delta}$.

Finally, it should be noted that the real cost of production as a function of output y_t is $w_t n_t(y_t)$, where $n_t(y_t)$ is the labor required to produce y_t. From the production function, we have $n_t(y_t) = (y_t/A_t)^{1/(1-\alpha)}$, which implies that marginal cost $m(y_t)$ can be expressed as

$$\text{(A6)} \qquad m(y_t) = \frac{w_t}{(1-\alpha)A_t}\left(\frac{y_t}{A}\right)^{\frac{1}{1-\alpha}-1} = \frac{w_t n_t}{(1-\alpha)y_t}.$$

If w_t is proportional to n_t^{δ}, then we have, after substituting for y_t and detrending by dividing by A_{t-1},

$$\text{(A7)} \qquad log(m(y_t)) = (\alpha+\delta)n_t - z_t$$

(ignoring constant terms). This is the expression that enters the Phillips curve equation (A5).

Parameter Values

The model requires $\rho > 1$ for inventories to complement consumption. However, getting inventory levels to be procyclical requires larger values of ρ. To that end, we set $\rho = 10$, although the results are not particularly sensitive to the choice of ρ. We also set $\beta = 0.99$ (which corresponds to an annualized discount rate of 4 percent) and $g = 0.005$, which corresponds to 2 percent trend productivity growth. Given these choices, to get the inventory-to-sales (I-S) ratio roughly in line with historical data, we set $\theta = 0.99$, which corresponds to a steady-state ratio of 0.96. When we lower the I-S ratio in simulating the impact of technological progress, we raise θ to 0.999, which implies a steady-state I-S ratio of 0.78.

After this, the parameter choices become more subjective, set more with a goal of having the model generate realistic fluctuations. But the results described below were qualitatively similar across a broad range of parameter choices. We set α, which could be thought of naively as 1 minus labor's share, equal to 0.2. This is smaller than the conventional value of 0.3 to 0.4, intended to offset the fact that we have no capital in the model, and hence no ability to vary capital or its utilization.

The remainder of the parameter assumptions are geared toward getting the relative volatilities of output, consumption, and inflation volatility in the vicinity of the data. We are not concerned with matching the volatilities precisely, in part because it is not clear what the "base case" should be, and in part because the simplifications in the model mentioned earlier (for example, the lack of durability of consumption) warrant against any precise correspondence to the data. With these considerations in mind, we set $\delta = 0.2$, $\gamma = 0.05$, and $\phi = 0.9$. Again, the results were similar over a broad range of parameter choices.

Appendix B: Kalman Filter Estimates of the I-S Ratio Target

To decompose the inventory-to-sales (I-S) ratio for the durable goods sector into its permanent and transitory components, we estimate the following model:

(B1) $$y_t = n_t + x_t$$

(B2) $$n_t = g_{t-1} + n_{t-1} + v_t \quad v_t \tilde{} iid, N(0, \sigma_v^2)$$

(B3) $$g_t = g_{t-1} + w_t \quad w_t \tilde{} iid, N(0, \sigma_w^2)$$

(B4) $$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t \quad e_t \tilde{} iid, N(0, \sigma_e^2),$$

where y_t is the I-S ratio, n_t is the permanent component, and x_t is the transitory component.

To address the question of whether σ_e^2 has fallen, we split the sample in 1984:1 (following McConnell and Perez-Quiros [2000]) and estimate:

(B5) $$y_t = n_t + x_t$$

(B6) $$n_t = g_{t-1} + n_{t-1} + v_t \quad v_t \tilde{} iid, N(0, \sigma_v^2)$$

(B7) $$g_t = g_{t-1} + w_t \quad w_t \tilde{} iid, N(0, \sigma_w^2)$$

(B8) $$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t \quad e_t \tilde{} iid, N(0, \sigma_{e,t}^2)$$

(B9) $$\sigma_{e,t}^2 = \sigma_{e,1}^2 (1 - I_t) + \sigma_{e,2}^2 I_t,$$

where $I_t = 1$ if $t > 1984{:}1$, and 0 otherwise.

The estimated values are

(B10) $$\sigma_v^2 = 0.000010 \ (0.000831)$$

(B11) $$\sigma_w^2 = 0.000253 \ (0.000093)$$

(B12) $$\sigma_{e,1}^2 = 0.018434 \ (0.001151)$$

(B13) $$\sigma_{e,2}^2 = 0.011650 \ (0.001036)$$

(B14) $$\phi_1 = 0.766974 \ (0.74982)$$

(B15) $$\phi_2 = 0.058569 \ (0.73654).$$

We reject the null hypothesis of $\sigma_{e,1}^2 = \sigma_{e,2}^2$ with a p-value of 0.000. An alternative specification in which we use the logs of the I-S ratio yields similar results.

Endnotes

1. Volatility is measured by the standard deviation of quarterly chain-weighted GDP growth (from the National Income and Product Accounts data).

2. For an example of the pure-policy argument, see Clarida, Galí, and Gertler (2000); Orphanides (2001) provides an opposing view on the question whether policy was in fact very inefficient before the early 1980s. Ahmed, Levin, and Wilson (2001) discuss the good luck/policy hypothesis. Blanchard and Simon (2001) argue that there has been a secular decline in volatility since the 1950s, and identify several proximate causes.

3. See McConnell and Perez-Quiros (2000) for details.

4. We discuss the determination of the 1984:1 date below.

5. The figures reported here are the standard deviations of the growth rates of the individual components and not of the growth contributions.

6. McConnell and Perez-Quiros (2000) test for the type of structural change described in Andrews (1993) and Andrews and Ploberger (1994) to estimate a break in the residual variance of an AR(1) specification for real GDP growth in 1984:1. They also test for additional breaks within each of the periods 1953:2 to 1983:4 and 1984:1 to 1999:2, and find no evidence of additional breaks. Hence, it is 1984:1 upon which we base our split between the second and third sample periods, and it is only this date that we view as relevant for the behavior of output volatility. The distinction between the first and second sample periods is made purely to illustrate the contrasting behavior of inflation volatility.

7. Since Table 2 presents only the standard deviation of the growth rates of each of these sectors, it does not provide an assessment of the effects of changes in the composition of nominal GDP. There has, in fact, been some shift in composition over time, with the average shares of the goods, services, and structures sectors changing from 0.47, 0.42, and 0.11 in the pre-1984 period to 0.39, 0.52, and 0.09, respectively, in the recent period. A second experiment that holds sectoral shares constant shows that the standard deviation of output would have declined to 2.6, which is very close to the actual value of 2.2. See McConnell and Perez-Quiros (2000) as well as Kim, Nelson, and Pigor (2001) and Warnock and Warnock (2000) for a more detailed discussion of the sectoral data.

8. The value of this ratio in the early period is not surprising, as a large literature exists documenting and seeking to understand the reasons why production is more volatile than sales.

9. Golob (2000) also points out the change in the covariance across these two samples and suggests that it provides evidence of greater production-smoothing behavior. Whether firms are indeed smoothing production (relative to sales) more now or are instead simply trying to match sales more closely remains an empirical question.

10. Because these plots are ratios of two chain-weighted series, the level of the inventory ratio is not meaningful, but movements in the ratio are.

11. The "target" was estimated using Kalman filter methods, assuming a permanent and transitory component, and allowing for the variance reductions post-1984. See Appendix B for details.

12. We should note that the nominal I-S ratio for the durables sector tells a slightly different story. In particular, while the nominal ratio has declined since the early 1980s, this decline only reverses a steady climb in the ratio over the early part of the sample. Hence, the nominal ratio is not at a historic low.

13. See Appendix A for formal tests of the hypothesis that there has been a reduction in the variance of deviations from the target.

14. In related work, Kahn, McConnell, and Perez-Quiros (2001) show that manufacturing inventory-to-sales ratios decline across all stages of fabrication for most durable goods industries starting in the mid-1980s.

15. IT capital refers to mainframe computers, personal computers, direct access storage devices, computer printers, computer terminals, computer tape drives, computer storage devices, photocopy equipment, instruments, communication equipment, and other information equipment. The source data for this calculation is the U.S. Department of Commerce, Bureau of Economic Analysis (1998). Unfortunately, the data do not include information on investment in such capital as computer numerically controlled machine tools.

16. In future research, we plan to endogenize the I-S ratio as in Kahn (1987).

17. Data from the National Association of Purchasing Managers survey indicate that there has been a reduction in the lead time for ordering production materials since the early 1980s. See McConnell, Mosser, and Perez-Quiros (1999).

18. See, for example, Clarida, Galí, and Gertler (2000).

19. This is in the spirit of, for example, Woodford (1999) in not simply trying to reduce output volatility, but rather recognizing that some fluctuations are part of an economy's efficient response to disturbances. What makes welfare analysis somewhat more complicated in our setting is that consumption is not the same as output, so the real distortion cannot be summarized by the deviation of output from its equilibrium value. In our model inventory, levels, consumption, and labor are all distorted from their equilibrium (and efficient) values. It turns out, however, that welfare evaluation in our simulations is not very sensitive to the precise way of computing the distortion, so we simply use the squared deviation of consumption from its equilibrium value. Although this usage understates the level of the distortion, it does not significantly alter its shape as a function of ψ.

20. While in the model this is represented as the proportion of the variance of the demand shock contained in the signal received by the firm, it can be thought of as the firm simply having a better forecast of final demand or as waiting until more information is available before committing to production.

21. See, for example, West (1990).

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