Preliminary - Comments Welcome

Do Not Cite without Permission

Volatility Accounting:

A Production View of Increased Economic Stability

Kevin J. Stiroh*

First Draft: March 29, 2005

This Draft: July 5, 2005

Abstract

This paper examines the declining volatility of U.S. output growth from a production perspective. At the aggregate level, increased output stability reflects decreased volatility in both labor productivity growth and hours growth, as well as a significant decline in the correlation between hours and labor productivity growth. The decline in labor productivity volatility can be traced to less volatile total factor productivity (TFP) growth and a smaller covariance between labor and TFP growth. This suggests labor market changes like increased flexibility due to just-in-time employment are an important source of the increased stability of U.S. output. At the industry-level, the decline in volatility appears widespread with about 80% of component industries showing smaller contributions to aggregate output volatility after 1984, although most of the aggregate decline reflects smaller covariances between industries. Looking across industries, there is strong evidence of a decline in the correlation between hours and labor productivity growth, which again suggests that the labor market dynamics are an important part of the decline in U.S. output volatility.

---

*Assistant Vice President, Federal Reserve Bank of New York, New York, NY; phone: (212) 720-6633; email: kevin.stiroh@ny.frb.org. I thank seminar participants at the Federal Reserve Bank of New York, Diego Comin, Mary Daly, Bart Hobijn, Meg McConnell, and Dan Sichel for helpful comments and discussions.

I. Introduction

A new stylized fact for the U.S. economy is the substantial decline in the volatility of output growth over the last two decades. Figure 1, for example, plots the rolling 20-quarter standard deviation of output growth for the U.S. business and nonfarm business sectors and shows a precipitous decline that appears to begin in the mid-1980s.[1] This observation has generated considerable research with a host of potential explanations: structural change, improved managerial practices (particularly inventory management) good luck in the form of smaller aggregate shocks, and improved monetary policy.[2] This large and growing literature, however, has not reached a consensus and considerable debate surrounds the underlying factors that have stabilized the U.S. economy.

This paper contributes to the debate by examining the increased stability of the U.S. economy from a production perspective using both aggregate and industry data. In particular, I build on the "growth accounting" framework and present a "volatility accounting" methodology that quantifies the sources of volatility associated with capital, labor, total factor productivity (TFP). In contrast, existing research has taken a national income and product account (NIPA) perspective and decomposed output into the final demand components of consumption, investment, government spending, and net exports.

This supply-side approach complements the demand-side focus of earlier work and makes several contributions. First, this supply-side approach explicitly accounts for changes in input markets and technology, which may lead to additional explanations and hypotheses. For example, U.S. labor markets have become more flexible and efficient, e.g., Schweitzer (2004) and Schreft and Singh (2003), and changing labor market dynamics may influence output volatility. Second, this approach can help to distinguish existing explanations. For example, if all of the volatility can be traced to a decline in TFP volatility, this may raise the plausibility of the explanations related to aggregate shocks and reduce the plausibility of industry-specific technology explanations. Finally, volatility accounting complements the well-known growth accounting literature and provides an internally consistent framework for evaluating both the sources of growth and the volatility of that growth.

I also examine volatility across the industries that comprise the U.S. economy. This "bottoms-up" perspective reveals the enormous differences in volatility across industries and quantifies each industry's contribution to the decline in aggregate output volatility.[3] As an example of this heterogeneity, Figure 2 plots the rolling 20-quarter standard deviation of output growth for the durable and non-durable

---

[1] I use data for the U.S. business and nonfarm business sectors from the BLS to be consistent with subsequent decompositions. This decline in variance is similar to the GDP estimates reported by McConnell and Perez-Quiros (2000), who identified 1984:Q1 as the break point in the variance of U.S. output growth.

[2] See Stock and Watson (2002) and Ramey and Vine (2004) for detailed reviews of the literature.

[3] Irvine and Schuh (2005) and Comin and Philippon (2005) also examine the increased stability from a disaggregated perspective.

manufacturing sectors, which are quite different. McConnell and Perez-Quiros (2000) have attributed much of the decline in aggregate volatility to durable goods production, while Ramey and Vine (2004) and Irvine and Schuh (2005) have pointed to the motor vehicle industry in particular. Distinguishing declines in aggregate volatility that can be traced to changes within particularly industries, e.g., smaller variances of particular industries, from those that reflect changes between industries, e.g., smaller covariances between industries, also helps to distinguish among some of the competing explanations.

The empirical work begins with the simplest output decomposition: output growth equals hours growth hours plus labor productivity growth. For broad U.S. private sectors and manufacturing sub-sectors, the data show that both hours and labor productivity became significantly less volatile after 1984. Moreover, the covariance between the two declined substantially in all sectors as the correlation between hours and labor productivity growth became significantly smaller and typically negative in the last two decades. For the U.S. business sector, for example, the raw correlation between hours growth and labor productivity growth fell from 0.03 for 1947:Q1-1983:Q4 to –0.41 for 1984:Q1-2004:Q4.

The declining correlation between hours and productivity, by definition, has a stabilizing impact on output growth and is consistent with several labor market explanations. One, there is anecdotal evidence that businesses are under increasing pressure to improve productivity and that this has restrained job growth.[4] In this view, increased competitive pressures are forcing firms to trade off hours and productivity. Two, the labor market has experienced a significant shift to "just-in-time employment" due to the rise in temporary workers, part-time workers, and increased overtime. Increased labor force flexibility will raise productivity and efficiency and could allow firms to be more cautious in their hiring; this combination would reduce the correlation of hours and productivity growth. This is also consistent with the observation that the period of increased economic stability has coincided with the two jobless recoveries after the 1990-91 and 2001 recessions. Three, measurement error associated with new technology and the shifts to service-related jobs may have increased so that hours are increasingly understated and productivity increasingly overstated. These types of labor market explanations are largely absent from earlier investigations of the increased stability of U.S. output, but appear to be an important part of the story.

To further examine this evolving relationship, I use the Baxter and King (1999) band-pass filter to identify whether the change in this correlation reflects changes in the trend, business cycle, or irregular components. The results for the nonfarm business sector indicate that the decline in aggregate volatility primarily reflects decreased variances of the cyclical and irregular components, but that the declining

[4]See Schweitzer (2004) for a brief discussion. Similarly, *The Wall Street Journal* (11/08/04) stated "high productivity growth dampens the need for companies to hire" and *Business Week* (10/25/04) stated "outsourcing is not the major reason for the slow job growth of this recovery. Productivity is the real reason."

correlations between hours and labor productivity growth is present in all components. This supports the idea that labor markets changes are indeed an important part of the decline in aggregate volatility in the U.S.

I then examine the production possibility frontier from Jorgenson and Stiroh (2000) where output growth reflects the contribution of primary inputs (capital and labor) and technology (measured as TFP growth). I decompose both TFP and capital into the portion associated with information technology (IT) and other sources. The most striking conclusion is that approximately half of the decline in aggregate output volatility after 1984 can be attributed to the decline in the covariance between labor and TFP growth, particularly TFP growth not associated with IT-production.

Finally, I build on the fact that aggregate output growth reflects the contribution from all component industries to identify the industry-level sources of the decline in volatility. By examining the complete set of industries that comprise the U.S. economy, I am able to identify precisely those industries that have contributed the most to the increase stability of the economy as a whole.[5] I can also distinguish the importance of aggregate shocks by examining the covariances between the industries, which may reflect common factors like policy or macro shocks, from those that reflect changes to particular industries. These very different "within" and "between" channels are obscured with aggregate data, but provide insight into the causes of the decline in aggregate volatility.

The results indicate that while most industries saw a decline in the volatility of output and TFP growth, a majority of the aggregate decline can be traced to smaller covariances between industries. For example, only about 15-20% of the decline in output variance after 1984 reflects smaller variances of output growth within industries, while the remaining 80-85% can be traced to a smaller covariance between industries. Similar results are true for hours growth and TFP growth. This critical role for between-industry covariances is most consistent with the good luck and good policy explanations, and less consistent with technology stories specific to particular industries. If common shocks across industries are dampened via smaller shocks or improved monetary or fiscal stabilization policy, for example, the idiosyncratic shocks will be relatively more important and industries will tend to fluctuate in a less harmonized manner.

Finally, the industry-level data provide strong cross-sectional evidence of a decline in the correlation of industry hours and labor productivity growth within industries. Panel estimates show that the strength of the negative relationship between hours and productivity growth increased significantly after the mid-1980s. Again, this suggests an important role for fundamental changes in labor market dynamics in explaining the increased stability of the U.S. economy.

---

[5]Ramey and Vine (2004) and Irvine and Schuh (2005) offer a similar motivation for their research.

II. Existing Explanations for the Increased Stability of U.S. Output Growth

The increased stability of U.S. output growth has generated considerable interest and many alternative hypotheses. This section briefly summarizes some of the main research and explanations to provide a framework for interpreting the empirical work done below. More detailed reviews of the literature are available in Stock and Watson (2002) and Ramey and Vine (2004). Broadly speaking, the potential explanations fall into four main categories, each with some evidence for and against, and there is not a consensus on a single explanation.[6]

Structural Composition - The service sector has historically been more stable than manufacturing, so the steady shift toward services and away from manufacturing could lead GDP volatility to decline. McConnel and Perez-Quiros (2000, p. 1473, hereafter MPQ) and Blanchard and Simon (2001, p. 162), however, have shown that changes within the durables good sector, rather than shifts between sectors, account for a large portion of the volatility decline.

I**nventory Management -** MPQ (2000) and Kahn, McConnell, and Perez-Quiros (2002) argue that changes in inventory management within durables goods accounted for a sizable portion of the volatility decline. As evidence, they cite a significant decline in the volatility of production, but no evidence of a decline in the volatility of sales. The implication is that inventory investment, the difference between production and sales, has become more stable. Similarly, Kim, Nelson, and Piger (2004) use Bayesian methods and report a decline in sales volatility, but also conclude that the decline in volatility is widespread and not limited to durable goods. Stock and Watson (2002), however, argue that the data is more mixed on this point and report declining volatility in both production and sales.

There is some evidence of changes in inventory management that is linked to particular industries. In particular, Ramey and Vine (2004) interpret the change in the relative volatility of sales and production as the impact of changes in the automobile production process. Similarly, Irvine and Schuh (2005) show a decline in cross-industry comovements that is centered around motor vehicle production, which they interpret as evidence of improved production and inventory management techniques in those industries.

Good Luck - The good luck argument is mostly about smaller aggregate shocks to the economy. Stock and Watson (2002, p. 22) conclude that most of the decline in GDP volatility, measured as changes in the covariance matrix of innovations in a reduce-form VAR. They attribute this to a combination of reduced monetary shocks, smaller fiscal shocks, productivity shocks, and oil price shocks. Similarly Ahmed, Levin and Wilson (2002) conclude that good luck - measured as reduced innovation variances in VARs - account for much of the decline in output volatility.

---

[6]See Stock and Watson (2002) for details, particularly pp. 28-41.

Good Policy - The improved policy argument is centered on the observation that monetary policy changed significantly in the early 1980s with the new regime introduced by Volcker and continued by Greenspan. Stock and Watson (2002, p. 41) estimate structural VARs and conclude that perhaps one quarter of the reduction in GDP volatility can be attributed improved monetary policy. A difficulty here, however, is that at least some evidence has focused on the decline in volatility in relatively narrow portions of the economy as in MPQ (2000). In addition, Blanchard and Simon (2001) argue the decline in volatility has been more of a gradual process than a discrete step in the 1980s.

One common attribute of this literature is a national income and products accounts perspective on aggregate output. McConnell, Mosser, and Perez-Quiros (1999), MPQ (2000), Blanchard and Simon (2001), Ahmed, Levin, and Wilson (2002), Kahn, McConnell, Perez-Quiros (2002), Kim, Nelson, and Piger (2004), Ramey and Vine (2004), and Irvine and Schuh (2005) for example, have all examined the volatility of output by looking at the volatility of the familiar demand-side components where output (*Y*) depends on consumption (*C*), investment (*I*), government spending (*G*), and net exports (*NX*), and investment reflects sales (*Sales*) plus changes in inventories (ΔInv):

$$\begin{aligned} Y &= f(C, I, G, NX) \\ I &= f(Sales, \Delta Inv) \end{aligned} \tag{1}$$

where I use a function due to the chain-aggregation in the U.S. NIPA that makes addition of real variables inappropriate.

This framework has led to the many alternative hypotheses about the underlying sources of the decline in volatility and identified the important role that durable goods production has played in the decline in U.S. output volatility. Obviously, there are many alternative approaches to decomposing aggregate output growth and the remainder of this paper examines both aggregate and industry-level data from a production perspective to quantify the sources of the decline in aggregate output volatility and to distinguish among competing explanations. An examination on industry-level factors, as in Irvine and Schuh (2005), Comin and Philippon (2005), and here, has the advantage of utilizing cross-sectional information to gain a broader perspective on the decline in volatility and to better distinguish among explanations.

III. Basic Aggregate Decomposition

This section presents a simple decomposition of aggregate output growth and volatility into the contributions from hours and labor productivity. A robust finding is that the correlation between hours and productivity has become more negative since the mid-1980s, which has stabilized the economy. Further analysis shows that this stabilizing factor is apparent in the long-run trends and the business cycle frequency. The final subsection discusses the results and presents several labor market-based interpretations.

a) Main Results

As an identity, aggregate output (*Y*) equals the product of hours (*H*) and average labor productivity (*ALP*), defined as output per hour worked (*y=ALP=Y/H*), so the simple growth decomposition is:

$$(2)\quad \dot{Y} = \dot{H} + \dot{y}$$

where dots over variables signify growth rates and time subscript are suppressed wherever possible.

The variance of output growth can be similarly decomposed into the variances of the components, *H* and *y*, and the covariance between the two as:

$$(3)\quad V(\dot{Y}) = V(\dot{H}) + V(\dot{y}) + 2 \cdot C(\dot{H}, \dot{y})$$

where V(.) is the variance and C(.,.) is the covariance of the variables in parentheses. I refer to each term on the right-hand side of Equation (3) as the "volatility contribution."[7]

To evaluate the decomposition in Equations (2) and (3), I use data from BLS (2005) for the U.S. business sector and nonfarm business sector for 1947:Q1-2004:Q4 and for the nonfinancial corporate sector for 1947:Q1-2004:Q3, and data from BLS (2003) for the U.S. manufacturing, durable manufacturing, and nondurable manufacturing for 1949:Q1-2003:Q3.[8] All data are quarterly and are available for output, hours, and labor productivity.

I begin by examining the growth and volatility decompositions in Equations (2) and (3) before and after 1984:Q1. 1984:Q1 was chosen as the breakpoint because several papers using different methods have identified this as the most probable breakpoint. MPQ (2000), for example, evaluate tests of structural change for various components U.S. GDP growth and conclude that 1984:Q1 is the breakpoint for real GDP growth and for growth in goods production, while Kim and Nelson (1999) and Kim et al. (2004) use Bayesian methods to conclude that the change point for volatility is 1984:Q1.[9] Of course, more recent data and the use of the BLS business sector could yield a different breakpoint, but using this data makes the results more comparable to earlier work.

---

[7]Blanchard and Simon (2002), Kahn et al. (2002), and Ramey and Vine (2004) also look at both variances and covariances on the demand side and show that a decline in the covariance between inventory investment and sales contributed to increased stability.

[8]The different periods for manufacturing are necessitated by the shift to the North American Industrial Classification System (NAICS), which led BLS to change industry classifications within manufacturing. For consistent manufacturing data over a long time horizon, one must use older data based on 1987 Standard Industrial Classifications (SIC) and described in BLS (2003).

[9]Blanchard and Simon (2001) argue for the interpretation of the decline in volatility as a more gradual decline that dates from the 1950s.

Table 1 compares mean growth rates and volatility contributions before 1984 and after 1983, and report statistical tests for the change in the growth rate and volatility contributions. For the mean growth rate, I compute a t-test of the null that the mean growth is this same for the two periods when the variance of the underlying distribution is allowed to vary. For the variance terms, I compute the test of equal standard deviations from Levene (1960), which is robust under non-normality of the underlying distributions. For the covariance terms, I compute a 2-sample Z-test that the underlying correlations are the same for each period. The correlations are most relevant here because they are invariant to the size of the variation of each variable.[10]

The first thing to note from Table 1 is that there is no evidence of changes in mean growth rates of output after 1984:Q1 for any sector except nondurable manufacturing, which shows a marginally significant decline. This is useful because it makes variances more directly comparable across these periods. For manufacturing, particularly durable manufacturing, labor productivity accelerated after 1984. This is consistent with Stiroh (1998), who quantified the large productivity gains associated with the production of information technology within manufacturing in the 1980s.

In terms of volatility of growth, a large decline is apparent across all BLS sectors and virtually all components. The magnitude of the declines for the business and nonfarm business sector is broadly consistent with the four-fold decline in the variance of GDP growth reported by MPQ (2000) and also shows the enormous stabilization in durable manufacturing. Figure 3 summarizes the sectoral differences by showing the total decline in the variance of output growth after 1984 and the contribution from each source.

The most striking observation is that the decline in output volatility reflects roughly equal declines in the volatility of hours, labor productivity, and the covariance between hours and labor productivity in the business, nonfarm business, and nonfinancial corporate sectors. In the manufacturing sectors, more stable hours growth was the primary determinant of increased output stability, although there was also a sizable decline in the covariance between hours and labor productivity growth in all sectors. This suggests that labor market dynamics have played a role in the declining volatility of U.S. output.

One concern is that the covariances in Table 1 reflect both the underlying correlation and the standard deviation of each series. To better identify the change in the comovements of the series, Table 2 reports the raw correlation between hours and labor productivity growth for the full period, the pre-1984 period, the post-1983 period, and the difference between the two. Significance levels for each period are

---

[10]There are obviously restrictions that link output, hours, and labor productivity so that these tests are not independent, but they provide a metric for gauging the statistical significance of the individual differences.

from t-tests of the correlation coefficient, while the significance for the change in the correlation is from a 2-sample Z-test of unpaired means.[11]

For the full period, the raw correlation between hours and labor productivity is typically close to zero as has been often noted, e.g., Hansen and Wright (1992), Gali (1999), and Estrella (2004).[12] Only in durable manufacturing is the correlation relatively large, 0.34. There are, however, substantial differences over time. For the early period, the correlation was always positive (and often statistically significant), while the correlation was typically negative in the post-1983 period. For all sectors, there was an economically large and statistically significant decline in the correlation between hours growth and labor productivity growth after 1983.

The declining correlation of hours and productivity growth is relevant for the recent debate about the short-run trade-offs between technology shocks and employment growth. Gali (1999) and Basu et al. (2004), for example, argue that nominal frictions provide one mechanism for an apparent negative correlation between technology shocks and hours as firms respond to positive technology shocks in the short-run by reducing input use. In contrast, Christiano et al. (2003, 2004) have interpreted the data differently and conclude that labor inputs rise in response to technology shocks. I do not take a stand on this debate and whether this reflects technology or demand shocks, but the evidence presented here suggests that the relationship changed in the mid-1980s and that this had a stabilizing impact on U.S. output growth.

b) Robustness to Break Point

The results discussed so far have taken the 1984:Q1 break point identified by MPQ (2000). As a robustness test, I also estimated the volatility contributions for a rolling 20-quarter period for various sectors of the economy and show results for the nonfarm business sector (Figure 4), durable manufacturing (Figure 5), and nondurable manufacturing (Figure 6).[13]

The primary conclusions from Table 1 remain clear. In particular, hours and labor productivity both became more stable throughout the economy; the covariance between hours and labor productivity provided stabilization in the post-1984 period; and there are stark differences between the aggregate economy and the manufacturing sectors. Interestingly, the covariance for the nonfarm businesss sector has been consistently negative since the mid-1980s. This shows that the results are not sensitive to the

---

Moreover, I have taken the 1984:Q1 breakpoint as a given, although this is something that could be determined empirically.

[11]See Cohen et al. (2003) for details.

[12]Estrella (2004) uses frequency domain techniques to sort out the relationship between productivity and employment across frequencies. At the business cycle frequency, he concludes that they are highly correlated in terms of coherence (a measure of correlation irrespective of phase leads), but the contemporaneous correlation is weak because they are largely out of phase.

particular choice of the 1984:Q1 breakpoint and imply an important role for the declining correlation of hours and productivity growth in the stabilization of the U.S. economy.[14]

c) Trend Decomposition

One relevant question concerning the previous results is whether they reflect changes in the trend components, the cyclical components, or even higher frequency noise components. Kim et al. (2004), for example, argue that a trend/cycle decomposition can help to distinguish among competing hypotheses and conclude that the decline in volatility is primarily in the cyclical component with little evidence of a break in trend GDP growth. Estrella (2004) also advocates decomposing productivity and employment into trend and cycle components and employs explicit frequency domain techniques.

I employ the band-pass filtering technique developed by Baxter and King (1999) to decompose the growth of output, hours, and productivity into a trend component, a cyclical component, and an irregular component. This approach disentangles the very low frequency movements (period greater than 32 quarters), the business cycle movements (period between 6 and 32 quarters), and the very high-frequency movements (period less than 6 quarters) by passing a moving-average filter through the raw data.[15]

Table 3 presents estimates of the mean and volatility of growth for the nonfarm business sector for output, hours, and labor productivity growth for the pre-1984 and post-1983 periods. For the raw data and trend component, I report the mean quarterly growth rate and the standard deviation of quarterly growth rate. For the cyclical and irregular components, I report the mean and standard deviation of the deviation from trend (in percentages). Significance tests are calculated as above. Figures 7a plots the quarterly growth rate of the hours and labor productivity trends, while Figure 7b plots the cyclical component, measured as the deviation from trend.[16]

The results show no significant change in the mean growth of the trend and no significant change in the mean cyclical or irregular deviation of output, hours, or productivity after 1983. For example, growth of the raw series fell from 3.67 to 3.53 when the trend fell from 3.65 to 3.53, the mean cyclical deviation rose from -0.09 to 0.14, and the irregular deviation fell from 0.01 to -0.01.

In terms of variation, however, there are large differences. Beginning with output growth, trend growth has stabilized, although much less than the raw data suggest. This is because both the cyclical and

---

[13]Estimates for the business sector are similar to the nonfarm business sector.

[14]The large spike in hours volatility in nondurable manufacturing in the late 1970s reflects enormous volatility around the 1973-1975 recession, e.g., hours fell 15% in 1974:Q4 and 26% in 1975:Q1, and then rose over 11% in 1975:Q3 and 1975:Q4.

[15]The choice of the period lengths follows the suggestion of Baxter and King (1999), as does the use of a truncation point for the filter at 12 quarters.

[16]Results are similar using the Hodrick-Prescott filter with the smoothing parameter set equal to 1600.

irregular components have been much more stable since 1983, which is consistent with Kim et al. (2004). For hours growth, trend growth has actually become more volatile since 1983, but the more stable deviations from trend made the raw data appear more stable. For labor productivity, there is no change in the volatility of trend growth, but again the cyclical and irregular deviations have become less volatile.

One apparent puzzle is the declining volatility of trend output growth, but increased volatility of trend hour growth and no change in volatility of labor productivity growth. While the independent filtering of each series means that there is not a tautological relationship as with the raw data, it is somewhat surprising to get different indications of relative stability. This can be reconciled, however, by recalling the importance of the covariance and correlation between hours and labor productivity as a source of output volatility.

Figures 7a suggests that hours and productivity have become less highly correlated since the mid-1980s. In 1950s and 1960s, for example, trend growth in hours and productivity moved together for long stretches, while the 1980s and 1990s and 2000s are marked by much less consistent movements. In particular, since the mid-1990s, the productivity trend has surged, while trend hours growth has languished. A similar story can be seen in the cyclical components, which show much less synchronization since 1984.

Table 4 quantifies this change by reporting the correlation between hours and labor productivity for all components for the pre-1984 and post-1983 period. The results indicate a significant decline in all components, e.g., the correlation of trend hours growth and trend labor productivity growth fell to -0.71, while the correlation of the deviations from trend fell to -0.47. This declining correlation appears to be a pervasive feature of the U.S. economy at both the trend and business cycle frequency.

d) Discussion and Potential Explanations

This analysis points to a robust decline in the covariance contribution between hours and labor productivity growth and can be interpreted in several ways. One, the change in the correlation could reflect the increased pressure on business to reap productivity and efficiency gains. Two, the results could reflect underlying changes in the labor market that helped stabilize output after 1984. Three, the results could simply reflect increased measurement error as hours growth became increasingly undermeasured, which would raise measured productivity growth and reduce the observed correlation.

Pressure to Improve Efficiency and Productivity - This explanation lies at the heart of the business press explanations cited earlier, i.e., firms must improve efficiency to be globally competitive and do so by putting increased pressure on their workforce and hiring fewer workers. As a result, measured productivity rises, employment and hours growth is reduced, and the correlation falls.

While this is a common argument, evidence is scant. Groshen and Potter (2003), for example, raise the possibility that new management strategies are promoting lean staffing in order to increase efficiency. As a result, production processes are reorganized, staff is cut, and inefficient plants or operations shut down. They simply raise this as a possibility, but provide no evidence. Similarly, Schweitzer (2004) notes that business has stressed the need to realign their business process without hiring additional workers, but admits that empirical verification is difficult (pg. 2). He does provide evidence, however, of increased "business restructuring," measured by the standard deviation of occupation share adjustments.

Labor Market Changes - The case for labor market changes rests on the idea that U.S. labor markets have become more flexible and efficient in the last few decades. Schreft and Singh (2003) document the steady rise of "just-in-time employment" and increased flexibility as the U.S. workforce is increasingly made up of temporary workers, part-time workers, and worker with increased overtime hours. According to Schreft and Singh (2003), temporary workers increased from 0.3 percent of total employment in 1972 to 2.4% by 2002; part-time workers increased from 14% of all workers in 1968 to 18% in 2002; and overtime hours for the average production worker in manufacturing jumped from 2.4 hours per week in 1960 to 4.1 hours 2002. Aaronson et al. (2004a) also suggest that just-in-time employment changes contributed to new labor market dynamics around the "jobless" recoveries of 1990-91 and 2001, which coincides with the period of increased stability.

Labor market changes that substantially increased the flexibility of the U.S. labor force could directly affect the correlation between hours and productivity. If firms are faced with uncertain and tentative demand, for example, increased flexibility allows them to delay hiring full-time employees and also increases efficiency and productivity of the existing workforce by shifting workers more easily across jobs, occupations, and tasks. As a result, productivity may increase and employment or hours growth may suffer as in the "jobless" recoveries from the 1990-91 and 2001 recessions. Schreft and Singh (2003) state that increased labor market flexibility "allows the economy to adjust more quickly to shocks (pg. 67)" and Aaronson et al. (2004a) conclude that recent macroeconomic shocks may have led to increased uncertainty and relatively sluggish demand growth. Of course, increased labor market flexibility could be a tool that developed in response to increased pressures for efficiency gains, so this explanation is not necessarily independent of the first explanation.

An alternative interpretation is based on the Groshen and Potter (2003) hypothesis that the U.S. economy is undergoing a period of relatively strong structural changes. They distinguish between permanent/structural and temporary/cyclical layoffs and conclude that permanent layoffs have become relatively more important since the 1980s, e.g., the share of employment undergoing cyclical changes increased from 51% in the early 1980s to 57% in the early 1990s to 79% currently. Moreover, they argue that structural employment takes longer to generate as it is more difficult and time-consuming to create new jobs than to recall workers to old jobs. As a result, hours growth may lag productivity growth and lead the contemporaneous correlation to fall. Arronson et al. (2004b), however, conclude that sectoral reallocation between industries have not been unusually large in recent years, but leave open the possibility of increased reallocations geographically or within industries.

Finally, one can think about the impact of increased flexibility in the spirit of Gali (1999) and Basu et al. (2004). If nominal rigidities and the pattern of technological shocks are unchanging, for example, then an increase in the flexibility of labor would lower the adjustment costs associated with changes in input accumulation. Ceteris paribus, firms would respond to a given technology shock by adjusting input use more and the correlation between hours and productivity would fall. Of course, I have not identified technology shocks from other demand shocks here as in Gali (1999) or Basu et al. (2004), but the logic seems internally consistent.

Increased Measurement Error - A final potential explanation is that measurement issues have increased and that the rising correlation is primarily a statistical artifact. In this view, the measurement of hours has become increasingly difficult due to the proliferation of information technology and the shift toward non-manufacturing jobs, so that hours growth is increasingly understated and productivity growth increasingly overstated. An implication is that both the productivity boom of the last decade and the relatively recent jobless recovery from the 2001 recession are two sides of the same measurement problem.

This mismeasurement story has been put forth most forcefully by Roach (1998, 2005), who points to the increasing demands on white-collar workers to utilize laptops, cell-phones, and fax machines in order to work more hours than captured by the national accounts data. As evidence, Roach (1998) cites results from a poll that pointed to a substantial increase in average weekly hours even as official estimates remained flat, while Roach (2005) points to the data in the BLS Time-Use Survey, which show some differences.

Competing arguments, however, are that an increased fraction of measured hours are actually used in pursuit of non-work activities (e.g., bidding on E-bay or making on-line travel reservations at work) and that output may be systematically mismeasured as quality, convenience, and variety improve.[17] As a result, the theoretical predictions about changes in measurement error are ambiguous.

Empirically, Frazis and Stewart (2004) compare new data on hours worked from the American Time Use Survey (ATUS) to estimates from the Consumer Population Survey (CPS) and conclude that the two estimates are quite close for CPS reference weeks, but that the CPS reference week is not representative of the entire month. The data suggest that the CPS data actually overstate hours for the full month due to the fact that the reference week typically avoids holidays. The ATUS, however, is a new

[17]See Dean (1999) for a survey of measurement issues related to output.

survey and it is not possible to draw conclusions about changing trends over time. Eldridge (2004) compares hours data from the CPS to the data from the Current Employment Survey (CES), which is the primary basis for the BLS productivity estimates, and shows a widening divergence between CPS and CES based estimates after 2000, e.g., a CPS-based estimate of hours fell to 0.64% per year for 2000-2003 while the productivity series fell to 1.72%. It is not clear, however, why the series are diverging and increased errors in the CES would lead to the largest bias in the productivity estimates and change the correlation between measured hours and productivity. Moreover, Eldridge (2004) also looks at the ATUS and concurs with Frazis and Stewart (2004) that the CPS data are likely to be biased upward.

IV. Aggregate Decomposition Using the Production Possibility Frontier

This section explicitly utilizes a production possibility frontier and presents a broader decomposition of output growth into the contribution of capital, labor, and the total factor productivity (TFP) residual. I then decompose labor productivity into contributions from capital deepening, labor quality, and the TFP residual. In both cases, I focus on the decomposition of aggregate volatility into the contribution from each factor and the corresponding covariances in order to quantify the underlying source of the decline in aggregate output volatility.

The key advantage is that this production approach explicitly captures the important role that inputs and technology play in the economy. This will allow a more in-depth analysis of the hours/productivity effects identified earlier. Moreover, recent studies by Jorgenson, Ho, and Stiroh (2002, 2004) and Oliner and Sichel (2000, 2002) have identified the critical role that information technology (IT) has recently played in the surging U.S. economy, while Greenwood et al. (1997) have pointed to the broader impact of investment-specific technical change. Finally, this perspective complements the well-known growth accounting literature and provides a familiar framework for evaluating both the sources of growth and the volatility of that growth.

a) Traditional Aggregate Production Possibility Frontier Decomposition

At least since the seminal work of Solow (1957), economists have used an aggregate production function to quantify the proximate sources of growth and Jorgenson (1966) extended this to a production possibility frontier. This approach has been recently applied to quantify the sources of the resurgence of U.S. productivity growth (Jorgenson, Ho, and Stiroh (2002, 2004) and Oliner and Sichel (2000, 2002)). This section presents the traditional growth accounting approach and a parallel volatility accounting methodology.

The production possibility frontier describes efficient combinations of outputs and inputs for the economy as a whole.[18] Aggregate output (Y), a composite of many heterogeneous outputs, is produced

[18]See Jorgenson and Stiroh (2000) for methodological details.

with aggregate capital services (K) and labor input (L). Total factor productivity (A) is a Hicks-neutral augmentation of aggregate inputs where:

$$(4) \quad Y = A \cdot f(K, L)$$

Under the assumptions that product and factor markets are competitive, producer equilibrium implies that the share-weighted growth of outputs is the sum of the share-weighted growth of inputs and growth in total factor productivity (TFP):

$$(5) \quad \dot{Y} = \overline{w}_K \dot{K} + \overline{w}_L \dot{L} + \dot{A}$$

where $\overline{w}$ is the two-period average shares of the subscripted variable in nominal output, each term on the right-hand side of Equation (5) is referred to as a "contribution to growth," and under the assumption of constant returns to scale, $\overline{w}_K + \overline{v}_L = 1$.

One can also decompose average labor productivity (ALP), defined above as $y=Y/H$. Under the same assumptions, the growth of ALP reflects the growth in capital services per hour worked ($k=K/H$), the growth in labor quality ($L_Q=L/H$), and TFP growth:

$$(6) \quad \dot{y} = \overline{w}_K \dot{k} + \overline{w}_L \dot{L}_Q + \dot{A}$$

where each term on the right-hand side of Equation (6) is referred to as a "contribution to labor productivity growth."

Equations (5) and (6) quantify the proximate sources of average growth on an annual or extended period basis. If one treats the growth and productivity contributions as random variables, this framework can be extended to account for the variance of output and productivity growth over the same year or period as:

$$(7) \quad \begin{aligned} V(\dot{Y}) = {} & V(\overline{w}_K \dot{K}) + V(\overline{w}_L \dot{L}) + V(\dot{A}) + \\ & 2 \cdot C(\overline{w}_K \dot{K}, \overline{w}_L \dot{L}) + 2 \cdot C(\overline{w}_K \dot{K}, \dot{A}) + 2 \cdot C(\overline{w}_L \dot{L}, \dot{A}) \end{aligned}$$

and

$$(8) \quad \begin{aligned} V(\dot{y}) = {} & V(\overline{w}_K \dot{k}) + V(\overline{w}_L \dot{L}_Q) + V(\dot{A}) + \\ & 2 \cdot C(\overline{w}_K \dot{k}, \overline{w}_L \dot{L}_Q) + 2 \cdot C(\overline{w}_K \dot{k}, \dot{A}) + 2 \cdot C(\overline{w}_L \dot{L}_Q, \dot{A}) \end{aligned}$$

where each term on the right-hand side is referred to as a "volatility contribution."[19]

I measure Equations (4) through (8) using data for the private, U.S. economy from 1948 to 2003 from Jorgenson, Ho, and Stiroh (2004).[20] These data correspond to the private business sector plus

---

[19]MQP (2000) argue for examining growth contributions because they potentially reflect causal impacts.
[20]A similar decomposition using data for the business and nonfarm business sectors from BLS yield similar results.

imputations for household services from owner-occupied real estate and consumer durable assets. Note that this is annual data, and the results are not directly comparable to the quarterly data from BLS examined earlier.

Table 5 reports results where the first three columns present the growth decomposition, while the next three present the volatility decomposition. The top panel reports estimates of the simple decomposition of output growth into hours growth and labor productivity growth that is most comparable to the estimates in Table 1. While the magnitudes and statistical significance are smaller due to the use of annual data, the same picture emerges. There is little change in the mean growth rates after 1984, but a substantial decline in volatility that reflects a decline in hours volatility, labor productivity volatility, and the covariance between hours and labor productivity. Note that the decline in the covariance of hours and labor productivity is large and statistically significant.

The middle panel reports the output decomposition described in Equations (5) and (7). Again, there is no significant change in the mean contributions, but large volatility declines. Nearly 90% of the decline in output volatility can be traced to labor and technology variables - more stable labor accounted for 14%, more stable TFP accounted for 27%, and the smaller covariance between the two accounted for 49%. The decline in the variance of TFP and the covariance are both statistically significant, while the decline in the variance of labor is not quite. The changes associated with capital are relatively minor and far from statistical significance.

While these data do not identify the technology component of the TFP residual, the substantial increase in the stability of TFP growth is consistent with the good luck hypothesis. If the economy were experiencing smaller supply or technology shocks, for example, fluctuations in output and conventionally-measured TFP growth would moderate. Increased TFP stability, however, is also consistent with improved policy. If monetary policy has real effects on the economy due to price rigidities, for example, than more successful policies would reduce the demand fluctuations that also lead the TFP residual to fluctuate.

The final panel reports the labor productivity decomposition in Equations (6) and (8). Perhaps not surprising, increased stability of TFP is the driving force behind the increased stability of labor productivity. It is interesting to note that covariance contribution of capital deepening and TFP has become much less negative and tended to increase volatility. This suggests that TFP fluctuations are now more likely to be linked with capital deepening, which is consistent with the idea of a technology-led productivity revival in Jorgenson and Stiroh (2000), Jorgenson, Ho, and Stiroh (2002, 2004), and Oliner and Sichel (2000, 2002). On the other hand, the covariance between labor quality and TFP has become more negative – TFP fluctuations seem to be less linked with increases in labor quality - as one might expect in a world of more flexible labor markets.

b) Extended Aggregate Production Possibility Frontier Decomposition

To better understand these linkages, I also evaluated an extended production possibility frontier like that of Jorgenson, Ho, and Stiroh (2002, 2004) and Oliner and Sichel (2000, 2002). This approach explicitly accounts for the impact of IT-production and IT-use and show that these two factors played important roles in the acceleration of U.S. productivity growth in the mid-1990s. In particular, capital services is decomposed into a portion related to IT (K_{IT}) and other non-IT capital (K_{NON}), while aggregate TFP is decomposed into a portion related to IT production (A_{IT}) and the remainder associated with non-IT TFP (A_{NON}). Thus, output growth reflects the contribution of IT-capital, non-IT capital, labor, IT-TFP, and non-IT-TFP, while the variance of growth reflects the variance of each component and all of the covariances.[21]

Table 6 reports estimates. The same picture emerges, but the decomposition of TFP growth into an IT and a non-IT component provides additional insights. In terms of growth rates, there is little change in aggregate growth over these periods, but the growing contribution of IT-capital and technological progress in IT-production are readily apparent, while non-IT capital declined in importance. This is simply a story of input substitution as firms shift toward relatively cheap IT assets.

In terms of volatility, the increased stability in TFP growth seems to have originated in the portion of the economy not involved in IT-production. While IT-production has experienced enormous growth rates of TFP, this growth has been relatively variable in the post-1984 period with a substantial acceleration after 1995. The still relatively small size of IT, however, leads to a small impact on aggregate volatility. Similarly, the decline in the covariance between labor and TFP primarily reflects non-IT TFP growth.

c) Changing Correlations

A final issue is the underlying driver of the decline in the covariances. As mentioned earlier, the covariance can decline if either the correlation declines or the volatility of the series declines, so it is useful to examine the correlations more closely. This provides a better indicator of how firms may changing the way they operate and choose inputs.

Table 7 reports the correlations for each of the decompositions in Tables 5 and 6 for the full period, each sub-period, and the difference between periods. As with the quarterly data from BLS, the correlation between hours and ALP has become much more negative since 1983, suggesting a change in labor market dynamics. In the standard growth accounting decomposition, the only significant changes in correlation after 1983 are between labor and TFP (from 0.51 to -0.13) and between labor quality and TFP

[21] I also estimated the variance decomposition of labor productivity using the extended production possibility frontier. Results are similar to the output decomposition and are not reported.

growth (from 0.15 to -0.60). Both become significantly more negative after 1983 and support the earlier view that this increasing trade-off between hours and productivity has contributed to the increased stability of the U.S. economy. For the extended production possibility frontier, the correlation between labor and non-IT TFP decreased significantly, while the correlation between IT-capital and non-IT capital and between non-IT capital and IT-related TFP increased significantly. In terms of economic importance (from Table 6), however, the decreased correlation between labor and non-IT TFP clearly dominates in explaining the decline in aggregate output volatility. The two significant positive changes, for example, contributed 0.27 to the change in output stability, while the one significant negative change contributed –2.62 to the change.

The main conclusion from these aggregate decompositions is the economically large and statistically significant contribution to the decline in aggregate output volatility from the declining correlation of labor input and TFP growth, particularly non-IT TFP. The change in the covariance alone accounts for more than half of the decline in the variance of output growth after 1984 and again supports the view from the hours/labor productivity decomposition that labor market dynamic play an important part of the explanation for the increased stability of the U.S. economy.

V. Industry Decomposition

This section uses industry-level data to provide a "bottoms-up" view of the decline in aggregate output volatility. The key advantage is that analysis of changes in volatility both within and between industries can help identify the specific source in the decline of aggregate volatility and can help distinguish among competing hypotheses. For example, a decline in the variance of particular industries is more consistent with the technology story proposed by MPQ (2000), Ramey and Vine (2004), or Irvine and Schuh (2005), while a decline in the covariances across many industries is more consistent with the good luck story of Stock and Watson (2002). A critical part of the industry analysis, therefore, is to quantify the portion of the change in aggregate volatility that can be traced to changes within industries, e.g., smaller variances of particular industries, and the portion that reflect changes between industries, e.g., smaller covariances among sets of industries. These very different channels are obscured with aggregate data.

a) Industry Growth Decomposition

An industry production function for industry *i* can be written as:

$$(9)\quad Y_i = f_i(K_i, L_i, M_i, T)$$

where Y is industry gross output, K is capital services, L is labor input, M is intermediate inputs (both materials and energy), and T is total factor productivity, all for industry i.

Note that aggregate output discussed in Equation (4) is a value-added concept, while industry output in Equation (9) is a gross output concept. To be more directly comparable, it useful to define a more restrictive industry value-added function, which gives the quantity of value-added, *V*, as a function of only capital, labor, and technology as:

$$(10) \qquad V_i = f_i(K_i, L_i, T)$$

This is useful because aggregate value-added, *Y*, can be defined as an explicit function of industry value-added:

$$(11) \qquad Y = V(V_1, ..., V_I)$$

where the *I* industries comprise the U.S. private economy.

Jorgenson, Ho, and Stiroh (2005) discuss alternative aggregation functions for Equation (11). The "aggregate production function" is the most restrictive and imposes identical value-added functions (up to a scalar multiple) across industries, while the "aggregate production possibility frontier" allows the value-added functions to differ across industries. These assumptions have different implications for aggregation and lead to different estimates of aggregate value-added growth.

The assumption of identical value-added functions in the aggregate production function implies that value-added from all industries face the same price and are perfect substitutes. As a result, aggregate output is a simple sum of industry value-added as:

$$(12) \qquad Y^p = \sum_i V_i$$

where the "p" superscript reflects the aggregate production function and the growth rate is the simple growth rate of this series.

This approach, however, imposes significant restrictions on the data that are often violated, particularly over short periods of time (Jorgenson (1990) and Jorgenson, Ho, and Stiroh (2005)). The aggregate production possibility frontier, in contrast, relaxes the restriction that all industries face the same value-added functions, so that value-added is not perfectly substitutable. As a result, aggregate value-added also represents substitution between industries with different value-added prices and growth. Growth in aggregate value-added can then be defined as the weighted sum of value-added in the component industries via a Tornqvist quantity index of industry value-added:

$$(13) \qquad \dot{Y} = \sum_i \bar{v}_{V,i} \dot{V}_i$$

where $\bar{v}_{V,i}$ is the two-period average nominal share of industry value-added in aggregate value-added. Each argument in the summation is the industry's contribution to aggregate value-added growth.[22]

One can further decompose industry output growth into an hours and a productivity component from each industry as in Table 1. Defining a value-added measure of industry productivity as $v_i=V_i/H_i$, the contribution of industry hours growth and industry labor productivity growth to aggregate output growth are:

$$(14) \qquad \dot{Y} = \sum_i \bar{v}_{V,i} \dot{H}_i + \sum_i \bar{v}_{V,i} \dot{v}_i$$

Finally, the earlier analysis showed that increased stability of aggregate TFP growth was an important determinant of the increased stability of aggregate output. At a fundamental level, aggregate TFP growth also reflects the contribution of industry-level TFP, as derived from Equation (10), as individual industries become more productive and efficient over time. Jorgenson, Ho, and Stiroh (2005), for example, show that industry TFP growth accounts for virtually all of aggregate TFP for the period 1977 to 2000. The appropriate method for aggregating industry TFP growth is through a "Domar-weighting" approach developed by Domar (1961). Aggregate TFP growth can be decomposed as:

$$(15) \qquad \dot{A} = \sum_i \frac{\bar{v}_{V,i}}{\bar{s}_{V,i}} \dot{A}_i + REALL$$

where $\bar{v}_{V,i}$ is the two-period average nominal share aggregate value-added, $\bar{s}_{V,i}$ is the two-period average nominal share of industry value-added in industry gross output, and REALL is the sum of capital and labor reallocation terms that reflect movements of primary inputs among industries.

The arguments in the summation are "Domar-weighted" rates of industry TFP growth. The weights are the ratio of two proportions and essentially yield the ratio of industry of gross output to aggregate value-added, which is the usual interpretation of the Domar-weight.[23] A distinctive feature of Domar-weights is that they typically sum to more than one. This reflects the fact that an improvement in industry TFP can have two effects: a direct effect on industry output, and an indirect effect via the output that is sold to other industries as intermediate goods.

The reallocation terms, *REALL*, create a wedge between aggregate measures of TFP growth and the Domar-weighted industry growth rates and reflect any departure from the assumptions on inputs

---

[22]A third alternative, which presents industry output as a function of gross output growth and intermediate growth based on Stiroh (2002), yields similar results.

[23]The standard formulation of a Domar-weight is the ratio of industry gross output to aggregate value-added, where weights are from the base period (Domar (1961), pg. 719). Use of Tornqvist indices implies use of two-period average weights, so the ratio of the two-period weights does not reduce exactly to the Domar formulation. The intuition is the same, however, and I refer to this ratio of two-period weights as the Domar-weight.

required to generate an the aggregate production possibility frontier and the aggregate production function. The reallocations tend to be small, however, particularly over long time periods, so ignoring the reallocations, I define $\dot{A}^D$ as the sum of the Domar-weighted TFP growth rates as:

$$(16) \qquad \dot{A}^D = \sum_i \frac{\bar{v}_{V,i}}{\bar{s}_{V,i}} \dot{A}_i$$

and will examine each industry's contribution to Domar-weighted TFP growth.

b) Industry Variance Decomposition

Corresponding to each decomposition of aggregate output and TFP growth is a variance decomposition. These are straightforward expressions of the components, but yield valuable insights into the sources of aggregate volatility. In particular, by quantifying the change in volatility both within individual industries and between industries, one can better describe and understand the underlying sources of U.S. output volatility and distinguish among competing explanations.

For the aggregate production function in Equation (12), the variance is simply the variance of the single series:

$$(17) \qquad V\left(\dot{Y}^P\right) = V\left(\dot{\sum_i V_i}\right)$$

For the industry value-added decomposition based on the aggregate production possibility frontier in Equation (13), one can treat the industry contribution as a random variable and decompose the variance into the sum of the direct variances contributions of individual industries and the sum of the covariances between industries as:

$$(18) \qquad V\left(\dot{Y}\right) = \sum_i V\left(\bar{v}_{V,i}\dot{V}_i\right) + \sum_i \sum_{j=i+1} 2 \cdot C\left(\bar{v}_{V,i}\dot{V}_i, \bar{v}_{V,j}\dot{V}_j\right)$$

The industry labor productivity variance decomposition of aggregate output associated with Equation (14) is defined similarly as:

$$(19) \qquad \begin{aligned} V\left(\dot{Y}\right) &= \sum_i V\left(\bar{v}_{V,i}\dot{H}_i\right) + \sum_i V\left(\bar{v}_{V,i}\dot{v}_i\right) + \\ &\sum_i \sum_{j=i+1} 2 \cdot C\left(\bar{v}_{V,i}\dot{H}_i, \bar{v}_{V,j}\dot{H}_j\right) + \sum_i \sum_{j=i} 2 \cdot C\left(\bar{v}_{V,i}\dot{H}_i, \bar{v}_{V,j}\dot{v}_j\right) + + \sum_i \sum_{j=i+1} 2 \cdot C\left(\bar{v}_{V,i}\dot{v}_i, \bar{v}_{V,i}\dot{v}_j\right) \end{aligned}$$

where the variances are direct contributions from each industry and the three covariances (hours/hours, hours/productivity, and productivity/productivity) are for all industry pairs.

Note that the hours/hours and productivity/productivity covariances are strictly between industry effects, while the hours/productivity covariances includes both between and within industry effects. To differentiate changes within and between industries, I further decompose the hours/productivity covariance into a "within" component that reflects covariances of hours and productivity for a given industry and a "between" component that reflects the covariances across different industries as:

$$\text{(20)} \qquad \sum_i \sum_{j=i} 2 \cdot C\left(\bar{v}_{V,i}\dot{H}_i, \bar{v}_{V,j}\dot{v}_j\right) = \sum_i 2 \cdot C\left(\bar{v}_{V,i}\dot{H}_i, \bar{v}_{V,i}\dot{v}_i\right) + \sum_i \sum_{j=i+1} 2 \cdot C\left(\bar{v}_{V,i}\dot{H}_i, \bar{v}_{V,j}\dot{v}_j\right)$$
$$= Within + Between$$

Finally, the TFP variance decomposition associated with Equation (16) is:

$$\text{(21)} \qquad V(\dot{A}^D) = \sum_i V\left(\sum_i \frac{\bar{v}_{V,i}}{\bar{s}_{V,i}} \dot{A}_i\right) + \sum_i \sum_{j=i+1} 2 \cdot C\left(\sum_i \frac{\bar{v}_{V,i}}{\bar{s}_{V,i}} \dot{A}_i, \sum_i \frac{\bar{v}_{V,j}}{\bar{s}_{V,j}} \dot{A}_j\right)$$

where the first term again reflects the direct industry variance contributions and the second reflects the between industry contributions.

c) Industry Data

Industry level data are taken from two sources. Jorgenson and Stiroh (2000) decompose the U.S. private economy into 35 industries for the period 1958 to 1996, while Jorgenson, Ho, and Stiroh (2005) decompose the U.S. private economy into 41 industries for the period 1977 to 2000. The first data set includes a longer pre-1984 period, but contains a shorter post-1983 period and is relatively stale data. The second data set has a somewhat longer post-1983 period that is more current, but has a relatively short pre-1984 period. Unfortunately, differences in industry definitions and aggregation levels prevent the data sets from being combined, so I examine both. I refer to the first data set as the 1958-1996 dataset and the second as the 1978-2000 dataset.

d) Industry Results

Table 8a summarizes the industry results for the 35 industries for the period 1958 to 1996 in the 1958-1996 dataset, while Table 8b summarizes results for 41 industries for the period 1978 to 2000 in the 1978-2000 dataset. As in the analysis of aggregate and sectoral data, I compare the mean growth rate for the pre-1984 and post-1983 periods and the corresponding variance decomposition of the growth rates. Note that because the variances and covariance terms are sums across the component industries, I do not report tests of statistical significance. Rather, these estimates should be interpreted as descriptive statistics that summarize the underlying industry data.

The first panels of Tables 8a and 8b show the estimates of aggregate output growth from the aggregate production function and the aggregate production possibility frontier. For both datasets, the two aggregation methods give similar results and show a marked decline in aggregate volatility.[24] The fact that these industry data show the same decline in aggregate volatility that is found in aggregate data are further evidence of the robustness of this stylized fact and indicate that further examination of industry data may be useful in identifying the underlying source.

The second panel reports the industry value-added decomposition in Equations (13) and (18). The growth decomposition columns show the sums of the weighted growth rates, while the volatility decomposition columns show the sum of the weighted variances and the sums of the covariances. For the variance decomposition, the first line, $\Sigma V(v_{V,i}V_i)$, shows the total within effect for each period (sum of the variances of the industry contributions), while the second line, $\Sigma\Sigma\, 2C(v_{V,i}V_i,v_{V,j}V_j)$, shows the between effect (sum of covariances for all pair-wise combinations). The 1958-1996 dataset includes 595 (35x34/2) pairs, while the 1978-2000 dataset includes 820 (41x40/2) pairs.

In both datasets, the results indicate that both the within and the between effects have contributed to increased stability, but the between effect clearly dominates in terms of magnitude. For example, in the 1958-1996 dataset, the covariances accounted for 85% of the aggregate declines in volatility (-4.68/-5.48), while the direct contribution of smaller variances accounted for only 15% (-0.79/-5.48). Irvine and Schuh (2005, Table 4) report a similar decomposition result with over 80% of the decline in variance of output growth in the manufacturing and trade sector due to the covariance effect.

This suggests that the majority of the volatility decline can be traced to common factors across industries, which seems most consistent with the good luck and good policy explanations of smaller macroeconomic shocks, and less consistent with specific stories of technological progress. For example, if the 1960s and 1970s were periods of large, common shocks, then one would expect industry output to move together. If these shocks dissipated in the 1980s and 1990s, then idiosyncratic shocks would be relatively more important and the covariance of output movements across industries would decline and help stabilize output. Alternatively, Irvine and Schuh (2005) interpret their results as evidence of improved production and inventory management that impacted the relationship between firms and industries.

The next panel of Tables 8a and 8b show the industry labor productivity decomposition in Equations (14), (19), and (20). Again, the results between the two datasets are similar. Hours and labor productivity have become more stable within industries, but the declining covariances are quantitatively much larger. For the 1958-1996 datasets, for example, the hours and labor productivity variances ($\Sigma V(v_{V,i}H_i)$ and $\Sigma V(v_{V,i}ALP_i)$) account for only about 10% of the decline in volatility (-0.04+-0.57)/-5.48),

---

[24]The p-values associated with the null of equal covariances after 1984 are p=0.06 for the aggregate production function and p=0.08 for the aggregate production possibility frontier for the 1958-1996 dataset and p=0.23 for the aggregate production function and p=0.06 for the aggregate production possibility frontier for the 1978-2000 data.

with the various covariances accounting for the remaining 90%. For the 1978-2000 dataset, the hours and labor productivity variance contribution rises to only one-quarter ((-0.67+-0.95)/-6.49).

The four covariance sums ($\Sigma\Sigma\, 2C(v_{V,i}H_i\ v_{Vji}H_j)$ = hours/hours between industries, $\Sigma\, 2C(v_{V,i}H_i, v_{V,i}ALP_i)$ = hours/productivity within industries, $\Sigma\Sigma\, 2C(v_{V,i}H_i, v_{V,j}ALP_j)$ = hours/productivity between industries, and $\Sigma\Sigma\, 2C(v_{V,i}ALP_i, v_{V,j}ALP_j)$ = productivity/productivity between industries) account for the majority of the decline in aggregate volatility. The covariances of hours growth between industries is the dominant factor in both datasets, accounting for between 40% and 50% of the decline in aggregate output volatility. This is consistent with the idea of more flexible labor markets discussed earlier: if labor markets are flexible, firms and workers can more easily respond to idiosyncratic shocks and reallocate across industries. There is also a large decline in the covariances of hours and labor productivity growth between industries, which also suggests more flexibility and mobility as productivity gains in one industry draw hours and labor input away from other industries.

The final panel of Tables 8a and 8b show the Domar decomposition in Equations (16) and (21). Again, the results are similar across datasets with the bulk of the decline due to a smaller covariance between industries ($\Sigma\, 2C(v_{V,i}/s_{V,i}TFP_i, v_{V,j}/s_{V,j}TFP_j)$), and a relatively small contribution from within variance contributions of individual industries ($\Sigma V(v_{V,i}/s_{V,i}TFP_i)$ This seems most consistent with the good luck hypothesis as common shocks dissipated in the 1980s and 1990s.

e) Robustness to Break Point

As with the aggregate data, there is the possibility that the results are particular to using 1984 as the breakpoint for aggregate volatility. To evaluate this, I estimated rolling variances and covariances for 13-year windows from 1958 to 1996 with the 1958-1996 dataset. The 13-year window was chosen to match the length of the post-1983 period reported in Table 8a. Figure 8 reports the industry value-added decomposition and shows the sum of the variance contributions and the covariance contributions (as in the second panel of Table 8a), while Figure 9 reports the same for the TFP decomposition (as in the fourth panel of Table 8a).

Both figures show similar patterns and several results stand out. First, both the variance and covariance sums rise and through the 1970s until the mid-1980s, and then decline. This hump-shaped pattern is apparent in Comin and Philippon (2005). Second, the covariance sums are much larger and account for the bulk of the change over time in the volatility of aggregate value-added growth and TFP growth. This is consistent with the idea of smaller common shocks in recent years so that industry fluctuations are more likely to be driven by idiosyncratic shocks.

It is also interesting to look at the correlation (rather than the covariances), so I estimate the weighted average correlation between industries for value-added growth, hours growth, labor productivity growth, and TFP growth. This indicates whether the declines in the covariance terms reflect changes in the underlying correlations or simply increased stability in the individual series. I calculate the rolling correlation between industries for each variable by estimating each pairwise correlation and applying the appropriate weights to generate a single aggregate series as:

$$\text{(22)} \qquad \overline{\rho}_{B,X} = \sum_{i} \sum_{j=i+1} Corr(\dot{X}_i, \dot{X}_j) \cdot \left(wt_i + wt_j\right) / (I-1)$$

where the "B" subscript indicates a between-industry effect and X is either value-added growth, hours growth, labor productivity growth, or TFP growth. I use value-added weights for all between correlations except for TFP growth, where I use Domar-weights.

Figure 10 shows the results using a 13-year rolling window for the 1958-1996 dataset.[25] The estimates for hours show a steady decline in the mid-1980s with the weighted average between-industry correlation falling from around 0.5 in the 1970s to 0.3 by the mid-1990s. In contrast, the between-industry correlation for value-added, hours, and TFP growth show little trend over time. This suggests that the declining contribution from the covariance terms for value-added, labor productivity, and TFP in Tables 8a and 8b primarily reflect the reduced variability of the underlying series and not the correlation. Only between-industry hours growth seems to be driven by a reduced correlation. These results are somewhat different from Comin and Philippon (2005), which could reflect different weighting schemes, e.g., this paper uses time-varying value-added and Domar-weights, while Comin and Philippon (2005) use time-invariant sales weights.

f) Industry-Specific Results

The industry decomposition of aggregate data has the clear advantage that it is built up directly from industry data, but there is still a concern that industry heterogeneity can be obscured.[26] That is, a summation over a set of industries yields the net contribution after any positive and negative contributions offset, which may obscure the impact of the individual component industries. Therefore, it is also useful to examine the contributions of individual industries. This is particularly useful for examining the hypothesis related to specific industries, e.g., decline in the persistence of sales and plant-level production convexities in the motor vehicles industry in Ramey and Vine (2004) and Irvine and Schuh (2005) or improved inventory management in the durable manufacturing sectors in MPQ (2000).

Tables 9a and 9b show the post-1983 change in the industry contributions to the variance of the aggregate variables from Equations (18), (19), and (21). More precisely, I calculated the difference

---

[25]Results are similar for the 1977-2000 dataset.
[26]This point has been made by Stiroh (2001b), Bosworth and Triplett (2003), and Jorgenson, Ho, and Stiroh (2005).

between the variance of the contribution in the pre-1984 period and the variance of the contribution in the post-1983 period as:

$$(23) \qquad \Delta V(X) = V(w_i \dot{X}_i)_{pre-84} - V(w_i \dot{X}_i)_{post-83}$$

where X is either the value-added, hours, labor productivity, TFP.

Table 9a again uses the 1958-1996 dataset, while Table 9b uses the 1978-2000 datasets. Note that the sum of these variance contributions equals those reported in Tables 8a and 8b. The key result in both tables is a broad-based decline in volatility across industries. In Table 9a, for example, 31 out of 35 industries showed a more stable contribution to aggregate output value-added growth with 10 of the declines statistically significant. In Table 9b, 31 out of 41 industries saw a decline with 15 of the declines statistically significant. The breadth of this stabilization is evidence against the structural composition and inventory management hypotheses and seems most consistent with the good luck or good policy arguments.

In terms of particular industries, for the 1958-1996 dataset, the industries with the largest decline in the variance of the value-added contribution are Services, Construction, and Agriculture, while Trade saw an increase. For the 1978-2000 dataset, the industries with the largest decline in the variance of the value-added contribution are Agriculture, Petroleum Refining, and Oil and Gas Mining, while Finance, Trade, and Electronic Components showed increases. Similar patterns emerge for the contribution of labor productivity growth and TFP growth. The contribution of hours growth is less consistent with 5 positive and significant changes in Table 9a and 8 positive significant changes in Table 9b. Finally, it is interesting to note that the large Trade industry, where inventory management techniques have supposedly improved, saw an increase in its contribution to aggregate volatility of both value-added and TFP growth in both datasets.

A second useful feature of this data is the ability to examine specific sub-groups. Jorgenson, Ho, and Stiroh (2005), for example, highlight the relatively large role of IT-producing and IT-using industries in the post-1995 productivity resurgence, while Triplett and Bosworth (2004) compare service to goods-producing industries. In terms of change in aggregate volatility, MPQ (2000) suggest a predominate role for durable manufacturing, while Irvine and Schuh (2005) focus on those industries that hold inventories. To extend this analysis, Tables 9a and 9b also break the U.S. economy into two groups - durable manufacturing industries (*Dur*) and the other industries in rest of the economy (*Other*). These estimates indicate that while most durable good industries did contribute to the increased stability of output since 1984, these industries, on net, make a relatively small direct contribution to the decline in aggregate volatility.

In terms of Ramey and Vine (2004) and Irvine and Schuh (2005) and the focus on the increased stability within the motor vehicle industry, these estimates support that contention, particularly in the 1958-1996 datase where there is a significant decline in the contribution from motor vehicles to aggregate output volatility from value-added, hours, labor productivity, and total factor productivity growth. The motor vehicle industry, however, remains relatively small (a nominal value-added share of less than 2% over this period), so it has contributed only -0.066 to the overall decline in aggregate volatility from value-added growth. This compares to –0.79 for the sum of the variances across all industries and –5.48 for the change in variance of aggregate output. Increased stability of motor vehicles, while important, appears to be a small part of the story.

g) Within and Between Correlation between Hours and Labor Productivity Growth

A robust and interesting finding from both the aggregate and industry-level results is a decline in the correlation between hours and productivity growth. For the nonfarm business sector as a whole, for example, the correlation fell from 0.17 for 1947:Q1-1983:Q4 to -0.44 for 1983:Q4-2004:Q4 (Table 2). For the industry data in the 1958-1996 dataset, the sum of the covariance contributions between hours and productivity fell from 0.89 for 1958-1983 to -1.31 for 1984-1996 (Table 8a). Both of these findings identify the declining correlation between hours and labor productivity as a potentially important source of increased output stability and this section examines this evolving relationship in more detail.

To focus on the changing correlations, I calculate the average of the within-industry and between-industry correlations of hours and labor productivity growth. As above, I generate a single aggregate series of the correlations by either taking the simple or weighting each industry by its value-added share over the rolling window. I use a 13-year rolling window for the 1958-1996 dataset and a 5-year rolling window for the 1978-2000 dataset in order to match the post-1983 and pre-1984 periods in each dataset, respectively.

The average within-industry correlation of hours and labor productivity growth are:

$$\begin{aligned} \bar{\rho}_{W,UN} &= \sum_i Corr(\dot{H}_i, A\dot{L}P_i) \cdot 1/I \\ \bar{\rho}_{W,WTD} &= \sum_i Corr(\dot{H}_i, A\dot{L}P_i) \cdot \bar{v}_{V,i} \end{aligned} \tag{24}$$

where the “W” subscript indicates a within-industry effect, $\dot{H}_i$ and $A\dot{L}P_i$ are the growth rates of hours and labor productivity for the rolling window, the *UN* subscript indicates unweighted, and the *WTD* subscript indicates value-added weighted.

The average between-industry correlation of hours and labor productivity growth are:

(25)
$$\bar{\rho}_{B,UN} = \sum_{i}\sum_{j=i+1} Corr(\dot{H}_i, A\dot{L}P_j)/(I \cdot (I-1))$$
$$\bar{\rho}_{B,WTD} = \sum_{i}\sum_{j=i+1} Corr(\dot{H}_i, A\dot{L}P_j)\cdot(v_{V,i}+v_{V,j})/((I-1)\cdot 2)$$

where the "B" subscript indicates a between-industry effect.[27]

Figure 11 plots the rolling average within-industry correlation of hours and labor productivity for all industries in each dataset. Both datasets show results that are quite similar - the correlation between hours and labor productivity growth in U.S. industries began to fall steadily in the mid-1980s. This is consistent with the aggregate results and provides further evidence that there has been some change in the link between labor input growth and productivity growth.

Figure 12 plots the rolling average between-industry correlation of hours and labor productivity for all industries in each dataset. Here, there is less evidence of a systematic trend in this correlation. In the 1978-2000 dataset, for example, the correlation became more negative, but it is quite volatile. In the 1958-1996 dataset, on the other hand, there is only a substantial decline in the last two years of observations. This evidence suggests that the large reduction in the between-industry covariance of hours and labor productivity largely reflects the more stable series, while the reduction in the within-industry covariance is due to a smaller correlation.

As a final way to examine how the within-industry relationship evolved, I estimate variations of a simple panel regression that allow the relationship between hours growth and labor productivity to change after 1984:

(26)
$$\dot{H}_{i,t} = \alpha_i + \alpha_t + \beta A\dot{L}P_{i,t} + \gamma D_{1984} + \delta A\dot{L}P_{i,t} D_{1984} + \varepsilon_{i,t}$$

where α_i is a dummy variable for industry i, α_t is a dummy variable for industry *t*, and D_{1984} is a dummy variable for the post-1983 period where D_{1984}=1 if year>=1983; =0 otherwise.

Before reporting results, it is useful to discuss the obvious econometric concerns with a simple regression of hours growth on labor productivity growth. First, there is a simultaneity concern because the same unobserved shocks are likely to affect both productivity and hours. In a standard real-business cycle model, for example, a positive technology shock raises the marginal product of labor and raises labor demand. This is likely to bias the simple coefficient upwards. Second, there is a measurement error concern as discussed earlier because, given output, any mismeasurement of hours growth translates directly into mismeasurement of labor productivity growth. This is likely to bias the simple coefficient downwards. Both of these concerns, however, have less bite when interpreting δ, the coefficient of

---

[27]Note that the weighting in Equation (25) differs from that in Equation (22). This is because the hours/productivity correlation sum has two sets of pairwise correlations, e.g., Corr (H_i, ALP_j) and C(H_j, ALP_i).

interest that tells how the relationship between hours growth and labor productivity has changed since 1983. For the simultaneity or mismeasurement error concerns to be relevant, one must think that these problems worsened after 1983. While certainly possible as discussed earlier, it requires a more nuanced explanation.

Table 10 reports estimates for various versions of Equation (26). The top panel uses the 35 industries from the 1958-1996 dataset, while the bottom panel uses the 41 industries in the 1978-2000 dataset. In both cases, the first column drops both the industry and year dummy variables; the second column includes the industry dummies; and the third column includes both the industry and the year dummy variables.

In all cases, the link between hours growth and labor productivity growth became significantly more negative after 1984. That is, the interaction of the Post-83 Dummy and ALP growth is negative and highly significant. Moreover, this change appears economically large with the coefficient about doubling in most cases as hours growth and labor productivity became more negative linked.

As a robustness check, I also estimated Equation (26) when the year dummy variable varied between 1960 and 1996 using the 1958-1996 dataset. Figure 13 plots the coefficient on the interaction between the post-breakpoint dummy and ALP growth, where the dotted lines represent two standard errors. The results indicate that declining correlation between hours and labor productivity growth is quite robust in the 1980s and not unique to choosing 1984 as the breakpoint. All years in the 1980s show a decline in the coefficient and most are statistically significant.[28] These are not independent confidence intervals, of course, and should not be interpreted as independent evidence of the break in the correlation. Rather, this chart simply shows the robustness to the choice of the breakpoint year.

VI. Conclusions

This paper examines the sources of the increased stability of the U.S. economy from a production perspective using both aggregate and industry data. At the aggregate level, the empirical results indicate a decline in the volatility of hours growth, labor productivity growth, and the covariances between them. A detailed production possibility frontier shows that the decline in labor productivity volatility is primarily due to increased stability of the TFP residual and the declining covariance between TFP and labor input.

At the industry level, the results indicate that while most industries saw a decline in output and TFP volatility, a majority of the aggregate decline reflects smaller covariances between industries with 80-85% of the decline in aggregate output volatility due to smaller covariances between industries. This

[28]When the breakpoint is an early or late year, the differential is much smaller and typically not significant. This simply reflects that fact that differences happened in the middle of the sample, so averaging across this makes it more difficult to identify a change.

large between-industry effect seems most consistent with the good luck and good policy explanations and less consistent with technology stories specific to particular industries.

These results suggest that part of the increased stability of the U.S. economy can be traced to changes in the U.S. labor markets. This could reflect increased pressure on firms to raise productivity or efficiency, increased flexibility of labor, or rising measurement error in hours worked. The increased flexibility story seems to be the most compelling as it could explain both the jobless recoveries of the last two decades and the rising stability of output growth over the same period. Sorting out these alternative explanations remains an important area for future research. For example, while there is strong evidence that the within-industry correlation between hours and productivity growth has declined, it would be interesting to link this decline with changes in labor market flexibility across industries.

References

Ahmed, S., Levin A., and Wilson B.A.. "Recent U.S. Macroeconomic Stability: Good Policies, Good Practice, or Good Luck." Federal Reserve Board, International Finance Discussion Papers #730, July 2002.

Arronson, Daniel, Ellen R. Rissman, and Daniel G. Sullivan. "Assessing the Jobless Recovery." Federal Reserve Bank of Chicago *Economic Perspectives*, 2004:Q2, 2-20.

_____. "Can Sectoral Reallocation Explain the Jobless Recovery?" Federal Reserve Bank of Chicago *Economic Perspectives*, 2004:Q2, 36-49.

Basu, Susanto, John Fernald, and Miles Kimball. "Are Technology Improvements Contractionary?" NBER Working Paper #10592, June 2004.

Baxter, Marianne and Robert G. King. "Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series." *Review of Economics and Statistics*, 81(4), November 1999, 575-593.

Blanchard, Olivier and John Simon. "The Long and Large Decline in U.S. Output Volatility," *Brookings Papers on Economic Activity*, 1:2001,135-174.

Bureau of Labor Statistics. "Productivity and Costs, 3rd Quarter, Revised," USDL 04-2461, December 7, 2004.

_____. "Superseded Historical SIC Measures for Manufacturing, Durable Manufacturing, and Nondurable Manufacturing Sectors, 1949-2003, December 3, 2003, http://www.bls.gov/lpc/home.htm#news.

Christiano, Lawrence, Martin Eichenbaum, and Robert Vigfusson. "What Happens after a Technology Shock?", NBER Working Paper No. 9819, July 2003.

_____. "The Response of Hours to a Technology Shock: Evidence Based on a Direct Measure of Technology." NBER Working Paper No. 10254, January 2004.

Cohen, Jacob, Patricia Cohen, Stephen G. West, and Leona S. Aiken. Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences. 2003, Mahwah, New Jersey: Lawrence Erlbaum Associates.

Comin, Diego and Thomas Philippon. "The Rise in Firm-Level Volatility: Causes and Consequences." New York University, Mimeo, January 2005.

Dean, Edwin R. "The Accuracy of BLS Productivity Measures." *Monthly Labor Review*, 122(2), February 1999, 24-34.

Domar, Evsey. "On the Measurement of Technical Change." *Economic Journal*, 71, 1961, 710-729.

Eldridge, Lucy P. "Hours Measures for Productivity Measurement and National Accounting." Bureau of Labor Statistics, Mimeo, September 1, 2004.

Estrella, Arturo. "Decoding Productivity: Business Cycle Properties of Labor Productivity Growth." Federal Reserve Bank of New York, Mimeo, June 2004.

Frazis, Harley and Jay Stewart. "What Can Time-Use Data Tell Us about Hours of Work?" *Monthly Labor Review*, December 2004, 3-9.

Gali, Jordi. "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations," *American Economic Review*, 89(1), March, 1999, 249-271.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell. "Long-Run Implications of Investment-Specific Technological Change." *American Economic Review*, 87(3), 1997, 342-362.

Groshen Erica L. and Simon Potter. “Has Structural Change Contributed to a Jobless Recovery?” Federal Reserve Bank of New York *Current Issues in Economics and Finance*, 9(8), August 2003.

Hansen, Gard D. and Randall Wright. “The Labor Market in Real Business Cycle Theory.” Federal Reserve Bank of Minneapolis *Quarterly Review*, 16(2), Spring 1992.

Irvine, Owen and Scott Schuh. “The Roles of Comovement and Inventory Investment in the Reduction of Output Volatility.” Federal Reserve Bank of Boston, Mimeo, March 2005.

Jorgenson, Dale W., “The Embodiment Hypothesis”, *Journal of Political Economy*, 74(1), February 1966, 1-17.

Jorgenson, Dale W., Mun S. Ho, and Kevin J. Stiroh. “Projecting Productivity Growth: Lessons from the U.S. Growth Resurgence, Federal Reserve Bank of Atlanta *Economic Review*, 87(3), 2002:Q3, 1-13.

_____ “Will the U.S. Productivity Resurgence Continue?” Federal Reserve Bank of New York *Current Issues in Economics and Finance*, 10(13), December 2004.

_____. “Growth of U.S. Industries and Investments in Information Technology and Higher Education,” with Dale W. Jorgenson and Mun S. Ho. Paper presented at NBER/CRIW Conference on Measurement of Capital in the New Economy, April 2002. Revised 2005.

Jorgenson, Dale W. and Kevin J. Stiroh. “Raising the Speed Limit: U.S. Economic Growth in the Information Age.” Brookings *Papers on Economic Activity*, 2000:1, 125-211.

Kahn, James A., Margaret M. McConnell, and Gabriel Perez-Quiros. “On the Causes of the Increased Stability of the U.S. Economy.” Federal Reserve Bank of New York *Economic Policy Review*, May 2002, 183-202.

Kim, Chang-Jin. and Charles R. Nelson. “Has the U.S. economy become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle.” *Review of Economics and Statistics*, 81(4), November 1999, 608-616.

Kim Chang-Jin., Charles. R. Nelson, and Jeremy Piger. “The Less Volatile U.S. Economy: A Bayesian Investigation of Timing, Breadth, and Potential Explanations.” *Journal of Business and Economic Statistics*, 22(1), January 2004, 80-93.

Levene, H. “Robust Tests for Equality of Variances.” In eds. I. Olkin, S. G. Ghurye, W. Hoeffding, W. G. Madow, and H.B. Mann. Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling, 1960, Stanford CA: Stanford University Press.

McConnell, Margaret M. and Gabriel Perez-Quiros. “Output Fluctuations in the United States: What Has Changed since the Early 1980s?” *American Economic review*, 90(5), December 2000, 1464-76.

McConnell, Margaret M., Patricia C. Mosser, and Gabriel Perez-Quiros. “A Decomposition of the Increased Stability of GDP Growth.” Federal Reserve Bank of New York *Current Issues in Economics and Finance*, 5(13), September 1999.

Oliner, Stephen D. and Daniel E. Sichel. “The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?” *Journal of Economic Perspectives*, 14(4), Fall 2000, 3-22.

_____. “Information Technology and Productivity: Where are We Now and Where are We Going?” Federal Reserve Bank of Atlanta *Economic Review*, 87(3), 2002:Q3.

Ramey, Valerie A. and Daniel J. Vine. “Tracking the Source of the Decline in GDP Volatility: An Analysis of the Automobile Industry.” NBER Working Paper #10384, March 2004.

Roach, Stephen S. "No Productivity Boom for Workers." *Issues in Science and Technology*. Summer 1998, 49-56.

_____. "The Great Productivity Fade." *Morgan Stanley Daily Economic Comment*, February 5, 2005.

Schreft Stacey L. and Aarti Singh. "A Closer Look at Jobless Recoveries." Federal Reserve Bank of Kansas City *Economic Review*, Second Quarter 2003, 46-73.

Schweitzer, Mark. "Economic Restructuring and the Slow Recovery of Employment." Federal Reserve Bank of Cleveland mimeo, December 31, 2004.

Solow, Robert M. "Technological Change and the Aggregate Production Function," *Review of Economics and Statistics*, 39, 1957, 312-320.

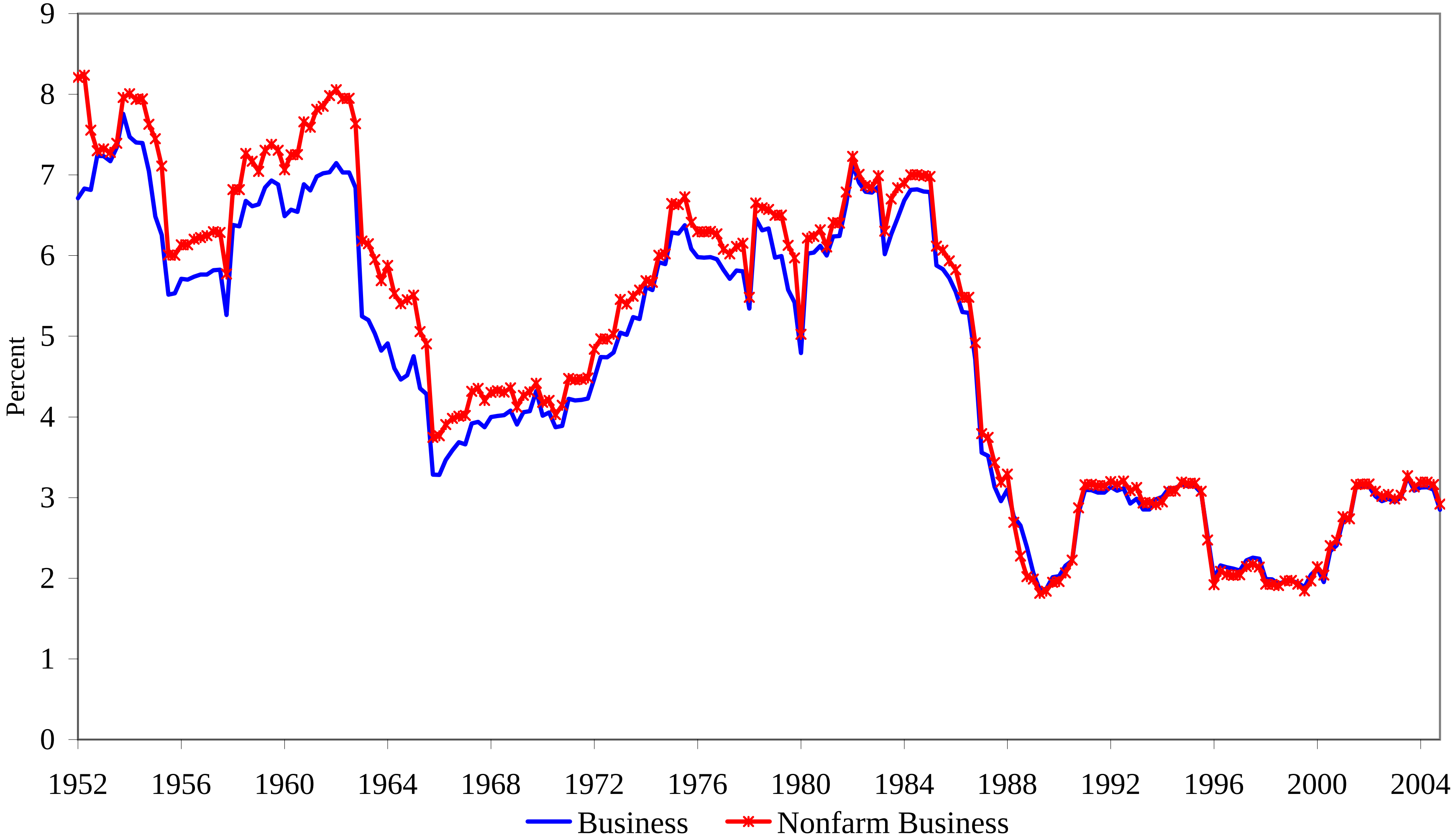
Stiroh, Kevin J. "Computers, Productivity, and Input Substitution." *Economic Inquiry*, XXXVI(2) April 1998, 175-191.

Stock, James H. and Mark W. Watson. "Has the Business Cycle Changed and Why?" NBER Working Paper #9127, September 2002.

Triplett, Jack E. and Barry P. Bosworth. Productivity in the U.S. Services Sector. 2004. Washington DC: The Brooking Institution.

Figure 1: Output Volatility for U.S. Business Sectors

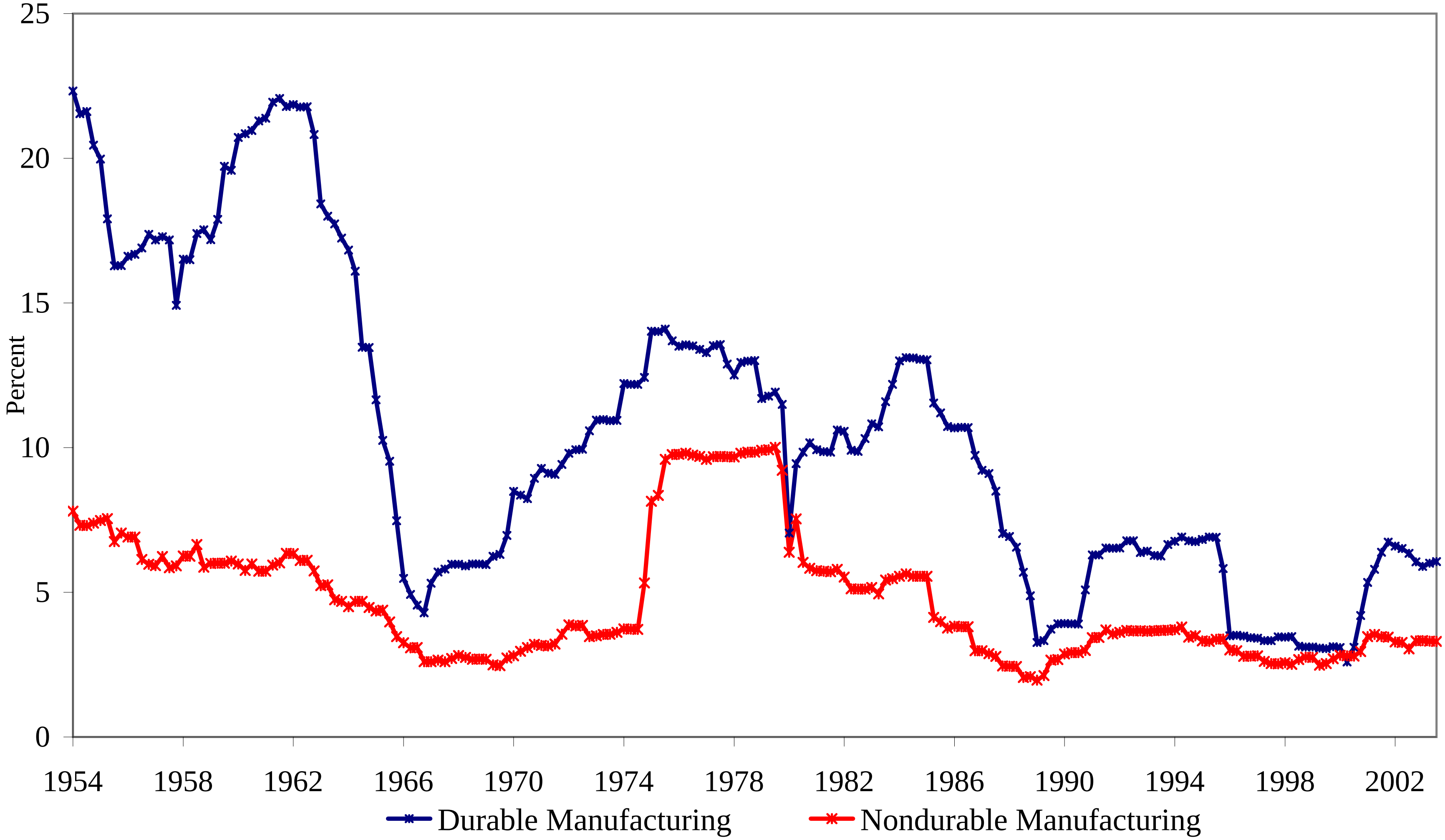
1947:Q1-2004:Q4



Note: Standard deviation of quarterly growth rates for trailing 20-quarters from BLS (2005).

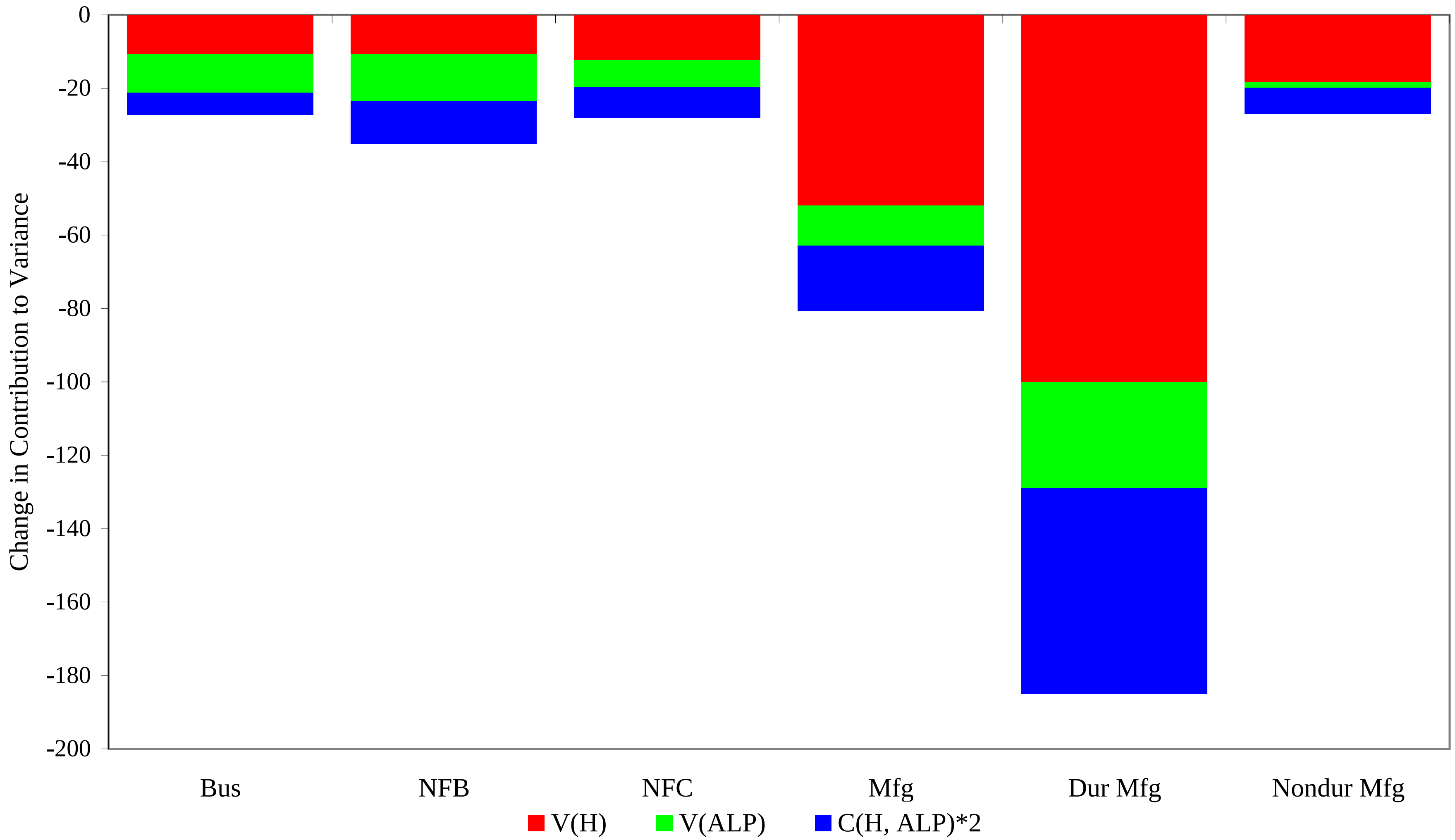
Figure 2: Output Volatility for U.S. Manufacturing Sectors

1949:Q1-2003:Q3



Note: Standard deviation of quarterly growth rates for trailing 20 quarters from BLS (2003).

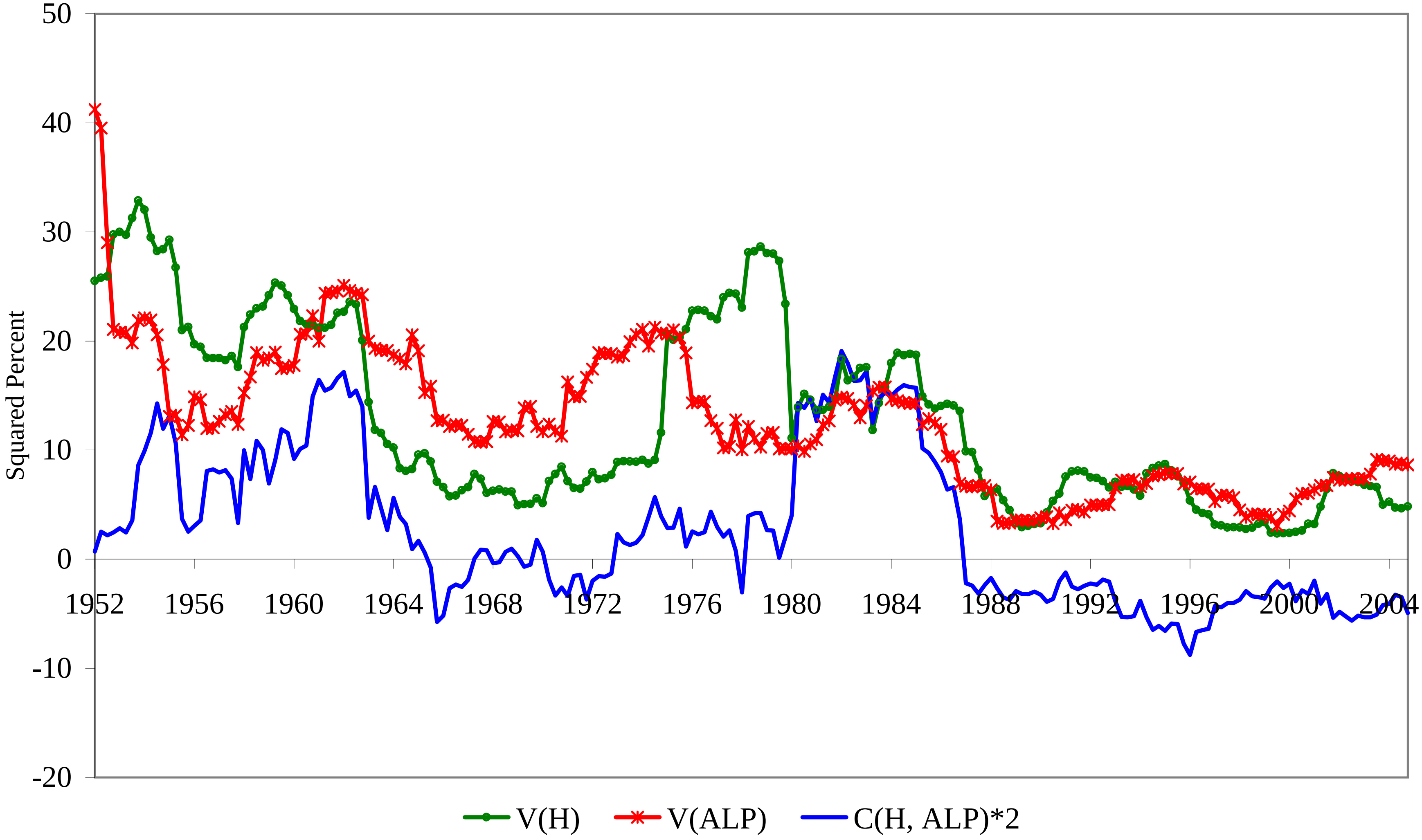
Figure 3: Decomposition of Change in Output Volatility across Sectors



Note: Estimates are from Table 1. Change in contribution to variance is the difference in volatility contribution from the pre-1984 period to the post-1983 period.

Figure 4: Rolling Decomposition of Nonfarm Business Sector Output Volatility

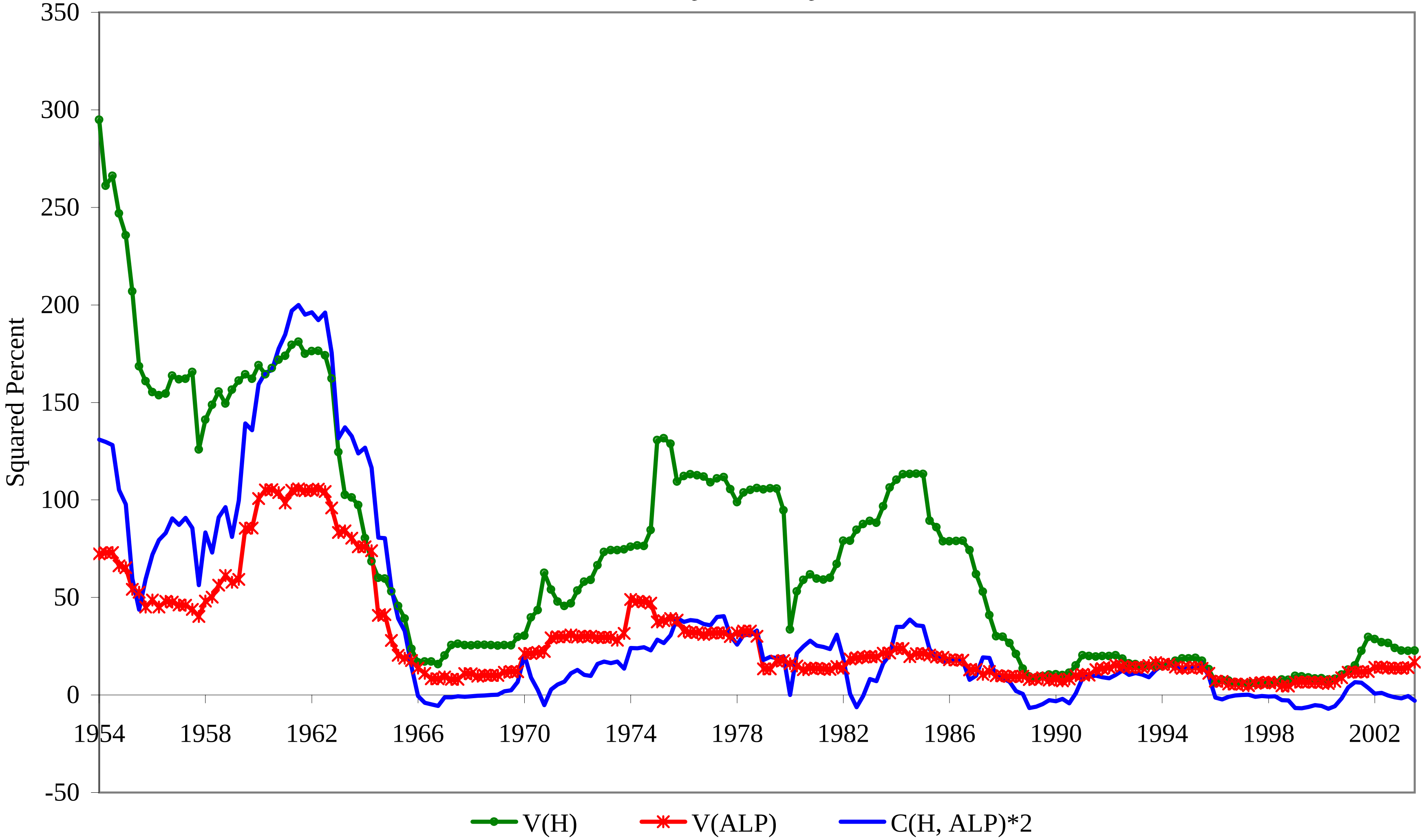
1947:Q1-2004:Q4



Note: Variances and covariances are calculated over trailing 20 quarters from BLS (2005).

Figure 5: Rolling Decomposition of Durable Manufacturing Output Volatility

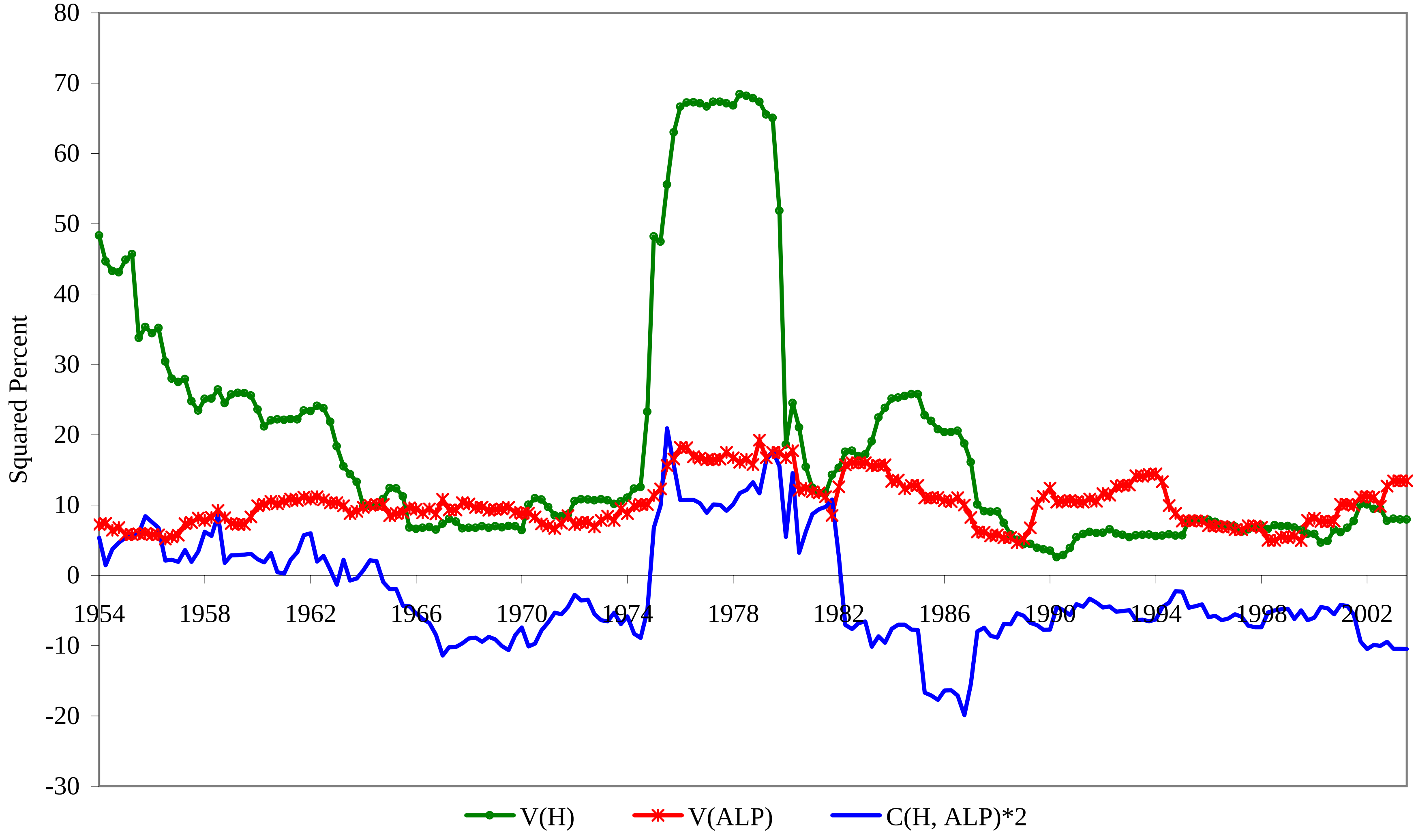
1949:Q1-2003:Q3



Note: Variances and covariances are calculated over trailing 20 quarters from BLS (2003).

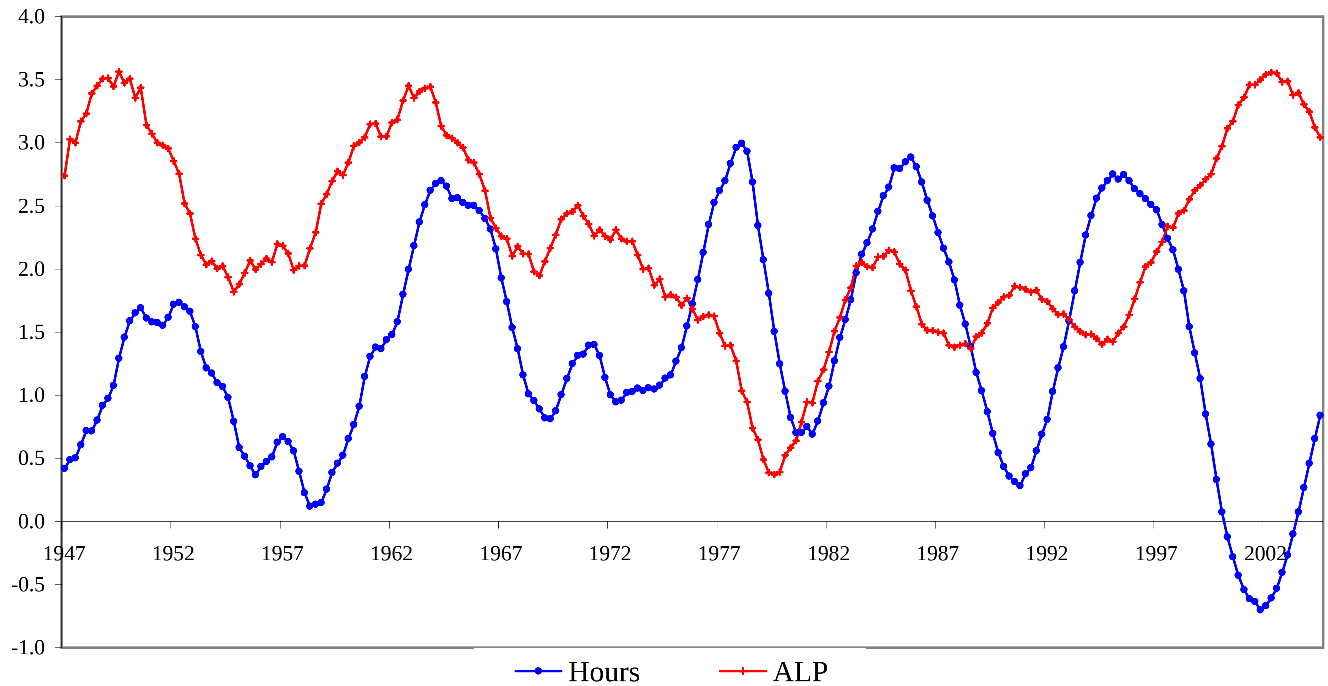
Figure 6: Rolling Decomposition of Nondurable Manufacturing Output Volatility

1949:Q1-2003:Q3



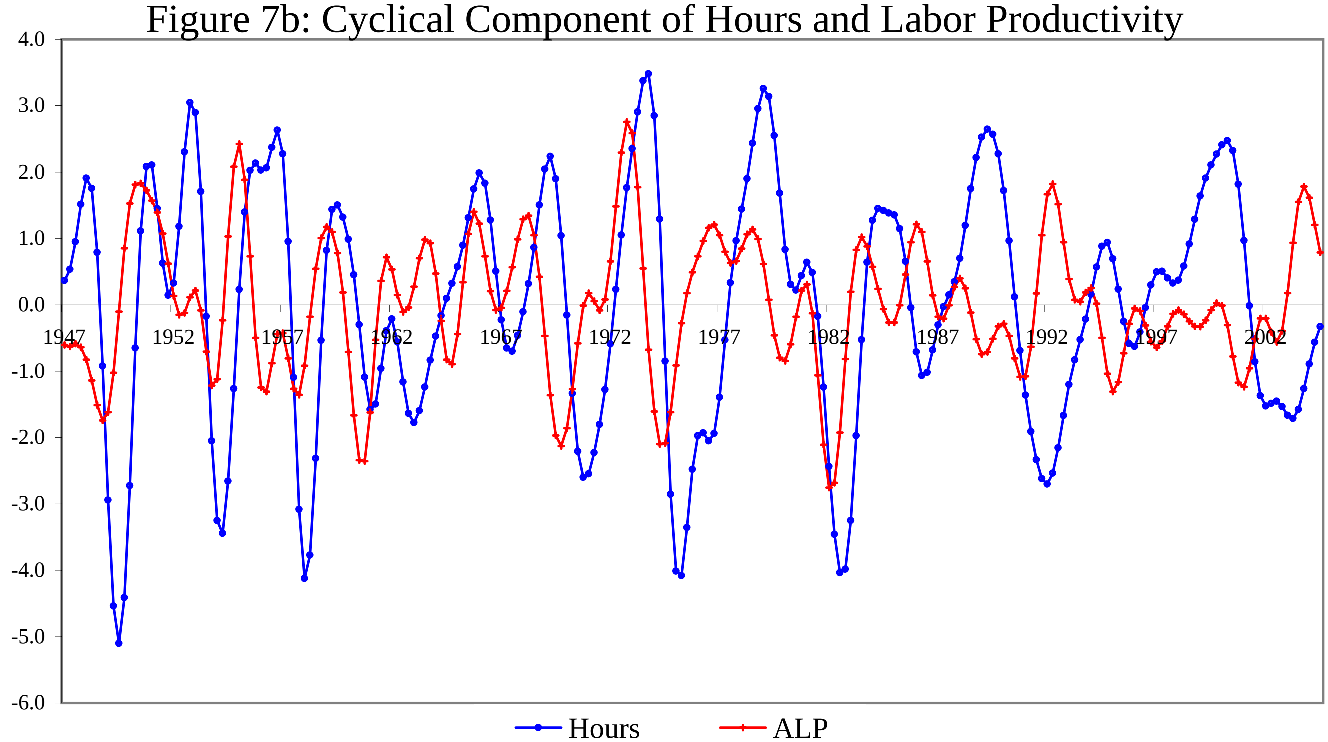
Note: Variances and covariances are calculated over trailing 20 quarters from BLS (2003).

Figure 7a: Trend Growth of Hours and Labor Productivity



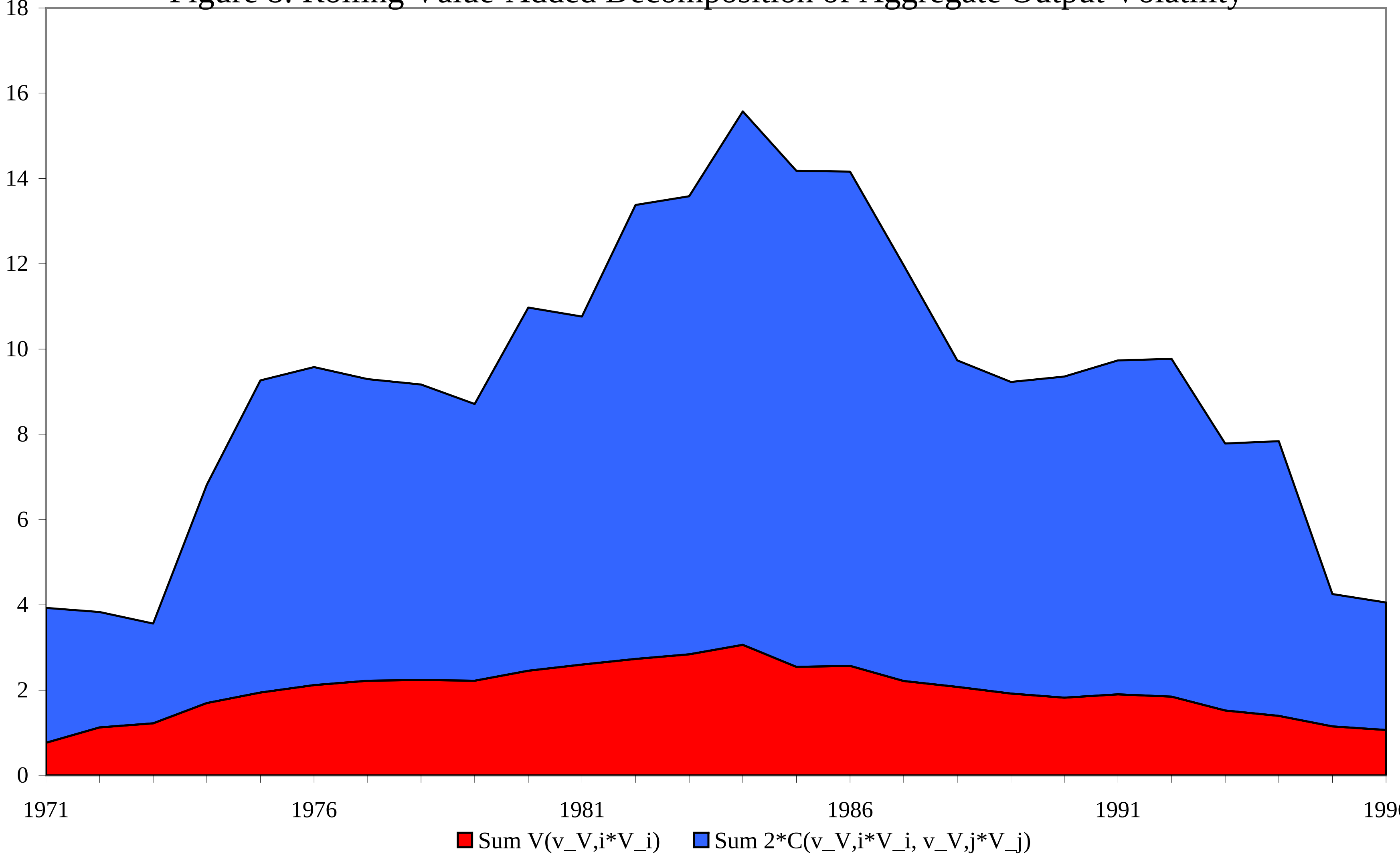
Note: Quarterly growth rate of trend component from Baxter-King band-pass filter. Data are for the U.S. nonfarm business sector for 1947:Q1-2004:Q4 from BLS (2005).

Figure 7b: Cyclical Component of Hours and Labor Productivity



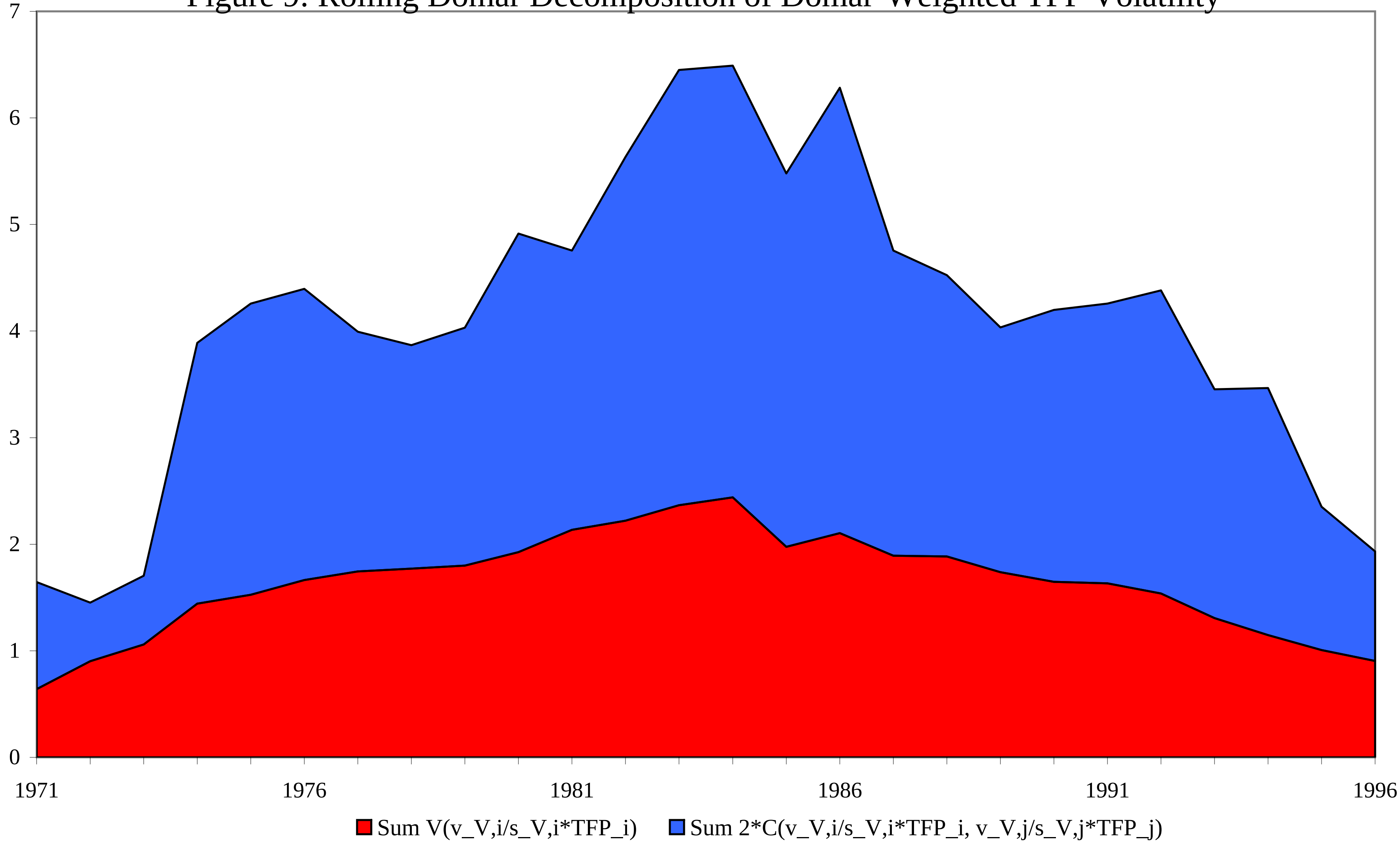
Note: Cyclical deviation from trend (in percentages) from Baxter-King band-pass filter. Data for the U.S. nonfarm business sector for 1947:Q1-2004:Q4 from BLS (2005).

Figure 8: Rolling Value-Added Decomposition of Aggregate Output Volatility



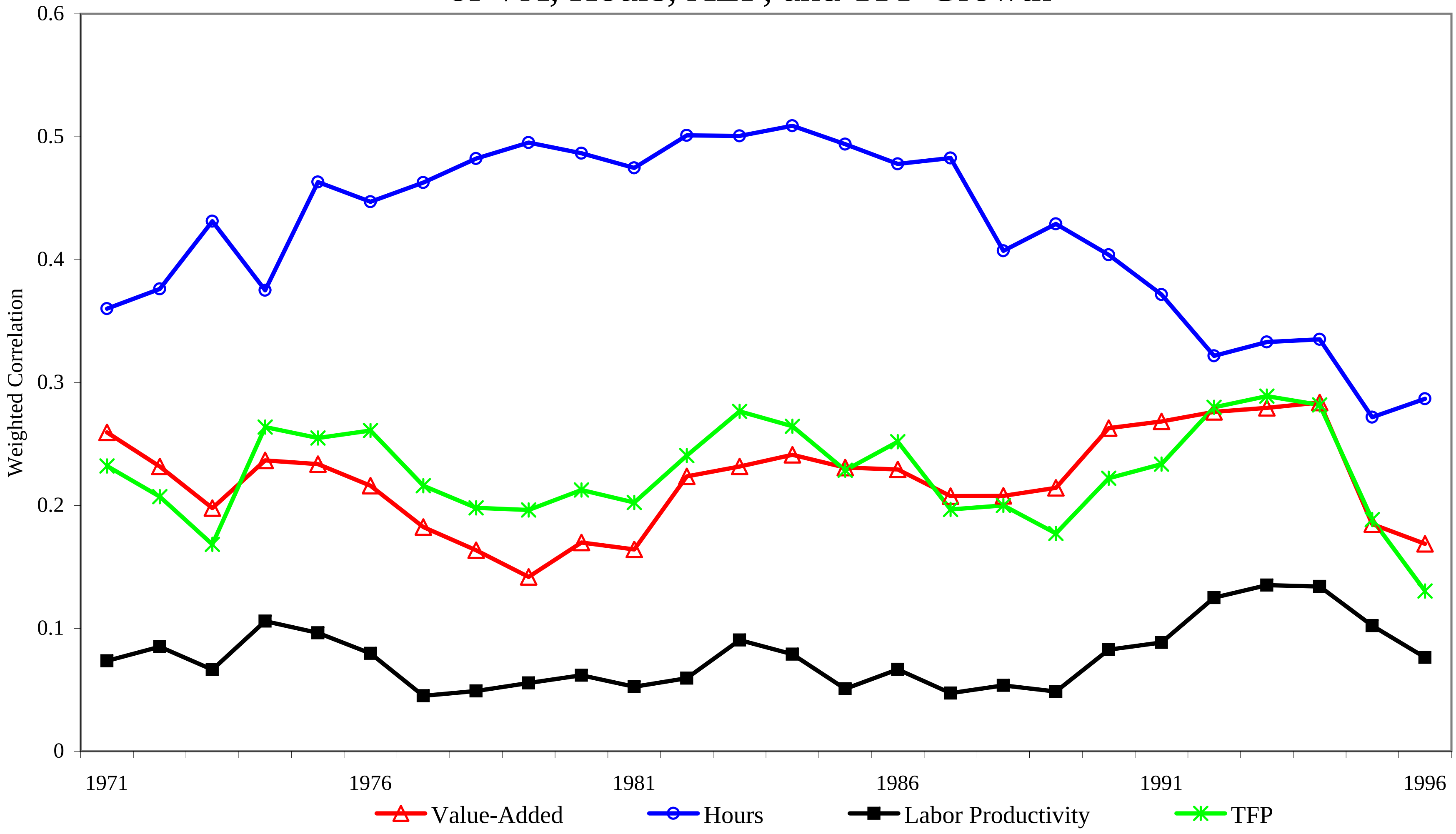
Note: 13-year rolling variance and coviariance estimates for 35 industries from the 1958-1996 dataset. Industry value-added growth rates are weighted by nominal value-added shares.

Figure 9: Rolling Domar Decomposition of Domar-Weighted TFP Volatility



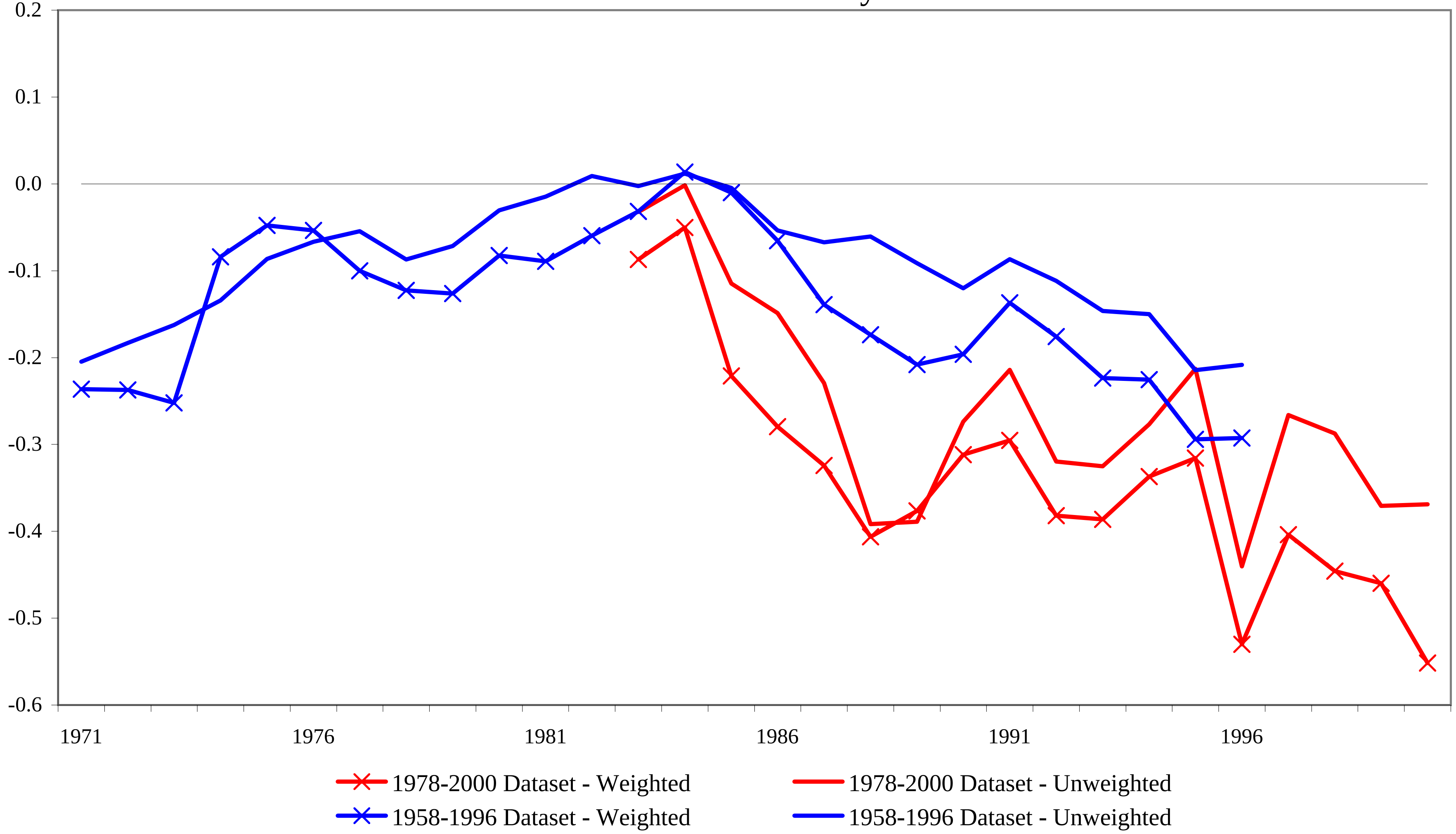
Note: 13-year rolling variance and coviariance estimates for 35 industries from the 1958-1996 dataset. Industry TFP growth rates are weighted by Domar weights.

Figure 10: Rolling Between-Industry Correlations
of VA, Hours, ALP, and TFP Growth



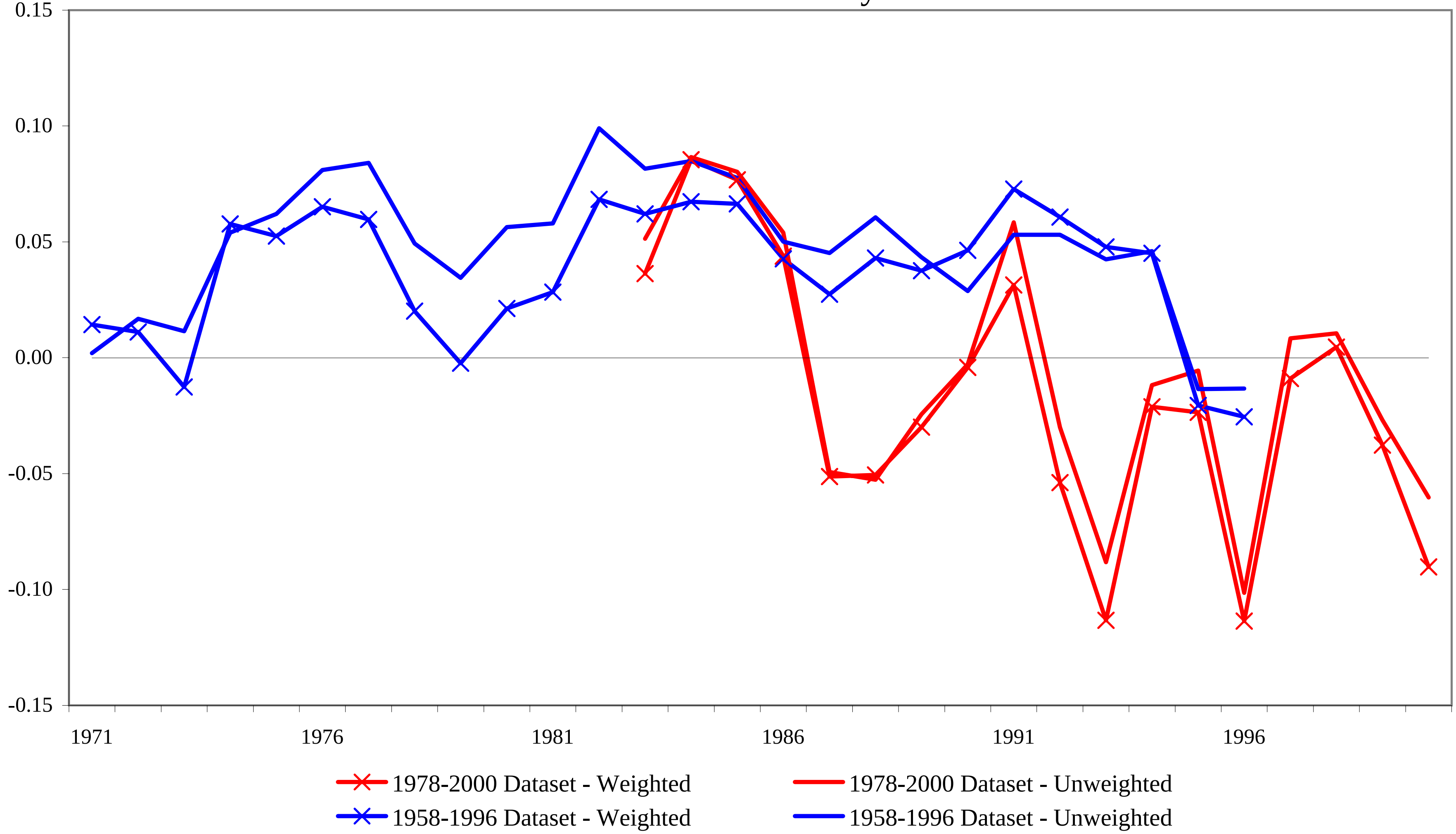
Note: 13-year rolling correlations for 35 industries from the 1958-1996 dataset. Each series is sum of the correlation of the weighted growth rate for each pairwise combination. Weights are nominal value-added shares for all series except TFP, which uses Domar-weights.

Figure 11: Rolling Within-Industry Correlation of Hours and Labor Productivity Growth



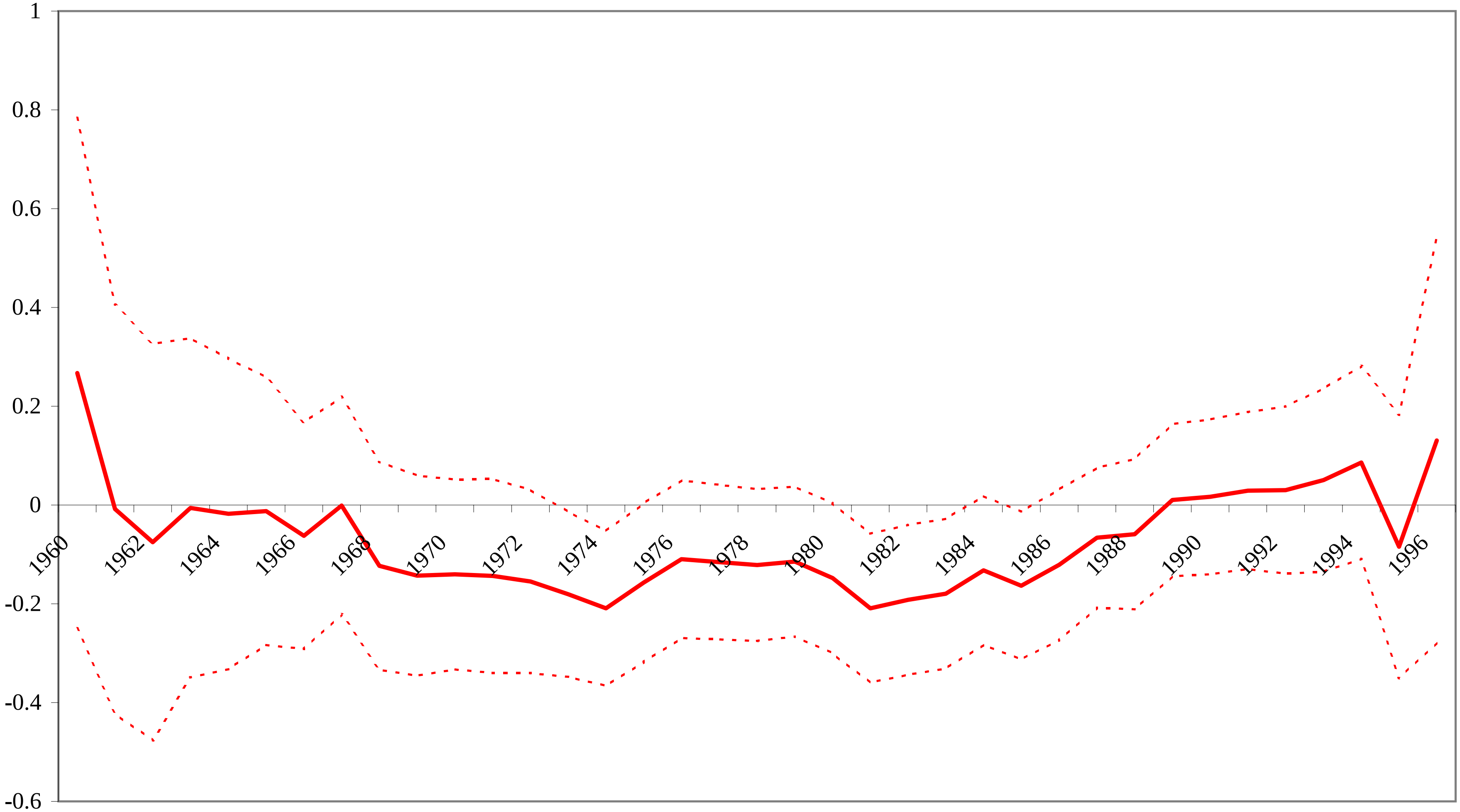
Note: 1978-2000 dataset uses a 5-year rolling window for 41 industries. 1958-1996 dataset uses a 13-year rolling window for 35 industries. Weights are nominal value added shares for each industry.

Figure 12: Rolling Between-Industry Correlation of Hours and Labor Productivity Growth



Note: 1978-2000 dataset uses a 5-year rolling window for 41 industries. 1958-1996 dataset uses a 13-year rolling window for 35 industries. Weights are nominal value added shares for each industry.

Figure 13: Rolling Regression Estimates



Note: Each year shows the estimated coefficient on the interaction between labor productivity growth and a post-year dummy variable (=1 for each subsequent year; =0 otherwise) from a regression like Equation (25). Dotted lines indicate 2 standard errors from the coefficient estimate.

Table 1: Growth and Variance Decomposition

Growth Decomposition shows the breakdown of output growth into hours growth and average labor productivity (ALP) growth. Significance levels are from a t-test of the null hypothesis that the mean growth rate (but not the variance) is the same for the two periods. *Variance Decomposition* shows the breakdown of the variance of output growth into the variance of hours growth, the variance of ALP growth, and twice the covariance. Significance levels for the variances are from Levene's test that the variance of the growth rate is the same for the two periods. Significance levels for the covariances are from a 2-sample Z-test on unpaired samples for the associated correlation. All growth rates are quarterly log differences multiplied by 400. Sample periods are 1947:Q1-1983:Q4 and 1983:Q4-2004:Q4 for Business and Nonfarm Business, 1947:Q1-1983:Q4 and 1983:Q4-2004:Q3 for Nonfinancial Corporations, and 1949:Q1-1983:Q4 and 1983:Q4-2003:Q3 for Manufacturing, Durable Manufacturing, and Nondurable Manufacturing.

	Growth Decomposition				**Variance Decomposition**		
	Pre-1984	**Post-1983**	**Change**		**Pre-1984**	**Post-1983**	**Change**
			Business: Y = f(H, ALP)				
Output	3.57	3.57	0.00	V(Output)	34.51	7.31	-27.20 ***
Hours	0.96	1.29	0.34	V(Hours)	16.90	6.30	-10.60 ***
ALP	2.61	2.28	-0.33	V(ALP)	16.63	6.11	-10.51 ***
				Cov(H, ALP)*2	0.98	-5.10	-6.08 ***
			Nonfarm Business: Y = f(H, ALP)				
Output	3.67	3.53	-0.14	V(Output)	42.03	6.98	-35.05 ***
Hours	1.34	1.37	0.03	V(Hours)	17.18	6.43	-10.75 ***
ALP	2.33	2.16	-0.17	V(ALP)	18.90	6.13	-12.77 ***
				Cov(H, ALP)*2	5.95	-5.58	-11.53 ***
			Nonfinancial Corporations: Y = f(H, ALP)				
Output	4.34	3.73	-0.61	V(Output)	39.06	11.06	-28.00 ***
Hours	2.32	1.44	-0.88 *	V(Hours)	19.98	7.67	-12.31 ***
ALP	2.02	2.29	0.27	V(ALP)	13.48	6.13	-7.35 ***
				Cov(H, ALP)*2	5.61	-2.74	-8.34 **
			Manufacturing: Y = f(H, ALP)				
Output	3.06	2.55	-0.51	V(Output)	97.40	16.63	-80.77 ***
Hours	0.64	-0.94	-1.58 **	V(Hours)	65.04	13.02	-52.01 ***
ALP	2.42	3.50	1.08 **	V(ALP)	17.61	6.71	-10.90 ***
				Cov(H, ALP)*2	14.76	-3.09	-17.85 ***
			Durable Manufacturing: Y = f(H, ALP)				
Output	3.47	3.40	-0.07	V(Output)	218.53	33.52	-185.01 ***
Hours	0.92	-0.93	-1.85 *	V(Hours)	120.24	20.20	-100.04 ***
ALP	2.54	4.32	1.78 **	V(ALP)	41.55	12.77	-28.78 ***
				Cov(H, ALP)*2	56.74	0.55	-56.19 ***
			Nondurable Manufacturing: Y = f(H, ALP)				
Output	2.70	1.54	-1.17 *	V(Output)	38.10	11.03	-27.07 ***
Hours	0.28	-0.96	-1.24 **	V(Hours)	27.28	8.93	-18.36 ***
ALP	2.43	2.50	0.07	V(ALP)	10.72	9.25	-1.46
				Cov(H, ALP)*2	0.10	-7.15	-7.25 ***

Note: Quarterly data from BLS (2005).

***, **, * denotes statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 2: Correlations of Hours and Labor Productivity Growth

Correlation between hours growth and labor productivity growth for various sectors before 1984 and after 1983. Significance level for each period is from a t-test for the significance of the correlation coefficient. Significance level for the difference in correlations is from a 2-sample Z-test on unpaired samples for correlations. All growth rates are quarterly log differences multiplied by 400. Sample periods are 1947:Q1-1983:Q4 and 1983:Q4-2004:Q4 for Business and Nonfarm Business, 1947:Q1-1983:Q4 and 1983:Q4-2004:Q3, for Nonfinancial Corporations, and 1949:Q1-1983:Q4 and 1983:Q4-2003:Q3 for Manufacturing, Durable Manufacturing, and Nondurable Manufacturing.

	Full Sample	Pre-1984	Post-1983	Change
Business	-0.05	0.03	-0.41 ***	-0.44 ***
Nonfarm Business	0.06	0.17 **	-0.44 ***	-0.61 ***
Nonfinancial Corporations	0.07	0.17 *	-0.20 *	-0.37 **
Manufacturing	0.15 **	0.22 ***	-0.17	-0.38 ***
Durable Manufacturing	0.34 ***	0.40 ***	0.02	-0.38 ***
Nondurable Manufacturing	-0.09	0.00	-0.39 ***	-0.40 ***

Note: Quarterly data from BLS (2005).

***, **, * indicate statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 3: Trend Decomposition for Nonfarm Business Sector

Results from Baxter-King (1999) band-pass filter of output, hours, and average abor productivity for the Nonfarm Business sector. *Mean* reports the average growth rates for the raw data and trend components, and average percent deviation from trend for the cyclical deviation and irregular deviation. Significance levels are from a t-test of the null hypothesis that the mean (but not the variance) is the same for the two periods. *Standard Deviation* reports the standard deviation of each series. Significance levels are from Levene's test that the variance is the same for the two periods. All growth rates are quarterly log differences multiplied by 400. Sample period is 1947:Q1-1983:Q4 and 1983:Q4-2004:Q4.

	Mean			**Standard Deviation**		
	Pre-1984	**Post-1983**	**Change**	**Pre-1984**	**Post-1983**	**Change**
			Output			
Raw Growth	3.67	3.53	-0.14	6.48	2.64	-3.84 ***
Trend Growth	3.65	3.53	-0.12	1.07	0.81	-0.26 **
Cyclical Deviation	-0.09	0.14	0.23	2.50	1.23	-1.27 ***
Irregular Deviation	0.01	-0.01	-0.01	0.73	0.28	-0.45 ***
			Hours			
Raw Growth	1.34	1.37	0.03	4.14	2.54	-1.61 ***
Trend Growth	1.37	1.36	-0.01	0.71	1.15	0.43 ***
Cyclical Deviation	-0.10	0.15	0.25	2.01	1.39	-0.61 ***
Irregular Deviation	0.01	-0.01	-0.01	0.37	0.21	-0.17 ***
			Average Labor Productivity			
Raw Growth	2.32	2.16	-0.16	4.30	2.42	-1.87 ***
Trend Growth	2.27	2.18	-0.09	0.79	0.72	-0.06
Cyclical Deviation	0.00	-0.01	-0.01	1.15	0.74	-0.41 ***
Irregular Deviation	0.00	0.00	0.00	0.55	0.30	-0.25 ***

Note: Quarterly data from BLS (2005).

***, **, * denotes statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 4: Correlations of Hours and Labor Productivity Growth for Trend Decomposition

Correlation between hours growth and labor productivity growth for the Nonfarm Business sector. Raw and trend components are growth rates, while cyclical deviation and irregular deviation are percentage deviation from trend. Significance levels for each period are from a t-test for the significance of the correlation coefficient. Significance levels for the difference in correlations are from a 2-sample Z-test on unpaired samples for correlations. All growth rates are quarterly log differences multiplied by 400. Sample periods are 1947:Q1-1983:Q4 and 1983:Q4-2004:Q4.

	Full Sample	Pre-1984	Post-1983	Change
Raw Growth	0.08	0.18 **	-0.42 ***	-0.60 ***
Trend Growth	-0.30 ***	0.01	-0.71 ***	-0.72 ***
Cyclical Deviation	0.05	0.18 **	-0.47 **	-0.65 ***
Irregular Deviation	0.13 **	0.22 ***	-0.38 ***	-0.60 ***

Note: Quarterly data from BLS (2005).

***, **, * indicate statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 5: Growth and Variance Decomposition - Traditional Production Possibility Frontier

Production possibility frontier variables are share-weighted growth rates. *Growth Decomposition* shows alternative decompositions of output and ALP growth. Significance levels are from a t-test of the null hypothesis that the mean growth rate (but not the variance) is the same for the two periods. *Volatility Decomposition* shows alternative decompositions of output and ALP variance. Significance levels for the variance are from Levene's test that the variance of the growth rate is the same for the two periods. Significance levels for the covariance are from a 2-sample Z-test on unpaired samples for the associated correlation. All growth rates are log differences of annual data multiplied by 100. Sample periods are 1948-1983 and 1983-2003.

	Growth Decomposition				Variance Decomposition		
	Pre-1984	Post-1983	Change		Pre-1984	Post-1983	Change
				Y = f(H, ALP)			
Output	3.75	3.72	-0.03	V(Output)	8.12	2.58	-5.53 ***
Hours	0.95	1.52	0.57	V(Hours)	6.25	3.79	-2.46
ALP	2.80	2.20	-0.60	V(ALP)	3.12	1.35	-1.77
				Cov(H, ALP)*2	-1.25	-2.56	-1.31 *
				Y = f(K, L, TFP)			
Output	3.75	3.72	-0.03	V(Output)	8.12	2.58	-5.53 ***
Capital	2.00	1.83	-0.17	V(Capital)	0.61	0.37	-0.24
Labor	0.92	1.11	0.19	V(Labor)	2.07	1.31	-0.76
TFP	0.83	0.78	-0.05	V(TFP)	2.63	1.14	-1.49 *
				Cov(Capital, Labor)*2	0.31	0.35	0.04
				Cov(Capital, TFP)*2	0.10	-0.27	-0.37
				Cov(Labor, TFP)*2	2.40	-0.31	-2.71 **
				ALP = f(k, L_Q, TFP)			
ALP	2.80	2.20	-0.60	V(ALP)	3.12	1.35	-1.77
CapDeep	1.60	1.17	-0.43	V(CapDeep)	1.59	0.76	-0.82
L_Q	0.37	0.25	-0.11	V(L_Q)	0.13	0.04	-0.09 **
TFP	0.83	0.78	-0.05	V(TFP)	2.63	1.14	-1.49 *
				Cov(CapDeep, L_Q)*2	0.17	-0.10	-0.26
				Cov(CapDeep, TFP)*2	-1.56	-0.24	1.32
				Cov(L_{+G11}, TFP)*2	0.17	-0.25	-0.42 ***

Note: Annual data from Jorgenson, Ho, and Stiroh (2004).

***, **, * indicate statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 6: Growth and Variance Decomposition - Extended Production Possibility Frontier

Production possibility frontier variables are share-weighted growth rates. *Growth Decomposition* shows decompositions of output growth. Significance levels are a t-test for the null hypothesis that the mean growth rate (but not the variance) is the same for the two periods. *Variance Decomposition* shows decomposition of output variance. Significance levels for the variance are from Levene's test that the variance of the growth rate is the same for the two periods. Significiance levels for the covariance are from a 2-sample Z-test on unpaired samples for the associated correlation. All growth rates are log differences of annual data multiplied by 100. Sample periods are 1948-1983 and 1983-2003.

	Growth Decomposition				**Variance Decomposition**		
	Pre-1984	**Post-1983**	**Change**		**Pre-1984**	**Post-1983**	**Change**
			$Y = f(K_{IT}, K_{NON}, L, TFP_{IT}, TFP_{NON})$				
Output	3.75	3.72	-0.03	V(Output)	8.12	2.58	-5.53 ***
K_{IT}	0.23	0.70	0.47 ***	$V(K_{IT})$	0.01	0.08	0.06 ***
K_{NON}	1.78	1.13	-0.65 ***	$V(K_{NON})$	0.70	0.24	-0.46
L	0.92	1.11	0.19	V(L)	2.07	1.31	-0.76
TFP_{IT}	0.10	0.37	0.27 ***	$V(TFP_{IT})$	0.01	0.03	0.02 **
TFP_{NON}	0.73	0.41	-0.31	$V(TFP_{NON})$	2.59	1.06	-1.53 **
				$Cov(K_{IT}, K_{NON})*2$	-0.10	0.06	0.16 ***
				$Cov(K_{IT}, L)*2$	0.02	0.06	0.03
				$Cov(K_{IT}, TFP_{IT})*2$	0.02	0.07	0.05
				$Cov(K_{IT}, TFP_{NON})*2$	-0.12	-0.06	0.06
				$Cov(K_{NON}, L)*2$	0.29	0.29	0.00
				$Cov(K_{NON}, TFP_{IT})*2$	-0.10	0.02	0.11 **
				$Cov(K_{NON}, TFP_{NON})*2$	0.30	-0.30	-0.60
				$Cov(L, TFP_{IT})*2$	0.10	0.01	-0.09
				$Cov(L, TFP_{NON})*2$	2.30	-0.32	-2.62 **
				$Cov(TFP_{IT}, TFP_{NON})*2$	0.03	0.05	0.02

Note: Annual data from Jorgenson, Ho, and Stiroh (2004).

***, **, * indicate statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 7: Correlations of Production Possibility Frontier Variables

Production possibility frontier variables are share-weighted growth rates. Correlation between capital, labor, and TFP components for alternative decompositions before 1984 and after 1983. Significance level for each period is from a t-test for the significance of the correlation coefficient. Significance level for the difference in correlations is from a 2-sample Z-test on unpaired samples for correlations of contributions. All growth rates are log differences of annual data multiplied by 100. Sample periods are 1948-1983 and 1983-2003.

	Full Sample	Pre-1984	Post-1983	Change
		$Y = f(H, ALP)$		
Corr(Hours, ALP)	-0.25 *	-0.14	-0.57 ***	-0.43 *
		$Y = f(K, L, TFP)$		
Corr(Capital, Labor)	0.16	0.14	0.25	0.11
Corr(Capital, TFP)	-0.01	0.04	-0.21	-0.25
Corr(Labor, TFP)	0.37 ***	0.51 ***	-0.13	-0.64 **
		$ALP = f(k, L_Q, TFP)$		
Corr(CapDeep, L_Q)	0.13	0.19	-0.28	-0.47
Corr(CapDeep, TFP)	-0.32 **	-0.38 **	-0.13	0.25
Corr(L_Q, TFP)	0.03	0.15	-0.60 ***	-0.76 ***
		$Y = f(K_{IT}, K_{NON}, L, TFP_{IT}, TFP_{NON})$		
Corr(K_{IT}, K_{NON})	-0.40 ***	-0.50 ***	0.22	0.72 ***
Corr(K_{IT}, L)	0.10	0.07	0.09	0.02
Corr(K_{IT}, TFP_{IT})	0.87 ***	0.83 ***	0.72 ***	-0.11
Corr(K_{IT}, TFP_{NON})	-0.19	-0.30 *	-0.10	0.21
Corr(K_{NON}, L)	0.11	0.12	0.26	0.14
Corr(K_{NON}, TFP_{IT})	-0.45 ***	-0.51 ***	0.10	0.62 **
Corr(K_{NON}, TFP_{NON})	0.08	0.11	-0.30	-0.41
Corr(L, TFP_{IT})	0.18	0.30 *	0.02	-0.29
Corr(L, TFP_{NON})	0.35	0.50 ***	-0.14	-0.63 **
Corr(TFP_{IT}, TFP_{NON})	-0.01	0.08	0.13	0.05

Note: Annual data from Jorgenson, Ho, and Stiroh (2004).

***, **, * indicate statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 8a: Decomposition of Aggregate Output and TFP Growth into Industry Contributions

Decomposition of aggregate output growth for 35 industries in the 1958-1996 dataset. *Growth Decomposition* shows alternative decompositions of aggregate output and TFP growth. *Variance Decomposition* shows alternative decompositions of aggregate output and TFP variance. For industry sums, V(.) indicates the variances of weighted growth rate, while C(.,.) indicates the covariance of the weighted growth rate. All growth rates are log differences of annual data multiplied by 100. Sample periods are 1958-1983 and 1984-1996.

	Growth Decomposition				Variance Decomposition		
	Pre-1984	**Post-1983**	**Change**		**Pre-1984**	**Post-1983**	**Change**
				Aggregate Output Decomposition			
				Aggregate Output Measures			
Production Function	3.22	3.18	-0.03		8.49	3.47	-5.02
Production Possibility Frontier	3.23	3.29	0.06		9.53	4.05	-5.48
				Industry Value-Added Decomposition of Output			
$\Sigma\, v_{V,i} V_i$	3.23	3.29	0.06	$\Sigma\, V(v_{V,i} V_i)$	1.86	1.07	-0.79
				$\Sigma\Sigma\, 2C(v_{V,i} V_i, v_{V,j} V_j)$	7.67	2.99	-4.68
				Industry Labor Productivity Decomposition of Output			
$\Sigma\, v_{V,i} H_i$	1.51	1.71	0.20	$\Sigma\, V(v_{V,i} H_i)$	0.56	0.53	-0.04
$\Sigma\, v_{V,i} ALP_i$	1.72	1.58	-0.14	$\Sigma\, V(v_{V,i} ALP_i)$	1.56	0.99	-0.57
				$\Sigma\Sigma\, 2C(v_{V,i} H_i, v_{V,j} H_j)$	4.63	2.52	-2.11
				$\Sigma\, 2C(v_{V,i} H_i, v_{V,j} ALP_i)$ = Within	-0.26	-0.45	-0.18
				$\Sigma\Sigma\, 2C(v_{V,i} H_i, v_{V,j} ALP_j)$ = Between	1.15	-0.86	-2.02
				$\Sigma\Sigma\, 2C(v_{V,i} ALP_i, v_{V,j} ALP_j)$	1.89	1.33	-0.56
				Domar-Weighted TFP Decomposition			
Domar-Weighted TFP	0.72	0.75	0.02	Domar_Weighted TFP	4.49	1.93	-2.55
$\Sigma\, v_{V,i}/s_{V,i} TFP_i$	0.72	0.75	0.02	$\Sigma\, V(v_{V,i}/s_{V,i} TFP_i)$	1.56	0.90	-0.66
				$\Sigma\Sigma\, 2C(v_{V,i}/s_{V,i} TFP_i, v_{V,j}/s_{V,j} TFP_j)$	2.92	1.03	-1.89

Note: Annual data from Jorgenson and Stiroh (2000).

7/5/2005 12:14

Table 8b:Decomposition of Aggregate Output and TFP Growth into Industry Contributions

Decomposition of aggregate output growth for 41 industries in the 1978-2000 dataset. *Growth Decomposition* shows alternative decompositions of aggregate output and TFP growth. *Variance Decomposition* shows alternative decompositions of aggregate output and TFP variance. For industry sums, V(.) indicates the variances of weighted growth rate, while C(.,.) indicates the covariance of the weighted growth rate. All growth rates are log differences of annual data multiplied by 100. Sample periods are 1978-1983 and 1984-2000.

	Growth Decomposition				**Variance Decomposition**		
	Pre-1984	**Post-1983**	**Change**		**Pre-1984**	**Post-1983**	**Change**
				Aggregate Output Decomposition			
				Aggregate Output Measures			
Production Function	0.96	3.79	2.84		11.40	4.86	-6.55
Production Possibility Frontier	0.95	3.73	2.77		9.95	3.46	-6.49
				Industry Value-Added Decomposition of Output			
$\Sigma\, v_{V,i}V_i$	0.95	3.73	2.77	$\Sigma\, V(v_{V,i}V_i)$	2.03	0.75	-1.29
				$\Sigma\Sigma\, 2C(v_{V,i}V_i,\, v_{V,j}V_j)$	7.91	2.71	-5.20
				Industry Labor Productivity Decomposition of Output			
$\Sigma\, v_{V,i}H_i$	0.59	1.83	1.24	$\Sigma\, V(v_{V,i}H_i)$	1.02	0.35	-0.67
$\Sigma\, v_{V,i}ALP_i$	0.37	1.90	1.53	$\Sigma\, V(v_{V,i}ALP_i)$	1.70	0.75	-0.95
				$\Sigma\Sigma\, 2C(v_{V,i}H_i,\, v_{V,j}H_j)$	5.46	2.21	-3.25
				$\Sigma\, 2C(v_{V,i}H_i,\, v_{V,j}ALP_i)$ = Within	-0.68	-0.35	0.33
				$\Sigma\Sigma\, 2C(v_{V,i}H_i,\, v_{V,j}ALP_j)$ = Between	2.22	-0.41	-2.62
				$\Sigma\Sigma\, 2C(v_{V,i}ALP_i,\, v_{V,j}ALP_j)$	0.23	0.90	0.67
				Domar TFP Decomposition			
Domar-Weighted TFP	-1.17	0.64	1.81	Domar_Weighted TFP	3.69	1.21	-2.48
$\Sigma\, v_{V,i}/s_{V,i}TFP_i$	-1.17	0.64	1.81	$\Sigma\, V(v_{V,i}/s_{V,i}TFP_i)$	1.70	0.63	-1.07
				$\Sigma\Sigma\, 2C(v_{V,i}/s_{V,i}TFP_i,\, v_{V,j}/s_{V,j}TFP_j)$	1.99	0.59	-1.40

Note: Annual data from Jorgensonl, Ho, and Stiroh (2005).

7/5/2005 12:14

Table 9a: Within Industry Change in Contribution to Volatility of Aggregate Variables

Results are for each of 35 industries from the 1958-1996 dataset. Each estimate is the difference in the industry's direct contribution to aggregate volatility from 1958-1983 to 1983-1996. Significance levels are from Levene's test that the variance of the contribution is the same for the two periods. *Dur* indicates a durble manufacturing sector and *Other* includes all remaining industries.

	Sector	Industry	Value-Added	Hours	ALP	TFP
1	Other	Agriculture	-0.097	-0.004	-0.101	-0.096
2	"	Metal Mining	0.000	-0.001	0.000	0.000
3	"	Coal Mining	-0.001	-0.002	-0.001	-0.001
4	"	Petroleum and Gas	-0.003	-0.019	-0.069	-0.051
5	"	Nonmetallic Mining	0.000	0.000	0.000	0.000
6	"	Construction	-0.141 **	-0.039	-0.117 ***	-0.124 ***
7	"	Food Products	-0.028	-0.002 **	-0.020	-0.023
8	"	Tobacco Products	0.000	0.000 ***	0.000	0.000
9	"	Textile Mill Products	-0.002 **	-0.001 **	-0.002 **	-0.002 **
10	"	Apparel and Textiles	-0.004 *	-0.002 **	-0.003 *	-0.003 **
11	Dur	Lumber and Wood	0.000	-0.002 *	-0.005 **	-0.003
12	Dur	Furniture and Fixtures	-0.001 **	-0.001 **	0.000	0.000
13	Other	Paper Products	-0.002	-0.002 *	0.003	0.001
14	"	Printing and Publishing	-0.001	0.000	-0.001	-0.001
15	"	Chemical Products	-0.049	-0.003	-0.039	-0.043
16	"	Petroleum Refining	-0.021	-0.001 *	-0.018	-0.018
17	"	Rubber and Plastic	-0.004	-0.003 **	0.000	0.000
18	"	Leather Products	0.000 ***	0.000 ***	-0.001 ***	-0.001 ***
19	Dur	Stone, Clay, and Glass	-0.003 **	-0.002 ***	0.000	-0.001 **
20	"	Primary Metals	-0.029 **	-0.014 ***	-0.002	-0.005
21	"	Fabricated Metals	-0.039 ***	-0.017 ***	-0.007 **	-0.012 **
22	"	Industrial Machinery and Equ	-0.031	-0.031 **	0.005	-0.001
23	"	Electronic and Electric Equ	-0.005	-0.016	0.007 *	0.003
24	"	Motor Vehicles	-0.066 ***	-0.024 ***	-0.012 **	-0.028 ***
25	"	Other Transportation Equ	-0.007	-0.010	-0.007 **	-0.007 *
26	"	Instruments	-0.003	0.000	0.000	-0.002
27	"	Miscellaneous Manufacturing	0.000	0.000 *	0.002	0.001
28	Other	Transport and Warehouse	-0.027 *	-0.006	-0.002	-0.013
29	"	Communications	0.002	-0.003	0.006	0.007
30	"	Electric Utilities	0.010	0.002 *	0.006	0.005
31	"	Gas Utilities	-0.007	0.000 ***	-0.008	-0.006
32	"	Trade	0.057	0.051	0.098	0.057
33	"	FIRE	-0.007	0.043 **	-0.015	-0.027
34	"	Services	-0.280	0.071 *	-0.264	-0.257
35	"	Goverment Enterprises	-0.002	0.000	-0.006	-0.007
		Sum	-0.79	-0.04	-0.57	-0.66
		Sum - Dur	-0.18	-0.12	-0.02	-0.05
		Sum - Other	-0.61	0.08	-0.55	-0.60

Note: Annual data from Jorgenson and Stiroh (2000).

***, **, * indicate statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 9b: Within Industry Change in Contribution to Volatility of Aggregate Variables

Results are for each of 41 industries from the 1978-2000 dataset. Each estimate is the difference in the industry's direct contribution to aggregate volatility from 1978-1983 to 1983-2000. Significance levels are from Levene's test that the variance of the contribution is the same for the two periods. *Dur* indicates a durble manufacturing sector and *Other* includes all remaining industries.

	Sector	Industry	Value-Added	Hours	ALP	TFP
1	Other	Agriculture	-0.227 **	0.001	-0.182	-0.207 *
2	"	Non Energy Mining	-0.002 ***	-0.002 ***	0.000	0.000
3	"	Coal Mining	-0.006 ***	-0.004 ***	-0.001 ***	-0.002 **
4	"	Oil and Gas Mining	-0.152 **	-0.347 ***	-0.202 *	-0.176 ***
5	"	Construction	-0.137	-0.100 *	-0.082	-0.086
6	Dur	Lumber, Wood, Furniture	-0.003	-0.008 **	-0.001	0.000
7	"	Stone, Clay, Glass	-0.003 **	-0.003 ***	0.000	-0.001
8	"	Primary Metal	-0.016	-0.012 ***	-0.007	-0.009
9	"	Fabricated Metal	-0.005	-0.013 ***	-0.006	-0.003
10	"	Machinery excl. Computers	-0.083 **	-0.047 ***	-0.003	-0.010
11	"	Computers and Office Equ	0.005	0.000	0.003	0.004
12	"	Other Electrical Mach	-0.002	-0.003 ***	0.000	0.000
13	"	Communications Equ	0.001	0.000 ***	0.000	0.001
14	"	Electronic Components	0.026 **	0.001	0.021 **	0.020 ***
15	"	Motor Vehicles	-0.023	-0.019 ***	0.001	-0.001
16	"	Other Transportation Equ	-0.013	-0.002	-0.008 **	-0.008 *
17	"	Instruments and Misc Mfg	-0.007	-0.001	-0.004	-0.002
18	Other	Food and Tobacco	-0.036 ***	-0.002 **	-0.046 ***	-0.039 ***
19	"	Textiles, Apparel, Leather	-0.002 **	-0.003	-0.004 ***	-0.004 ***
20	"	Paper	0.004	-0.001 **	0.004	0.003
21	"	Printing and Publishing	0.003	0.000	0.003 **	0.003 **
22	"	Chemicals	-0.099 **	-0.002	-0.098 **	-0.100 **
23	"	Petroleum Refining	-0.211 *	-0.001 ***	-0.199 *	-0.207 *
24	"	Rubber and Plastic	-0.001	-0.002 ***	0.000	0.000
25	"	Transportation	-0.054 ***	-0.018	-0.005	-0.037
26	"	Communications	-0.015	0.000	-0.014	-0.012
27	"	Electricity	-0.005	0.003 *	0.001	-0.001
28	Other	Gas	-0.108 ***	0.000	-0.107 ***	-0.105 ***
29	"	Wholesale Trade	0.054	-0.003	0.079	0.072
30	"	Retail and Eating	0.030	0.008	0.017	0.018
31	"	Finance	0.036	0.015 **	0.045	0.031
32	"	Insurance	0.001	0.001 **	0.001	0.002
33	"	Real Estate (rental)	-0.044 **	-0.163 **	-0.015	-0.022
34	"	Computer Services	-0.004	0.008 **	0.003	0.007
35	"	Business Svc excl. Computer	-0.003	0.012	0.000	-0.010
36	"	Health private	-0.003	0.010 *	0.001	-0.006
37	"	Legal	0.001	0.002 **	0.002	0.004
38	"	Education, private	0.000	0.000	0.000	0.000
39	"	Professional and Social Svcs.	-0.138 **	0.019 *	-0.097	-0.141 *
40	"	Other Services	-0.035	0.004	-0.043	-0.043
41	"	Government Enterprises	-0.008 ***	-0.001	-0.005 *	-0.006 **
		Sum	-1.29	-0.67	-0.95	-1.07
		Sum - Dur	-0.12	-0.11	0.00	-0.01
		Sum - Other	-1.16	-0.56	-0.95	-1.07

Note: Annual data from Jorgenson, Ho, and Stiroh (2005).

***, **, * indicate statistical significance at the 1%, 5%, or 10% level, respectively.

7/5/2005 12:14

Table 10: Changing Relationship between Hours and Labor Productivity Growth

Regressions of hours growth on labor productivity growth (gross output per hour), post-1983 dummy variable (=0 if year>=1984; =0 otherwise), and interaction between productivity growth and post-1983 dummy variable. Second column includes industry dummy variables. Third column includes industry dummy variables and year dummy variables. 1985-1996 Dataset includes 35 industries with data from 1958 to 1996. 1978-2000 Dataset includes 41 industries with data from 1978 to 2000. Standard errors in parentheses

	1958-1996 Dataset		
ALP Growth	-0.140***	-0.143***	-0.197***
	(0.035)	(0.034)	(0.030)
Post-83 Dummy * ALP Growth	-0.172***	-0.152**	-0.132***
	(0.060)	(0.059)	(0.051)
Post-83 Dummy	-0.149	-0.193	-3.483***
	(0.312)	(0.305)	(0.946)
Constant	0.875***		
	(0.182)		
Industry Dummies		Yes	Yes
Year Dummies			Yes
Adjusted-R^2	0.04	0.09	0.40
No. Obs.	1,330	1,330	1,330
	1978-2000 Dataset		
ALP Growth	-0.056	-0.086*	-0.089**
	(0.049)	(0.045)	(0.041)
Post-83 Dummy * ALP Growth	-0.095*	-0.116**	-0.127***
	(0.057)	(0.051)	(0.046)
Post-83 Dummy	0.871**	0.995***	0.493
	(0.394)	(0.348)	(0.817)
Constant	0.531		
	(0.338)		
Industry Dummies		Yes	Yes
Year Dummies			Yes
Adjusted-R^2	0.03	0.26	0.43
No. Obs.	902	902	902

Note: Annual data from Jorgenson and Stiroh (2000) and Jorgenson, Ho, and Stiroh (2005).

***, **, * denotes statistical significance at the1%, 5%, and 10% level respectively.

7/5/2005 12:14