NOTES

DIVERGING TRENDS IN AGGREGATE AND FIRM VOLATILITY

Diego Comin and Sunil Mulani*

Abstract—This note documents the diverging trends in volatility of the growth rate of sales at the aggregate and firm levels. We establish that the upward trend in firm volatility is not simply driven by a compositional bias in the sample studied. We argue that this new fact brings into question the proposed explanations for the decline in aggregate volatility and that, given the symmetry of the diverging trends at the micro and macro levels, a common explanation is likely. We conclude by describing one such theory.

I. Introduction

THE volatility of macroeconomic variables has received increasing interest in recent years. McConnell and Perez-Quiros (2000) showed that the volatility of the GDP has declined significantly since the mid-1980s. Blanchard and Simon (2001) established the presence of a downward trend in the volatility of the GDP beginning in the 1950s with an interruption in the 1970s. In addition, Stock and Watson (2002) analyzed the time series of 124 macro variables since 1960 and found that the decline in aggregate volatility, beginning in 1984, is pervasive.

In an attempt to increase our understanding of volatility, this paper examines its evolution at the micro level. Specifically, the volatility of the growth rate of sales at the firm level is examined using the COMPUSTAT database, and compared with the aforementioned evolution of volatility at the aggregate level. The main finding is that while the growth rate of aggregate sales has become more stable, the growth rate of sales at the firm level has become more volatile. Put differently, volatility at the aggregate and at the firm level have followed diverging trends.[1]

Several exercises are undertaken to verify the robustness of the upward trend in firm-level volatility. An important concern when using a sample of firms gathered from the COMPUSTAT database to establish firm-level facts is whether it is representative of firms in the U.S. economy. In section II B, we argue that the upward trend in volatility is not simply the result of changes in the composition of the sample that are not reflected in the economy. This is done by showing that the upward trend persists after removing the predictable effects of age and size on the firm-level volatility and after including firm-level fixed effects. Section II C addresses the evolution of firm-level volatility across different sectors and finds that most sectors exhibit the upward trend.

Having verified the robustness of the upward trend in firm-level volatility, focus is shifted to the volatility at the aggregate level. We examine the volatility of aggregate sales in the COMPUSTAT sample (our sample). The aggregate volatility of our sample exhibits a mild decline in comparison with the volatility of aggregate final sales.[2] To gain further insight into the mechanical determinants of this pattern, a variance decomposition is undertaken in section III A.

Section IV briefly addresses the cyclical patterns of volatility, observing that both the aggregate and the firm-level volatility of sales (and sales per worker) are procyclical, albeit the maximum cross-correlation between aggregate volatility and output seems to take place with a longer lag than for firm-level volatility.

We conclude the paper by using our empirical findings to evaluate the explanations proposed to understand the decline in aggregate volatility. These explanations can be divided in two groups. The first group attempts to explain the decline in macro volatility through mechanisms that lead to a decline in volatility at the firm level and then, trivially, aggregate up the micro trends. The second group of explanations attempts to directly explain the decline in macro volatility. Both of these approaches are unsatisfactory in the light of the facts presented in this paper. The first is at odds with the increase in micro volatility. The second, though not inconsistent, is insufficient to account per se for the upward trend in firm-specific uncertainty. To fill this gap, we propose a new explanation that simultaneously accounts for the opposite trends observed in micro and macro volatility.

II. Firm-Level Volatility

Consider the time series for a random variable X_t. The volatility of X_t is defined as the time series of standard deviations of ten-year rolling windows of X_t. Formally, we compute the time series for the volatility of X_t as

$$\sigma(X_t) = \sqrt{\frac{\sum_{\tau=t-4}^{t+5}(X_\tau - \bar{X}_t)^2}{10}},$$

where $\bar{X}_t$ is the average of X_t between $t - 4$ and $t + 5$.

In order to examine volatility at the firm level, annual data on net sales is gathered for a sample of firms extracted from COMPUSTAT,

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* New York University, NBER, and New York Federal Reserve Bank; and Analysis Group, respectively.

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[1] There exists some prior evidence of increasing uncertainty in the firm's economic environment. Comin (2000) finds that the volatility of individual stock returns has increased (almost) monotonically since the 1950s. Campbell et al. (2001) find the same upward trend in firm-specific risk, that is, the cross-sectional dispersion of the component of returns that is orthogonal to the average return in the four-digit sector. However, aggregate stock returns have also become more volatile. The volatility of monthly aggregate stock returns in the U.S. markets (measured by the standard deviation of a ten-year rolling window of returns) remained low between the end of World War II and 1968. It then increased, reaching a high plateau, between 1968 and 1983. It declined over the next decade until 1993, after which it restarted its increase, reaching the high volatility levels of the 1970s.

[2] *Aggregate final sales* refers to final sales of domestic product, gathered from the Bureau of Economic Analysis (BEA).

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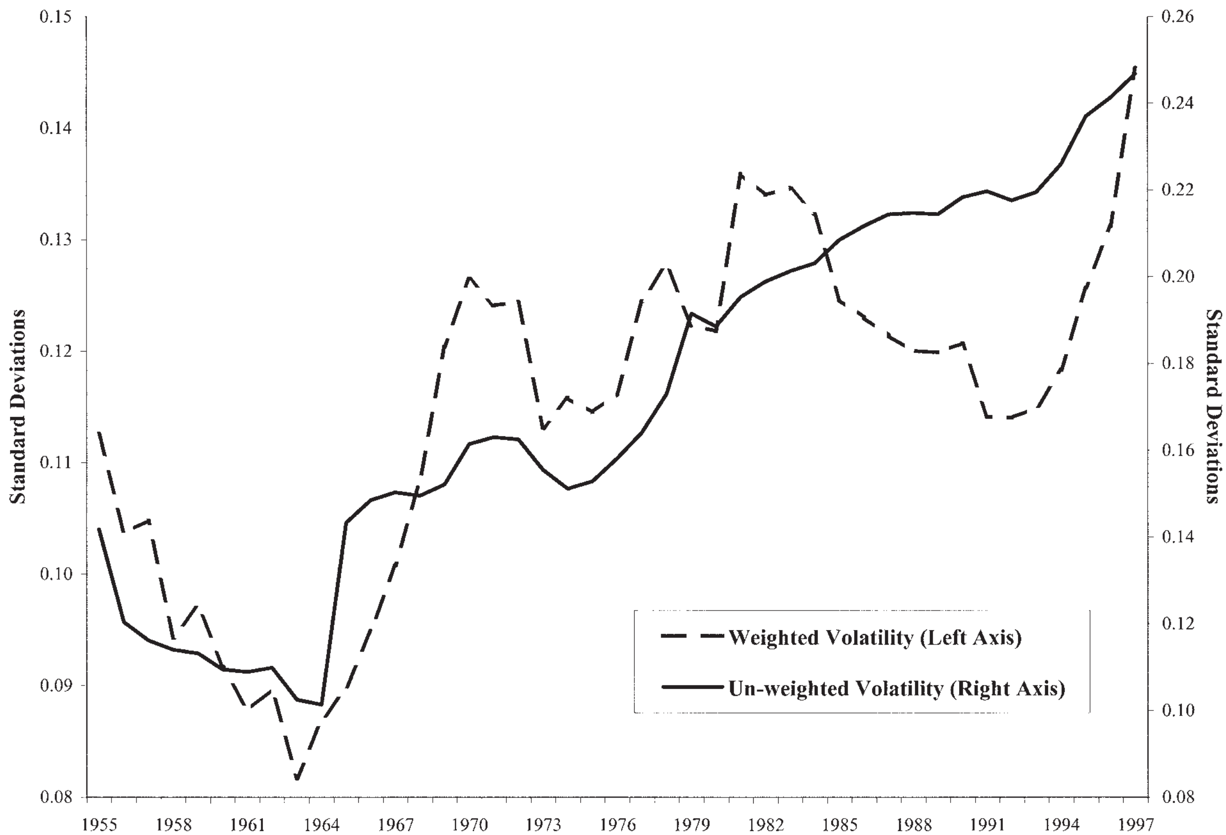
FIGURE 1.—VOLATILITY OF THE GROWTH RATE OF REAL FIRM-LEVEL SALES



comprising publicly traded companies between 1950 and 2002.[3] The sample is restricted to companies that have nonzero values of net sales for any of the years in the sample period. Both currently active and inactive companies are included in the sample, but international firms are eliminated.[4] Also eliminated are companies that exhibit gaps in annual data on net sales or that do not have eleven years of sales in sample. The total sales by year for the remaining firms constitute, on average, 78% of GDP.

For every firm, the series $\sigma(\gamma_{\text{sales}\,it}$ is computed, where $\gamma_{\text{sales}\,it}$ represents the growth rate of real sales for the company, the deflator being the aggregate producer price index (PPI). These standard deviations are then averaged across all the firms in a year to arrive at the average volatility for every year.[5] As illustrated in figure 1, volatility at the firm level exhibits a significant upward trend. In order to build a more representative measure of volatility, firm-level volatility measures are weighted using the firm's share of sales in total sales in a given year. Figure 1 also shows the persistent upward trend after the use of these weights.

The source of this increase in volatility, however, may be subject to question. Though the upward trend may, as we claim, accurately reflect changes in the economy, the increase in volatility may be a feature specific to the sample or the variable in use. Our claims necessitate discrediting these possibilities.

A. *Bias Due to Price Divergence*

The lack of price deflators at the firm level has, thus far, made impossible an analysis of the growth rate of nominal sales in real terms. There exists then the possibility that the increase in volatility may be driven by a divergence in the prices at the firm level.[6] To address this issue, two exercises are undertaken. First, a subset of our sample is created, comprising all firms in the manufacturing sector (subsample). For this subsample of firms, net sales are adjusted using

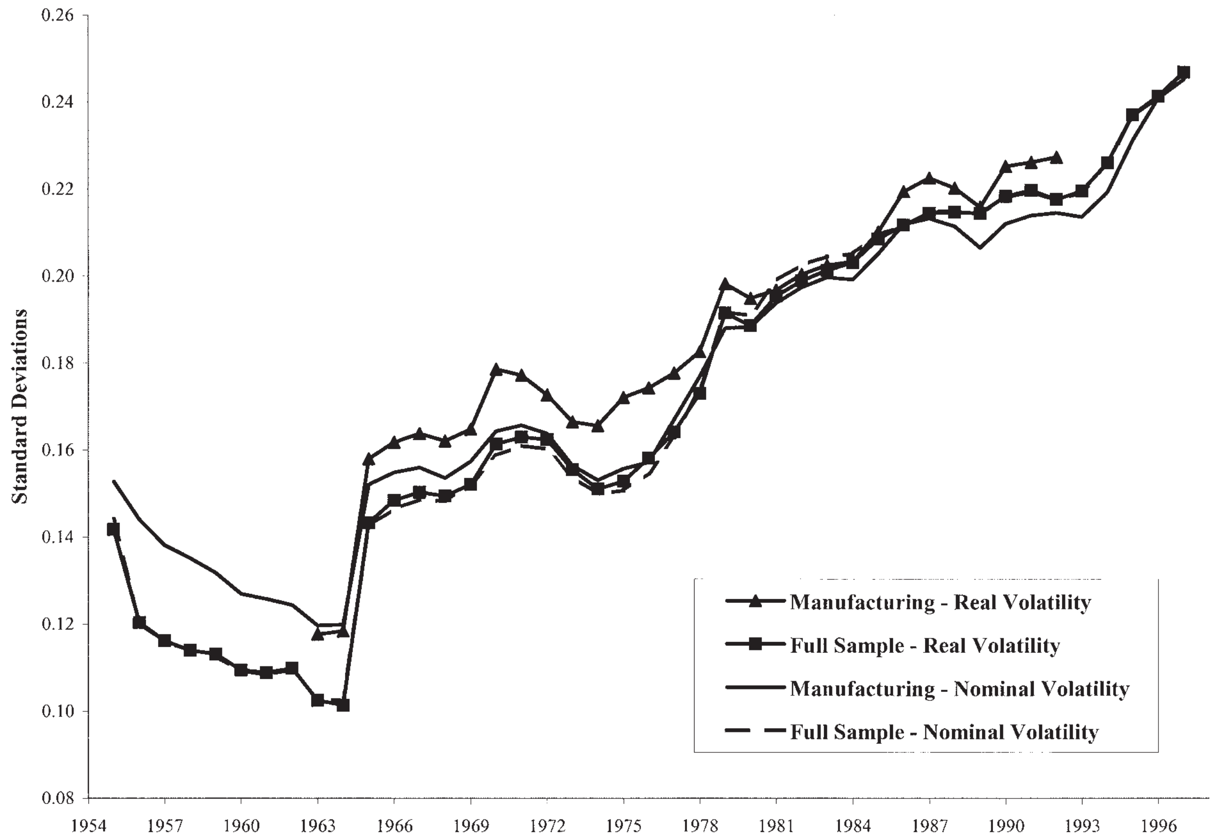
[3] Standard & Poor's COMPUSTAT North America is a database of financial, statistical, and market information covering publicly traded companies in the United States and Canada. Net sales is defined as gross sales (the amount of actual billings to customers for regular sales completed during the year) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers.

[4] Sensitivity tests were performed by varying the characteristics of the firms included in the sample along the following lines: (i) companies with nonzero net sales versus net sales greater than $1 million, (ii) only active companies versus both active and inactive companies, and (iii) including or excluding foreign companies. The results are consistent across the combinations of sample characteristics.

[5] Another way of measuring the volatility inherent in the firm's environment is by focusing on the cross section, as Campbell et al. (2001) do. Specifically, we could compute standard deviations of growth rates across all the firms in a given year. We believe that the time series measure of volatility used in this paper is more appealing in that it is less likely to be affected by compositional biases. When computing the standard deviation of the window in the time series, we remove the average growth rate for the firm in the window, and in effect control for firm-specific aspects that affect the growth rate of sales. These aspects, however, potentially show up in the cross-sectional measure and may be the medium through which a compositional bias operates.

[6] As will be evident in figure 2, CPI inflation plays no role in the volatility of the growth rate of nominal sales at the firm level.

FIGURE 2.—COMPARISON OF UN-WEIGHTED VOLATILITY IN FULL SAMPLE AND MANUFACTURING SUBSAMPLE



deflators at the four-digit level.[7] Figure 2 presents the average volatility of the growth rate of nominal and real firm-level sales for both the full sample and the manufacturing subsample.

Two conclusions are drawn from this figure. First, the evolution of the average volatility is similar for the growth rate of nominal sales for firms in the full sample and for firms in the manufacturing subsample. Second, in the manufacturing sector, the evolution of volatility for the growth rate of nominal and real sales is the same.[8]

Although this result does not eliminate the possibility that the upward trend in volatility is driven by firm-level price divergence, it suggests that the divergence operates, if at all, within four-digit sectors, a scenario we consider unlikely. However, to rule out this possibility, a more "real" measure of input for the firm is examined in the form of employment.[9] Figure 3 plots the evolution of the weighted and unweighted measures of volatility for the growth rate of employment at the firm level. The upward trends are evident.

B. *Controlling for Changes in the Sample Composition*

The sample used ranges from 1950 through 2002 and is extracted from the COMPUSTAT database. The size of the sample increases drastically in the 1970s, raising the possibility that the upward trend in the firm-level volatility is the result of a compositional bias. Firms that are incorporated in the data set in the post-1970s period are potentially more volatile than the firms in the pre-1970s period, either because the sector in which they operate is more volatile, or on account of firm-specific attributes such as being younger or smaller. In order to show that the upward trend in micro volatility is not due to a compositional bias in the sample studied, three exercises are undertaken.[10]

First, the sample of firms is divided up at any point in time into five quintiles according to the level of sales, to examine whether the increase in volatility is driven by any specific quintile or whether it holds across the distribution. Comin and Mulani (2004) show that the increase in firm-level volatility is not confined to any one section of the distribution, but is rather pervasive across the sample. This finding, though, does not necessarily negate the compositional bias argument. In theory, given the higher probability of sampling smaller (and/or younger) firms in the post-1970 period, all the quintiles might be composed to a larger extent of smaller, more volatile firms.

Hence, as a second exercise, we focus our analysis on the component of volatility that is not explained by firm-level characteristics that are changing in the sample. Specifically, we run a pooled regression of the firm-level standard deviations (σ_{it}) on a vector of the firms' characteristics (X_{it}) that contains the log of the share of firm sales in GDP and the log of the firm's age:

$$\sigma_{it} = \alpha_0 + \alpha_1 X_{it} + \varepsilon^{\sigma}_{it}. \quad (1)$$

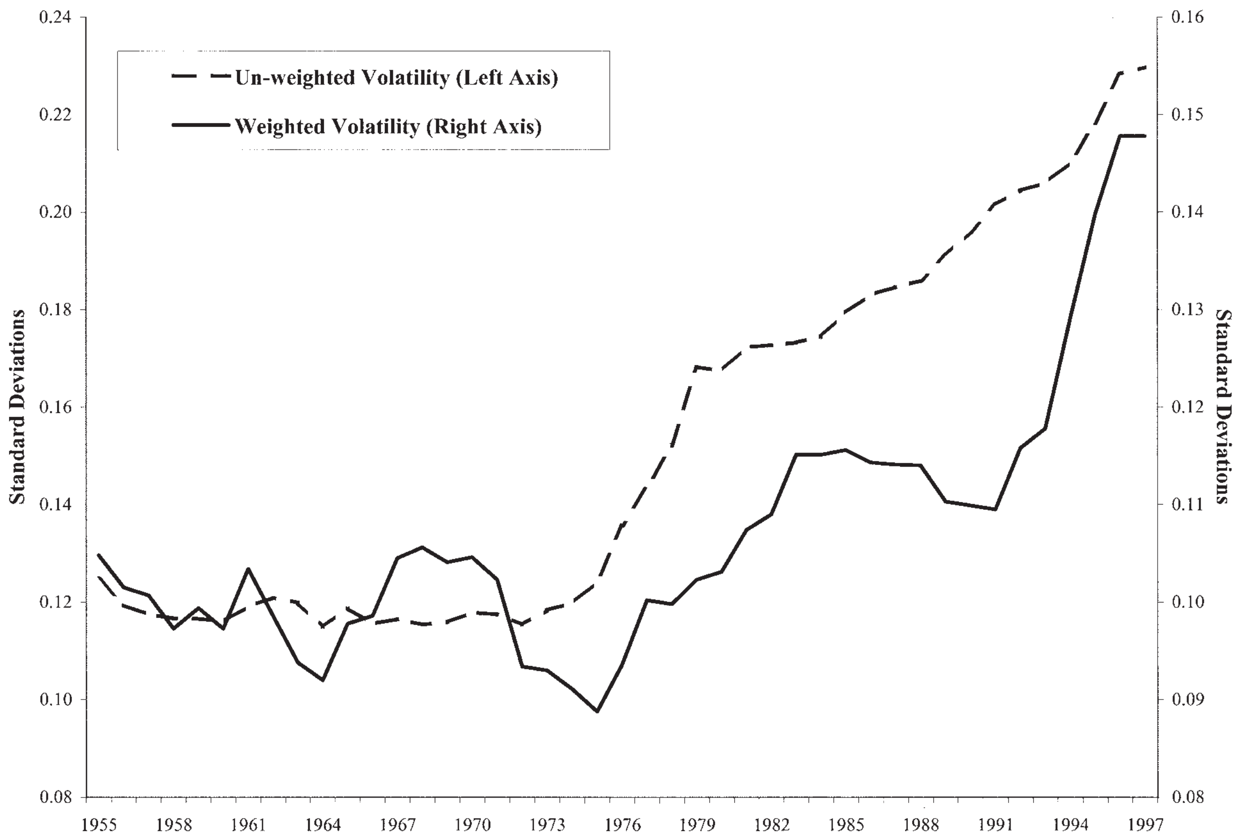
[7] Deflators for sales at the four-digit level are acquired from the NBER manufacturing data set.

[8] The same conclusions can be drawn by inspecting weighted measures of volatility.

[9] Data on numbers of employees are also gathered from COMPUSTAT, using the same criteria.

[10] An alternative approach is to track down the evolution of the volatility of the firms initially in sample, but this would generate survivorship bias.

FIGURE 3.—VOLATILITY OF THE GROWTH RATE OF NUMBER OF EMPLOYEES



The unpredictable component of volatility ($\varepsilon_{it}^{\sigma}$) is then aggregated, resulting in a time series for firm-level volatility. As in the previous section, both weighted and unweighted measures of residual volatility are considered, where the weights are given by the firm's share in total sales in the year. Figure 4 shows the prominent upward trend in residual volatility, though the trend flattens during the 1980s and 1990s in the weighted measures.

The evidence presented thus far refutes the hypothesis that the observed upward trend in firm-specific uncertainty is simply the result of the inclusion of a larger share of smaller or younger (more volatile) firms in the sample since 1970. However, it may still be argued that factors other than size or age induce higher volatility in the new population of firms sampled, leading to a compositional bias. To rule out this possibility, as a third exercise, firm dummies are used to eliminate the effect of firm-specific variables (both observable and unobservable) on volatility. Removing this firm-specific component of volatility leaves only the component that is orthogonal to fixed firm characteristics and therefore immune to any compositional bias in the sample.

Note that this exercise constitutes a stringent test of the hypothesis of an upward trend in micro volatility. To illustrate this point, suppose that our hypothesis is true and the upward trend is due to the fact that new firms *in the economy* are just more volatile. Removing the firm-specific component of all the firms in sample eliminates the component that is more volatile for new firms—the precise component we are looking to examine. Nevertheless, using a firm fixed effect in the regression is an informative exercise, because if the upward trend still holds, a compositional bias can be ruled out as a driver of the upward trend.

Formally, we run the following regression, where α_i is a set of firm-specific dummies and the set of controls included in X_{it} contains the log of age and the log of the share of sales in GDP:

$$\sigma_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it}^{\sigma}.$$

Figure 4 also plots the average residual volatility series (ε_t^{σ}). Even after removing the firm-specific component in volatility, the upward trend persists.[11]

C. *Firm-Level Volatility by Sectors*

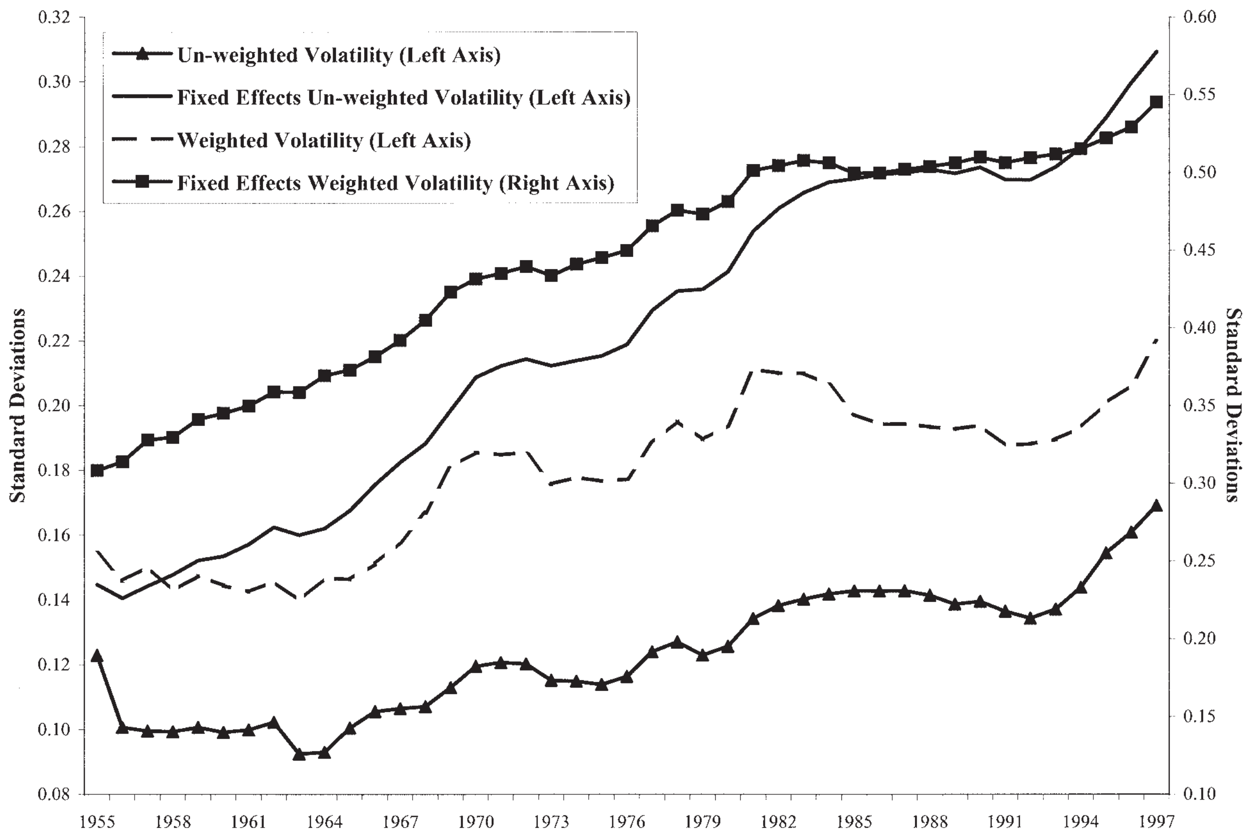
Having verified the robustness of the upward trend in volatility, we investigate whether the increase in volatility is pervasive or whether instead it is limited to a few sectors. To address this question, the following regressions are run for each two-digit sector:

$$\sigma_{it} = \alpha + \beta X_{it} + \delta D_{st} + \varepsilon_{it}^{\sigma},$$

$$\sigma_{it} = \alpha_i + \beta X_{it} + \delta D_{st} + \varepsilon_{it}^{\sigma},$$

[11] Further tests of robustness are conducted by controlling for cohort effects and for cohort effects interacted with age and size. In addition, we allow for an autocorrelated error structure. The steep upward trend in firm volatility persists.

FIGURE 4.—RESIDUAL VOLATILITY AFTER CONTROLLING FOR LOG(AGE) AND LOG(SIZE)



where D_{st} is a set of sector-specific time dummies. By running these regressions with and without firm weights, we can construct the time series for the weighted and nonweighted average firm-level volatility after controlling for the effect of age and size and (possibly) for a firm-specific intercept in volatility. For each two-digit sector, table 1 reports the average estimated coefficient on the year dummies for each decade from the regression with firm-level fixed effects. Table 1 shows that the upward trend in firm-level volatility is pervasive across sectors with the exception of construction. Results are very similar for the regressions without firm-specific intercepts.

III. Aggregate Volatility

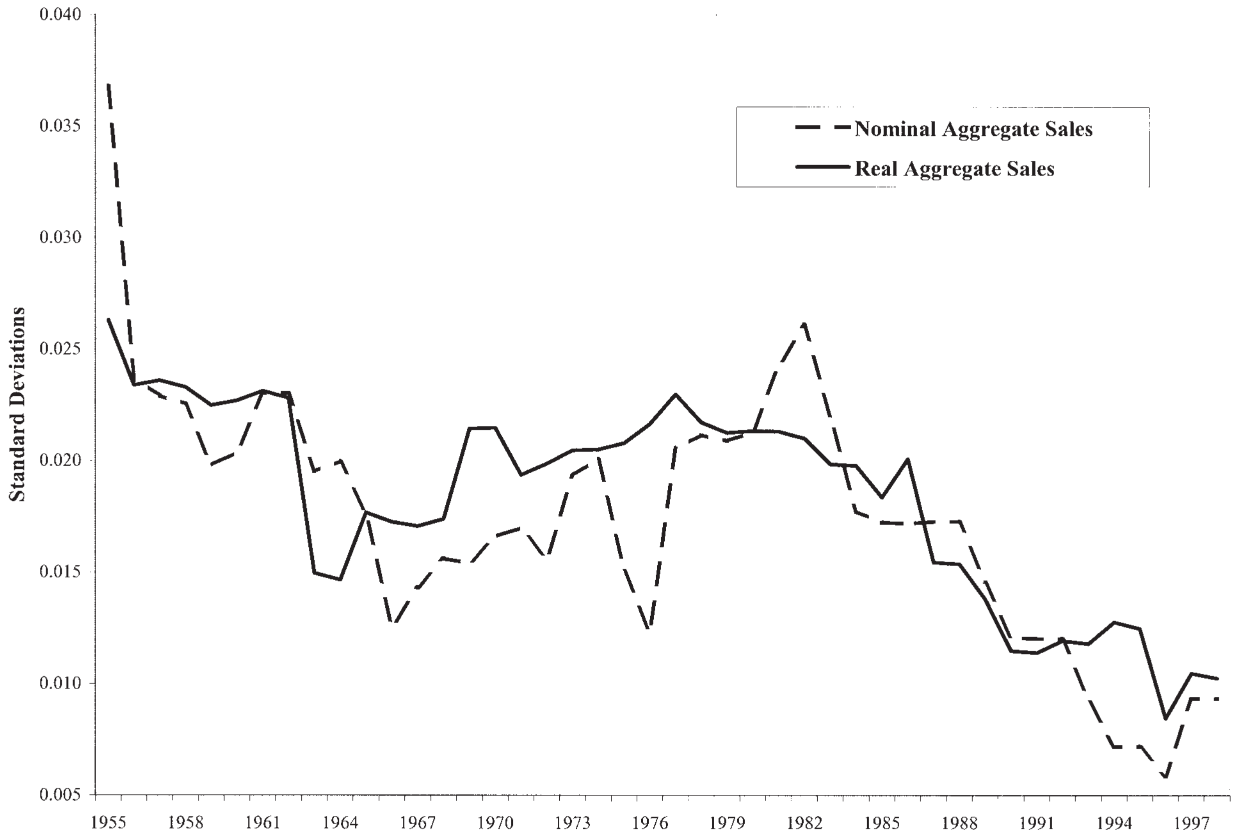
The evolution of volatility at the aggregate level does not mirror the upward trend in firm-level volatility. Several authors have observed that a variety of macro variables have become more stable over the same time period. Figure 5 plots the time series of $\sigma(\cdot)$ for the growth rates of both nominal and real aggregate final sales from the BEA.

Several points are worth mentioning here. First, the growth rate of aggregate sales exhibits a significant decline in volatility beginning in the 1980s. Second, as emphasized by Blanchard and Simon (2001) for

TABLE 1.—AVERAGE FIRM-LEVEL VOLATILITY BY TWO-DIGIT SECTORS AND DECADE

	Un-weighted					Weighted				
Sector	1950s	1960s	1970s	1980s	1990s	1950s	1960s	1970s	1980s	1990s
Agriculture and mining	0.26	0.30	0.34	0.39	0.38	0.57	0.73	0.90	1.00	1.06
Construction	0.25	0.21	0.22	0.23	0.19	0.35	0.36	0.39	0.40	0.37
Nondurable manufacturing	0.17	0.23	0.28	0.34	0.35	0.28	0.33	0.42	0.47	0.47
Durable manufacturing	0.21	0.22	0.26	0.30	0.31	0.32	0.34	0.37	0.40	0.41
Transportation	0.17	0.18	0.22	0.28	0.27	0.25	0.27	0.32	0.39	0.34
Communication	0.04	−0.01	−0.01	0.05	0.06	0.21	0.21	0.23	0.28	0.29
Utilities	0.11	0.13	0.18	0.21	0.24	0.20	0.22	0.29	0.32	0.35
Wholesale trade	0.14	0.19	0.22	0.27	0.30	0.17	0.19	0.22	0.25	0.30
Retail trade	0.11	0.14	0.18	0.23	0.25	0.25	0.30	0.36	0.42	0.44
Finance and insurance	−0.04	0.01	0.09	0.09	0.08	0.34	0.51	0.63	0.60	0.61
Real estate	−0.06	0.07	0.14	0.19	0.21	0.33	0.39	0.47	0.61	0.55
Services	0.07	0.16	0.24	0.32	0.40	0.32	0.40	0.45	0.54	0.57
Public administration	−0.01	0.05	0.13	0.10	0.13	0.45	0.53	0.58	0.66	0.68

FIGURE 5.—VOLATILITY OF GROWTH RATE OF AGGREGATE FINAL SALES



the GDP, the time series volatility of aggregate sales is best characterized by a secular decline that started in the 1950s and was interrupted from the mid 1960s through the 1970s. Finally, given the similar downward trends in both nominal and real sales, inflation does not seem to be a significant issue.

When this time series is compared with the volatility at the firm level (figure 6), the secular diverging trends in the postwar period are evident.[12]

To understand the mechanics of the divergence in the evolution of volatility, we decompose the variance of the aggregate growth rate of sales in the COMPUSTAT sample into a variance component and a covariance component.

A. *Variance Decomposition*

Before undertaking the variance decomposition, we verify that our sample exhibits similar characteristics at the aggregate level to those of the aggregate final sales. Figure 7 plots the volatility of the growth rate of aggregate sales for the firms in our sample. The downward trend in volatility is not as prominent as for the volatility of GDP, for two reasons. First, the growth rate of total sales in our sample varies as the comprehensiveness of the sample varies. Fluctuations in the comprehensiveness of the sample, accentuated by the addition of firms incorporated in the NASDAQ, will add noise to the growth rate of aggregate sales in the post-1970 period. This force may tend to induce an upward bias in the trend of volatility of the growth rate of total sales in the sample. This problem is particularly important in the last observation, where a significant reduction in the number of firms in the sample in 2002 results in a substantial decline in total sales. This abnormally large negative growth rate causes the spike in the volatility for the last observation.

Second, our sample is substantially smaller than the U.S. economy. As we move to lower levels of aggregation in the U.S. economy—levels that better represent the size of our sample—the downward trend in aggregate volatility is difficult to observe.[13,14]

To conduct the variance decomposition, the following notation is introduced. Let γ_{X_t} be the growth rate of aggregate real sales in our sample deflated using the aggregate PPI, $\gamma_{x_{it}}$ be the growth rate of real sales for firm *i,* and s_{it} be the share of sales for firm *i* in the total sales for our sample, all in year *t*. Also, let $V([Z_\tau]_{t-4}^{t+5})$ denote the variance of $\{Z_{t-4}, Z_{t-3}, \ldots, Z_t, \ldots, Z_{t+4}, Z_{t+5}\}$ for any generic variable *Z,* and Cov $([Z_\tau]_{t-4}^{t+5}, [Y_\tau]_{t-4}^{t+5})$ be the covariance between $\{Z_{t-4}, Z_{t-3}, \ldots, Z_t, \ldots, Z_{t+4}, Z_{t+5}\}$ and $\{Y_{t-4}, Y_{t-3}, \ldots, Y_t, \ldots, Y_{t+4}, Y_{t+5}\}$.

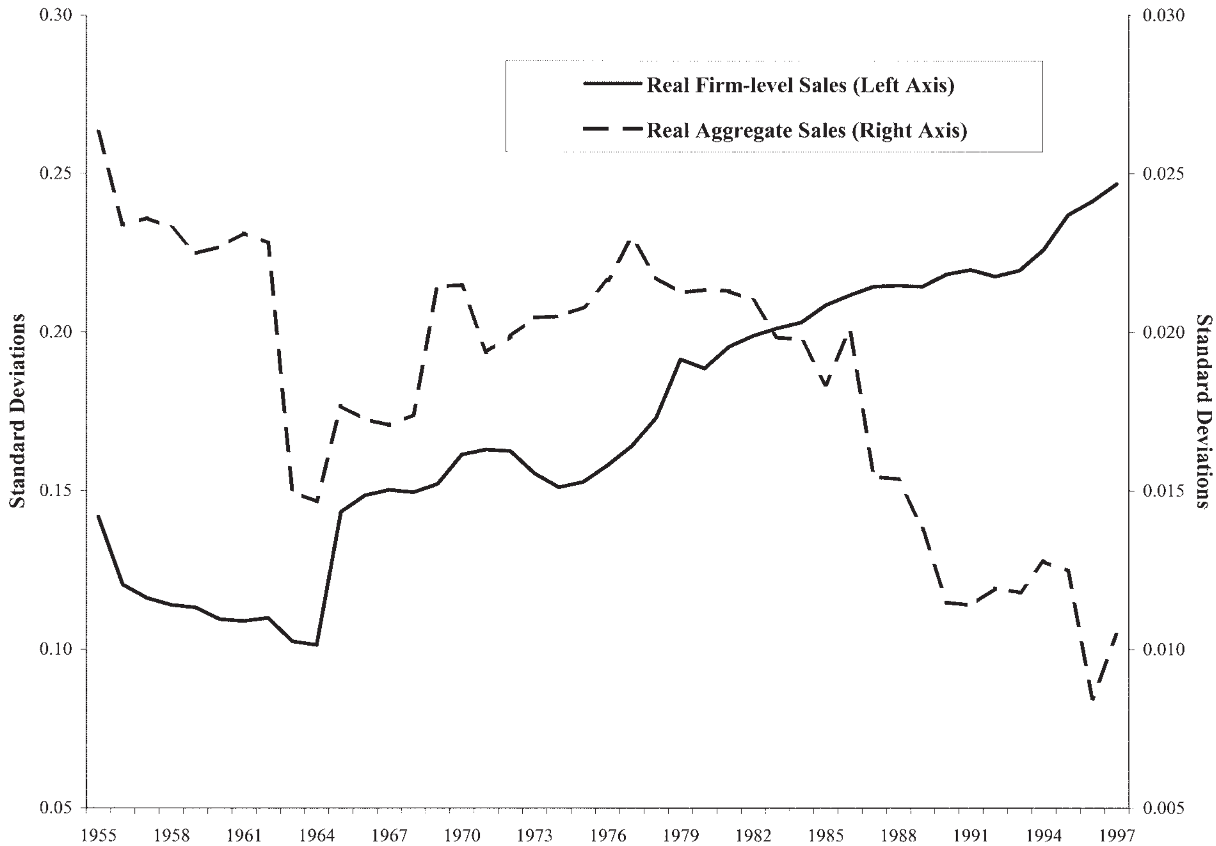
Note that $\gamma_{X_t} = \sum_i \gamma_{x_{it}} s_{it}$. Then, using the definition of variance, and assuming that $s_{it} = s_i$ for all the firms *i* and all years *t,* the variance

[12] The divergence persists at higher frequencies as well. The correlation between ten-year rolling windows extracted from these two series is negative in more than two-thirds of the windows.

[13] On average, the sales of the firms in our COMPUSTAT sample represents 78% of GDP. Because the materials and energy share is approximately 50% of gross output, this means that the COMPUSTAT sample represents approximately 40% of the economic activity in the United States.

[14] See figure 9 in Comin and Mulani (2004) for the evolution of the average volatility of the growth rate of real sales for the two-digit sectors in the U.S. economy.

FIGURE 6.—VOLATILITY OF GROWTH RATE OF AGGREGATE FINAL SALES AND FIRM-LEVEL SALES



of aggregate growth in a ten-year window, $V([\gamma_{X_t}]_{t-4}^{t+5})$, can be decomposed into two terms—the first is related to the firm-level variance of sales (variance component), and the second reflects the covariances between the growth rates of sales at different firms (covariance component):[15]

$$V([\gamma_{X_T}]_{t-4}^{t+5}) = \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_i \gamma_{x_{i\tau}} s_{i\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\sum_i \gamma_{x_{i\tau}} s_{i\tau}\right)^2$$

$$= \underbrace{\sum_i s_i^2 V([\gamma_{x_{i\tau}}]_{t-4}^{t+5})}_{\text{variance component}}$$

$$\underbrace{+ \sum_{\mathrm{i}} \sum_{\mathrm{j}\neq \mathrm{i}} \mathrm{s_i s_j}\ \mathrm{Cov}\ ([\gamma_{x_{i\tau}}]_{t-4}^{t+5}, [\gamma_{x_{j\tau}}]_{t-4}^{t+5}).}_{\text{covariance component}}$$

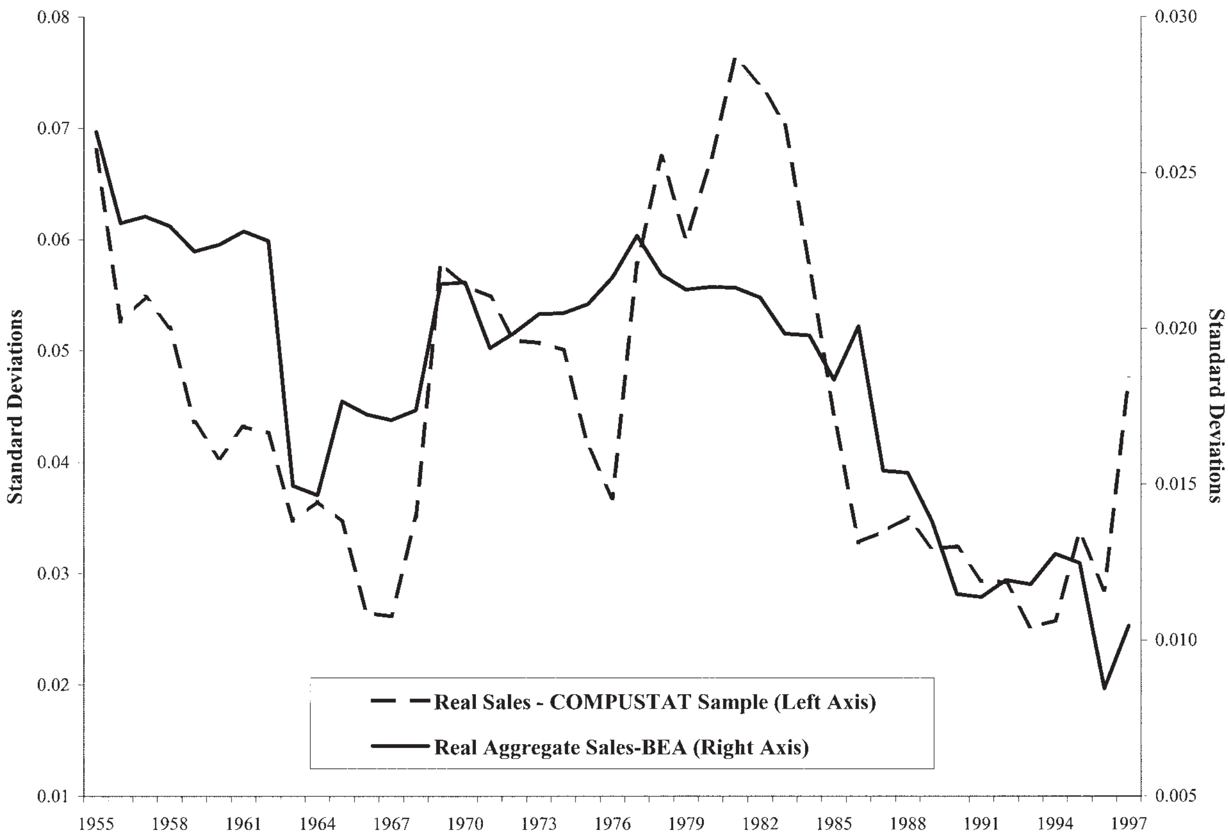
Figure 8 shows the evolution of these terms since 1950. We make three important remarks. First, the small discrepancy between the total variance and the sum of these two components implies that the time variation of the shares does not have a significant effect on the total variance. Second, the evolution of the volatility of aggregate growth rate of sales in our COMPUSTAT sample is entirely driven by the covariance term. The variance term is an order of magnitude smaller and has no significant effect on the aggregate volatility. In other words, to understand the evolution of aggregate volatility, we need to understand the forces that drive the covariance of sales growth between firms as opposed to what affects the volatility of firm sales. Third, the decline in the variance component is entirely driven by the decline in the sum of squared shares ($\sum_i S_i^2$), which is in turn due to the dramatic increase in the number of firms in our sample.

IV. Volatility over the Cycle

To conclude the empirical investigation, an issue of independent interest is examined: namely, the procyclicality of volatility. To address this question, we follow Comin and Gertler (forthcoming) in filtering nonfarm business output and the various series of volatility using a bandpass filter that removes frequencies corresponding to cycles with periods shorter than 50 years. This filter generates six cycles in the U.S. postwar period. Such a filter is employed rather than more standard (higher-frequency) filters such as the Hodrik-Prescott because movements at medium term frequencies are larger than movements at higher frequencies and are, in all likelihood, connected to the high-frequency fluctuations. We then compute the cross-correlogram between output and weighted and unweighted measures of firm and aggregate-level volatility. Figure 9 displays the cross-correlograms. Two observations are made. First, the volatility (both aggregate and firm-level) seems procyclical. Second, the primary difference in cyclical patterns is that, following a boom, firm-level volatility increases almost immediately, whereas aggregate volatility increases with a lag. Specifically, the maximum response period is 5

[15] See Comin and Mulani (2004) for a derivation.

FIGURE 7.—COMPARISON OF VOLATILITY OF BEA AGGREGATE SALES AND COMPUSTAT AGGREGATE SALES



to 6 years for aggregate volatility, 3 to 4 years for weighted firm-level volatility, and less than a year for unweighted firm-level volatility.[16]

V. Conclusions

The U.S. economy has experienced opposite trends in volatility at the aggregate and the firm level. At the aggregate level, several variables have become less volatile, with an interruption of this trend during the 1970s and early 1980s. At the micro level, however, the volatility of these very variables exhibits an upward trend. We believe the symmetric nature of these diverging trends (figure 6) makes a common explanation (or set of explanations) likely.

Importantly, the upward trend in micro volatility has interesting implications when evaluating the proposed explanations for the decline in aggregate volatility. McConnell and Perez-Quiros (2000) proposed that new inventory management methods, such as just-in-time inventory management, are the source of the reduction in volatility in GDP. This mechanism operates at the firm level, and therefore implies that the volatility of output at the firm level should decline as well. This hypothesis is inconsistent with the evidence presented in this paper.[17]

Another line of research argues that part of the decline in aggregate volatility is due to a more effective monetary policy that helps stabilize shocks that hit the U.S. economy (Boivin & Gianonni, 2002; Clarida, Gali, & Gertler, 2000; Congley & Sargent, 2001; Gali, Lopez-Salido, & Valles 2002; Justiniano & Primiceri, 2002; Sims & Zha, 2002). This argument has two drawbacks. First, from a quantitative perspective, an increase in the effectiveness of monetary policy can account for, at most, 30% of the reduction in aggregate volatility according to Stock and Watson (2002).[18] Second, it is difficult to find mechanisms that link a more active monetary policy to the increase in firm-level volatility. This hypothesis, thus, leaves unexplained the opposite trends observed in aggregate and firm-level volatility.

Inasmuch as we have reasons to believe that the two symmetric trends are related,[19] we devote the last paragraphs of the paper to presenting a brief sketch of a new explanation for the decline in aggregate volatility, one that simultaneously explains the increase in firm-level volatility.[20]

To motivate our explanation, it is relevant to know some additional facts. First, the upward trend observed for the volatility of firm-level sales also holds for sales per worker and the growth rate of firm-level

[16] Very similar cross-correlograms are obtained when the rolling windows are computed over 5 years.

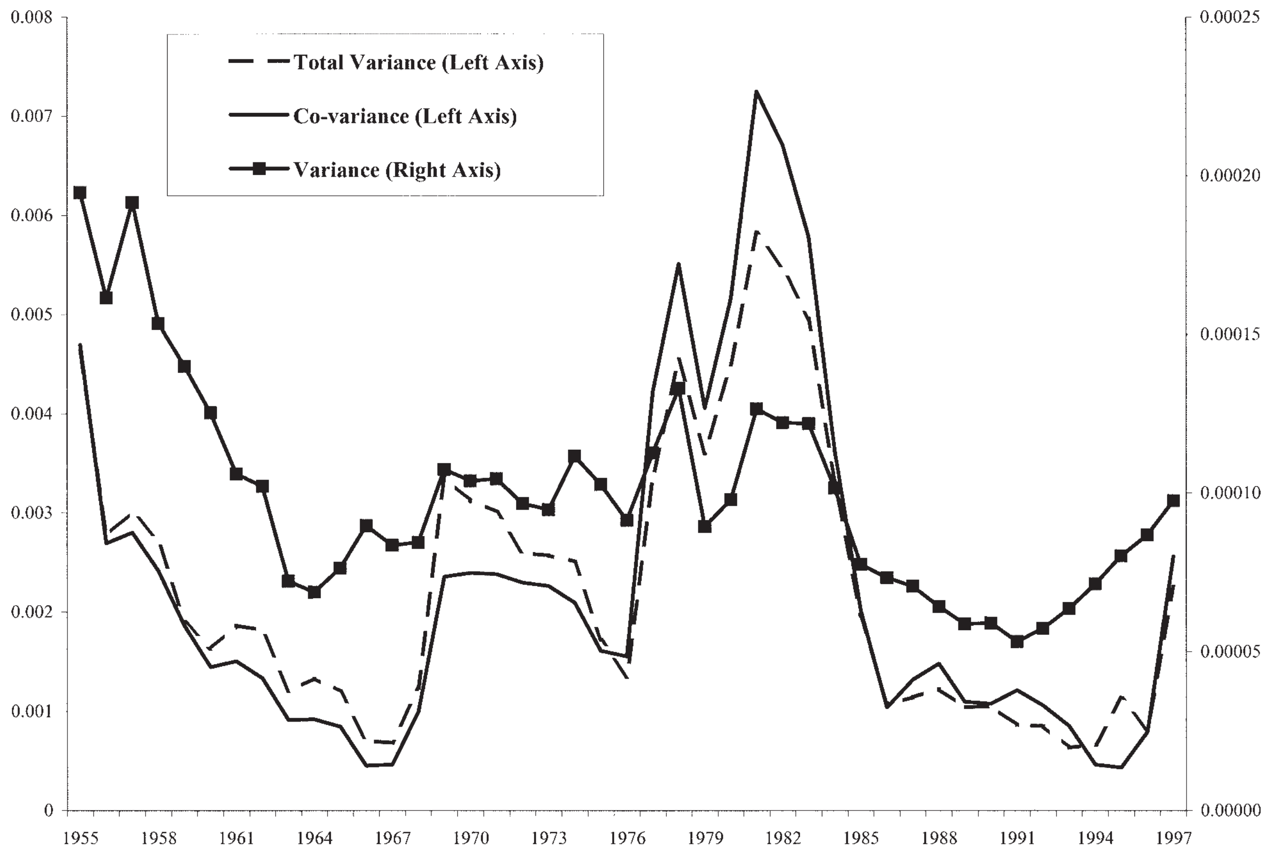
[17] McConnell and Perez-Quiros (2000) stress as evidence in favor of their hypothesis the fact that there has been a larger decline in the volatility of the quarterly growth rate in manufacturing output than in the volatility of the quarterly growth rate of manufacturing sales. However, at the annual frequency, Stock and Watson (2002) find that the declines in the volatilities of aggregate sales and output have been about the same for all production sectors: durables, nondurables, services, and structures.

[18] Stock and Watson analyze the volatility of quarterly growth. Surely, the role of a more active monetary policy in the reduction of volatility will be smaller when examining annual data.

[19] Comin and Philippon (2005) discuss these reasons in more detail.

[20] Comin and Mulani (2004) develop the model that underlies this explanation, provide evidence, and calibrate its quantitative importance.

FIGURE 8.—VARIANCE-COVARIANCE DECOMPOSITION OF AGGREGATE GROWTH RATE OF COMPUSTAT SALES



employment. Similarly, the decline in volatility of aggregate output is accompanied by declines in the volatility of aggregate productivity growth and aggregate employment growth. In our view, this means that the volatility of productivity is of primary importance. To explain the divergence in the evolution of the volatility of productivity growth at the firm and aggregate levels, we build a model of endogenous productivity growth. In our model, productivity grows because of two types of innovations.

Embodied innovations are patentable innovations à la Aghion and Howitt (1992). These research efforts lead firms to develop new versions of existing products or new products that replace the current market leaders. Such improvements in productivity lead to substantial firm-level volatility, because incumbents incur losses whereas entrants enjoy capital gains. However, at the aggregate level, the effects of R&D investments on volatility are relatively minor, because individual gains and losses cancel each other.[21]

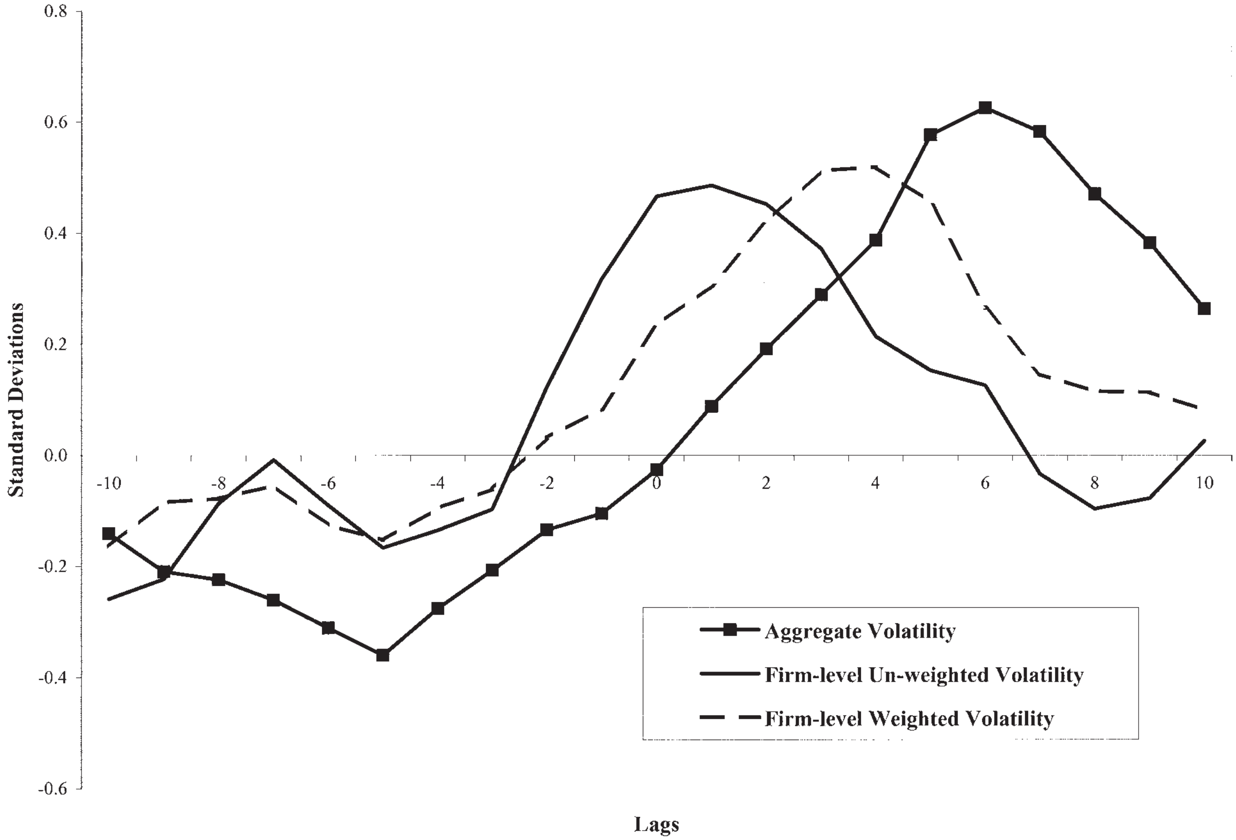
To explain the movements in aggregate volatility, it is necessary to consider a second type of innovations. We call these *disembodied innovations.* Disembodied innovations have two properties. First, they symmetrically affect both the firm that develops them and the rest of the firms. Second, a firm that develops a disembodied innovation (by and large) cannot appropriate the benefits enjoyed by the other firms when adopting it. This is because disembodied innovations (such as mass production, new personnel and accounting practices, or the use of electricity as the source of energy in a plant) are hard to patent and easy to reverse-engineer.

These two properties are responsible for the interesting implications of our model. The fact that a disembodied innovation symmetrically affects all firms implies that it will have a large aggregate effect. Therefore, investments in the development of disembodied innovations may lead to substantial volatility in aggregate productivity growth. The fact that innovators cannot appropriate the social value of disembodied innovations implies that their incentives to develop them are increasing in the value of the firm. A small nonconvexity in the costs of conducting disembodied innovations can imply that, in equilibrium, only large firms, which are the market leaders, invest in developing such innovations.

Interestingly, the model predicts a negative relationship between the aggregate investments in embodied and in disembodied innovations. This follows from three facts: (i) the value of market leaders is higher when the expected duration of their market leadership is longer; (ii) market turnover is increasing in the investments in embodied innovations, (iii) for a market leader, the return from investing in a disembodied innovation is increasing in the value of the company. Hence, a force that leads the economy to invest more in developing embodied innovations may induce a decline in disembodied investments. One such shock can simultaneously induce a decline in aggregate volatility and an increase in firm-level volatility.

[21] Other investments in improving the sales of the company, such as marketing and advertising, play a similar role to investments in the development of embodied innovations in this framework.

FIGURE 9.—CROSS-CORRELOGRAM OF FILTERED NON-FARM BUSINESS OUTPUT AND FILTERED AGGREGATE AND FIRM-LEVEL VOLATILITY



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