1 Introduction

Over the past thirty years, there has been a decline in aggregate volatility (McConnell and Perez-Quiros 2000, Stock and Watson 2002). At the same time, there has been a large increase in the volatility of firms (Comin 2000; Campbell, Lettau, Malkiel, and Xu 2001; Comin and Mulani 2003; and Chaney, Gabaix, and Philippon 2002).

Our paper has five parts. We first document the upward trend in various measures of firm volatility. Second, we present a decomposition of aggregate volatility between the average volatility of sectors and the correlation of growth across sectors. This decomposition suggests that the decline in aggregate volatility is mostly due to a decline in the correlation growth rates across sectors.

Third, we explore whether the firm-level trend toward more volatility and the aggregate trend toward more stability are related, or whether the two have moved in opposite directions by coincidence. The two trends appear to be related. We find that TFP growth in industries where firms have become more volatile tends to be less correlated with aggregate TFP growth. Across countries, there also seems to be a negative relationship between aggregate and firm-level volatility.

Fourth, we explore the potential explanations for the increase in firm-level volatility. We find support for the idea that firm volatility has increased because of higher competition in the goods market. We find that firm volatility increases after deregulation. We also find that the increase in firm-level volatility is correlated with high research and development (R&D) activity as well as more access to debt and equity markets. However, we find no evidence that sectors with more access to external finance have become less correlated with the rest of the
economy, while we do find evidence that sectors with larger increases in R&D investment have become less correlated with the rest of the economy.

2 The Facts


Throughout the paper, we will use aggregate data from the National Income and Product Accounts and firm-level data from COMPUSTAT and CRSP. We will also use the sectoral data set developed by Jorgenson and Stiroh (from now on, KLEM data).

2.1 Volatility: GDP Versus Firm Sales

In this section, we document the increase in firm volatility using real measures, like sales, employment, or capital expenditures. Our sample includes all the firms in COMPUSTAT with at least eleven consecutive observations of the relevant variable. Table 3.1 contains the basic descriptive statistics for our sample.

Figure 3.1 shows the evolution of idiosyncratic and aggregate volatility. Aggregate volatility \( \sigma^a_t \) is defined as the standard deviation of the annual growth rate \( \gamma_t \) of real GDP:

\[
\sigma^a_t = \left[ \frac{1}{10} \sum_{\tau=-4}^{+5} (\gamma_{t+\tau} - \bar{\gamma}_t)^2 \right]^{1/2}
\]  

(3.1)

where \( \bar{\gamma}_t \) is the average growth rate between \( t - 4 \) and \( t + 5 \). For each firm \( i \), we compute the volatility of the growth rate of sales \( \gamma_{t,i} \) as:

\[
\sigma_{i,t} = \left[ \frac{1}{10} \sum_{\tau=-4}^{+5} (\gamma_{t+\tau,i} - \bar{\gamma}_{t,i})^2 \right]^{1/2}
\]  

(3.2)
Table 3.1
Firm-Level Summary Statistics

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Firms</th>
<th>Average Real Sales</th>
<th>Median Sales Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>1955</td>
<td>810</td>
<td>1.30</td>
<td>0.096</td>
</tr>
<tr>
<td>1956</td>
<td>829</td>
<td>1.35</td>
<td>0.093</td>
</tr>
<tr>
<td>1957</td>
<td>849</td>
<td>1.38</td>
<td>0.090</td>
</tr>
<tr>
<td>1958</td>
<td>927</td>
<td>1.22</td>
<td>0.084</td>
</tr>
<tr>
<td>1959</td>
<td>982</td>
<td>1.28</td>
<td>0.081</td>
</tr>
<tr>
<td>1960</td>
<td>1,589</td>
<td>0.87</td>
<td>0.095</td>
</tr>
<tr>
<td>1961</td>
<td>1,727</td>
<td>0.84</td>
<td>0.098</td>
</tr>
<tr>
<td>1962</td>
<td>1,952</td>
<td>0.82</td>
<td>0.099</td>
</tr>
<tr>
<td>1963</td>
<td>2,171</td>
<td>0.81</td>
<td>0.099</td>
</tr>
<tr>
<td>1964</td>
<td>2,351</td>
<td>0.83</td>
<td>0.098</td>
</tr>
<tr>
<td>1965</td>
<td>2,506</td>
<td>0.86</td>
<td>0.100</td>
</tr>
<tr>
<td>1966</td>
<td>2,680</td>
<td>0.89</td>
<td>0.108</td>
</tr>
<tr>
<td>1967</td>
<td>2,861</td>
<td>0.89</td>
<td>0.114</td>
</tr>
<tr>
<td>1968</td>
<td>3,450</td>
<td>0.82</td>
<td>0.120</td>
</tr>
<tr>
<td>1969</td>
<td>3,633</td>
<td>0.92</td>
<td>0.122</td>
</tr>
<tr>
<td>1970</td>
<td>3,705</td>
<td>0.91</td>
<td>0.128</td>
</tr>
<tr>
<td>1971</td>
<td>3,898</td>
<td>0.92</td>
<td>0.141</td>
</tr>
<tr>
<td>1972</td>
<td>4,073</td>
<td>0.96</td>
<td>0.139</td>
</tr>
<tr>
<td>1973</td>
<td>4,502</td>
<td>1.02</td>
<td>0.134</td>
</tr>
<tr>
<td>1974</td>
<td>6,110</td>
<td>0.88</td>
<td>0.139</td>
</tr>
<tr>
<td>1975</td>
<td>6,175</td>
<td>0.84</td>
<td>0.138</td>
</tr>
<tr>
<td>1976</td>
<td>6,224</td>
<td>0.91</td>
<td>0.139</td>
</tr>
<tr>
<td>1977</td>
<td>6,262</td>
<td>0.97</td>
<td>0.142</td>
</tr>
<tr>
<td>1978</td>
<td>6,187</td>
<td>1.04</td>
<td>0.146</td>
</tr>
<tr>
<td>1979</td>
<td>6,081</td>
<td>1.15</td>
<td>0.149</td>
</tr>
<tr>
<td>1980</td>
<td>6,187</td>
<td>1.18</td>
<td>0.151</td>
</tr>
<tr>
<td>1981</td>
<td>6,226</td>
<td>1.17</td>
<td>0.157</td>
</tr>
<tr>
<td>1982</td>
<td>6,530</td>
<td>1.09</td>
<td>0.167</td>
</tr>
<tr>
<td>1983</td>
<td>6,771</td>
<td>1.05</td>
<td>0.174</td>
</tr>
<tr>
<td>1984</td>
<td>6,827</td>
<td>1.09</td>
<td>0.179</td>
</tr>
<tr>
<td>1985</td>
<td>7,135</td>
<td>1.06</td>
<td>0.184</td>
</tr>
<tr>
<td>1986</td>
<td>7,394</td>
<td>1.03</td>
<td>0.188</td>
</tr>
<tr>
<td>1987</td>
<td>7,448</td>
<td>1.11</td>
<td>0.190</td>
</tr>
<tr>
<td>1988</td>
<td>7,295</td>
<td>1.20</td>
<td>0.192</td>
</tr>
<tr>
<td>1989</td>
<td>7,202</td>
<td>1.27</td>
<td>0.187</td>
</tr>
<tr>
<td>1990</td>
<td>7,239</td>
<td>1.33</td>
<td>0.181</td>
</tr>
<tr>
<td>1991</td>
<td>7,375</td>
<td>1.27</td>
<td>0.175</td>
</tr>
</tbody>
</table>
Table 3.1  
(continued)

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Firms</th>
<th>Average Real Sales</th>
<th>Median Sales Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>1992</td>
<td>7,786</td>
<td>1.22</td>
<td>0.171</td>
</tr>
<tr>
<td>1993</td>
<td>8,907</td>
<td>1.11</td>
<td>0.160</td>
</tr>
<tr>
<td>1994</td>
<td>9,288</td>
<td>1.17</td>
<td>0.163</td>
</tr>
<tr>
<td>1995</td>
<td>10,101</td>
<td>1.18</td>
<td>0.172</td>
</tr>
<tr>
<td>1996</td>
<td>10,282</td>
<td>1.23</td>
<td>0.180</td>
</tr>
<tr>
<td>1997</td>
<td>10,020</td>
<td>1.33</td>
<td>0.197</td>
</tr>
<tr>
<td>1998</td>
<td>10,286</td>
<td>1.39</td>
<td>0.212</td>
</tr>
<tr>
<td>1999</td>
<td>10,294</td>
<td>1.51</td>
<td>0.211</td>
</tr>
<tr>
<td>2000</td>
<td>9,819</td>
<td>1.76</td>
<td>0.207</td>
</tr>
</tbody>
</table>

Average sales in 2000 in billions of dollars.

Figure 3.1  
GDP Versus Individual Firm Sales Volatility: 10-Year Centered Rolling Standard Deviation of Growth Rates
The Rise in Firm-Level Volatility

![Distribution of Firm Volatility](image)

**Figure 3.2**
Distribution of Firm Volatility: 10-Year Centered Rolling Standard Deviation of Sales Growth

We then take the median across all firms present in the sample at time \( t \) as our measure of typical firm volatility:

\[
\sigma^f_t = \text{median}_i \{ \sigma_{i,t} \}
\]

Figure 3.1 shows the decline in \( \sigma^d_t \) and the increase in \( \sigma^f_t \). Note also the difference of scale between the two measures. Idiosyncratic volatility is an order of magnitude larger than aggregate volatility.\(^2\) Figure 3.2 shows the evolution of the 25th and 75th percentiles of the distribution of firm volatility. It is clear that the whole distribution has moved upward and that the increase in volatility is even more pronounced at the top.\(^3\)

Our first task is to show the robustness of these findings. The main issues are sample selection bias and measurement errors. Sample selection is an issue because more small firms have entered the COMPU-STAT database over time. Since small firms tend to be more volatile, the changing composition could explain the trend. We deal with this first issue by controlling for size and age, and showing that the increase in firm volatility holds within groups of comparable firms. Comin and Mulani (2003) also show that the results are robust to the inclusion of firms’ fixed effects.\(^4\)

The second issue is whether firm-level results are economically meaningful. To take an extreme example, suppose that we live in a world of constant returns without financial frictions or incentive
problems, in which boundaries of organizations do not matter. Plants could move among firms without any real consequences, yet firms would appear to be volatile. Firms would simply not be the right units of observation. One could perhaps argue that mergers and acquisitions (M&As) fall partly into the category of irrelevant ownership changes. Thus, as a robustness check, we are going to show that our results are not driven by M&As.

Figure 3.3 shows that the trend increase in firm volatility is not driven by the entry of young and small firms, or by an upsurge in M&A activity. Another way to show that our results are economically meaningful is to show that they relate to results obtained in other data sets. Guvenen and Philippon (2005) show that firm volatility measured across industries in COMPUSTAT is a good predictor of both unemployment risk and wage inequality measured across the same industries in PSID. Comin, Groshen, and Rabin (2005) relate firm-level volatility to wage volatility at the occupation level by taking advantage of a unique data set that contains firm-level and worker-level information for a sample of firms in Ohio. They document a positive relationship between firm-level volatility and the volatility and dispersion of wages at the occupation level. We will not discuss these results further, but we note that they show that our measures of volatility capture real economic risks, not just measurement error or sample composition bias.
The Rise in Firm-Level Volatility

2.2 Turnover of Leaders Within Industries

The distribution of firm sizes is famously skewed, and a few firms account for most of the sales in each industry. Thus, one might argue that firm volatility is relevant only if it affects the industry leaders. We define turnover in industry \( I \) at time \( t \) as the probability of leaving the top quintile of the industry over a five-year period:

\[
\text{TopTurn}_{i,t} = P(Z_{i+5} < Z_{i+5}^{\text{top},I(i)} \mid Z_{it} > Z_{i}^{\text{top},I(i)})
\]

where \( Z_{it} \) is either operating income or market value of firm \( i \) at time \( t \), and \( Z_{t}^{\text{top},I(i)} \) is the 80th percentile of the distribution of \( Z_{it} \) at time \( t \) in industry \( I(i) \). This measure is robust to the entry of small firms in the particular industry. We then define average turnover as the median of turnover across all industries.

Figure 3.4 shows the increase in turnover among leaders for both operating income and market value. There are too few firms in the sample in the 1950s to obtain a reasonable estimate of the probability, so we also computed the correlation of ranking over time, using all the firms and not only the top 20 percent. For a particular measure \( Z \), we define:

\[
\text{RkCorr} = \text{Corr}_{i \in I}(\text{rank}_{i,t}(Z_{it}), \text{rank}_{i,t}(Z_{it+t}))
\]

where \( \text{rank}_{i,t}(Z_{it}) \) is the rank of firm \( i \) in industry \( I \) at time \( t \) according to \( Z \). The picture using market value or operating income is similar to
Figure 3.5
Correlation of Labor Productivity Rankings
Note: Five and ten years ahead correlation of within sector ranking, based on sales per employee.

the one in figure 3.4 and, for the sake of completeness, we present the results based on labor productivity rankings.

Figure 3.5 shows the evolution of the ranking correlation of firms, over five and ten years, based on labor productivity. There has been a clear decline in the ranking correlations over time. We will return to the interpretation of these findings when we discuss product market competition.

2.3  **Equity Return Volatility**
Real data are probably more directly relevant for macroeconomics. However, there are at least two good reasons to explore financial data as well. The first is that financial data will allow us to look at firm volatility before World War II. The second is that financial data can help us disentangle risk from predictable variations in firm dynamics.

We start by looking at equity returns. Let $r_{i,t,m}$ be the return to shareholders of firm $i$ in month $m$ of year $t$, and let $r_{t,m}^{VW}$ be the monthly return on the Value Weighted Index. All the returns come from CRSP.
The Rise in Firm-Level Volatility

For each firm, we estimate the CAPM model over rolling windows of thirty-six months:

\[ r_{i,t,m} = \beta_{i,t} r_{m}^{VW} + \epsilon_{i,t,m}, \quad \text{for } m = 1, \ldots, 12 \]

We therefore allow \( \beta_{i,t} \) to vary (smoothly) over time, as seems plausible since we use data from 1926 to 2004. We take the median across all firms/months observations in year \( t \) as our measure of idiosyncratic financial volatility:

\[ \sigma_{i}^{fin} = \text{median}_{i,m}(|\epsilon_{i,t,m}|) \]

The nice thing about monthly data is that it allows us to construct non-overlapping annual measures of firm volatility. We define the explanatory power of the CAPM model as the share of total firm return volatility that one can explain with the market return, i.e., the \( R^2 \) of the CAPM regression.

Figure 3.6 shows the historical decline in the explanatory power of CAPM. CAPM used to explain 40 percent of firm returns before the 1950s, but its explanatory power is now around 10 percent. \( R^2 \) is the ratio of two volatilities, however, and we also want to know what has happened to the level of idiosyncratic volatility. Figure 3.7 shows a U-shaped pattern for \( \sigma_{i}^{fin} \). Firm volatility was high in the late 1920s, and it
increased dramatically during the market crash and the early years of the great depression. It then declined steadily from the mid-1930s to the mid-1950s. At that point in time, we can make the link with the real data presented in the previous section. Since the mid-1950s, both real and financial volatility have increased steadily, with large spikes around the first oil shock and the rise and fall of the Internet bubble. For a discussion of the link between financial and real volatility at the firm level, see Veronesi and Pastor (2003).

Finally, note that our measure of firm volatility falls from 2001 to 2003. First, many firms have delisted from the stock exchanges, and delisting is more common for small, risky firms. Second, holding constant the composition of the sample, there has been a decrease in firm volatility. This is not unprecedented. The same happened in the early 1990s, and we expect firm volatility to start increasing again in the near future.

2.4 Credit Ratings and Credit Spreads
If firms have really become more risky, then this should also be reflected in corporate bond spreads and corporate bond ratings. For the spread, we use Moody's seasoned Aaa corporate bond yield minus the ten-year treasury rate. For bond ratings, we use S&P long-term do-
The Rise in Firm-Level Volatility

Figure 3.8
Average Credit Ratings and Credit Spreads
Note: Rating ranges from 2 (AAA) to 20 (CCC). Index adjusted for age, size, and industry.

mestic issuer credit rating from COMPUSTAT, coded from 2 for AAA to 27 for D (default). We first regress the rating on firm-level characteristics (age, assets, sales, SIC code), and we then average the residuals across firms. Figure 3.8 shows that the Aaa spread over treasury has increased overtime, and also that the average credit rating of firms in COMPUSTAT has deteriorated. Both trends suggest an increase in risk, consistent with the increase in cash flow volatility. For more on this topic, see Campbell and Taksler (2003).

Historical default rates on corporate bonds have also varied a lot over time. The average default rate from 1900 to 1943 was 1.7 percent. It dropped to a mere 0.1 percent from 1945 to 1965 (Sylla 2002). It then increase again, to 0.64 percent between 1970 and 1985, and to 1.85 percent between 1986 and 2001 (Moody’s 2002). These evolutions are also consistent with the importance of rating agencies. These agencies played an important role before World War II, became largely irrelevant in the 1950s and 1960s, and have regained their previous importance in the past thirty years (Sylla 2002).

Conclusion 1: Firm-level risk has increased over the past fifty years.

Conclusion 2: Firm-level risk was higher in the 1920s and 1930s than in the 1950s and 1960s.
3 Sectoral Evidence

We have established that the aggregate stabilization of the U.S. economy has coincided with a large increase in firm-level risk. However, in a statistical sense, this is only one observation. Our goal in this section is to explore sectoral dynamics and see how they relate to firm volatility. We are first going to show that the decline in aggregate volatility is accounted for by a decrease in the comovement of the different sectors and not by a decrease in the average volatility of each sector. Second, we are going to show that sectors in which firms have become more volatile have typically become less correlated with the aggregate. Sectoral data comes from Jorgenson and Stiroh’s 35 KLEM data set.

3.1 Decomposition of Aggregate Volatility

We now perform a decomposition of the aggregate variance of the growth rate of real value added, TFP, and real value added per worker into sector variances and correlations. Let \( \gamma_{s,t} \) be the growth rate of the particular variable in sector \( s \) at time \( t \), and let \( \omega_{s,t}^{sec} \) be the share of sales for sector \( s \) in the aggregate sales in the economy. Also, let \( V([Z_t]_{t-4}^{t+5}) \) 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 \( Cov([Z_t]_{t-4}^{t+5}, [Y_t]_{t-4}^{t+5}) \) be the covariance between \( \{Z_{t-4}, Z_{t-3}, \ldots Z_t, \ldots Z_{t+4}, Z_{t+5}\} \) and \( \{Y_{t-4}, Y_{t-3}, \ldots Y_t, \ldots Y_{t+4}, Y_{t+5}\} \). By definition, the aggregate growth rate is:

\[
\gamma_t = \sum_i \gamma_{s,t} \omega_{s,t}^{sec}
\]

Then, using the definition of the variance:

\[
V([\gamma_t]_{t-4}^{t+5}) = \frac{1}{10} \sum_{t-4}^{t+5} \left( \sum_i \gamma_{s,t} \omega_{s,t}^{sec} - \frac{1}{10} \sum_{t-4}^{t+5} \sum_i \gamma_{s,t} \omega_{s,t}^{sec} \right)^2
\]

For simplicity, suppose that \( \omega_{s,t}^{sec} = \omega_s^{sec} \) for all the sectors \( i \) and all years \( t \). Then \( V([\gamma_t]_{t-4}^{t+5}) \) can be written as follows:

\[
V([\gamma_t]_{t-4}^{t+5}) = \sum_s (\omega_s^{sec})^2 V([\gamma_{s,t}]_{t-4}^{t+5}) + \sum_s \sum_{j \neq s} \omega_s^{sec} \omega_j^{sec} Cov([\gamma_{s,t}]_{t-4}^{t+5}, [\gamma_{j,t}]_{t-4}^{t+5})
\]

Hence, the variance of the growth rate of aggregate sales is decomposed into two terms: the first is related to the sector level variance
of sales (variance component), and the second reflects the covariances between the growth rates of sales at different sectors (covariance component).

The first two rows in figure 3.9 show the evolution of the variance and covariance components of the variance of the growth rate of aggregate value added, aggregate value added per worker, and TFP. The variance component of all three variables displays a hump-shaped pattern over time, with no obvious decline over our sample period, 1959 to 1996. On the other hand, for all three variables, we can observe that there has been a decline since the 1970s in the covariance of growth across sectors. For value added per worker and TFP, there has been an important decline in the covariance of growth over our sample period, while for value added growth there has been no trend.

For the three variables, the covariance component is substantially larger than the variance component. The difference in magnitude ranges from twice larger (TFP growth) to an order of magnitude larger (value added growth). As a result, the relevant component for understanding the dynamics of aggregate volatility is the covariance of growth across sectors.

The covariance component is affected by the sectoral variance and by the correlation of a sector with the others. To increase further our understanding, we also compute the correlation component. Specifically, we define first the correlation of each sector with the other sectors:

$$Corr_{s,t}^{sec} = \sum_{j \neq s} \frac{\omega_j^{sec}}{\sum_{h \neq s} \omega_h^{sec}} Corr([y_{s,t},j]^{t+5}, [y_{j,t},l_{t-4}])$$

Then we define aggregate correlation as a weighted average of the sectoral correlations:

$$Corr_{t}^{a} = \sum_{s} \omega_s^{sec} Corr_{s,t}^{sec}$$

The third row in figure 3.9 shows a clear decline in aggregate correlation for value added, TFP, and value added per worker growth over time. Hence, we conclude that, in order to understand the decline in aggregate volatility, we should try to understand what drives this decline in the correlation between sectors. The results presented in this section are based on the KLEM sectoral data set. We have obtained similar results for the decomposition of aggregate volatility using manufacturing data from the BLS.
Figure 3.9
Variance-Covariance Correlation
Table 3.2
Sectoral Correlation and Firm Volatility, Panel Regression, Thirty-Five Sectors

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Sectoral Correlation of Growth in Value Added</th>
<th>Sectoral Correlation of Growth in Employment</th>
<th>Sectoral Correlation of Growth in Labor Productivity</th>
<th>Sectoral Correlation of Growth in TFP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average firm volatility</td>
<td>-0.036 (0.096)</td>
<td>-0.23 (.12)</td>
<td>-0.264 (.126)</td>
<td>-0.22 (.08)</td>
</tr>
<tr>
<td>N</td>
<td>1011</td>
<td>1011</td>
<td>1011</td>
<td>1011</td>
</tr>
</tbody>
</table>

Firm volatility measured in COMPUSTAT. Sector correlation measured in Jorgenson's data set. All regressions include a time trend and sector fixed effects. Newey-West standard errors in parentheses.

Conclusion 3: The decline in aggregate volatility is mostly due to a decrease in the correlation of growth rates across sectors. The contribution of average sector volatility is less important.

3.2 Firm Volatility and Sector Comovements

We now ask if the decline in comovement across sectors is linked to the increase in volatility within each sector. We start from our measure of idiosyncratic firm volatility $\sigma_{i,t}$ defined in equation (2). We aggregate this measure within each sector to obtain a sector-specific measure of firm volatility:

$$\sigma_{s,t}^{sec} = \text{mean}_{i \in s} (\sigma_{i,t})$$

On the other hand, we have the sector-specific correlation measure, $\text{Corr}_{s,t}^{sec}$, defined in equation (3). We run the following regressions:

$$\text{Corr}_{s,t}^{sec} = \alpha + \beta t + \gamma \sigma_{s,t}^{sec} + \varepsilon_{s,t}$$

Table 3.2 shows the results when the dependent variable is the correlation of value added, employment, labor productivity, and TFP. We estimate a negative $\gamma$ in all specifications, and it is significant for the last three. Of course since both $\sigma_{s,t}^{sec}$ and $\text{Corr}_{s,t}^{sec}$ are autocorrelated, we use Newey-West to assess the significance of $\beta$. As a robustness check, we estimate the relationship between sectoral correlation and firm volatility, replacing the time trend by sector dummies. In this alternative specification, we continue to obtain a negative estimate of $\gamma$ that is statistically significant.

To have a more graphical image of the relationship between firm volatility and sectoral correlation, figures 3.10a and 3.10b show the
The Rise in Firm-Level Volatility

Figure 3.10a
Firm Volatility and Sectoral Correlation, 1964–1977

Figure 3.10b
change in the correlation of output per worker against the change in the volatility of firms between 1964 and 1977 and between 1978 and 1991, respectively, for the thirty-five sectors in our sample. In these figures, there is a clear and significant negative cross-sectional relationship between the change in firm volatility and the change in sectoral correlation for the two periods that cover the whole time-span of our sample. In various robustness checks, we have found that the results for productivity (either value added per worker, or TFP) are robust, while the results for quantities (either employment or value added) are not always significant.

Conclusion 4: Comovement has decreased more in sectors where firm volatility has increased more.

4 International Evidence

So far our exploration has been restricted to the United States because of data availability. Some research, however, has been done on non-U.S. data. Frazzini and Marsh (2002) do not find the same increase in firm volatility in the United Kingdom. Thesmar and Thoenig (2004) show an increase in France, especially for listed firms. Li, Morck, Yang, and Yeung (2004) show that the CAPM explains a larger part of firm equity returns in emerging markets than in developed economies.

Adding to this evidence, we explore the evolution of firm-level volatility using a short panel of international firms in the COMPUSTAT GLOBAL data set. This sample covers publicly traded companies between 1993 and 2004 in more than eighty countries, representing over 90 percent of the world’s market capitalization, including coverage of over 96 percent of European market capitalization and 88 percent of Asian market capitalization. Due to the short nature of the panel, we compute volatility using four-year rolling windows. Specifically, for every firm in the sample, we compute the standard deviation of the growth rate of employment on a rolling window of four consecutive years. Our measure of firm volatility in year $t$ is either the mean or the median of the standard deviations across all firm in year $t$. Table 3.3 reports the evolution of these measures of firm volatility. We can observe a clear increase in both measures of firm-level volatility during the 1990s. Unfortunately, the panel is too short to see if the upward trend in firm volatility holds in the postwar period.

The length of the panel limits the time series exploration of firm volatility, but it does not preclude us from investigating the cross-section
Table 3.3
Firm-Level Volatility in the World

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Firms</th>
<th>Median Volatility</th>
<th>Average Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>2,685</td>
<td>0.0694</td>
<td>0.1301</td>
</tr>
<tr>
<td>1996</td>
<td>2,752</td>
<td>0.0737</td>
<td>0.1417</td>
</tr>
<tr>
<td>1997</td>
<td>2,762</td>
<td>0.0872</td>
<td>0.1587</td>
</tr>
<tr>
<td>1998</td>
<td>3,429</td>
<td>0.0999</td>
<td>0.1859</td>
</tr>
<tr>
<td>1999</td>
<td>3,652</td>
<td>0.1126</td>
<td>0.1983</td>
</tr>
<tr>
<td>2000</td>
<td>3,711</td>
<td>0.1205</td>
<td>0.2161</td>
</tr>
<tr>
<td>2001</td>
<td>1,831</td>
<td>0.1281</td>
<td>0.2269</td>
</tr>
</tbody>
</table>

determinants of volatility. In particular, one interesting issue that we can address is the relationship between income per capita and volatility. At the aggregate level, figure 3.11a shows a well-known fact from, for example, Acemoglu and Zilibotti (1997): namely, that there is a negative relationship between the volatility and the initial level of income per capita. In this case, the sample contains a cross-section of seventy countries during the 1990s. At the firm level, though, we do not see any relationship between the firm-level volatility in a country and income per capita. In particular, figure 3.11b illustrates this lack of association between median firm volatility of employment growth and income per capita in a cross-section of fifty-seven countries. This result holds whether or not we aggregate firm volatilities at the country level using the mean or the median.

Finally, we wish to explore the relationship between aggregate and firm-level volatility in the cross-section of countries. Figure 3.12a plots the scatter plot for our sample of fifty-eight countries, which includes both developed and developing economies. It is clear from this figure that when we look at all the countries in the COMPUSTAT GLOBAL there is no relationship between aggregate and firm-level volatility. However, this may be the result of the noisiness of the data for some low income countries.

To mitigate this problem, we explore the subsample of twenty-eight OECD economies. Figure 3.12b contains the scatter plot of aggregate and firm volatility for each of our cross-section of OECD economies during the 1990s. There we can observe a statistically significant negative relationship between aggregate and firm volatility. Interestingly, this negative relationship between aggregate and firm volatility remains significant after controlling for the log of income per capita, the
Figure 3.11a
Aggregate Volatility in a Cross-Section of Countries

Figure 3.11b
Firm-Level Volatility in a Cross-Section of Countries
The Rise in Firm-Level Volatility

Figure 3.12a
Aggregate and Firm Volatility: Cross-Section of Countries

Figure 3.12b
Aggregate and Firm Volatility: Cross-Section of OECD Countries
log average size of firms in a country, or the log number of firms in a country.

We do not want to push too far this relationship between aggregate and firm volatility in the cross-section of OECD countries, but in any case, it supports the conclusions we have drawn previously while exploring the postwar panel of U.S. sectors: namely, that there seems to exist a negative correlation between the evolution of aggregate and firm-level volatilities.

**Conclusion 5:** Aggregate volatility and income per capita are negatively related across countries.

**Conclusion 6:** Firm volatility and income per capita are uncorrelated across countries.

**Conclusion 7:** Firm and aggregate volatility are negatively related among OECD countries.

### 5 Theoretical Discussion

We are now going to discuss a few possible explanations for the facts that we have uncovered so far. In the last part of the paper, we will try to test these explanations. On the link between sectoral diversification, volatility, and growth, see Acemoglu and Zilibotti (1997), Imbs and Wacziarg (2004), and Koren and Tenreyro (2004).

The first potential explanation is that aggregate stabilization led to more risk taking by firms. The cause of the aggregate stabilization could be luck or better monetary policy. The link with individual risk taking could be the following. Suppose that reallocation is inefficiently low in recessions. Then entrepreneurs may be reluctant to start risky ventures because of the eventuality that they fail at a time where the economy is in a bust. This applies equally to human capital (unemployment risk) or physical capital (fire sales). A decline in aggregate volatility could therefore lead to more individual risk taking.

Other explanations assume that there is a change at the firm level that drives the increase in firm volatility and leads, directly or indirectly, to a decrease in aggregate volatility. Some of these explanations start from an increase in competition in the goods market. It is easy to see how competition can drive up firm-level risk. The explanations differ in how they link competition to aggregate volatility. One explanation, formalized in Philippon (2003), is that more competition leads firms to adjust their prices faster, which reduces the impact of aggre-
gate demand shocks. While intuitively appealing, the simple sticky price explanation cannot be complete because it also implies more volatile inflation, which is contrary to the evidence.9

The third explanation, formalized in Comin and Mulani (2005), is that more competition leads to a decline in the correlation of sectoral TFP shocks. To see why this could be the case, suppose that firms decide how much to invest in the development of two kinds of innovations. Idiosyncratic, R&D innovations are patentable and benefit mostly the innovator. General innovations—such as the mass production system and other organizational innovations, improved process controls, product development, testing practices and preproduction planning, new personnel, and accounting practices—are hard to patent and can potentially affect all the firms in the economy. An increase in R&D leads to market turnover and to a reduction in the value of market leaders. Since the marginal value of general innovations is proportional to the value of market leaders, an increase in R&D leads to a decline in the development of general innovations. As a result, the correlation of TFP growth across sectors declines and so does aggregate volatility.

Finally, financial innovation could explain our facts. Financial innovation can lead to more risk taking (see Arrow 1971, Obstfeld 1994). Financial innovation can also work through the competition channel since financial development favors entry of new competitors. On the other hand, financial innovation could prevent credit crunches, make collateral constraints less binding (Bernanke, Gertler, and Gilchrist 1996) and lead to lower aggregate volatility.

6 Product Market Competition

We have already shown that turnover at the top of industries has significantly increased over time (see figures 3.4 and 3.5). Is competition behind this evolution?

6.1 Profit Margins

Figure 3.13 shows the evolution of profit margins. The profit margin for firm i at time t is defined as:

\[ \pi_{it} = \frac{OL_{it}}{S_{it}} \]
where $OI_{it}$ is operating income and $S_{it}$ is sales. The key question is how to aggregate profit margins. One way is to take the mean across all firms:

$$\bar{\pi}_{it}^{\text{nonweighted}} = \text{mean}_{i \in I}(\pi_{it})$$

Another way is to take the sales-weighted average, or equivalently:

$$\bar{\pi}_{it}^{\text{weighted}} = \frac{\sum_{i \in I} OI_{it}}{\sum_{i \in I} S_{it}}$$

As figure 3.13 shows, the two measures have had very different evolutions. The stability of the weighted margin means that leaders are as profitable today as they were fifty years ago. However, firms are less likely to remain leaders for very long. The decline of the nonweighted margin is due to the entry of new firms (that often have negative cash flows) and the downfall of previous leaders.

Conclusion 8: Aggregate margins have remained stable because, conditional on being an industry leader, the margins of today are just as high as the margins of yesterday. The key evolution is that firms are less likely to remain leaders now than they were fifty years ago.

6.2 Evidence from Deregulation

The results presented in this section follow Irvine and Pontiff (2005), who document that return volatility increases after episodes of deregul-
The Rise in Firm-Level Volatility

Figure 3.14
Deregulation and Sales Volatility Relative to Nonderegulated Firms
Note: Firm volatility is the standard deviation of sales growth over the past 5 years.

Volatility. Some industries have been deregulated. For these industries, we can estimate the volatility of firms before and after deregulation, relative to firms in industries that do not experience deregulation. This is a standard difference-in-difference estimation.

For each firm, we define \( \sigma^I_t \) like in equation (2), except that we use only the past five years of data to make the timing more transparent:

\[
\sigma^I_t = \text{std.dev}(y_{it})_{t=1...t-4..t}
\]

We are therefore using a purely backward-looking measure of volatility. For each year, we measure the volatility of firm in industry \( I \) against firms in the other industries. The deregulated industries are airlines (1978), entertainment (1984), gas (1978), trucking (1980), banking (1994), railroad (1980), electricity (1978), and telecom (1982). Figure 3.14 shows the evolution of the backward-looking relative volatility measure around the year where deregulation happens. The increase in firm volatility is not very large (about 1.5 percent after five years), but it is statistically significant. In the underlying difference-in-difference regression, the \( p \)-value of the test that volatility at \( t + 5 \) is the same as volatility at \( t - 1 \) is 0.0123.

Conclusion 9: Deregulation can account for some of the increase in firm volatility.
Table 3.4

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Mean Volatility of Sales</th>
<th>Mean Volatility of Sales per Worker</th>
<th>Median Volatility of Sales</th>
<th>Median Volatility of Sales per Worker</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D/sales</td>
<td>3</td>
<td>2.88</td>
<td>0.65</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>(0.93)</td>
<td>(0.83)</td>
<td>(0.29)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>N</td>
<td>1,260</td>
<td>1,258</td>
<td>1,260</td>
<td>1,258</td>
</tr>
</tbody>
</table>

Newey-West Standard errors in parentheses. All regressions include a time trend and sector dummies.

7 R&D, Innovations, and Firm Dynamics

Following the Schumpeterian tradition, Comin and Mulani (2005) argue that the observed increase in R&D-driven innovations may be responsible for the increase in the turnover in market leadership and firm volatility. Consistent, with this idea, Chun, Kim, Lee, and Morck (2004) find that firm-specific stock return volatility is higher in industries that invest more in information technology. To explore this hypothesis, we estimate the following regression in a panel of thirty-five two-digit sectors in the United States during the period 1950–2003:

$$\sigma_{s,t} = \alpha_s + \beta t + \gamma RD_{s,t} + \epsilon_{s,t}$$

where $\sigma_{s,t}$ denotes the measure of firm-level volatility in sector $s$ at time $t$, $\alpha_s$ is a sector-specific intercept, and $RD_{s,t}$ denotes total R&D expenses over total sales in sector $s$ during year $t$.

Table 3.4 reports the estimates of $\gamma$ for various measures of volatility. In all the cases, there is a positive and statistically significant association between R&D and firm volatility. These estimates are robust to substituting the time trend for time dummies. Further, the estimated coefficient is economically significant. R&D intensity has increased by about 2 percent since the mid 1950s. This implies that the increase in R&D could account for an increase in firm volatility of between 1.5 and 6 percentage points of the total increase of approximately 10 percentage points.

Of course, there is a long way between correlation and causation. Further, the reserve causality argument is particularly plausible in this
One crude way to check whether R&D has a positive effect on firm volatility consists of exploring whether the increase in firm volatility after 1980 has been larger in the sectors that invested more heavily in R&D before 1980. This is the motivation for the following specification:

$$\bar{\sigma}_{s, POST} = \alpha + \beta \bar{\sigma}_{s, PRE} + \gamma \bar{R}D_{s, PRE} + \epsilon_s$$

(3.4)

By fixing R&D prior to 1980, we avoid the reverse effect of volatility on R&D. In this specification, this comes at the cost of reducing the initial panel to a cross-section of increments in volatility. Table 3.5 reports the estimates for $\gamma$ in equation (4) for various measures of firm volatility. For all of them, there is a positive effect of pre-1980 R&D intensity on post-1980 firm volatility. This effect is statistically significant at conventional levels for the mean of the volatility of sales and sales per worker and for the median of the volatility of sales. For the median volatility of sales per worker, the effect of R&D before 1980 on firm volatility after 1980 becomes significant if we restrict to the nonprimary economy.

To increase our understanding of the interaction between firm volatility and R&D, we proceed to estimate the following equation:

$$\sigma_{st} = \alpha_s + \beta t + \gamma(j)RD_{s,t-j} + \epsilon_{st}$$

for values of $j$ between 10 and $-10$. For concreteness, we focus now on the median volatility of sales per worker as a measure of $\sigma_{st}$, though the results are very robust to the other volatility measures. Figure
3.15a reports the estimate of $\gamma$ for various lags ($j$), and figure 3.15b reports the associated $p$-values (in an inverse scale) after computing Newey-West standard errors. In these figures, the lead-lag relationship between R&D and volatility is very clear. As we suspected, current volatility has a significant impact on future R&D that peaks at approximately $t + 3$. However, there is a very apparent effect of past R&D on current volatility that peaks at $t - 5$. This effect is always positive, statistically significant, and typically larger than the contemporaneous correlation between R&D and firm volatility.

Finally, since R&D seems to be an important determinant of firm volatility, we can explore how R&D affects the comovement of sectoral growth. To this end, we estimate the following equation:

$$Corr_{s,t}^{sec} = \alpha_s + \beta t + \gamma RD_{s,t} + \epsilon_{st}$$

where $Corr_{s,t}^{sec}$ is defined in expression (3). The estimates of $\gamma$ when $Corr_{s,t}^{sec}$ is measured by the correlations of productivity and TFP growth are $-3$ and $-2.4$, respectively, with $p$-values of 2 percent. Hence, the increase in R&D is associated with a decline of between 5 and 6 percentage points in the sectoral correlation of TFP or productivity growth of the observed decline of between 10 and 25 percentage points. These estimates are robust to replacing the time trend by time dummies.

Conclusion 10: Increases in R&D intensity are correlated with significant increases in firm volatility.
Conclusion 11: Growth in sectors with larger increases in R&D spending has become less synchronized with aggregate growth in the economy.

8 Financial Development

Before the Great Depression, financial markets for high-risk companies were very active. Corporate defaults were common, and IPOs were numerous (see above for defaults; see Jovanovic and Rousseau [2001] for IPOs). In the 1950s and 1960s, defaults were extremely rare, and IPOs almost disappeared. The high-yield market was reinvented in the 1970s, and IPOs reached historical highs in the 1990s. Li, Morck, Yang, and Yeung (2004) find that firm-specific volatility is linked to the openness of capital markets across emerging countries, but not to openness to trade. Thesmar and Thoenig (2004) find that, among French firms, volatility increased more for publicly traded companies following financial deregulation.

On the macroeconomic side, there are many models and a lot of evidence to support the idea that financial development can reduce aggregate volatility. Recently, Campello (2003) finds that industry markups are more countercyclical when leverage ratios are high, and Braun and Larrain (2004) show that industries that rely more on external finance
are more sensitive to aggregate shocks and that the effect is stronger in countries that are less financially developed.

We were not able to find a plausible instrument for financial development, so we can only present reduced form regressions. We want to learn if industries that use a lot of external finance also experience large increases in firm volatility:

$$\sigma_{s,t} = \alpha_s + \beta t + \gamma^R D_{s,t} + \gamma^E Q_{s,t} + \gamma^L D_{s,t} + \epsilon_{s,t}$$

For sector $s$ at time $t$, $EQ_{s,t}$ is the ratio of total issues of common and preferred stocks over total sales, and $LD_{s,t}$ is the ratio of total long-term debt issues over total sales. As before, $\sigma_{s,t}$ is the median firm volatility, measured between $t - 4$ and $t + 5$, and $RD_{s,t}$ is total R&D expenditures over total sales. We obtain the following results for our sample of thirty-five sectors between 1952 and 2002:

<table>
<thead>
<tr>
<th></th>
<th>$\gamma^R D$</th>
<th>$\gamma^E Q$</th>
<th>$\gamma^L D$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>.974</td>
<td>.267</td>
<td>.106</td>
</tr>
<tr>
<td>Standard error</td>
<td>.125</td>
<td>.070</td>
<td>.024</td>
</tr>
</tbody>
</table>

**Conclusion 12:** Increases in firm volatility are associated with significant increases in R&D intensity and with significant increases in debt and equity issuances.

We can also look at the link between external finance and sectoral correlations (using the correlation of the growth rate of TFP in sector $s$ at time $t$ with the aggregate TFP growth of the economy):

$$Corrs_{s,t} = \alpha_s + \beta t + \gamma^R D_{s,t} + \gamma^E Q_{s,t} + \gamma^L D_{s,t} + \epsilon_{st}$$

and we find:

<table>
<thead>
<tr>
<th></th>
<th>$\gamma^R D$</th>
<th>$\gamma^E Q$</th>
<th>$\gamma^L D$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>-1.93</td>
<td>.256</td>
<td>.109</td>
</tr>
<tr>
<td>Standard error</td>
<td>.619</td>
<td>.322</td>
<td>.102</td>
</tr>
</tbody>
</table>

The negative link between TFP comovement and R&D appears robust, but there is no significant link with external financing.

**Conclusion 13:** R&D intensity is associated with decreases in comovement, while external financing is not.
9 Conclusion

We document a widespread increase in firm-level volatility, which we argue is primarily due to more competition in product markets. We show that competition is best viewed as an increase in the turnover of market shares, as opposed to the more traditional approach emphasizing average markups, or indexes of concentration. We find that average industry profit margins have been roughly stable over the past fifty years because, at any point in time, industry leaders account for most of the sales, and the profit margins conditional on being a leader have not changed much. However, we show that the expected length of leadership by any particular firm has declined dramatically.

We then explore the possible causes for the increase in competition, and we find several explanations. First, we show that firm volatility increases after deregulation. Second, volatility increases more in industries that experience larger increases in R&D investment and in industries that issue more debt and equity.

The contrast between the decline in aggregate risk and the increase in idiosyncratic firm volatility is striking, and we present evidence that the two trends are related. Stock and Watson (2002) show that most of the decline in volatility is due to smaller shocks. We bring two new pieces to the puzzle. First, we show that the decline in the volatility of aggregate shocks is primarily due to a decrease in the correlation of shocks across sectors rather than a decline in sectoral volatility. Second, we show that the correlation of a particular sector with the rest of the economy declines more when firm volatility within this sector increases more. Therefore, we claim that there is a negative relationship between firm and aggregate volatility.

Several theories can help us understand this connection, and we classify them in two broad categories. The first group takes the aggregate shocks as given and emphasizes a decline in a particular amplification mechanism, like the credit multiplier or nominal rigidities. We do not find supporting evidence for a role of the investment-financial multiplier in the decline in aggregate volatility. Our data does not allow us to explore the role of nominal rigidities. The second group of explanations argues that competition can lead to a reduction in the correlation of TFP shocks across sectors. We find evidence supportive of this hypothesis: R&D spending at the industry level predicts both an increase in firm volatility within the industry and a decrease in the comovement of the industry with the rest of the economy.
10 Appendix

In this appendix, we derive the decomposition of the variance of aggregate growth into the variance of sectoral growth and the covariance of growth across sectors. The growth rate of the aggregate variable of interest ($\gamma_t$) is related to sectoral growth ($\gamma_{s,t}$) as follows:

$$\gamma_t = \sum_s \omega_s^{sec} \gamma_{s,t}$$

where $\omega_s^{sec}$ are the relevant sectoral weights. Aggregate variance of $\gamma_t$ between $\tau = t - 4$ and $\tau = t + 5$ can be expressed as:

$$V(\gamma_{\tau|t-4}^{t+5}) = \frac{1}{10} \sum_{\tau=t-4}^{t+5} \left( \sum_s \gamma_{s,\tau} \omega_s^{sec} - \frac{1}{10} \sum_{\tau=t-4}^{t+5} \sum_s \gamma_{s,\tau} \omega_s^{sec} \right)^2$$

Imposing the restriction that sectoral weights are constant during the interval $[t - 4, t + 5]$, we can express aggregate variance as:

$$V(\gamma_{\tau|t-4}^{t+5}) = \frac{1}{10} \sum_{\tau=t-4}^{t+5} \left( \sum_s \omega_s^{sec} \left( \gamma_{s,\tau} - \frac{1}{10} \sum_{\tau=t-4}^{t+5} \gamma_{s,\tau} \right) \right)^2$$

Expanding and manipulating, we obtain the variance-covariance decomposition:

$$V(\gamma_{\tau|t-4}^{t+5})$$

$$= \frac{1}{10} \sum_{\tau=t-4}^{t+5} \left( \sum_s \sum_j \omega_s^{sec} \omega_j^{sec} \left( \gamma_{s,\tau} - \frac{1}{10} \sum_{\tau=t-4}^{t+5} \gamma_{s,\tau} \right) \left( \gamma_{j,\tau} - \frac{1}{10} \sum_{\tau=t-4}^{t+5} \gamma_{j,\tau} \right) \right)$$

$$= \sum_s \sum_j \omega_s^{sec} \omega_j^{sec} \left( \frac{1}{10} \sum_{\tau=t-4}^{t+5} \gamma_{s,\tau} \left( \gamma_{j,\tau} - \frac{1}{10} \sum_{\tau=t-4}^{t+5} \gamma_{j,\tau} \right) \right)$$

$$= \sum_s (\omega_s^{sec})^2 V(\gamma_{\tau|t-4}^{t+5}) + \sum_s \sum_{j \neq s} \omega_s^{sec} \omega_j^{sec} \text{Cov}(\gamma_{s,\tau|t-4}^{t+5}, \gamma_{j,\tau|t-4}^{t+5})$$

Endnotes

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and Ken Rogoff for their suggestions, to Janice Eberly and Daron Acemoglu for their insightful discussions, and to the participants of the 2005 NBER conference on macroeconomics for their comments.

1. We have checked the robustness of our findings using Bureau of Labor Statistics (BLS) sectoral data.

2. Another way to measure firm volatility is to estimate an autoregressive process and compute the volatility of the innovations. The increase in volatility is the same if we measure it in that way.

3. For a decomposition of firm dynamics into permanent and transitory shocks, see Franco and Philippon (2004).

4. Comin and Mulani (2003) also allow for cohort-specific age and size effects and for autocorrelated errors.

5. This is not to say that M&As are not important. They do not matter much here because we use the median to aggregate across firms. If we had used the mean as our benchmark for figure 3.1, then some large mergers would have affected our measure, and removing these mergers would have made a difference.

6. All of our results also hold using BLS manufacturing data.

7. See the appendix for the derivation details.

8. This lack of association between firm-level volatility and income per capita persist if we compute firm volatility after filtering firm growth from shocks to aggregate growth. Specifically, we regress firm growth on country-time specific dummies and compute the standard deviation of the residuals to measure firm volatility.

9. This is because the standard sticky price model assumes a constant velocity, hence \( y = m - p \), and for a given volatility of \( m \), the only way to decrease the volatility of \( y \) is to increase the volatility of \( p \). Sticky price models are one example in the class of models with countercyclical markups. Models with real countercyclical markups would not make the counterfactual prediction.

References


