The Rise in Firm-Level Volatility: Causes and Consequences

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Abstract

We document that the recent decline in aggregate volatility has been accompanied by a large increase in firm level risk. The negative relationship between firm and aggregate risk seems to be present across industries in the US, and across OECD countries. Firm volatility increases after deregulation. Firm volatility is linked to research and development spending as well as access to external financing. Further, R&D intensity is also associated with lower correlation of sectoral growth with the rest of the economy.

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Introduction

Over the past 30 years, there has been a decline in aggregate volatility (McConnell and Perez-Quiros (2000) and Stock and Watson (2002)). At the same time, there has been a large increase in the volatility of firms (Campbell, Lettau, Malkiel, and Xu (2001), Comin and Mulani (2003) and Chaney, Gabaix, and Philippon (2002)).

Our paper has two parts. We first explore whether the firm level trend towards more volatility and the aggregate trend towards 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.

In the second part, 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 activity, as well as more access to debt and equity markets.

Section 1 presents the facts, using various measures of firm level risk.

1 The Basic Facts

The decline in aggregate volatility has been documented by McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Stock and Watson (2002).

On the other hand, firm level volatility has increased. Firm level volatility can be measured using financial data or real data. Using financial data for the US, Comin (2000) and Campbell, Lettau, Malkiel, and Xu (2001) document an increase in volatility of idiosyncratic stock returns. Using accounting data, Chaney, Gabaix, and Philippon (2002) and Comin and Mulani (2003) show an increase the idiosyncratic volatility of employment, sales, earnings and capital expenditures.

Throughout the paper, we will use aggregate data from the NIPA, and firm level data from COMPUSTAT and CRSP. We will also use the sectoral data set of Jorgenson.

1.1 Volatility: GDP versus Firm Sales

In this section, we document the increase in firm volatility using real measures, like sales, employment or capital expenditures.

Figure 1 shows the evolution of idiosyncratic and aggregate volatility. Aggregate volatility (σ_t^a) is defined as the standard deviation of the annual growth rate (γ_t) of real GDP

$$\sigma_t^a = \left[\frac{1}{10} \sum_{\tau=-4}^{+5} \left(\gamma_{t+\tau} - \bar{\gamma}_t \right)^2 \right]^{\frac{1}{2}} \tag{1}$$

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 $\left(\gamma_{t,i}\right)$ as

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

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

$$\sigma_t^f = \text{median}_i \left\{ \sigma_{i,t} \right\}$$

Figure 1 shows the decline in σ_t^a and the increase in σ_t^f. Note also the difference of scale between the two measures. Idiosyncratic volatility is an order of magnitude larger than aggregate volatility.[1] **Figure 2** shows the evolution of the 25^{th} and 75^{th} 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.[2]

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 COMPUSTAT 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.

[1] Another way to measure firm volatility is to estimate an auto-regressive process and compute the volatility of the innovations. The increase in volatility is the same if we measure it in that way.

[2] For a decomposition of firm dynamics into permanent and transitory shocks, see Franco and Philippon (2004)

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 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 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.[3] 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.

1.2 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,

$$TopTurn_{I,t} = P\left(Z_{it+5} < Z_{t+5}^{top,I(i)} \mid Z_{it} > Z_t^{top,I(i)}\right) ,$$

where Z_{it} is either operating income or market value of firm i at time t, and $Z_t^{top,I(i)}$ is the 80^{th} percentile of the distribution of Z_{it} at time t in industry $I\left(i\right)$. This measure is robust

[3] 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 1, then some large mergers would have affected our measure, and removing these mergers would have made a difference.

to the entry of small firms in the particular industry. We then define average turnover as the median of turnover across all industries. **Figure 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%. For a particular measure Z, we define

$$RkCorr = Corr_{i \in I} \left(rank_{I,t} \left(Z_{it} \right), rank_{I,t} \left(Z_{it+\tau} \right) \right)$$

where $rank_{I,t} \left(Z_{it} \right)$ 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 the one in **figure 4**, and, for the sake of completeness, we present the results based on labor productivity rankings. **Figure 5** shows the evolution of the ranking correlation of firms, over 5 and 10 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.

1.3 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. For each firm, we estimate the CAPM model over rolling windows of 36 months

$$r_{i,t,m} = \beta_{i,t} r_{t,m}^{VW} + \varepsilon_{i,t,m} \text{ , for } m = 1, .., 12$$

We therefore allow $\beta_{i,t}$ to vary over (smoothly) 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

$$\sigma_t^{fin} = \text{median}_{i,m} \left(\left| \varepsilon_{i,t,m} \right| \right)$$

The nice thing about monthly data is that is 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 6 shows the historical decline in the explanatory power of CAPM. CAPM used to explain 40% of firm returns before the 1950s, but its explanatory power is now around 10%. 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 7** shows a U-shaped patter for σ_t^{fin}. Firm volatility was high in the late 1920's ,and it increased dramatically during the market crash and the early years of the great depression. It then declined steadily from the mid 1930's to the mid 1950's. At that point in time, we can make the link with the real data presented in the previous section. Since the mid 1950's, 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).

1.4 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 10-year treasury rate. For bond ratings, we use S&P long term domestic 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 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%. It dropped to a mere 0.1% from1945 to 1965 (Sylla (2002)). It then increase again, to 0.64% between 1970 and 1985, and to 1.85% 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 2, became largely irrelevant in the 1950s and 1960s, and have regained their previous importance in the past 30 years (Sylla (2002)).

Conclusion 1: Firm level risk has increased over the past 50 years.

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

2 Sectoral Evidence

We have established that the aggregate stabilization of the US 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 co-movement 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 come from Jorgenson.

2.1 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 ω_{st}^{sec} be the share of sales for sector s in the aggregate sales in the economy. Also, let $V([Z_\tau]_{t-4}^{t+5})$ denote the variance of $\{Z_{t-4},\ Z_{t-3},\ ...\ \ Z_t, ...\ Z_{t+4},\ Z_{t+5}\}$ for any generic variable Z and $Cov([Z_\tau]_{t-4}^{t+5}, [Y_\tau]_{t-4}^{t+5})$ be the covariance between $\{Z_{t-4},\ Z_{t-3},\ ...\ \ Z_t, ...\ Z_{t+4},\ Z_{t+5}\}$ and $\{Y_{t-4},\ Y_{t-3},\ ...\ Y_t, ...\ Y_{t+4},\ Y_{t+5}\}$. By definition, the aggregate growth rate is

$$\gamma_t = \sum_i \gamma_{s,t}\omega_{s,t}^{\text{sec}} \ .$$

Then, using the definition of the variance,

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

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

$$V([\gamma_\tau]_{t-4}^{t+5}) = \underbrace{\sum_s (\omega_s^{\text{sec}})^2 V([\gamma_{s,\tau}]_{t-4}^{t+5})}_{\text{Variance Component}} + \underbrace{\sum_s \sum_{j \neq s} \omega_s^{\text{sec}} \omega_j^{\text{sec}} Cov([\gamma_{s,\tau}]_{t-4}^{t+5}, [\gamma_{j,\tau}]_{t-4}^{t+5})}_{\text{Covariance Component}}$$

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 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:

$$Corr_{s,t}^{\text{sec}} = \sum_{j \neq s} \frac{\omega_j^{\text{sec}}}{\sum_{h \neq s} \omega_h^{\text{sec}}} Corr([\gamma_{s,\tau}]_{t-4}^{t+5}, [\gamma_{j,\tau}]_{t-4}^{t+5}) \ , \tag{3}$$

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

$$Corr_t^a = \sum_s \omega_s^{\text{sec}} Corr_{s,t}^{\text{sec}}.$$

Figure 9 shows the decline in aggregate correlation for value added, TFP and value added per worker. Sectoral variances display an hump-shaped pattern over time, with no obvious decline over our sample period, 1959 to 1996. On the other hand, there is a clear decline in correlations over time, for all three variables of interest.

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.

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.

2.2 Firm Volatility and Sector Co-movements

We now ask if the decline in co-movement 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

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

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

$$Corr_{s,t}^{\text{sec}} = \alpha_i + \beta t + \gamma \sigma_{s,t}^{\text{sec}} + \varepsilon_{s,t}$$

Table 2 shows the results when the dependent variable is the correlation of value added, employment, labor productivity and TFP. We estimate a negative γ in all specifications, and it is significant for the last three. Of course since both $\sigma_{s,t}^{\text{sec}}$ and $Corr_{s,t}^{\text{sec}}$ are autocorrelated we use Newey-West to assess the significance of β. 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 estimate of γ that is statistically significant.

To have a more graphical image of the relationship between firm volatility and sectoral correlation, **Figures 10a and 10b** show the change in the correlation of output per worker against the change in the volatility of firms between 1964 and 1977 (10a) and between 1978 and 1991 (10b) for the 35 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: Co-movement has decreased more in sectors where firm volatility has increased more.

3 International Evidence

So far our exploration has been restricted to the US because of data availability. Some research, however, has been done on non-US data. Frazzini and Marsh (2002) do not find the same increase in firm volatility in the UK. Thesmar and Thoenig (2004) show an increase in France, especially for listed firms. 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 80 countries, representing over 90% of the world's market capitalization, including coverage of over 96% of European market capitalization and 88% of Asian market capitalization. Due to the short nature of the panel we compute volatility using 4-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 4 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** reports the evolution of these measures of firm volatility. We can observe a clear increase in both measures of firm-level volatility during the nineties. Unfortunately, the panel is too short to see if the upward trend in firm volatility holds in the post-war 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 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 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 70 countries during the 1990's. At the firm-level, though, we do not see any relationship between the firm-level volatility in a country and income per capita.[4] In particular, **Figure 11b** illustrates this lack of association between median firm volatility of employment growth and income per capita in a cross-section of 57 countries. This result holds irrespective of whether 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 12a** plots the scatter plot for our sample of 58 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

[4] 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.

relationship between aggregate and firm-level volatility. This, however, may be the result of the noisiness of the data for some low income countries..

To mitigate this problem, we explore the sub-sample of 28 OECD economies. **Figure 12b** contains the scatter plot of aggregate and firm volatility for each of our cross-section of OECD economies during the 90's. 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 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 post-war panel of US 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

4 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.

Other 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 aggregate demand shocks. While intuitively appealing, the simple sticky price explanation cannot be complete because it also implies more volatile inflation, contrary to the evidence.[5]

The third explanation, formalized in Comin and Mulani (2005), is that more competition leads to a decline in the variance of aggregate TFP shocks. To see why this could be the case, assume that each firm can choose to invest in the development of two kinds of innovations. Idiosyncratic, embodied innovations are patentable and benefit mostly the innovator. GPT-style innovations can potentially affect all the firms in the economy. With a large number of firms, if all the research effort is devoted to embodied innovations, we would expect smooth aggregate TFP growth. On the contrary, GPT-style innovations can create fluctuations in aggregate TFP growth. To the extent that competition can lead firms to favor embodied innovations, it could explain the decline in aggregate volatility. Comin and Mulani (2005) present a model where the willingness to spend resources on the development of GPT-style innovations increases with the stability of the market share of the industry leader. As competition increases and market shares become more volatile, firms endogenously decide to focus more on embodied innovations, and less on GPT innovations.

Finally, financial innovation could explain our facts. Financial innovation can lead to more risk taking (see Thesmar and Thoenig (2004) for instance). 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 and

[5] This is because the standard sticky price model assumes a constant velocity, hence $y = m - p$ and , for 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 counter-cyclical markups. Models with real counter-cyclical markups would not make the counter-factual prediction.

lead to lower aggregate volatility.

5 Product Market Competition

We have already shown that turnover at the top of industries has significantly increased over time. **See figures 4 and 5**. Is competition behind this evolution?

5.1 Profit Margins

Figure 13 shows the evolution of profit margins. The profit margin for firm i at time t is defined as

$$\pi_{it} = \frac{OI_{it}}{S_{it}}$$

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

$$\bar{\pi}_{It}^{non-weighted} = mean_{i \in I} \left(\pi_{it} \right) \ .$$

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

$$\bar{\pi}_{It}^{weighted} = \frac{\sum\limits_{i \in I} OI_{it}}{\sum\limits_{i \in I} S_{it}}$$

As **figure 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 50 years ago. However, firms are less likely to remain leaders for very long. The decline of the non-weighted 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 50 years ago.

5.2 Evidence from Deregulation

The results presented in this section follow Irvine and Pontiff (2005) who document that return volatility increases after episodes of deregulation.

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 σ_t^i like in equation 2 except that we use only the past 5 years of data to make the timing more transparent.

$$\sigma_t^i = std.dev\,(\gamma_{i\tau})_{\tau=t-4\ldots t}$$

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 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% after 5 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.

6 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. To explore this hypothesis we estimate the following regression in a panel of 35 2-digit sectors in the US during the period 1950-2003:

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

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

The first four columns in **Table 4** report the estimates of γ 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 50's. 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 context. Namely, when it is easier to take over market leaders, and therefore there is more firm volatility, firms have more incentives to invest in R&D to materialize this possibility.

One crude way to check whether R&D has a positive effect on firm volatility consists on 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:

$$\bar{\sigma}_{s,POST} = \alpha + \beta\bar{\sigma}_{s,PRE} + \gamma\overline{RD}_{s,PRE} + \varepsilon_s \tag{4}$$

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 5** reports the estimates for γ 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 to 1980 on firm volatility after 1980 becomes significant if we restrict to the non-primary 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 σ_{st}, though the results are very robust to the other volatility measures. **Figure 15a** reports the estimate of γ for various lags (j) and **figure 15b** reports the associated p-values (in an inverse scale) after computing Newey-West standard errors. In these figures it is very clear the lead-lag relationship between R&D and volatility. As we suspected, current volatility has a significant impact on future R&D that peaks approximately at $t+3$. 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 co-movement of sectoral growth. To this end, we estimate the following equation:

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

where $Corr_{s,t}^{\text{sec}}$ is defined in expression (3). The estimates of γ when $Corr_{s,t}^{\text{sec}}$ is measured by the correlations of productivity and TFP growth are -3 and -2.4 respectively with p-values of 2%. Hence, the increase in R&D is associated to 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.

7 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, and Jovanovic and Rousseau (2001) for IPOs). In the 1950's and 1960's, defaults were extremely rare, and IPOs almost disappeared. The high yield market was reinvented in the 1970's, and IPOs reached historical highs in the 1990's.

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

$$\sigma_{s,t} = \alpha_s + \beta t + \gamma^{RD} RD_{s,t} + \gamma^{EQ} EQ_{s,t} + \gamma^{LD} LD_{s,t} + \epsilon_{s,t},$$

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 35 sectors between 1952 and 2002:

	γ^{RD}	γ^{EQ}	γ^{LD}
Coefficient	.974	.267	.106
St. Error	.125	.070	.024

.

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):

$$Corr^{\text{sec}}_{s,t} = \alpha_s + \beta t + \gamma^{RD} RD_{s,t} + \gamma^{EQ} EQ_{s,t} + \gamma^{LD} LD_{s,t} + \epsilon_{st} \ ,$$

and we find

	γ^{RD}	γ^{EQ}	γ^{LD}
Coefficient	-1.93	.256	.109
St. Error	.619	.322	.102

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

Conclusion 13: R&D intensity is associated with decreases in co-movement, while external financing is not.

8 Conclusion

We have documented that the interplay of product market competition, technological innovations and financial development accounts for the increase in firm level volatility. However, our analysis falls short of establishing causality between these different factors. The difficulty of establishing causality is illustrated on **Figure 16**. As argued in Jovanovic and Rousseau (2001), it appears that companies that first listed at the close of the 19th century were as young as the companies that entered the stock exchanges in 1990s. In turn, it appears that times of slow entry are also times of low idiosyncratic volatility. One interpretation is that technological progress was best achieved in large and stable firms in the 1960s, while, for some reason, it required the entry of young firms in the 1900s and 1990s. Another interpretation is that financial markets were repressed after the great depression, and that the financing of radical innovations dried up. We leave for future research the exploration of the causal links between technological and financial innovations.

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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.

$$
\begin{aligned}
V([\gamma_\tau]_{t-4}^{t+5}) &= \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_s \gamma_{s,\tau}\omega_s^{\text{sec}} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\sum_s \gamma_{s,\tau}\omega_s^{\text{sec}}\right)^2 \\
&= \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_s \omega_s^{\text{sec}}\left(\gamma_{s,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{s,\tau}\right)\right)^2 \\
&= \frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\sum_s\sum_j \omega_s^{\text{sec}}\omega_j^{\text{sec}}\left(\gamma_{s,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{s,\tau}\right)\left(\gamma_{j,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{j,\tau}\right)\right) \\
&= \sum_s\sum_j \omega_s^{\text{sec}}\omega_j^{\text{sec}}\left(\frac{1}{10}\sum_{\tau=t-4}^{t+5}\left(\gamma_{s,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{s,\tau}\right)\left(\gamma_{j,\tau} - \frac{1}{10}\sum_{\tau=t-4}^{t+5}\gamma_{j,\tau}\right)\right) \\
&= \underbrace{\sum_s (\omega_s^{\text{sec}})^2\, V([\gamma_{s,\tau}]_{t-4}^{t+5})}_{\text{Variance Component}} + \underbrace{\sum_s\sum_{j\neq s}\omega_s^{\text{sec}}\omega_j^{\text{sec}} Cov([\gamma_{s,\tau}]_{t-4}^{t+5}, [\gamma_{j,\tau}]_{t-4}^{t+5})}_{\text{Covariance Component}}
\end{aligned}
$$

Table 2: Sectoral Correlation and Firm Volatility, Panel Regression, 35 Sectors

Dependent Variable	Sectoral correlation of growth in value added	Sectoral correlation of growth in employment	Sectoral correlation of growth in labor productivity	Sectoral correlation of growth in TFP
Avg. Firm Volatility	-0.036 (0.096)	-0.23 (.12)	-0.264 (.126)	-0.22 (.08)
N	1011	1011	1011	1011

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

Table 3: Firm Level Volatility in the World

year	Number of firms	Median Volatility	Average Volatility
1995	2685	0.0694	0.1301
1996	2752	0.0737	0.1417
1997	2762	0.0872	0.1587
1998	3429	0.0999	0.1859
1999	3652	0.1126	0.1983
2000	3711	0.1205	0.2161
2001	1831	0.1281	0.2269

Table 4: R&D and Firm Volatility, Panel Regression, 1956-1997, 35 sectors

	Dependent Variable			
	Mean Volatility of Sales	Mean Volatility of Sales per Worker	Median Volatility of Sales	Median Volatility of Sales per Worker
R&D/Sales	3 (0.93)	2.88 (0.83)	0.65 (0.29)	0.49 (0.21)
N	1260	1258	1260	1258

Newey-West Standard errors in parenthesis

All regressions include a time trend and sector dummies.

Table 5: R&D and Firm Volatility, Cross-Section of 35 sectors before/after 1980

	Dependent Variable, Mean Post 1980			
	Mean Volatility of Sales	Mean Volatility of Sales per Worker	Median Volatility of Sales	Median Volatility of Sales per Worker
Firm Vol. pre 1980	1 (.14)	1.1 (0.2)	0.94) (0.12)	1.01 (0.13)
R&D/Sales pre 1980	5.26 (2.27)	5.96 (2.15)	1.98 (1)	1.35 (0.88)
N	35	35	35	35

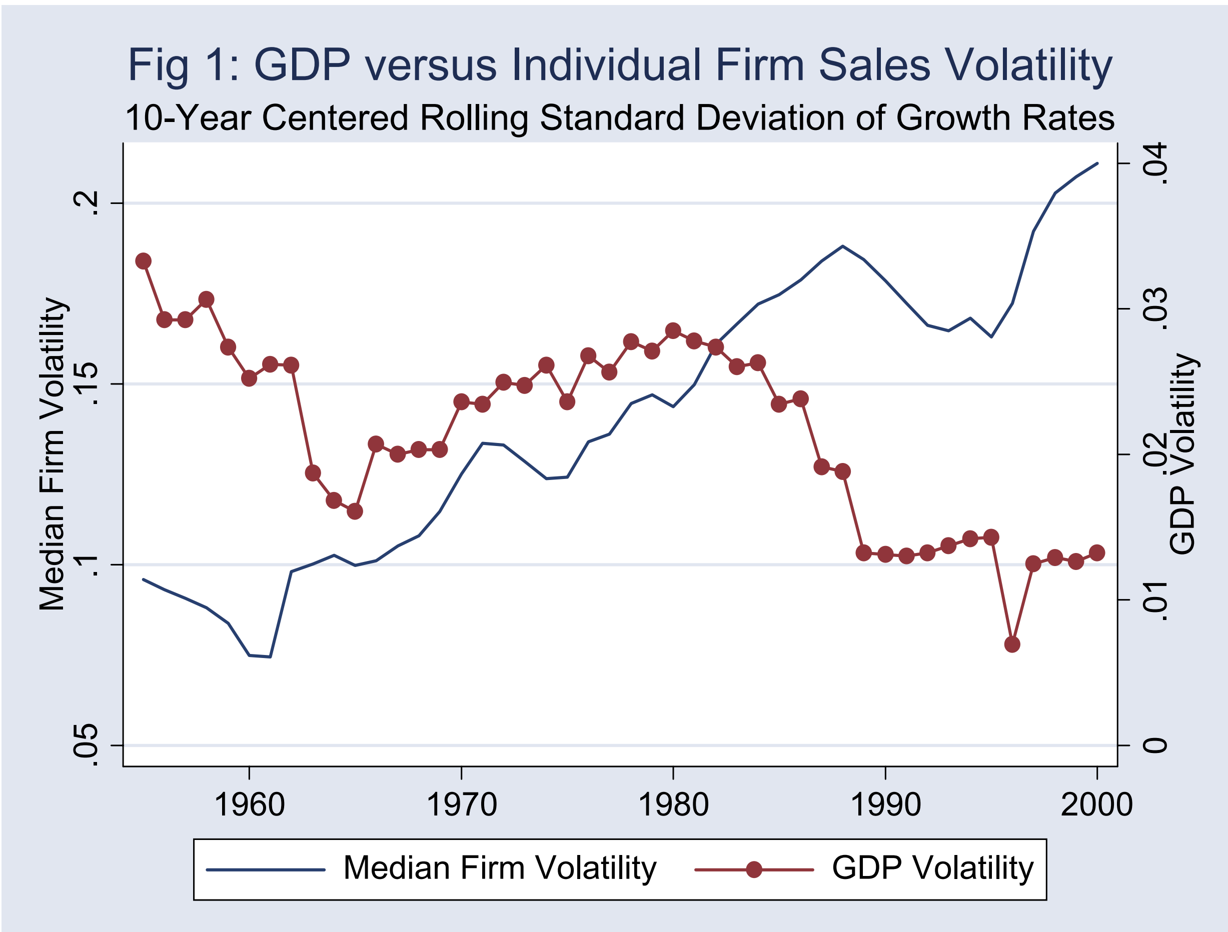
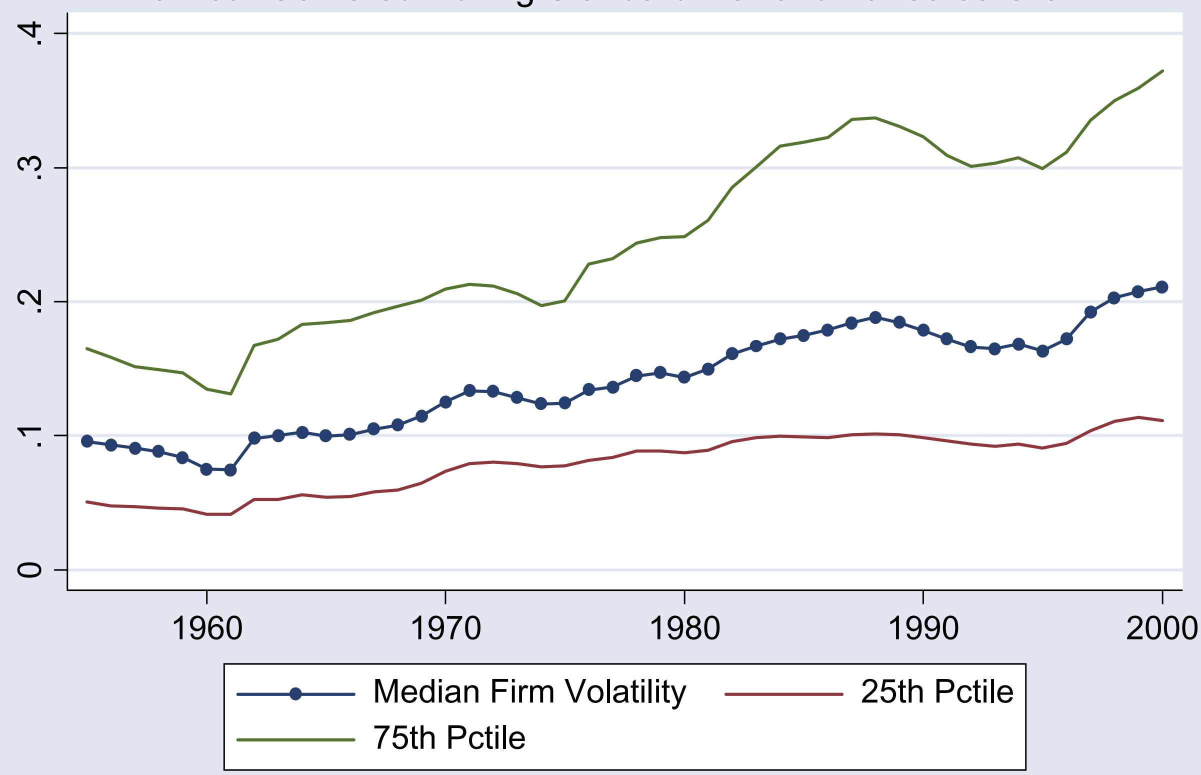


Fig 1: GDP versus Individual Firm Sales Volatility
10-Year Centered Rolling Standard Deviation of Growth Rates
Median Firm Volatility
GDP Volatility
.05
.1
.15
.2
0
.01
.02
.03
.04
1960
1970
1980
1990
2000
Median Firm Volatility
GDP Volatility

Fig 2: Distribution of Firm Volatility

10-Year Centered Rolling Standard Deviation of Sales Growth



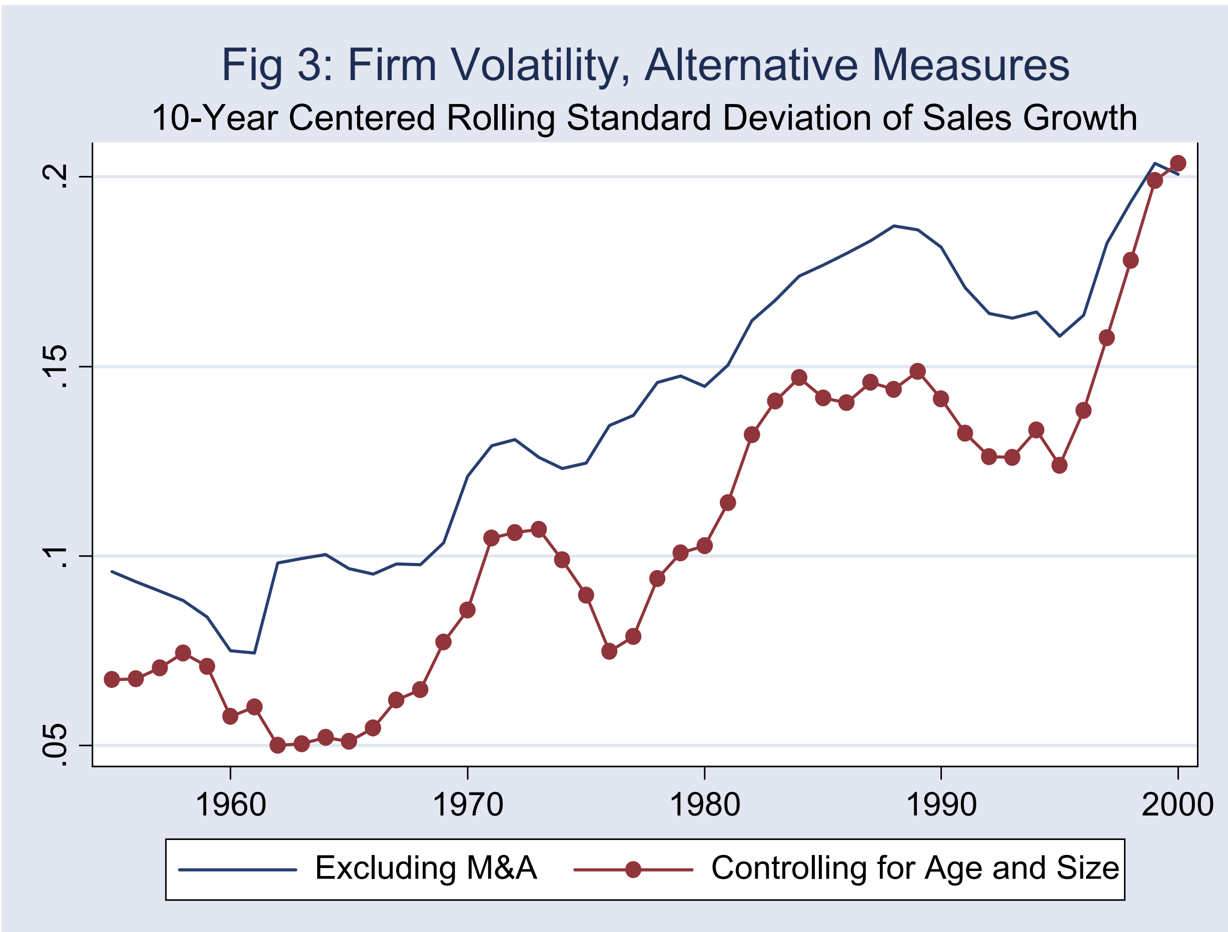


Fig 3: Firm Volatility, Alternative Measures
10-Year Centered Rolling Standard Deviation of Sales Growth
.2
.15
.1
.05
1960
1970
1980
1990
2000
Excluding M&A
Controlling for Age and Size

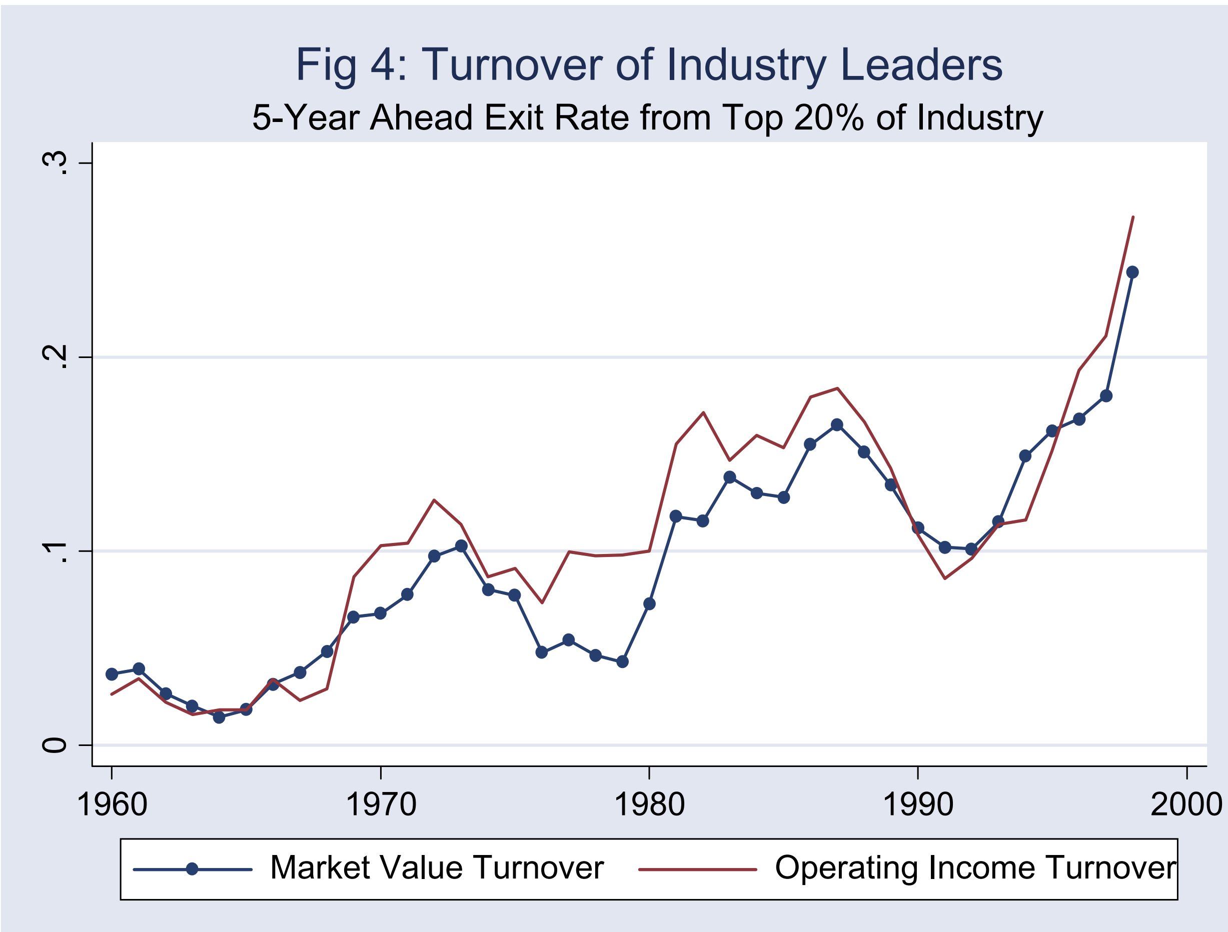
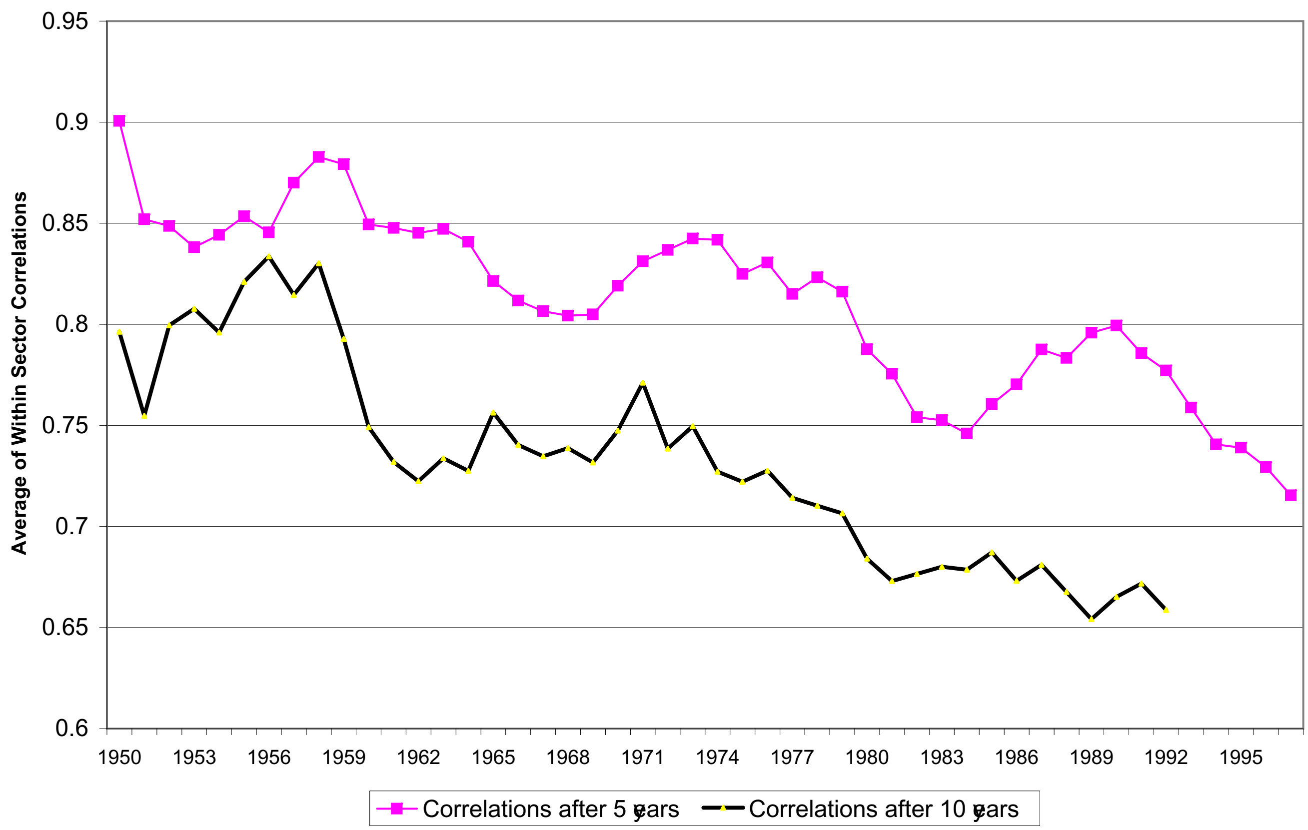


Fig 4: Turnover of Industry Leaders
5-Year Ahead Exit Rate from Top 20% of Industry
0
.1
.2
.3
1960
1970
1980
1990
2000
Market Value Turnover
Operating Income Turnover

Fig5 : Correlation of Labor Productivity Rankings



Note: 5 and 10 years ahead correlation of within sector ranking,based on Sales per Employee

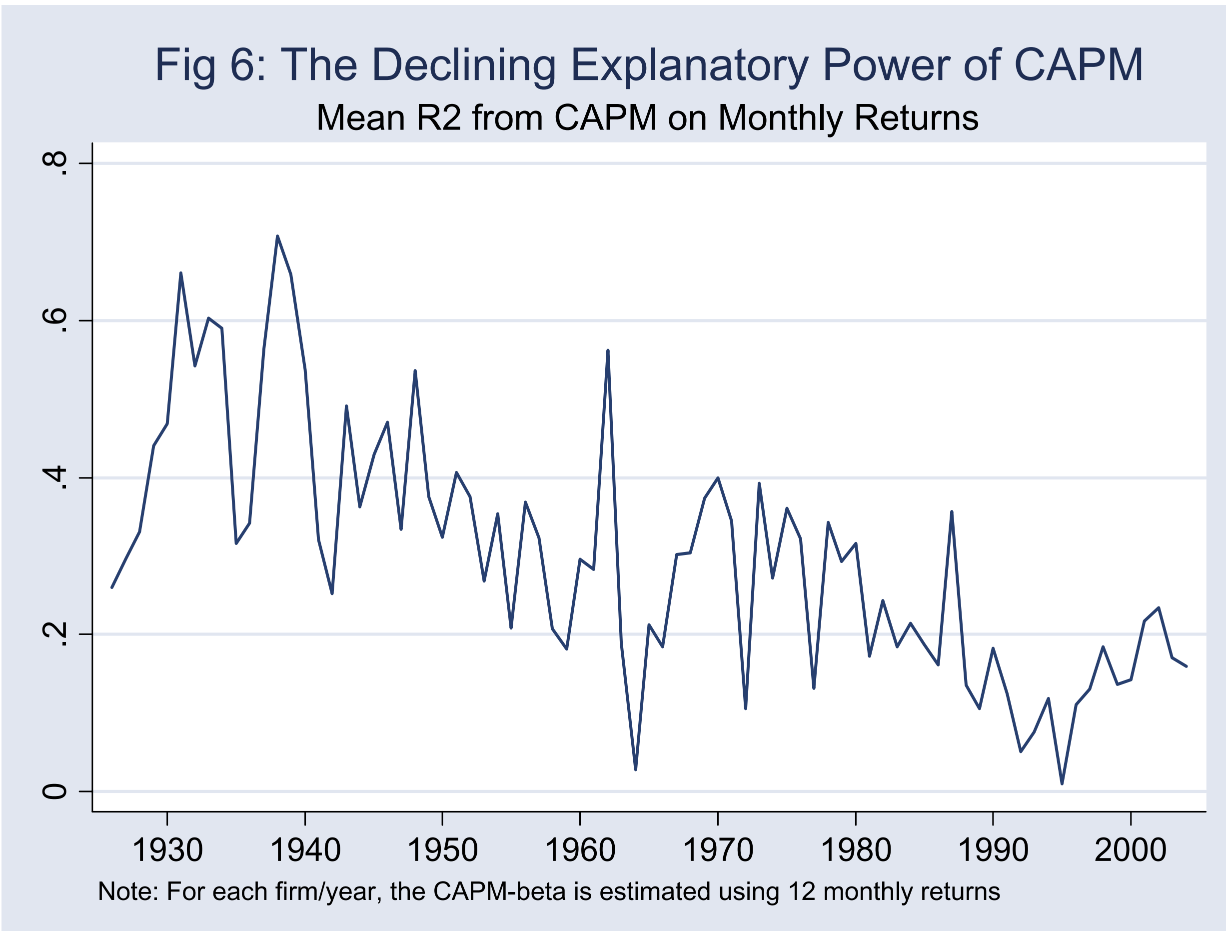
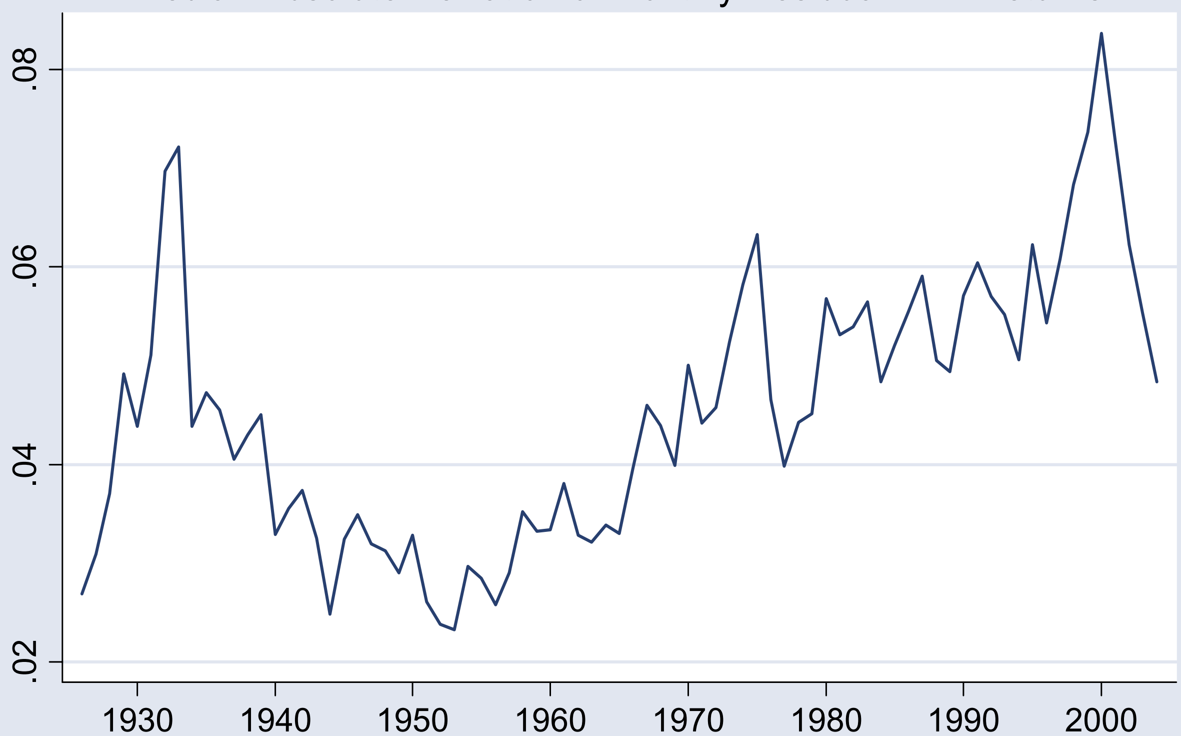


Fig 6: The Declining Explanatory Power of CAPM
Mean R2 from CAPM on Monthly Returns
0
.2
.4
.6
.8
1930
1940
1950
1960
1970
1980
1990
2000
Note: For each firm/year, the CAPM-beta is estimated using 12 monthly returns

Fig 7: The Evolution of Idiosyncratic Return Volatility

Median Absolute Deviation of Monthly Residual Firm Returns



Note: Firm Returns are CAPM-adjusted using betas estimated on 12 monthly returns

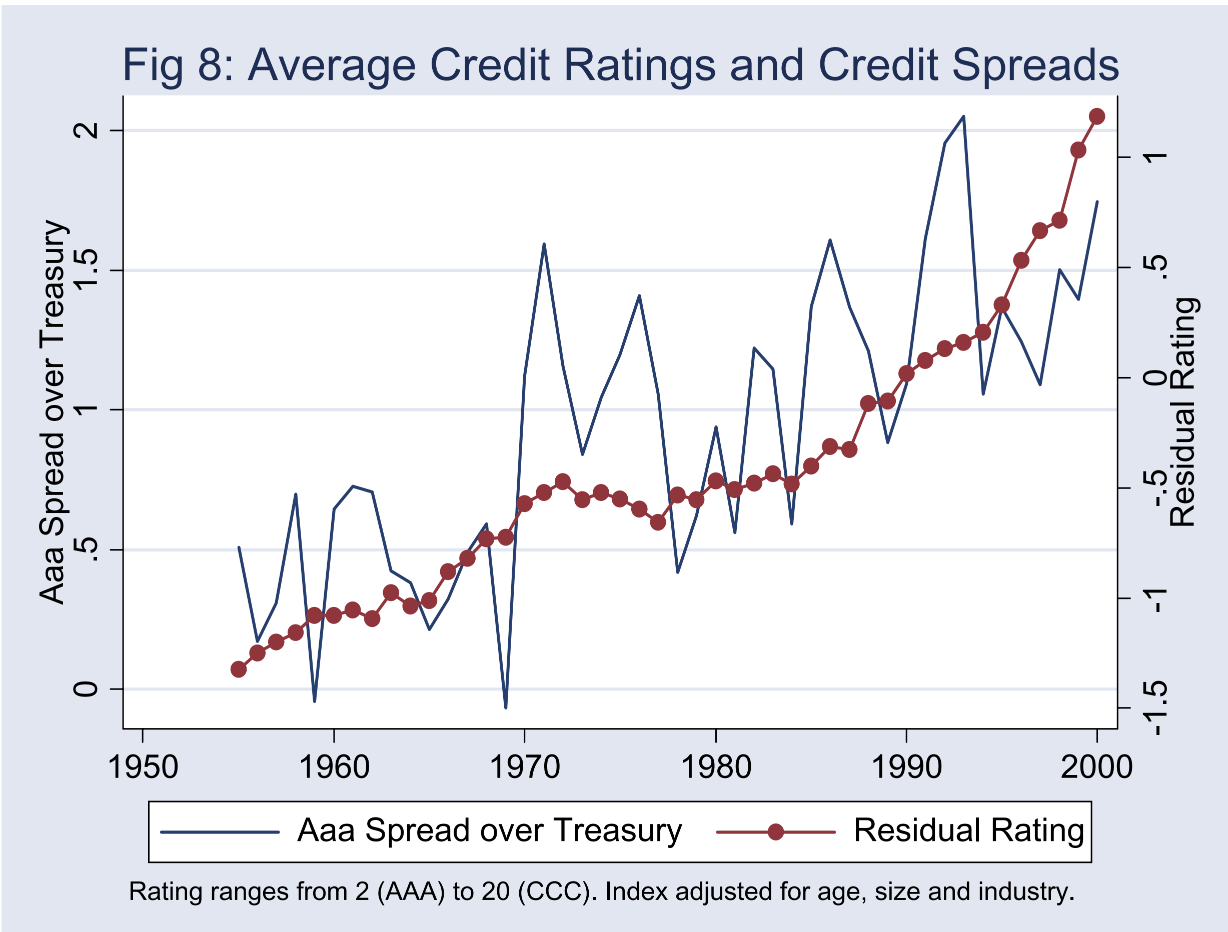


Fig 8: Average Credit Ratings and Credit Spreads
Aaa Spread over Treasury
Residual Rating
0
.5
1
1.5
2
-1.5
-1
-.5
0
.5
1
1950
1960
1970
1980
1990
2000
Aaa Spread over Treasury
Residual Rating
Rating ranges from 2 (AAA) to 20 (CCC). Index adjusted for age, size and industry.

Figure 9: Variance-Covariance-Correlation

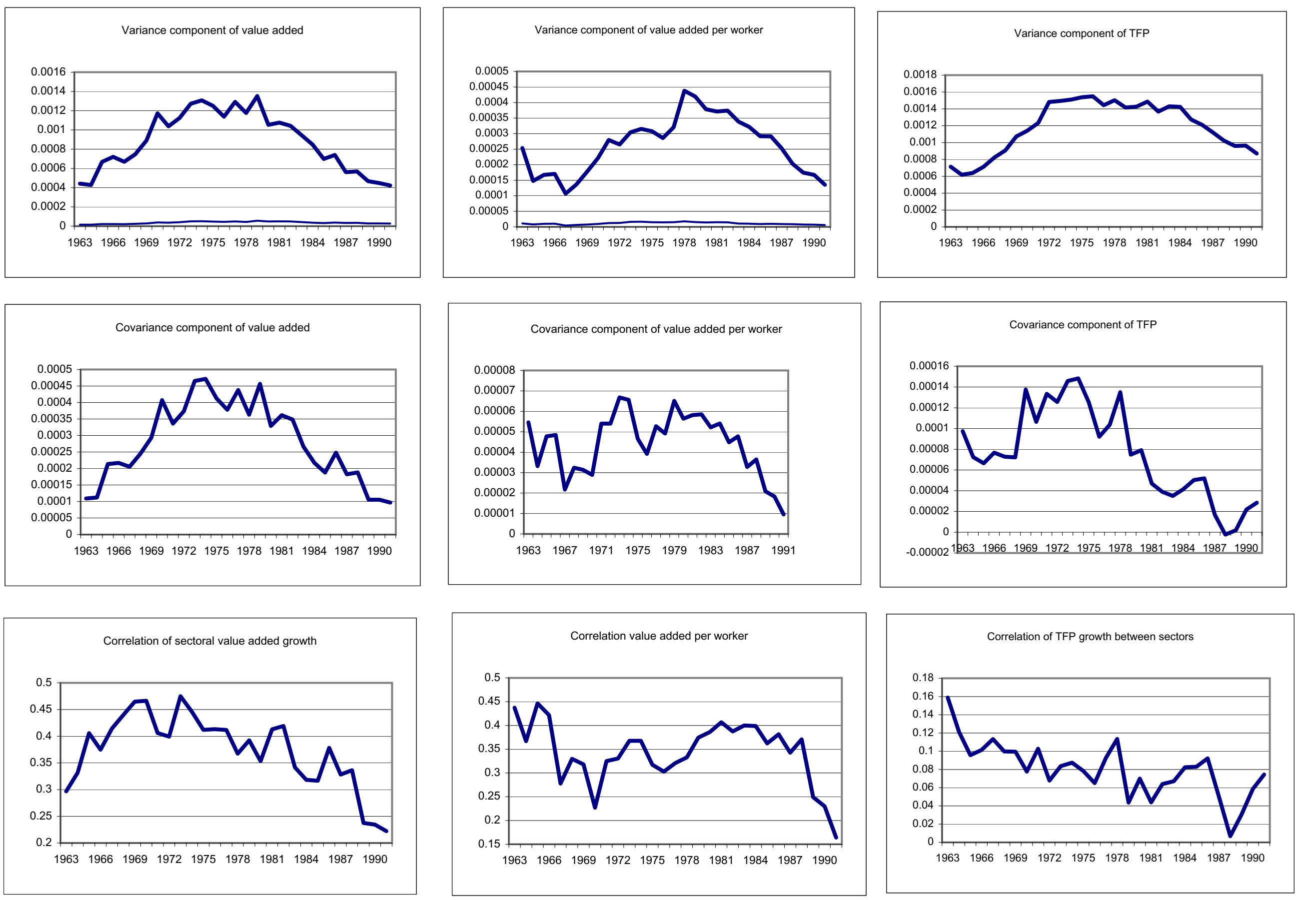


Fig. 10a: Firm Volatility and Sectoral Correlation 1964-1977

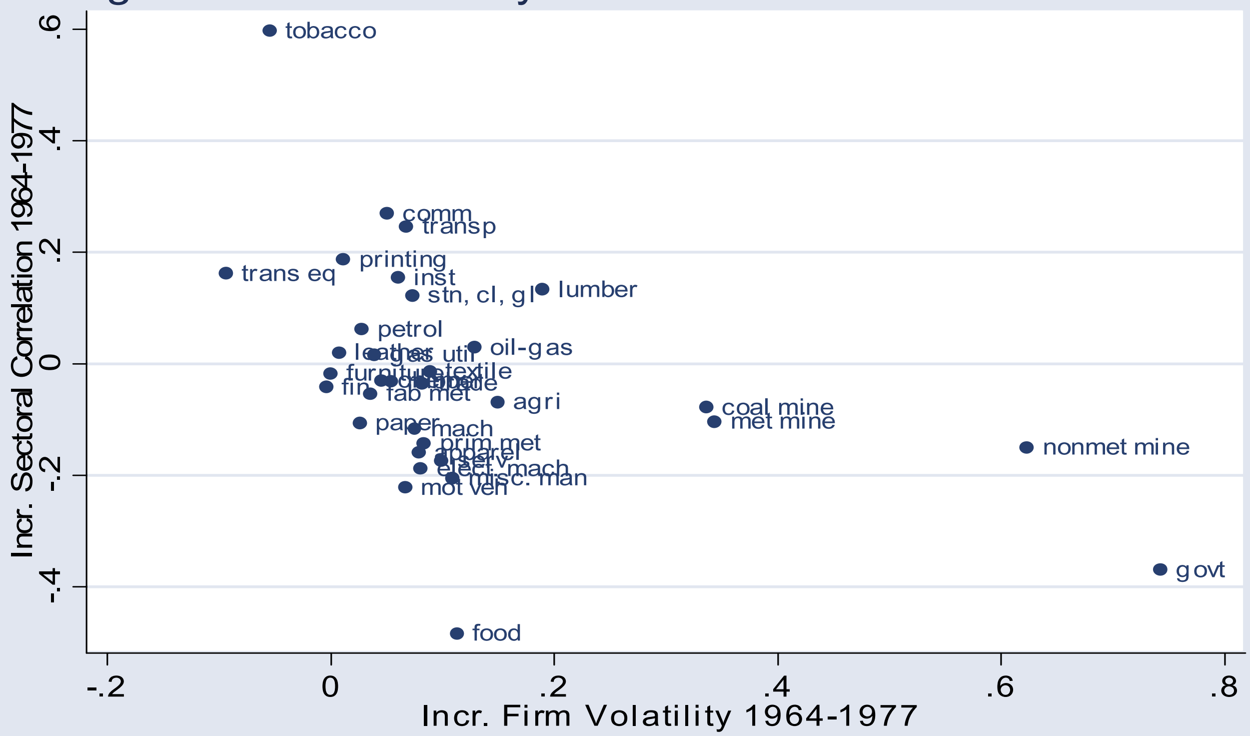


Fig. 10b: Firm Volatility and Sectoral Correlation 1978-1991

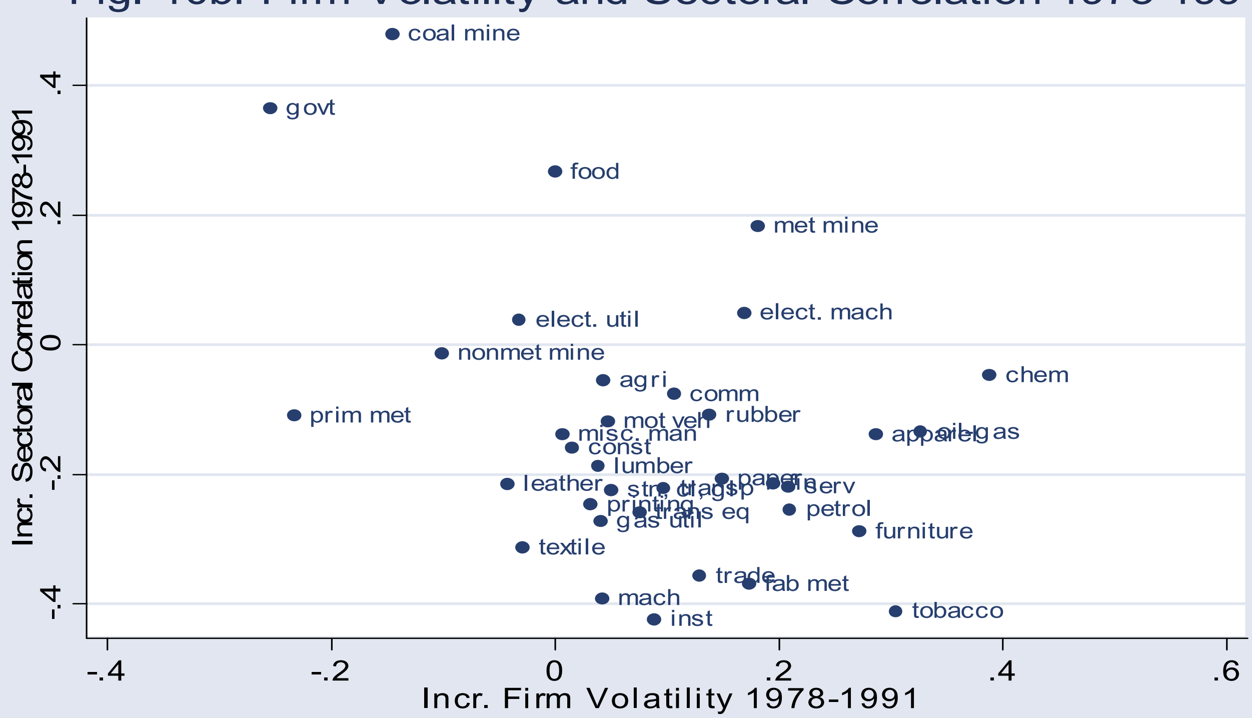


Fig. 11a: Aggregate Volatility in a Cross-Section of Countries

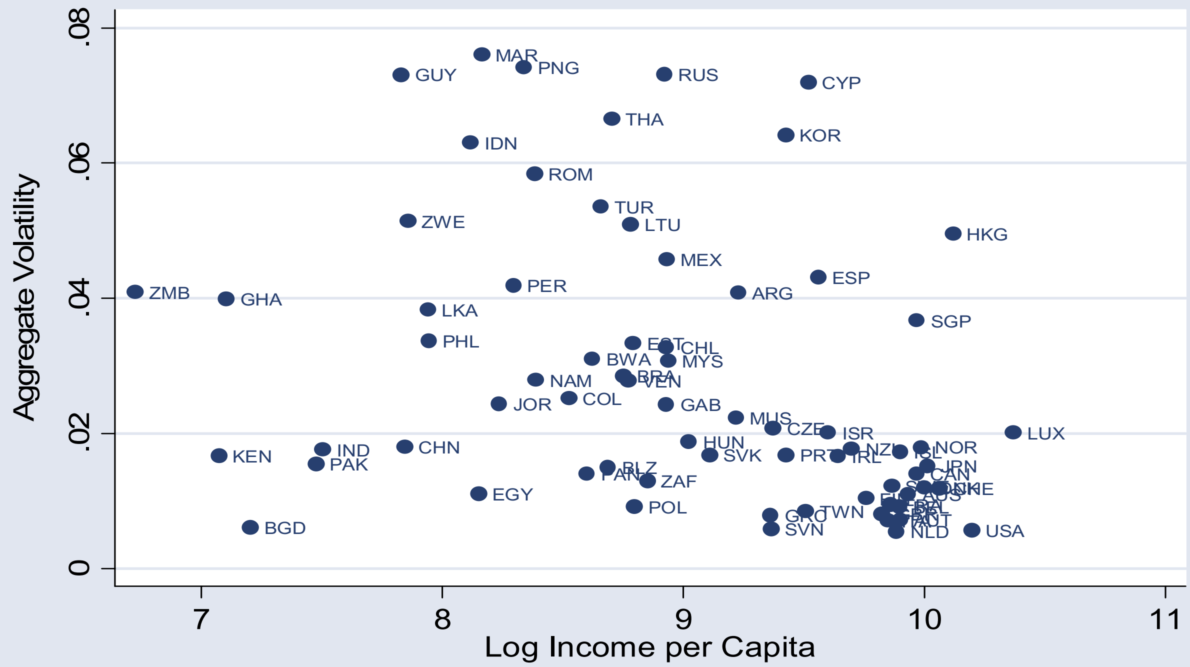


Fig. 11b: Firm Level Volatility in a Cross-Section of Countries

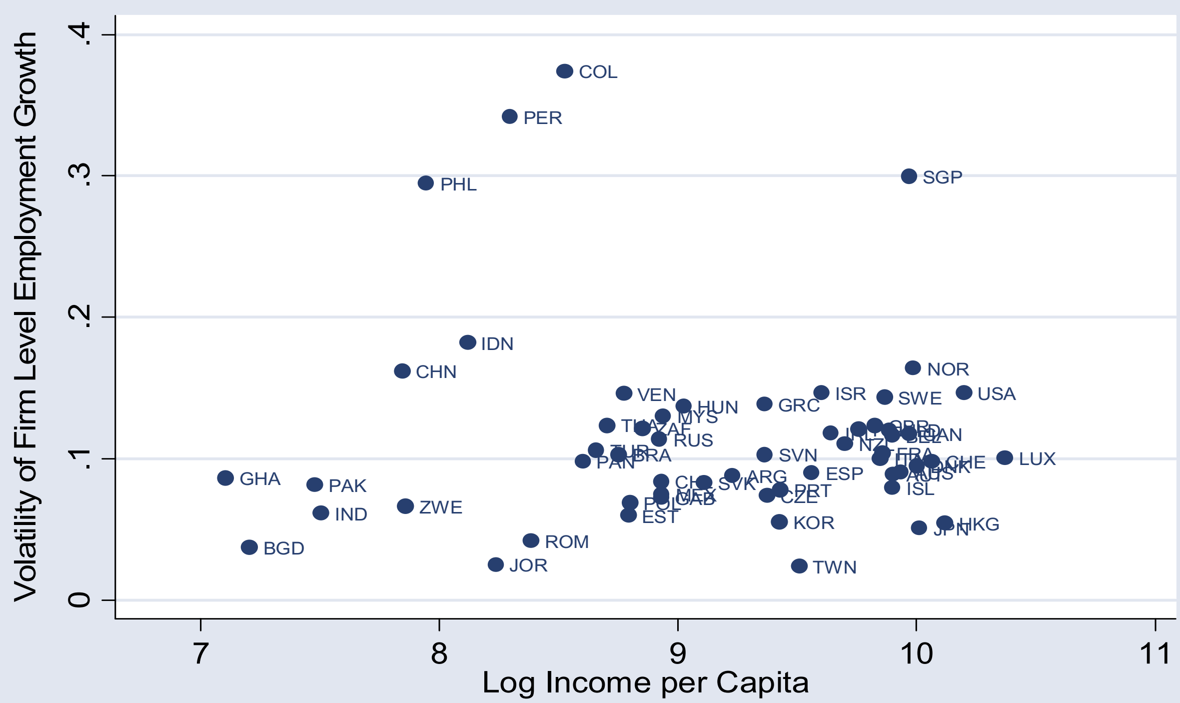


Fig. 12a: Aggregate and Firm Volatility
Cross-Section of Countries

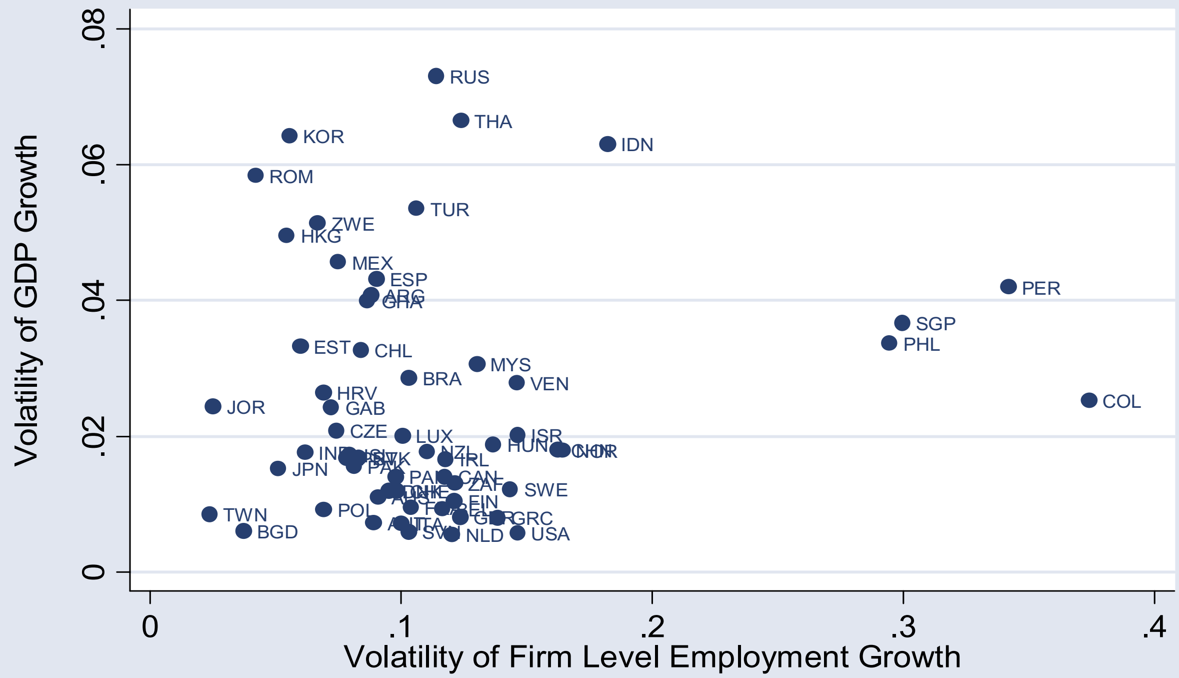
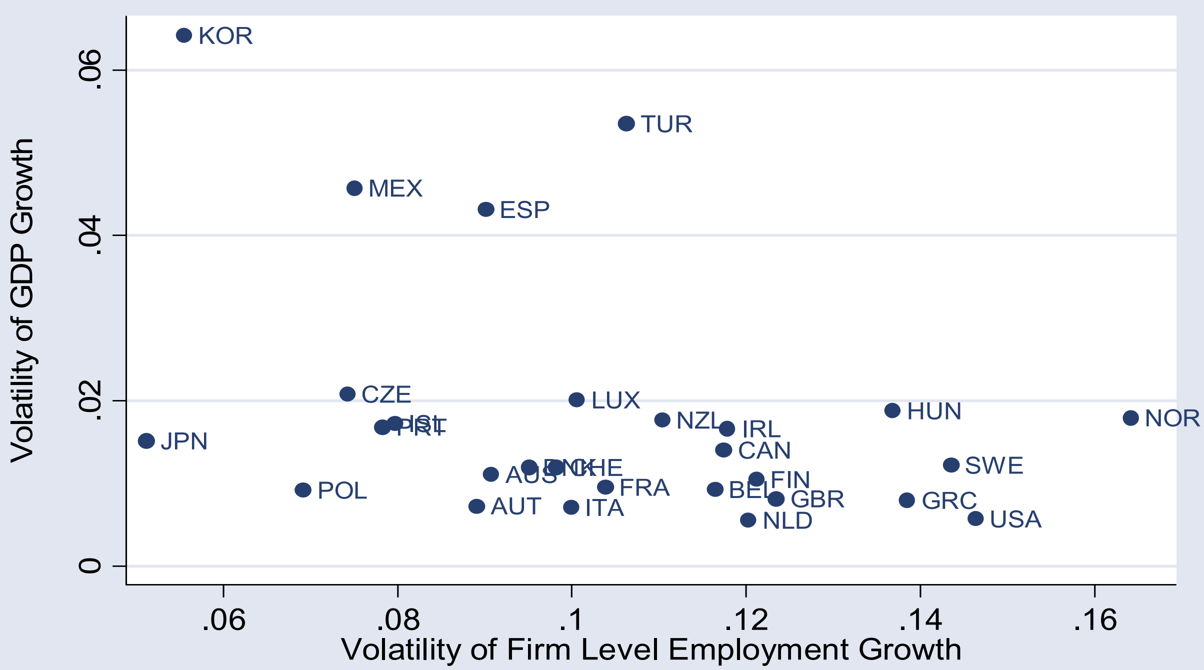


Fig. 12b: Aggregate and Firm Volatility
Cross-Section of OECD Countries



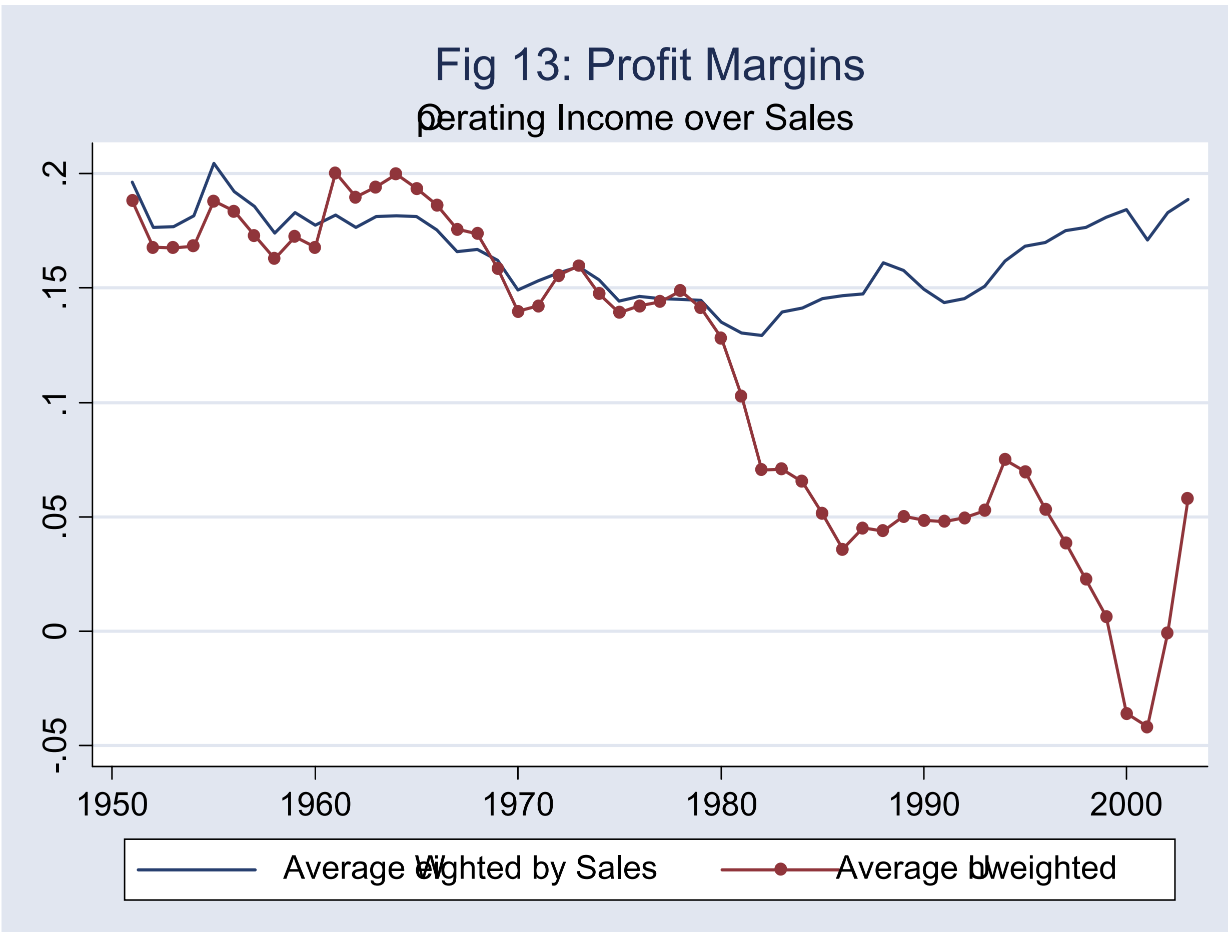


Fig 13: Profit Margins
Operating Income over Sales
-.05
0
.05
.1
.15
.2
1950
1960
1970
1980
1990
2000
Average Weighted by Sales
Average Unweighted

Fig 14: Deregulation and Sales Volatility

Relative to Non Deregulated Firms

Note: Firm Volatility is the Standard Deviation of Sales Growth over Past 5 Years

Fig. 15a: Effect of R&D at t-j on Firm Volatility at t

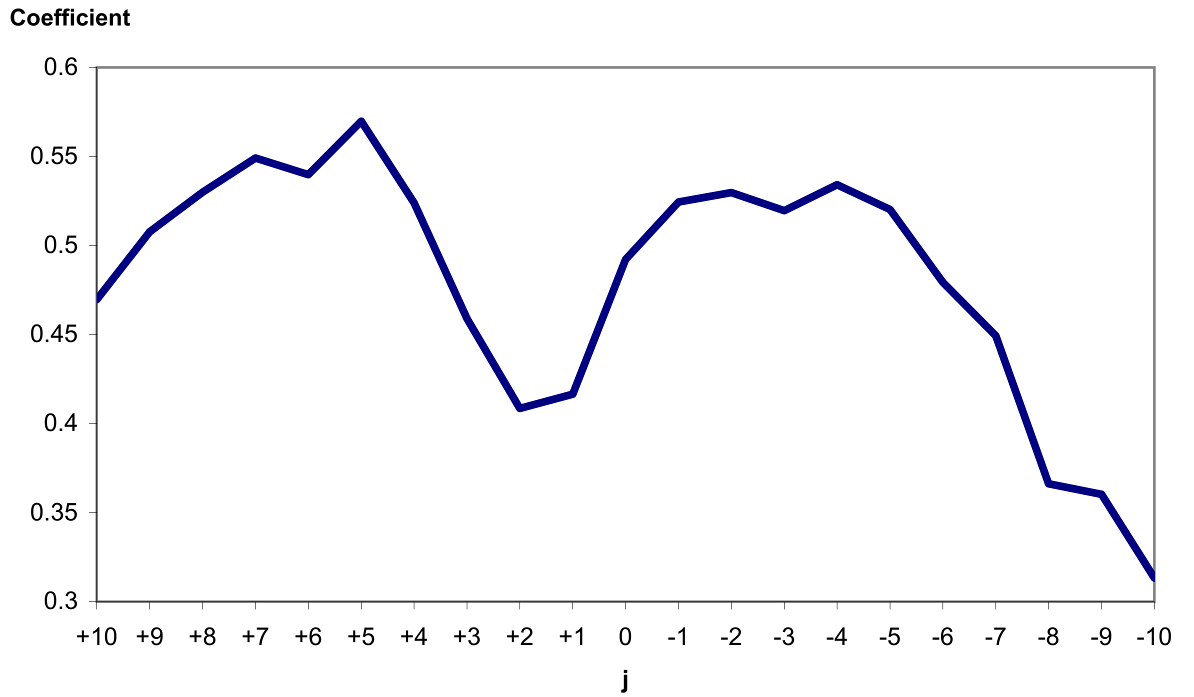
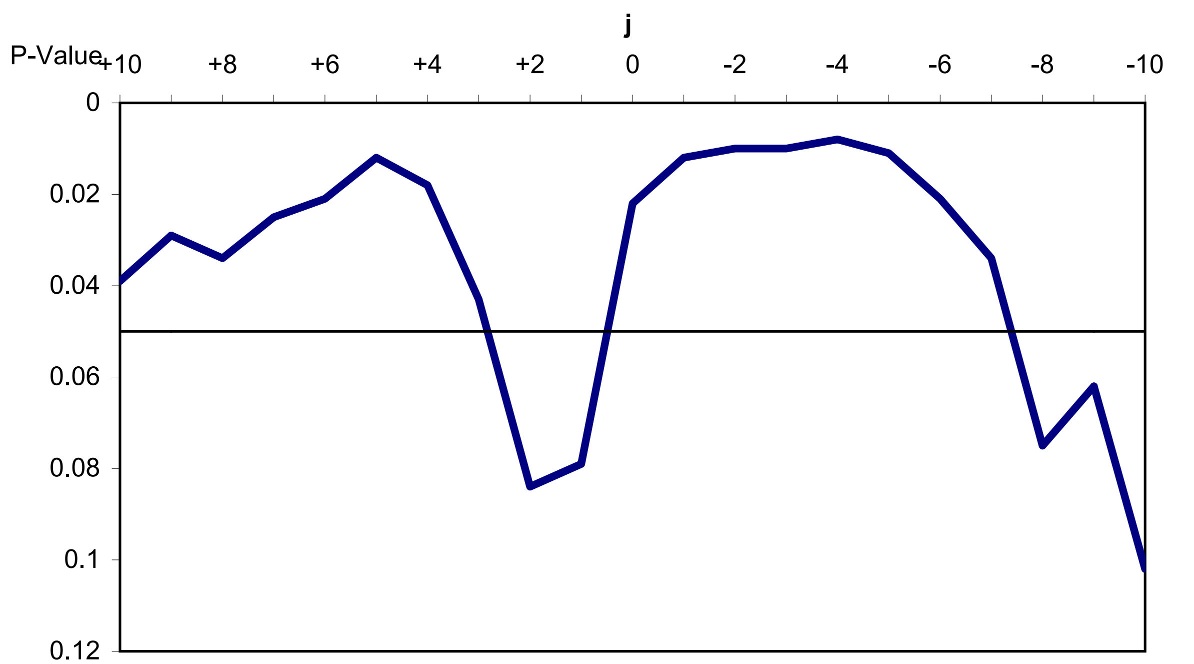
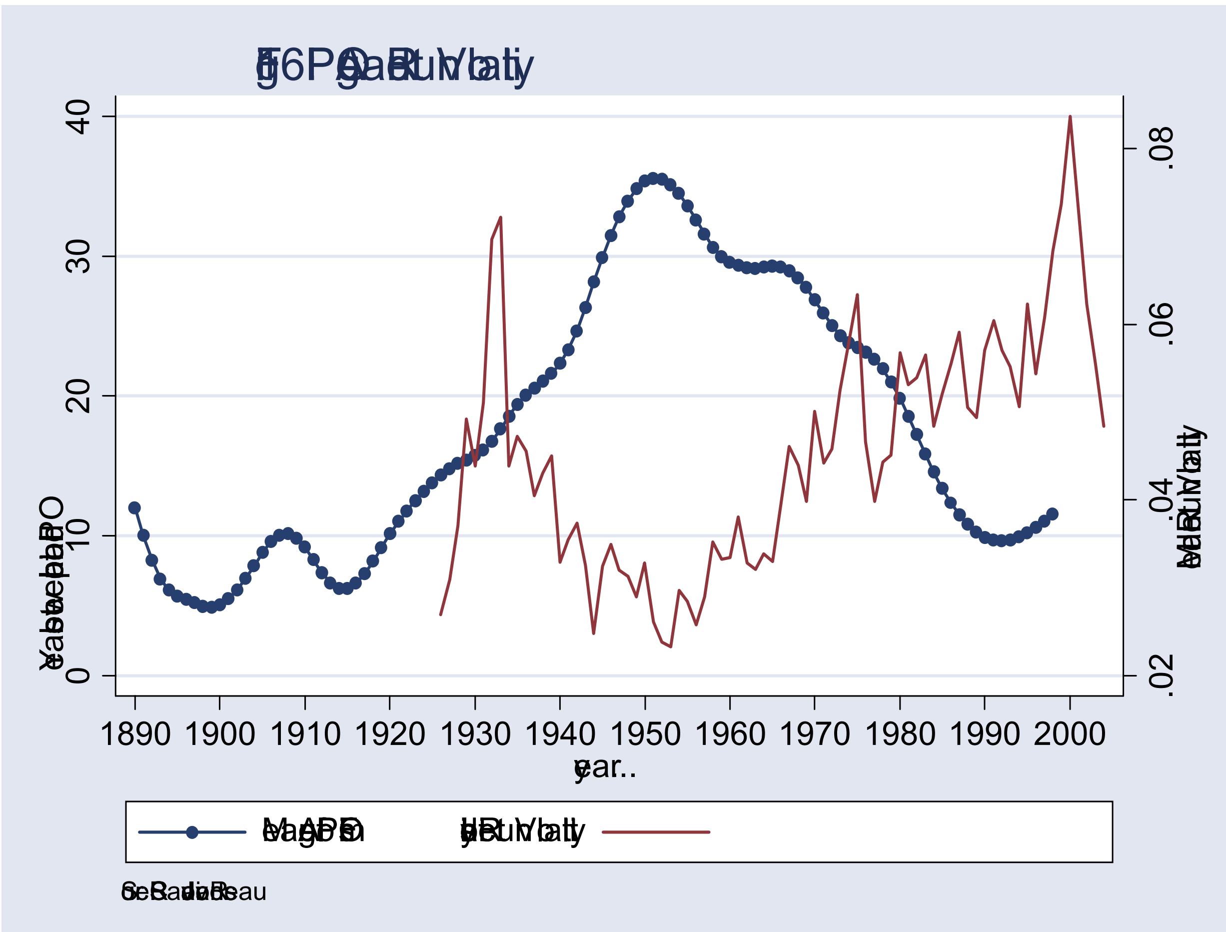


Fig. 15b: P-value of the Effect of R&D at t-j on Firm Volatility at t





0
10
20
30
40
.02
.04
.06
.08
1890
1900
1910
1920
1930
1940
1950
1960
1970
1980
1990
2000