Growth and Volatility*

Jean Imbs
HEC Lausanne, Swiss Finance Institute
and CEPR

July 2006

Abstract

Growth and volatility correlate negatively across countries, but positively across sectors. Analytically, whether or not sectoral growth and volatility are correlated positively is irrelevant in the aggregate. Cross-country estimates identify the detrimental effects of macroeconomic volatility on growth, but they cannot be used to dismiss theories implying a positive growth-volatility coefficient, which appear to hold in sectoral data. In particular, volatile sectors command high investment rates, as they would in a mean-variance framework.

Keywords: Sectors, Growth, Volatility.
JEL Classification: E32, O40

*Comments from audiences at ESSIM, the CEPR Conference on Productivity, Technology and Growth (Alghero), UQAM, University of Liverpool, INSEAD, University of Michigan, the NY Fed and UCSD all helped improving this paper. Most of this work was completed while I was a Resident Scholar at the IMF Research Department, whose hospitality I gratefully acknowledge. I am indebted to Denis Gromb, Fabio Canova, an anonymous referee and Bob King for helpful comments. Thanks are due to the Leverhulme Foundation and the National Center of Competence in Research "Financial Valuation and Risk Management" for financial support. The National Centers of Competence in Research (NCCR) are a research instrument of the Swiss National Science Foundation. HEC Lausanne, Dept of Economics, BFSH 1, Lausanne Switzerland 1015. jimbs@unil.ch. +41 21 692 3365.

1 Introduction

The link between economic growth and volatility is theoretically ambiguous. Endogenous growth will be affected by business cycle volatility, negatively in the presence of irreversibility or diminishing returns to investment, positively in the presence of precautionary saving, innovative creative destruction, liquidity constraints or if high returns technologies also entail high risks.[1] Ramey and Ramey (1995) present evidence that countries with highly volatile GDP grow at a lower rate, particularly so in a reduced sample of OECD countries.[2]

But that aggregate growth and volatility should correlate negatively does not clinch the theoretical case. It is entirely possible for instance that creative destruction or a positive correlation between risk and returns should prevail in disaggregated data, but remain masked by aggregation. Suppose volatile sectors grow faster in two countries, but growth is higher everywhere in the first country. Aggregate growth will be higher there, too, but low aggregate volatility is possible if growth rates happen to be uncorrelated across sectors. If volatile sectors grow fast, but sectoral growth rates are negatively correlated, aggregate volatility will be low in fast growing economies, as in Ramey and Ramey (1995) [henceforth RR].[3]

In other words, a negative link between aggregate growth and aggregate volatility could but mean aggregate shocks are large and important in low growth economies.

[1] Irreversibility does not necessarily lower investment, as it also creates an "overhang" effect, whereby capital ends up accumulating faster than is optimal. For detailed exposition of these arguments, see Abel and Eberly (1999), Pindyck (1991), Ramey and Ramey (1991, 1995), Black (1987), or the literature review in Aghion and Howitt (1998). Jones, Manuelli and Stacchetti (2000) show that a standard neo-classical model with endogenous growth is able to generate either relation, depending on the parametrization of preferences and the nature of shocks. Scott and Uhlig (1999) introduce "fickle" agents, whose investment choices reflect their dislike for volatility. Jovanovic (forthcoming) shows pre-commitment to a risky technology results in a negative time-series relation between growth and volatility, but may imply a positive cross-sectional link. Barlevy (2004) shows a negative relation obtains as soon as growth is concave in investment.

[2] These results are largely confirmed in Martin and Rogers (2000), who use European regional data, and a slightly different international sample. To be precise, Martin and Rogers find a coefficient non-different from zero for a large sample of 97 countries, but negative in a reduced sample focused on developed economies. Ramey and Ramey find a substantially smaller (in absolute value) negative coefficient in a sample of 92 countries than in a reduced sample of 24 OECD countries.

[3] RR also show that investment rates are not lower in volatile countries, and infer that the growth effects of aggregate volatility work through lower technology adoption rather than capital accumulation. But again, it is entirely possible that aggregate volatility should leave aggregate investment unchanged, and it is the allocation of the available pool of capital that responds to risk differentials, for instance following standard portfolio theory.

And in fact, the paper shows that aggregate estimations will only capture the covariance between sectoral growth and the *country* specific component of aggregate variance. That aggregate volatility should correlate negatively with aggregate growth reflects that the country specific component of aggregate variance, for instance fiscal or monetary policy, is detrimental to aggregate growth. It does not inform the growth-volatility question beyond that.[4]

This paper investigates the growth-volatility question within an international sectoral dataset covering manufacturing activities at the three-digit level in 47 countries which is used to show that growth and volatility correlate *positively* at the sectoral level.[5] The positive correlation is significant statistically and sizable economically, particularly in a reduced sample of OECD countries. In addition, once aggregated up, these data confirm the established *negative* correlation between aggregate growth and aggregate volatility.[6] This reversal is distinct from the classic econometric argument that within- and between-group estimators can imply opposite conclusions. This is a point about slopes, not about intercepts.

The paper then proceeds with an explanation for the difference in results that is more economic in nature. With sectoral information on investment it is possible to verify whether investment rates respond to volatility, as they would in a mean-variance framework where volatility measured risk. RR showed the mechanism was absent from aggregate data. But while the pool of available investment could be invariant to volatility, its allocation across sectors may not be. The paper shows there is in most cases a significantly *positive* relationship between sectoral investment rates and sectoral volatility. Volatile sectors grow fast because they command high

[4] For instance, Acemoglu et al (2003) present evidence that aggregate volatility stems from the weakness of constraints imposed on the executive. This same variable also significantly hampers long term growth.

[5] Disaggregated data offer additional advantages from an econometric standpoint. The large cross-sectional dimension is useful when estimating the determinants of output growth, an exercise famously sensitive to the conditioning set. The higher dimensionality of the data relative to cross-country studies, and the fact that the variation of interest is specific to each country-sector pair makes it possible to account for all country and sector specific determinants of growth, both in a pure cross-section and using panel techniques.

[6] For the sake of brevity, these results are detailed in the working version of this paper. The working paper also shows the same conclusions obtain in an alternative disaggregated dataset, covering all sectors in the economy, but at a coarser level. These alternative data come from the United Nations YearBook. See Imbs (2005).

investment rates. Factor allocation across sectors may follow optimal portfolio theory, even though it surely does not across countries.

The rest of the paper is structured as follows. Section 2 develops analytical expressions for the point estimates of the coefficient on volatility in (panel) growth regressions. Section 3 presents the paper's key evidence and shows the same panel data techniques used in RR or Martin and Rogers (2000) imply a significantly positive relation between sectoral growth and volatility. Section 4 shows the relation exists as well between sectoral volatility and investment rates. Section 5 concludes.

2 Analytics

Consider $g_{ij,t}$, the growth rate of output in sector $i = 1...I$, country $j = 1...N$ and at time t, given by

$$g_{ij,t} = \gamma_{ij} + \eta_t^1 + \eta_{i,t}^2 + \eta_{j,t}^3 + \eta_{ij,t}^4 \tag{1}$$

Sectoral output growth can deviate from an average γ_{ij} because of four zero-mean, independent shocks: a global shock η_t^1 affecting all sectors in all countries, sector-specific developments $\eta_{i,t}^2$, a country specific shock $\eta_{j,t}^3$ and a residual specific to sector i in country j, $\eta_{ij,t}^4$.[7]

We seek to obtain analytical expressions for the point estimate of the coefficient on volatility in an aggregate growth regression. Growth and variance at the country level are given by

$$\begin{aligned} E_t\left(\frac{1}{I}\sum_i g_{ij,t}\right) &= \frac{1}{I}\sum_i \gamma_{ij} \equiv \Gamma_j \\ V_t\left(\frac{1}{I}\sum_i g_{ij,t}\right) &= \theta^1 + \theta_j^3 + \frac{1}{I^2}\sum_i \theta_{ij}^4 \equiv \Sigma_j \end{aligned}$$

where $\theta^1 = E_t\left[\left(\eta_t^1\right)^2\right]$, $\theta_j^3 = E_t\left[\left(\eta_{j,t}^3\right)^2\right]$, $\theta_{ij}^4 = E_t\left[\left(\eta_{ij,t}^4\right)^2\right]$ and for simplicity all sectors are assumed to have the same share in aggregate output.[8] Across countries,

[7]This follows an enormous literature proposing to decompose various macroeconomic variables into their country, sector or global components. Early contributors include Costello (1993), Stockman (1988) or Norrbin and Schlagenhauf (1990). More recently, see Kose et al (2003) or Koren and Tenreyro (forthcoming).

[8]Introducing actual weights only complicates the derivation without altering the intuition. We have assumed $E_t\left[\eta_{ik,t}^4 . \eta_{jk,t}^4\right] = 0$ for all $i \neq j$. This simplifies the algebrae, with identical intuition.

the empirical link between growth and volatility is given by estimates of β in

$$\Gamma_j = \alpha + \beta \ \Sigma_j + \varepsilon_j \tag{2}$$

By definition,

$$\hat{\beta} = \frac{\frac{1}{I}\sum_i cov\left(\gamma_{ij} \ ; \theta_j^3\right) + u}{var\left(\Sigma_j\right)}$$

with $u = cov\left(\frac{1}{I}\sum_i \gamma_{ij} \ ; \frac{1}{I^2}\sum_i \theta_{ij}^4\right)$, and making use that θ^1 is constant across countries. The sign of $\hat{\beta}$ is given by its numerator. The first term captures the covariance between growth and the country specific component of Σ_j, e.g. the volatility of monetary or fiscal shocks. This is the very component of aggregate volatility that is argued to hamper growth in the literature. For instance, RR instrument output volatility by that of government spending. Fatas and Mihov (2003) find that the component of aggregate volatility detrimental to growth is precisely that arising from exogenous fiscal shocks. Acemoglu et al (2003) show that the cross-section of θ_j^3 is well explained by a variable capturing constraints on the executive, which also accounts for poor growth performance. In all these cases, Σ_j is approximated or instrumented by θ_j^3. Thus, it seems to be empirically plausible that $cov\left(\gamma_{ij} \ ; \theta_j^3\right) < 0$. But that possibility is silent on the sector-level relation between growth and volatility, which is driven by the covariance between γ_{ij} and $\sigma_{ij} = \theta^1 + \theta_i^2 + \theta_j^3 + \theta_{ij}^4$. That covariance enters estimates of β only indirectly.

The sign of u is indeterminate in general, but the expression is negligible for large I. This is important, for this is also the only term through which the sectoral link between growth and volatility affects aggregate estimates. To see this more clearly, suppose growth and volatility correlate *perfectly* at the sectoral level. In particular, assume γ_{ij} is perfectly correlated with the sector-level component of σ_{ij}, i.e. $\theta_i^2 + \theta_{ij}^4$. When all sectors have the same weights, this is equivalent to assuming that γ_{ij} and θ_{ij}^4 correlate perfectly.[9] Then,

$$\hat{\beta} = \frac{\frac{1}{I}\sum_i cov\left(\gamma_{ij} \ ; \theta_j^3\right) + \frac{1}{I^3} var\left(\theta_{ij}^4\right)}{var\left(\Sigma_j\right)}$$

In general and for a large number of sectors, the second term in $\hat{\beta}$ is negligible. As a result, an estimate of β will tend to have the sign of $cov\left(\gamma_{ij} \ ; \theta_j^3\right)$: it will tend to

[9] θ_i^2 would enter the expression for $\hat{\beta}$ under a more general weighting scheme, but the exact same intuition would follow.

capture the effect of macroeconomic volatility on growth, which an extensive empirical literature has proved to be negative. This is true irrespective of the effective signs of $cov\left(\gamma_{ij}\ ;\theta_i^2\right)$ and $cov\left(\gamma_{ij}\ ;\theta_{ij}^4\right)$, i.e. irrespective of how sectoral growth and volatility correlate. To fix ideas, Figure 1 illustrates the possibility that $\hat{\beta}$ be significantly negative, even though the covariance between γ_{ij} and σ_{ij} is unambiguously and significantly positive. As the Figure suggests, the two are far from mutually exclusive.

In other words, (i) the sectoral link between growth and volatility is irrelevant for aggregate estimates, (ii) what matters for aggregate estimates is the country specific component of aggregate volatility, θ_j^3. That $\hat{\beta}$ should be negative cannot be used to draw inferences on what theories are supported by the data. Such inferences must build on separate estimates based on disaggregated data. These empirics are the purpose of the rest of the paper.

3 Data and Methodology

This Section first describes the dataset used in the paper, and discusses how the growth-volatility relation is estimated using sectoral information. The econometrics follow closely RR to facilitate comparison with existing results.

3.1 Data

Our data contain yearly sectoral value added, employment and factor content in manufacturing activities, published by the United Nations Industrial Development Organization (UNIDO). Although observations go from 1963 to 1996, the data are incomplete at the beginning and end of the sample.[10] In order to limit the number of missing observations, the period of focus extends from 1970 to 1992, which selects a maximum of 47 countries, listed in the Appendix. Sectoral data present a specific difficulty, as the collection of observations on a given activity may begin in the middle of the sample. This makes it hard to differentiate between a new sector

[10] The "System of National Accounts" was changed in 1993, which is why sectoral information comparable over time and across countries typically becomes incomplete after 1992.

emerging and a simple measurement problem.[11] The issue is particularly relevant when attempting to decompose aggregate variables into sectoral components. Thus, sectors without observations from 1970 are arbitrarily excluded from the sample. The main purpose of this truncation is to avoid confusing newly introduced activities with mere improvement in the collection of sectoral information. It should not affect the aggregation effect this paper documents.[12] The number of sectors in each country remains constant over time, but varies (arbitrarily) across countries.[13]

A subset of the UNIDO data composed of OECD economies only is also considered, which reduces the sample to 23 countries. The purpose of this reduced dataset is to focus on economies at a comparable stage of development. The OECD sample excludes developing countries where industrialization -and the associated structural change- has played an important role in economic growth. Structural change is directly related to the correlation between sectoral growth rates in a given country, and thus to the difference between aggregate volatility and the sum of sectoral volatilities. By definition, aggregate volatility differs from the sum of its components to an extent that increases with the covariance between sectoral growth rates. It may therefore be amongst rich economies, where this covariance might be highest, that aggregation plays a most important role as regards the growth-volatility question.[14]

There is a maximum of 28 sectors, listed in the Appendix. Value added is deflated by Producer Price Index series, taken from the International Monetary Fund's International Financial Statistics.[15] Data on aggregate capital and output growth rates come from the Penn-World Tables. Table 1 presents some summary statistics on the cross-section of γ_{ij} and σ_{ij}. On average, the variance of sectoral output is larger in the extended sample, suggesting output in manufacturing sectors is more stable in

[11] See Imbs and Wacziarg (2003) for details.

[12] The truncation eliminates emerging and relatively new sectors, which are precisely those where one would expect both high growth and high volatility. Thus, the truncation tends to bias the growth-volatility link downward, which goes against the main result in this paper. Furthermore, in the working paper version of this paper, an alternative, coarser, dataset where this problem does not exist is used to show the same results.

[13] Sectors whose definitions in the ISIC classification system vary in the sample are also eliminated. These arbitrary truncations are later accounted for via country fixed-effects. Finally, outliers are excluded, but their inclusion only reinforces the results.

[14] Comin and Mulani (2006) make a similar point when going from firm-level volatility to the aggregate.

[15] Or alternatively an index of industrial production when the PPI was not available. This follows Rajan and Zingales (1998).

developed economies. This could be reflecting at the sectoral level the well-known fact that aggregate volatility tends to decrease with the level of economic development.[16] The unconditional correlation between average sectoral growth and its variance over time is positive in both cases, albeit not significantly.

3.2 Methodology

The effects of sectoral volatility on growth are given by panel estimates of β_1 in

$$\ln y_{ij,T} - \ln \ y_{ij,T-1} = \beta_1 \ V_T \ \left(\Delta \ln y_{ij,t}\right) + \beta_2 \ \ln X_{ij,T} + \alpha_i + \alpha_j + \delta_T + \varepsilon_{ij,T} \tag{3}$$

where $y_{ij,t}$ is sectoral value added in sector i, country j and time t, $X_{ij,T}$ is a vector of control variables and $V_T\left(.\right)$ denotes the variance operator, computed over period $[T-1, T]$. α_i denotes a sector specific intercept, reflecting the inherent (permanent) tendency of some sectors to display high volatility, for instance because of durability. α_j captures time-invariant country characteristics liable to affect both aggregate volatility and growth, such as political instability or the measure of "constraints on the executive" proposed by Acemoglu et al (2003).[17] The sub-period index T reflects arbitrary partitions of the time-dimension of the data. δ_T is a period dummy variable.

Because of its disaggregated nature, a difficult and relatively uncharted issue in equation (3) is what to include in the set of controls $X_{ij,T}$. A stylized model may be helpful. Consider a two-country two-sector world with two factors of production, capital and labor. Assume sector 1 is capital-intensive and sector 2 labor-intensive. Suppose country A has a higher aggregate capital-labor ratio than country B. With aggregate diminishing returns to capital, country B accumulates capital faster, and factor price equalization favors growth in sector 1 there. Similarly, factor price equalization and neoclassical convergence suggest sector 2 will grow relatively faster in country A. Thus, from a theoretical point of view, the determinants of relative sectoral growth are two-fold. First, a variable capturing country specific capital accumulation interacted with sector specific capital content. This is the approach adopted

[16] See Kraay and Ventura (2001) or Koren and Tenreyro (forthcoming).

[17] As the number of sectors used in obtaining the aggregate data varies (potentially arbitrarily) between countries, it is necessary to control for country effects.

in Bernard and Jensen (2001), who show sectoral factor content is important in explaining higher than average sectoral output growth in a cross-section of US regions. A similar term is included in equation (3). Although UNIDO provides information on (nominal) sectoral wage bill and value added, the resulting labor shares tend to be noisy. In addition, an assumption of constant returns to scale must be maintained in all sectors if the capital share is to be inferred from the wage bill, which is not uncontroversial empirically.[18]

Fortunately, the previous simple model suggests an alternative. If initial sectoral specialization patterns correspond to the balance of aggregate endowments, i.e. if sector 1 is initially larger in country A and sector 2 is larger in country B, then in both countries the fastest growing sector is also the smallest initially. This occurs because of diminishing returns to capital, and suggests including a measure of the initial size of each sector in equation (3). Another, more technical reason to include a term capturing initial conditions in equation (3) is related to transition dynamics in the usual neoclassic sense. These are potentially important here as they tend to result in high and fast decreasing growth, and thus a growth rate with both high mean and high variance. This may result in an upward bias when estimating the relationship between growth and volatility.[19] The initial share of each sector in value added is therefore added to equation (3), and a negative sign can be attributable either to a convergence term or to comparative advantage.[20]

For comparability, the estimation strategy seeks to mimic the methods implemented in the relevant literature. Martin and Rogers (2000) use cross-sectional estimators, based on both regional and international evidence, akin to equation (3). RR introduce dynamics, and estimate the correlation between growth and the variance in its non-predictable component, as measured by the residual of a forecasting equation for GDP growth. This is potentially important, as it accounts for the possibility that high growth be intrinsically volatile, because the determinants of growth also happen

[18] See for instance Burnside, Eichenbaum and Rebelo (1996)

[19] Since this bias is positive, it is particularly relevant here. However, Imbs and Wacziarg (2003) show that the notion of a "steady state economic structure", to which growing economies would converge, is not supported by the data. Countries first diversify, thus allocating resources across sectors increasingly equally, but start re-specializing once they reach a relatively high level of income per capita.

[20] The same results obtain when aggregate capital-labor ratios are interacted with sectoral dummy variables.

to translate in high volatility. Both papers find a significantly negative coefficient, particularly in a reduced sample of OECD countries.

For completeness, therefore, we also follow RR in estimating jointly

$$\begin{aligned} \ln\ y_{ij,t} - \ln\ y_{ij,t-1} &= \beta_0 + \beta_1\ \tilde{\sigma}_{ij} + \beta_2\ X_{ij,t} + \varepsilon_{ij,t} \\ \tilde{\sigma}_{ij} &= V_t\ (\varepsilon_{ij,t}) \end{aligned} \tag{4}$$

Equations (3) and (4) constitute the empirical backbone of the paper. In both cases, attention is paid to reproducing as closely as possible across sectors what has been done across countries with well known results.[21]

4 Growth and Volatility

This Section discusses results of estimating equations (3) and (4) on disaggregated data, for the complete dataset comprising 47 countries, and then for the reduced sample of OECD economies.[22] All estimates are reported in Table 2. Panels A, B and C correspond to equation (3), computed over different numbers of sub-periods, and Panel D corresponds to equation (4), where volatility is that of the residual in the growth equation.

Estimates of β_1 in Table 2 are overwhelmingly positive and significant. Of the sixteen specifications, only three are insignificant, and they obtain in the large sample of 47 countries. The estimates are always positive and significant in the reduced sample, no matter the controls, sub-periods or estimation techniques. This constitutes the paper's main empirical contribution. From the point of view of the positive bias that could arise from transitional dynamics, it is reassuring that estimates of β_1 should be most positive in the sample where this bias is a priori least prevalent, i.e. in the OECD. Second, in both RR and Martin-Rogers, it is within a reduced sample

[21] In fact, the working version of this paper verifies that the very same data, once aggregated up at the country level, indeed implies a negative relation between growth and volatility. With or without the control variables that now belong in standard cross-country growth regressions, the UNIDO data do imply that aggregate volatility affects growth negatively, for the aggregated versions of both equations (3) and (4). This is true as well in an alternative, coarser but more exhaustive dataset. Finally, as in RR or Martin-Rogers (2001), the evidence on a negative coefficient is most pronounced amongst OECD economies.

[22] The Appendix lists countries in both samples.

of OECD countries that the aggregate evidence is most significantly negative (and the working version of this paper verifies this is the case in the present data as well, once aggregated up). It is in this very sample that the reversal of the evidence is most prevalent, which is consistent with the hypothesis that aggregate volatility differs most from the sum of its sectoral components in developed economies, where sectoral growth rates tend to be synchronized.

In addition, the Table suggests some support for the possibility that capital intensive sectors grow faster in capital rich economies, with coefficients on the corresponding interaction term estimated to be positive, though not always significant. This confirms findings in Bernard and Jensen (2001) in an international dataset, and controlling for both country and sector-specific intercepts. Similarly, there is some evidence in favor of a significant convergence term in Panels A, B and C. Initially smaller sectors tend to grow subsequently faster, and volatility tends to lose some significance once initial conditions are controlled for. This confirms the potential importance of transitional dynamics in explaining why growth relates positively to volatility in the extended sample.

Figure 1 illustrates the paper's point in the growth-volatility space for three countries A, B and C, and two sectors 1 and 2.[23] The relation between growth and volatility is negative between countries, yet positive between sectors. It is because the question has so far been addressed within international datasets that growth and volatility are presumed to correlate negatively. Between sectors, it is the opposite.

5 Investment and Volatility

An explanation for the reversal documented in this paper is the possibility that aggregation should obscure a negative relation between volatility and investment, as implied for instance by a mean-variance framework. In the aggregate, RR reject any relation at all, and the working version of this paper confirms the same result obtains in the aggregated version of the present data. But while the aggregate pool of invest-

[23] The point developed here was first proposed by Canova and Marcet (1995) in an application to cross-country growth regressions.

ment does not respond to volatility, it is entirely possible that its allocation across sectors does. This is next investigated.

Both RR and Martin-Rogers (2000) estimate versions of equations (3) and (4) where the dependent variable is the investment rate, and investigate whether volatility enters significantly.[24] Table 3 reproduces the approach in a disaggregated dataset. The results suggests the response of investment rates to sectoral volatility is always strongly positive and significant in the OECD sub-sample, irrespective of the conditioning variables. This stands in stark contrast with the aggregate evidence in RR, and with the results implied by an aggregated version of the sectoral data in this paper.[25]

These results suggest that investment is stronger in volatile activities. Sectoral data lend support to a diversification motive akin to the one described in Obstfeld (1994), where reallocation of resources from safe low-yield to risky high-yield activities is shown to have substantial growth and welfare effects. Since the aggregate evidence appears to invalidate this mechanism, the results in this paper call for some reappraisal of our interpretation of the data, with potentially important welfare consequences. For instance, RR conclude in saying: "Investment-based theories of the link between volatility and growth do not seem to be verified by the data" (p.1148). This paper suggests otherwise.

This may have far ranging implications in light of some of the recent work seeking to evaluate the welfare costs of business cycles fluctuations. Since Lucas (1987) argued business cycles had a minute welfare cost relative to what could be gained from higher growth, numerous papers have sought to relate growth itself to the business cycle, not least in reaction to the empirical evidence proposed by RR.[26] As argued in Barlevy

[24] Investment intensity is measured by the average of the ratio of sectoral investment to sectoral value added, both expressed in nominal terms. Using initial values does not change any of the results.

[25] Growth, volatility and investment could move in unison at the sectoral level because of lumpiness in investment, averaged away in the aggregate. A sector growing fast through capital accumulation would display high investment rates as well as highly volatile growth rates just because sectoral investment is lumpy. This would also translate in skewed sectoral output growth rates, as they would tend to peak (plummet) whenever investment (disinvestment) occurs. In unreported results, measures of skewness in output growth rates are included in all estimations in Table 3. None of the results are altered, and skewness is insignificant more often than not.

[26] See among many others Mendoza (1997), Jones, Manuelli and Stacchetti (1999), or Epaulard and Pommeret (2003).

(2004), the mechanism common to these papers is an effect on the level of investment. Getting rid of economic fluctuations can increase growth as it increases the *average* rate of investment, but it is bound to give rise to small welfare gains only, since then initial consumption has to decrease. Barlevy argues the mechanism was invalidated by RR, who find investment is not responsive to volatility. Instead, he introduces a model where a decrease in the *volatility* of investment has growth effects because of diminishing returns to investment. Thus, reducing the volatility of the business cycle can have large welfare benefits for a given level of initial investment and consumption.

There are several ways in which the results in this paper inform the welfare question. From a modeling standpoint, disaggregated data point to an effect of uncertainty that works through the average level of investment, with a positive sign. That is not inconsistent with models in Jones, Manuelli and Stacchetti (1999) or Epaulard and Pommeret (2003) for instance, with adequate utility parameters. At the sectoral level, the positive responses of *average* investment and growth to volatility suggest negative (and probably small) welfare costs of fluctuations, because lowering volatility would now *increase* initial consumption and lower growth. Inasmuch as diminishing returns to investment continue to prevail (homogeneously) at the sectoral level, the volatility of investment may continue to retard growth, with the large welfare costs simulated by Barlevy. But now, responses in the level and the volatility of investment work in opposite directions, with ambiguous end effects. Results in this paper seem to suggest the former effect dominates and/or sector-level estimates of the return to investment are not as homogeneously diminishing as they are in the aggregate.

In particular, estimates for β_1 in Table 2 range from 0.15 to 0.65 for OECD countries. Using an average value of 0.4, and a standard deviation for per capita growth equal to 2.5 percent as in the US, this suggests eliminating volatility would increase the annual growth rate by a full percentage point. According to Lucas, this represents a fifth of consumption.[27] Of course, the exercise has only limited value, since sectoral volatility of output is only part of what a representative agent would want to insure against. As a matter of fact, one of the key points of this paper is to argue aggregate output volatility tends to average away sector specific development, whose volatility is precisely where estimates in Table 2 stem from. The last word will

[27] This follows exactly Barlevy (2004).

require a model of sectoral and aggregate volatility, and potential heterogeneity in the returns to investment at the sector level. This is outside of this paper's scope.

6 Conclusion

This paper provides novel evidence on an old question. For sufficiently disaggregated data, volatile activities within countries grow fast, and command high investment rate. This does not necessarily contradict the aggregate evidence, which isolates a component of aggregate volatility that is common across all activities and happens to correlate negatively with growth. By contrast, sectoral data isolates a component of aggregate volatility that is specific to each sector, and tends to be associated with high growth. As a result, risk and return can be positively correlated, even though volatile countries experience lower growth. Aggregation may obscure the empirical verdict on a number of fundamental macroeconomic issues, ranging from the validity of the mean-variance framework, the relevance of creative destruction or the irreversibility of investment, to the welfare cost of economic fluctuations.

Appendix: Coverage

UNIDO Three-Digit Classification (28 sectors)

300 Total manufacturing

311 Food products

313 Beverages

314 Tobacco

321 Textiles

322 Wearing apparel, except footwear

323 Leather products

324 Footwear, except rubber or plastic

331 Wood products, except furniture

332 Furniture, except metal

341 Paper and products

342 Printing and publishing

351 Industrial chemicals

352 Other chemicals

353 Petroleum refineries

354 Miscellaneous petroleum and coal products

355 Rubber products

356 Plastic products

361 Pottery, china, earthenware

362 Glass and products

369 Other non-metallic mineral products

371 Iron and steel

372 Non-ferrous metals

381 Fabricated metal products

382 Machinery, except electrical

383 Machinery, electric

384 Transport equipment

385 Professional and scientific equipment

390 Other manufactured products

UNIDO Countries

Australia	Hungary	Pakistan
Austria[a]	India	Panama
Bangladesh	Indonesia	Peru
Belgium	Iran	Philippines
Canada[a]	Ireland[a]	Poland
Chile	Israel	Portugal[a]
Colombia	Italy[a]	Singapore
Costa Rica	Japan[a]	South Africa
Cyprus	Jordan	Spain[a]
Denmark[a]	Kenya	Sweden[a]
Egypt	Korea[a]	Turkey[a]
Fiji	Luxembourg[a]	United Kingdom[a]
Finland[a]	Malaysia	United States[a]
France[a]	Mexico[a]	Uruguay
Germany[a]	The Netherlands[a]	Zimbabwe
Greece[a]	New Zealand[a]	
Hong Kong	Norway[a]	

a: reduced UNIDO dataset

References

Abel, A., Eberly, J., 1999. *The Effect of Irreversibility and Uncertainty on Capital Accumulation,* Journal of Monetary Economics, 44, 3, pp.339-377.

Acemoglu, D., Johnson, S., Robinson, J., Thaicharoen, Y., 2003. *Institutional Causes, Macroeconomic Symptoms: Volatility, Crises and Growth*, Journal of Monetary Economics, v. 50, pp. 49-123

Aghion, P., Howitt, P., 1998. *Endogenous Growth Theory,* Cambridge: MIT Press.

Barlevy, G., 2004. *The Cost of Business Cycles Under Endogenous Growth*, American Economic Review, Vol. 94, No.4, pp.964-990.

Bernard, A., Jensen, B., 2001. *Who Dies? International Trade, Market Structure and Industrial Restructuring,* NBER Working Paper No. 8327.

Black, F., 1987. *Business Cycles and Equilibrium*, Cambridge, MA: Blackwell.

Burnside, C., Eichenbaum, M., Rebelo, S., 1996. *Sectoral Solow Residuals,* European Economic Review, Vol.40, pp.861-869.

Canova, F., Marcet, A., 1995. *The Poor Stay Poor: Non-Convergence Across Countries and Regions*, CEPR Discussion Paper No. 1265.

Comin, D., Mulani, S., 2005. *A Theory of Growth and Volatility at the Aggregate and Firm level*, NBER Working Paper No. 11503.

Costello, D., 1993. *A Cross-Country, Cross-Industry Comparison of Productivity Growth*, Journal of Political Economy, Vol.101, pp.207-222.

Epaulard, A., Pommeret, A., 2003. *Recursive Utility, Growth and the Welfare Costs of Volatility*, Review of Economic Dynamics, 6(2), pp. 263-86.

Fatas, A., Mihov, I., 2003. *The Case for Restricting Fiscal Policy Discretion*, Quarterly Journal of Economics, Vol.118(4), pp.1419-1448.

Imbs, J., 2005. *Growth and Volatility*, Working Paper version available at www.hec.unil.ch/jimbs.

Imbs, J., Wacziarg, R., 2003. *Stages of Diversification*, American Economic Review, Vol.93(1), pp.63-86.

Jones, L., Manuelli, R., Stacchetti, E., 2000. *Technology (and Policy) Shocks in Models of Endogenous Growth*, Federal Reserve Bank of Minneapolis Research Department Staff Report 281.

Jovanovic, B., 2003. *Asymmetric Cycles*, Review of Economic Studies, forthcoming.

Koren, M., Tenreyro, S., forthcoming. *Volatility and Development*, Quarterly Journal of Economics.

Kose, A., Otrok, C., Whiteman, C., 2003. *International Business Cycles: World, Region and Country Specific Factors*, American Economic Review, Vol. 93(4), pp.1216-1239.

Kraay, A., Ventura, J., 2001. *Comparative Advantage and the Cross-Section of Business Cycles*, NBER Working Paper No.8104, CEPR Discussion Paper No. 3000.

Lucas, R. J., 1987. *Models of Business Cycles*, Oxford: Basil Blackwell.

Martin, P., Rogers, C. A., 2000. *Long-Term Growth and Short-Term Economic Instability,* European Economic Review, Vol.44(2), pp.359-381.

Norrbin, S., Schlagenhauf, D., 1990. *The Identification of the Causes of Business Cycles Across Countries*, IMF Working Paper No. 90/4.

Obstfeld, M., 1994. *Risk-Taking, Global Diversification and Growth*, American Economic Review, 84(5), pp. 1310-1329.

Pindyck, R., 1991. *Irreversibility, Uncertainty and Investment,* Journal of Economic Literature, Vol.29(3), pp.1110-1148.

Rajan, R., Zingales, L., 1998. *Financial Dependence and Growth,* American Economic Review, Vol.88(3), pp.559-586.

Ramey, V., Ramey, G., 1991. *Technology Commitment and the Cost of Economic Fluctuations,* NBER Working Paper No. 3755, June.

Ramey, V., Ramey, G., 1995. *Cross Country Evidence on the Link between Volatility and Growth,* American Economic Review, Vol.85(5), pp.1138-1159.

Scott, A., Uhlig, H., 1999. *Fickle Investors: An Impediment to Growth?*, European Economic Review, 43(7), pp. 1345-1370.

Stockman, A., 1988. *Sectoral and National Aggregate Disturbances to Industrial Output in Seven European Countries*, Journal of Monetary Economics, 21, pp.387-409.

Table 1: Summary Statistics

	Mean	Median	Min	Max
Extended Sample (894 obs - 47 countries)				
γ_{ij}	4.03	3.39	-12.13	26.51
σ_{ij}	0.042	0.022	0.001	0.352
Correlation = 0.152				
OECD Sample (423 obs - 23 countries)				
γ_{ij}	3.15	2.81	-8.41	26.51
σ_{ij}	0.017	0.009	0.001	0.204
Correlation = 0.314				

Table 2: Growth and Volatility

	(i)	(ii)	(iii)	(iv)
A. One Period				
$V_T \ (\Delta \ln y_{ij,t})$	0.184^{***} (5.80)	0.074^{**} (2.03)	0.335^{***} (5.84)	0.471^{***} (4.83)
$\ln\ y_{ij,T-1}$		-0.008^{***} (6.91)		-0.006^{***} (3.41)
Comparative Advantage	0.005 (1.17)	0.011^{**} (2.37)	0.016 (2.65)	0.021^{***} (3.00)
Country FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
Obs	894	894	423	423
B. Two Periods				
$V_T \ (\Delta \ln y_{ij,t})$	0.099^{***} (2.86)	-0.020 (0.58)	0.549^{***} (7.78)	0.394^{***} (5.42)
$\ln\ y_{ij,T-1}$		-0.013^{***} (8.10)		-0.012^{***} (5.58)
Comparative Advantage	0.024^{***} (4.93)	0.023^{***} (4.75)	0.000 (0.08)	0.000 (0.07)
Country FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
Obs	1202	1112	647	602
C. Four Periods				
$V_T \ (\Delta \ln y_{ij,t})$	0.007 (0.27)	-0.018 (0.77)	0.206^{***} (4.27)	0.156^{***} (3.26)
$\ln\ y_{ij,T-1}$		-0.016^{***} (8.75)		-0.008^{***} (4.65)
Comparative Advantage	0.011 (2.10)	0.015^{***} (2.90)	0.004 (0.61)	0.007 (1.13)
Country FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
Obs	2527	2527	1289	1289
D. Residual Volatility				
$\tilde{\sigma}_{ij}$	0.4338^{***} (3.16)	0.4270^{***} (3.09)	0.6602^{***} (2.83)	0.6417^{***} (2.74)
$\ln\ y_{ij,0}$		$-1.41.10^{-15}$ (1.00)		$-1.32.10^{-15}$ (0.92)
Comparative Advantage	0.1198^{***} (21.79)	0.1191^{***} (21.57)	0.1057^{***} (16.91)	0.1062^{***} (16.97)
Country FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
Obs	11,052	11,011	6,352	6,352

Notes: The dependent variable is γ_{ij}. The two periods are 1970-1981 and 1982-1992, and the four periods are 1970-1975, 1976-1981, 1982-1987 and 1988-1992. Initial values are computed on the initial year of the sub-period. Variances are computed over each sub period. Period dummies are included everywhere except in panel D. t statistics are reported between parentheses. (i) and (ii) concern the whole sample; (iii) and (iv) focus on the reduced OECD sample.

Table 3: Investment and Volatility

	(i)	(ii)	(iii)	(iv)
A. One Period				
β_1	0.654^{*} (1.76)	0.235 (0.45)	0.508^{***} (3.45)	0.729^{***} (3.34)
Controls	no	yes	no	yes
Country FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
B. Two Periods				
β_1	0.454^{*} (1.57)	-0.012 (0.03)	0.481^{***} (4.21)	0.753^{***} (4.87)
Controls	no	yes	no	yes
Country FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes
C. Four Periods				
β_1	0.105 (0.66)	0.086 (0.43)	0.427^{***} (5.63)	0.405^{***} (5.25)
Controls	no	yes	no	yes
Country FE	yes	yes	yes	yes
Sector FE	yes	yes	yes	yes

Notes: The dependent variable is the investment rate in sector i and country j. The two periods are 1970-1981 and 1982-1992, and the four periods are 1970-1975, 1976-1981, 1982-1987 and 1988-1992. Controls include initial value added, the comparative advantage interaction term and period dummies.. t statistics are reported between parentheses. (i) and (ii) concern the whole sample; (iii) and (iv) focus on the reduced OECD sample.

Figure 1