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ABSTRACT

Why the Link Between Volatility and Growth Is Both Positive and Negative*

I revisit the relationship between growth and volatility in two different disaggregated datasets. I confirm that growth and volatility are negatively related across countries, but show that the relation reverses itself across sectors. This phenomenon, sometimes called the 'Simpson's fallacy', has a natural interpretation in the present context: it is the component of aggregate volatility that is common across sectors that correlates negatively with aggregate growth. Furthermore, while investment and volatility are unrelated in the aggregate, sectoral investment is shown to be more intense in volatile activities, as if the return to capital were higher there. These results call for a distinction between macroeconomic and sectoral volatilities, not unlike that between macroeconomics, where volatility often means policy-driven instability, and finance, where volatility reflects risk, and thus high returns.

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1 Introduction

The nature of the link between macroeconomic growth and volatility has long been the focus of intense scrutiny. Since Lucas's (1988) conclusion that understanding the mechanics of growth holds more promise than understanding business cycles, many authors have sought to question the dichotomy between high and low frequency macroeconomic developments implicit in Lucas's prescription. New growth theories have developed that make long-run capital deepening and technology adoption endogenous, and in particular potentially dependent on business cycles characteristics. For instance, growth could be affected by business cycle volatility: negatively if investment is irreversible or if firms must commit to their technology in advance, but positively in the presence of precautionary saving or if high returns technologies also entail high risks.[1] In an influential recent contribution, Ramey and Ramey (1995) present evidence that countries with highly volatile Gross Domestic Product (conditionally) grow at a lower rate. They also show the absence of any role for investment, and conclude the negative link between (aggregate) growth and volatility works through low technology adoption in a volatile environment.[2]

In this paper, I present a simple argument whereby the relationship between growth and volatility can depend on the aggregation level. In particular, I show under what conditions it is possible for output growth and volatility to correlate negatively in the aggregate, yet positively in the disaggregate. The intuition is straightforward: suppose sectoral growth depends (linearly) on volatility. While aggregate growth is simply a (weighted) average of sectoral growth rates, aggregate volatility on the other hand is not, as it includes covariance terms. Thus, the relationship between sectoral growth and volatility does not necessarily carry through at the country level. In particular, aggregate volatility increases with the extent of the synchronization in sectoral growth rates, so that it may be high even if each composing sector tends to display both low growth and volatility. If most shocks are aggregate as opposed to sectoral, a country with little volatility at the sectoral level, low sectoral growth -and thus low aggregate growth- will display high aggregate volatility. Conversely, if most shocks are sectoral, high aggregate growth -a weighted average of high sectoral growth rates- can be associated with low aggregate volatility, even though sectors themselves dis-

[1] For detailed exposition of these arguments, see Pindyck (1991), Ramey and Ramey (1991, 1995) or Black (1987).

[2] These results are largely confirmed in Martin and Rogers (2000), who use European regional data, and a slightly different international sample.

play high volatility. This possibility is investigated in two international sectoral datasets, one covering manufacturing activities at the three-digit level in 47 countries, the other covering all economic activities at the one-digit level in 17 countries. The former is used to show how growth and volatility correlate (conditionally) *positively* at the sectoral level, yet negatively across countries.[3] The latter is used as a robustness check.

There are several reasons why an approach based on disaggregated data is promising to address the question at hand. Firstly, theories could be dominant at the sectoral level, and yet appear irrelevant in the aggregate. This would happen for instance if investment allocation across sectors were motivated by differentials in sectoral volatility, without any observable effects of volatility in the aggregate. The strong relationship between domestic aggregate investment and savings rates, notoriously first documented in Feldstein and Horioka (1980), squares well with this possibility, while nothing prevents the available investment pool being allocated across sectors according to volatility-based theories. Similarly, there is increasing empirical evidence that a large share of productivity growth originates in the reallocation of factors *within* narrowly defined sectors.[4] This suggests that the mechanics of technology adoption -and whether they relate to volatility- are best examined at the disaggregated level. Secondly, international sectoral data offers a large cross-sectional dimension, quite usefully when estimating the determinants of output growth, an endeavour famously sensitive to the conditioning set. In particular, the higher dimensionality of the data relative to cross-country studies, and the fact that the variation of interest is country-sector specific opens the possibility to account for *all* country- and sector-specific determinants of growth, both in a pure cross-section and using panel techniques. Thirdly, the question at hand can be addressed *both* at the country and sector level, while using the same data.

As already mentioned, this paper is related to the new growth literature, whereby the determinants of long-run growth are endogenous to the characteristics of the economy, and possibly to business cycles volatility. It is also related, albeit less closely, to the branch of the business cycle literature concerned with the long-run effects of temporary shocks. For instance, recessions are often argued to have positive long-run effects on growth, through "opportunity costs" arguments whereby productivity-enhancing activities are best left for

[3] This is known as the "Simpson fallacy", whereby panels with two cross-sectional dimensions can yield opposite results depending on which dimension is used in the estimation.

[4] See for instance Caballero and Hammour (2000) for a recent survey.

recessionary periods, or "cleansing" effects whereby recessions eliminate less productive units, thus increasing average productivity.[5] However, these theories have no prediction on the relationship between growth and volatility. Testing them empirically has involved tracking the time series effects on productivity of appropriately identified temporary shocks.[6] But even in a world where recessions have long-run virtues, business cycle volatility will not necessarily display any relationship at all with long-run growth, since presumably, by symmetry, the models imply that booms are "wasteful". Bad times may have virtues, but the empirical question addressed in this paper is not directly related to this possibility.

The rest of the paper is structured as follows. In section 2, I describe a simple two-country two-sector economy, and use it to analyze the effects of aggregation on growth and volatility. Section 3 presents the disaggregated results in manufacturing sectors only, and, using a variety of recent panel techniques, establish that *sectoral* growth and volatility are positively related. I also investigate the relationship between sectoral investment and volatility. Section 4 uses the same dataset to confirm that growth and volatility *across countries* are negatively related. I then implement an estimation method able to directly isolate the estimates implied by cross-country as opposed to cross-sector variation. Section 5 repeats all results in a slightly coarser dataset, with information on all sectors that compose GDP and not only manufactures. Section 6 concludes.

2 Growth and Volatility in the aggregate and the disaggregate

In this section I describe a stylized model to illustrate the possibility for the link between growth and volatility to depend on the aggregation level. Consider an economy composed of two countries, A and B, each producing in sectors 1 and 2. Suppose value added growth in sector i and country J, dy_i^J, is randomly distributed with mean γ_i^J and variance $\left(\sigma_i^J\right)^2$. Define aggregate output $Y^J = y_1^J + y_2^J$ and $\varpi^J = \frac{y_1^J}{Y^J}$. It is easy to see that aggregate growth dY^J is randomly distributed with mean $\Gamma^J = \varpi^J\ \gamma_1^J + \left(1-\varpi^J\right)\ \gamma_2^J$ and variance $\left(\Sigma^J\right)^2 = \left(\varpi^J\ \sigma_1^J\right)^2 + \left(\left(1-\varpi^J\right)\ \sigma_2^J\right)^2 + 2\ \varpi^J \left(1-\varpi^J\right)\ cov\left(dy_1^J,\ dy_2^J\right)$. Finally, without loss of generality, assume $\Gamma^A > \Gamma^B$

[5] See among many others Aghion and St Paul (1991), Dellas (1993) or Caballero and Hammour (1994). Aghion and Howitt (1998) provide a detailed survey of this literature.

[6] See for instance Gali and Hammour (1991) or Bean (1990).

The model seeks to establish under what conditions aggregation can reverse the measured link between growth and volatility. To investigate this possibility, assume the link is positive at the sectoral level, with $\gamma_i^J = \alpha + \beta\ \sigma_i^J$ and $\beta > 0$ for $i = 1, 2$ and $J = A, B$. Then, $\Gamma^A > \Gamma^B$ implies

$$\left[\varpi^A\ \sigma_1^A + \left(1 - \varpi^A\right)\ \sigma_2^A\right]^2 > \left[\varpi^B\ \sigma_1^B + \left(1 - \varpi^B\right)\ \sigma_2^B\right]^2$$

Therefore, a necessary condition for the aggregate link to be negative, i.e. for $\left(\Sigma^A\right)^2 < \left(\Sigma^B\right)^2$, is given by

$$\varpi^B\left(1 - \varpi^B\right)\ \sigma_1^B\sigma_2^B\ \left(1 - \rho_{12}^B\right) < \varpi^A\left(1 - \varpi^A\right)\ \sigma_1^A\sigma_2^A\ \left(1 - \rho_{12}^A\right) \tag{1}$$

where ρ_{ik}^J denotes the correlation coefficient between growth rates in sectors i and k in country J. The intuition in (1) is straightforward. Under the null hypothesis that sectoral growth and volatility are linearly related, if country A grows faster than B, then a weighted average of sectoral volatilities in A is larger than in B. The only way to reverse the ranking of aggregate volatilities is if sectoral growth rates are sufficiently more synchronized in B than in A, since this will add to aggregate volatilty. Condition (1) formalizes this intuition, since $1 - \rho_{12}^B$ decreases with the correlation coefficient between sectoral growth rates. These results are easily derived in a model with N sectors, with condition (1) generalizing into

$$\sum_{i<k}^{N} \varpi_i^B\ \varpi_k^B\ \sigma_i^B\sigma_k^B\ \left[1 - \rho_{ik}^B\right] < \sum_{i<k}^{N} \varpi_i^A\ \varpi_k^A\ \sigma_i^A\sigma_k^A\ \left[1 - \rho_{ik}^A\right] \tag{1'}$$

with $\varpi_i^J = \frac{y_i^J}{Y^J}$.

Condition (1') suggests aggregate volatility has two components, with opposite relationships with growth: a weighted average of sectoral volatilities, and a covariance term. The negative link could originate in the latter, i.e. "macroeconomic" shocks affecting the whole economy simultaneously. There $\rho_{ik}^J \gg 0$ and the discrepancy, captured in (1'), between aggregate volatility and a weighted average of sectoral volatilities is large. Actually, Ramey and Ramey (1995) show how a (time-varying) measure of volatility as instrumented by government spending does relate negatively with aggregate growth. Arguably, government spending shocks are of a macroeconomic nature, in the sense that they tend to affect all sectors simultaneously, with very little of a sectoral indiosyncratic component. [7] In short,

[7] In a recent contribution, Fatas and Mihow (2002) confirmed this fact, showing that it is the component of aggregate volatility predicted by government spending that tends to correlate negatively with aggregate growth.

condition (1') explicits the possibility that sectoral growth and volatility correlate positively, while the reverse holds true between countries because aggregate volatility includes both sector-specific turbulences and macroeconomic shocks.[8] Furthermore, the existing macroeconomic evidence may have *de facto* excluded the component of aggregate volatility that correlates positively with growth, by focusing on macroeconomic instruments for aggregate volatility.

3 Sectoral Volatility and Growth

3.1 Data

I use yearly data on sectoral value added, employment and factor content in manufacturing activities, as published by the United Nations Industrial Development Organization (UNIDO). Although observations go from 1963 to 1996, the data is incomplete in the early and latest part of the sample.[9] .In order to limit the number of missing observations, I focus on the period extending from 1970 to 1992, which selects a maximum of 47 countries listed in the Appendix. Sectoral data present a specific difficulty, as quite often the collection of observations on a given activity begins in the middle of the sample. This makes it hard to differentiate between a new sector emerging or a mere statistical artefact.[10] The issue is particularly relevant when attempting to decompose aggregate variables into their sectoral components. Thus, I arbitrarily exclude from the sample activities without observations from 1970; this should not invalidate the reversal discussed in the previous section, and avoids creating artificial aggregate growth or volatility stemming from whole sectors appearing or disappearing -perhaps for no economic reason- over time.[11]

I also consider a subset of the UNIDO data composed of OECD economies only, which further reduces the sample to 23 countries. The purpose of a reduced dataset is to focus on

[8] Condition (1') also suggests an immediate way of correcting for the "macroeconomic" component of aggregate volatility, provided sectoral data are available. Unfortunately as will become clearer, in the data things are not that simple since the true sectoral relationship holds with country and sector-effects, say $\gamma_i^J = \alpha + \gamma_i + \eta_J + \beta\ \sigma_i^J$. These fixed effects complicate substantially the derivation of condition (1'), to an extent that makes the "macroeconomic" component of aggregate volatility impossible to derive with any precision from the data.

[9] 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.

[10] See Imbs and Wacziarg (2002) for details.

[11] I also eliminate sectors whose definitions in the ISIC classification system varies in the sample. Finally, I exclude outliers, whose inclusion only reinforce the results.

economies at a comparable stage of development. The OECD sample excludes developing countries where industrialization -and the afferent structural change- has played an important role in economic growth. Furthermore, structural change is directly related to the correlation between sectoral growth rates, presumably less positively correlated in a developing economy than in more homogenous, industrialized economies. Thus, the importance of condition (1') should depend on the level of development of the sampled countries.

In both datasets, there is a maximum of 28 sectors, listed in the Appendix. I follow Rajan and Zingales (1998), and deflate value added by Producer Price Index series taken from the International Monetary Fund's International Financial Statistics.[12] Data on aggregate capital and output growth rates come from the Penn-World Tables.

Table 1 presents some summary statistics. I report statistics for the cross-section of time average and time variance of sectoral output growth. In both samples, median sectoral growth is substantially smaller than the mean, suggesting the distribution of average relative growth is markedly skewed leftwards. The mean variance of sectoral output is larger in the extended sample, suggesting the growth rates of sectoral shares in overall manufacturing activity are more stable in developed economies. This could reflect at the sectoral level the well-known fact that (aggregate) volatility tends to decrease with the level of economic development.[13] Finally, Table 1 reports the unconditional correlation between average sectoral growth and its variance over time: it is positive in both case, albeit not significantly.

I also use an alternative dataset gathered from the United Nations Statistical Yearbook, and based on questionnaire evidence. This data is coarser and is only reported at the one-digit aggregation level, but it covers all economic activities in 17 developed countries, classified across nine sectors that are described in the Appendix. Inasmuch as it covers the whole range of economic activities, and it comes from an alternative source, this data provides a useful robustness check. However, it should be borne in mind that it is also coarser, something this whole paper argues is far from innocuous. Table 1 presents some summary statistics. Firstly, aggregation into one-digit sectors appears to average away a substantial amount of sector-specific developments, as the mean and median of sectoral volatility are much lower here. This should not be surprising as it is a simple application

[12] Or alternatively an index of industrial production when the PPI was not available, as in Rajan and Zingales (1998).

[13] See Kraay and Ventura (2001) for a discussion.

of the law of large numbers: manufactures as a whole are liable to display substantially less volatility than, say, Leather Products. Skewedness seems also smaller in this data, at least for average sectoral growth whose mean and median are not far apart. Finally, the unconditional correlation between growth and volatility is very weakly negative.

3.2 Cross-Sectional Evidence

In this section, I focus on the pure cross-section in sectoral growth and volatility. In general, growth regressions are notorious for their sensitivity to conditioning variables and a substantial literature has concerned itself with the choice of an appropriate conditioning set. This literature culminated with Levine and Renelt (1992) who proposed a list of four robust explanatory variables of aggregate GDP growth.[14] International sectoral data make it possible to control for all (time invariant) country-specific considerations even in a cross-section, and thus do away with the potential issue of sensitivity that is prevalent in this area. Similarly, sector-specific effects control for any tendency of one sector to display systematically high growth rates, e.g. because of sectoral shocks, and focus on systematic deviations from an international average. In what follows, all (time-invariant) country- and sector-specific characteristics are held constant, and the focus is instead on individual country-sector variation.[15] Specifically, consider

$$\ln y_{i,j,T} - \ln y_{i,j,0} = \beta_0 + \beta_1 \; V_T \; (\ln y_{i,j,t} - \ln y_{i,j,t-1}) + \beta_2 \; X_{i,j} + \varepsilon_{i,j} \tag{2}$$

where i and j index industry and country, respectively, $y_{i,j,t}$ is sectoral value added at time t, $X_{i,j}$ is a vector of control variables and $V_T(.)$ is the (time) variance operator, computed over period T.[16] The coefficient of interest is β_1. There are numerous reasons why the residual $\varepsilon_{i,j}$ is liable to contain both industry- and country-specific effects, say γ_i and η_j, respectively. To list only two, suppose for instance political instability translates in both high aggregate volatility and low growth, as in Alesina *et al* (1992): the residual is then negatively correlated with the regressor, through η_j. Suppose instead industry specific technological progress is associated with both high sectoral volatility and growth:

[14] The Levine-Renelt variables are initial income per capita, average population growth, initial human capital as measured by schooling years and average investment rate.

[15] This is inspired from Rajan and Zingales (1998)

[16] Basu and Fernald (1997) argue that gross output is a better measure of sectoral activity than value added when investigating external effects of aggregate activity onto sectoral production. We checked that the results obtain as well when using gross output.

the residual is now positively correlated with the regressor, through γ_i. Accounting for these fixed-effects is a serious issue in most growth regressions, especially so when the issue is to identify the significance of one particular variable, such as volatility in the present case. Here however, (1) can be estimated simply in deviations from means as in

$$F\left(\ln y_{i,j,T} - \ln y_{i,j,0}\right) = -\gamma_0 + \beta_1 \ FV_T \ \left(\Delta \ln y_{i,j,t}\right) + \beta_2 \ FX_{i,j} + F\varepsilon_{i,j} \tag{3}$$

where $FZ_{i,j} = Z_{i,j} - \frac{1}{I}\sum_i Z_{i,j} - \frac{1}{J}\sum_j Z_{i,j}$. The country or sector fixed effects are now controlled for, as $\gamma_0 = -\beta_0 + \frac{1}{I}\sum_i \gamma_i + \frac{1}{J}\sum_j \eta_j$.[17] Equation (3) leaves open the question of what country-industry specific variables ought to be included in the set of controls, denoted by $X_{i,j}$. I now turn to this question.

Numerous authors have concerned themselves with the dynamics of sectoral specialization, using insights from growth and international trade theories.[18] A very stylized model may be helpful here. Consider the two-country two-sector model in the previous section, and supplement it with two factors of production, with sector 1 capital-intensive and sector 2 labour-intensive. Suppose country A is capital rich, and thus has a higher aggregate capital-labour ratio than country B. With aggregate diminishing returns to capital, country B accumulates capital faster, and factor price equalization favours growth in sector 1 there. Similarly, factor price equalization and neo-classical convergence suggest sector 2 will grow relatively faster in country A.[19] Thus, from an empirical point of view, the determinants of relative sectoral growth are two-fold. Firstly, a variable capturing country-specific capital-labour growth interacted with sector-specific capital content. This is the approach adopted in a recent paper by Bernard and Jensen (2001), which shows sectoral factor content is important in explaining higher than average sectoral output growth in a cross-section of US regions. I estimate (3) with such an interaction term between sectoral capital content and the aggregate growth of the capital-labour ratio. However, the measurement of this variable raises a number of issues: although UNIDO provides information on the sectoral wage bill and sectoral value added (both nominal), the resulting labour shares tend to be quite noisy. Secondly, an assumption of constant returns to scale must be maintained if the

[17] This is a generalization of the estimation procedure used in Rajan and Zingales (1998), where only the dependent variable is demeaned, and the focus is on the significance of an interaction term between (sector-specific) need for and (country-specific) availability of external finance. Since they use the UNIDO data as well, Rajan and Zingales also have to present results for manufacturing sectors only.

[18] For theoretical approaches, see Ventura (1997) or Cuñat (2000). For an empirical analysis, see Imbs and Wacziarg (2002).

[19] For details, see Ventura (1997).

capital share is to be inferred from the wage bill. Although the evidence suggests sectoral production functions by and large display constant returns to scale, there seems to be ample cross-sectoral variation.[20] Thus, an interaction term *à la* Bernard and Jensen must be taken as an approximation in the present context.

Fortunately, the previous sketch of a model suggests an obvious 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 happens of course because of diminishing returns to capital, and suggests the inclusion of a measure of the initial relative size of a sector in the estimation of (3), which has the substantial advantage of being readily available. Actually, there is at least one additional reason to include such an "initial condition" term in (3), which is more of an econometric nature. Transition dynamics in the usual neo-classical sense are potentially important here, as they tend to result in both high and monotonically-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.[21] I therefore include the initial sectoral share in value added in (3), and note that a negative sign could be interpreted equally as a "convergence" term or as dictated by comparative advantage.

Table 2 presents estimations of (3), for both UNIDO samples and various specifications of $X_{i,j}$. The main result that should be taken from the table is the significantly positive sign of β_1. The coefficient on the variance of value added growth is positive and significant in all cases, and particularly in the OECD sub-sample.[22] Volatility is also important economically. In the OECD, the smallest estimate of β_1 across specifications is 0.338, which implies one standard deviation of the volatility measure (measured across country-sectors) translates into around a 85% of a percentage point of average yearly sectoral output growth.[23]

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

[21] There are reasons to believe that this bias is not as important in the sectoral data as it is in the aggregate. Imbs and Wacziarg (2002) have shown that the notion of a "steady state economic structure", to which growing economies would converge is not supported in the data. Countries are shown to first diversify, thus allocating resources across sectors increasingly equally, but start re-specializing once they reach a relatively high level of income per capita.

[22] 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 putative bias is a priori least prevalent, i.e. in the OECD.

[23] In the extended sample, the effect is smaller, around a third of a percentage point (to be precise, 0.32 using the smallest estimate of β of 0.066).

Several other comments are in order. Firstly, our results are in agreement with Bernard and Jensen (2001), as we find robust evidence that capital intensive sectors grow faster in economies with high rates of capital accumulation. This suggests Hecksher-Ohlin based arguments in explaining sectoral performance are important empirically. Indeed, there are two important differences between this study and Bernard and Jensen's: firstly our sample is international whereas theirs is inter-regional in the US, secondly our estimations are ran with both country and sector fixed effects.[24]

Secondly, Table 2 provides evidence in favour of a significant "convergence" term, as measured by initial sectoral value added, either in absolute or in relative term. In both samples, initially "smaller" sectors tend to display higher subsequent growth rates. As expected, the significance of a convergence term is strongest in the extended sample, where the volatility term loses substantial significance once initial conditions are held constant (although not below the standard 10% threshold). This confirms the importance of a bias due to "transitional dynamics" in explaining why growth relates positively to volatility. In the reduced sample however, volatility continues to be positive at the 1% significance level even controlling for initial conditions, which calls for an alternative explanation than the aforementioned bias. In short, there is evidence that the relationship between growth and volatility is biased upwards by transitional dynamics, but this evidence is quite limited between rich countries. The next section generalizes the estimation procedure introducing a panel dimension in the data.

3.3 Dynamic Panel Evidence

Recent years have seen important developments in the use of panel techniques to estimate growth equations.[25] In this section, I implement some of them, thus making use of the panel dimension of our data. A generalized specification of (2) is

$$\ln y_{i,j,T} = \beta_1 \; V_T \left(\Delta \ln y_{i,j,t}\right) + (\beta_2 + 1) \;\; \ln y_{i,j,T-1} + \beta_3 \; COMP.ADV._T$$

$$\gamma_i + \eta_j + (\delta_T) + \varepsilon_{i,j,T} \tag{4}$$

[24] Bernard and Jensen focus on the U.S economy, and show sectoral growth is lowest in least capital- and skill-intensive industries.

[25] See Caselli, Esquivel and Montfort (1996) for a seminal contribution, and Forbes (2000) for a recent one.

with $t \in [T-1, T]$. The main difference with (3) is the partition of the data into T sub-periods. The conditioning set includes initial sectoral value added and an interaction term between initial sectoral capital content and aggregate capital growth over the sub-period $[T-1, T]$, labeled $COMP.ADV.$[26] δ_T denotes a period-specific indicator variable, included whenever meaningful. An obvious procedure to obtain estimates for β_1 involves estimating (4) in deviations from country and sector means. However, a well-known problem in doing so is that, while it controls for the presence of a time-invariant component in the residuals, it leaves open the possibility that the lagged dependent variable be correlated with the residuals, with possible consequences on the estimates of β_2 and β_1. Arellano and Bond (1991) suggest to instrument the lagged dependent variable (in deviations from mean) with all of its available lagged values (as well as its lagged first-differences). Crucially, this technique, based on the Generalized Method of Moments, requires zero serial correlation in the residuals for the instruments to be consistent. We next present the results of two estimations of (4), firstly using simple within-group OLS and secondly implementing the Arellano-Bond GMM method.

Table 3 presents the results of the two dynamic panel specifications, with or without initial conditions. The generality of (4) is appealing, but measurement error is likely to obscure substantially the resulting estimation. Firstly, variances are now computed on fewer observations; secondly, the resulting measurement error is likely to be exacerbated by first-differencing. As data quality tends to vary with aggregate income level, measurement error is likely to be strongest in our extended sample. In other words, within-groups estimation of (3) is likely to give estimates of β_1 and β_2 that are seriously biased downward. From this point of view, the results in table 3 are remarkably robust. The top panel presents the results of the estimation of (4) in fixed effects over two sub-periods, where $\ln y_{i,j,T}$ and $V_T(\Delta \ln y_{i,j,t})$ are computed over [1970,1981] and [1982,1992], respectively, and initial variables are measured in 1970 and 1982.[27] First and foremost, β_1 is non-negative in all cases, and significantly positive in the OECD sub-sample. In both samples, the convergence effect is estimated to be strong, with very negative estimates of β_2. As expected, transitional dynamics as proxied by β_2 are both more significant and larger in magnitude in the extended sample. Secondly, the comparative advantage variable is still significantly positive in the extended sample, yet no different from zero in the OECD sample. We conclude that the

[26] Thus initial values are measured in $T-1$.

[27] The number of observations is lower than in table 2 because of countries missing observations in 1982.

presence the relationship between growth and volatility remains positive at the sectoral level even in a dynamic context.

However, estimates of β_2 are suffering from a possible bias, due to the presence of lagged dependent variables in (4). The lower panel in table 3 partitions the data into four sub-periods, and compares standard fixed-effect estimation over these periods with the Arellano-Bond GMM estimator, using all available lags of the dependent variables as instruments (both in levels and in differences). Several comments are in order: firstly, the Arellano-Bond estimator has very little impact on the estimates for β_1, which remain significantly positive in the OECD sample, yet non-negative in the extended one. Secondly, the Arellano-Bond estimator renders the comparative advantage term significantly positive in both samples. Thirdly, the coefficient on initial conditions changes in magnitude and significance with Arellano-Bond, a result that confirms the possibility that the presence of a lagged dependent variable on the right-hand side does not go without some endogeneity issues, but which illustrates that the bulk of this bias falls on the coefficient on the lagged dependent variable itself.[28]

As already mentioned, second-order serial correlation in the residuals of equation (4) is liable to cast doubt on the consistency of the Arellano-Bond estimation. Standard (unreported) t-tests suggest this is a serious problem in the extended sample, where the hypothesis of no serial correlation is rejected in both specifications.[29] In the reduced sample, however, it is substantially harder to reject the hypothesis of no second-order serial correlation in the residuals.[30] We conclude the results from the OECD sample of countries are probably to be taken most seriously, although we notice that the coefficient on volatility is non-negative in both samples.

The maintained assumption in the previous estimations has been that volatility is strictly exogenous to the dependent variable, output growth. This assumption is of course questionable as output volatility could very well be endogenous to output growth, which is why previous authors have either used a residual (or "forward-looking") measure of output

[28] For example, Judson and Owen (1996) simulate that with 5 time periods, the bias in the lagged dependent variable is over 50 percent, whereas the bias in the other coefficients is only about 3 percent.

[29] The test-statistics are $N(0,1) = 3.88$ and 2.62 depending whether the comparative advantage variable is included. This rejects the null at 1% confidence level. See Arellano and Bond (1991) for details on the serial correlation tests.

[30] The test-statistics are now $N(0,1) = 1.20$ and 1.52, respectively. This rejects the null at only 23% and 13% confidence levels.

volatility, or have instrumented output volatility, for instance using changes in government spending. Due to data limitations, these approaches are impossible in disaggregated data. However, this paper aims at showing how aggregation may *reverse* the evidence on the link between growth and volatility. In other words, while an endogeneity bias might obscure both aggregate and sectoral evidence, it is hard to think of reasons why its *direction* would change with the level of aggregation. In other words, the endogeneity of volatility is probably not a leading candidate in explaining the reversal of the evidence with disaggregation. Nevertheless, the flexibility of the Arellano-Bond procedure offers a first step towards addressing some of the endogeneity of output volatility. The estimation remains consistent even when allowing for the possibility that $V_T(\Delta \ln y_{i,j,t})$ be correlated with $\varepsilon_{i,j,S}$ for all $T > S$. This makes it possible to consider current volatility as a manifestation of past high growth, thus somewhat forward-looking. I perform once again the Arellano-Bond estimation, eschewing the assumption of strict exogeneity, and compare its performance to the one reported in Table 3. The resuts, unreported for clarity, are quite clear. In all cases, allowing for volatility to be predetermined results in rejection of the overidentifying restrictions at standard confidence levels. [31] Furthermore, serial correlation becomes a serious problem in the OECD sub-samples as well. The evidence thus favours a specification that assumes perfect exogeneity of output volatility, relative to one that allows volatility to be predetermined.

3.4 The role of investment

Several of the theories summarized in the introduction imply that growth and volatility are related via the intensity of investment. Ramey and Ramey (1995) showed that, in the aggregate, the link does not work through investment. In particular, they show that (i) conditioning growth regressions on investment does not affect the coefficient on volatility, (ii) investment intensity is not related with volatility. However, these cross-country results do not necessarily carry through at the sectoral level, particularly when the evidence appears to reverse through disaggregation. It is indeed possible that, while the aggregate pool of available investment does not respond to volatility, its allocation across sectors does. In this section, I investigate this possibility.

[31] In the order of the specification in the low panel of table 3, the P-values of the Sargan tests become 0.112 and 0.023, respectively.

In table 4, I reproduce the estimations in Ramey and Ramey (1995), at the disaggregated level. Panel A repeats the cross-sectional and dynamic estimations described earlier in this section, but adding investment intensity in the set of independent variables. Investment intensity is measured by the ratio of sectoral investment to sectoral value added, both expressed in nominal terms. The table reports the coefficients on volatility and investment intensity. The results pertaining to the extended sample are not particularly interesting, as the coefficient on volatility was not systematically significantly positive in tables 2 and 3. Typically, correcting for investment intensity does not change that fact. The results in the reduced OECD sample are much more interesting. As is evidence from a quick comparison between tables 2, 3 and 4, controlling for investment substantially reduces the coefficient on volatility, up to rendering it insignificant in the four-period estimation. This is accompanied with very significantly positive coefficients on investment intensity. These results suggest that sectoral investment goes towards volatile activities, as if sectoral risk and return were positively related. To confirm this possibility, Panel B evaluates the direct effect of sectoral volatility on sectoral investment, and reports the coefficient on volatility when investment intensity is the dependent variable. The coefficient is non-negative in all cases, and very significantly positive in the reduced OECD sample, no matter what controls are included. This stands in stark contrast with the aggregate evidence presented in Ramey and Ramey (1995), which showed the absence of any *aggregate* relationship between volatility and investment, quite possibly because aggregate investment tends to be mostly governed by the availability of domestic savings.

To summarize, disaggregated data points to a significantly *positive* link between sectoral growth and volatility, somewhat weakly in a sample inclusive of developing countries, but quite robustly in one only including OECD economies. Furthermore, this positive link seems to work through sectoral investment, as highly volatile sectors also display high investment rates. Interestingly, the positive link is strongest precisely in the sample of countries where the aggregate evidence in Ramey and Ramey (1995) or Martin and Rogers (2000) is most robustly pointing to a *negative* coefficient. From the standpoint of the model sketched in section 2, this might be happening because OECD countries are those where "macroeconomic" shocks are the largest component of aggregate volatility. In the next section, I turn to an account of this discrepancy.

4 Why the Aggregate Link is Negative

Ramey and Ramey (1995) and Martin and Rogers (2000) use a number of aggregate cross-sections to establish what appears to be an extremely robust feature of cross-country data: aggregate growth (conditionally) correlates negatively with aggregate volatility. Both papers refer extensively to the empirical growth literature in choosing a conditioning set. When conditioning GDP growth on the set of variables proposed in Levine-Renelt (1992), both papers find high variance of GDP to be associated with low aggregate growth on average, although the result holds most robustly within a sample of developed OECD economies.[32] The two papers differ somewhat in their methodology, but not fundamentally in their results. Ramey and Ramey implement a maximum likelihood estimation and focus on the variance of *innovations* to GDP growth, as measured by the residual of a forecasting equation for GDP growth. Thus, they take care of the putative endogeneity of output volatility, and show the negative link continues to prevail. Martin and Rogers use cross-region as well as cross-country evidence, and include a measure of sectoral shares to account for putative transitional effects. Again, the aggregate link is found to be negative, particularly amongst OECD countries. In this section, I seek to reconcile the evidence in this paper with the literature, in two steps: (i) I show the same sectoral data used previously can be aggregated to yield a negative coefficient, (ii) I use an estimator allowing for the possibility that the coefficient on volatility be different depending on the dimension of the panel, and interpret these results in the context of the model in section 2.

4.1 Aggregation of Sectoral Data

Firstly, I report the results implied by an aggregated version of (3) and (4). In particular, I estimate

$$\ln \sum_i y_{i,j,T} = \beta_1 \; V_T \left(\Delta \ln \sum_i y_{i,j,t} \right) + (\beta_2 + 1) \; \ln \sum_i y_{i,j,T-1} + \alpha_j + (\delta_T) + \varepsilon_{j,T} \qquad (5)$$

where the "comparative advantage" term is eschewed, and country-specific fixed effects are allowed for. Admittedly, the aggregates used here differ somewhat from standard GDP

[32] 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 lower (in absolute value) negative coefficient in a sample of 92 countries than in a sample of 24 OECD countries. The coefficient is actually not significant in the extended sample when Ramey and Ramey use a time-varying measure of volatility.

measures, as they are sums over manufacturing activities only; the exercise remains however interesting, at least to document the effects of aggregation. A difficulty in using an aggregate of manufacturing activities is the choice of a conditioning set: the Levine-Renelt variables pertain to aggregate GDP, and thus do not belong in (5). Somewhat arbitrarily, I report results with no conditioning variables at all (but country effects and period indicator variables), and with the Levine-Renelt variables.[33] Since the number of sectors per country is (arbitrarily) different, I only report dynamic estimations, where country fixed effects are held constant.

The results in table 5 stand in stark contrast with the disaggregated evidence. Estimates of β_1 are now never positive, and significantly *negative* in all but one case. As in the literature based on aggregate evidence, β_1 is particularly negative in a reduced sample of OECD countries. Arellano-Bond estimations are well-specified, both as Sargan tests fail to reject the overidentifying restrictions, and as the hypothesis of no serial correlation is never rejected at any standard confidence levels.

4.2 Heterogenous Coefficients

Figure 1 illustrates graphically the growth-volatility relationship between three countries A, B and C, sharing the same two sectors, 1 and 2.[34] On the figure, the relationship between growth and volatility is negative between countries, yet negative between sectors. This is known more generally as "Simpson's fallacy", i.e. the possibility that, in panel datasets where there are two cross-sectional dimensions, the evidence depends on which dimension is used in the estimation. Note that the figure is drawn allowing for country- or sector-specific fixed effects. In other words, for clarity intercepts are allowed to vary along the panel dimensions. It should be clear however that the fallacy will persist even after these intercepts are controlled for. This exemplifies the important fact that "Simpson's fallacy" cannot be taken care of through simple panel techniques, as the heterogeneity concerns the estimated coefficient, rather than intercepts. From the standpoint of the model described in section 2, "Simpson's fallacy" is only possible in disaggregated data if condition (1') holds.[35]

[33] The next section shows the results extend to a dataset not limited to manufactures only, thus assuaging concerns about the conditioning set, as well as confirming the generality of the phenomenon presented in this paper.

[34] Canova and Marcet (1997) make a similar point, applied to cross-country growth regressions.

[35] With the already mentioned caveat that both disaggregated and aggregated relationships hold with (country and sector) fixed effects, something not on Figure 3, and that renders direct testing of (1') impos-

In other words, it is the component of aggregate volatility that is common across sectors which tends to account for the aggregate evidence, and that adds to aggregate volatility without changing aggregate growth. I now turn to a direct test of this possibility.

I make use of an estimation method that evaluates directly the data pattern illustrated in Figure 1. In particular, there is need for a procedure which, in the international disaggregated data, enables to choose which cross-section the estimation makes use of. The "random coefficients" estimator introduced by Hildreth and Houck (1968) offers this possibility. The estimation can be summarized as

$$Y_i = X_i \; B_i + e_i$$

where $E(e_i) = 0$, $E(e_i e_i') = \sigma^2 I$ and crucially, $B_i = B + v_i$ is allowed to vary randomly along the i dimension, $E(v_i) = 0$ and $E(v_i v_i') = \Gamma$. Hildreth and Houck show the model is equivalent to

$$Y_i = X_i \; B + \eta_i$$

with $E(\eta_i) = 0$ and $E(\eta_i \eta_i') = \sigma^2 I + X_i \; \Gamma \; X_i'$ which can be estimated immediately using Generalized Least Squares. Thus, this estimator is a generalized version of simple Random Effects procedure, where the whole vector of independent variables is allowed to be random and not only the intercept. In the context of a panel with two cross-sectional dimensions, it makes it possible to choose the relevant dimension of randomness, e.g. across countries or sectors.

In what follows, I implement this procedure using the disaggregated data from section 3, and run three estimations: (i) for comparison purposes, a simple random effects estimation of sectoral growth on volatility, (ii) a random coefficients estimation allowing for randomness in β_1 across countries, and (iii) a random coefficients estimation allowing for randomness in β_1 across sectors. The results are reported in Table 6, with the same choice of subperiods as in section 3. The presence of a lagged dependent variable is not a problem anymore, since the whole vector of independent variables is assumed to be random. The first conclusion to draw from the upper panel in table 6 is that Hausman tests reject a random effect specification, thus potentially casting doubt on the relevance of the (more general) random coefficient estimator. This is not necessarily problematic however. Firstly,

sible.

the Hausman procedure tests a fixed vs. random effect specification, while the point in this section is not to claim the data is well represented by random effect estimation. Rather it is simply reassuring that estimates of β_1 in the upper panel of table 6 remain positive and very similar in magnitude to those in table 3. This suggests the link between sectoral growth and volatility remains positive even if country and sector effects are assumed random as opposed to time-invariant. In particular β_1 is significantly positive in OECD countries, and the question the random coefficient estimator will answer is whether this is due to cross-country or cross-sector variation. Secondly, it is easy to see that the Hausman test rejects random effects mostly because estimates of β_2 and β_3 depart substantially from their values in table 3, *not* because of the estimated effect of volatility, still significantly positive and of similar order.

The second, most important, conclusion from table 6 is that the positive estimates of β_1 originate in the cross-sector variation of the data. When the coefficient is estimated on the basis of the cross-sector variation, the evidence points to a positive link, particularly so in the OECD as in previous estimations. When on the other hand the coefficient is estimated on the basis of the cross-country variation, it is not significantly different from zero, with negative point estimates.[36]

Thus, the evidence in Table 6 suggests Figure 3 provides a reasonably good rendition of the pattern of growth and volatility in manufacturing sectors, as well as an explanation for the difference between aggregate and sectoral evidence. The random coefficient estimation also has a useful side-product. Pervading all empirical exercises concerned with a relationship between growth and volatility is the possibility that volatility be endogenous to growth, i.e. the previous estimations suffer from an endogeneity bias. Ramey and Ramey (1995) bypass this issue by measuring volatility as that of the residual of a typical growth regression. This exercise would be difficult to reproduce at the sectoral level given the largely time-invariant conditioning set for sectoral growth suggested here.[37] However, the discrepancy between the evidence across countries and across sectors (as well as that based

[36] Ideally, one would have wanted the cross-country variation to point to significantly negative estimates of β_1, but the evidence presented in the previous sub-section indicates this might be an issue related to the conditioning set.

[37] Country and sector specific intercepts are obviously time-invariant. The comparative advantage variable display very little time variation, being an interaction term between sectoral capital intensity, a production function parameter usually assumed constant over time, and aggregate capital growth, famously very persistent as well. Initial sectoral output does vary over time, but is insufficient, taken alone, to explain much of the time-variation of sectoral volatility.

on aggregated vs. disaggregated data) presumably exists irrespective of the presence of an endogeneity bias. In other words, even if the bias is prevalent in the previous estimations, there is no particular reason to expect it to be more prevalent across countries, say, than across sectors. The reversal of the evidence discussed in this paper remains therefore an empirical fact driven by something different than an endogeneity bias. The next section takes this reasoning one step further, by using an alternative dataset whose properties are well-known, and in particular where the aforementioned endogeneity problem has already been taken care of by prominent authors.

4.3 Beyond Manufacturing Sectors

In this section, I repeat some of the previous analysis using an alternative source of sectoral data, from the UN Statistical Yearbook, with a larger country coverage and more exhaustive, yet coarser sectoral information. This repetition is useful for a variety of reasons. First and foremost, this data covers all economic activities, at the one-digit disaggregation level. This opens the possibility of truly decomposing aggregate Gross Domestic Product into its sectoral components, rather than manufacturing output. Similarly, an extensive literature is there to guide the choice of a conditioning set for growth in GDP as opposed to industrial production. Secondly, this is data where we have known since Ramey and Ramey (1995) that the negative link in the aggregate is *not* due to the endogeneity of volatility to growth. Thus presumably, the reversal of this evidence at the sectoral level cannot either be ascribed to an endogeneity problem

Before moving to the description of Table 7, which summarizes all the estimations based on the UN Statistical Yearbook data, a word of caution is in order. This dataset is more aggregated than the one used previously. Now, the whole purpose of this paper is to establish that aggregation is of special importance to the relationship between growth and volatility: it should be so as well when shifting from a three- to a one-digit level of disaggregation (as well as, admittedly, to a dataset covering more than manufacturing sectors). Suppose (three-digit) sectoral output growth is perturbed by aggregate as well as idiosyncratic shocks, say in equal proportions. Because of the law of large numbers, the contribution of sector-specific shocks will decrease with the level of aggregation of the data under analysis. In particular, sector-specific developments could largely be averaged away in a one-digit sectoral dataset. If, as our previous evidence suggests, the sector-specific component of aggregate volatility is the one correlating positively with growth, whereas the opposite holds true for its common component, the link between growth and volatility will be more negative the more aggregated the dataset.

With this in mind, consider Table 7. Panel A reports fixed effects estimations, akin to those presented in section 3, both in the disaggregated original data, and in its derived aggregated version. Panel B and C, in turn, implement the Random Coefficients estimation. Several comments are in order. Firstly as before, panel A confirms that the coefficient on volatility becomes strongly negative with aggregation at the country level. The reversal is less marked than in the three-digit UNIDO dataset, as the disaggregated link between volatility and growth is at best non-negative at the one-digit level. There is however no reason to expect aggregation from the three- to the one-digit level to be without averaging effect. In the one-digit data, the sector-specific component of aggregate volatility is liable to have become smaller, and dominated by a common "macroeconomic" component. Nevertheless, the discrepancy between disaggregated and cross-country estimates remains substantial. Secondly, moving to a random effects specification has no impact on the coefficient on volatility, confirming that the zero-correlation between growth and volatility at the one-digit level is not a figment of fixed-effects estimations.[38] Thirdly, the random coefficient estimates establish clearly which cross-section is responsible for the sign between sectoral growth and volatility: while the cross-country variation yields a very significantly negative estimate, growth and volatility are essentially unrelated across sectors. Thus, the fallacy illustrated in figure 1 is also to an extent at play in this data, although the sectoral positive sign is less present here, possibly because of its coarser aggregation level.

5 Conclusion

This paper provides novel evidence on an old question. I confirm the existing result that volatile countries grow slowly, but show that, at least for sufficiently disaggregated data, volatile activities within countries grow fast. In spite of appearances, the two results are not contradictory. They simply correspond to distinct components of aggregate volatility: one, common across all activities in a country, limits growth, and another, specific to each sector in a given country, is associated with fast growth. Risk and return are positively correlated,

[38] As before, Hausman tests reject equality of coefficients between fixed and random effects, and as before this is almost entirely happening because of the coefficient on initial conditions.

even though volatile countries do not grow. I also document that, although investment is unresponsive to volatility in the aggregate, volatile activities within a country typically attract high investment rates, in a way not inconsistent with well-established theories in finance. These results cast a new light on the theoretical welfare costs of business cycles, and in particular call for a dichotomy between macroeconomic and sector-specific volatilities. Economic turbulences may very well signal economic opportunities.

Appendices: A. Sectoral Coverage

1. 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

2. UN Statistical Yearbook One-Digit Classification (9 sectors)

1. Agriculture, hunting, forestry and fishing
2. Mining and quarrying
3. Manufacturing
4. Electricity, gas and water
5. Construction
6. Wholesale trade and retail trade, restaurants and hotels
7. Transport, storage and communication
8. Finance, insurance, real estate and business services
9. Community, social and personal services

B. Geographic Coverage

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

a: reduced UNIDO dataset

b: UN Statistical Yearbook data

c: UN Statistical Yearbook, but not UNIDO

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Table 1: Summary Statistics

Extended UNIDO Sample (894 obs – 47 countries)

	Mean	Median	Min	Max
Average Yearly Sectoral Growth	4.029	3.395	-12.128	26.513
Average Yearly Sectoral Variance	0.042	0.022	0.001	0.352
Correlation = 0.152				

Reduced UNIDO Sample (398 obs – 23 countries)

	Mean	Median	Min	Max
Average Yearly Sectoral Growth	3.153	2.810	-8.411	26.513
Average Yearly Sectoral Variance	0.017	0.009	0.001	0.204
Correlation = 0.314				

UN Yearbook Sample (138 observations – 17 countries)

	Mean	Median	Min	Max
Average Yearly Sectoral Growth	2.817	2.723	-2.959	11.653
Average Yearly Sectoral Variance	0.0022	0.0016	0.0000	0.0113
Correlation = -0.038				

Table 2: Cross-sectional Evidence

A. Extended Sample (894 obs)

	(i)	(ii)	(iii)	(iv)
V_t ($\Delta(\ln y_{i,j,t}$))	0.170 (5.61)	0.184 (5.80)	0.074 (2.03)	0.066 (1.79)
$\ln(y_{i,j,0})$			-0.008 (6.91)	
$\ln(y_{i,j,0} / \Sigma_i\ y_{i,j,0})$				-0.010 (7.10)
Comp. Adv.		0.005 (1.17)	0.011 (2.37)	0.012 (2.65)
Intercept	-0.033 (20.77)	-0.033 (19.74)	-0.199 (8.31)	-0.002 (0.39)
R-Square	0.033	0.038	0.087	0.090

B. OECD Sample (445 obs)

	(i)	(ii)	(iii)	(iv)
V_t ($\Delta\ln$ ($y_{i,j,t}$))	0.338 (6.03)	0.341 (6.10)	0.526 (5.80)	0.420 (4.58)
$\ln(y_{i,j,0})$			-0.006 (3.44)	
$\ln(y_{i,j,0} / \Sigma_i\ y_{i,j,0})$				-0.011 (5.11)
Comp. Adv.		0.015 (2.56)	0.019 (2.81)	0.018 (2.80)
Intercept	-0.031 (19.67)	-0.033 (19.05)	-0.150 (4.25)	0.006 (0.81)
R-Square	0.074	0.085	0.124	0.158

Results for estimation of (2), with country and sector fixed-effects. $y_{i,j,t}$ is the real value added in sector i, country j at time t. The dependent variable is $\ln(y_{i,j,1992})$ - $\ln(y_{i,j,1970})$. Initial values are measured in 1970, or the nearest data available. The comparative advantage variable (Comp. Adv.) is an interaction term between average aggregate capital-labour growth between 1970 and 1985, and measured capital share in 1970. t-statistics are reported between parentheses.

Table 3: Dynamic Panel Estimations:

Two Periods	Full Sample		OECD Sample	
Volatility	0.099 (2.86)	-0.020 (0.59)	0.549 (7.78)	0.422 (5.85)
Comparative Advantage	0.024 (4.93)	0.023 (5.09)	0.000 (0.08)	0.003 (0.61)
Initial VA		-0.016 (9.90)		-0.014 (6.34)
R-Square	0.092	0.175	0.232	0.302
# Obs.	1202	1112	647	602

Four Periods	Full Sample			OECD Sample		
			Arellano Bond			Arellano Bond
Volatility	0.006 (0.27)	-0.018 (0.77)	-0.018 (0.71)	0.206 (4.27)	0.156 (3.26)	0.292 (2.47)
Comparative Advantage	0.011 (2.10)	0.015 (2.90)	0.016 (2.85)	0.004 (0.61)	0.007 (1.13)	0.024 (3.04)
Initial VA		-0.016 (8.75)	-0.018 (7.90)		-0.015 (6.74)	-0.009 (2.64)
R-Square	0.034	0.063		0.132	0.163	
# Obs.	2527	2527		1289	1289	

The dependent variable is sectoral value added growth in [1970,1981] and [1982,1992] in the upper panel (boundary dates are 1970, 1976, 1982, 1988 and 1992 for the four-period estimation). Initial values are measured in 1970 and 1981 (1970, 1976, 1982 and 1988 for the four-period estimation). Variances are computed over the corresponding sub-periods. t-statistics are reported between parentheses.

Table 4: The Role of Investment

Estimation	47-country sample		OECD sample	
A. Growth Equation (Coefficients on Volatility and Investment Intensity)				
	VOL	INV	VOL	INV
Cross-Section	0.074	2×10^{-4}	0.462	0.004
	(2.01)	(1.91)	(5.13)	(4.12)
Fixed effects (Two Periods)	-0.011	0.004	0.156	0.110
	(0.32)	(1.44)	(2.39)	(5.68)
Fixed effects (Four Periods)	-0.020	0.007	0.049	0.112
	(0.82)	(2.83)	(1.14)	(6.51)
B. Investment Equation (coefficient on sectoral volatility)				
Cross-Section				
No controls	10.629		8.813	
	(1.51)		(3.39)	
Controls	1.946		14.494	
	(0.20)		(3.22)	
Fixed effects (Two Periods)				
No controls	0.454		0.522	
	(1.57)		(4.87)	
Controls	-0.012		0.769	
	(0.03)		(5.68)	
Fixed effects (Four Periods)				
No controls	0.105		0.428	
	(0.66)		(6.33)	
Controls	0.086		0.412	
	(0.43)		(6.02)	

For panel A: all estimations include initial relative value added and the comparative advantage variables. For panel B: these are the controls included when indicated.

Table 5: Aggregate Estimations

Estimation	47-country sample	OECD sample
A. Coefficient on Aggregate Volatility		
Fixed effects (Two Periods)		
No Controls	-8.186	-0.943
	(1.66)	(0.05)
Controls	-9.703	-25.12
	(2.04)	(1.65)
Fixed effects (Four Periods)		
No Controls	-5.630	-9.975
	(3.76)	(2.44)
Controls	-5.477	-17.761
	(4.21)	(4.72)
Arellano-Bond		
No Controls	-3.936	-15.300
	(2.75)	(3.28)
Controls	-1.837	-15.676
	(1.15)	(2.69)

<u>Table 6: Random Coefficients Estimations</u>

Simple Random Effects	Full Sample (47 countries)		OECD Sample (21 countries)	
	Two Periods	Four Periods	Two Periods	Four Periods
V_t ($\Delta(\ln y_{i,j,t})$)	-0.019 (0.58)	-0.048 (1.97)	0.594 (7.34)	0.283 (5.43)
Initial Income	0.001 (1.62)	0.000 (0.47)	0.002 (2.01)	0.000 (0.47)
Comparative Advantage	0.041 (12.27)	0.034 (7.60)	0.021 (5.19)	0.027 (5.41)
R Square	0.152	0.043	0.295	0.138
Hausman Test (P-value)	0.000*	0.000	0.000	0.000

Random Coefficients by Sector	Full Sample (47 countries)		OECD Sample (21 countries)	
	Two Periods	Four Periods	Two Periods	Four Periods
V_t ($\Delta(\ln y_{i,j,t})$)	0.026 (0.37)	-0.013 (0.24)	0.904 (3.74)	0.409 (2.78)
Initial Income	0.001 (1.61)	0.0006 (1.19)	0.001 (0.77)	0.0006 (0.79)
Comparative Advantage	0.047 (8.09)	0.047 (7.47)	0.036 (4.40)	0.053 (5.94)

Random Coefficients by Country	Full Sample (47 countries)		OECD Sample (21 countries)	
	Two Periods	Four Periods	Two Periods	Four Periods
V_t ($\Delta(\ln y_{i,j,t})$)	-0.081 (0.54)	-0.027 (0.27)	-0.142 (0.54)	-0.083 (0.45)
Initial Income	-0.004 (1.86)	-0.005 (2.10)	-0.003 (1.00)	-0.005 (1.48)
Comparative Advantage	0.016 (1.52)	0.020 (1.17)	0.011 (1.03)	0.005 (0.41)

The dependent variable is sectoral growth as measured by $\Delta(\ln y_{i,j,t})$ between the relevant sub-periods (1970, 1982 and 1992 in the within-2 estimation and 1970, 1976, 1982, 1988 and 1992 in the within-4 estimation). Period dummy variables are included when meaningful. Hausman test reports the P-values associated with the hypothesis that the Random Effects model is more efficient, except when marked with *, where the null hypothesis is that the Fixed Effects model is more efficient.

Table 7: UN Yearbook Data

A. Fixed Effects Estimations – Coefficient on Volatility

	Disaggregated	Aggregated
Cross-Section	2.401 (3.00)	0.343 (0.10)
Two Periods	-0.676 (1.35)	-5.502 (2.03)
Four Periods	-0.595 (1.77)	-7.114 (5.75)

B. Simple Random Effects – Coefficient on Volatility

	Disaggregated
Two Periods	-0.558 (1.10)
Four Periods	-0.500 (1.48)

C. Random Coefficients Estimations – Coefficient on Volatility

	Cross-Country	Cross-Sector
Two Periods	-3.338 (2.39)	-0.208 (0.26)
Four Periods	-1.756 (2.00)	-0.207 (0.19)

The disaggregated cross-sectional estimation is run with country and sector effects. The aggregate estimations in Panel A are run controlling for the Levine-Renelt variables, i.e. initial income, average investment rate and initial human capital. Controls include period indicator variables when appropriate and initial sectoral output level (measured in 1970 in the cross-sectional estimation, in 1970 and 1982 in the two-period estimation and in 1970, 1976, 1982 and 1988 in the four-period estimations)

Figure 1