

# The Great Diversification and its Undoing\*

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## Abstract

We investigate the hypothesis that macroeconomic fluctuations are primitively the results of many microeconomic shocks, and show that it has significant explanatory power for the evolution of macroeconomic volatility. We define “fundamental” volatility as the volatility that would arise from an economy made entirely of idiosyncratic microeconomic shocks, occurring primitively at the level of sectors or firms. In its empirical construction, motivated by a simple model, the sales share of different sectors vary over time (in a way we directly measure), while the volatility of those sectors remains constant. We find that fundamental volatility accounts for the swings in macroeconomic volatility in the US and the other major world economies in the past half century. It accounts for the “great moderation” and its undoing. Controlling for our measure of fundamental volatility, there is no break in output volatility. The initial great moderation is due to a decreasing share of manufacturing between 1975 and 1985. The recent rise of macroeconomic volatility is chiefly due to the increase of the size of the financial sector. As the origin of aggregate shocks can be traced to identifiable microeconomic shocks, we may better understand the origins of aggregate fluctuations. (JEL: E32, E37)

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# 1 Introduction

This paper explores the hypothesis that changes in the microeconomic composition of the economy during the post-war period can account for the “great moderation” and its unraveling, both in the US and in the other major world economies. We call “fundamental volatility” the volatility that would be derived only from microeconomic shocks. If aggregate shocks come in large part from microeconomic shocks (augmented by amplification mechanisms), then aggregate volatility should track fundamental volatility. To operationalize this idea, the key quantity we consider (which constitutes one departure from other studies) is the following definition of “fundamental volatility”:

$$\sigma_{Ft} = \sqrt{\sum_{i=1}^n \left( \frac{S_{it}}{\text{GDP}_t} \right)^2 \sigma_i^2}, \quad (1)$$

where  $S_{it}$  is the gross output (not just value added) of sector  $i$ , and  $\sigma_i$  is the standard deviation of the total factor productivity (TFP) in the sector. Note that the evolution of  $\sigma_{Ft}$  will only reflect the changing weights of different sectors in the economy, as micro-level TFP volatility is held constant through time. Notice also that in this measure the weights  $S_{it}/\text{GDP}_t$  do not add up to one. These are the “ $n$  weights” that research in productivity studies (Domar 1961, Hulten 1978) has identified as the proper weights to study the impact of microeconomic shocks.

Figure 1 plots  $\sigma_{Ft}$  for the US. We see a local peak around 1975, then a fall (due to the decline of a handful of manufacturing sectors), followed by a new rise (which we will relate to the rise of finance). This looks tantalizingly like the evolution of the volatility of US GDP growth. Indeed, we show statistically that the volatility of the innovations to GDP is well explained by the fundamental volatility  $\sigma_{Ft}$ . In particular, our measure explains the great moderation: the existence of a break in the volatility of US GDP growth around 1984. After controlling for fundamental volatility, there is no break in GDP volatility. Our measure also accounts for the recent rise in GDP volatility: as finance became large from the mid 1990s onward, this led to an increase in fundamental volatility, rising moderately in the late 1990s and then steeply from the early 2000s on.

In Figure 2 we present a similar analysis for the major economies for which we could get disaggregated data about shares and TFP movements: Japan, Germany, France, and the United Kingdom. The results also indicate that fundamental volatility tracks GDP volatility.

Our conclusion is that fundamental volatility appears to be a quite useful explanatory construct. It provides an operational way to understand the evolution of volatility, and sheds

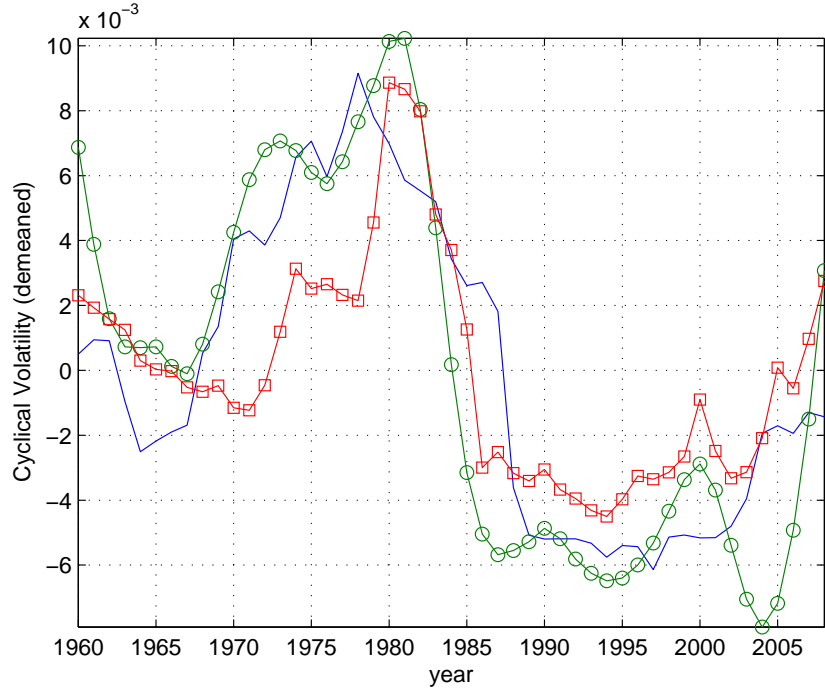


Figure 1: Fundamental Volatility and GDP Volatility. The squared line gives the fundamental volatility ( $4.5\sigma_{F_t}$ , demeaned). The solid and circle lines are annualized (and demeaned) estimates of GDP volatility, using respectively a rolling window estimate and an HP trend of instantaneous volatility.

more light on the origins of the latter.

Hence, our paper may bring us closer to a concrete understanding of the origin of macroeconomic shocks. What causes aggregate fluctuations? It has proven convenient to think about aggregate productivity shocks, but their origin is mysterious: what is the common high-frequency productivity shock that affects Wal-Mart and Boeing? This is why various economists have progressively developed the hypothesis that macroeconomic fluctuations can be traced back to microeconomic fluctuations. This literature includes Long and Plosser (1983), who proposed a baseline multi-sector model. Its implementation is relatively complex, as it requires sector sizes that are constant over time (unlike the evidence we rely on), and the use of input-output matrices. Horvath (1998, 2000) perhaps made the greatest strides toward developing these ideas empirically, in the context of a rich model with dynamic linkages. The richness of the model might make it difficult to see what drives its empirical features, and certainly prevents the use of a simple concept like the concept of fundamental volatility. Dupor (1999) disputes that the origins of shocks can be microeconomic, on the grounds of the law of large numbers: if there is a large number of sectors, aggregate volatility should vanish proportionally to the square root of the number of sectors. Hence, Horvath’s result would stem from poorly disaggregated data. Carvalho (2010), taking a network perspective on sectoral linkages, shows that the presence of hub-like, general-purpose inputs, can undo the law of large numbers argument and enable microeconomic shocks to affect aggregate volatility<sup>1</sup>. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2010) show how this perspective leads to volatility cascades.

Gabaix (2011) points out that “sectors” may be arbitrary constructs, and the fat-tailed Zipf distribution of firms (or perhaps very disaggregated sectors) necessarily leads to a high amount of aggregate volatility coming from microeconomic shocks, something he dubs the “granular” hypothesis. In that view, microeconomic fluctuations create a fat-tailed distribution of firms or sectors (Simon 1955, Gabaix 1999, Luttmer 2007). In turn, the large firms or sectors coming from that fat-tailed distribution create GDP fluctuations. Gabaix also highlights the conceptual usefulness of the notion of fundamental volatility. Di Giovanni and Levchenko (2009) show how that perspective helps explain the volatility of trade fluctuations across countries.

Against this backdrop, we use a simple way to cut through the complexity of the situation, and rely on a simple, transparent microeconomic construct, fundamental volatility, to predict

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<sup>1</sup>Interesting other conceptual contributions for the micro origins of macro shocks include Bak *et al.* (1993), Jovanovic (1987), Durlauf (1993), and Nirei (2006).

an important macroeconomic quantity, GDP volatility.

By bringing fundamental volatility into the picture, we contribute to the literature on the origins of the “great moderation,” a term coined by Stock and Watson (2002): the decline in the volatility of US output growth around 1984, up until about 2007 and the financial crisis. The initial contributions (McConnell and Perez-Quiros 2000, Blanchard and Simon 2001) diagnosed the decline in volatility, and conjectured that some basic explanations (including sectoral shifts – to which we will come back) did not seem promising. Perhaps better inventory management (Irvine and Schuh 2007) or better monetary policy (Clarida, Gali and Gertler 2000) were prime candidates. However, given the difficulty of relating those notions to data, much of the discussion was conjectural. Later, more full-fledged theories of the great moderation have been advanced. Arias, Hansen, and Ohanian (2007) attribute the changes in volatility to changes in TFP volatility within a one-sector model. Our work sheds light on the observable microeconomic origins of this change in TFP volatility. Justiniano and Primiceri (2008) demonstrate that much of the great moderation could be traced back to a change in the volatility of the investment demand function. Gali and Gambetti (2009) document a change in both the volatility of initial impulses and the impulse-response mechanism. Compared to those studies, we use much more disaggregated data, which allows us to calculate the fundamental volatility of the economy. Because we use richer disaggregated data, we can obviate some of the more heavy artillery of dynamic stochastic general equilibrium (DSGE) models, and have a parsimonious toolkit to think about volatility. Jaimovich and Siu (2009) find that changes in the composition of the labor force account for part of the movement in GDP volatility across the G7 countries: as the young have a more elastic labor supply, the aggregate labor supply elasticity should be increasing in the fraction of the labor force who is between 15 and 29 years old. We verify in the online appendix that fundamental volatility measure has substantial explanatory power over the JS measure Jaimovich and Siu (2009). In general, we view our proposal as complementary to those other mechanisms presented in the literature.

Finally, we relate to the literature on technological diversification and its effects on aggregate volatility. Imbs and Wacziarg (2003) and Koren and Tenreyro (2007) have shown that cross-country variation in the degree of technological diversification helps explain cross-country variation in GDP volatility and its relation with the level of development of an economy. With respect to these papers, the key difference is that here we focus on measures of sector-specific volatility derived from microeconomic TFP accounting and use theoretically founded  $n$  weights

for aggregation, while the aforementioned papers are essentially a-theoretical.<sup>2</sup> Also related to this paper, is the calibrated two-sector business cycle model presented in Moro (2009) stressing the contribution of structural change to changes in U.S. business cycle volatility. In particular, Moro (2009) explores the well known fact that manufacturing is more intermediate input intensive than services to show that a manufacturing-intensive economy will be more volatile (in the aggregate) than a service-based economy. While we concur to the finding that structural change forces have contributed to the low frequency decline in aggregate volatility, our setup also accommodates the important observed higher frequency movements around that trend, something that the structural change setup - by design- does not allow for.

The methodological principle of this paper is to use as simple and transparent an approach as possible. In particular, we find a way to avoid the use of the input-output matrix, which has no claim to be stable over time, and is not necessary in our framework. We examine the economics through a very simple two-period model, rather than an infinite-horizon DSGE model. Useful as they are for a host of macroeconomic questions, those models have many free parameters, and we find it instructive to focus our attention on a zero-free parameter construct, the fundamental volatility of the economy. This said, a potentially fruitful next step is to build a DSGE model on the many sectors in the economy.

Section 2 presents a very simple framework that motivates our concept of fundamental volatility and its implementation. Section 3 summarizes the basic empirical results. Section 4 presents a brief history of fundamental volatility. Section 5 presents variants on the basic empirical construct (including the non-zero covariances, use of value added vs. sales, firms vs. sectors, and other robustness checks). It also speaks to the role of correlation in the business cycle, and why previous analyses were pessimistic about the role of microeconomic shocks. Section 6 concludes on the role of policy and the use of fundamental volatility as an early warning system. The Appendices provide an account of the data and procedures we employ, as well as the proofs.

## 2 Framework and Motivation

In this section, we present a simple multisector model that exposes the basic ideas and motivates our empirical work. There are  $n$  sectors that produce intermediate and final goods, and

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<sup>2</sup>See also the recent contribution of Koren and Tenreyro (2011) who provide a quantitative model of technological diversification that generates a decline of volatility that is consistent with empirical evidence. Also related, Caselli et al (2010) analyze how increased trade openness may have contributed to diversification of cost shocks.

two primitive factors, capital and labor. Sector  $i$  uses capital and labor inputs  $K_i$  and  $L_i$ , and a vector of intermediary inputs  $\mathbf{X}_i = (X_{ij})_{j=1\dots n} \in \mathbb{R}^n$ : it uses a quantity  $X_{ij}$  from sector  $j$ . It produces a gross output  $Y_i = A_i F_i(K_i^{1-\alpha} L_i^\alpha, \mathbf{X}_i)$ , where  $F_i$  is homogenous of degree 1. We call  $\mathbf{C} = (C_1, \dots, C_n)$  and  $\mathbf{A} = (A_1, \dots, A_n)$  the vectors of consumption and productivity.

The utility function is  $\mathcal{C}(\mathbf{C}) - L^{1+1/\phi}$ , where  $\mathcal{C}$  is homogenous of degree 1, so that  $\mathcal{C}$  is like an aggregate good. Hence, given inputs  $K$  and  $L$ , the aggregate production function is defined as:

$$F(K, L; \mathbf{A}) = \max_{\substack{C_i, L_i, K_i, X_{ij} \\ 1 \leq i, j \leq n}} \mathcal{C}(\mathbf{C}) \text{ subject to} \\ \sum_i K_i \leq K; \quad \sum_i L_i \leq L; \quad \forall i, C_i + \sum_j X_{ji} \leq A_i F_i(K_i^{1-\alpha} L_i^\alpha, \mathbf{X}_i).$$

Note that this economic structure admits quite general linkages between sectors via the production functions  $F_i$  and the factor markets. The following lemma, whose proof is in the Appendix, describes some aggregation results in this economy.

**Lemma 1** *The aggregate production function can be written:*

$$F(K, L; \mathbf{A}) = \Lambda(\mathbf{A}) K^{1-\alpha} L^\alpha$$

for an aggregate TFP  $\Lambda(\mathbf{A})$ . After sectoral-level TFP shocks  $dA_i$ , the shock to aggregate TFP  $\Lambda$  is:

$$\frac{d\Lambda}{\Lambda} = \sum_{i=1}^n \frac{S_i}{Y} \frac{dA_i}{A_i} \quad (2)$$

where  $S_i$  is the value (i.e., price times quantity) of the gross output of sector  $i$ .

Formula (2) is Hulten (1978)'s result. We rewrite it slightly, using the “hat” notation for fractional changes,  $\hat{Z} \equiv dZ/Z$ ,<sup>3</sup> and time subscripts. Shocks  $\hat{A}_{it}$  to the productivity in sector  $i$  result in an aggregate TFP growth  $\hat{\Lambda}_t$  expressed as:

$$\hat{\Lambda}_t = \sum_{i=1}^n \frac{S_{it}}{Y_t} \hat{A}_{it} \quad (3)$$

where  $S_{it}$  is the value of sales (gross output) in sector  $i$ , and  $Y_t$  is GDP.  $S_{it}/Y_t$  is called the “Domar” weight.

Note that the sum of the weights  $\sum_{i=1}^n S_{it}/Y_t$  can be greater than 1. This is a well-known and important feature of models of complementarity. If on average the sales to value added

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<sup>3</sup>The rules are well known and come from taking the logarithm and differentiating. For instance,  $\widehat{X^\alpha Y^\beta Z^\gamma} = \alpha \hat{X} + \beta \hat{Y} + \gamma \hat{Z}$ .

ratio is 2, and each sector has a TFP increase of 1%, the aggregate TFP increase is 2%. This effect comes from the fact that a Hicks-neutral productivity shock increases gross output (sales), not just value added, and has been analyzed by Domar (1961), Hulten (1978), and Jones (2011).<sup>4</sup>

Consider the baseline case where productivity shocks  $\hat{A}_{it}$  are uncorrelated across  $i$ 's, and unit  $i$  has a variance of shocks  $\sigma_i^2 = \text{var}(\hat{A}_{it})$ . Then, we have  $\sigma_\Lambda = \sigma_F$ , where we define:

$$\sigma_F = \sqrt{\sum_{i=1}^n \left(\frac{S_{it}}{Y_t}\right)^2 \sigma_i^2}. \quad (4)$$

This defines the “fundamental” volatility, which comes from microeconomic shocks. Gabaix (2011) calls this the “granular” volatility.

To see the changes in GDP, we assume that capital can be rented at a price  $r$ . The agent's consumption is  $Y - rK$  with  $Y = \Lambda K^{1-\alpha} L^\alpha$ . The competitive equilibrium implements the planner's problem, which is to maximize the agent's utility subject to the resource constraint:

$$\max_{K,L} C - L^{1+1/\varphi} \text{ subject to } C = \Lambda K^{1-\alpha} L^\alpha - rK.$$

The solution is obtained by standard methods detailed in the proof of Proposition 1.

$$Y = v \Lambda^{\frac{1+\varphi}{\alpha}},$$

for a constant  $v$  independent of  $\Lambda$ . Taking logs,  $\ln Y = \frac{1+\varphi}{\alpha} \ln \Lambda + \ln v$ , and a change in TFP  $\hat{\Lambda}$  creates a change in GDP equal to<sup>5</sup>

$$\hat{Y} = \frac{1+\varphi}{\alpha} \hat{\Lambda}. \quad (5)$$

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<sup>4</sup>The intuition for (3) is the following. Suppose there are just two sectors, say cars (a final good, sector 1) and plastics (both a final and an intermediary good, sector 2). Cars use plastics as an intermediary input. Suppose furthermore there is productivity growth of  $\hat{A}_{1t} = 1\%$  in cars and  $\hat{A}_{2t} = 3\%$  in plastics. Suppose that, after the shock, there is no reallocation of factors. We then have 1% more cars in the economy and 3% more plastics. Those goods have not yet been reallocated to production, but still, they have a “social value,” captured by their price. Hence, if the economy uses the same quantity of factors, GDP has increased by  $dY_t = 1\% \times \text{initial value of cars} + 3\% \times \text{initial value of plastic}$ , i.e.,  $dY_t = S_{1t} \times \hat{A}_{1t} + S_{2t} \times \hat{A}_{2t}$ . Dividing by  $Y_t$ , we get  $\frac{dY_t}{Y_t} = \sum_{i=1}^2 \frac{S_{it}}{Y_t} \hat{A}_{it}$ . However, what has increased is the productive capacity of the economy. So, it is really TFP that has increased by  $\hat{\Lambda}_t = \sum_{i=1}^2 \frac{S_{it}}{Y_t} \hat{A}_{it}$ . GDP might increase more or less once we take into account the response of labor supply, something we shall consider very soon.

<sup>5</sup>In general, we would have  $\hat{Y} = \frac{1+\varphi}{\alpha} \hat{\Lambda} + \hat{v}$ . Here we want to focus entirely the impact of productivity shocks  $\hat{\Lambda}$ , and abstract from factors that will change the value of the  $v$ , e.g. changes in the world interest rate etc.



Given that the volatility of TFP is the fundamental volatility  $\sigma_{Ft}$ , the volatility of GDP is  $\sigma_{GDPt} = \frac{1+\varphi}{\alpha} \sigma_{Ft}$ . We summarize the situation in the next proposition.<sup>6</sup>

**Proposition 1** *The volatility of GDP growth is*

$$\sigma_{Yt} = \mu \cdot \sigma_{Ft}, \quad (6)$$

where the fundamental volatility  $\sigma_{Ft}$  is given by (4), and the productivity multiplier  $\mu$  is equal to

$$\mu = \frac{1+\varphi}{\alpha}. \quad (7)$$

Here  $\alpha$  is the labor share and  $\varphi$  is the Frisch elasticity of labor supply.

Our hypothesis is that, indeed,  $\sigma_{Ft}$  explains a substantial part of GDP volatility, as motivated by (6). In our baseline specification, we construct  $\sigma_{Ft}$  as in equation (4), taking the sales to value added weights directly from detailed sectoral data provided by Dale Jorgenson and associates. We use the same data source to compute sectoral TFP growth - by standard TFP accounting (with intermediate inputs) methods; see for example Jorgenson et al. (1987) - and then take its standard deviation to obtain  $\sigma_i$ <sup>7</sup>. Notice that we keep  $\sigma_i$  time-independent. We do this for two reasons. First, Section 5.1 shows that the volatility of TFP does not exhibit any marked trend at the micro level, and that our results are robust to time-varying volatility. Second, by using a constant  $\sigma_i$ , we highlight that the changes in fundamental volatility come only from changes in the shares of the largest sectors in the economies, rather than from their volatilities (which would make the explanation run the risk of being circular). We thus explain time-varying GDP volatility solely with time-varying shares of economic activity within the economy.

To interpret the results, it is useful to comment on the calibration. We interpret the Frisch elasticity of labor supply broadly, including not only changes in hours worked per employed

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<sup>6</sup>Here, capital can be elastically rented at a marginal cost  $r$ , as in a model with utilization cost or a small open economy. The result generalizes, e.g. to the case where using more capital costs  $rK^\xi$ , where  $\xi_K \geq 0$  reflects that higher utilization is marginally more costly, and  $r$  is then simply a scale parameter. Then, the problem becomes  $\max_{K,L} C - L^{1+1/\varphi}$  subject to  $C = \Lambda K^{1-\alpha} L^\alpha - rK^\xi$ . The solution is  $Y = \nu' \Lambda^{\mu'}$ , for  $\mu' = 1/(1 - \alpha/(1 + 1/\phi_L) - (1 - \alpha)\xi)$  and a  $\nu'$  independent of  $\Lambda$ . For simplicity we take  $\xi = 0$ , but a  $\xi > 0$  would be defensible too.

<sup>7</sup>The original data is annual and provides a breakdown of the entire US economy into 88 sectors. Following much of the sectoral productivity literature we focus on private sector output and drop government sectors. See Appendix A for further details on the data sources and on the construction of our fundamental volatility measure.

worker, but also changes in employment, and changes in effort.<sup>8</sup> Using this notion, recent research (e.g., summarized in Hall 2009a,b) is consistent with a “macro elasticity” of  $\varphi = 2$ , in part because of the large reaction of unemployment and effort (as opposed to simply hours worked per employed worker) to business cycle conditions.<sup>9</sup> Using these values and the labor share of  $\alpha = 2/3$ , we obtain a multiplier of  $\mu = 4.5$ .

Figure 1 shows the fundamental volatility graphs from 1960 to 2008. We see that fundamental volatility and GDP volatility track each other rather well. By 2008 we are already at mid 1980s levels. This suggests a good correlation between fundamental volatility and GDP volatility. The next section studies this systematically.

### 3 Fundamental Volatility and Low-Frequency Movements in GDP Volatility

#### 3.1 US Evidence

##### 3.1.1 Basic Facts

As a baseline measure of cyclical volatility, we first obtain deviations from the HP trend of log quarterly real GDP (smoothing parameter 1600; sample 1947:Q1 to 2009:Q4; source FRED database). We then compute the standard deviation at quarter  $s$  using a rolling window of 10 years (41 quarters, centered around quarter  $s$ ). In order to extend the period to the latest recession, for 2005:Q1 until 2009:Q4 we use uncentered (i.e., progressively more one-sided) windows. We refer to this measure as  $\sigma_{Yt}^{\text{Roll}}$ . To construct its annual counterpart, for a given year  $t$ , we average  $\sigma_{Yt}^{\text{Roll}}$  over the four quarters of that year.

As a robustness check, we also consider a different measure of cyclical volatility, namely the instantaneous quarterly standard deviation as computed by McConnell and Quiros (2000). For this measure, we start by fitting an AR(1) model to real GDP growth rates (1960:Q1 until 2008:Q4):

$$\Delta y_s = \psi + \phi \Delta y_{s-1} + \epsilon_s \quad (8)$$

where  $y_s$  is log GDP in quarter  $s$ . We obtain as estimates  $\psi = 0.006$  ( $t = 6.78$ ) and  $\phi = 0.292$  ( $t = 4.20$ ). As is well known, an unbiased estimator of the annualized standard deviation is

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<sup>8</sup>We can also take it as reduced-form for richer acceleration mechanisms, e.g. a financial accelerator.

<sup>9</sup>This model implies  $\widehat{L} = \frac{\phi}{1+\phi} \widehat{Y} = 2/3 \widehat{Y}$ , which is in line with the main features of the business cycle, which reflects a similar roughly volatility of GDP and hours worked. It reflects how a “macro” elasticity is necessary to replicate this fact, as a small elasticity  $\phi$  would create a too small volatility of hours over the business cycle.

given by  $2\sqrt{\frac{\pi}{2}}|\hat{\epsilon}_s|$ , where the factor 2 converts quarterly volatility into annualized volatility, and the  $\sqrt{\frac{\pi}{2}}$  comes from the fact that, if  $\varepsilon \sim N(0, \sigma^2)$ , then  $\sigma = E\left[\sqrt{\frac{\pi}{2}}|\varepsilon|\right]$ . To construct an annual measure of volatility in year  $t$ , we take the average of the four measures  $2\sqrt{\frac{\pi}{2}}|\hat{\epsilon}_{t:q}|$  of quarterly volatility (where date  $t : q$  is the  $q$ th quarter of year  $t$ ). Namely, we construct the annualized volatility in year  $t$  as:  $\sigma_{Yt}^{\text{Inst}} \equiv \frac{1}{2}\sqrt{\frac{\pi}{2}}\sum_{q=1}^4|\hat{\epsilon}_{t:q}|$ , and call it the “instantaneous” measure of GDP volatility in year  $t$ . We shall also use  $\sigma_{Yt}^{\text{HP}}$ , the Hodrick-Prescott smoothing of the instantaneous volatility  $\sigma_{Ys}^{\text{Inst}}$ .

Figure 1 plots the familiar great moderation graphs depicting the halving of volatility in the mid 1980s. Interestingly, both measures also point to a significant increase in volatility from the early 2000s on, mostly as a result of the recent crisis. It also depicts the sample fit of our fundamental volatility measure,  $\sigma_{Ft}$ , for the annual case given a baseline value of  $\mu = 4.5$ . In particular, it shows  $\sigma_{Yt}^{\text{Roll}}$  and  $\sigma_{Yt}^{\text{HP}}$  (annualized and demeaned), together with  $4.5\sigma_{Ft}$  (demeaned).

We run least squares regressions of the type:

$$\sigma_{Yt} = a + b\sigma_{Ft} + \eta_t \quad (9)$$

where  $\sigma_{Ft}$  is our measure of fundamental volatility, and  $\sigma_{Yt}$  is one of the measures of volatility described above:  $\sigma_{Yt}^{\text{Roll}}$  for the rolling window estimate,  $\sigma_{Yt}^{\text{Inst}}$  for the instantaneous standard deviation measure. Note that  $\sigma_{Ft}$  is only available on an annual basis. As such we pursue two different strategies: i) annualizing the standard deviation measure by averaging the left-hand side over four quarters (“annual” below), or ii) linearly interpolating our measures of fundamental volatility in order to obtain quarterly frequency data.

Table 1: GDP Volatility and Fundamental Volatility

|           | Annual Data- $\sigma_{Yt}^{\text{Roll}}$ | Annual Data- $\sigma_{Yt}^{\text{Inst}}$ |
|-----------|--|--|
| $\hat{a}$ | −0.029<br>(−5.53;0.005)                  | −0.0483<br>(−4.47;0.019)                 |
| $\hat{b}$ | 4.815<br>(8.39;0.574)                    | 7.015<br>(5.89;1.190)                    |
| $R^2$     | 0.60                                     | 0.43                                     |

*Notes:* Regression of GDP volatility on fundamental volatility:  $\sigma_{Yt} = a + b\sigma_{Ft} + \eta_t$ . In parentheses are  $t$ -statistics and standard errors.

Table 1 summarizes the results.<sup>10</sup> We find good statistical and economic significance of

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<sup>10</sup>Note that  $\sigma_{Ft}$  is only available on an annual basis. In Table 1, we have used annual measures of aggregate

$\sigma_F$ .<sup>11</sup> It is the sole regressor, and its  $R^2$  is around 60% for the rolling estimate of volatility.<sup>12</sup> This shows that  $\sigma_{Ft}$  explains a good fraction of the historical evolution on GDP volatility. Of course, the  $R^2$  of  $\sigma_{Yt}^{\text{Inst}}$  is lower than for  $\sigma_{Yt}^{\text{Roll}}$ , as  $\sigma_{Yt}^{\text{Inst}}$  is a much more volatile measure of GDP volatility.

Note that, in our regressions, all the movements come from the sizes of sectors: their volatilities are fixed in our construction of  $\sigma_F$ . We do this for parsimony's sake, and also because it is warranted by the evidence: the average volatility of sectoral-level microeconomic volatility did not have noticeable trends in the sample. Indeed, the average sectoral-level volatility is 3.4% in the 1960-2005 period, 3.5% in the 1960-1984 period, and 3.2% in the 1984-2005 period. We cannot reject the null of equal mean volatility across the two sample periods (the  $p$ -value is 0.18). This results hold broadly at the sectoral level. That is, for each sector, we test whether that sector's TFP growth variance in the period 1984-2005 is statistically different from that computed in the period 1960-1983. We have implemented Levene's test for equality of variances in these two sub-samples. At a 5% significance level we fail to reject the null of equal variances for 66 of the 77 sectors considered, i.e. the vast majority of sectors does not show statistically different volatility in the two subsamples.<sup>13</sup> In addition, there is a very low correlation between movements in sectoral volatility and changes in Domar weights. The baseline of no change in sectoral volatility seems both reasonable and parsimonious to us. and our construction of  $\sigma_F$  allows to isolate the impact of the changes in microeconomic composition of the economy. This assumption is relaxed later in section 5.1.3.

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volatility on the left hand side. Alternatively, we can linearly interpolate our measure of fundamental volatility and run the regression at a quarterly frequency. The latter strategy yields very similar - and significant- point estimates.

<sup>11</sup>Our model predicts an intercept  $a = 0$ . Simple variants  $\sigma_Y = g(\sigma_F)$  could predict a positive  $a$ , or a negative  $a$ , as we find here empirically. A positive  $a$  is generated by adding other shocks to GDP. A negative  $a$  is generated if  $g$  is convex, i.e. when the environment is more volatile, the economy's technologies are more flexible (as in the Le Chatelier principle). To be more precise, take the case with  $g$  convex,  $g(0) = 0$  and a small dispersion of  $\sigma_F$ . Then, in the regression  $\sigma_{Yt} = a + \beta\sigma_{Ft}$ , we find  $\beta = g'(\overline{\sigma_F})$  and a  $a = \overline{g(\sigma_F)} - g'(\overline{\sigma_F})\overline{\sigma_F} < 0$ . Equivalently, the model generates  $\overline{\sigma_Y} < \beta\overline{\sigma_F}$ .

<sup>12</sup>As a two-step OLS can be inefficient econometrically, we have also performed an ARCH-type maximum-likelihood estimation, based on the joint system (8) and  $\sigma_t = \alpha + \beta\sigma_{Ft} + \eta_t$ . Its results are very similar to those in Table 1.

<sup>13</sup>One exception is finance, which shows a decline in sectoral volatility in the later part of our sample, which ends in 2008. We conjecture this decline will prove nothing only temporary when more years of data are available.

### 3.1.2 Accounting for the Break in US GDP Volatility

A common way of quantifying the great moderation is to test the null hypothesis of a constant level in GDP volatility

$$\sigma_{Yt} = a + \eta_t$$

against an alternative representation featuring a break in the level

$$\sigma_{Yt} = a + cD_t + \eta_t$$

where  $D_t$  is a dummy variable assuming a value of 1 for periods  $t \geq T$  given an estimated break date  $T$ . Following common practice in the literature (see McConnell and Quiros (2000), Stock and Watson (2002) and Sensier and van Dijk (2004), we take  $\sigma_{Yt}$  to be given by the instantaneous volatility measure  $\sigma_{Yt}^{\text{Inst}}$ , and test for the presence of a break in level using Bai and Perron's (1998) SupLR test statistic<sup>14</sup>. In what follows, we look for a single break date  $T$ , where we assume  $T$  lies in a range  $[T_1, T_2]$  with  $T_1 = 0.2n$  and  $T_2 = 0.8n$ , and  $n$  is the total number of observations (i.e., the trimming percentage is set at 20% of the sample).<sup>15</sup>

To assure comparability and since our sample period does differ, we start by reconfirming the findings first reported in McConnell and Quiros (2000). We do find strong support for a level break. The estimated break date  $T$  is 1983 (estimated with a 90% confidence interval given by 1980 and 1986) when we do not control for fundamental volatility.<sup>16</sup> The estimated value of  $c$  is  $-0.010$  ( $t = -5.50$ ), implying a decrease in aggregate volatility after this date.

We next test the hypothesis that, once our fundamental volatility measure is accounted for in the dynamics of  $\sigma_{Yt}^{\text{Inst}}$ , there is no such level break in aggregate volatility. That is, we test for the null of no break in the intercept of the equation:<sup>17</sup>  $\sigma_{Yt}^{\text{Inst}} = a + b\sigma_{Ft} + \eta_t$ . To rule

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<sup>14</sup>McConnell and Quiros (2000) and Stock and Watson (2002) show that, for U.S. quarterly GDP, one cannot reject the null of no break in the autoregressive coefficients in the equation for GDP growth, thus enabling us the residuals in (8) to test for a break in the variance.

<sup>15</sup>Bai and Perron (2006) find that serial correlation can induce significant size distortions when low values of the trimming percentage are used, and recommend values of 15% or higher. We use code made available by Qu and Perron (2007) to compute the test statistics and obtain critical values.

<sup>16</sup>The NBER Working Paper version of this paper uses quarterly estimates of volatility, and give similar estimates and results. The estimated break date  $T$  is 1984:1 and is estimated with a 90% confidence interval given by 1981:2–1986:4.

<sup>17</sup>The resulting SupLR test statistic reported in the Table is computed under the assumptions of no serial correlation in  $\eta_t$  and the same distribution of  $\eta_t$  across segments. The key conclusion (failure to reject the null of no break in  $a$  when we account for fundamental volatility) is unchanged when we relax either or both of these assumptions.

Table 2: Break Tests with Fundamental Volatility

|                  | Break Test With or Without Fundamental Volatility on the Right-Hand Side |                                  |                                  |                                     |
|------------------|--|----------------------------------|----------------------------------|-------------------------------------|
|                  | Without  | With                             |                                  |                                     |
|                  | H <sub>0</sub> : No break in $a$   | H <sub>0</sub> : No Break in $a$ | H <sub>0</sub> : No Break in $b$ | H <sub>0</sub> : No Break in $a, b$ |
|                  | (i)  | (ii)                             | (iii)                            | (iv)                                |
| SupLR stat.      | 26.50  | 8.32                             | 8.64                             | 8.91                                |
| Null of no break | Reject   | Accept                           | Accept                           | Accept                              |
| Est. break date  | 1983   | None                             | None                             | None                                |

*Notes:* We perform a break test for equation  $\sigma_{Yt}^{Inst} = a + \eta_t$  (column i) and  $\sigma_{Yt}^{Inst} = a + b\sigma_{Ft} + \eta_t$ , the regression of instantaneous GDP volatility on fundamental volatility (columns ii-iv). Column (i) confirms that, without conditioning on fundamental volatility, there is a break in GDP volatility (the great moderation). Next, column (ii) performs a test on the  $a$  coefficient. We cannot reject the null hypothesis of no break. This means that, once we control for fundamental volatility, there is no break in GDP volatility. The subsequent tests for breaks in  $b$  and  $(a, b)$  are extra robustness checks (columns iii-iv); they confirm the conclusion that, after controlling for fundamental volatility, there is no break in GDP volatility. From Qu and Perron (2007), the 5% asymptotic critical values reported for the *SupLR* statistic are 13.34 for (ii) and (iii), and 11.17 for (iv).

out the additional possibility that the break in aggregate volatility is the result of a break in its link with fundamental volatility, we also test the null of no break on the slope parameter  $b$  and the joint null of no break in both  $a$  and  $b$ .<sup>18</sup>

The results are in Table 2. We cannot reject the null of no break in any of these settings. We conclude that, after controlling for the time series behavior of fundamental volatility, there is no break in GDP volatility. This is the sense in which fundamental volatility explains the great moderation (and its undoing): after controlling for the changes in fundamental volatility, there is no statistical evidence of a residual great moderation.<sup>19</sup>

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<sup>18</sup>When testing for the null of no break in only one of the parameters (either the intercept or the slope), we are imposing the restriction that there is no break in the other parameter.

<sup>19</sup>As a robustness check, the results do not materially change if we drop the last four years of the data.

## 3.2 International Evidence

We now extend the previous analysis to the four other major economies: France, Japan, Germany, and the UK. As is well known (see Stock and Watson 2005), these countries have exhibited quite different low-frequency dynamics of GDP volatility throughout the last half-century. Under the hypothesis of this paper, it should be the case that the evolution of our measure of fundamental volatility is also heterogenous across these economies.

Relative to the US, we face greater data limitations, along both the time series and cross-sectional dimensions. We are able to construct the Domar weight measures from 1970 to 2005 (from 1973 for Japan). Though we have considerable sectoral detail for nominal measures, sector-specific price indexes are only available for half or less of the sectors in each country.<sup>20</sup> This renders impossible to construct sectoral TFP growth at the level of detail that is available for the nominal gross output and value added data. To overcome this, we assume that a sector's TFP volatility is a technological characteristic of a sector and is invariant across countries. Thus we use the sectoral volatility  $\sigma_i$  that we have computed for sector  $i$  in the US<sup>21</sup>

$$\sigma_{Fct} = \sqrt{\sum_{i=1}^n \left( \frac{S_{ict}}{Y_{ct}} \right)^2 \sigma_i^2} \quad (10)$$

where the  $c$  superscripts now denote country  $c$  specific variables and  $i$  still denotes sector level variables. Motivated by our discussion above, we consider a multiplier  $\mu = 4.5$  to obtain the volatility of GDP implied by our fundamental volatility measure, i.e.,  $\sigma_{Yt} = 4.5\sigma_{Fct}$ . As in the US case, we take as a baseline measure of cyclical volatility the 10-year rolling window standard deviation of HP-filtered quarterly real GDP. Figure 2 compares the evolution of these measures (where we, again, demean both measures).

As in the US case, our proposed measure seems to account well for the (different) low-frequency movements in GDP volatility in this set of countries. In the UK it captures the

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<sup>20</sup>See Appendix A for more details on the sources, description, and construction of these measures.

<sup>21</sup>The online appendix details how to match sectors across countries. As a robustness check we also considered an alternative measure of country specific fundamental volatility. Specifically, we consider averaging over the standard deviation of sectoral TFP growth for the limited subset of sectors for which we are able to back TFP growth series. That is we construct  $\bar{\sigma}_{Fct} = \sqrt{\sum_{i=1}^N \left( \frac{S_{ict}}{Y_{ct}} \right)^2 \bar{\sigma}_c^2}$ , where  $\bar{\sigma}_c$  is the average standard deviation of TFP growth. All results presented in this section are robust to this alternative measure. The online appendix presents yet another measure,  $\bar{\sigma}_{Fct} = \sqrt{\sum_{i=1}^N \left( \frac{S_{ict}}{Y_{ct}} \right)^2 \sigma_{ic}^2}$ , where we measure industry volatility is country specific, which perhaps less well measured than  $\sigma_i = \sigma_{i,US}$  used in (10). The results are quite similar the results in this section.

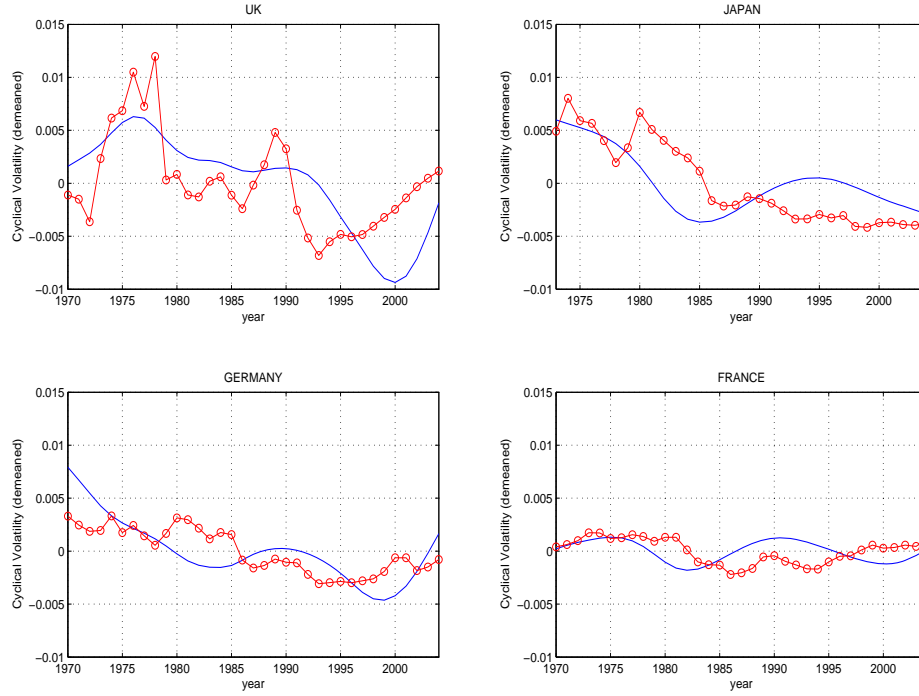


Figure 2: GDP Volatility and Fundamental Volatility in Four OECD countries. Solid line: smoothed rolling window standard deviation of deviations from HP trend of quarterly real GDP. Circle line: fundamental volatility measure,  $\sigma_{Yt} = 4.5\sigma_{Ft}^j$ . Both measures are demeaned. We report results for the four large countries for which we have enough disaggregated data.

reduction in volatility in the late 1970s, its leveling off until the early 1990s and its renewed decline during that decade. As Stock and Watson (2005) had noticed, Germany provides a different picture, that of a large but gradual decline. Again, our measure does well, displaying a much smoother negative trend. For Japan, fundamental volatility tracks well the fall in GDP volatility in the late 1970s and early 1980s, as well as its levelling off around the mid 1980s. For France, our measure displays no discernible trend, hovering around its mean throughout the sample period. This is in line with the muted low-frequency dynamics of French GDP volatility.

To complement this, we consider running panel regressions

$$\sigma_{Yct} = \alpha_c + \alpha_t + \beta\sigma_{Fct} + \varepsilon_{ct} \quad (11)$$

where  $\sigma_{Yct}$  is our rolling window measure of cyclical volatility for country  $c$  in year  $t$  and  $\sigma_{Fct}$  are the country-specific fundamental volatility measures discussed above. We include the US



Table 3: GDP Volatility and Fundamental Volatility: International Evidence

|               | $\sigma_{ct}$        | $\sigma_{ct}$         |
|---------------|----------------------|-----------------------|
| $\hat{\beta}$ | 3.08<br>(7.94;0.388) | 2.172<br>(3.52;0.618) |
| $\alpha_t$    | No                   | Yes                   |
| Observations  | 172                  | 172                   |

*Notes:* We run the regression  $\sigma_{Yct} = \alpha_c + \alpha_t + \beta\sigma_{Fct} + \varepsilon_{ct}$ , where  $\sigma_{Yct}$  is the country volatility using a rolling window measure,  $\sigma_{Fct}$  is the fundamental volatility of the country defined in (10),  $\alpha_c$  a country fixed effect and  $\alpha_t$  a time fixed effect.  $t$ -statistics and robust standard errors (Newey-West with two lags) in parentheses.

along with the four other economies mentioned. We use both country fixed effects  $\alpha_c$ , and run the pane with and without time fixed effects  $\alpha_t$ . We view the specification without a time trend as the cross-country analog of the regressions run above for the US alone. The specification with time fixed effects allows us to control for potential common factors affecting volatility in all countries at a given time, and therefore identifies  $\beta$  through cross-country timing differences in the evolution of fundamental volatility. While this specification renders the value of  $\beta$  not comparable to the values obtained for the simple US regression, it strengthens our results by minimizing possible spurious regression type problems in our baseline specification.<sup>22</sup>

Table 3 reports the results. All results are significant at the 1% level (they are also significant without the US). Again, we confirm the existence of a tight link between aggregate volatility and our fundamental volatility measure. Note that, for the specification without time fixed effects, our measure is quantitatively similar to the U.S. univariate case reported above. Its significance survives when we allow for a time fixed effects <sup>23</sup>.

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<sup>22</sup>We report heteroskedasticity-autocorrelation robust standard errors by using a Newey-West estimator with 2 lags.

<sup>23</sup>We also experimented with instrumenting  $\sigma_{Fct}^j$  by its own lag or allowing for a (common) linear time trend. All results survive.

### 3.3 How Much of the Break in US volatility does Fundamental Volatility Account for?

A natural question is: how much of the break in volatility does fundamental volatility account for? There are different ways to answer this.

One way is with the break test of Table 2: after controlling for FV, we do not reject the hypothesis of no break in the US volatility. In that sense, we cannot reject the hypothesis that fundamental volatility explains 100% of the break. Furthermore, fundamental volatility leads us to precise narrative causes for the break in GDP volatility (see section 4.2.1).

Another way to answer the question is by observing that, using the appropriately smooth estimator of US volatility, FV explains (in a statistical,  $R^2$ , sense) about 60% of US volatility (Table 1).

A third way is the following: we compute the average aggregate volatility,  $\sigma_{Yct}$ , over the subperiods 1970-1984 and 1985-2000, which implies a decline in business cycle volatility of 0.96 percentage point. Across these two periods, the decline of our fundamental volatility measure in the US is of 0.016 percentage points. Using the US multiplier of  $\mu = 4.5$ , the decline in FV explains  $\mu = 0.016/0.096 = 75\%$  of the decline in FV. Using the international estimates (which have time and country dummies, hence are arguably harder to interpret), with  $\mu = 2.17$ , this implies that FV explains 36% of the change in US volatility.

All of these estimates are arguably defensible. We can get a point estimate by taking the average estimate over the above four procedures (100%, 60%, 75% and 36%). We conclude that fundamental volatility explains 68% of the decline in US GDP volatility. If we consider the break test, however, we cannot reject the null that fundamental volatility explains all of it.

Here, we have used the “statistical” notion of explanatory power. We will soon consider to a “substantial” notion at the end of US narrative (section 4.2.1). We now lay out more material to arrive there.

## 4 A Brief History of Fundamental Volatility

The previous section has shown that fundamental volatility correlates well with GDP volatility. In this section, we present a brief account of the evolution of our fundamental volatility measure in the last half-century.<sup>24</sup> We first present evidence showing that most movements in

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<sup>24</sup>See Jorgenson and Timmer (2011) for another analysis of structural change.

fundamental volatility are due to a diversification effect, i.e. changes in a share in the value added produced by the different sectors. Then, we present a country-by-country narrative accounting for the main movements in fundamental volatility.

#### 4.1 Movements in Fundamental Volatility: Changing Diversification vs other Factors

We can rewrite fundamental volatility (1) as

$$\sigma_{F_t} = \sqrt{\sum_{i=1}^n \left( \frac{S_{it}}{Y_{it}} \frac{Y_{it}}{Y_t} \right)^2 \sigma_i^2}$$

It is clear from this expression that time variation in fundamental volatility may obtain from three distinct sources. First, fundamental volatility may change because the typical *sectoral gross output-value added ratio*  $S_{it}/Y_{it}$  may change over time. That is, even if sectoral value added shares,  $Y_{it}/Y_t$ , did not change over time and volatility,  $\sigma_i^2$ , was held constant across sectors, fundamental volatility could decrease if the average sector in the economy had a lower  $S_{it}/Y_{it}$ . Second, there is a potential *diversification* effect: holding the other sources of variation fixed, fundamental volatility will decrease when the economy goes from one where the value added shares are concentrated in a few sectors to one where these are spread out more equally across different production technologies. Finally, fundamental volatility may be varying over time due to what can be termed a *compositional* effect: if there is a shift in Domar weights away from high volatility sectors and in to low volatility sectors, fundamental volatility will decline even if there is no diversification effect.

In order to assess the relative importance of each of these sources for movements in  $\sigma_{F_t}$ , we proceed by constructing three counterfactual fundamental volatility measures where we shut down the different sources of variation. Thus, in Panel A of Figure 3, we first shut down time variation in value-added weights and cross-sectoral heterogeneity in volatility thus isolating the contribution of variation in  $S_{it}/Y_{it}$ . To do this, we take  $Y_{it}/Y_t$ , for each sector  $i$ , to be given by its sample average (across time) and  $\sigma_i^2$  to be the same across sectors (and given by the cross-sectoral average). In the same manner, in Panel B, we shut down time variation in  $S_{it}/Y_{it}$  and cross sectoral heterogeneity in volatility, but keep  $Y_{it}/Y_t$  variable to isolate the contribution of the diversification effect. Finally, in Panel C, we shut down the compositional effect by  $\sigma_i^2$  to be the same across sectors (given by the average  $\sigma_i^2$ ) while letting  $S_{it}/Y_{it}$  and  $Y_{it}/Y_t$  vary over time.

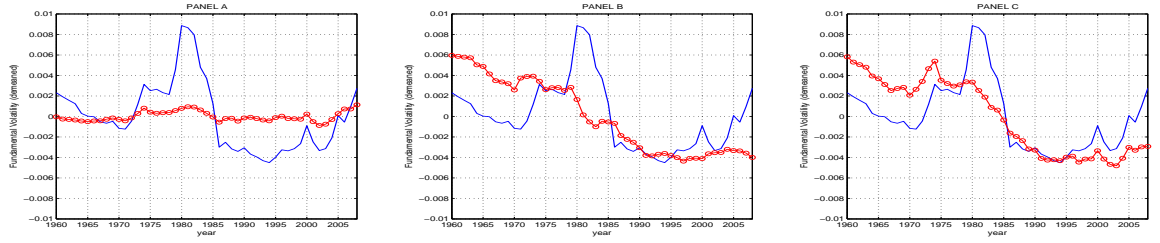


Figure 3: For each panel., the solid line is the baseline fundamental volatility measure ( $4.5\sigma_{F_t}$ , demeaned) and the circle line is a counterfactual fundamental volatility measure. In Panel A the counterfactual measure shuts down time variation in value added weights and sectoral variation in volatility. Panel B shuts down variation in sector level gross output to value added and sectoral variation in volatility. Panel C shuts down variation in sectoral volatility only.

As is clear from Panel A, time variation in sectoral gross output to value added ratios  $S_{it}/Y_{it}$  alone does not play much of a role. This comes from the fact that the average  $S_{it}/Y_{it}$  is roughly constant around its mean of 2.2<sup>25,26</sup> Things are different when we consider the diversification effect depicted in Panel B. The variation in value added shares alone seems to account for a significant fraction of the low frequency decline in fundamental volatility. However, it does not account for the spikes in fundamental volatility observed in the late 70s and early 80s nor for the increase in fundamental volatility observed from the mid 90s on. Given that we've already seen that time variation in  $S_{it}/Y_{it}$  is muted, it has to be the case that these are accounted by the compositional effect described above. This is confirmed in Panel C, where we shut down variation in sectoral volatility: the movements in fundamental volatility in the late 70s and from the mid 90s stem largely from putting more weight in more volatile sectors.

<sup>25</sup>Which is consistent with an average intermediate input share of 0.5 as documented in Jones (2011).

<sup>26</sup>This is also the case when we look at a more disaggregated level. Thus, looking at aggregates of sectors such as Agriculture and Mining, Manufacturing, Transportation and Utilities again reveals little time variation in their average  $S_{it}/Y_{it}$ .

## 4.2 A Brief History of Fundamental Volatility

### 4.2.1 United States

We find it useful to break our account of fundamental volatility into three questions: i) What accounts for the “long and large decline” of fundamental volatility from the 1960s to the early 1990s? ii) What accounts for the interruption of this trend from the mid 1970s to the early 1980s? iii) What is behind the reversal of fundamental volatility dynamics observed around the early 2000s<sup>27</sup> and its subsequent increase until 2008?

Our answers are the following: i) The long and large decline of fundamental volatility from the 1960s to the early 1990s is due to the smaller size of a handful of heavy manufacturing sectors. ii) The growth of the oil sector (which itself can be traced to the rise of the oil price) accounts for the burst of volatility in the mid 1970s. iii) The increase in the size of the financial sector is an important determinant of the increase in fundamental volatility.

We now detail our answers. To make them quantitative, we define:

$$H_i(t_1, t_2) = \frac{\left(\frac{S_{it_2}}{Y_{t_2}}\right)^2 \sigma_i^2 - \left(\frac{S_{it_1}}{Y_{t_1}}\right)^2 \sigma_i^2}{\sigma_{Ft_2}^2 - \sigma_{Ft_1}^2}. \quad (12)$$

That is,  $H_i(t_1, t_2)$  indicates how much of the change in squared fundamental volatility between  $t_2$  and  $t_1$  can be explained by the corresponding change in the squared Domar weight of industry  $i$ . By construction,  $\sum_i H_i(t_1, t_2) = 1$  for all  $t_1 \neq t_2$ .

The low-frequency decline in fundamental volatility observed from 1960 to 1990 can be accounted for almost entirely by the demise of a handful of heavy manufacturing sectors: Construction, Primary Metals, Fabricated Metal Products, Machinery (excluding Computers), and Motor Vehicles.<sup>28</sup> While only moderately large in a value-added sense in 1960 – accounting for 18% of total value added in 1960 –, these sectors are both relatively more intensive intermediate input users and relatively more volatile, thus accounting for a disproportionately large fraction of aggregate fundamental volatility in 1960 (30% of  $\sigma_F^2$ ).<sup>29</sup> In this sense, the relatively high aggregate volatility in the early 1960s was the result of an undiversified technological portfolio, loading heavily on a few heavy manufacturing industries. Their

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<sup>27</sup>Figures 1 and 6 show that  $\sigma_{Ft}$  has a last (local) minimum in 2002, and  $\sigma_F^{\text{Full}}$  has a last minimum in 2003. The  $\sigma_{Yt}$  volatility via a rolling windows is basically flat between 1990 and 2001, while  $\sigma_{Yt}$  measured by the HP filter has a last minimum in 2004. This can be summarized by saying that those measures start increasing in the early 2000s.

<sup>28</sup>Between 1960 and 1989, their  $H$  is 0.58. The main drivers are Construction ( $H = 0.36$ ) and Primary Metals ( $H = 0.12$ ).

<sup>29</sup>The share of  $\sigma_F^2$  due to sector  $i$  is defined as  $\left(\frac{S_{it}}{Y_t}\right)^2 \sigma_i^2 / \sigma_F^2$ . Those shares add up to 1.

demise, starting around the early 1970s and accelerating around 1980, meant that by 1990 they accounted for only 10% of aggregate volatility.

Another way to see this is to compute a counterfactual fundamental volatility measure where we fix the Domar weights of these sectors to their sample average, while using the actual, time-varying Domar weights for the other sectors. This enables us to ask what would have happened to fundamental volatility had these sectors not declined during the period of analysis. We find (see Figure 4) that in this counterfactual economy the level of fundamental volatility would have barely changed from the early 1960s to the early 1990s. At the same time, it is also clear that the dynamics of these sectors do not account either for the spike in fundamental volatility around 1980 nor do they play a role in its continued rise from the mid 1990s onwards.

Instead, we find that the spectacular rise and precipitous decline in fundamental volatility from the early 1970s to the mid 1980s are largely accounted for by the dynamics of two energy-related sectors: Oil and Gas Extraction, and Petroleum and Coal Products: the  $H$  (1971, 1980) of these sectors is 0.64 and 0.30, respectively. By 1981, these two sectors accounted for 41% of fundamental volatility, a fourfold increase from the average over the remainder of the sample. The decline of these two sectors also accounts for the bulk of the fall in fundamental volatility during the 1981-1986 period ( $H$  (1981, 1986) = 0.43 and 0.16). Three heavy-industry sectors decline as well, and account for some more of the decline of volatility: Primary Metals, Chemicals excluding Drug, and Machinery excluding Computers, which together have an  $H$ (1981, 1986) = 0.23. Hence, the “break” in fundamental volatility in the early 1980s is made of a fall in the share of energy, and a fall in the share of heavy industries around 1983.

To analyze the rise in fundamental volatility since the mid 1990s, we build on Philippon’s (2008) analysis of the evolution of the GDP share of the financial sector, but revisit it through the metric of fundamental volatility. We find that the combined contribution of three finance-related sectors – Depository Institutions, Non-Depository Financial Institutions (including Brokerage Services and Investment Banks), and Insurance – to fundamental volatility increased tenfold from the early 1980s to the 2000s, with the latest of these sharp movements occurring in the mid 1990s and coinciding with the rise of our fundamental volatility measure ( $H$ (1990, 2007) is 0.44 for Non-Depository Financial Institutions and 0.19 for Depository Institutions). From the late 1990s onward, these three sectors have accounted for roughly 20% of fundamental volatility.

In a counterfactual economy where the weights of these sectors are held fixed, fundamental volatility would have prolonged its trend decline until the early 2000s (see Figure 5). While the

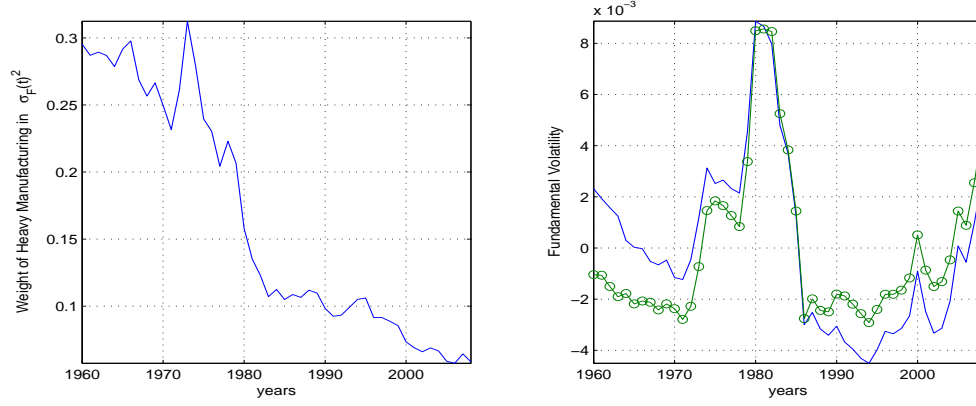


Figure 4: **Left:** Weight of heavy manufacturing sectors in  $\sigma_{Ft}^2$ . **Right:** The continuous line is the baseline fundamental volatility measure ( $4.5\sigma_{Ft}$  demeaned). The circled line gives a counterfactual volatility measure (also demeaned) where weights of heavy manufacturing sectors are fixed at their sample average.

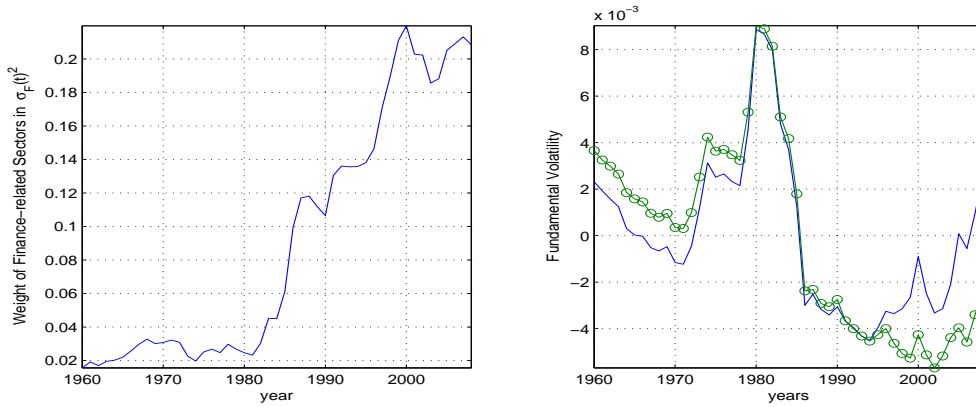


Figure 5: **Left:** Weight of finance-related sectors in  $\sigma_{Ft}^2$ . **Right:** The continuous line is the baseline fundamental volatility measure ( $4.5\sigma_{Ft}$  demeaned). The circled line gives a counterfactual volatility measure (also demeaned) where weights of finance-related sectors are fixed at their sample average.

renewed exposure to energy-related sectors from the mid-2000s onwards would have reversed this trend somewhat, the implied level of fundamental volatility at the end of the sample would have been lower, in line with that observed in the early 1990s (and not that of the early 1960s and 1970s as our baseline measure implies). The rise of finance is thus key to explaining the recent rise in aggregate volatility and the undoing of the great moderation: as the US economy loaded more and more on these sectors, fundamental volatility rose sharply, reflecting a return to a relatively undiversified portfolio of sectoral technologies.

**On the sense in which fundamental volatility “explains” GDP volatility** We have seen above how FV “explains,” in a statistical sense, movements of GDP volatility. The above narrative helps us get a better feel for the “substantial” sense in which FV explains GDP volatility. To start the discussion, we would like to invite the reader to a quotation by Richard Feynman (cited in Gleick (2003, p. 370)): <sup>30</sup>

You see, when you ask why something happens, how does a person answer why something happens? For example, Aunt Minnie is in the hospital. Why? Because she went out on the ice and slipped and broke her hip. That satisfies people. But it wouldn’t satisfy someone who came from another planet and knew nothing about things... When you explain a why, you have to be in some framework that you’ve allowed something to be true. Otherwise you’re perpetually asking why... You go deeper and deeper in various directions. Why did she slip on the ice? Well, ice is slippery. Everybody knows that-no problem. But you ask why the ice is slippery... And then you’re involved with something, because there aren’t many things slippery as ice... A solid that’s so slippery? Because it is in the case of ice that when you stand on it, they say, momentarily the pressure melts the ice a little bit so that you’ve got an instantaneous water surface on which you’re slipping. Why on ice and not on other things? Because water expands when it freezes. So the pressure tries to undo the expansion and melts it... I’m not answering your question, but I’m telling you how difficult a why question is.

Hence, “Explaining” is really explaining at one more level in the causal chain (a “proximate” cause), and not all the way down (an elusive “ultimate” cause). In that sense, fundamental volatility is arguably a useful explanatory construct that points to the relevant substantive developments in US history.

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<sup>30</sup>We thank Avinash Dixit for that quotation.



Take the rise in fundamental volatility and GDP volatility in the last part of the sample. We found that the rise in fundamental volatility since the early 2000s come in large part from the rise of the rise of finance. However, we stop short of explaining *why* the financial sector rose in size. That is a very interesting question but one that may take much research to answer: laxer regulation, new financial technology, globalization and US comparative advantage in finance, savings glut, etc. (see Philippon (2008)). Fundamental volatility is silent about the ultimate cause of it, but it pinpoints to the “next thing to explain” in the causal chain – the rise of finance.

Likewise, for the 1981-86 break in fundamental and GDP volatility. Looking at fundamental volatility showed earlier that a few sectors (energy and heavy manufacturing ) shrunk in size in that period. As a result, the US economy was more diversified, and more stable. FV pinpoints to a simple causal explanation. However, of course, it doesn’t answer “why is it that those heavy manufacturing firms downsized in the early 1980s,” which might be attributed to competition from Japan, the Volcker recession, the rise in interest rates, and a host of interesting factors. However, looking at things through the lenses of FV helps pinpoint the “proximate” causal factors, which might help future research find the “ultimate” ones.

For the rise in energy in the 1970s, the message from fundamental volatility is a bit duller. However, it allows us to put that energy price in the context of a more systematic framework for the relative importance of sectors. Indeed, regressing GDP volatility with oil prices leads to very poor  $R^2$ .<sup>31</sup> One way to interpret that is that the oil price changes explain GDP volatility not in its naive “raw” form (as in oil price level or volatility), but only when properly channeled (adjusted for their relative size squared) via fundamental volatility.

All in all, fundamental volatility is a simple tool that is well-microfounded, and allows to both organize quantitatively and systematically the contributions of various parts of the economy to changes in volatility, and hence allows to trace back researchers’ attention to the next, deeper levels.

Likewise, fundamental volatility allows us to pinpoint the main chain. Fundamental volatility (i) teaches us things that we did not really know, and (ii) organizes things in a systematic quantitative framework that we may already know qualitatively.

We next turn to our four other major economies.

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<sup>31</sup>Regressing  $\sigma_{Y_t}^{Roll}$  on oil price level, growth or volatility yields a very low  $R^2$  of 3% to 7%, compared to  $R^2$  of 60% associated with  $\sigma_F$ .

### 4.2.2 United Kingdom

The UK time series starts off with a short-term spike in fundamental volatility between 1972 and 1976 which is almost single-handedly explained by the high-frequency developments for Petroleum and Coal Products, yielding  $H(1972, 1976) = 0.88$ . Thereafter, there is a steep decline from 1978 until the mid 1980s, again mostly explained by Petroleum and Coal Products ( $H(1978, 1986) = 1.00$ ). That decline is followed by high-frequency developments which are primarily due to Construction ( $H(1986, 1989) = 1.29$  and  $H(1989, 1993) = 0.97$ ). Fundamental volatility stabilizes in 1993, and then gradually increases until 2005. While a large portion of that long-term surge in fundamental volatility can still be attributed to Construction ( $H(1993, 2005) = 0.64$ ), the rise of the financial sector also contributes to the modest but continuous rise in fundamental volatility since 2000: the combined  $H(2000, 2005)$  for Financial Intermediation and Insurance equals 0.13.

### 4.2.3 Japan

The most salient characteristic of the Japanese time series is the steep decline in fundamental volatility from 1973 to 1987. The decline of the steel industry and construction explains the development in fundamental volatility very well:  $H(1973, 1987) = 0.41$  and 0.34 for Basic Metals and Construction, respectively. Despite the decline from 1973 to 1987, fundamental volatility reaches high levels in the 1970s, especially compared to Germany and France. The prominent role of the steel industry also explains this pattern of short-term spikes with  $H(1973, 1974) = 0.25$  and  $H(1978, 1980) = 0.13$  for Basic Metals, and  $H(1978, 1980) = 0.09$  for Construction. Finally, the very modest increase in fundamental volatility from 1987 to 1990 is primarily due to Construction, whose  $H(1987, 1990)$  is 1.43.

### 4.2.4 Germany

The major trend in the German time series of fundamental volatility is the latter's downturn from 1970 to 1987 which is very well explained by the drop in GDP shares for Basic Metals (mostly steel) and Construction: the respective values for  $H(1970, 1987)$  are 0.45 and 0.33. Furthermore, the downturn of fundamental volatility during the 1980s can be attributed to Petroleum and Coal Products, with  $H(1981, 1988) = 0.64$ .

#### 4.2.5 France

The French time series can be split as follows: a decline in fundamental volatility from 1970 to 1987/8, followed by a ten-year sequence of hardly any movement, and a steep increase from 1998 to 2005. Construction strongly contributes to this drop ( $H(1970, 1987) = 0.31$ ), and is accompanied by Petroleum and Coal Products in the 1980s ( $H(1981, 1988) = 0.51$ ). Lastly, the steep increase in fundamental volatility since 1998 is due to “other business activities,” which contain the bulk of business services. This category comprises heterogenous activities, ranging from operative services such as security activities to services requiring highly qualified human capital.

## 5 Discussion and Robustness Checks

We now explore a few reasonable variants on the definition of fundamental volatility. Depending on the context, they may be even preferable to our definition (1), though in the main, we think that our definition is preferable because of its simplicity and transparency.

### 5.1 Variants in the Empirical Constructs

#### 5.1.1 Basic Fundamental Volatility vs Correlation-Enriched Fundamental Volatility

We proceed as if TFP innovations were uncorrelated. This is a good benchmark, as the average correlation in TFP innovations in different sectors is only 2.3% in the US, and even that small correlation could be due to measurement error and factor hoarding.

Still, call  $\rho_{ij} = \text{corr}(\hat{A}_i, \hat{A}_j)$  the cross-correlation in TFP innovation between sectors  $i$  and  $j$ . We can also define:

$$\sigma_{Ft}^{\text{Full}} = \sqrt{\sum_{i,j=1\dots n} \left(\frac{S_{it}}{Y_t}\right) \left(\frac{S_{jt}}{Y_t}\right) \rho_{ij} \sigma_i \sigma_j} \quad (13)$$

Note that  $\sigma_{Ft}^{\text{Full}}$  should be, essentially by construction, the volatility of TFP. The advantage of this construct, though, will be to do the following thought experiment. Suppose that the shares  $S_{it}/Y_t$  change and the variance-covariance matrix  $(\rho_{ij} \sigma_i \sigma_j)$  does not change, how much should GDP volatility change? Figure 6 shows the “fundamental volatility” graph including the full covariance matrix, i.e., accounting for cross terms.

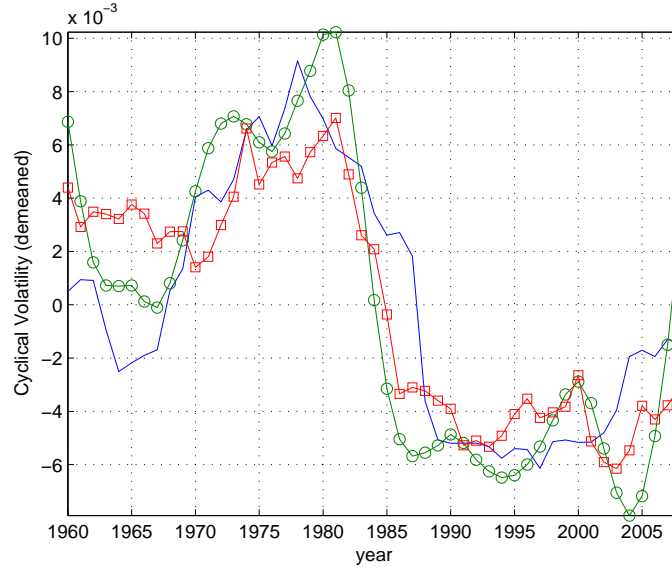


Figure 6: Fundamental Volatility (Full Matrix) and GDP Volatility. The squared line gives the fundamental volatility drawn from the full variance-covariance matrix of TFP ( $4.5\sigma_{Ft}^{\text{Full}}$ , also demeaned). The solid and circle lines are annualized (and demeaned) estimations of GDP volatility. The solid line depicts rolling window estimates of the standard deviation of GDP volatility. The circle line depicts the HP trend of the instantaneous standard deviation.

Table 4: GDP Volatility and Fundamental Volatility

|           | Annual Data- $\sigma_{Yt}^{\text{Roll}}$ | Annual Data- $\sigma_{Yt}^{\text{Inst}}$ |
|-----------|--|--|
| $\hat{a}$ | -0.041<br>(-7.13;0.006)                  | -0.0459<br>(-4.27;0.013)                 |
| $\hat{b}$ | 3.981<br>(9.74;0.409)                    | 5.727<br>(4.70;1.085)                    |
| $R^2$     | 0.67                                     | 0.38                                     |

*Notes:* Regression of GDP volatility on fundamental volatility. We regress  $\sigma_{Yt} = a + b\sigma_{Ft}^{\text{Full}} + \eta_t$  on fundamental volatility. In parentheses are  $t$ -statistics and standard errors.

Table 4 shows that the results of Table 1 hold also with  $\sigma_{Ft}^{\text{Full}}$ , the  $R^2$ 's are actually a bit higher. Similarly, the break tests results of Table 2 are similar with  $\sigma_F^{\text{Full}}$ .

The advantage of  $\sigma_F^{\text{Full}}$ , with all covariance terms, over  $\sigma_F$  within only diagonal terms, is that  $\sigma_F^{\text{Full}}$  (i) it is conceptually closer to the natural concept and perhaps as a result (ii) it is slightly more precise, and yields a bit higher  $R^2$ . In addition, the two measures differ in some details, which might reflect that sometimes the major sectors are more strongly positively correlated than at other times.

On the other hand, the advantage of  $\sigma_F$  over  $\sigma_F^{\text{Full}}$  is that: (i)  $\sigma_F$  is easier to interpret as we only have to study “which” of the 88 terms (for 88 sectors) change over time, whereas with  $\sigma_F^{\text{Full}}$  we need to handle 3,916 (i.e.,  $n + n(n-1)/2$ ) changing terms, and see which one varied most (e.g. in a historical analysis such as the one in section 4.2.1), and (ii) it requires less “processed” data (it does not require the additional 3,828 (i.e.,  $n(n-1)/2$ ) correlation terms for the USA), so it is easier to apply to non-US countries (where the data are sparser, and we replace all variances by a constant and all covariances by 0), and (iii)  $\sigma_F^{\text{Full}}$  may be dangerously close to being a tautology, as it is conceptually very much like the volatility of TFP (by Hulten’s theorem), where  $\sigma_F$  more directly expresses the hypothesis that most movements come from composition effects with non-infinitesimal sectors or firms.

Ultimately, though Ockham’s razor makes lean towards using  $\sigma_F$  as the baseline in most of this paper, we think that both measures,  $\sigma_F$  and  $\sigma_F^{\text{Full}}$ , are sensible and useful.

### 5.1.2 Sectors vs. Firms

In this paper, we primarily use sectors, because we have measures of gross output and value added for sectors in several countries. The firm-level data are spottier, yet encouraging, as we shall see. We start with firms in the US, using the Compustat data set. We define the firm-

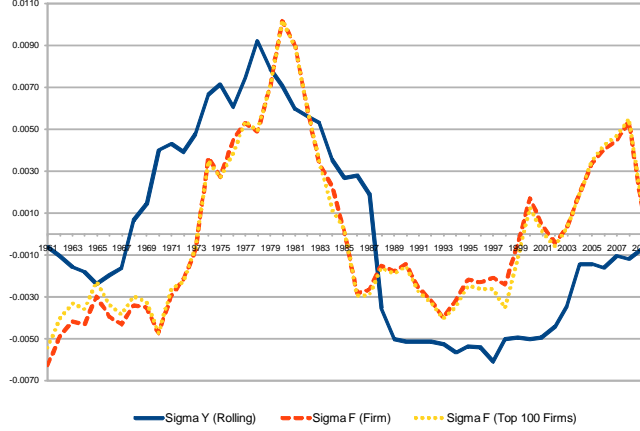


Figure 7: Firm-based Fundamental Volatility and GDP Volatility. The solid line gives the GDP volatility,  $\sigma_{Yt}^{\text{Roll}}$  (demeaned). The dotted and dashed lines give the fundamental volatility based on firms (rather than sectors),  $4.5\sigma_F^{\text{Firms}}$  (demeaned). The dotted line is based on the largest 100 firms by sales in each year. The dashed line is based on all firms in Compustat.

based fundamental volatility as we did for sectors, cf. (1):[NEW]  $\sigma_{Ft}^{\text{Firms}} = \sqrt{\sum_{i=1}^n \left(\frac{S_{it}}{\text{GDP}_t}\right)^2 \sigma_i^2}$ , where  $S_{it}$  are the sales of firm  $i$  (Compustat's Data 12), and the summation is over the  $n$  firms with the largest sales each year. To implement this formula, Compustat has several limitations which are rather important when studying long-run trends. It is not quite consistent over time, as it covers more and more firms. Additionally, the data are on worldwide sales, rather than domestic output. There are some data on domestic sales, which are unfortunately too spotty to be used. For firm-level volatility, a firm-by-firm estimation gives quite volatile numbers, so we proceed as in the international section of this paper, using constant values of  $\sigma_i$  across firms. We use  $\sigma_i = 12\%$ , the typical volatility of sales/employees, sales and employee growth found in Gabaix (2011).

Figure 7 plots the detrended firm-level fundamental volatility for the top 100 firms and for all firms in the data set. As the top 100 firms are very large, most of the variation in  $\sigma_F^{\text{Firms}}$  is driven by them. We see that they track GDP volatility quite well. We also see that firm-based fundamental volatility and GDP volatility have a similar evolution.

To be more quantitative, we proceed as in Table 1 and regress  $\sigma_{Yt} = a + b\sigma_{Ft}^{\text{Firms}}$ . We find a coefficient  $b = 4.8$  (s.e. 0.8) for  $\sigma_{Yt}^{\text{Roll}}$  and yearly data, with an  $R^2$  equal to 0.44. We also replicate the break test of Table 2. Controlling for  $\sigma_{Ft}^{\text{Firms}}$ , there is no break in GDP volatility at the conventional confidence level. We conclude that the firm-based fundamental volatility

does account for the great moderation and its undoing, just like the sector-based fundamental volatility we use in the rest of the paper.

The chief difficulty is for non-US data. For European countries the main data set is Amadeus. Unfortunately, it starts only in 1996, which is too short a time period to detect the long-run trends that are the key object of this paper. We can only hope that a researcher will compile a historical database of the actions of the top firms in the major economies. We conjecture that going to more disaggregated data would enrich the economic understanding of microeconomic developments (e.g., the big productivity growth of the retail sector was due to Wal-Mart, rather than a mysterious shock affecting a whole sector), but data availability prevents us from pursuing that idea in this paper.

### 5.1.3 Constant vs. Time-Varying Sectoral Volatility

Our  $\sigma_{Ft}$  uses a constant sectoral volatility – largely for the sake of parsimony. We examine that benchmark here. First, we find that micro TFP volatility is not significantly different pre and post 1984: its average is 3.49% for 1960-1983 and 3.16% for 1984-2005, and the difference is not statistically significant. This warrants the benchmark of constant micro volatility.

Another way to explore whether our results depend on time-varying sectoral volatility is to construct  $\sigma'_{Ft} = \sqrt{\sum_i (S_i./Y.)^2 \sigma_{it}^2}$ , i.e.,  $\sigma_{Ft}$  with time-varying sectoral volatility while keeping sectoral shares constant at their time-series average, and  $\sigma''_{Ft} = \sqrt{\sum_i (S_{it}/Y_t)^2 \sigma_{it}^2}$ , which has time-varying shares and volatility. We estimate  $\sigma_{it}$  by running a GARCH(1,1) for each sector  $i$ . We re-run the regression (9) with  $\sigma_Y^{Inst}$  and  $\sigma_Y^{Roll}$  on the right-hand side:  $\sigma'_{Ft}$  has insignificant explanatory power and a very low  $R^2$  (about 0.05). On the other hand,  $\sigma''_{Ft}$  has significant explanatory power and a good  $R^2$  (about 0.38). We conclude that the crucial explanatory factor is indeed the time-varying shares in the economy, not a potential change in sectoral-level volatility.

### 5.1.4 Gross vs. Net output

In this paper, we use the concept of gross output, rather than net output (i.e., value added), in that we follow the common best practice of the productivity literature (e.g., Basu, Fernald and Kimball 2006). Part of the reason is data availability, part is conceptual: most models use inputs such as labor, capital, and other goods (the intermediary inputs), and for productivity there is no good reason to subtract the intermediary inputs.<sup>32</sup> Nonetheless, we did examine

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<sup>32</sup>To think about the problem, take a gross output production function  $F(L, X)$ : the inputs are labor and an intermediary input  $X$ , the net output is  $V(L, X) = F(L, X)$ . A Hicks-neutral increase in gross output

our results with a value-added productivity notion,  $\sigma_{Ft}^{VA} = \sqrt{\sum_{i=1}^n \left(\frac{Y_{it}}{Y_t}\right)^2 \sigma_{i,VA}^2}$ , with  $\sigma_{i,VA}^2$  the volatility of value added TFP growth. We found them to be quite similar (e.g. the basic  $R^2$  in the regressions of Table 1 is 0.58 and 0.40), which is natural, because of the high (84%) correlation between  $\sigma_{Ft}^{VA}$  and  $\sigma_{Ft}$ .

## 5.2 Idiosyncratic Shocks and Comovement

We next discuss how our results are consistent with comovement in the economy. We need some notations. Calling  $Y_i$  the value added of sector  $i$ , GDP growth is  $\hat{Y} = \sum_i \frac{Y_i}{Y} \hat{Y}_i$ , and its variance can be decomposed as:

$$\sigma_{Yt}^2 = D_t + N_t \quad (14)$$

$$D_t = \sum_{i=1}^n \left(\frac{Y_{it}}{Y_t}\right)^2 \text{var}(\hat{Y}_{it}), \quad N_t = 2 \sum_{1 \leq i < j \leq n} \frac{Y_{it}}{Y_t} \frac{Y_{jt}}{Y_t} \text{cov}(\hat{Y}_{it}, \hat{Y}_{jt})$$

The term  $D_t$  represents the diagonal terms in GDP growth, while the term  $N_t$  represents the non-diagonal terms, i.e., in an accounting sense, the terms that come from common shocks or from linkages in the economy.

In this section, we address why previous research was pessimistic about the importance of microeconomic shocks (Blanchard and Simon 2001, McConnell and Perez-Quiros 2000, Stock and Watson 2002), and answer the following questions. (i) Previous research showed that comovement (the  $N_t$  term) accounts for the bulk of GDP volatility, so why focus on the diagonal terms ( $D_t$ )? (ii) Previous literature showed that the off-diagonal  $N_t$  terms fell in volatility, doesn't that mean that the common shock they reflect is the main story (see, for instance, Stiroh 2009)? (iii) Don't we also detect comovement of TFP across sectors, which must mean that there is an extra common factor to take into account?

We present a summary of our answers. (i) This model exhibits comovement, in which all the primitive shocks are idiosyncratic (at the sector level). However, because of linkages, there is comovement. Indeed, to a good approximation, in this model

$$D_t \simeq c_D \sigma_{Ft}^2, \quad N_t \simeq c_N \sigma_{Ft}^2 \quad (15)$$

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productivity by a ratio of  $A$  means that the production function becomes  $AF(L, X)$ , so that the net output changes by  $AF(L, X) - X$ . In contrast, a neutral increase in productivity of net output would change the production function to  $AF(L, X) - AX$ . The interpretation of the latter is rather odd: with  $A = 1.1$ , the firm can produce 10% more gross output, but has also become 10% less efficient at handling inputs. This is one reason why it is conceptually easier to think about productivity in the gross output function.



for two coefficients  $c_D$  and  $c_N$ . In our calibration, like in data, about 90% of the variance of output is indeed due to comovement ( $N_t/\sigma_Y^2 \simeq 0.9$ ). That comovement itself comes entirely from the primitive diagonal shocks whose variance is measured by  $\sigma_{Ft}^2$ . Hence, the off-diagonal terms are just the shadow of the primitive shocks, which are the diagonal terms captured by  $\sigma_{Ft}^2$ .

(ii) In terms of time-series evolution, in our hypothesis the prime mover is the change in  $\sigma_{Ft}^2$ , which comes from sectoral-level shares. By linkages, the off-diagonal terms  $N_t$  will reflect those changes. The fact that the magnitude of off-diagonal terms changes simply reflects the fact that the primitive shocks captured by  $\sigma_{Ft}^2$  change.<sup>33</sup>

(iii) In our model, all primitive shocks are idiosyncratic. Hence, TFP movements across sectors are uncorrelated. However, even small measurement errors will create a comovement in measured TFP. Suppose that, when times are good (i.e., when the average idiosyncratic shock is positive), people work more, but this partly comes as higher effort, so that measured employment underestimates the true increase in labor supply. Each firm will look more productive than it really is. There will be a measured common productivity increase, but it is only due to mismeasurement. Quantitatively, our model shows that a small measurement error can account for the observed comovement in measured TFP.

We next sketch the essentials of the model that allows us to reach those conclusions. It is a parametrized version of the general model given in Lemma 1, and is detailed in the online appendix. In particular, sector  $i$  has a production function  $Q_i = \kappa A_i (L_i^\alpha K_i^{1-\alpha})^b X_i^{1-b}$ , where  $X_i$  is the quantity of intermediary inputs it uses. The intermediary inputs is a share of the aggregate, Dixit-Stiglitz good, so that GDP, net of intermediary inputs, is  $Y = (\sum_i Q_i^{1/\psi})^\psi - \sum_i X_i$ . Then, we submit the economy to shocks, like in Lemma 1. As above, the change in GDP is

$$\hat{Y} = \frac{1+\varphi}{\alpha} \sum \frac{S_i}{Y} \hat{A}_i = \frac{1+\varphi}{\alpha} \hat{\Lambda} \quad (16)$$

We derive the changes in sales, employment, etc. at the sectoral level. They take the shape:

$$\hat{S}_i = \hat{Y}_i = \beta \hat{A}_i + \bar{\Phi} \hat{Y}, \quad \hat{L}_i = \beta' \hat{A}_i + \bar{\Phi}' \hat{Y} \quad (17)$$

for some coefficients  $\beta, \beta'$  and  $\bar{\Phi}, \bar{\Phi}'$ . The economy behaves like a one-factor model with an “aggregate shock,” the GDP factor  $\hat{Y}$ . However, this common factor is nothing but the sum

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<sup>33</sup>However, in the model of Section 5.2, the fall in fundamental volatility will make all sectors’ volatilities fall, and will indeed make a simulated shock  $\hat{Y}_t^* = \sum_{i=1}^N (Y_i/Y)^* \cdot \hat{Y}_{it}$  fall in variance, keeping constant output shares  $(Y_i/Y)^*$  but using the observed shocks  $\hat{Y}_{it}$ . (A more analytical note on this point is available upon request.)

of many idiosyncratic shocks (equation 16). It causes all microeconomic-level quantities to comove.<sup>34</sup> Economically, when sector  $i$  has a positive shock, it makes the aggregate economy more productive and affects the other sectors in three different ways. First, other sectors can use more intermediary inputs produced by sector  $i$ , thereby increasing their production. Second, sector  $i$  demands more inputs from the other firms (equation 25), which leads their production to increase. Third, given that sector  $i$  commands a large share of output, it will use more of the inputs of the economy, which tends to reduce the other sectors' output. The net effect depends on the magnitudes of the elasticities.

## 6 Conclusion

We have investigated the explanatory power of “fundamental volatility” to understand the swings in macroeconomic volatility, and found it to be quite good. Fundamental volatility explains the great moderation and its undoing. It has a clear economic foundation and has the advantage of being easy to measure.

Our findings do support the view that the key to macroeconomic volatility might be found in microeconomic shocks. This is a meaningful, nontrivial empirical result: many other factors (e.g., policy, taxes, globalization) change the structure of the economy, so it is not clear a priori that the microeconomic composition of the economy would have such a large explanatory power.

Of course, microeconomic shocks need to be enriched by some propagation mechanisms. Their identification might be simplified if we think that microeconomic shocks are the primary factors that are propagated. For instance, we do not deny that monetary shocks may be important. However, they may largely be part of the response to other shocks (e.g., real shocks caused by oil or finance).

Our findings pose the welfare consequences of the microeconomic composition of an economy. In models with financial frictions, a rise in volatility is typically welfare-reducing. Perhaps finance was too big and created too much volatility in the 2000s? Perhaps the oil-dependent industries were too big and created too much volatility in the 1970s?

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<sup>34</sup>We note that this model could explain the interesting findings of Foerster, Sarte and Watson (2011), who find that the common component well-explained by a simple average of sectoral growth. In this model (with many sectors), the simple average would be  $\widehat{\overline{\Phi Y}}$ , and would statistically account for GDP growth. But in the same model, GDP growth is nothing but a sum of idiosyncratic shocks. In addition, it would be interesting to extend Foerster, Sarte and Watson (2011), who solely study industrial production, to other sectors that are important for fundamental volatility, e.g. finance.

In addition, fundamental volatility can serve as an “early warning system” to measure future volatility. In retrospect, the surge in the size of finance in the 2000s could have been used to detect a great source of new macroeconomic volatility.

In any case, we think that fundamental microeconomic volatility is a useful theoretical and empirical concept to consider when thinking about the causes and consequences of aggregate fluctuations.

## References

**Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi.** 2010. “Cascades in Networks and Aggregate Volatility.” Massachusetts Institute of Technology Working Paper.

**Arias, Andres, Gary Hansen, and Lee Ohanian.** 2007. “Why Have Business Cycle Fluctuations Become Less Volatile.” *Economic Theory*, 32(1): 43–58.

**Bak, Per, Ken Chen, José Scheinkman, and Michael Woodford.** 1993. “Aggregate Fluctuations from Independent Sectoral Shocks: Self-Organized Criticality in a Model of Production and Inventory Dynamics.” *Ricerche Economiche*, 47(1): 3–30.

**Bai, Jushan, and Pierre Perron.** 1998. “Estimating and testing linear models with multiple structural changes.” *Econometrica*, 66(1): 47–78.

**Bai, Jushan, and Pierre Perron.** 2006. “Multiple Structural Change Models: A Simulation Analysis.” In *Econometric Theory and Practice: Frontiers of Analysis and Applied Research*, ed. D. Corbea, S. Durlauf and B. E. Hansen, 212–37. Cambridge, MA: Cambridge University Press.

**Basu, Susanto, John Fernald, Jonas Fisher, and Miles Kimball.** 2009. “Sector-Specific Technical Change.” Unpublished.

**Basu, Susanto, John Fernald, and Miles Kimball.** 2006. “Are Technology Improvements Contractionary?” *American Economic Review*, 96(5): 1418–48.

**Blanchard, Olivier, Giovanni Dell’Ariccia, and Paolo Mauro.** 2010. “Rethinking Macroeconomic Policy.” IMF Staff Position Note, SPN/10/03.

**Blanchard, Olivier, and John Simon.** 2001. “The Long and Large Decline in U.S. Output Volatility.” *Brookings Papers on Economic Activity*, 165–71.

**Buera, Francisco, and Joseph Kaboski.** 2009. “The Rise of the Service Economy.” National Bureau of Economics Working Paper 14822.

**Carvalho, Vasco.** 2010. “Aggregate Fluctuations and the Network Structure of Inter-sectoral Trade.” Universitat Pompeu Fabra Working Paper 1206.

- Caselli, Francesco, Miklós Koren, Milan Lisicki, and Silvana Tenreyro.** 2010. “Volatility and Openness to International Trade.” London School of Economics Working Paper.
- Clarida, Richard, Jordi Galí, and Mark Gertler.** 2000. “Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory.” *Quarterly Journal of Economics* 115: 147–80.
- Domar, Evsey.** 1961. “On the Measurement of Technological Change.” *Economic Journal*, 71: 709–29.
- Dupor, William.** 1999. “Aggregation and Irrelevance in Multi-Sector Models.” *Journal of Monetary Economics*, 43: 391–409.
- Durlauf, Steven.** 1993. “Non Ergodic Economic Growth.” *Review of Economic Studies*, 60(2): 349–66.
- Foerster, Andrew T., Pierre-Daniel G. Sarte, and Mark W. Watson.** 2011. “Sectoral vs. Aggregate Shocks: A Structural Factor Analysis of Industrial Production.” *Journal of Political Economy*, 119(1): 1–38.
- Gabaix, Xavier.** 1999. “Zipf’s Law for Cities: An Explanation.” *Quarterly Journal of Economics*, 114(3): 739–67.
- Gabaix, Xavier.** 2011. “The Granular Origins of Aggregate Fluctuations.” *Econometrica*, 79(3): 733–72.
- Gali, Jordi, and Luca Gambetti.** 2009. “On the Sources of the Great Moderation.” *American Economic Journal: Macroeconomics*, 1(1): 26–57.
- di Giovanni, Julian, and Andrei Levchenko.** 2009. “International Trade and Aggregate Fluctuations in Granular Economies.” Unpublished.
- Gleck, James.** 2003. *Genius: The Life and Science of Richard Feynman*. Vintage.
- Hall, Robert.** 2009a. “Reconciling Cyclical Movements in the Marginal Value of Time and the Marginal Product of Labor.” *Journal of Political Economy*, 117(2): 281–323.
- Hall, Robert.** 2009b. “By How Much Does GDP Rise if the Government Buys More Output?” *Brookings Papers on Economic Activity*, 2: 183–231.
- Horvath, Michael.** 1998. “Cyclicalities and Sectoral Linkages: Aggregate Fluctuations from Sectoral Shocks.” *Review of Economic Dynamics*, 1: 781–808.
- Horvath, Michael.** 2000. “Sectoral Shocks and Aggregate Fluctuations.” *Journal of Monetary Economics*, 45(1): 69–106.
- Hulten, Charles.** 1978. “Growth Accounting with Intermediary Inputs.” *Review of Economic Studies*, 45: 511–18.

- Imbs, Jean, and Romain Wacziarg.** 2003. "Stages of Diversification." *American Economic Review*, 93: 63–86.
- Irvine, Owen, and Scott Schuh.** 2007. "The Roles of Comovement and Inventory Investment in the Reduction of Output Volatility." *Federal Reserve Bank of San Francisco Proceedings*, Nov.
- Jaimovich, Nir, and Henry Siu.** 2009. "The Young, the Old, and the Restless: Demographics and Business Cycle Volatility." *American Economic Review*, 99(3): 804–26.
- Jones, Charles I.** 2011. "Intermediate Goods and Weak Links in the Theory of Economic Development." *American Economic Journal: Macroeconomics*, 3(2): 1–28.
- Jorgenson, Dale W., Frank M. Gollop, and Barbara M. Fraumeni.** 1987. *Productivity and U.S. Economic Growth*. Cambridge, MA: Harvard University Press.
- Jorgenson, Dale, Mun Ho, and Kevin Stiroh.** 2008. "A Retrospective Look at the U.S. Productivity Growth Resurgence." *Journal of Economic Perspectives*, 22(1): 3–24.
- Jorgenson, Dale, and Marcel Timmer.** 2011. "Structural Change in Advanced Nations: A New Set of Stylised Facts." *Scandinavian Journal of Economics*, 113(1): 1–29.
- Jovanovic, Boyan.** 1987. "Micro Shocks and Aggregate Risk." *Quarterly Journal of Economics*, 102(2): 395–409.
- Justiniano, Alejandro, and Giorgio E. Primiceri.** 2008. "The Time-Varying Volatility of Macroeconomic Fluctuations." *American Economic Review*, 98(3): 604–41.
- Kalemli-Ozcan, Sebnem, Bent Sorensen, and Vadym Volosovych.** 2010. "Deep Financial Integration and Macroeconomic Volatility," National Bureau of Economic Research Working Paper 15900.
- Koren, Miklós, and Silvana Tenreyro.** 2007. "Volatility and Development," *Quarterly Journal of Economics*, 122(1): 243–87.
- Koren, Miklós, and Silvana Tenreyro.** 2011. "Technological Diversification." Central European University and London School of Economics Working Paper.
- Long, John, and Charles Plosser.** 1983. "Real Business Cycles." *Journal of Political Economy*, 91(1): 39–69.
- Luttmer, Erzo G. J.** 2007. "Selection, Growth, and the Size Distribution of Firms." *Quarterly Journal of Economics*, 122(3): 1103–44.
- McConnell, Margaret, and Gabriel Perez-Quiros.** 2000. "Output Fluctuations in the United States: What has Changed Since the Early 1980's." *American Economic Review*, 90(5): 1464–76.
- Moro, Alessio.** 2009. "The Structural Transformation between Manufacturing and Ser-

vices and the Decline in US GDP Volatility.” Universidad Carlos III Working Paper.

**Nirei, Makoto.** 2006. “Threshold Behavior and Aggregate Critical Fluctuations.” *Journal of Economic Theory*, 127: 309–22.

**Oi, Walter.** 1962. “Labor as a Quasi-Fixed Factor.” *Journal of Political Economy*, 70: 538–55.

**Philippson, Thomas.** 2008. “The Evolution of the US Financial Industry from 1860 to 2007.” New York University Working Paper.

**Qu, Zhongjun, and Pierre Perron.** 2007. “Estimating and testing structural changes in multivariate regressions.” *Econometrica*, 75(2): 459–502.

**Sensier, Marianne, and Dick van Dijk.** 2004, “Testing for Volatility Changes in U.S. Macroeconomic Time Series.” *The Review of Economics and Statistics*, 86(3): 833–39.

**Shea, John.** 2002. “Complementarities and Comovements.” *Journal of Money, Credit and Banking*, 42(2): 412–33.

**Simon, Herbert.** 1955. “On a Class of Skew Distribution Functions.” *Biometrika*, 42(3-4): 425–40.

**Stiroh, Kevin.** 2009. “Volatility Accounting: A Production Perspective on Increased Economic Stability.” *Journal of the European Economic Association*, 7(4): 671–96.

**Stock, James, and Mark Watson.** 2002. “Has the Business Cycle Changed and Why?” *National Bureau of Economic Research Macroeconomics Annual*, 17: 159–218.

**Stock, James, and Mark Watson.** 2005. “Understanding Changes in International Business Cycle Dynamics,” *Journal of the European Economic Association* 3(5): 968–1006.

**Timmer, Marcel, Ton van Moergastel, Edwin Stuivenwold, Gerard Ypma, Mary O’Mahony, and Mari Kangasniemi.** 2007. “EU KLEMS Growth and Productivity Accounts Version 1.0, Part 1: Methodology.” EU KLEMS Working Paper.

## A Data Appendix

*US data.* The main data source for this paper was constructed by Dale Jorgenson and associates, and provides a detailed breakdown of the entire US economy into 88 sectors.<sup>35</sup> The data is annual and covers the period between 1960 and 2005. The original sources are input-output tables and industry gross output data compiled by the Bureau of Labor Statistics and the Bureau of Economic Analysis. The data are organized according to the KLEM methodology reviewed in Jorgenson, Gallop, and Fraumeni (1987) and Jorgenson, Ho, and Stiroh (2005).

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<sup>35</sup>The data set is available at <http://dvn.iq.harvard.edu/dvn/dv/jorgenson>.

In particular, the input data incorporate adjustments for quality and composition of capital and labor. To the best of our knowledge, this is the most detailed (balanced) panel coverage of US sectors available, offering a unified data set for the study of sectoral productivity.<sup>36</sup>

In this data set, for each year-industry pair, we observe nominal values of sectoral gross output, capital, labor, and material inputs supplied by the 88 sectors (plus non-competing imports) as well as the corresponding price deflators. Following Jorgenson, Ho, and Stiroh (2008) and Basu et al. (2009), we concentrate on private sector output, thus excluding services produced by the government, but including purchases of private-sector goods and services by the government (a robustness check shows that this does not materially affect our result). We also exclude from the analysis the imputed service flow from owner-occupied housing.<sup>37</sup> This yields a panel of 77 sectors which forms the basis of all computations.

Finally, given our interest in analyzing the recent behavior of our fundamental volatility measure we have extended the original Dale Jorgenson and Associates dataset through 2008.<sup>38</sup> To do this we have used the BLS Inter-Industry Relationships database as the source for 2006-2008 data. In particular, we have used the "Nominal dollar input-output" series to construct sectoral gross output and value added. The latter are based on a NAICS classification and at a higher level of disaggregation (202 industries). We then applied a correspondence - kindly supplied by Mun Ho - between the sectoral classification used in the 1960-2005 Jorgenson dataset and the NAICS system (used by the BLS) to recover gross output and value added for each sector in the Jorgenson dataset between 2006 and 2008.<sup>39</sup>

To construct aggregate output volatility measures, we obtained quarterly real GDP data from the Federal Reserve Economic Data (FRED).

*International data.* For UK, Japan, Germany, and France we resort to the EU KLEMS database (Timmer et al. 2007). As the name indicates, this database is again organized according the KLEM methodology proposed by Jorgenson and associates. To preserve comparability, we focus on private sector accounts by excluding publicly provided goods and

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<sup>36</sup>The NBER-CES database is more detailed in its coverage but only includes manufacturing industries. As made clear in the paper, it is crucial to account for the growth of service sectors when looking at cross-sectoral diversification, the great moderation and its undoing.

<sup>37</sup>Finally we drop two sectors for which there are no data in the original data set, "Uranium Ore" and "Renting of Machinery."

<sup>38</sup>The original data by Dale Jorgenson and associates runs through 2005. We are grateful to Dale Jorgenson and Mun Ho for their guidance on how to extend their dataset till 2008.

<sup>39</sup>Notice however that from this BLS data we cannot compute sectoral TFP growth (the BLS Inter-Industry dataset is nominal). Hence, our measures of the standard deviation of sectoral TFP growth,  $\sigma_i$ , are solely based on the original Jorgenson dataset.

services. We thus exclude sectors under the heading "non-market services" in the data set. These also include real estate services as the database does not make a distinction between real estate market services and the service flow from owner-occupied residential buildings (see Timmer et al. 2007, Appendix Table 3 for definitions and discussion).

For each country we obtain a panel of nominal sectoral gross output and value added at the highest level of disaggregation possible. For the UK we end up with 66 sectors, Japan 58, Germany 50, and France 46. For roughly half of these sectors we can compute TFP growth from the gross output perspective. We then compute the average (across sectors) standard deviation of TFP growth during the entire sample period. For UK, Germany, and France the resulting panel runs from 1970-2005. For Japan it starts in 1973 due to the unavailability of earlier data.

To obtain aggregate output volatility for these four countries we extended the quarterly GDP data in Stock and Watson (2005) till 2009:Q4 with data from the OECD Economic Outlook.

## B Proof Appendix

**Proof of Lemma 1:** The lemma makes two claims: the Cobb-Douglas form and the Hulten formula. We start with the Cobb-Douglas form. The Lagrangean is

$$\mathcal{L} = \mathcal{C}(\mathbf{C}) + \sum_i p_i \left( A_i F_i(K_i^{1-\alpha} L_i^\alpha, \mathbf{X}_i) - C_i + \sum_j X_{ji} \right) + r \left( K - \sum_i K_i \right) + w \left( \sum_i L_i - L \right)$$

Defining  $I_i = K_i^{1-\alpha} L_i^\alpha$ , the aggregate factor input in sector  $i$ , and  $I = \sum_i I_i$ , we have:

$$\frac{\partial \mathcal{L}}{\partial K_i} = \frac{1-\alpha}{K_i} I_i p_i A_i \partial_1 F_i - r = 0, \quad \frac{\partial \mathcal{L}}{\partial L_i} = \frac{\alpha}{L_i} I_i p_i A_i \partial_2 F_i - w = 0$$

$$\begin{aligned} \therefore \frac{K_i}{L_i} &= \frac{1-\alpha}{\alpha} \frac{w}{r} = \frac{\sum_j K_j}{\sum_j L_j} = \frac{K}{L} \\ \therefore \frac{K_i}{K} &= \frac{L_i}{L} = \left( \frac{K_i}{K} \right)^{1-\alpha} \left( \frac{L_i}{L} \right)^\alpha = \frac{I_i}{K^{1-\alpha} L^\alpha} \\ \therefore 1 &= \sum_i \frac{K_i}{K} = \sum_i \frac{I_i}{K^{1-\alpha} L^\alpha} = \frac{I}{K^{1-\alpha} L^\alpha} \end{aligned}$$

so that  $I = K^{1-\alpha} L^\alpha$ . The production function is homogenous of degree 1 in  $(I_i, X_{ij})$ : if a plan  $(\mathbf{C}, I_i, X_{ij})$  is doable, so is a plan  $(\lambda \mathbf{C}, \lambda I_i, \lambda X_{ij})$ . Hence, the production function has a form  $Y = I \cdot \Lambda(\mathbf{A}) = K^{1-\alpha} L^\alpha \Lambda(\mathbf{A})$ .



Second, we turn to the Hulten formula. Shocks  $dA_i$  create a change in welfare:

$$d\mathcal{L} = \sum_i p_i F_i (K_i^{1-\alpha} L_i^\alpha, \mathbf{X}_i) dA_i = \sum_i A_i p_i F_i \frac{dA_i}{A_i} = \sum_i S_i \frac{dA_i}{A_i}$$

i.e.,  $\frac{dY}{Y} = \sum_i \frac{S_i}{Y} \frac{dA_i}{A_i}$ , or  $\frac{d\Lambda}{\Lambda} = \sum_i \frac{S_i}{Y} \frac{dA_i}{A_i}$ .

**Proof of Proposition 1** The planner's problem is  $\max_{K,L} \Lambda K^{1-\alpha} L^\alpha - L^{1+1/\varphi} - rK$ . The first order conditions with respect to  $K$  and  $L$  give:  $(1-\alpha) \frac{Y}{K} = r$ ,  $\alpha \frac{Y}{L} = (1+1/\varphi) L^{1/\varphi}$ , so that  $K = (1-\alpha) Y/r$ ,  $L = \left( \frac{\alpha}{1+1/\varphi} Y \right)^{\frac{\varphi}{1+\varphi}}$  and

$$Y = \Lambda K^{1-\alpha} L^\alpha = \Lambda \left( (1-\alpha) \frac{Y}{r} \right)^{1-\alpha} \left( \frac{\alpha}{1+1/\varphi} Y \right)^{\frac{\alpha\varphi}{1+\varphi}} = \left( \frac{1-\alpha}{r} \right)^{1-\alpha} \left( \frac{\alpha}{1+1/\varphi} \right)^{\frac{\alpha\varphi}{1+\varphi}} \Lambda Y^{1-\frac{\alpha}{1+\varphi}}$$

Finally,  $Y = v \Lambda^{\frac{1+\varphi}{\alpha}}$  with  $v = \left[ \left( \frac{1-\alpha}{r} \right)^{1-\alpha} \left( \frac{\alpha}{1+1/\varphi} \right)^{\frac{\alpha\varphi}{1+\varphi}} \right]^{\frac{1+\varphi}{\alpha}}$ .

Online Appendix (not for publication) to  
 “The Great Diversification and Its Undoing”  
 October 2011

## C A Tractable Model Exhibiting Comovement

### C.1 Model Setup

To think quantitatively about comovement, we specify the model of Section 2. We use a CES production function for one final good.<sup>40</sup> Thus, we can solve the structure of this economy in closed form, and quantify its comovement. Our model differs in a series of small ways from Long and Plosser (1983), Horvath (1998, 2000), Shea (2002), Foerster, Sarte, and Watson (2011), and Carvalho (2010).<sup>41</sup> Its main virtue is that it is solvable in closed form, so that the mechanisms are fairly transparent.

There is an aggregate good and  $n$  intermediary goods. Unit  $i$  uses  $L_i, K_i, X_i$  of labor, capital, and the aggregate good to produce  $Q_i$  goods  $i$ :

$$Q_i = \kappa A_i (L_i^\alpha K_i^{1-\alpha})^b X_i^{1-b} \quad (18)$$

with  $\kappa = 1/(b^b(1-b)^{1-b})$ , and  $1-b$  is share of intermediate inputs, so that  $b$  will be the ratio of value added to sales, both at the level of the unit and of the economy.<sup>42</sup> GDP is production net of the intermediate inputs, the  $X_i$ ’s:

$$Y = (\sum_i Q_i^{1/\psi})^\psi - \sum_i X_i \quad (19)$$

with  $\psi > 1$ . The transformation from the goods  $Q_i$  to the final good  $(\sum_i Q_i^{1/\psi})^\psi$  and the intermediary inputs is made by a competitive fringe of firms.

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<sup>40</sup>In the CES world that we parameterize (with positive elasticity of substitution), a positive TFP shock increases a sector’s size. This is not necessarily a good thing. When a sector is very new (say electronic gadgets), the size of that sector grows as the sector becomes more productive (that is, as more products are invented). However, perhaps in a long run sense, some sectors shrink as they become very productive (e.g., agriculture). Following the macro tradition, we eschew here a calibrated modeling of this heterogeneity in the link between productivity and size.

<sup>41</sup>Long and Plosser (1983) impose a Cobb-Douglas structure, with zero idiosyncratic movement in the sales per employee and value of sales.

<sup>42</sup>This uniformity of the sales / value added ratio is only an approximation of reality. We conjecture that this is purely for convenience, and that the economics would go through with non-uniform  $S_{it}/Y_{it}$ , though the algebra would be harder to handle.

The representative agent's utility function is  $U = Y - L^{1+1/\varphi}$ . Capital can be rented at a rate  $r$ . Thus, the social planner's problem is:  $\max_{\{K_i, L_i, X_i\}} Y - L^{1+1/\varphi} - rK$  subject to  $\sum K_i = K; \sum L_i = L$ . We assume that the prices equal marginal cost. This could be caused by competition or by an input subsidy equal to  $\psi$  for the intermediary firms.

The model gives:

$$\text{GDP : } Y = \Lambda L^\alpha K^{1-\alpha} \quad (20)$$

$$\text{TFP : } \Lambda = \left( \sum_i A_i^{1/(\psi-1)} \right)^{(\psi-1)/b} \quad (21)$$

$$\frac{\text{Sales}_i}{\text{GDP}} : \frac{p_i Q_i}{Y} = \frac{1}{b} \left( \frac{A_i}{\Lambda^b} \right)^{1/(\psi-1)} \quad (22)$$

## C.2 Comovement in Output

To study comovement, we assume that we start from a steady state equilibrium, and study the one-shot response of our economy to shocks.

Models such as (18) always deliver a Sales/Employees ratio that is independent of the unit's productivity. The reason for this almost surely counterfactual prediction is that labor is assumed to be costlessly adjustable. To capture the realistic case of labor adjustment costs, we assume that a fraction  $1 - \nu$  of labor is a quasi-fixed factor, in the sense of Oi (1962). Technically, we represent  $L_i = L_{V,i}^\nu L_{F,i}^{1-\nu}$ , where  $L_{V,i}$  and  $L_{F,i}$  are respectively the variable part of labor and the quasi-fixed part of labor. After a small shock, only  $L_{V,i}$  adjusts. The disutility of labor remains  $L^{1+1/\varphi}$ , where  $L = L_V^\nu L_F^{1-\nu}$  is aggregate labor. We assume that capital and intermediary inputs are flexible. The Online Appendix relaxes that assumption.

One can now study the effect of a productivity shock  $\hat{A}_i$  to each unit  $i$ . We call  $S_i = p_i Q_i$  the sales of unit  $i$ . The next proposition, whose proof is in the Online Appendix (which contains a generalization to the case where all factors have finite elasticity), describes how the economy reacts to microeconomic shocks.

**Proposition 2** (*Aggregate factor emerging from microeconomic shocks*) Suppose that each unit  $i$  receives a productivity shock  $\hat{A}_i$ . Macroeconomic variables change according to

$$\text{GDP and TFP : } \hat{Y} = \frac{1+\varphi}{\alpha} \hat{\Lambda}, \quad \hat{\Lambda} = \sum \frac{S_i}{Y} \hat{A}_i = \sum \frac{\text{Sales}_i}{\text{GDP}} \hat{A}_i \quad (23)$$

$$\text{Employment and Wage : } \hat{L} = \frac{\varphi}{1+\varphi} \hat{Y}, \quad \hat{w} = \frac{1}{1+\varphi} \hat{Y} \quad (24)$$

and microeconomic-level variables change according to

$$\text{Value of sales and value added: } \hat{S}_i = \hat{Y}_i = \beta \hat{A}_i + \bar{\Phi} \hat{Y} \quad (25)$$

$$\text{Production: } \hat{Q}_i = \psi \beta \hat{A}_i + (1 - \psi \Phi) \hat{Y} \quad (26)$$

$$\text{Price: } \hat{p}_i = -(\psi - 1) \beta \hat{A}_i + (\psi - 1) \beta \Phi \hat{Y} \quad (27)$$

$$\text{Employment: } \hat{L}_i = \nu \beta \hat{A}_i + \left( \frac{\varphi}{1 + \varphi} - \nu \Phi \right) \hat{Y} \quad (28)$$

$$\text{Use of intermediary inputs and capital: } \hat{X}_i = \hat{K}_i = \hat{S}_i \quad (29)$$

$$\beta = \frac{1}{\psi - 1 + b\alpha(1 - \nu)}, \quad \Phi = \frac{\beta b\alpha}{1 + \varphi}, \quad \bar{\Phi} = 1 - \Phi \quad (30)$$

In other terms, this economy exhibits a common factor  $\hat{Y}$  (equations 25-29) which is itself nothing but a sum of idiosyncratic shocks (equation 23).

The new results are the sectoral-level changes, in equations (25)-(29). The economy behaves like a one-factor model with an “aggregate shock,” the GDP factor  $\hat{Y}$ . Again, this factor stems from a multitude of idiosyncratic shocks (equation 23).<sup>43</sup> It causes all microeconomic-level quantities to comove. Economically, when sector  $i$  has a positive shock, it makes the aggregate economy more productive and affects the other sectors in three different ways. First, other sectors can use more intermediary inputs produced by sector  $i$ , thereby increasing their production. Second, sector  $i$  demands more inputs from the other firms (equation 25), which leads their production to increase. Third, given that sector  $i$  commands a large share of output, it will use more of the inputs of the economy, which tends to reduce the other sectors’ output. The net effect depends on the magnitudes of the elasticities<sup>44</sup>. For instance, when  $\psi$  is higher, so that all goods are less substitutable, the loading of the above sales, production and employment on the GDP shock becomes higher (and indeed, more positive in the calibration). This makes sense: as good are less substitutable, a productivity shock in one area makes the economy wish to consume more of all goods.

We calibrate the model using conventional parameters to the extent possible,<sup>45</sup> with pa-

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<sup>43</sup>In this economy, firms are affected by this GDP factor, but this GDP factor is entirely made of firm-level shocks. That makes identification very difficult. It’s an instance of the “reflection problem” identified by Manski (1993). It has no general solution, but some of the partial techniques generated by Manski’s impulse might be useful to identify causality in the type of macroeconomic equilibrium described by Proposition 2.

<sup>44</sup>See Baumol (1967) for an early analysis of models with more than 1 sector.

<sup>45</sup>For instance,  $\psi = 1.2$  is may be a typical estimate. As Chad Jones (2011, -p.23, who takes  $\psi = 1.5$ ) says this parameter is not “especially well pinned down in the literature”. By taking a  $\psi = 1.2$ , we are rather conservative about the importance of comovement: a higher  $\psi$  (like Jones’ would create even more comovement).

Table 5: Model Calibration

| Calibrated Values  |                    |
|--|--------------------|
| Labor share  | $\alpha = 2/3$     |
| One minus share of intermediate inputs                     | $b = 1/2$          |
| Elasticity of labor supply                                 | $\varphi = 2$      |
| Product differentiation parameter                          | $\psi = 1.2$       |
| Share of labor that is variable in the short run           | $\nu = 1/2$        |
| Fraction of mismeasured temporary labor utilization        | $\theta = 0.43$    |
| Resulting Values   |                    |
| Micro-level productivity multiplier                        | $\beta = 2.7$      |
| Aggregate productivity multiplier                          | $\mu = 4.5$        |
| Elasticity $\Phi$  | $\Phi = 0.3$       |
| Fraction of GDP variance attributed to comovement          | $f^{GDP} = 0.90$   |
| Fraction of employment variance attributed to comovement   | $f^{Labor} = 0.95$ |
| Fraction of measured TFP variance attributed to comovement | $f^{TFP,m} = 0.59$ |

*Notes:* The first part of the table shows the postulated values. The second part shows the resulting values for a few quantities. Because of linkages, the fraction of variances attributed to comovement is non-zero although all primitive shocks are assumed to be idiosyncratic.

rameters summarized in Table 5. Using the decomposition (14), the ratio  $f^{GDP} \equiv N/\sigma_Y^2$  captures how much of GDP variance is due to comovement.

**Proposition 3** (*Magnitude of the comovement in output and employment*) Call  $f^{GDP}$  (resp.  $f^{Labor}$ ) the fraction of GDP (resp. employment) variance attributed to comovement in a variance-accounting sense. An exact value is given in equation (52) of the Appendix. If most shocks are idiosyncratic at the micro level ( $\beta^2 \sigma_A^2 \gg \bar{\Phi}^2 \sigma_Y^2$ ), we have

$$f^{GDP} = 1 - \left( \frac{b\beta}{\mu} \right)^2, \quad f^{Labor} = 1 - \left( \nu \left( 1 + \frac{1}{\phi} \right) \frac{b\beta}{\mu} \right)^2 \quad (31)$$

and we have (15) with  $c_D \simeq b^2 \beta^2$  and  $c_N \simeq \mu^2 - b^2 \beta^2$ . However, economically, all the shocks are primitively idiosyncratic.

Of course, as  $\mu$  (defined in equation 7) increases, so does the fraction attributed to comovement. Using our calibration, we find  $f^{GDP} = 90\%$  and  $f^{Labor} = 95\%$ . This is to say

that, even though primitive shocks are purely idiosyncratic in our model, linkages create such a large comovement that, in a volatility-accounting sense, 93% are mechanically attributed to comovement. This measure is congruent with the empirical findings of Shea (2002), who finds estimates of  $f^{GDP}$  in the range 80%-85% and  $f^{Labor} = 95\%$ . It might also explain why Foerster, Sarte, and Watson (2011) find that a large part of fluctuations come from the non-diagonal part,  $N_t$ .

### C.3 Comovement in Measured TFP

The data show a positive correlation (average pairwise correlation is 2.3%) in measured TFP innovations across sectors. The previous model generates positive comovement from independent TFP shocks. Hence, if there is perfect measurement of TFP, it will generate no comovement of TFP. Against this background, we interpret the data in the following way. We say that a fraction  $\theta$  of the change in the effective number of hours is not measured. For instance, a secretary will work harder when there is much work to do, and less intensely when there is less work. Still, the total number of hours that are counted is the same, say 40 hours per week. In that case,  $\theta = 1$ . If she does some overtime, so that some of her extra efforts appear in the labor supply statistics, then  $\theta < 1$ . For simplicity, we assume that only labor is mismeasured (the same argument would go through if more factors were mismeasured). The measured number of hours is:

$$\widehat{L}_i^m = (1 - \theta) \widehat{L}_i,$$

where the superscript  $m$  denotes the *measured* quantities. Measured TFP growth in sector  $i$  is:

$$\begin{aligned} \widehat{A}_i^m &= \widehat{Q}_i - b\alpha \widehat{L}_i^m - b(1 - \alpha) \widehat{K}_i - (1 - b) \widehat{X}_i \\ &= \left[ \widehat{Q}_i - b\alpha \widehat{L}_i - b(1 - \alpha) \widehat{K}_i - (1 - b) \widehat{X} \right] + \theta b\alpha \left( \widehat{L}_i - \widehat{L}_i^m \right) \end{aligned}$$

Hence:

$$\widehat{A}_i^m = \widehat{A}_i + \theta b\alpha \widehat{L}_i. \tag{32}$$

In other terms, the measured TFP is the true TFP plus the increase in effective labor  $\widehat{L}_i$  times labor share in output-cum-intermediary-inputs  $b\alpha$  times the mismeasurement factor  $\theta$ .

In this benchmark economy, the comovement in true productivity growth  $\widehat{A}_i$  is 0. However, there will be some comovement in measured productivity growth, as all sectors tend to increase factor utilization (in a partially unmeasured way) during booms. The following proposition quantifies this.

**Proposition 4** (*Magnitude of the comovement in measured TFP*) *Measured TFP follows the factor structure:*

$$\widehat{A}_i^m = c_A \widehat{A}_i + c_Y \widehat{Y}, \quad (33)$$

where  $c_A \equiv 1 + \theta b \alpha \nu \beta$  and  $c_Y \equiv \theta b \alpha \left( \frac{\varphi}{1+\varphi} - \nu \Phi \right)$ . Hence, if there is mismeasurement, measured TFP covaries. Call  $f^{TFP,m}$  the fraction of measured TFP variance attributed to comovement in a variance-accounting sense. If most shocks are idiosyncratic at the micro level, we have

$$f^{TFP,m} = 1 - \left( 1 + \frac{c_Y \mu}{c_A b} \right)^{-2}. \quad (34)$$

Note that, if there is no mismeasurement ( $\theta = 0$ ),  $c_Y = 0$  and  $f^{TFP,m} = 0$ : there is no comovement in TFP.

Empirically, we measure  $f^{TFP,m} = 0.59$  in US data. Solving for  $\theta$  in equation (34), this corresponds to  $\theta = 43\%$  of the variable labor input being undermeasured. It says that, if from trough to peak measured hours go up by 5.7%, effort goes up 4.3%.<sup>46</sup> The corresponding value of  $\sigma_F^m / \sigma_F$  is simply  $c_A = 1.19$ . So, mismeasurement of inputs affects a lot the apparent comovement between sectors (as it is the cause of comovement, and the productivity multiplier is large), but only relatively little the measurement of sectoral-level productivity (idiosyncratic factors generally dominate aggregate factors at the microeconomic level). In our model, all primitive shocks come from idiosyncratic microeconomic shocks, but there is comovement in output because of production linkages. In other terms, there is positive comovement in measured TFP because statistical agencies do not control well for unmeasured increases in labor inputs, i.e., “effort” or “utilization.”

We wish to conclude that our model simply illustrates important quantitative features of an economy with comovement. We suspect that the highlighted features will survive with other sources of comovement, e.g., a financial accelerator or expectations.

## D Derivations

**Proof of Proposition 2** We found it useful to state a general proposition with an arbitrary number of fixed and variable factors. We call  $\mathcal{F}$  the primitive factors (e.g., labor and capital) and  $\mathcal{F} \cup X$  the set of all factors – the primitive factor and the intermediary inputs.

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<sup>46</sup> Adding the possibility of mismeasurement in capital utilization would decrease  $\theta$ .

Consider the microeconomic production function:

$$Q_i = \kappa A_i \left( \prod_f F_{if}^{\alpha_f} \right)^b X_i^{1-b}$$

with  $\kappa = 1 / \left( b^b (1-b)^{1-b} \right)$ , where sector  $i$  produces a quantity  $Q_i$  using  $F_{if}$  of factor  $f \in \mathcal{F}$  and  $X_i$  intermediary inputs. This can be rewritten

$$Q_i = \kappa A_i \prod_{f \in \mathcal{F} \cup X} F_{if}^{\gamma_f} \quad (35)$$

where we define  $\gamma_f = b\alpha_f$  for  $f$  a primitive factor, and  $\gamma_f = (1-b)$  for  $f$  the intermediary input. Using this notation, the intermediary inputs in sector  $i$  are  $X_i = F_{iX}$ .

For instance, in the economy studied in Section 5.2 there are three factors:

$$(F_f)_{f=1\dots 3} = (\text{Labor, Capital, Intermediary inputs}) = (L, K, X)$$

and their weights are:  $(\gamma_f)_{f=1\dots 3} = (\alpha b, (1-\alpha)b, 1-b)$ . We will call it the “3-factor economy.”

Each factor  $F_f$  has a cost  $C_f F_f^{1/\xi_f}$  for a constant  $f$ . In the the 3-factor economy,  $1/\xi_1 = 1 + 1/\varphi$ , i.e.,  $\xi_1 = \varphi / (1 + \varphi)$ . On the other hand, as the cost of the intermediary good  $X$  is linear in  $X$ ,  $\xi_3 = C_3 = 1$ . If capital is elastic in the short run,  $\xi_2 = 1$  and  $C_2 = r$ ; if it is completely inelastic,  $\xi_2 = 0$  in all results below.

GDP is output net of intermediary inputs:  $Y = H - X = H - \sum_i F_{iX}$ , with

$$H = \left( \sum_i Q_i^{1/\psi} \right)^\psi \quad (36)$$

GDP is the solution of the planner’s problem:

$$\max_{F_{if}} H - \sum_f C_f F_f^{1/\xi_f} \text{ such that for all } f, \sum_i F_{if} \leq F_f$$

Finally, as in the body of the paper, a fraction  $\nu_f$  of a factor  $f$  is flexible in the short run.

We start with a general proposition.

**Proposition 5** (*General case*) *The static equilibrium is described by  $Y = \Lambda \prod_{f \in \mathcal{F}} F_f^{\alpha_f}$  with (21)-(22). Furthermore, suppose that each unit  $i$  receives a productivity shock  $\hat{A}_i$ . Macroeco-*



nomic variables change according to:

$$TFP: \hat{\Lambda} = \sum_i \frac{S_i}{Y} \hat{A}_i = \sum_i \frac{Sales_i}{GDP} \hat{A}_i \quad (37)$$

$$GDP: \hat{Y} = \frac{1}{1 - \sum_f \alpha_f \xi_f} \hat{\Lambda} \quad (38)$$

$$Employment \text{ of factor } f: \hat{F}_f = \xi_f \hat{Y} \quad (39)$$

$$Wage \text{ of factor } f: \hat{w}_f = (1 - \xi_f) \hat{Y} \quad (40)$$

Microeconomic-level variables change according to:

$$Value \text{ of sales: } \hat{S}_i = \beta \hat{A}_i + \Phi \hat{Y} \quad (41)$$

$$Production: \hat{Q}_i = \psi \beta \hat{A}_i + (1 - \psi \Phi) \hat{Y} \quad (42)$$

$$Price: \hat{p}_i = -(\psi - 1) \beta \hat{A}_i + (\psi - 1) \beta \Phi \hat{Y} \quad (43)$$

$$Employment \text{ of factor } f: \hat{F}_{if} = \nu_f \beta \hat{A}_i + (\xi_f - \nu_f \Phi) \hat{Y} \quad (44)$$

$$Use \text{ of intermediary input: } \hat{X}_i = \hat{S}_i \quad (45)$$

where

$$\begin{aligned} \beta &= \frac{1}{\psi - \sum_f \gamma_f \nu_f} = \frac{1}{\psi - (1 - b) - b \sum_f \alpha_f \nu_f} \\ &= \frac{1}{\psi - \sum_{f \in \mathcal{F} \cup X} \text{Share of factor } f \times \text{Flexibility ratio of factor } f} \end{aligned}$$

and

$$\begin{aligned} \Phi &= \beta \left( 1 - \sum_f \gamma_f \xi_f \right) = \beta b \left( 1 - \sum_f \alpha_f \xi_f \right) \\ &= \beta \left( 1 - \sum_{f \in \mathcal{F} \cup X} \text{Share of factor } f \times \text{Adjusted supply elasticity of factor } f \right) \end{aligned}$$

where  $f \in \mathcal{F} \cup X$  denotes the primitive factors (labor, capital) and also the intermediary input  $X$ .

**Proof of Proposition 5** *Step 1. Frictionless equilibrium.* The price of unit  $i$  is  $p_i = \frac{\partial H}{\partial Q_i}$ , hence by (36):  $S_i/H = p_i Q_i/H = Q_i \frac{\partial H}{\partial Q_i}/H$  and

$$\frac{S_i}{H} = \left( \frac{Q_i}{H} \right)^{1/\psi} \quad (46)$$

Because  $H$  is homogenous of degree 1,  $H = \sum \frac{\partial H}{\partial Q_i} Q_i = \sum S_i$ .  $H$  is the sum of sales in the economy.

Unit  $i$  solves:  $\max_{F_{if}} p_i Q_i - \sum_f w_f F_{if}$ , which gives:  $F_{if} = S_i \gamma_f / w_f \propto S_i$ . We use  $\propto$  to mean that the variables are proportional, up to a factor that does not depend on  $i$ . So,  $S_i^\psi \propto Q_i \propto A_i S_i$  by (18), so  $S_i \propto A_i^{1/(\psi-1)}$ . Calling  $B = \sum_i A_i^{1/(\psi-1)}$ , and using the adding up constraint  $\sum F_{if} = F_f$ , we find the constant of proportionality:  $F_{if} = F_f A_i^{1/(\psi-1)} / B$ . Plugging this in (36), we obtain  $H = \kappa B^{\psi-1} \prod_{f \in \mathcal{F} \cup X} F_f^{\gamma_f}$ . Now, we solve for  $X$ :  $\max_X Y = H - X$ , i.e.,  $\max_X \kappa B^{\psi-1} \left( \prod_{f \in \mathcal{F}} F_f^{\alpha_f} \right)^b X^{1-b} - X$ . The solution yields  $X = (1-b)H$ ,  $Y = H - X = B^{(\psi-1)/b} \prod_{f \in \mathcal{F}} F_f^{\alpha_f}$ , i.e.,

$$Y = \Lambda \prod_{f \in \mathcal{F}} F_f^{\alpha_f}, \quad \Lambda = B^{(\psi-1)/b} \quad (47)$$

as announced in the statement of Proposition 5. In the 3-factor economy we obtain (20). Also,  $Y = H - X = bH$ .

*Step 2. Changes, assuming  $\nu_f = 1$ .* To keep the proof streamlined, we first consider the case  $\nu_f = 1$ , i.e., the case with no frictions in the adjustment of labor, and with the possibility that  $\sum_f \gamma_f$  is not 1. TFP growth comes from (21), and is also Hulten's formula.  $Y = bH$  gives  $\hat{Y} = \hat{H}$ . The optimal use of factor  $f$  maximizes  $Y - \sum C_f F_f^{1/\xi_f}$ , for constants  $C_f$ . Hence  $\gamma_f Y / F_f = C_f F_f^{1/\xi_f - 1}$ , and  $F_f = Y^{\xi_f}$  times a constant, and

$$\hat{F}_f = \xi_f \hat{Y} \quad (48)$$

Equation (47) implies that:

$$\hat{Y} = \hat{\Lambda} + \sum_f \alpha_f \hat{F}_f = \hat{\Lambda} + \left( \sum_f \alpha_f \xi_f \right) \hat{Y}$$

and  $\hat{Y} = \frac{\hat{\Lambda}}{1 - \sum_f \alpha_f \xi_f}$ . The wage is  $w_f = \frac{1}{\xi_f} L^{1/\xi_f - 1}$ , so:  $\hat{w}_f = \left( \frac{1}{\xi_f} - 1 \right) \hat{F}_f$ , hence

$$\hat{w}_f = (1 - \xi_f) \hat{Y}. \quad (49)$$

It is convenient that one can solve for changes in the macroeconomic variables without revisiting the sectors' decision problems.

We now turn to the unit-level changes. Optimization of the demand for labor gives  $w_f F_{if} = \gamma_f S_i$ , so

$$\hat{F}_{if} = \hat{S}_i - \hat{w}_f = \hat{S}_i - (1 - \xi_f) \hat{Y}$$

We have, from (18),

$$\begin{aligned}\widehat{Q}_i &= \widehat{A}_i + \sum_f \gamma_f \widehat{F}_{if} = \widehat{A}_i + \sum_f \gamma_f \left( \widehat{S}_i - (1 - \xi_f) \widehat{Y} \right) \\ &= \widehat{A}_i + \left( \sum_f \gamma_f \right) \widehat{S}_i - \sum_f \gamma_f (1 - \xi_f) \widehat{Y}\end{aligned}$$

Eq. (46) gives  $\widehat{Q}_i = \psi \widehat{S}_i + (1 - \psi) \widehat{H}$ , and using  $\widehat{Y} = \widehat{H}$ ,

$$\psi \widehat{S}_i + (1 - \psi) \widehat{Y} = \widehat{Q}_i = \widehat{A}_i + \left( \sum_f \gamma_f \right) \widehat{S}_i - \sum_f \gamma_f (1 - \xi_f) \widehat{Y}$$

which gives

$$\begin{aligned}\widehat{S}_i &= \frac{\widehat{A}_i + \left[ \psi - 1 - \sum_f \gamma_f (1 - \xi_f) \right] \widehat{Y}}{\psi - \sum_f \gamma_f} = \frac{\widehat{A}_i}{\psi - \sum_f \gamma_f} + \left( 1 - \frac{1 - \sum_f \gamma_f \xi_f}{\psi - \sum_f \gamma_f} \right) \widehat{Y} \\ &= \beta \widehat{A}_i + \Phi \widehat{Y}\end{aligned}$$

where

$$\beta = \frac{1}{\psi - \sum_f \gamma_f}, \quad \Phi = \beta \left( 1 - \sum_f \gamma_f \xi_f \right)$$

and, as  $\widehat{Q}_i = \psi \widehat{S}_i + (1 - \psi) \widehat{Y}$ , we obtain the announced expressions for  $\widehat{S}_i$  and  $\widehat{Q}_i$ .  $\widehat{F}_{if}$  comes from  $\widehat{F}_{if} = \widehat{S}_i - \widehat{w}_f$ .  $S_i$  was defined as  $S_i = p_i Q_i$ , which gives  $\widehat{p}_i = \widehat{S}_i - \widehat{Q}_i$ .

*Step 3.* With general  $\nu_f \in [0, 1]$ . After the changes  $\widehat{A}_i$ , only  $L_{V,i}$  can adjust. The planner optimizes the variable part of labor supply:  $\max_{L_{Vf}} A \prod_f \left( F_{Vf}^{\nu_f} F_{Ef}^{1-\nu_f} \right)^{\gamma_f} - \left( F_{Vf}^{\nu_f} F_{Ef}^{1-\nu_f} \right)^{1/\xi_f}$ .

Note that this is isomorphic to optimizing the total labor supply, defining  $F_f = F_{Vf}^{\nu_f} F_{Ef}^{1-\nu_f}$ . Hence, we have (48) and (49).

For the unit-level variables, one replaces  $(\alpha_f, \gamma_f, \xi_f)$  by  $(\alpha'_f, \gamma'_f, \xi'_f) = (\alpha_f \nu_f, \gamma_f \nu_f, \xi_f / \nu_f)$ , which delivers

$$\beta = \frac{1}{\psi - \sum_f \gamma_f \nu_f}, \quad \Phi = \beta \left( 1 - \sum_f \gamma_f \xi_f \right).$$

Remember that (25). Then, the expression for employment stemming from the optimization of labor demand becomes:

$$\begin{aligned}\widehat{F}_{V,i} &= \nu_f \left[ \widehat{S}_i - \left( 1 - \frac{\xi_f}{\nu_f} \right) \widehat{Y} \right] = \nu_f \left[ \beta \widehat{A}_i + (1 - \Phi) \widehat{Y} - \left( 1 - \frac{\xi_f}{\nu_f} \right) \widehat{Y} \right] \\ &= \nu_f \left[ \beta \widehat{A}_i + \left( \frac{\xi_f}{\nu_f} - \Phi \right) \widehat{Y} \right] = \nu_f \beta \widehat{A}_i + (\xi_f - \nu_f \Phi) \widehat{Y}\end{aligned}$$

This concludes the proof of Proposition 5.

**Proof of Proposition 2** We apply the results from Proposition 5. We particularize them to the case of flexible capital ( $\xi_2 = 1, \nu_2 = 1$ ) and flexible intermediary inputs ( $\xi_3 = 1, \nu_3 = 1$ ), whereas labor is less flexible ( $\xi_1 = \xi, \nu_1 = \nu$  can be less than 1). Then, using  $\xi = \varphi / (1 + \varphi)$ ,

$$\begin{aligned}\widehat{Y} &= \frac{1}{1 - (1 - \alpha) - \alpha\xi_1} \widehat{\Lambda} = \frac{1}{\alpha(1 - \xi)} \widehat{\Lambda} = \frac{1 + \varphi}{\alpha} \widehat{\Lambda} \\ \widehat{L} = \xi \widehat{Y} &= \frac{\varphi}{1 + \varphi} \widehat{Y}, \quad \widehat{w} = (1 - \xi) \widehat{Y} = \frac{\widehat{Y}}{1 + \varphi}.\end{aligned}$$

Also,

$$\begin{aligned}\beta^{-1} &= \psi - \sum_f \gamma_f \nu_f = \psi - b\alpha\nu - b(1 - \alpha) - (1 - b) = \psi - 1 + b\alpha(1 - \nu) \\ \Phi &= \beta \left( 1 - \sum_f \gamma_f \xi_f \right) = \beta(1 - b\alpha\xi - b(1 - \alpha) - (1 - b)) = \beta b\alpha(1 - \xi) = \beta b\alpha \frac{1}{1 + \varphi}.\end{aligned}$$

**Proof of Proposition 3** In this model, value added is proportional to sales,  $Y_i = bS_i$  (this comes from the first order condition with respect to  $X_i$ ). So

$$\begin{aligned}D &\equiv \sum_i \left( \frac{Y_i}{Y} \right)^2 \text{var}(\widehat{Y}_i) = \sum_i b^2 \left( \frac{S_i}{Y} \right)^2 \text{var}(\widehat{S}_i) \\ &= b^2 \sum_i \left( \frac{S_i}{Y} \right)^2 \text{var}(\beta \widehat{A}_i + \overline{\Phi} \widehat{Y})\end{aligned}\tag{50}$$

and  $f = N/\sigma_Y^2 = 1 - D/\sigma_Y^2$ . Consider first the case where most shocks at the microeconomic level are idiosyncratic, i.e.,  $\beta^2 \sigma_A^2 \gg \overline{\Phi}^2 \sigma_Y^2$ . Then,

$$f^{GDP} \simeq 1 - \frac{b^2 \sum_i \left( \frac{S_i}{Y} \right)^2 \beta^2 \sigma_A^2}{\sigma_Y^2} = 1 - \frac{b^2 \beta^2 \sigma_F^2}{\mu^2 \sigma_F^2} = 1 - \frac{b^2 \beta^2}{\mu^2}.\tag{51}$$

and  $c_D \simeq b^2 \beta^2$  and  $c_N \simeq \mu^2 - b^2 \beta^2$ .

In the general case, (23) implies  $\text{cov}(\widehat{A}_i, \widehat{Y}) = \frac{S_i}{Y} \mu \sigma_A^2$ , so (50) gives:

$$\begin{aligned}f^{GDP} &= 1 - \frac{b^2 \sum_i \left( \frac{S_i}{Y} \right)^2 \left[ \beta^2 \sigma_A^2 + \overline{\Phi}^2 \mu^2 \sigma_F^2 + 2\beta \overline{\Phi} \left( \frac{S_i}{Y} \right) \mu \sigma_A^2 \right]}{\mu^2 \sigma_F^2} \\ &= 1 - \frac{b^2 \beta^2}{\mu^2} - \overline{\Phi}^2 b^2 \left( \sum_i \left( \frac{S_i}{Y} \right)^2 \right) - \frac{2b^2 \beta \overline{\Phi} \sigma_A^2}{\mu \sigma_F^2} \sum_i \left( \frac{S_i}{Y} \right)^3 \\ \therefore f^{GDP} &= 1 - \frac{b^2 \beta^2}{\mu^2} - \overline{\Phi}^2 b^2 \sum_i \left( \frac{S_i}{Y} \right)^2 - \frac{2b^2 \beta \overline{\Phi}}{\mu} \frac{\sum_i \left( \frac{S_i}{Y} \right)^3}{\sum_i \left( \frac{S_i}{Y} \right)^2}.\end{aligned}\tag{52}$$

We verify numerically that the approximation (51) is quite good. Likewise, the comovement in labor follows, using (24), (28), and  $L_i/L = bS_i/Y$

$$\begin{aligned} 1 - f^{Labor} &= \frac{\sum_i \text{var}(\widehat{L}_i) (L_i/L)^2}{\text{var}(\widehat{L})} \simeq \frac{\sum_i (\nu\beta)^2 \sigma_A^2 (bS_i/Y)^2}{\left(\frac{\varphi}{1+\varphi}\right)^2 \sigma_Y^2} \\ &= \left(\frac{\nu\beta(1+\phi)}{\phi}\right)^2 \frac{b^2 \sigma_F^2}{\mu^2 \sigma_F^2} = \left(\frac{\nu(1+\phi)b\beta}{\phi\mu}\right)^2. \end{aligned}$$

**Proof of Proposition 4** Equation (33) comes from (28) and (32). The measured change in productivity is (using  $\sum_i S_i/Y = 1/b$ )

$$\widehat{\Lambda}^m = \sum_i \frac{S_i}{Y} \widehat{A}_i^m = \sum_i \frac{S_i}{Y} (c_A \widehat{A}_i + c_Y \widehat{Y}) = c_A \widehat{\Lambda} + \frac{c_Y}{b} \widehat{Y} = \left(c_A + \frac{c_Y}{b} \mu\right) \widehat{\Lambda}$$

so the volatility of measured TFP,  $\sigma_F^{Full,m} = \text{Var}(\widehat{\Lambda}^m)^{1/2}$ , is  $\sigma_F^{Full,m} = (c_A + \frac{c_Y}{b} \mu) \sigma_F$ . On the other hand, the measured productivity using only the diagonal terms is  $\sigma_F^m = c_A \sigma_F$  by (33). Hence, we obtain

$$\frac{\sigma_F^{Full,m}}{\sigma_F^m} = 1 + \frac{c_Y \mu}{c_A b} \quad (53)$$

Finally, we yield  $f^{TFP,m} = 1 - \left(\frac{\sigma_F^{Full,m}}{\sigma_F^m}\right)^{-2} = 1 - \left(1 + \frac{c_Y \mu}{c_A b}\right)^{-2}$ .

## E Some Additional Empirical Results

### E.1 Construction of the International Data

Because of data limitations, to construct the fundamental volatility in country  $c$ ,  $\sigma_{Fct} = \sqrt{\sum_{i=1}^n \left(\frac{S_{ict}}{Y_{ct}}\right)^2 \sigma_i^2}$ , we use the sectoral volatility  $\sigma_i$  that we have computed for sector  $i$  in the US.

To implement it we have contacted Dale Jorgenson and Mun Ho, who kindly provided us with a bridge between the sectoral classification used by Dale Jorgenson & Associates (DJA henceforth; our main source of data) and the sectoral definitions in the NACE classification system used by the EUKLEMS project (where we've obtained the data for France, Germany, Japan and the UK).

The match performs best for the UK since this is the country with most disaggregated data in the EUKLEMS dataset. Thus, for most sectors, we have a one to one match. In these cases we simply impute the TFP volatility for the UK sector from the corresponding sector

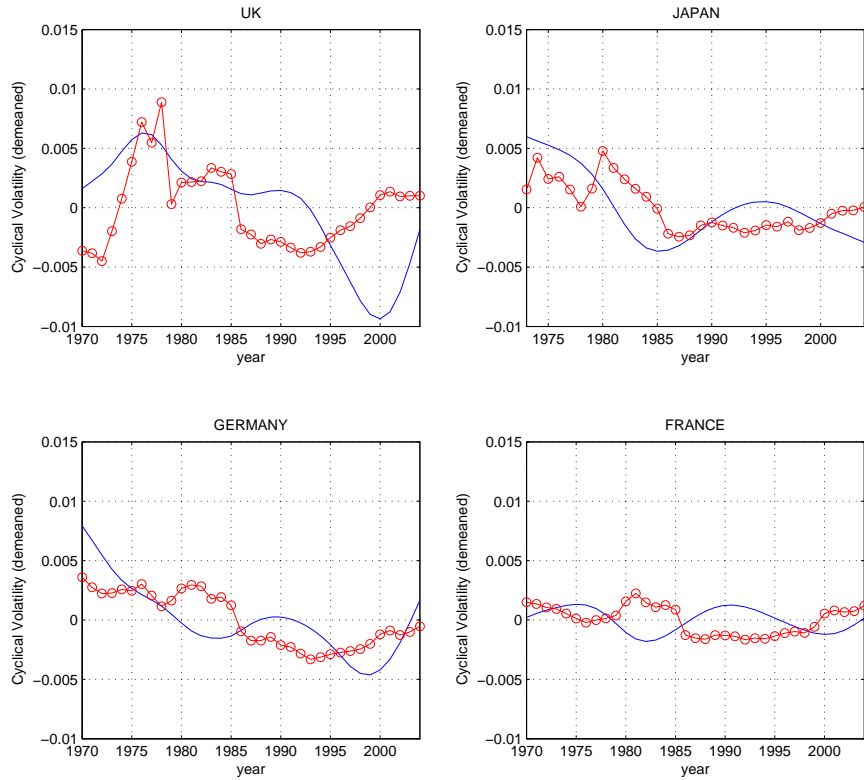
in the DJA dataset. There are three sectors for which the UK data is more aggregated than the original DJA sectors: "Hotels and Restaurants", "Other Inland Transport" and "Legal, Technical and Advertising Sectors". For these sectors we first compute TFP volatility in the corresponding DJA sectors and then take a simple average. For example, in the DJA data we observe the sectors "Hotels" and "Eating and Drinking" which both correspond to the NACE category "Hotels and Restaurants". We then compute TFP for the DJA sectors and then take a simple average to obtain the corresponding TFP volatility of "Hotels and Restaurants". For two other sectors - "Recycling" and "Water Supply"- the match is not possible since there is no corresponding sector in the DJA data. In this case, we have chosen to apply the average sector-level TFP volatility.

For Japan, Germany and France we have followed the exact same procedure, the only difference being that in these countries the original EUKLEMS data is more aggregated (Japan has 6 sectors that are more aggregated than the original DJA data, Germany 11 and France 16)

## **E.2 Alternative International Evidence (industry volatility $\sigma_i$ varying by country)**

Here we present an alternative to the computations in the international evidence presented above. The key difference is that while above we were imputing  $\sigma_i^2$  from the US Jorgenson data here we are using EUKLEMS  $\sigma_i^2$ , with variation at country-and industry level.

The problem we face here is that we do not have  $\sigma_i^2$  for every sector, but rather for aggregates of sectors (since we only have sector specific price data at this higher level of disaggregation). For example, for the UK we only have TFP growth data for the aggregate sector "Electrical and Optical Equipment" but we use more detailed data covering "Office, accounting and computing machinery", "Insulated wire", "Other electrical machinery and apparatus nec", "Electronic valves and tubes", "Telecommunication equipment", "Radio and television receivers", "Scientific instruments", "Other instruments", all subsectors of the aggregate sector for which we have data. Thus, for each of these more disaggregated sectors, we opt to assign  $\sigma_i^2$  for which we do have TFP data of the more aggregated sector. The graph summarizes the evolution of fundamental volatility and aggregate volatility when we consider this method:



The long term trends in volatility are broadly consistent both with the alternative method presented above and with the trends currently on the paper. The panel regressions (with and without) fixed effects are also similar

|               | $\sigma_{ct}$         | $\sigma_{ct}$         |
|---------------|-----------------------|-----------------------|
| $\hat{\beta}$ | 3.401<br>(6.45;0.527) | 3.411<br>(4.51;0.757) |
| $\alpha_t$    | No                    | Yes                   |
| Observations  | 172                   | 172                   |

We can again use these estimates for a quantitative accounting of the role of fundamental volatility. Thus, as above, looking at the US and computing average aggregate volatility,  $\sigma_{Yct}$ , over the subperiods 1970-1984 and 1985-2000 implies a decline in business cycle volatility of 1 percentage point. Across these two periods, the decline of our fundamental volatility measure in the US is of 0.2 percentage points. Using the new panel estimate in this section (with country and time fixed effects), this implies a decline of  $0.2 \times 3.411 = 0.43$  percentage points or 68% of the observed low frequency decline in aggregate volatility.

### E.3 Technological Diversification Patterns

Recall that, in the construction of our fundamental volatility measure, the only time-varying element that we allow for is the sum of squared Domar weights,  $H_t^D = \sum_{i=1}^n (S_{it}/Y_t)^2$ , where  $S_{it}$  is sector  $i$  nominal gross output in year  $t$  and  $Y_t$  gives the total (nominal) value added for the private sector economy in year  $t$ . While Domar weights do not sum to one – as gross output at the sector level exceeds sectoral value added by the amount of intermediate input consumed by that sector – this measure is akin to the more usual Herfindahl indexes of concentration. In particular, looking at the cross-sectional (uncentered) second moment to characterize dispersion/concentration in technology loadings is still valid. The graph below shows the evolution of this measure for the US.

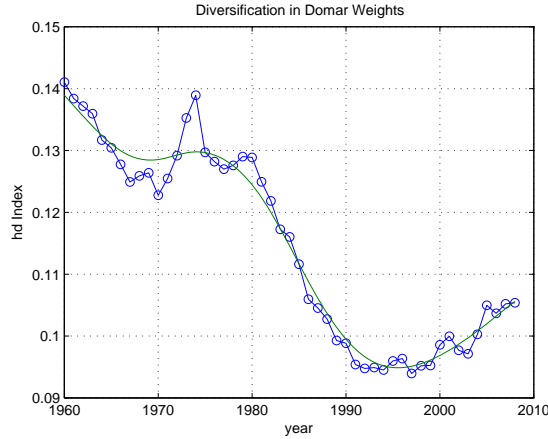


Figure 8: Evolution of  $H_t^D$ , 1960-2008

From the peak in 1960 to the trough in 1997, there is a 33% drop in the  $H_t^D$  measure. These dynamics are key to explaining the evolution of our fundamental volatility measure. As such, it is important to perform a number of robustness checks and confirm that the same pattern obtains: i) in more disaggregated data and across different classification systems, ii) for different dispersion/concentration measures, and iii) for value-added shares.

#### E.3.1 More Disaggregated Data

First, we look at the raw BLS data underlying much of the construction of Jorgenson’s data set. These data are both defined at a more disaggregated level and according to different classification systems. Namely, we source two different vintages of BLS “interindustry relationships” data (i.e., Input-Output data). The first is based on SIC classifications (a mixture



of two and three digit SIC sectors) running from 1977 to 1995 for a total of 185 sectors. The second is the latest vintage produced by the BLS, based on the newer NAICS classification system, and runs from 1993-2008 (for a total of 200 sectors).

Based on these data, we calculate the implied Herfindahl-like measure. Note that, given the difference in underlying classification systems, the levels are not comparable, neither among themselves nor with the ones reported above. Nevertheless, the dynamics seem to be in broad agreement with those above: a fall in technological concentration in the late 1970s and early 1980s and, if anything, a stronger reversal of this pattern from the late 1990s onwards.

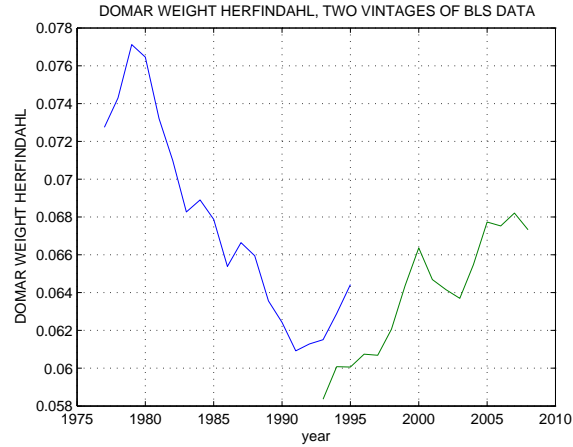


Figure 9: Herfindahl Measure for Domar Weights Computed from Two Vintages of Raw BLS Data (1977-1995 SIC Data; 1993-2008 NAICS Data)

### E.3.2 Checking Against Other Dispersion Measures

Though directly relevant to the story of this paper, Herfindahl indexes of concentration are not the only dispersion measure. However, looking at alternative measures of concentration, such as the Gini Index, the broad story is unchanged: there is a decline in concentration for both measures up until the early 1990s, followed by re-concentration from the mid to late 1990s where the latter now shows up much more strongly.

The patterns above are robust to other measures of dispersion: cross-sectional standard deviation; coefficient of variation; max-min spread and max-median spread.

An alternative is to look into diversification patterns in sectoral value-added shares where the corresponding Herfindahl in year  $t$ ,  $H_t^{VA}$ , is defined as  $H_t^{VA} = \sum_{i=1}^n (Y_{it}/Y_t)^2$ , where  $Y_{it}$  is nominal value added in sector  $i$  in year  $t$ . Figure 11 depicts the evolution of this index and

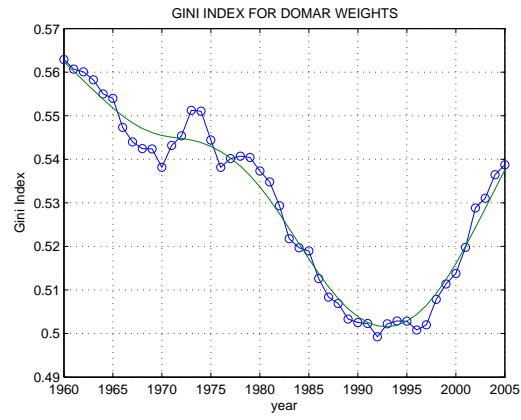


Figure 10: Gini Index for Sectoral Domar Weights

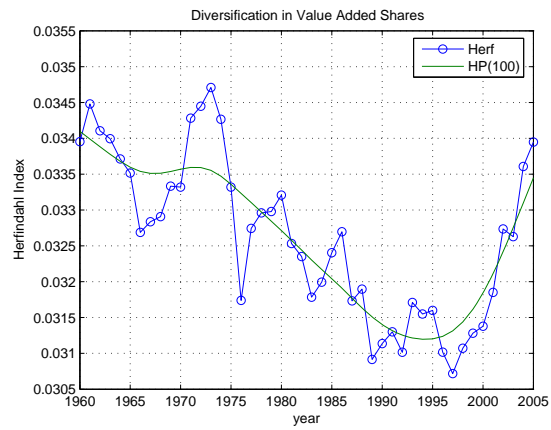


Figure 11: Herfindahl Index of Sectoral Concentration from Value-added Shares Data from 1960-2005.

the corresponding HP-filtered series.

Again, looking at value-added shares leads to the same U-shaped pattern. We also see that, quantitatively, the peak to trough movement in the value-added Herfindahl is smaller. This is as it should be: manufacturing technologies are relatively more intermediate input intensive. As such, the gradual move away from manufacturing and into services implies that the Domar weights-based measure of concentration fell relatively more than the value added one: not only has economic activity relied more on what were initially small – in a value added sense – sectors but these latter sectors have relatively lower gross output to value added ratios.<sup>47</sup>

## E.4 Time-Varying Elasticity of Labor Supply

Jaimovich and Siu (JS, 2009) find that changes in the composition of the labor force account for part of the movement in GDP volatility across the G7 countries. As the young have a more elastic labor supply, the aggregate labor supply elasticity should be increasing in the fraction of the labor force who is between 15 and 29 years old – which is the  $JS_t$  variable.

In terms of our model in (6)-(7), this corresponds to having a time-varying Frisch elasticity of labor supply  $\varphi_t$ , i.e.,

$$\sigma_{Yt} = \frac{1 + \varphi_t}{\alpha} \sigma_{Ft}. \quad (54)$$

The JS composition of the workforce effect is in the term  $\varphi(t) = A + B \cdot JS_t$ , while the effect we focus on in this paper is the  $\sigma_{Ft}$  term. Put differently, the JS variable is about the amplification of primitive shocks, while our variable is about the primitive shocks themselves. To investigate (54), we run the panel regression:

$$\sigma_{Yct} = \alpha_c + \alpha_t + \beta \sigma_{Fct} + \gamma JS_{ct} + \varepsilon_{ct} \quad (55)$$

That is, we return to the cross-country exercise above, this time including the JS measure of the labor force share of the “volatile age group” in each of our economies,  $JS_{ct}$ . The inclusion of this measure shortens our sample somewhat as it extends only to 1999 (and only begins in 1979 for the case of the UK). Finally, we run with or without time fixed-effects.

Table 6 reports the results. Both coefficients  $\beta$  and  $\gamma$  are positive and significant in all specifications. We conclude that the JS labor supply elasticity and the fundamental volatility are both relevant to explain the cross-country evolution of business cycle volatility.

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<sup>47</sup>A way to confirm this is to regress the average growth rate of each sector’s value-added share on the average weight of intermediate input purchases in sectoral gross output (average over the entire sample period 1960-2005). We obtain a negative and significant slope coefficient.

Table 6: Fundamental Volatility and Jaimovic-Siu Variable

|                | (1)                   | (2)                   |
|----------------|-----------------------|-----------------------|
| $\hat{\beta}$  | 1.261<br>(3.25;0.388) | 2.440<br>(3.30;0.740) |
| $\hat{\gamma}$ | 0.054<br>(4.97;0.011) | 0.060<br>(5.51;0.011) |
| $\alpha_t$     | No                    | Yes                   |
| Observations   | 134                   | 134                   |

*Notes:* We run the regression  $\sigma_{Yct} = \alpha_c + \alpha_t + \beta\sigma_{Fct} + \gamma JS_{ct} + \varepsilon_{ct}$  where  $\sigma_{Yct}$  is the country volatility using a rolling window measure,  $\sigma_{Fct}$  is the fundamental volatility of the country defined in (10),  $\overline{\sigma_F}$  is the mean of the  $\sigma_{Fct}$ 's,  $JS_{ct}$  is the Jaimovich-Siu (2009) measure of the labor force share of the “volatile age group,”  $\overline{JS}$  is the mean of the  $JS_{ct}$ 's,  $\alpha_c$  a country fixed effect and  $\alpha_t$  a time fixed effect.  $t$ -statistics and Newey-West standard errors (2 lags) in parentheses.

## E.5 References

**Baumol, William.** 1967. “Macroeconomics of unbalanced growth: the anatomy of urban crisis” *The American Economic Review* 57(3): 415–426.