The Great Diversification and its Undoing*

Vasco M. Carvalho Xavier Gabaix

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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 shares 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 sources of aggregate shocks can be traced to identifiable microeconomic shocks, we may thus better understand the origins of aggregate fluctuations. (JEL: E32, E37)

*Carvalho: CREI, U. Pompeu Fabra and Barcelona GSE, vcarvalho@crei.cat. Gabaix: NYU, CEPR and NBER, xgabaix@stern.nyu.edu. We thank Alex Chinco and Farzad Saidi for excellent research assistance. For helpful advice, we thank the editor and referees, as well as G.M. Angeletos, Susanto Basu, V. V. Chari, Robert Engle, Dale Jorgenson, Alessio Moro, Robert Lucas, Giorgio Primiceri, Scott Schuh, Silvana Tenreyro, and seminar participants at Cambridge, CREI, ESSIM, IIES-Stockholm, Harvard, LSE, Minnesota, NBER, Northwestern, Paris School of Economics, Richmond Fed, Sciences-Po, SED, Toulouse, Rio (PUC), UCLA, World Bank, and Yale. We also thank Mun Ho for help with the Jorgenson data. Carvalho acknowledges financial support from the Government of Catalonia (grant 2009SGR1157), the Spanish Ministry of Education and Science (grants Juan de la Cierva, JCI2009-04127, ECO2008-01665 and CSD2006-00016) and the Barcelona GSE Research Network. Gabaix acknowledges support from the NSF (grants DMS-0938185 and SES-0820517).

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:"

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

where S_{it} is the gross output (not just value added) of sector i, and σ_i is the standard deviation of the total factor productivity (TFP) in the sector. Note that the evolution of σ_{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}/GDP_t do not add up to one. These are the "Domar 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 σ_{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 σ_{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 since the early 2000s.

In Figure 2 we present a similar analysis for the major economies for which we could attain 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

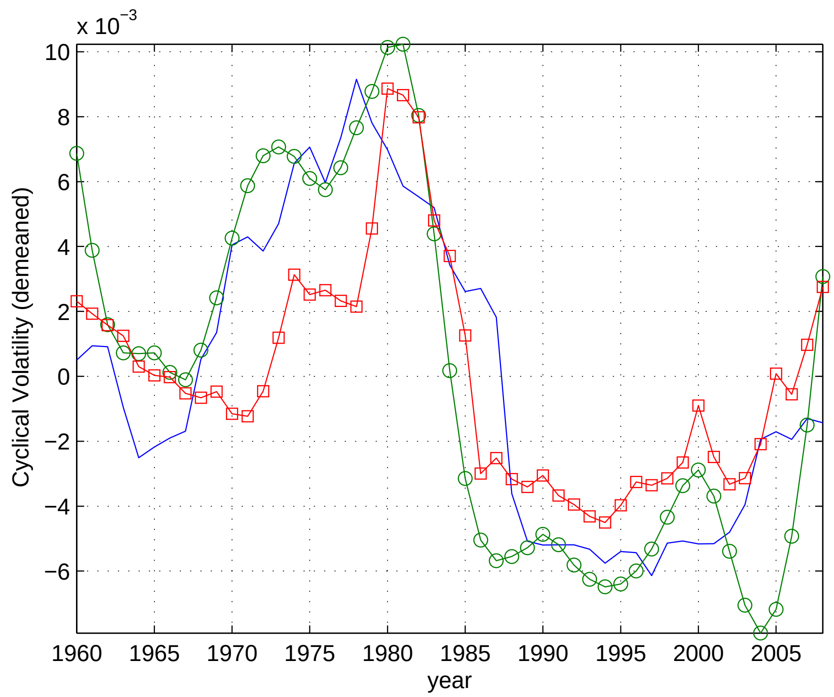

Figure 1: Fundamental Volatility and GDP Volatility. The squared line gives the fundamental volatility ($4.5\sigma_{Ft}$, demeaned). The solid and circle lines are annualized (and demeaned) estimates of GDP volatility, using respectively a rolling-window estimate and an HP trend of instantaneous volatility.

more light on the origins of the latter.

Hence, our paper may bring us closer to a concrete understanding of the sources 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 the empirical features of the model, 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, thus, enables microeconomic shocks to affect aggregate volatility[1]. 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 (2011) 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, namely fundamental volatility, to

[1] Other interesting conceptual contributions for the micro origins of macro shocks include Bak et al. (1993), Jovanovic (1987), Durlauf (1993), and Nirei (2006).

predict 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, Galí, and Gertler 2000) were prime candidates. However, given the difficulty of relating such 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. Galí 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 that is between 15 and 29 years old. We verify in the online appendix that fundamental volatility has substantial explanatory power over the measure proposed by Jaimovich and Siu (2009). In general, we view our proposal as complementary to the 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 Domar weights for aggregation, while the aforementioned papers are essentially atheoretical.[2] 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 US 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 of 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 discusses variants on the basic empirical construct (including 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. 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 multi-sector model that exposes the basic ideas and motivates our empirical work. There are n sectors that produce intermediate and final goods, and two primitive factors, capital and labor. Sector i uses capital and labor inputs K_i and L_i,

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

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

The utility function is $\mathcal{C}(\boldsymbol{C}) - L^{1+1/\phi}$, 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:

$$
\begin{aligned}
F(K, L; \boldsymbol{A}) &= \max_{\substack{C_i, L_i, K_i, X_{ij} \\ 1 \le i,j \le n}} \mathcal{C}(\boldsymbol{C}) \text{ subject to} \\
\sum_i K_i &\le K; \qquad \sum_i L_i \le L; \qquad \forall i, C_i + \sum_j X_{ji} \le A_i F_i \left(K_i^{1-\alpha} L_i^{\alpha}, \mathbf{X}_i\right).
\end{aligned}
$$

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

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

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

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

$$\frac{d\Lambda}{\Lambda} = \sum_{i=1}^{n} \frac{S_i}{Y} \frac{dA_i}{A_i}, \tag{2}$$

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, $\widehat{Z} \equiv dZ/Z$,[3] and time subscripts. Shocks $\widehat{A}_{it}$ to the productivity in sector i result in aggregate TFP growth $\widehat{\Lambda}_t$ expressed as:

$$\widehat{\Lambda}_t = \sum_{i=1}^{n} \frac{S_{it}}{Y_t} \widehat{A}_{it}, \tag{3}$$

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 ratio of sales to value

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

added 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).[4]

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

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

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 Λ. Taking logs, $\ln Y = \frac{1+\varphi}{\alpha}\ln\Lambda + \ln v$, and a change in TFP $\widehat{\Lambda}$ creates a change in GDP equal to[5]

$$\widehat{Y} = \frac{1+\varphi}{\alpha}\widehat{\Lambda}. \tag{5}$$

[4] 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 $\widehat{A}_{1t} = 1\%$ in cars and $\widehat{A}_{2t} = 3\%$ 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. These 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 $dY_t = 1\%\times$ initial value of cars $+3\%\times$ initial value of plastic, i.e., $dY_t = S_{1t}\times\widehat{A}_{1t} + S_{2t}\times\widehat{A}_{2t}$. Dividing by Y_t, we get $\frac{dY_t}{Y_t} = \sum_{i=1}^{2}\frac{S_{it}}{Y_t}\widehat{A}_{it}$. However, what has increased is the productive capacity of the economy. So, it is really TFP that has increased by $\widehat{\Lambda}_t = \sum_{i=1}^{2}\frac{S_{it}}{Y_t}\widehat{A}_{it}$. GDP might increase more or less once we take into account the response of labor supply, something we shall consider very soon.

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

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

Proposition 1 *The volatility of GDP growth is*

$$\sigma_{Yt} = \mu \cdot \sigma_{Ft}, \tag{6}$$

where the fundamental volatility σ_{Ft} is given by (4), and the productivity multiplier μ is equal to

$$\mu = \frac{1+\varphi}{\alpha}. \tag{7}$$

Here, α is the labor share and φ is the Frisch elasticity of labor supply.

Our hypothesis is that, indeed, σ_{Ft} explains a substantial part of GDP volatility, as motivated by (6). In our baseline specification, we construct σ_{Ft} as in equation 4, taking the sales-to-value-added weights directly from detailed sectoral data provided by Dale Jorgenson and Associates (see Jorgenson, Ho and Stiroh, 2005). 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 σ_i.[7] Note that we keep σ_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 σ_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

[6] 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^{ξ}, $\xi_K \geq 0$ reflects that higher utilization is marginally more costly, and r is 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 ν' independent of Λ. For simplicity we take $\xi = 0$, but $\xi > 0$ would be defensible, too.

[7] The original data are annual and provide 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 the construction of our fundamental-volatility measure.

worker but also changes in employment and changes in effort.[8] Using this notion, recent research (summarized in, for instance, 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.[9] 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 high 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 1,600; 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 $\sigma_{Yt}^{\mathrm{Roll}}$. To construct its annual counterpart, for a given year t, we average $\sigma_{Yt}^{\mathrm{Roll}}$ 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):

$$\Delta y_s = \psi + \phi \Delta y_{s-1} + \epsilon_s, \tag{8}$$

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

[8] We can also take it as a reduced form for richer acceleration mechanisms, e.g., a financial accelerator.

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

given by $2\sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_s|$, 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 $2\sqrt{\frac{\pi}{2}}|\widehat{\epsilon}_{t:q}|$ of quarterly volatility (where date $t:q$ is the qth quarter of year t). Namely, we construct the annualized volatility in year t as $\sigma_{Yt}^{\text{Inst}} \equiv \frac{1}{2}\sqrt{\frac{\pi}{2}}\sum_{q=1}^{4}|\widehat{\epsilon}_{t:q}|$, and call it the "instantaneous" measure of GDP volatility in year t. We shall also use σ_{Yt}^{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. The graph also depicts the sample fit of our fundamental-volatility measure σ_{Ft} for the annual case given a baseline value of $\mu = 4.5$. In particular, it shows $\sigma_{Yt}^{\text{Roll}}$ and σ_{Yt}^{HP} (annualized and demeaned), together with $4.5\sigma_{Ft}$ (demeaned).

We run least-squares regressions of the type:

$$\sigma_{Yt} = a + b\sigma_{Ft} + \eta_t, \tag{9}$$

where σ_{Ft} is our measure of fundamental volatility, and σ_{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. Table 1 summarizes the results.[10] We find high statistical and economic

Table 1: GDP Volatility and Fundamental Volatility

	Annual Data-$\sigma_{Yt}^{\text{Roll}}$	Annual Data-$\sigma_{Yt}^{\text{Inst}}$
$\widehat{a}$	-0.029 $(-5.53;0.005)$	-0.0483 $(-4.47;0.019)$
$\widehat{b}$	4.815 (8.39;0.574)	7.015 (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.

[10] Note that σ_{Ft} is only available on an annual basis. In Table 1, we have used annual measures of aggregate 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.

significance of σ_F.[11] It is the sole regressor, and its R^2 is around 60% for the rolling-window estimate of volatility.[12] This shows that σ_{Ft} explains a good fraction of the historical evolution on GDP volatility. Of course, the R^2 for $\sigma_{Yt}^{\text{Inst}}$ 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 σ_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 result holds 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 subsamples. At the 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 do not showcase statistically different volatilities in the two subsamples.[13] 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 σ_F allows to isolate the impact of the changes in the microeconomic composition of the economy. This assumption is relaxed later in Section 5.1.3.

[11] 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 Le Chatelier's principle). To be more precise, consider the case with g convex, $g(0) = 0$, and a small dispersion of σ_F. Then, in the regression $\sigma_{Yt} = a + \beta\sigma_{Ft}$, we find $\beta = g'(\overline{\sigma_F})$ and $a = \overline{g(\sigma_F)} - g'(\overline{\sigma_F})\,\overline{\sigma_F} < 0$. Equivalently, the model generates $\overline{\sigma_Y} < \beta\overline{\sigma_F}$.

[12] 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.

[13] One exception is finance, which shows a decline in sectoral volatility in the later part of our sample, which ends in 2008. In view of the financial crisis, it seems fair to conjecture that this apparent decline in the volatility of finance will prove only temporary once more years of data become 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 σ_{Yt} to be given by the instantaneous-volatility measure $\sigma_{Yt}^{\text{Inst}}$, and test for the presence of a break in levels using Bai and Perron (1998)'s SupLR test statistic.[14] 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).[15]

To assure comparability and since our sample period differs, we start by reconfirming the findings first reported in McConnell and Quiros (2000). We 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.[16] 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:[17] $\sigma_{Yt}^{\text{Inst}} = a + b\sigma_{Ft} + \eta_t$. To rule out the additional possibility that the break in aggregate volatility is the result of a break in its link

[14] McConnell and Quiros (2000) and Stock and Watson (2002) show that for US quarterly GDP one cannot reject the null of no break in the autoregressive coefficients in the equation for GDP growth, thus enabling us to use the residuals in (8) to test for a break in the variance.

[15] 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.

[16] The NBER Working Paper version of this paper uses quarterly estimates of volatility, and yields similar estimates and results. The estimated break date T is 1984:1, and is estimated with a 90% confidence interval given by 1981:2 and 1986:4.

[17] The resulting SupLR test statistic reported in the table is computed under the assumptions of no serial correlation in η_t and the same variance of η_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			
	$\sigma_{Yt}^{Inst} = a + \eta_t$	$\sigma_{Yt}^{Inst} = a + b\sigma_{Ft} + \eta_t$		
	H_0: No break in a	H_0: No Break in a	H_0: No Break in b	H_0: 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).

with fundamental volatility, we also test the null of no break in the slope parameter b and the joint null of no break in both a and b.[18]

The results are in Table 2. We cannot reject the null of no break in any of these settings.[19] 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.

[18] 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.

[19] 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). Although we have considerable sectoral detail for nominal measures, sector-specific price indices are only available for half or fewer of the sectors in each country.[20] This renders it impossible to construct sectoral TFP growth at the level of detail of the data that are available for the nominal gross output and value added. 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 σ_i that we have computed for sector i in the US:[21]

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

where the c superscripts now denote country c-specific variables, and i still denotes sectoral-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).

[20] The main source of international data is EUKLEMS. See Appendix A for more details on the sources, description, and construction of these measures.

[21] 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 considered averaging over the standard deviation of sectoral TFP growth for the limited subset of EUKLEMS sectors for which it is possible to calculate TFP growth series. That is, we constructed $\overline{\sigma}_{Fct} = \sqrt{\sum_{i=1}^{N} \left(\frac{S_{ict}}{Y_{ct}}\right)^2 \overline{\sigma}_c^2}$, where $\overline{\sigma}_c$ is the average standard deviation of TFP growth (taken across the subset of sectors for which we can calculate TFP). All results presented in this section are robust to this alternative measure. Yet another alternative is to take advantage of the fact that, for each country, we can construct TFP growth for more aggregated sectors. Thus, for a given industry i we considered assigning it the volatility of the corresponding aggregated sector for which we do have σ_{ic}^2. We detail this second alternative measure in the online appendix and show that its results are again quite similar to the results in this section.

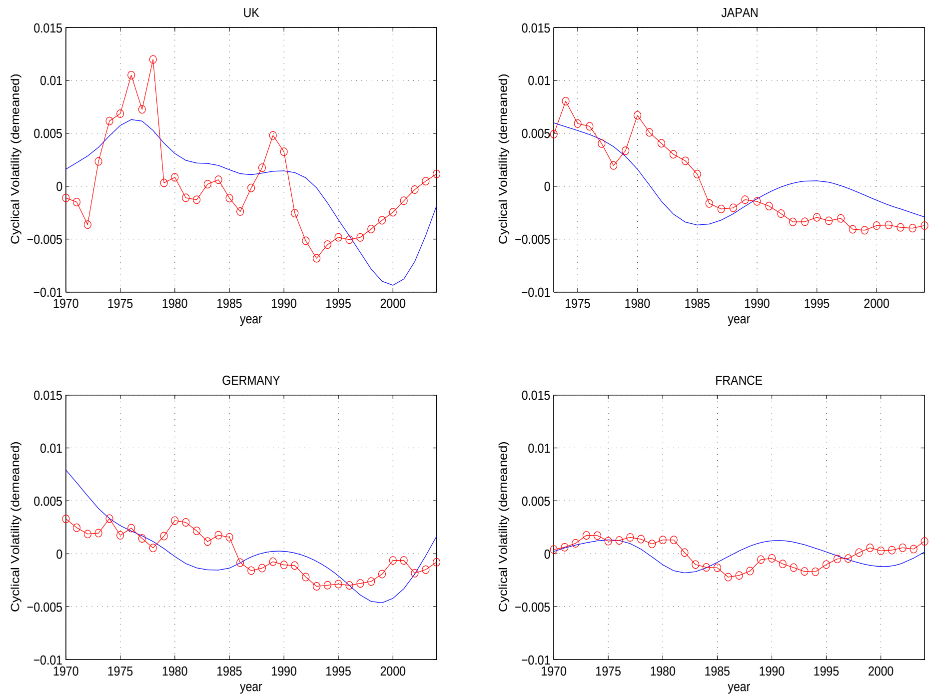

Figure 2: GDP Volatility and Fundamental Volatility in Four OECD countries. Solid line: smoothed rolling-window standard deviation of deviations from HP trend of quarterly real GDP. Circle line: fundamental-volatility measure, $\sigma_{Yt} = 4.5\sigma^{j}_{Ft}$. Both measures are demeaned. We report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

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 reduction in volatility in the late 1970s, its leveling off until in the early 1990s, and its renewed decline during that decade. As Stock and Watson (2005) noticed, Germany provides a different picture, namely 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 of the form:

$$\sigma_{Yct} = \alpha_c + \alpha_t + \beta\sigma_{Fct} + \varepsilon_{ct}, \tag{11}$$

Table 3: GDP Volatility and Fundamental Volatility: International Evidence

	σ_{ct}	σ_{ct}
$\widehat{\beta}$	3.08 (7.94;0.388)	2.172 (3.52;0.618)
α_t	No	Yes
Observations	172	172

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

where σ_{Yct} is our rolling-window measure of cyclical volatility for country c in year t, and σ_{Fct} is the country-specific fundamental volatility discussed above. We include the US along with the four other economies mentioned. We use both use country fixed effects α_c and run the panel with and without time fixed effects α_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 β through cross-country timing differences in the evolution of fundamental volatility. While this specification renders the value of β 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.

Table 3 reports the results. All results are significant at the 1% level (they are also significant without the US).[22] 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 US univariate case reported above. Its significance survives even when we allow for time fixed effects.[23]

[22] We report heteroskedasticity-autocorrelation robust standard errors by using a Newey-West estimator with 2 lags.

[23] We also experimented with instrumenting σ^j_{Fct} by its own lag or allowing for a (common) linear time trend. All results are robust.

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 to use the break test of Table 2: after controlling for fundamental volatility, we do not reject the hypothesis of no break in US GDP volatility. In that sense, we cannot reject the hypothesis that fundamental volatility statistically accounts for 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, fundamental volatility 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, σ_{Yct}, over the subperiods 1970-1984 and 1985-2000, which implies a decline in business-cycle volatility of 0.96 percentage points. Across these two periods, the decline of our fundamental-volatility measure in the US is 0.16 percentage points. Using the US multiplier of $\mu = 4.5$, the decline in fundamental volatility explains $\mu \times 0.16/0.96 = 75\%$ of the decline in GDP volatility. Using the international estimates (which have time and country dummies, and are therefore arguably harder to interpret), with $\mu = 2.17$, implies that fundamental volatility explains 36% of the change in US GDP volatility.

All of these estimates are arguably defensible. We can arrive at a point estimate by taking the average estimate over the above four procedures (100%, 60%, 75%, and 36%), and 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.

It is useful to move from statistics to a narrative, to which we turn next.

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.[24] We first present evidence showing that most movements in

[24] 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 ratio of *sectoral gross output to value added* 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, σ_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 moves 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 vary over time due to what can be termed a *compositional effect*: if there is a shift in Domar weights away from high-volatility sectors 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 σ_{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, thereby 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 σ_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 taking σ_i^2 to be the same across sectors (given by the average σ_i^2) while letting S_{it}/Y_{it} and Y_{it}/Y_t vary over time.

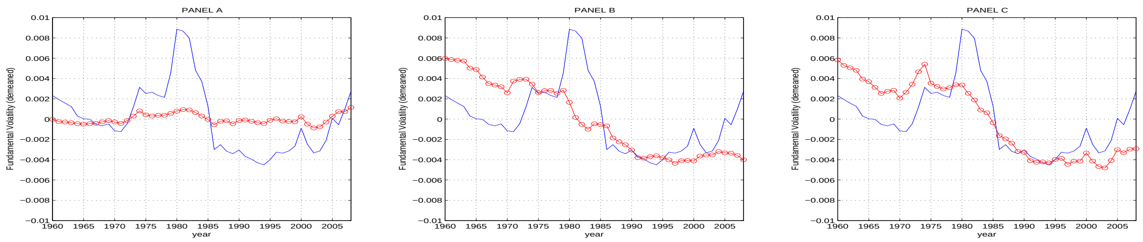

Figure 3: For each panel, the solid line is the baseline fundamental-volatility measure ($4.5\sigma_{F_t}$, demeaned), and the circle line is a counterfactual fundamental-volatility measure. In Panel A, the counterfactual measure shuts down time variation in value-added weights and variation in sectoral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

As is clear from Panel A, time variation in the ratio of sectoral gross output to value added 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.[25,26] 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 accounts neither for the spikes in fundamental volatility observed in the late 1970s and early 1980s nor for the increase in fundamental volatility observed from the mid 1990s on. Given that we have already seen that time variation in S_{it}/Y_{it} is muted, it has to be the case that these are accounted for 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 1970s and from the mid 1990s stem largely from putting more weight on more volatile sectors.

[25] This is consistent with an average intermediate input share of 0.5, as documented in Jones (2011).

[26] This is also the case when we consider 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[27] and the subsequent increase in fundamental volatility 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 in the 2000s.

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

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

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.[28] 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 fundamental volatility in 1960 (30% of σ_F^2).[29] 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 demise, starting

[27] Figures 1 and 6 show that σ_{Ft} has a last (local) minimum in 2002, and σ_F^{Full} has a last minimum in 2003. The σ_{Yt} volatility via a rolling window is basically flat between 1990 and 2001, while σ_{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.

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

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

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 at 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 neither account 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 in 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 the result of the declining shares of energy and of heavy-manufacturing industries around 1983.

To analyze the rise in fundamental volatility since the mid 1990s, we build on Philippon (2008)'s 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 renewed exposure to energy-related sectors from the mid 2000s onwards would have reversed

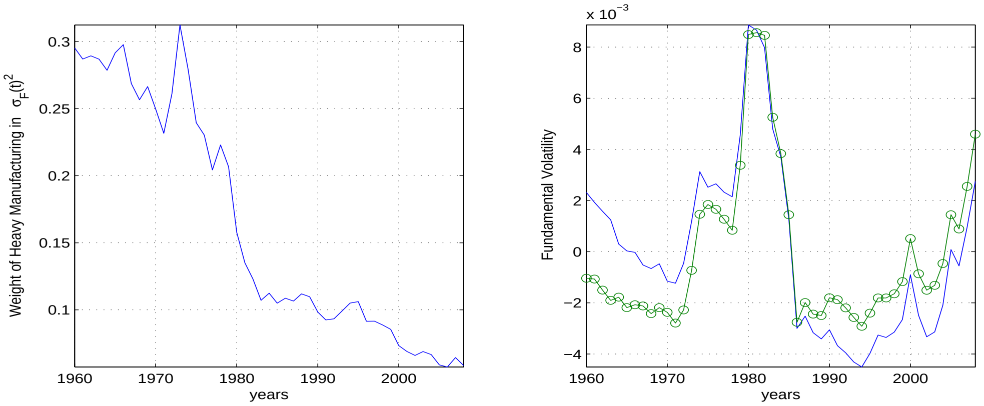

Figure 4: **Left:** Weight of heavy-manufacturing sectors in σ^2_{Ft}. **Right:** The continuous line is the baseline fundamental-volatility measure ($4.5\sigma_{Ft}$ demeaned). The circled line gives a counterfactual-volatility measure (also demeaned) where weights of heavy manufacturing sectors are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

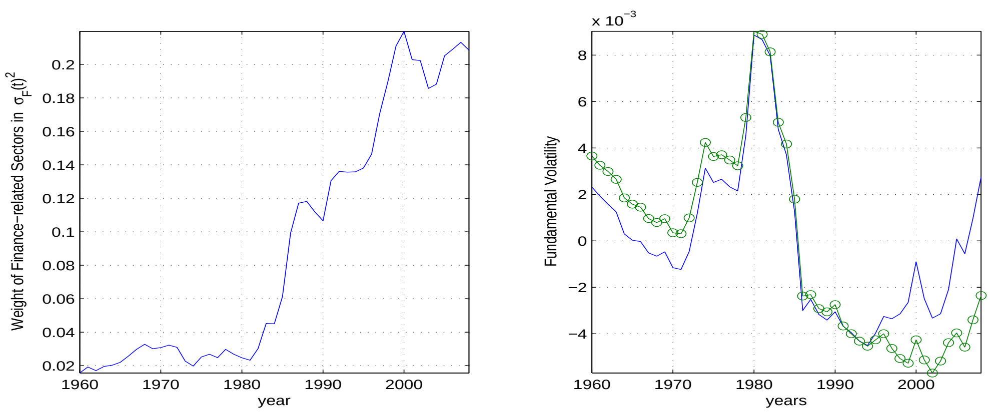

Figure 5: **Left**: Weight of finance-related sectors in σ^2_{Ft}. **Right**: The continuous line is the baseline fundamental-volatility measure ($4.5\sigma_{Ft}$ demeaned). The circled line gives a counterfactual-volatility measure (also demeaned) where weights of finance-related sectors are fixed at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

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. 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.

Overall, the above narrative helps us get a better feel for the "substantial" sense in which fundamental volatility explains GDP volatility and is a useful complement to the econometric analysis of the previous sections. Still, in this paper we stop short of explaining *why* the importance of particular sectors is changing over time.

Take, for instance, 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 comes in large part from 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: less 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, but it pinpoints to the "next thing to explain" in the causal chain – the rise of finance.

Likewise, for the 1981-1986 break in fundamental and GDP volatility. Looking at fundamental volatility revealed 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. Fundamental volatility pinpoints to a simple explanatory factor "one level deeper." However, of course, it does not answer why it is 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. Nevertheless, looking at things through the lens of fundamental volatility helps pinpoint the "proximate" causal factors, which might aid future research in finding 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 the energy price in the context of a more systematic framework for the relative importance of sectors. Indeed, regressing GDP volatility on oil prices leads to a very poor R^2.[30] One way to interpret this is to say that oil price changes explain GDP volatility not in their naïve "raw" form (as reflected by the oil price level or volatility), but only when properly channeled (i.e., adjusted for their relative size squared) via fundamental

[30] Regressing σ_{Yt}^{Roll} on oil price level, growth, or volatility yields a very low R^2 of 3% to 7%, compared to the R^2 of 60% associated with σ_F.

volatility.

All in all, fundamental volatility is a simple tool that is well microfounded, and allows to organize both quantitatively and systematically the contributions of various parts of the economy to changes in volatility and, thus, directs researchers' attention to the next, deeper level of causality.[31]

We next turn to our four other major economies.

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 that 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 increase 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

[31] We thank Avinash Dixit for suggesting the following quote by Richard Feynman. "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... I'm not answering your question, but I'm telling you how difficult a why question is." (cited in Gleick, 2003, p. 370). Hence, "explaining" is really explaining at one more level in the causal chain (a "proximate" cause) and not all the way down (to 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.

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 the weights of 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 the decline in fundamental volatility ($H(1970, 1987) = 0.31$), and is accompanied by Petroleum and Coal Products in the 1980s ($H(1981, 1988) = 0.51$). Lastly, the steep increase 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 even be preferable to our definition (1), although in the main, we think that our definition is more suitable 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 across different sectors is only 2.3% in the US, and even such a low correlation could be due to measurement error and factor hoarding.

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

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

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 $\left(\rho_{ij}\sigma_i\sigma_j\right)$ does not, how much should GDP volatility change? Figure 6 shows the fundamental-volatility graph including the full covariance matrix, i.e., accounting for cross terms.

Table 4: GDP Volatility and Correlation-enriched Fundamental Volatility

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

Notes: Regression of GDP volatility on correlation-enriched fundamental volatility (as defined in (13)): $\sigma_{Yt} = a + b\sigma_{Ft}^{\text{Full}} + \eta_t$. 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^2s are actually a bit higher. Similarly, the break-test results of Table 2 are similar when using σ_F^{Full}.

The advantage of σ_F^{Full}, with all covariance terms, over σ_F, with only diagonal terms, is that σ_F^{Full} is (i) conceptually closer to the natural concept and, perhaps as a result, (ii) slightly more precise and yields a somewhat 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.

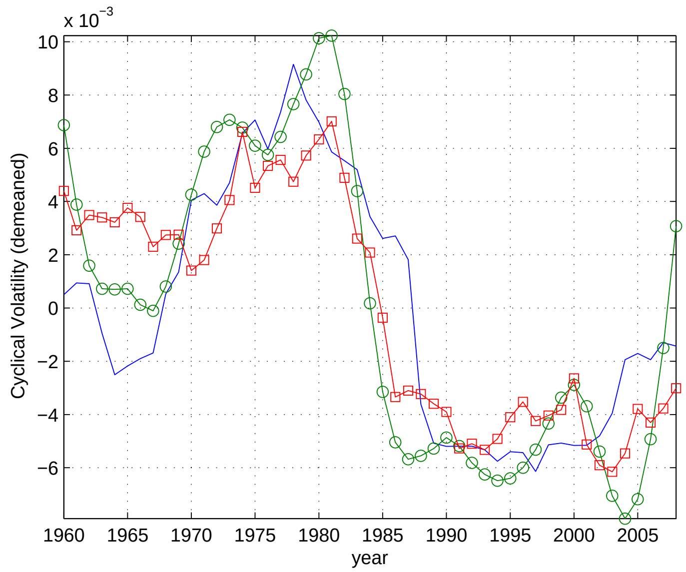

Figure 6: Fundamental Volatility (Full Matrix) and GDP Volatility. The squared line gives the fundamental volatility drawn from the full variance-covariance matrix of TFP ($4.5\sigma_{Ft}^{\mathrm{Full}}$, also demeaned). The solid and circle lines are annualized (and demeaned) estimates of GDP volatility.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

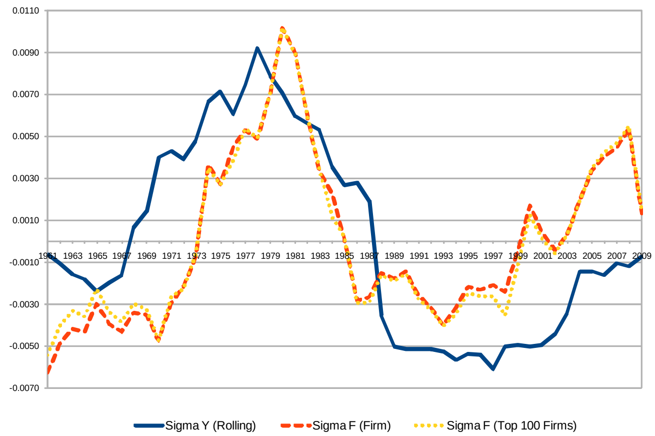

Figure 7: Firm-based Fundamental Volatility and GDP Volatility. The solid line gives the GDP volatility, $\sigma_{Yt}^{\text{Roll}}$ (demeaned). The dotted and dashed lines give the fundamental volatility based on firms (rather than sectors), $4.5\sigma_F^{\text{Firms}}$ (demeaned). The dotted line is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

On the other hand, the advantage of σ_F over σ_F^{Full} is that: (i) σ_F is easier to interpret, as we only have to study "which" of the 88 terms (for 88 sectors) change over time, whereas with σ_F^{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). (ii) It does not require the knowledge of the full variance-covariance matrix of TFP growth which - especially for countries other than the US- is many times unavailable to the researcher.[32] (iii) σ_F^{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 σ_F more directly expresses the hypothesis that most movements come from composition effects with non-infinitesimal sectors or firms.

Ultimately, although Ockham's razor makes lean towards using σ_F as the baseline in most of this paper, we believe that both measures, σ_F and σ_F^{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-based fundamental volatility as we did for sectors, cf. (1): $\sigma_{Ft}^{\text{Firms}} = \sqrt{\sum_{i=1}^{n} \left(\frac{S_{it}}{\text{GDP}_t} \right)^2 \sigma_i^2}$, where S_{it} are the sales of firm i (Compustat Data 12), and the summation is over the n firms with the highest sales each year. To implement this formula, Compustat has several limitations which are rather important when studying long-run trends. Compustat 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 yields quite volatile numbers, so we proceed by using constant values of σ_i across firms. We use $\sigma_i = 12\%$, the typical volatility of the growth rates of sales, of number of workers and of sales per number of workers found in Gabaix (2011).

Figure 7 plots the demeaned 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 σ_F^{Firms} is driven by them. We see that they track GDP volatility quite well. We also witness 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 conventional significance levels. We conclude that firm-based fundamental volatility does account for the great moderation and its undoing, just like the sector-based fundamental-volatility measure 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 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

[32] As we have noted in the International Section above, this is the case even for advanced economies such as France and Germany. Further, as we detail in the online Appendix, in terms of medium-long run trends in fundamental volatility, not much is lost by replacing all variance terms by a constant and setting all covariance terms to zero.

that idea in this paper.

5.1.3 Constant vs. Time-varying Sectoral Volatility

Our σ_{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 $\sigma'_{Ft} = \sqrt{\sum_i \overline{(S_{i\cdot}/Y_{\cdot})}^2 \sigma_{it}^2}$, i.e., σ_{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 σ_{it} by running a GARCH(1,1) for each sector i. We re-run the regression (9) with σ_Y^{Inst} and σ_Y^{Roll} on the right-hand side: σ'_{Ft} has insignificant explanatory power and a very low R^2 (about 5%). On the other hand, σ''_{Ft} has significant explanatory power and a good R^2 (about 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 doing so, 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.[33] Nonetheless, we did examine 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^2s in the regressions of Table 1 are 58% and 40%), which is natural because of the high correlation (84%) between σ_{Ft}^{VA} and σ_{Ft}.

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

5.2 Idiosyncratic Shocks and Comovement

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

$$\sigma_{Yt}^2 = D_t + N_t \tag{14}$$

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

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 (McConnell and Perez-Quiros 2000, Blanchard and Simon 2001, 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) Furthermore, the previous literature showed that the off-diagonal N_t terms declined the most. Does that imply 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?

Here we present a summary of our answers based on a model we sketch below and develop fully in the online Appendix. Regarding question (i), in our model all primitive shocks are idiosyncratic (at the sectoral level). However, because of input linkages, there is comovement across sectors. Indeed, to do a good approximation, in this model

$$D_t \simeq c_D \sigma_{Ft}^2, \qquad N_t \simeq c_N \sigma_{Ft}^2 \tag{15}$$

for two coefficients c_D and c_N. In our calibration, like in the 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 σ_{Ft}^2. Hence, the off-diagonal terms are just the shadow of the primitive shocks, which are the diagonal terms captured by σ_{Ft}^2.

Regarding (ii), in terms of time-series evolution, in our analysis the prime mover is the change in σ_{Ft}^2, which comes from sectoral-level shares. However, in the model, and again through intermediate input linkages, the off-diagonal terms N_t will reflect those changes. The fact that the magnitude of the off-diagonal terms changes simply reflects the fact that the primitive shocks captured by σ_{Ft}^2 change.[34]

Finally, with respect to (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 allow us to reach those conclusions: a parametrized version of the general model given in Lemma 1, which is detailed in the online appendix. In particular, sector i has a production function $Q_i = \kappa A_i \left(L_i^\alpha K_i^{1-\alpha}\right)^b X_i^{1-b}$, where X_i is the quantity of intermediary inputs it uses. The intermediary inputs are shares 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:

$$\widehat{Y} = \frac{1+\varphi}{\alpha} \sum \frac{S_i}{Y} \widehat{A}_i = \frac{1+\varphi}{\alpha} \widehat{\Lambda}. \tag{16}$$

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

$$\widehat{S}_i = \widehat{Y}_i = \beta \widehat{A}_i + \overline{\Phi} \widehat{Y}, \qquad \widehat{L}_i = \beta' \widehat{A}_i + \overline{\Phi}' \widehat{Y} \tag{17}$$

for some coefficients β, β' and $\overline{\Phi}, \overline{\Phi}'$ which are simply functions of the structural parameters of the model. The economy behaves like in a one-factor model with an "aggregate shock," the GDP factor $\widehat{Y}$. However, this common factor is nothing but the sum of many idiosyncratic shocks (equation 16). It causes all microeconomic-level quantities to comove.[35] 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

[34] However, in our model, the fall in fundamental volatility will make all sectors' volatilities fall, and will indeed make a simulated shock $\widehat{Y}_t^* = \sum_{i=1}^N (Y_i/Y)^* \cdot \widehat{Y}_{it}$ fall in variance, keeping constant output shares $(Y_i/Y)^*$ but using the observed shocks $\widehat{Y}_{it}$. (A more analytical note on this point is available upon request.)

[35] We note that this model could explain the interesting findings of Foerster, Sarte, and Watson (2011), who find that the common component is explained well by a simple average of sectoral growth. In this model (with many sectors), the simple average would be $\overline{\Phi}\widehat{Y}$, 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.

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' outputs. 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 features the advantage of being easy to measure.

Our findings 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) affect the structure of the economy, so it is not clear a priori that the microeconomic composition of the economy would have such a high 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?

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.

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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.[36] The data are annual and cover 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). 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.[37]

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 results). We also exclude from the analysis the imputed service flow from owner-occupied housing.[38] 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 data set until 2008.[39]

[36] The data set is available at: http://dvn.iq.harvard.edu/dvn/dv/jorgenson

[37] 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.

[38] Finally, we drop two sectors for which there are no data in the original data set, "Uranium Ore" and "Renting of Machinery."

[39] 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 data set until 2008.

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 are defined 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 data set and the NAICS system (used by the BLS) to recover gross output and value added for each sector in the Jorgenson data set between 2006 and 2008.[40]

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, O'Mahony and Timmer 2009). As the name indicates, this database is again organized according to the KLEM methodology proposed by Jorgenson and Associates. To preserve comparability, we focus on private-sector accounts by excluding publicly provided goods and 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) until 2009:Q4 using data from the OECD Economic Outlook.

[40] Note, however, that from the BLS data we cannot compute sectoral TFP growth (the BLS Inter-industry data set is nominal). Hence, our measures of the standard deviation of sectoral TFP growth, σ_i, are based solely on the original Jorgenson data set.

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

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

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

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

$$\therefore \frac{K_i}{L_i} = \frac{1-\alpha}{\alpha} \frac{w}{r} = \frac{\sum K_j}{\sum L_j} = \frac{K}{L}$$

$$\therefore \frac{K_i}{K} = \frac{L_i}{L} = \left(\frac{K_i}{K} \right)^{1-\alpha} \left(\frac{L_i}{L} \right)^{\alpha} = \frac{I_i}{K^{1-\alpha} L^{\alpha}}$$

$$\therefore 1 = \sum_i \frac{K_i}{K} = \sum_i \frac{I_i}{K^{\alpha} L^{\alpha}} = \frac{I}{K^{1-\alpha} L^{\alpha}},$$

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

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

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

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