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Why Is Productivity Slowing Down?[†]

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We examine the contribution of different explanations to the slowdown of labor productivity. Comparing the post-2005 period with the preceding decade for five advanced economies, we seek to explain a slowdown of 0.8 to 1.8 pp. No single explanation accounts for the slowdown, but we have identified a combination of factors that, taken together, account for much of what has been observed. In the countries we have studied, these are mismeasurement, a decline in the contribution of capital per worker, lower spillovers from the growth of intangible capital, the slowdown in trade, and a lower growth of allocative efficiency. Sectoral reallocation and a lower contribution of human capital may also have played a role in some countries. In addition to our quantitative assessment of explanations for the slowdown, we qualitatively assess other explanations, including whether productivity growth may be declining due to innovation slowing down. (*JEL* E23, E24, J24, L16, O33, O47)

1. *Introduction*

Labor productivity growth is widely seen as the main long-run determinant of per capita output growth and improving living standards.[1]

The decline in measured labor productivity growth over recent decades is a matter of considerable concern and debate among academics, as it is in business and government. Three decades after Robert Solow's famous quip that "you can see the computer age everywhere but in the productivity statistics"

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[1] By definition, the growth in output per capita is equal to the growth in output per *worker* plus the growth of the ratio of number of workers over the total population. In this paper, we focus on the first term, labor productivity, but changes to labor participation and employment rates have been (and will continue to be) important, particularly due to aging (see e.g., Ramey 2020 and Vollrath 2019). We also mostly exclude from our discussion the debate over which measure of output is the best metric for welfare evaluation.

TABLE 1
Labor Productivity (LP) Slowdown and Per Capita GDP Gap

	LP growth				
	1996–2005	2006–17	Slowdown	GDP per capita 2017	"Missing" GDP per capita
France	1.65	0.66	0.99	€30,512	€3,836
Germany	1.85	0.91	0.94	€35,217	€4,203
Japan	1.68	0.85	0.82	¥4,155,243	¥356,944
United Kingdom	2.21	0.45	1.75	£27,487	£6,443
United States	2.62	1	1.61	$59,015	$12,610

Sources: Growth of labor productivity is per hour worked and GDP per capita is in 2017 national currency units using data from EU KLEMS 2019 (Stehrer et al. 2019) and the Conference Board. The periods for Japan (1995–2015) and the United States (1998–2017) are slightly different due to data coverage. See appendix A.1 for details.

(Solow 1987), this slowdown remains a puzzle, not least for those who believe that technological change is accelerating.

The slowdown is indisputable. Table 1 demonstrates that labor productivity growth rates have at least halved since the 1996–2005 period, making GDP per capita in 2017 several thousand dollars lower than it would have been based on the previous trend (Syverson 2017). Why is productivity slowing down?

Broader Historical Context.—By definition, a slowdown is by comparison to a previous period of faster growth, so a starting hypothesis is simply that previous rates of growth were exceptional and could have been the result of an adjustment of productivity *levels*, rather than a permanent increase in growth rates. Thus, the current slowdown should be considered within the broader historical context. On long run historical time scales, fast productivity growth is a relatively recent phenomenon. Within the twentieth century, Bergeaud, Cette, and Lecat (2016) identify two major accelerations and subsequent slowdowns: the large postwar boom and a smaller acceleration around 2000, generally associated with gains from information and communication technologies (ICTs).

The second acceleration is typically invoked as explanation of the US slowdown: since growth was already sluggish in the 1980s, the fairly high rates of the late 1990s/early 2000s constituted a "productivity revival" (see figure 1), and therefore, the low rates after around 2005 constituted, in comparison to the revival, a slowdown. In Europe and Japan, in contrast, labor productivity growth was relatively high in the '80s, so the slowdown appears more secular, but could in principle just reflect the end of convergence to the frontier (United States).

While there is some truth in the fact that the current low productivity growth rates simply reflect a more "normal" growth rate for a set of economies that are now all "frontier," the current slowdown goes beyond this. In appendix A.2 we show two things. First, there was no convergence in the 1996–2005 decade, so slower convergence cannot explain the slower rates in Europe after 2005 compared to 1996–2005. Second, while it is true that the frontier may be returning to more "normal" rates of growth after the 1996–2005 ICT boom, the rates of labor productivity growth in all countries are still, broadly speaking, lower than at any time in the twentieth century and are low in all of the five countries we study at the

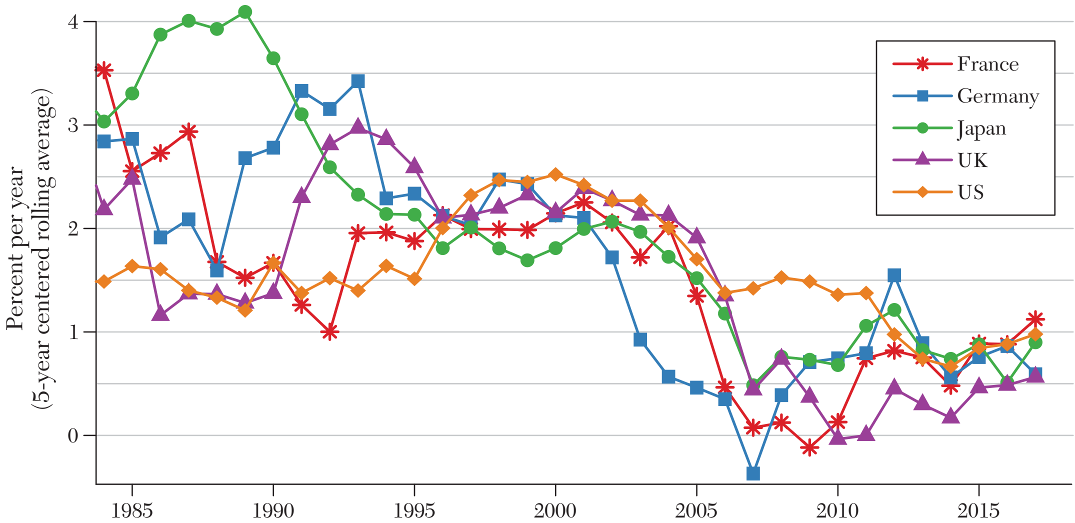

Figure 1. Recent Trends in Labor Productivity

Source: Data from the Long-Term Productivity Database (Bergeaud, Cette, and Lecat 2016, 2021).

same time. Thus, while we see part of the slowdown as simply reflecting the fact that all five advanced economies are now more or less frontier economies progressing at a "normal" rate, the rates observed are very low by historical standards and appear surprising in a context of technological transformations. That said, throughout the paper, we examine the role of both secular trends, such as aging and structural change, and cyclical or market phenomena, such as declines in investment.

Major Theories: Past and Present.—Our investigation builds on work that sought to explain previous slowdowns. Early research emphasized the importance of the relative share of different industries, with, for example, Nordhaus (1972) attributing the 1965–71 slowdown to a changing industry mix toward industries with a lower productivity level. Baily and Gordon (1989) argued that there is a one-off effect of technology, where productivity growth is interpreted as an adjustment toward a higher level, while accounting for implementation lags. Bruno (1982) largely attributed the 1973–79 slowdown to the productivity-reducing adaptation of capital to rising energy costs. Notions of input utilization and mismeasurement were prominent; for example, it was suggested that energy-intensive capital was being utilized less intensively and scrapped faster, leading to a decline in the capital services obtained from a given level of capital stocks (Baily, Gordon, and Solow 1981). Sichel (1997) and Baily, Gordon, and Solow (1981) examined the effect of mismeasurement and found that it explained less than a third of the aggregate slowdown. Mismeasurement and lags in technological adoption also featured prominently in explanations of the productivity paradox of the 1990s, together with an emphasis on complementary investment and adjustment costs (David 1990; Brynjolfsson 1993; Brynjolfsson and Hitt 2000).

Many of these theories remain relevant to an understanding of the recent productivity slowdown,[2] including: mismeasurement (Byrne, Fernald, and Reinsdorf 2016; Syverson 2017), structural change (Baily and Montalbano 2016, Gordon and Sayed 2019), properties of the capital stock (Goodridge, Haskel, and Wallis 2018), the recognition that many productivity-enhancing factors are one-off effects (Gordon 2016, Gordon and Sayed 2019), and lags in translating new technologies into productivity (Brynjolfsson, Rock, and Syverson 2021). But there are also new theories, and a deeper analysis of previously explored topics that we review. First, there is a large and rapidly growing literature on firm-level dynamics, including entry-exit, concentration, markups, profits, productivity dispersion, and misallocation, which has been made possible by the availability of firm-level data (see Bartelsman and Doms 2000 and Syverson 2011 for reviews). Second, intangible assets have become the focus of growing attention, and have been seen to contribute to mismeasurement, lower investment, and lower competition, but also to higher economies of scale and firm-level productivity. Third, there is a growing recognition of the role of trade and globalization, which we show may explain a sizable part of the productivity slowdown. Finally, mismeasurement is being seen in new ways, providing for a lively source of debate—new goods and services from the ICT revolution trigger the need for new metrics of welfare (Brynjolfsson et al. 2020), new methods for deflating GDP (Byrne and Corrado 2020), and a careful consideration of the production and asset boundaries of GDP (Coyle 2019; Corrado, Hulten, and Sichel 2009). These explanations have been widely reported in reviews (Askenazy et al. 2016; Cusolito and Maloney 2018; Erber, Fritsche, and Harms 2017; Crafts 2018; Bauer et al. 2020; Modery et al. 2021). Here, we provide a more systematic synthesis, attempting to evaluate quantitatively each explanation.

What Makes a Good Explanation?—In considering what constitutes an effective explanation we have sought to satisfy three criteria. First, a good explanation must be quantitatively significant (the *scale* criterion). Roughly speaking (see table 1), we are looking for a missing 1 percentage point of labor productivity growth per year. For this reason, as an example, while price indices for high-tech investment goods probably overestimate inflation, the bias is small, and these sectors themselves are not large enough in size to explain a significant part of the slowdown.

Second, a good explanation needs to show consistency in the sequencing of cause and effect (the *sequencing* criterion). At least for the United States, there is a broad consensus that productivity started slowing down around 2004–05 (Fernald 2014; Cette, Fernald, and Mojon 2016; Fernald and Inklaar 2020). To explain this, a causal factor needs to exhibit a change around or before that period. Therefore, for instance, because the global financial crisis of 2007–08 occurred after the slowdown, it can be dismissed as the only cause, even though, as we show below, it may have accentuated and deepened the slowdown. Explanations that depend on slow secular developments, such as aging, or a slowdown or acceleration

[2] Our review is limited to the recent slowdown, and to labor productivity, rather than total output. Vollrath (2019) provides a comprehensive study of the *secular* slowdown in output per *person*. He concludes that the slowdown is the result of positive changes, such as increasing life expectancy. For Vollrath (2019) this is neither surprising nor worrying, as aging implies that a lower share of the population is working, and rising overall wealth leads to higher consumption of services.

of technological change on the basis of this criteria also are unlikely to provide a complete explanation on their own, unless it can be shown that something significant changed in these trends prior to the slowdown. The sequencing criterion is not as sharply defined for Europe, where there was no obvious productivity revival around the turn of the century. While we consistently use 2005–06 as the break date throughout the paper, the end date for our second period varies depending on the availability of data for each explanation we investigate.

Third, a good explanation needs to have wide geographical scope and applicability (the *scope* criteria). The productivity slowdown is to a large extent a worldwide phenomenon, with almost all Organisation for Economic Co-operation and Development (OECD) countries and many emerging economies exhibiting lower productivity growth over a similar period (Askenazy et al. 2016; Cusolito and Maloney 2018; Erber, Fritsche, and Harms 2017). It is implausible, although possible, that all these countries experienced the slowdown at roughly the same time but for different reasons; the synchronised collapse in productivity therefore leads us to identify factors that go beyond local conditions. So, for example, changes to labor market institutions unique to a specific country are unlikely to explain either the sustained national or global scope of the productivity slowdown (Askenazy et al. 2016).

Key Results and Structure of the Paper.— This paper synthesizes a large literature that attempts to explain the slowdown. Before delving into explanations, in section 2 we clarify the nature of the problem by using standard growth accounting for five large developed countries: France, Germany, Japan, the United Kingdom, and the United States, with data from EU KLEMS 2019 (Stehrer et al. 2019). Comparing the period 2006–17 against 1996–2005, we confirm the well-established result that most of the slowdown is driven by total factor productivity (TFP) and capital deepening, with a smaller contribution from labor composition and non-negligible variation across countries. The slowdown is pervasive across industries, with changing sectoral shares explaining very little of the slowdown (except in Germany). Manufacturing is the only industry that is a substantial contributor in all countries.

Section 3 evaluates whether increasing measurement biases have caused a decline in measured productivity growth. This appears compelling as an explanation of the productivity “paradox,” since it reconciles the slowdown with perceived rapid technological change. We discuss biases in deflators, and issues with GDP asset and production boundaries. Nevertheless, as has been widely acknowledged, mismeasurement alone cannot explain the whole productivity slowdown—we estimate, for the United States, that it explains 0.21 pp out of the 1.61 pp slowdown in labor productivity growth.

We next consider the dynamics of the inputs of productivity growth, starting in section 4 with the growth of capital per worker (“capital deepening”). We find that a decline in the rate of capital deepening has contributed to the slowdown, mostly driven by non-ICT physical capital, but also ICT capital and intangibles. We distinguish two core arguments to explain this phenomenon. The first relates to the financial crisis, and suggests that the decline in investment is a cyclical phenomenon driven by financial constraints and weak aggregate demand. A second candidate explanation recognizes that the slowdown started before the crisis, so that structural factors may have been more important, including primarily a change in the composition of capital toward intangibles (which are riskier), but also lower competition, increasing short termism, and the off-shoring of physical investment in the context of increasingly global value chains.

We are unable to derive relative contributions for all of these factors, but as a whole we estimate that capital deepening explains 44 percent of the labor productivity slowdown in the United States. In addition to this, we report evidence of the slowdown in intangible capital services, which contributes to lower TFP growth.

Section 5 focuses on labor markets and the composition of the labor force, where we consider education, skills, migration, aging, and labor market institutions. We find that labor composition makes only a small contribution in growth-accounting exercises, but recent or secular changes may also contribute to the TFP slowdown, although unfortunately this is difficult to evaluate.

Section 6 investigates the role of trade and globalization. Growing international trade and better organization of international production into global value chains led to productivity gains in the past. Due to the recent slowdown in trade, it is possible that the productivity slowdown reflects the end of an adjustment due to the gains from greater trade having been reaped. Using published estimates of the impact of global value chain integration on labor productivity growth (Constantinescu, Mattoo, and Ruta 2019), we estimate that the slowdown in trade may have contributed 0.13 percentage points to the productivity slowdown, with fairly large uncertainties and not consistently across countries. We also briefly discuss regional dispersion, although there is a lack of research addressing specifically the post-2005 slowdown.

Section 7 attempts to take stock of the vast literature on business dynamism, competition, and misallocation. The evidence indicates that entry and exit rates have declined, and that pure profits and concentration have gone up. There is some debate on the magnitude and international scope of these findings, and considerable disagreement on the consequences for productivity. For some, superstar firms can charge high markups and capture higher market shares because they have low marginal costs and are highly productive; this may be good for aggregate productivity. For others, these profits are rents driven by barriers to entry, leading to lower investment and lower productivity. To provide an estimate, we use the data and results from Baqaee and Farhi (2020), who decompose TFP into an allocative efficiency and a technology component, where allocative efficiency is driven by the magnitude and heterogeneity of markups. They find that allocative efficiency contributed around half of TFP growth between 1997 and 2014; we compute that it also contributed to roughly half of its slowdown between 1997–2005 and 2006–14.

Section 8 examines explanations related to technology. We find that research efforts do not appear to have slowed dramatically, but there does appear to be a decline in how well research translates into productivity. As Gordon (2016) has pointed out, the technologies of the past 150 years have had such a profound impact that it is not surprising if current technologies are not able to produce the same impressive effects. However, for others, such as Brynjolfsson, Rock, and Syverson (2019), current technologies do have a revolutionary potential, even though this may not yet be fully realized. We present this debate and critically assess the arguments, identifying that it is plausible that there has been an acceleration of innovation and that this is consistent with a slowing of productivity growth as large parts of the economy and institutions lag behind. It also is the case that in previous periods, there have been considerable lags between technological change and higher productivity.

Finally, in section 9 we summarize the key findings and conclude by showing that while no single factor accounts for the slowdown entirely, a small number of explanations taken together appear to account for the scale, sequencing, and geographical scope of the slowdown.

2. *Accounting for the Slowdown*

In this section, we provide two standard decompositions of labor productivity growth, using the 2019 vintage of KLEMS (Stehrer et al. 2019). The first, "sources of growth" decomposition, provides an organizing framework for the rest of the paper. It separates labor productivity growth into an increase in inputs (labor composition and capital per worker) and a residual, corresponding to a pure increase in efficiency in the use of inputs, TFP. We find considerable heterogeneity between countries, and that the slowdown in TFP broadly represents the largest contributor to the labor productivity slowdown, with a smaller role played by the slowdown of capital deepening.

The second decomposition we present is a "within-between" decomposition of labor productivity growth by industry. This allows us to show to which extent the slowdown is pervasive, or whether it is confined to specific industries or is due to a reallocation toward low productivity or low productivity growth industries. As with the sources-of-growth decomposition, there is some heterogeneity across countries, but patterns are discernible. The slowdown is broadly pervasive, but a large part of the overall slowdown can be traced back to key industries, in particular manufacturing. Structural change appears to play a limited role, which may reflect the relatively short time periods considered.

2.1 *Contributions of Inputs Growth and TFP*

Growth Accounting.—The premise of growth accounting is that aggregate output grows either because more inputs are used, or because they are used more efficiently. Solow (1957) introduced a straightforward method to produce this decomposition: the contribution of each input is computed as its growth rate times its share in income. The contribution of efficiency is then the part of output growth than is left after the contribution of all inputs has been accounted for. This decomposition is rooted in clear economic assumptions: a stable and smooth functional relationship between inputs and outputs at the economy-wide aggregation level, inputs paid at their marginal product, constant returns to scale, and Hicks-neutral technical change. Solow (1957) originally found that most of postwar US growth was not due to the growth of inputs, but to inputs being used more efficiently. This was dubbed the "Solow residual" and came to be described as "a measure of our ignorance" (Abramovitz 1956), prompting a significant strand of research into improving measurement of inputs to reduce this unexplained growth of output. In particular, Jorgenson and Griliches (1967) showed the importance of improvements in human capital. Much research today still concerns better measurements of inputs, such as intangible capital.

While major efforts of data collection and harmonization have taken place, modern growth accounting still often starts from a relatively simple decomposition, which we report here. Throughout the paper, we denote real output by Y, the number of workers by L (in practice, KLEMS and OECD STAN use hours worked), the capital stock by K, and we define labor productivity $y = Y/L$ and capital per worker $k = K/L$. The growth rate in real output per unit of labor, $\Delta \log y_t$, can be decomposed as

$$(1) \quad \Delta \log y_t = \Delta \log A_t + (1-\alpha_t)\Delta \log k_t + \alpha_t \Delta \log h_t,$$

where A_t denotes TFP, h_t is an index of the composition of the labor force, and Δ is the first difference operator, that is, $\Delta x_t \equiv x_t - x_{t-1}$. The labor compensation share of income,

TABLE 2
Sources of Growth Decomposition for the Slowdown in Labor Productivity Growth Pre- and Post-2005

	$\Delta \log y_t$	$\Delta \log A_t$	$(1-\alpha_t)\Delta \log k_t$	$\alpha_t \Delta \log h_t$
France				
1996–2005	1.65	1.18	0.16	0.30
2006–17	0.66	0.17	0.09	0.40
Slowdown	0.99	1.01	0.07	−0.09
Share	1.00	1.02	0.07	−0.10
Germany				
1996–2005	1.85	1.10	0.61	0.15
2006–17	0.91	0.87	0.07	−0.03
Slowdown	0.94	0.23	0.54	0.17
Share	1.00	0.24	0.57	0.18
Japan				
1995–2005	1.68	0.29	1.07	0.33
2006–15	0.85	0.31	0.26	0.28
Slowdown	0.82	−0.02	0.80	0.04
Share	1.00	−0.03	0.98	0.05
United Kingdom				
1996–2005	2.21	1.14	0.70	0.37
2006–17	0.45	0.30	0.18	−0.02
Slowdown	1.75	0.84	0.53	0.39
Share	1.00	0.48	0.30	0.22
United States				
1998–2005	2.62	1.37	1.09	0.16
2006–17	1.00	0.46	0.38	0.17
Slowdown	1.61	0.91	0.71	−0.01
Share	1.00	0.57	0.44	−0.00

Source: Data from EU KLEMS 2019.

α_t, is computed as a Törnqvist index $\alpha_t \equiv (w_t L_t/Q_t + w_{t-1}L_{t-1}/Q_{t-1})/2$, where $Q_t = P_t Y_t$ is nominal output, and w_t is the wage rate per unit of labor.

This decomposition makes it possible to trace the sources of growth, and thus the sources of the slowdown—efficiency (TFP), physical capital, or human capital.

Results.—Table 2 reports the decomposition from equation (1). TFP and capital deepening are the largest contributors. Labor composition appears to contribute only modestly, and only in Germany and the United Kingdom.[3] Labor composition is

[3] For Germany, Elstner, Feld, and Schmidt (2018) point to labor market reforms of the early 2000s, which increased the employment of low-skill workers. However, our results for the United Kingdom differ from other studies that rely on data from the Office for National Statistics (ONS), the UK's statistical agency (Goodridge, Haskel, and Wallis 2018; Riley, Rincon-Aznar, and Samek 2018). KLEMS notes that its labor composition index also differs from previous vintages in the case of the United Kingdom,

an index of labor services computed assuming that workers in specific gender, age, and educational attainment groups are paid their marginal productivity. Because its changes are driven in large part by changes in the relative size of each group, it is unlikely to change very quickly. It is therefore not surprising that it contributes only marginally to the productivity slowdown, compared to capital deepening and TFP.

While the relative contributions of TFP and capital deepening are balanced in the United States, we cannot simply assume that this is the case everywhere. In particular, capital deepening is almost the only source of decline in Japan,[4] and TFP is almost the only source of decline in France. However, in appendix C.3, we repeat the exercise using the OECD's STructural ANalysis (STAN) data, and find that capital deepening contributed more than 20 percent in France, and TFP almost 30 percent in Japan (STAN does not include labor composition). Throughout the paper, we will discuss TFP and capital deepening as the main causes of the slowdown.

These results are largely in agreement with previous studies, which use different datasets and slightly different periods. In appendix C.1, table 14 reports the qualitative conclusions from papers relying on growth accounting to explain the productivity slowdown.

pointing to discrepancies in labor survey data managed by the ONS and Eurostat (Stehrer et al. 2019).

[4]Japan's TFP growth from KLEMS data shows an improvement post-2005. The literature in this area, covered in Jorgenson, Nomura, and Samuels (2018) and revisited by Baily, Bosworth, and Doshi (2020), emphasizes Japan's recovery from its lost decade of growth in the 1990s, followed by TFP levels catching up to the United States in the late 2000s.

2.2 *Industry-Specific Contributions and Structural Change*

A hypothesis for the productivity slowdown is Baumol's disease. Baumol (1967) theorized that service industries have a lower intrinsic capacity to increase their labor productivity, perhaps because they require in-person services, in contrast to manufacturing. Because similar wage growth would apply to all industries, and because the demand for services such as health and entertainment tends not to decline despite increasing relative cost, these low productivity growth industries represent an increasing aggregate share of spending, leading to declining aggregate productivity growth.

To examine this hypothesis we ask: do all industries suffer from a productivity slowdown, or is it worse in some industries than in others? Is the slowdown of the aggregate an artifact of the changing relative sizes of industries, with industries with low levels or productivity growth becoming larger?

Our preferred method in measuring structural change is from Tang and Wang (2004) (see also Nordhaus 2002 and Riley, Rincon-Aznar, and Samek 2018). It decomposes aggregate labor productivity growth into a "within" and a "between"contribution from N industries as

(2)

$$\frac{\Delta y_t}{y_{t-1}} = \underbrace{\sum_{i=1}^{N}\left[\frac{Q_{i,t-1}}{Q_{t-1}} \times \frac{\Delta y_{i,t}}{y_{i,t-1}}\right]}_{\text{Within}}$$

$$+\underbrace{\sum_{i=1}^{N}\left[\Delta\left(\frac{P_{i,t}L_{i,t}}{P_tL_t}\right) \times \frac{y_{i,t-1}}{y_{t-1}} \times \left(1+\frac{\Delta y_{i,t}}{y_{i,t-1}}\right)\right]}_{\text{Between}}.$$

The "within" term keeps the relative shares of the sector constant; it is simply the weighted average of industry-level growth rates, with the weights given by the sectors' nominal shares of total output $Q_{i,t}/Q_t$. The between term, however, contains a factor that reflects structural change, notably the changes in the relative shares of industries, where industry size is in terms of the share of labor resources $L_{i,t}/L_t$ and relative price $P_{i,t}/P_t$. The changes in shares are multiplied by both industry *growth rates* and industry relative productivity levels. As noted by Nordhaus (2002) and Tang and Wang (2004), aggregate productivity can still go up even if the growth rates of each industry are zero (i.e., the last factor is equal to 1), because resources are reallocated toward sectors with a high productivity *level*.

Equation (2) measures growth in percentages, rather than log points as in equation (1), so there will be slight differences in the calculated growth rates and slowdowns in tables 2 and 3.

Results.—Table 3 shows the results. We report only key industries, chosen because they are often mentioned in the literature and/or were found to be important in our results. The main takeaway is the strong contribution to the slowdown of manufacturing in all countries. Other substantial contributors are more country-specific: ICT service industries in France and the United Kingdom, wholesale and retail trade in Germany, Japan, and the United States. Financial and insurance activities also played a role in the United Kingdom and United States. The reallocation term is large in Germany, and significant in France, but not elsewhere. Together, these components explain much of the slowdown in each country. The large contribution of "other industries" in the United Kingdom is driven by real estate (which is notoriously difficult to measure and dropped in most other studies) and the oil and gas industry (Goodridge, Haskel, and Wallis 2018).

Table 3 is broadly in line with previous work, although methodological and aggregation differences make a systematic comparison more difficult than for the decomposition by factors of production.

The US experience is defined by strong TFP growth pre-2005 in ICT *using* industries, highlighting a point often emphasized by Gordon (2016): productivity growth can be thought of as an adjustment of the levels, with an innovation leading to a new normal level of productivity. Baily and Montalbano (2016); Cette, Fernald, and Mojon (2016); Murray (2018); and Baily, Bosworth, and Doshi (2020), among others, thus demonstrate that the industries responsible for most of the slowdown in TFP post-2004/05 are those that experienced an acceleration pre-2004/05, namely manufacturing, wholesale and retail trade services, and, to some degree, agriculture. Some studies, such as Cette, Fernald, and Mojon (2016); Inklaar et al. (2019); and Baily, Bosworth, and Doshi (2020) highlight a strong TFP slowdown in ICT *producing* industries.

Cette, Fernald, and Mojon (2016); van Ark (2016a); and Gordon and Sayed (2019) directly contrast the European experience with that of the United States; ICT-using industries did not experience much growth before 2005, and the slowdown in manufacturing is not due to ICT producers specifically. Inklaar et al. (2019) specifically searched for the best industry taxonomy for the productivity slowdown but, except for a pattern of slowdown in offshoring industries, their findings are largely inconclusive for Europe. In addition to manufacturing, studies of the United Kingdom place greater emphasis on financial industries, and also some combination of information and communication services (Riley, Rincon-Aznar, and Samek 2018; Tenreyro 2018), wholesale and retail trade (Goodridge, Haskel, and Wallis 2018), oil and gas (Goodridge, Haskel, and Wallis 2018; Riley, Rincon-Aznar, and Samek 2018) and professional, scientific, and technical services (Tenreyro 2018). In all, the

TABLE 3
Industry Decomposition for the Slowdown in Labor Productivity Growth Pre- and Post-2005

	Total	Manufacturing	Wholesale, retail, and repair	Financial and insurance activities	Information and communication	Other	Reallocation
France							
1996–2005	1.67	0.65	0.17	0.09	0.23	0.52	0.02
2006–17	0.67	0.28	0.12	0.03	0.11	0.23	−0.10
Slowdown	1.00	0.37	0.05	0.05	0.11	0.29	0.12
Share	1.00	0.37	0.05	0.05	0.11	0.29	0.12
Germany							
1996–2005	1.87	0.69	0.31	−0.08	0.17	0.45	0.33
2006–17	0.93	0.46	0.17	0.06	0.18	0.15	−0.08
Slowdown	0.95	0.23	0.15	−0.14	−0.01	0.31	0.41
Share	1.00	0.25	0.16	−0.14	−0.01	0.32	0.43
Japan							
1996–2005	1.74	0.86	0.33	0.15	0.16	0.00	0.24
2006–15	0.87	0.48	0.07	0.05	0.07	−0.05	0.24
Slowdown	0.87	0.37	0.26	0.09	0.09	0.05	0.01
Share	1.00	0.43	0.30	0.11	0.10	0.06	0.01
United Kingdom							
1996–2005	2.24	0.51	0.16	0.37	0.32	0.64	0.25
2006–16	0.42	0.12	0.20	0.01	0.07	−0.28	0.29
Slowdown	1.82	0.38	−0.04	0.35	0.25	0.92	−0.05
Share	1.00	0.21	−0.02	0.19	0.14	0.51	−0.02
United States							
1998–2005	2.54	0.96	0.55	0.29	0.50	0.40	−0.16
2006–17	0.92	0.20	0.11	0.04	0.45	0.31	−0.19
Slowdown	1.61	0.76	0.43	0.26	0.05	0.09	0.02
Share	1.00	0.47	0.27	0.16	0.03	0.06	0.01

Source: Data from EU KLEMS 2019.

slowdown for Europe is more widespread across industries.

In line with our results, the reallocation between industries in France, Japan, the United Kingdom, and the United States is rarely seen as an important factor (Byrne, Fernald, and Reinsdorf 2016; Murray 2018; Tenreyro 2018; Cantner et al. 2018; Nishi 2019), and actually improved labor productivity in the United Kingdom (Goodridge, Haskel, and Wallis 2018; Riley, Rincon-Aznar, and Samek 2018). However, the strong effect of reallocation that we find for Germany appears to be missing from the literature, and warrants further research. In line with our results, the literature offers little evidence that Baumol's cost disease is strong enough to explain the productivity slowdown over the fairly short time scales we are considering, although Nishi (2019) and Duernecker, Herrendorf, and Valentinyi

(2023) highlight long-term, secular patterns in Japan and the United States.

In summary, reallocation fails to explain the pervasive productivity slowdown, which is therefore due to a decline in at least some industries. Indeed, some industries are more affected than others, with manufacturing being a strong contributor to the slowdown due to both its decline in productivity and its relatively large size. High contributions from other industries appear more country-specific, although the evidence suggests that the current slowdown may reflect a pause in the adjustment of productivity toward higher levels initiated by the ICT revolution.

2.3 *Organization of the Rest of the Paper*

From our analysis so far, the labor productivity slowdown appears to be mostly driven by a slowdown of TFP and capital deepening, with this slowdown across all industries, although with interesting industry-specific and country-specific differences.

As a guide to the organization of the rest of our enquiry, we present a basic extension of the growth-accounting equation. Assuming that true and observed output differ, and assuming that TFP is the sum of a "pure technology" and an "allocative efficiency" effect, we can write a (conceptual) extension of equation (1) (see appendix B),

$$(3)\quad \Delta \log y_t = \underbrace{-\mathcal{B}}_{\substack{\text{Mismeasurement}\\ \text{(section 3)}}} + \underbrace{(1-\alpha_t)\Delta \log k_t}_{\substack{\text{Capital Deepening}\\ \text{(section 4)}}} + \underbrace{\alpha_t \Delta \log h_t}_{\substack{\text{Human Capital}\\ \text{(section 5)}}} + \underbrace{\Delta \log A_t^{\text{Alloc}}}_{\substack{\text{Trade and Allocative Efficiency}\\ \text{(sections 6 \& 7)}}} + \underbrace{\Delta \log A_t^{\text{Tech}}}_{\substack{\text{Technology}\\ \text{(section 8)}}}.$$

While equation (3) provides a conceptual structure that helps us organize the various explanations that have been put forward in the literature, in practice every section will touch upon evidence and mechanisms that cut across several terms. For instance, the mismeasurement of intangibles affects both the right-hand side and the left-hand side, technology affects TFP as well as investment, and aging affects resource allocation as well as labor composition.

3. *Mismeasurement*

In this section, we clarify the main sources of mismeasurement and provide an estimate of the contribution of mismeasurement to the productivity slowdown, mainly focusing on the United States.

Mismeasurement of labor productivity can be due to three main sources: a mismeasurement of nominal output (perhaps due to changing boundaries of GDP), a mismeasurement of deflators, which has received the most attention in the literature, and a mismeasurement of labor inputs. To see this, consider the definition of labor productivity as real output per hour, where real output Y is nominal output $\bar{Y}$ divided by a price index P. In growth rates, we have

$$(4)\quad \Delta \log y = \underbrace{\Delta \log \bar{Y}}_{\text{Boundary issues}} - \underbrace{\Delta \log P}_{\text{Issues with deflators}} - \underbrace{\Delta \log L}_{\substack{\text{Mismeasured}\\ \text{labor inputs}}}.$$

The first potential source of mismeasurement is nominal GDP. While we will briefly discuss the emerging literature on measuring welfare in the digital era, our objective is not to enter into a discussion about the limitations of GDP, but to discuss the extent of mismeasurement within its scope. This leads us to discuss profit shifting, the informal sector, and intangible investment.

The second is a bias in the measurement of deflators. If quality-adjusted price growth is overestimated, typically because the rise in quality is underestimated, output growth and therefore labor productivity growth will be underestimated. We collect estimates for biases for health care and ICT goods and services, which have received most attention, and for two other biases (the imputation bias and the foreign sourcing bias).

Equation (4) shows a third source of potential mismeasurement: labor inputs. Generally, labor inputs are expressed in number of workers or number of hours. We are not aware of studies that look into a potential increased bias for these quantities, so we assume that it is unlikely to be relevant and do not discuss it further.

When providing estimates of biases in published data, it is not always evident, for each identified bias, whether statistical offices have already implemented new methods to deal with it and whether the data that they make available already contains consistent revisions for all previous periods. Moreover, the data we use (e.g., KLEMS) uses specific vintages of data made available by statistical offices, so we would need to know which revision applies to the specific vintages used by KLEMS or STAN. In addition, while we focus on the United States, different statistical offices may have slightly different practices, which further complicates any evaluation. Our solution has been to focus our attention on recent papers and assume that the biases they discuss apply to the data we are using.

3.1 *Deflators*

A large literature describes potential biases in deflators. The main sources of bias include: issues with sampling and measuring prices and relative weights of items in consumption (or other final demand) baskets; issues with aggregating low-level price changes into indices, in view of the difficulty of assessing whether the shares of each item in the baskets are changing because of substitution induced by changes to relative prices; issues with the addition of new products and removal of disappearing products; issues with assessing quality change; and more broadly, issues with new forms of commercialization (i.e., new retail outlets). We refer the interested reader to the specialist literature (Boskin et al. 1997, Lebow and Rudd 2003, Moulton 2018), and focus here on estimates of the biases and their changes that are relevant to the productivity slowdown.

Computing Contributions to the Productivity Slowdown.—To compute the contribution of the mismeasurement of deflators to the productivity slowdown, we follow the literature, and in particular Groshen et al. (2017). We consider a few specific categories of goods or services that are suspected to be characterized by either growing mismeasurement or that are mismeasured and growing in size. These products can be part of investment or household consumption.

For each product, we compute the contribution to the productivity slowdown as follows. For simplicity, we consider two periods, 1995–2005 and 2006–15. As the dates vary slightly across different studies, we call the first period “around 2000,” and the second period “around 2010.” For each period we obtain an average inflation bias from the literature and an average share of GDP. Within each period the contribution of the bias in one product to GDP growth is its inflation bias times its share of GDP times (–1), since an overestimate of price growth leads to an underestimate of real GDP growth (equation (4)). We then obtain the contribution to the productivity slowdown as the difference

TABLE 4
Contribution of Biases in Deflators of Specific Products to the US Productivity Slowdown

	Around 2000			Around 2010			
	Bias	Share	Contrib.	Bias	Share	Contrib.	Slowdown
Consumption							
Prescription drugs	1.20	1.30	1.56	1.20	1.90	2.28	0.72
Nonprescription drugs	0.50	0.20	0.10	0.50	0.30	0.15	0.05
Medical services	0.76	9.80	7.45	0.76	12.20	9.27	1.82
Digital access services	12.90	0.99	12.77	19.40	1.57	30.42	17.65
Total consumption			22			42	20
Investment							
Commu. equipment	5.80	1.20	6.96	7.60	0.60	4.56	−2.40
Computers and periph.	8.00	1.00	8.00	12.00	0.50	6.00	−2.00
Other info. syst. equip.	8.30	0.70	5.81	5.40	0.70	3.78	−2.03
Software	1.40	1.80	2.52	0.90	1.70	1.53	−0.99
Total investment			23			16	−7

Notes: Bias is the pp difference between the official and corrected price growth; *share* is the share in GDP; *contrib.* (for contribution) is the product of bias and share times 100, so the units are base points. *Slowdown* is the difference between the contributions in 2010 and in 2000. Totals are rounded to bp.

between the contributions to growth for the two periods, see table 4.

In addition to identifying the biases arising for specific items within the consumption and investment deflators, we briefly argue that biases to other items are unlikely to be large, except for an imputation bias uncovered in Aghion et al. (2019), and we report a form of substitution bias arising in imports and exports deflators ("sourcing bias"). These will be reported in table 5.

Quality Change in Health Care.— Measuring quality changes in health care matters for the productivity slowdown because there is a clear secular rise in health expenses, making any bias, even fixed, more impactful over time. The rise in real spending is due to aging, obesity, new technologies, and the provision of preventive-type services (Dunn et al. 2018). Table 4 reports Groshen et al.'s (2017) update of Lebow and Rudd's (2003) estimate of the bias, based on the work of Cutler, Rosen, and Vijan (2006). Summing up the contributions of the three categories, the contribution to the slowdown is 0.026 pp of GDP growth, which is on the order of 1–2 percent of the productivity slowdown of 1.61 pp.

Would other studies lead to substantially different estimates? Possibly, yes. Dunn, Rittmueller, and Whitmire (2015), discussing the introduction of the Health Care Satellite Account, report estimates showing that prices may have increased *faster* than the Bureau of Economic Analysis's (BEA's) published numbers, with an overall *negative* effect of 0.1 pp for GDP estimates. Aizcorbe and Highfill (2020) find that biases can change sign over time, but their study stops in 2006, so it is not useful for our analysis. Overall, this suggests that the impact of these biases on the productivity slowdown is somewhat ambiguous, so it appears appropriate to

TABLE 5
Contribution of Mismeasurement to the US Productivity Slowdown (in BP, Rounded)

	Around 2000	Around 2010	Slowdown
Deflators			
Consumption	22	42	20
Investment	23	16	−7
Imputation for new products	63	70	7
Offshoring bias	−5.0	−2.5	2.5
Total deflators	103	125	22
Boundaries			
Profit shifting	5	0	−5
Intangibles	−9	−5	4
Total boundaries	−4	−5	−1
Total	99	120	21

Note: The numbers for consumption and investment are reported from table 4.

use the estimates from Groshen et al. (2017), which lead to small overall effects.

Quality Change in ICT.—Alternative deflators for ICT-related goods and services, both for personal consumption expenditures and for business investment, have been developed.

For personal consumption, while Groshen et al. (2017) report a bias for personal computer services including internet services, we prefer to use the recent estimates by Byrne and Corrado (2020), which are based on a detailed study of internet access, mobile phones, cable television, and streaming services, and are presented for different periods.[5] For investment, we reproduce the results from Groshen et al. (2017), which are based on biases to the price indices derived from Byrne, Fernald, and Reinsdorf (2016), based on the work by Byrne, Oliner and Sichel (2018) and Byrne and Corrado (2017), and are provided for two periods. Overall, table 4 suggests substantially accelerating mismeasurement in digital services to consumers and a smaller decelerating mismeasurement for ICT investment.

Other studies provide alternative numbers that question these findings. The original numbers provided in Groshen et al. (2017) for ICT in the consumption deflator are based on fixed shares and a bias derived for PC services by Greenstein and McDevitt (2011). These estimates suggest a substantially smaller contribution of this category to the slowdown. Another study (Ahmad, Ribarsky, and Reinsdorf 2017) suggested an upper bound for ICT-related mismeasurement by applying the ICT price index of the country with the largest decline to a number of OECD countries. Considering two categories of investment (ICT and software) and one category of consumption

[5] We compute the bias as the difference between Alternative and Official price indices in Byrne and Corrado's (2020) table 2. We take their 1998–2007 average for our "around 2000" period, and their 2008–18 average for our "around 2010" period. Byrne and Corrado (2020) report shares in personal consumer expenditures, which we translate to shares of GDP by using the share of personal consumer expenditures in GDP for 2000 and 2010 (≈ 2/3, taken from BEA (2022) table 1.1.5).

(communication services), they found an overall upper bound for the bias of 0.2 pp, which is close to the total biases reported in table 4.

Reinsdorf and Schreyer (2020) focus on the deflator for household consumption, and quantify upper bounds for three effects: quality change, substitution between digital and non-digital products, and increased variety. After an extensive review of the recent specialist literature (Bean 2016, Byrne and Corrado 2017, Greenstein and McDevitt 2011, Abdirahman et al. 2017, Goolsbee and Klenow 2018), they provide semi-judgmental estimates of which products are affected and by how much; overall, they find a bias of more than half a percentage point, which appears large, but recall that this is an upper bound and concerns only consumption.

Overall, inflation in ICT-related goods and services for private consumption and business investment is likely to be substantially mismeasured, contributing perhaps between 0.1 and 0.5 pp of mismeasurement of economic growth per year. However, the case for accelerated mismeasurement is more difficult to make. Our aggregate estimate is almost entirely due to accelerated mismeasurement of a sector rising in size, namely digital access services for consumers (Byrne and Corrado 2020).

Other Sectors.—Groshen et al. (2017) report a bias for all other personal consumption expenditures, which we omit here because the biases are small and stable,[6] so they do not contribute to the slowdown. In addition to consumption and investment, we should have considered government expenditures, exports, and imports consistently. Our review follows closely from Groshen et al. (2017), who note that the government component of the expenditure approach to GDP has not been the focus of the current productivity literature (Moulton 2018 takes a step in this direction by considering biases to the deflation of government expenditures that can affect nonfarm business sector output). There are undoubtedly measurement issues in the education and public sectors (Atkinson 2005), where cost-based input measurements are often used as a proxy for real output, but here again the shares in GDP are relatively stable and no studies appear to have made a case for increasing biases. Another notable missing element in table 4 is that we do not report a bias to ICT *equipment* in personal consumption expenditure price indices. Here again we have simply followed Groshen et al. (2017). The synthesis by Reinsdorf and Schreyer (2020) suggests that IT services create a larger bias than IT goods in the personal consumption expenditure price index, but it would certainly be interesting to see further research attempting a more comprehensive assessment than the one we provide here.[7]

Creative Destruction and Imputation.—Taking the 12 months ending in November 2014 as an example, around 2 percent of items sampled in the Consumer Price Index (CPI) were considered as having disappeared permanently and with no other old or new products in the sample being "similar enough" to match with them (Groshen et al. 2017).[8] In this case, the statistical office

[6] In principle, one should of course account for declining shares of all other sectors if using increasing shares of the sectors considered. However, this would not make a large difference to our results.

[7] A comprehensive study would also need to consider carefully whether IT goods are imported or domestically produced and used as intermediate or final demand (Ahmad, Ribarsky, and Reinsdorf 2017, annex 2).

[8] When products are exactly or almost exactly the same, any change in price can be attributed to inflation rather than to a change of characteristics. This is the *matched model*, a "cornerstone" of constructing price indices (Groshen et al. 2017). This is what statistical agencies use in the vast majority of cases. When characteristics are

initiates a quality adjustment process (with cost data from the manufacturer for the replacement goods, hedonics on product characteristics, judgmental adjustments, and/or other approaches) to estimate the change in the relative price of the old item that has disappeared from the sample (Groshen et al. 2017, Moulton 2018). Triplett (2006) argues that the characteristics of each product category, the data available to the statistical office, and the product sampling process can bias the adjustment either way (overstating or understating quality change), but both the matched model and hedonic models provide similar estimates as long as product markets are competitive. Using empirical data to test this effect, Aghion et al. (2019), guided by a growth model with endogenous creative destruction, find a substantial understatement of growth of around 0.5 pp, mostly due to hotels and restaurants. The missing growth from this imputation method increased from 0.48 pp in 1996–2005 to 0.65 pp in 2006–13. These results should be interpreted with caution, given the strong assumptions on which they rely (Reinsdorf and Schreyer 2020), the smaller acceleration of mismeasurement when using more disaggregated sectors (their table 9), and the change of results in terms of slowdown when using an alternative approach derived from Garcia-Macia, Hsieh, and Klenow (2019) (section IIIB in Aghion et al. 2019). Thus, we take a more conservative approach, and in table 5 we prefer to report numbers derived in one of their robustness checks rather than their headline numbers.

Sourcing Bias.—When domestic producers shift to cheaper offshore suppliers (from a domestic supplier or from a supplier in another foreign country), there is an upward bias in the import deflator akin to the outlet substitution bias of the CPI.[9] For the period 1997–2007, where this bias was potentially of significance in the United States due to the large increase in imports from China, Reinsdorf and Yuskavage (2018, p. 143) estimate an annual bias on GDP of around 0.07 pp, but note that this may be partly offset by a corresponding, although presumably smaller, bias in the export price index. To reflect this, we arbitrarily remove 0.02 pp and consider that the bias during our first period is 0.07 – 0.02 = 0.05 pp. According to Byrne, Fernald, and Reinsdorf (2016), this sourcing bias is small after 2007. To reflect the fact that it is likely that growth was slightly less overestimated after 2007 compared to 1997–2007, in table 4 we report a bias of –0.05 pp in the first period, and, somewhat arbitrarily, half of this during the second period, so that the sourcing bias makes a small contribution to explaining the productivity slowdown.

Finally, we note that Nakamura (2020) finds an impressive 1 pp mismeasurement acceleration between the twentieth and twenty-first centuries. The periods do not match ours, but this shows the considerable uncertainty that exists in these estimates.

3.2 *Boundary Issues*

Profit Shifting.—Several studies have argued that large multinational entities (MNEs) take advantage of lower corporate taxes in tax havens and disproportionately book their profits in these areas, rather than in the places where they actually originate. A typical example would be an intangible asset, such

changing, a popular method is to estimate *hedonic regressions*, where, broadly speaking, the price is regressed on characteristics so that one can infer inflation as the change in price holding characteristics constant.

[9] The outlet substitution bias arises when consumers buy the same product but from a different kind of retail outlet. For instance, if consumers switch from a traditional to a discount store, then the strict application matched model treats the product sold in a discount store as a new product, not as the same product sold cheaper, therefore creating a bias.

as intellectual property, created in the United States but sold by a parent company in the United States to its subsidiary in a tax heaven at a low price. The profits from this asset, such as licensing revenues, are part of gross *national* product, but not part of gross *domestic* product, since they are returns on US assets held abroad. When these assets are indeed produced in the United States and sold at an unfairly low price to a foreign multinational, US GDP can be considered underestimated.[10] Guvenen et al. (2022), using confidential data from surveys of MNEs by the BEA, compute that 38 percent of this income attributed to US assets abroad is actually reattributable to the United States, domestically. They compute explicitly how this affects output and labor productivity, and find that while labor productivity growth was underestimated by 0.05 pp on average during 1994–2004, it was not underestimated during 2004–16 (Guvenen et al. 2022, table V). As a result, these numbers imply that profit shifting does not explain the productivity slowdown, in fact it makes it very slightly worse.

Would other studies overturn these results? There is a debate around double counting of foreign profits (Blouin and Robinson 2020, Wright and Zucman 2018, Saez and Zucman 2019), which is linked to increasing corporate complexity over time (Blouin and Krull 2018), so it is possible that further studies would lead to updated numbers.

Informal Sectors.— In principle, statistical offices provide estimates of the input and output from the informal sectors. Substantial mismeasurement errors of output and labor productivity of the informal sector could have a non-negligible effect for aggregate statistics, since the informal sector is estimated to represent, on average, 14 percent of GDP in high-income OECD countries during the period 1999–2007 (Schneider, Buehn, and Montenegro 2010). The informal sector also appears to be declining. In the United States, the shadow economy is estimated to have dropped from 8.5 percent of GDP in 2003 to 5.1 percent in 2018, in Germany from 16.7 percent to 9.6 percent, and in Japan from 11 percent to 8.5 percent during the same period (Enste 2018, Medina and Schneider 2018). In principle, we could try to estimate the labor productivity levels and growth of the informal sectors, as well as their share of the economy, and an estimate of how much is already captured in national accounts. We could then see whether any bias to labor productivity has changed over our two decades. Considering the difficulty and uncertainty involved in doing this, and anticipating relatively small effects, we assume that this issue did not contribute substantially to the productivity slowdown, but a full study would be helpful.

Investment in Intangible Assets.— Corrado, Hulten, and Sichel (2009) argued that some expenses by businesses are currently considered intermediate consumption (and thus netted out of GDP), while in principle they should be considered investments (see section 4.3 for an extended discussion). While this implies that true output is probably higher than actually measured, the effect on GDP growth rates and on the productivity slowdown is less clear a priori.[11]

[10] Symmetrically, the GDP of the tax havens would be overestimated. Thus profit shifting would not explain a world-level productivity slowdown. However, profit shifting appears concentrated in a handful of small economies, so it remains legitimate to study profit shifting in our five large economies.

[11] This also creates a substantial bias in how growth is attributed to capital deepening or TFP (Corrado, Hulten, and Sichel 2009; Crouzet and Eberly 2021; McGrattan 2020), but we do not delve into this here (see also appendix B). Furthermore, if investment growth rates are changing over time so that investment and capital growth rates differ, this can create a TFP mismeasurement cycle (Brynjolfsson, Rock, and Syverson 2021).

The EU KLEMS data we used in the previous section (Stehrer et al. 2019) is available in two formats: the tables based on existing official national accounts, and tables that are recomputed using an intangibles-extended asset boundary. Table 17 in appendix C.4 performs the same growth decomposition as in table 2 using the extended dataset. Comparing the two and considering the United States, we find that productivity growth in the extended accounts was slower during both periods, but the bias was larger during the first period. As a result, the slowdown is a little bit smaller in the extended accounts compared to the official accounts, 1.57 instead of 1.61 pp, a difference of 0.04 pp we report in table 5. Computing equivalent figures for other countries gives a range of –0.08 to 0.04 pp, so it is indeed possible that mismeasurement of intangibles makes the slowdown worse rather than explaining it. According to these numbers, this explanation fails the scale and scope criteria. However, two other studies have found substantially larger effects of the mismeasurement of intangibles on productivity.

Brynjolfsson, Rock, and Syverson (2021) try to estimate how much higher output growth would be if we accounted for unmeasured investments that are complementary to current investment in artificial intelligence. Roughly speaking, in 2017 investment in artificial intelligence was on the order of 1/1,000 of US GDP. Brynjolfsson, Rock, and Syverson (2021) claim that the market value of unmeasured complementary investments could be 10 times as large as measured investment, so there would be 1 pp of GDP growth missing, which is the entire scale of the productivity slowdown. This calculation assumes an extremely high rate of complementary investment and uses artificial intelligence (AI) investment rates from recent years (2017), so it cannot explain the productivity slowdown for the earlier years of the slow decade, where AI investments were very small. Brynjolfsson, Rock, and, Syverson (2021) also infer intangibles investment (research and development (R&D)), computer hardware and software) using firm-level data, so that they can provide an estimate of the contribution of the mismeasurement of intangibles to the US TFP slowdown (2005–17 compared to 1995–2004). They find that mismeasurement was higher in the first period, so it makes the slowdown more puzzling.

Crouzet and Eberly (2021) provide a detailed analysis of the biases to TFP in terms of the biases to GDP growth, capital growth, and factor income shares. They note that capitalizing (at 100 percent) three service industry groups (professional, scientific, and technical services, administrative and support services, and management of companies and enterprises) leads to a cumulative adjustment of GDP of around 12 percent in 1997, increasing to approximately 15 percent by 2018 (Crouzet and Eberly 2021, figure 3). Because this mismeasurement is increasing, it would contribute to explaining the productivity slowdown.

Free Goods and Services.—Free goods and services lead to two issues: accounting challenges, even within the scope of GDP, and large unmeasured gains to consumer surplus. First, regarding the issue of accounting for free goods and services within the existing GDP boundaries, Nakamura, Samuels, and Soloveichik (2017) proposed a method to reintegrate free goods and services within GDP by valuing them at cost. This has an impact on GDP, but virtually no impact on TFP since this adjustment implies an increase of both inputs and output. They explicitly found that these adjustments would have no impact on the TFP slowdown. There are several examples where one can make a case that GDP or GDP growth is missing, but it is both unlikely to be very high and, more importantly, any correction would also entail correcting for inputs, including labor inputs. Examples include Wikipedia (Ahmad, Ribarsky, and Reinsdorf 2017) and output, such as some banking services that are now performed directly by households rather than by paid employees ("do-it-yourself" made possible by digital technologies, see Coyle 2019). While more research would be valuable because these corrections affect both inputs and outputs and are unlikely to be very high, we ignore these effects.

Second, digital technology can affect consumers in ways that are excluded from the scope of GDP. Of course, GDP was never intended to measure consumer surplus and there have been large increases in consumer surplus in the past, well beyond what is accounted for in GDP (Gordon 2016). Yet several internet-related services, such as search and social media, have appeared only in the early/mid-2000s and have quickly become a fairly important share of time use, prompting concern that they provide vast benefits that are not reflected in GDP. Syverson (2017) reviews and updates a number of estimates based on willingness to pay or the valuation of time spent (Goolsbee and Klenow 2006; Brynjolfsson and Oh 2012), concluding that consumer surplus is unlikely to be as large as missing GDP from the slowdown, but can represent a non-negligible fraction of it.

There is clearly an important research agenda going forward on the evaluation of consumer surplus from digital services. However, because it does not directly affect GDP, and because studies comparing consumer surplus from digital and non-digital or pre-2005 technologies are rare, we refrain from providing estimates of the contribution of consumer surplus from digital technologies to the productivity slowdown.

3.3 *Summary*

Table 5 provides a summary and an aggregate of all our estimates. Mismeasurement has increased during the past decades and may account for 0.21 pp of the productivity slowdown in the United States (13 percent of the 1.61 pp slowdown), with very large uncertainties surrounding these numbers. In our estimates, accelerated mismeasurement comes mostly from digital services quality adjustments from Byrne and Corrado (2020) and biases in imputing inflation rates for new products, derived by Aghion et al. (2019). This is a substantial effect, and it is plausible that similar estimates could be obtained for other countries. In sum, mismeasurement contributed to the productivity slowdown, but on its own cannot explain it.

4. *Capital Deepening and Investment Cycles*

In section 2, we found that a slowdown in capital deepening is a large driver of the productivity slowdown. To understand the origins of this decline, this section examines recent work on the changing nature of capital and on the determinants of investment. We start by briefly describing the evolution of investment over the last decades, with evidence disaggregated by key subcategories of capital. Because the global financial crisis was a major event and investment is highly procyclical, we then discuss whether lackluster investment simply reflects a cyclical effect, including as a response to the potential credit crunch one expects following a financial crisis. There is some evidence that increasing default risk led to financing difficulties that may have harmed investment. But as cyclical effects do not appear to fully explain the patterns of investment in the last decades, we consider other more structural factors. The first is the rise in intangibles, which explains some of the investment slowdown, partly because intangibles are mismeasured, so investment is not as low as it seems, and partly because intangibles have different properties, so the nature and

TABLE 6
Types of Capital and Their Coverage in National Accounts, Constructed from the EU-KLEMS Manual by Stehrer et al. (2019)

	in NA?	Depreciation	% of capital stock 1995	2005	2015
Physical Non-ICT					
Total nonresidential investment	✓	0.032	39.41	37.55	36.46
Residential structures	✓	0.011	38.58	38.96	38.15
Other machinery and equipment	✓	0.131	11.56	11.35	11.77
Transport equipment	✓	0.189	2.74	2.91	3.19
Cultivated assets	✓	0.200	0.27	0.19	0.17
Total			92.56	90.96	89.73
Physical ICT					
Computing equipment	✓	0.315	0.48	0.79	0.94
Communications equipment	✓	0.115	0.46	0.79	1.02
Total			0.94	1.58	1.96
Included intangible					
Research and development	✓	0.200	4.42	4.64	5.15
Computer software and databases	✓	0.315	1.40	2.25	2.60
Other intellectual property products	✓	0.131	0.73	0.62	0.59
Total			6.55	7.50	8.35
Excluded intangible					
Design and other product developments	×	0.200	1.84	1.74	2.29
Advertising, market research, and branding	×	0.550	1.34	1.36	1.30
Purchased organizational capital	×	0.400	0.76	0.99	1.28
Vocational training	×	0.400	0.65	0.42	0.52
Own-account organizational capital	×	0.400		unavailable	
Total			4.60	4.52	5.38

Notes: "In NA?" refers to whether the asset type is capitalized under the current System of National Accounts (United Nations 2010). Percentages of the capital stock are in percent of the national accounts capital stock, so the first three subtotals add up to 100.

level of investment is changing, possibly permanently. Finally, we discuss three other explanations that have been put forward: offshoring, which leads to investment being performed and recorded abroad; changes in corporate governance; and weakening competition leading to lower incentives to invest.

4.1 *The Evidence*

What is aggregate capital made of, how has it changed, and how does this explain the growth-accounting results of section 2? Table 6 shows the different kinds of capital considered by the "analytical" accounts in KLEMS, which include a broader set of assets than national accounts. While three categories of intangibles are now included, after the 1993 and 2008 revisions of the

TABLE 7
Decomposing the Slowdown in Capital Deepening between Its Various Types

	$(1-\alpha_t)\Delta\log k_t$	Non-ICT	ICT	Intangible
France				
1996–2005	0.16	0.08	0.03	0.06
2006–17	0.09	0.00	0.02	0.07
Slowdown	0.07	0.08	0.01	−0.02
Share	1.00	1.14	0.13	−0.27
Germany				
1996–2005	0.61	0.49	0.03	0.08
2006–17	0.07	0.02	−0.01	0.07
Slowdown	0.54	0.48	0.05	0.02
Share	1.00	0.88	0.08	0.04
Japan				
1995–2005	1.07	0.44	0.34	0.29
2006–15	0.26	0.06	0.07	0.13
Slowdown	0.80	0.38	0.27	0.16
Share	1.00	0.47	0.33	0.20
United Kingdom				
1996–2005	0.70	0.55	0.12	0.03
2006–17	0.18	0.17	0.03	−0.02
Slowdown	0.53	0.38	0.09	0.05
Share	1.00	0.73	0.18	0.10
United States				
1998–2005	1.09	0.63	0.24	0.21
2006–17	0.38	0.18	0.07	0.12
Slowdown	0.71	0.45	0.17	0.09
Share	1.00	0.64	0.23	0.13

Source: Data from EU KLEMS 2019.

UN System of National Accounts (SNA), it has been widely argued that other kinds of expenses in intangibles could be capitalized (see section 4.3).

In the growth decomposition of section 2, we used data compatible with national accounts, so the effects of intangibles that are outside the asset boundary would show up in TFP. For the categories of capital that we do consider, table 7 shows the breakdown of the contribution to the slowdown. In France, the contribution of capital deepening to the slowdown was relatively small (0.07 pp) and comes entirely from a slowdown of non-ICT physical capital. For the other countries, the contribution of non-ICT physical capital remains dominant, but the slowdown in the contribution of physical ICT capital is also substantial, contributing 8 and 33 percent of the capital deepening slowdown, or 0.05 to 0.27 pp of labor productivity growth. The contribution of intangible capital to the slowdown is substantial in Japan, non-negligible in the United Kingdom and United

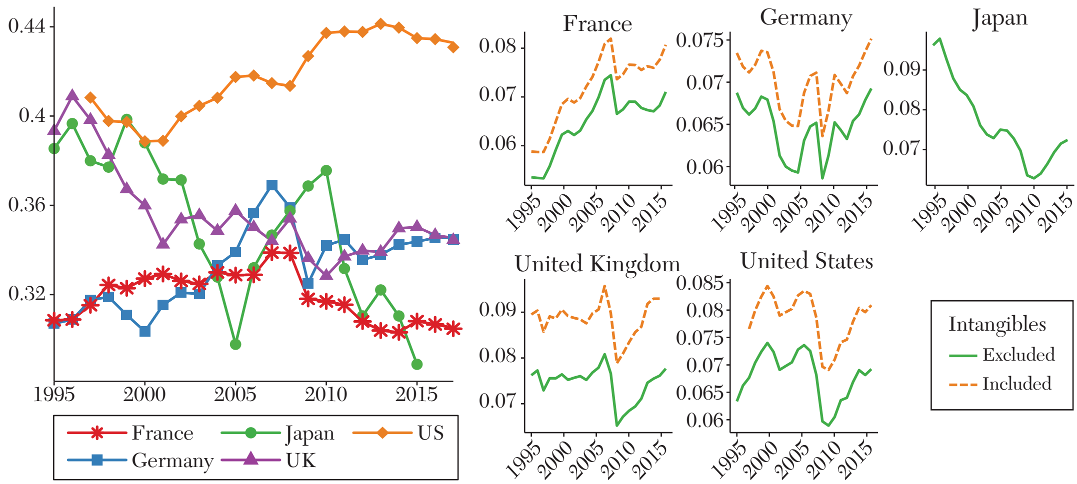

Figure 2. Capital Share of Income

Notes: Left: capital share of income computed as the capital compensation, divided by the sum of capital and labor compensation (in Japan capital and labor compensations do not sum up to VA). Right: investment rates, calculated as constant price gross fixed capital formation divided by the total capital stock. Data from EU KLEMS 2019 (and RIETI (2018) for Japan).

States, and small in Germany. For Japan, the United Kingdom, and the United States, the fairly substantial contribution of ICT capital deepening to the productivity slowdown corresponds to a decline that is large because these contributions were high in 1995–2005, confirming a well-established narrative for the United States.

In the standard growth-accounting methodology that we use, the contribution of capital deepening is computed as the growth rate of capital per hour worked multiplied by the capital income share. Figure 2 (left) shows that over the last decades, the capital share increased by around 4 pp in the United States and Germany, was more or less stable in France, declined by around 5 pp in the United Kingdom, and by almost 10 pp in Japan. These changes are substantial, and we will discuss income shares further in section 7, but these are still too small to help us explain our growth-accounting results. Thus, the decline in the contribution of capital deepening is largely due to a decline of capital deepening. Figure 2 (right) shows investment rates (I/K),[12] suggesting three observations. First, as expected, investment rates increased in France, where most of the productivity slowdown is attributed to TFP, and declined in Japan, where most of

[12]The connection between investment rates and capital growth rates can be seen from the equation of the perpetual inventory method for capital accumulation, $\dot{K}/K = I/K - \delta$. A decline of the investment rate induces a lower growth rate of capital. Note also that a change of the composition of investment would have an effect, since different kinds of capital have different depreciation rates. In fact, Ollivaud, Guillemette, and Turner (2016) document a secular rise in aggregate capital stock depreciation rates from about 3 to 5 percent between 1990 and 2015, which they attribute to the rise of ICT capital (see the depreciation rates in table 6). Finally, note that growth accounting uses capital per worker K/L (not just K), so understanding the growth contribution from capital deepening requires understanding the joint dynamic of employment and investment.

the slowdown is due to capital deepening. Second, the fluctuations around the time of the financial crisis are clearly visible, but not large. This suggests that part—but only part—of the productivity slowdown is due to a procyclical slowdown of investment. Third, the patterns are very similar if we include intangibles that are excluded from national accounts.

These results will guide our discussion of the financial crisis, the role of intangibles, and the role of other drivers of investment.

4.2 *Cyclical Effects from the Financial Crisis*

Decomposing cyclical and secular factors is particularly important to understand whether slow labor productivity growth is "the new normal" or not.

While a slowdown in investment may be responsible for part of the postcrisis slowdown, Fernald et al. (2017) argue that investment had a "normal" cyclical behavior, and the particularly disappointing recovery of total output must thus be attributed to slower TFP growth and weaker labor force participation. This finding is based on removing cyclical fluctuations based on the assumption of a stable relationship between macroeconomic variables (for example, output) and unemployment (Okun's law) and comparing investment with previous periods of recovery. Simpler or alternative methods lead to similar evaluations (see, for example, the discussion by Reichlin in Fernald et al. (2017). Most strikingly, the capital-output ratio returned to its prerecession trend in these models. Fernald and Inklaar (2020) show that if the growth-accounting decomposition for Europe is done with the capital to output ratio, rather than capital per unit of labor,[13] the contribution to the slowdown of the term including capital is very low.

We list three explanations for a cyclical crisis-driven slowdown of investment. The first is that the crisis led to a substantial increase in financial frictions. The returns on productive capital (including intangibles intellectual property products) have remained relatively stable at around 6.5 percent in the United States, while the returns on safe assets have decreased, suggesting a substantial increase in the risk premium. This has been the case since 2000, but has become more marked since the financial crisis of 2008 (Caballero, Farhi, and Gourinchas 2017). Besley, Roland, and Van Reenen (2020) derive an aggregate measure of credit frictions by modeling firms' probability of defaulting, and find that credit frictions may have contributed to a half of the 9.3 percent fall in UK labor productivity levels between 2008 and 2009. Financing constraints may not be a major factor outside the crisis years, however (Strauss and Yang 2020).

The second explanation for procyclical investment behavior is that depressed aggregate demand led to slower investment growth (Askenazy et al. 2016). Calibrating investment equations for the OECD with an accelerator effect, whereby investment depends on output, Ollivaud, Guillemette, and Turner (2016) estimate that the demand shock from the financial crisis may explain half of the decreased contribution of capital to labor productivity growth. Bussière, Ferrara, and Milovich (2015), also using an accelerator model and proxying expected demand using analysts' forecasts, found in their baseline model that a 3.3 out of 4 pp decline in business investment for

[13] More precisely, equation (1) can be rewritten as $\Delta \log y_t = (1/\alpha_t)\Delta \log A_t + \big((1-\alpha_t)/\alpha_t\big)\Delta \log(K/Y) + \Delta \log h_t$.Fernald and Inklaar (2020) also show that using the Penn World Tables, rather than EU KLEMS, capital per unit of output contributed to *more* growth in 2007–17 than in 1995–2007.

2008–14, compared to the precrisis period, in 22 advanced economies could be attributed to lower expected demand. Looking at the United States, Reifschneider, Wascher, and Wilcox's (2015) unobserved components model also suggests sizable effects of the financial crisis on output, through a lower potential output endogenous to these demand shocks.

The third is that government investment also fell postcrisis, contributing around one-fifth of the fall of investment as a share of GDP in OECD countries, with potentially longer-run (and harder to measure) consequences for productivity (Ollivaud, Guillemette, and Turner 2016).

We will discuss the role of intangibles as a secular trend below, but we briefly note here two ways in which the financial crisis affected intangibles and TFP. First, the negative consequences of a lack of investment in infrastructure also apply to "soft" infrastructure. These "public intangibles," as defined by Corrado, Haskel, and Jona-Lasinio (2017b), are built from investments in information, scientific and cultural assets, and investment in societal competencies, such as human health and knowledge capital built through a nation's health and school systems. Second, Redmond and Van Zandweghe (2016), looking at US data, found that stricter credit conditions prevailing during the crisis led to a substantial decline of R&D investment, and thus of TFP growth. To abstract from purely cyclical effects and evaluate the role of slowing investment on *trend* labor productivity growth, Ollivaud, Guillemette, and Turner (2016) use potential output data derived by the OECD.[14] Trend labor productivity growth fell from about 1.8 percent to 1 percent between 2000 and 2008, with most of the decline being due to the slowdown of TFP growth from about 1 percent to 0.4 percent. In contrast, the postcrisis (2008–15) decline (from around 1 to 0.7 percent) can be almost entirely attributed to a slower growth of capital deepening. Ollivaud, Guillemette, and Turner (2016) develop a simple dynamic macroeconometric model where the increasing output gap due to the financial crisis leads to a further decline of capital growth, and thus of output. They estimate that this effect can explain half of the decline in the contribution of capital deepening to trend productivity growth.

[14] Broadly speaking, potential output is defined as output that would be achieved using the actual observed levels of capital, but contributions of labor and TFP computed based on their trends (from HP filtering of the relevant series). The output gap is the difference between actual and potential output.

4.3 *Intangible Capital*

The patterns of investment can be explained by a shift toward more intangible capital through two effects: a measurement channel, as intangibles are generally underestimated, and a real channel, because the nature of intangible capital makes it harder to accumulate. We start by clarifying the definition of intangibles and explain measurement challenges. We then explain how intangible capital differs from tangible capital and how this might have led to lower investment rates.

What is Intangible Capital?—Table 6 provides some details over the categories of intangible investment considered by EU KLEMS 2019. While the UN SNA has gradually expanded to include Software (1993) and R&D (2008), Corrado, Hulten, and Sichel (2009) have argued that other activities lead to capital formation (i.e., expenses incurred during one year that provide benefits for more than one year). The main issues to address are the asset boundary (identifying which expenses contribute to capital formation), the capitalization factor (identifying what share of an expense category contributes to capital formation), and depreciation. Corrado, Hulten, and Sichel (2009); Corrado and Hulten (2014); and Corrado et al. (2020) have provided a revised version of the Corrado–Hulten–Sichel framework, and EU KLEMS 2019 provides comprehensive data.

There is also active research in finance attempting to measure firm-level intangible capital stocks. Peters and Taylor (2017) compute intangible capital stocks as the book value of intangibles (this is mostly goodwill that appears on the books after a merger or acquisition), plus an intangible capital stock obtained by capitalizing 100 percent of R&D expenses (with industry-specific depreciation rate) and 30 percent of selling, general, and administrative expenses (depreciated at 20 percent), which are thought to cover investment in organizational capital. Tobin's Q regressions, which explain I/K by the Q ratio (market capitalization over book value of assets) have better explanatory power with the intangibles-extended investment and capital stock time series.

The Nature of Intangible Capital and Incentives to Invest.—Haskel and Westlake (2018) describe intangible capital and its consequences using four Ss. It is more *scalable* because it is essentially non-rival and with low marginal cost, creating economies of scale that may increase concentration. It is more *sunk* because it is more uniquely linked to the firms that originally create it. This makes intangible capital a fixed cost, which creates barriers to entry, and this also makes it a bad collateral as illiquid markets for intangibles make their financing more difficult in the first place. Intangible capital is more conducive of *spillovers*, because of non-rivalry and non-excludability of knowledge. This lack of appropriability may weaken the incentive to invest. And finally, Haskel and Westlake (2018) argue that intangible capital has strong *synergies* with IT capital, so that these complementarities in investment, if associated with adjustment costs, can largely explain long lags in diffusion.

While not all of these arguments apply to all categories of intangibles, overall this suggests that financing and accumulating intangible capital may be intrinsically more difficult. The idea that financing intangible capital is more costly squares well with Caballero, Farhi, and Gourinchas's (2017) findings of an increasing risk premia, and would suggest that credit constraints following the financial crisis may have affected intangible investment disproportionately. In fact, Duval, Hong, and Timmer (2020) present evidence that the financially more vulnerable firms had a higher decline in TFP growth after the crisis, and this effect was stronger in countries with a higher credit supply shock.

Besides R&D, intangibles also include economic competencies and good management practices. Haldane (2017) argues that management practices are indeed a good predictor for productivity at the firm level, and slower diffusion of best practices could help explain the productivity gap between frontier and laggard firms. In order to lead to productivity improvements, technological change typically requires a change in companies' internal processes and organization. During the productivity paradox of the 90s, insufficient organizational change was identified as one of the key factors holding back technology diffusion (Brynjolfsson 1993, Brynjolfsson and Hitt 2000). Similar arguments can be made today, where organizational changes complementary to the development of artificial intelligence are just starting and will take time to fully impact businesses and productivity (Brynjolfsson, Rock, and Syverson 2019).

Spillovers from Intangible Capital and the TFP Slowdown.—There is a concern that because of their higher spillover effects compared to tangible capital, a slowdown

TABLE 8
Growth of Intangible Capital Services

	France	Germany	Japan	UK	US
1996–2005	2.53	2.62	3.30	1.83	4.27
2006–17	2.88	2.31	0.90	1.85	2.89
Slowdown	−0.36	0.31	2.40	−0.03	1.38
Slowdown × 0.2	−0.07	0.06	0.48	−0.01	0.28

Sources: Data from EU KLEMS 2019 (Stehrer et al., 2019), Analytical Growth Accounts, variable CAPIntang_QI. Missing values: 2016–17 for Japan, 1996 for the United States.

in intangible investment is worse than a slowdown in physical capital investment. Goodridge, Haskel, and Wallis (2018) suggested that part of the TFP growth slowdown might be due to missing lagged spillovers, resulting from the slowdown of R&D investment in the 1990s and 2000s.

Corrado, Haskel, and Jona-Lasinio (2017a) computed the effect of intangible-related spillovers on TFP. To do this, one first needs to create complete intangible capital accounts, new measures of output growth that include intangible investment, and then compute TFP. Corrado et al. (2020) reproduced earlier results suggesting that, in this updated system of accounts, a 1 pp increase in intangible capital services growth is associated with 0.2 pp increase in TFP growth. Comparing intangible capital services growth between the precrisis (1999–2007) and postcrisis (2008–16) periods, they find that the slowdown of intangible capital services from 4.9 percent to 2 percent led to a slowdown of TFP of $(4.9 - 2) \times 0.2 = 0.58$ pp in the United States, which is a very large share of the TFP slowdown. The same calculation for Europe would explain 0.3 pp of the TFP slowdown.

Table 8 repeats this calculation using intangible capital services data from EU KLEMS 2019. We reuse the elasticity of 0.2 of Corrado et al. (2020), even though strictly speaking it should be used to compute an effect on intangibles-corrected TFP rather than "raw" TFP.[15]

These results suggest that, for the United States, the slowdown in intangible capital services led to a decline of TFP growth of 0.28 pp, representing more than a quarter of the TFP slowdown, and 17 percent of the labor productivity slowdown. This is a substantial effect. However, the effect for other countries is inconsistent. For the United Kingdom, France, and Germany, it is much closer to zero. For Japan, it is very strong, but this is somewhat surprising given that Japan's productivity slowdown comes almost entirely from capital deepening, not from TFP.

We have repeated the same calculation using Corrado's et al. (2016) data on intangible capital services,[16] which is different from KLEMS. It does not contain data for Japan, but confirms closer to zero effects for France, Germany, and the United Kingdom. For the United States, the effect is much stronger than in table 8, and closer to Corrado et al.'s

15 Comparing tables 2 and 17, we find only small differences between TFP slowdowns in the official and intangible-corrected accounts. We use the variable CAPIntang_QI in KLEMS, which includes all types of intangible capital services listed in table 6 (included in national accounts or not). Corrado, Haskel, and Jona-Lasinio (2017a) exclude software and databases in estimating the elasticity.

16 http://www.intaninvest.net.

(2020) estimate (who use slightly different periods).

Considering that this explanation somewhat fails our scope criteria, in the conclusion we will report the results from table 8, which are more conservative than those from Corrado et al. (2020). Our (subjective) estimates for the uncertainty range will reflect the fact that the results are much weaker outside the United States, but much stronger in the United States using a different dataset.

4.4 *Other Structural Effects*

Competition.—As we will see in detail in section 7, there are concerns that competitive pressures may have declined in the United States, and to some extent in Europe, over the last decades. To the extent that market power is associated with incentives to restrict output, a rise in market power can explain a decline of investment.

Several papers have documented correlations between intangible intensity and indicators of lower competition, such as business dynamism (Calvino, Criscuolo, and Verlhac 2020) and concentration (Affeldt et al. 2021, with some caveats), and with lower investment (Gutiérrez and Philippon 2017). However, there is considerable debate about whether this is "good" (intangible investments by productive firms), or "bad" for productivity (section 7). Using industry- and firm-level data, Gutiérrez and Philippon (2017) find that concentration indices (e.g., the Herfindhal index) contribute to explain why firms invest less than what would have been expected in view of Tobin's Q.

Common Ownership, Corporate Governance, and Short-Termism.—Declining investment rates could also be due to an increase in short-termism among top managers (Haskel and Westlake 2018, Lazonick 2014). In firms where the pay of the top management is linked to firm performance on the stock market with the purpose of aligning the incentives of managers with those of the firms, Lazonick (2014) find that an increasing amount of resources are spent on stock buybacks instead of long-term investment that would improve productivity. Similarly, Gutiérrez and Philippon (2017) investigate whether variables capturing common ownership and the kind of ownership (such as passive index funds) explain lower-than-expected investment and found that these changes in corporate governance did lead to lower investment rates. As noted in Anton et al. (2021), however, if common ownership does create lower competition, this might also imply a lower innovation shortfall from non-appropriability. In other words, if common ownership implies that one can think of several firms as one, it implies monopoly power but also reduces issues of non-appropriability of innovation efforts.

Globalization.—Using data on publicly traded firms in the United States, Alexander and Eberly (2018) found that the slowdown of investment relative to fundamentals started in the early 2000s, and ascribed this to a shift toward intangibles but also to a shift of investment toward industries in which capital cannot be relocated easily (for example, energy production or telecommunication transmission). Gutiérrez and Philippon (2017) also find some support to the idea that globalization may have contributed to lower aggregate investment, as industries with higher foreign profits tend to also feature lower investment.

4.5 *Summary*

The weakness in investment is a major cause of the slowdown. The key question is whether investment has declined because of cyclical or structural reasons. On the one hand, cyclical explanations are strong—the financial crisis depressed aggregate demand

and increased financial constraints, both for firms and governments. These effects have been evaluated quantitatively and taken together can account for a sizable portion of the decline in the postcrisis period. The financial crisis was global, and we may expect financial frictions to be affected in a relatively similar fashion in all countries. On the other hand, the slowdown in investment started, at least in the United States, in the early 2000s, before the crisis, so structural explanations are necessary to account for the part of the slowdown due to lower capital deepening. Several explanations have been put forward, such as a higher share of intangible capital, a decline in competition, a rise in short-termism and common ownership, and globalization. All of these factors may have applied relatively similarly in advanced economies, satisfying our scope criteria, and taken together have a plausibly large impact, satisfying our scale criteria.

It has proved difficult to combine and quantify these effects, but we estimate that approximately half of the slowdown of the contribution of capital deepening is due to the financial crisis (mostly depressed demand and credit frictions), and half is due to secular trends (mostly due to a shift to intangibles, and also possibly to lower competition, changes in corporate governance, and globalization). In table 11 in the conclusion, we will use the estimates of the contribution of capital deepening from growth accounting, that is, 0.71 for the United States, and allocate half of this to cyclical and the other half to secular effects.

5. *Human Capital and Labor Markets*

In section 2, we have found that the contribution of labor composition to the productivity slowdown ranges from –10 to 22 percent. A decline in human capital growth, which we discuss in the first subsection below on educational attainment and skill mismatch, is therefore rarely seen as a major explanation of the slowdown. However, there are several other channels through which labor markets may have contributed to the slowdown in TFP. We discuss demographic factors, including aging and migration, and how they affect productivity through direct channels (e.g., age-productivity relationships) as well as indirect channels (e.g., savings or shifting consumption preferences). We then briefly examine an emerging literature on the role of technology in lowering labor supply, as well as the possible impact of the recent rise of digital labor markets, before reviewing the discussion surrounding labor market institutions.

5.1 *Education and Skills*

The importance of education for labor productivity and wages is well established in the economic literature (Mincer 1958, Jorgenson and Griliches 1967). In a traditional framework, wages are equal to the marginal product of labor, and subsequent wage premia are associated with higher output. In this context, a general slowdown in educational or skill attainment could cause a productivity slowdown.

Most studies, including ours, show that labor composition mostly improved during the period we review: Goodridge, Haskel, and Wallis (2018) in the United Kingdom; Askenazy et al. (2016) in France; and Bosler et al. (2018) and Jorgenson, Ho, and Samuels (208) in the United States all document a shift of employment toward high-skilled workers, accelerated by the financial crisis in 2008. Germany is an exception; Elstner, Feld, and Schmidt (2018) attribute worsening labor composition to a higher equilibrium rate of employment among low-skill workers from deregulation. In all, a secular slowdown in educational attainment is not a candidate explanation for the recent global productivity slowdown.[17]

Whether this trend will be sustained going forward is unclear; concerns have been raised about rising tuition fees impacting enrollment in the United Kingdom and, to a lesser degree, in the United States (Gordon 2016; Gordon and Hedlund 2019; Corrado, O'Mahony, and Samek 2020). The eventual plateauing of high school diplomas in the United States is a long-term trend investigated in Goldin and Katz (2008) and Fernald and Jones (2014), but they fall short in attributing it to the current productivity slowdown. Additionally, Bosler et al. (2018) forecast a negative impact from a return to pre-recession levels of low-skill employment.

Given the shift toward high-skilled employment, a potential explanation for the productivity slowdown is a growing mismatch between the supply and demand of specific skills. For instance, in periods of fast technological change, we should expect the skills associated with new technologies to be in short supply, and that skill biased technological change leads to a differential impact on a range of occupations (Acemoglu and Autor 2011). There is a consensus that skill-biased technological change led to the hollowing out of the wage distribution in the 2000s, when middle wage cognitive routine occupations were automated (Goos, Manning, and Salomons 2014). This may have led to deskilling technological change, contributing to the skills mismatch and pushing workers with intermediate levels of education to take low-productivity jobs. In combination with the emergence of digital platforms, a larger share of such workers now participates in the gig economy (Coyle 2017). In one study, Patterson et al. (2016) calculate that most labor was reallocated to low-productivity occupations, accounting for up to two-thirds of the slowdown in the United Kingdom. This conclusion clashes with that of Goodridge, Haskel, and Wallis (2018) and that of table 1; we observe that the reallocation between broad industry groups did not contribute to the overall slowdown, so Patterson et al. (2016) might be measuring a reallocation effect between three-digit occupations within the one-digit industries considered by Goodridge, Haskel, and Wallis (2018).

5.2 *Aging*

Increasing longevity and declining birth rates are responsible for an aging population globally. We disentangle three potential effects of aging on productivity: a direct effect due to a link between age and productivity, a structural change effect due to changing patterns of demand, and a macroeconomic effect of aging on saving rates.

Understanding how worker productivity changes with age is often problematic due to selection bias (old workers remain in the workforce because of good health, and are therefore not representative), omitted variables in determining wages (seniority and anti-ageism laws), and generational effects. Indeed, various studies fail to find any relationship between worker productivity and age; Börsch-Supan (2013) provides a thorough review of studies debunking the inverse relationship between age and productivity. More recent research, such as Liang, Wang, and Lazear's (2018), concerns itself with the negative relationship between aging and business formation. If anything, the effect of age on productivity is indirect. For

[17] Vollrath (2020), focusing on the United States, finds that the decline in human capital growth is the main driver of the GDP growth slowdown. This is not necesarily incompatible with the results in the productivity literature because Vollrath's (2020) results are mostly due to the decline of labor participation (workers per inhabitant), rather than to the decline of human capital per worker (table 5.1), although comparisons are difficult due to the different choice of periods.

instance, aggregate regional productivity declines with age because the structure of demand is different, despite the workers themselves not being any less productive, or because firm and population demography are related (Hopenhayn, Neira, and Singhania 2018, see section 7).

Baumol's (1967) cost disease plays a role in the aging literature because consumption baskets shift demand toward low-productivity growth sectors, such as health care and entertainment. Siliverstovs, Kholodilin, and Thiessen (2011) document a shift of employment shares away from agriculture and industry toward personal services and the financial sector caused by a growing share in the total population of individuals aged 65+ in a panel of countries. Moreno-Galbis and Sopraseuth (2014) identify that the shift toward personal services due to aging is also responsible for job polarization, since these services require low-paid labor. However, our discussion in section 2 fails to relate the productivity slowdown to a reallocation toward low productivity growth industries.

Finally, aging affects the availability and rate of return of capital inputs, but there is no consensus on the nature and extent of the effect on productivity (Lee 2016). Lower and negative population growth rates would increase the supply of savings, to the extent that individuals need to save for retirement. At the same time, a higher saving rate would lead to lower demand for consumption goods, reducing investment opportunities for firms. Both shifts lead to a lower equilibrium rate of interest. However, Eichengreen (2015), citing earlier research, notes a lack of evidence for the negative impact that old-age dependency ratios hold on savings. The interesting hypothesis posited by Acemoglu and Restrepo (2017) is that older societies pursue capital-biased technical change, leading to higher productivity. They observe a faster rate of adoption of automation in countries with older populations, which more than offsets any effects on output caused by labor scarcity.

5.3 *Migration*

The post-2005 period coincides with larger migrant flows from east to west Europe. According to data from the International Labour Organization (ILO),[18] the share of foreign-born employees increased in the United Kingdom and the United States, remained largely unchanged in France, and declined in Germany. Oulton (2019) links the United Kingdom's labor productivity growth slowdown to immigration: a slowdown in export growth, combined with growth in labor inputs from immigration, reduced capital accumulation. However, as we see later, the higher employment levels that are the subject of Oulton (2019) are typically attributed to more flexible labor markets observed across Europe in general, rather than inflows of foreign labor.

A large literature documents immigrants' propensity to promote entrepreneurship and innovation, so the downturn in migrant employment could explain a slowdown in TFP growth. Peri (2012) estimates the effect of foreign-born employees, as a share of total employment, on TFP in US states, controlling for skill intensity and using log border distances to instrument for migration. However, while he estimates substantial elasticities, the changes in the share of foreign-born employees and their acceleration or slowdown are not large enough to produce a substantial effect on TFP growth rates for our selected countries. Migration thus fails to fulfill our requirements for scale and scope in providing an explanation for the labor productivity growth slowdown.

[18] Source data: https://www.ilo.org/shinyapps/bulkexplorer47/?lang=en&segment=indicator&id=MST_FORP_SEX_CBR_NB_A.

5.4 *Leisure Technology*

Another notable trend related to labor markets is the rapid improvement of leisure technologies. Labor force participation is often modeled as a trade-off between consumption, financed through wages, and leisure, such that higher enjoyment of leisure activities should shift participation rates downward. This effect is documented in time use surveys by Aguiar et al. (2021), who specifically note the increase in time allocated toward video games among young men. Bridgman (2022) finds that imputed leisure productivity has persistently declined since 1978. Rachel (2022) supports Bridgman's (2022) conclusion with a theoretical model of an "attention economy," and notes that the diversion of resources toward R&D effort in leisure technologies can lower long-run productivity growth, in addition to any cognitive repercussions of distracted workers (see also Ward et al. 2017). While such habits certainly could worsen productivity at work, the same technologies enabled a rise in working time outside the office, while commuting, at home, traveling, or on holiday.

5.5 *Labor Market Institutions*

Labor market institutions affect labor productivity beyond a direct effect on labor composition, and may therefore also affect TFP. We discuss four channels: labor hoarding, barriers to worker mobility, digital labor markets, and lower discrimination.

Labor hoarding, by which firms keep workers on the payroll despite falling demand to avoid future rehiring costs, contributes to a slowdown by maintaining labor inputs constant despite dropping output. It was a leading explanation in Askenazy et al. (2016) for the differences in labor productivity following the financial crisis across European countries. Higher wage flexibility meant workers accepted a lower real wage, and unemployment recovered quickly; Pessoa and Van Reenen (2014), for the United Kingdom, and Elstner, Feld, and Schmidt (2018), for Germany, draw on this mechanism to explain low unemployment and low productivity growth after the crisis. Pessoa and Van Reenen (2014) add that credit constraints made capital less attractive, leading to capital substitution with labor. The resulting lower capital deepening is detrimental to labor productivity, thus presenting a compelling explanation that may also have applied to other countries. However, whether such wage flexibility would continue to reduce productivity growth long after the crisis has not been demonstrated.

The decline in job reallocation, particularly in the United States (see section 7.1.2), may be attributable to higher levels of regulation, with this offering another potential explanation for declining productivity growth. Noncompete agreements, whereby employees agree not to join competing firms within a particular timeframe or location, have received attention in the United States. However, concrete evidence for an effect on labor productivity is lacking, despite having noticeable effects on wages (Starr, Prescott, and Bishara 2021). The prime concern regarding these agreements is that they hamper the diffusion of innovations by employees transitioning, but they can allow business to make crucial investments. "No-poaching" agreements are similar in nature to noncompete contracts, but are agreed upon between employers instead of between employers and their employees: Krueger and Ashenfelter (2022) find that a staggering 58 percent of major franchises in the United States include agreements by which employers agree not to "poach" employees from each other. Beyond labor market regulation, Cette, Fernald, and Mojon (2016) find that product and labor market regulation may help explain the lack of an ICT boom in Europe, but there is no indication that such regulation worsened post-2005. Fernald et al. (2017) fail to make the case for regulation in their analysis of text data for broad industry-level regulations in the United States.

In the United Kingdom, a persistent increase in self-employment, zero-hour contracts, and the rise of the "gig economy" may be responsible for a recent increase in unskilled labor (Coyle 2017). On the one hand, the gig economy may be detrimental to overall labor productivity because of lower rates of investment in skill accumulation, as compared to long-term job contracts. On the other hand, such platforms often improve utilization rates for certain services, enhance skill matching, especially for rarer skills, and reduce hiring costs (Nakamura et al. 2009). The most notable case is that of Uber, for which Cramer and Krueger (2016) do not find a clear effect on productivity or wages.

Finally, Hsieh et al. (2019) studied the allocation of talent across occupations in the United States between 1960 and 2010. In the 1960s, the vast majority of professionals in high-skilled occupations, such as medical doctors, were white males, while optimal allocation of talent would have suggested a higher presence of women and Black men. Using a model of occupational choice with frictions, Hsieh et al. (2019) estimate that frictions have declined over time, making it possible for innately talented women and Black men to enter into these professions. In their estimates, this increasingly better allocation of human resources was responsible for between 20 and 40 percent of the increase in market output per person between 1960 and 2010. In view of the quantitatively important effects of lowering discrimination on productivity, it is conceivable in principle that a slowdown in the reduction of discrimination may have contributed to the productivity slowdown.

5.6 *Summary*

The supply of skills, as measured in growth-accounting databases, is not a significant explanation of the labor productivity slowdown. But technologies have disrupted labor markets, and we expect that many of these changes would affect TFP growth. Aging has not accelerated evenly in all countries we consider, and there has not been a marked change in aging preceding the slowdown, thus it does not satisfy our sequencing criterion. The argument that new leisure technologies may decrease labor supply remains under-researched. Changes to labor market institutions are emerging from the introduction of digital platforms, which may fit the sequencing and scope of the slowdown. Lowering discrimination has had an important quantitative effect on productivity in the past, so it is possible that a slowdown of progress in this area had material consequences on aggregate productivity.

6. *Global Trade*

Historically, trade has been an important driver of productivity growth. Gains from international trade are traditionally seen as gains from "world" allocative efficiency, hence its inclusion with the allocative efficiency part of the TFP term in equation (3). The positive effects of trade through other channels, such as increasing innovation following exposure to international competition or simply access to higher-quality or cheaper capital goods, have also been highlighted in the recent literature. In this section, we first discuss the slowdown in global trade, before considering the recent literature on productivity gains from global value chains (GVCs). This leads us to provide a rough estimate of the effect of a slowdown in trade on the productivity slowdown. We conclude with a discussion on the geographical location of production within countries, pointing to a lack of research connecting regional dispersion to the productivity slowdown.

6.1 *Slowdown in Global Trade*

Weakness in consumer demand in the aftermath of the global financial crisis is a primary cause of the slowdown in trade, since it is notably more pronounced in countries hit hardest by the crisis (Constantinescu, Mattoo, and Ruta 2016). The collapse of investment accounts for another significant share of the slowdown in the growth in trade for the G7 countries, as imports are much more responsive to investment than changes in private consumption (Bussière et al. 2013). The recent studies by Riley, Rincon-Aznar, and Samek (2018); Oulton (2019); and Inklaar et al. (2020) note that much of their observed industry composition of the slowdown in labor productivity growth mimics the collapse in international demand for exports.

Constantinescu, Mattoon, and Ruta (2016) note that weakness in aggregate demand accounts for roughly half the gap between trend and realized import growth, concluding that structural components also played a role. The rate of increase in trade between the mid-1980s and mid-2000s may itself have been exceptional, largely due to the emergence of China as an exporter, and the collapse of communism. In addition to these geopolitical factors, technological advancements, notably in communications and transportation, fueled an expansion in the use of GVCs (Baldwin 2016).

6.2 *Productivity Gains from GVCs*

The emergence of global value chains enabled cheaper production, specialization, competition, and the diffusion of technologies and knowledge (Criscuolo and Timmis 2017). Here, we provide a qualitative overview for the role of trade and offshoring on productivity by considering, in turn, the impact on productivity, human capital, and technology.

Trade has a direct impact on aggregate productivity levels through the exit of the least productive firms and the extra exports generated by the most productive firms (Melitz 2003). Exporters tend to be more productive, and many of the most productive exporters engage in offshoring (Antràs and Helpman 2004; Delgado, Fariñas, and Ruano 2002; Helpman, Melitz, and Yeaple 2004). Exporting alone has been shown to significantly boost firm productivity by up to 19 percent in American plants sampled between 1984 and 1992 (Bernard and Jensen 1999).

The overall impact of trade on human capital is debatable. Exposure to Chinese import competition in the United States has contributed to a 25 percent decline in manufacturing employment within commuting zones, with similar findings for local labor markets in Europe (Autor, Dorn, and Hanson 2013). However, using evidence on the expansion in export activity in the United States, Feenstra, Ma, and Xu (2019) estimate that the net effect of access to foreign markets on employment is near zero within commuting zones. This would indicate that labor reallocates into other occupations, notably high-skilled ones, which are less prone to being moved offshore. This builds on earlier work of Feenstra and Hanson (1999), who determine that offshoring increased employment of high-skilled workers within industries in the United States, in turn raising the skill premium by 15 percent between 1979 and 1990. Vollrath (2020) provides a back-of-the-envelope calculation to estimate whether the "China shock" could have affected productivity by lowering the share of manufacturing and finds a small effect.

Recent innovations in ICTs have changed the traditional paradigm, whereby services provided abroad through foreign investment are often supplied at the location of production. A growing number of service inputs are now offshored, and outputs are sold to suppliers and consumers abroad (Freund and Weinhold 2002). Amiti and Wei (2009) show that the offshoring of services has grown at an annual rate of 6.3 percent in the United States between 1992 and 2000. They find that service offshoring has accounted for 10 percent of the average growth in labor productivity in those years, arguing that this is largely due to a reallocation of labor to more productive tasks. The offshoring of services also contributes significant knowledge spillovers. Javorcik (2004) estimates that a 4 percent increase in the share of foreign-owned firms increases output of domestic firms by 15 percent in a sample of Lithuanian firms. In some instances, foreign direct investment inflows come in the form of acquisitions with the intent to acquire skilled workers and technological expertise (Griffith, Redding, and Reenen 2004). Antràs and Helpman (2004) note the importance of strong property rights in enabling the outsourcing of administrative, or "headquarter," services and investigate this in the context of R&D specifically: protection of intellectual property rights abroad leads to faster offshoring of R&D and higher aggregate rates of innovation, especially for high-tech industries (Şener and Zhao 2009, Canals and Şener 2014). The rate of domestic innovation can also be affected by foreign competition—Autor et al. (2020a) find a lower issuance of patents following increased exposure to Chinese imports within regions in the United States.

6.3 *Effect of the Slowdown in Trade on the Productivity Slowdown*

Given the documented slowdown in global trade, an estimate of the elasticity of labor productivity growth to international trade growth would provide an evaluation of the impact of the trade slowdown on the productivity slowdown. Any causal estimate for the aggregate impact of the trade slowdown on productivity growth rates would need to address the considerable endogeneity, however.

The key variable capturing the integration of GVCs is the amount of foreign value added embodied as intermediates in exports, termed "backward linkages." Constantinescu, Mattoo, and Ruta (2019), using panel data on manufacturing and tradable services industries in 40 countries for the period 1997–2009, regress labor productivity on backward linkages. They show several specifications, including one including tradable service industries and some using instrumental variables.

We use these results to derive reasonable lower and upper bounds for the effect of a slowdown in trade on productivity (table 9, see appendix D.1 for details). For the lower bound, we use the lowest coefficient reported by Constantinescu, Mattoo, and Ruta (2019) and apply it for manufacturing industries alone. Perhaps unsurprisingly, the slowdown in labor productivity explained is close to zero in each country. For the upper bound, we take the largest coefficient documented in Constantinescu, Mattoo, and Ruta (2019) and apply it to manufacturing and tradable services industries, thus capturing a larger share of the economy and making any potential effect mechanically larger. Here, we explain 0.26 pp of the labor productivity slowdown in the United States, and around 1 pp in Japan and the United Kingdom, which would appear very high. France is the only country not substantially affected. The low contribution of trade to explaining France's TFP slowdown, which was large, and the large contribution to explaining Japan's TFP slowdown, which was very low, suggests that

TABLE 9
Slowdown in Backward Linkages and Labor Productivity Growth

Indus.	Backward linkages		Elasticity	Productivity effect		
	1996–2005	2006–14	β^{GVC}	1996–2005	2006–14	Slowdown
France						
M	0.89	0.72	0.03	0.03	0.02	0.01
M&S	3.87	3.90	0.24	0.95	0.96	−0.01
Germany						
M	2.15	1.58	0.03	0.07	0.05	0.02
M&S	7.39	5.00	0.24	1.81	1.23	0.58
Japan						
M	1.53	1.76	0.03	0.05	0.06	−0.01
M&S	6.50	2.24	0.24	1.59	0.55	1.04
United Kingdom						
M	0.48	0.29	0.03	0.02	0.01	0.01
M&S	7.85	4.09	0.24	1.92	1.00	0.92
United States						
M	0.77	0.78	0.03	0.03	0.03	−0.00
M&S	5.32	4.25	0.24	1.30	1.04	0.26

Sources: Data retrieved from World Input-Output Database (WIOD), versions 2013 and 2016 (Timmer et al. 2015, 2022).

Notes: M denotes an aggregate for all manufacturing industries, and M&S an aggregate of all manufacturing plus tradable service industries, as listed in Constantinescu, Mattoo, and Ruta (2019). All values, except for the elasticity, are reported in percentage points (pp). See appendix D.1 for details.

this explanation may somewhat fail our scope criteria.

Another important issue with this explanation is its sequencing; growth in backward linkages was substantial in the years leading up to the financial crisis—2006 to 2008—and so the slowdown in backward linkages does not line up directly with the slowdown in labor productivity growth starting in 2005. Backward linkages also appear stable in the years before 2000 (see figure 7 in appendix D.1). Comparing the period 1996–2005 to 2006–14 still reveals some trends. The slowdown in trade is particularly pronounced when accounting for tradable service industries in Germany and the United States. When considering manufacturing industries only, the growth of backward linkages remains relatively stable. Again, this is partly an artifact of our choice of periods.

When summarizing our results in the conclusion, our estimate of the contribution of trade to the productivity slowdown will be the simple average between the lower and upper bounds, and we will use these bounds as our reporting of uncertainty.

6.4 *Regional Dispersion*

The economic geography literature often distinguishes between different types of agglomeration externalities, such as labor and input markets pooling, and knowledge spillovers, with an ongoing debate on whether these externalities operate within narrow sectors (as in Marshallian districts) or if diversity in large cities is a support to innovation. This provides several candidate mechanisms to explain the productivity slowdown. The changes in sectoral shares, geographical allocation of resources, and the nature of spillovers may collectively induce patterns that affect aggregate productivity. As with global trade, it is conceivable that large one-off gains from a better spatial organization of production have been reaped, explaining the slowdown as a "return to normal." Unfortunately, while there are a number of studies on regional disparities, there is a dearth of studies evaluating quantitatively how a specific mechanism contributes to the aggregate productivity slowdown.

An interesting fact is that in the last two decades, within-country regional dispersion has increased whereas OECD-wide dispersion has declined due to the significant catch-up from poor regions in Eastern Europe, Chile, and Mexico, mostly due to a specialization in tradable sectors (OECD 2018). Martin et al. (2018), in a rare attempt at dissecting the productivity slowdown at the city level, analyzed city-level data for the United Kingdom after 1971. They find that the shift toward service sectors has been a negative contributor to productivity, leaving manufacturing regions of the north more affected by this structural change. But their data also suggest that regions have converged in terms of their sectoral structure, and that within-sector productivity dynamics are largely responsible for the slowdown.

Thus, the limited available evidence available points to sector-specific dynamics, which we reviewed in section 2, and the role of trade, which we reviewed above. These are among the areas that would benefit from further research, for example, in evaluating whether the increasingly intangible nature of investment changes agglomeration economies and how this affects aggregate productivity.

6.5 *Summary*

In recent decades, trade integration has been associated with well documented gains in productivity through direct and indirect channels. It is likely that many of the gains from world allocative efficiency have already been reaped. If a large part of the possible trade integration has already taken place, a perceptible productivity slowdown would take place as a result of slowing integration. The decline in global trade after the financial crisis adds to the reduction in the positive impact of trade on productivity growth, suggesting that between 1996–2005 and 2006–17 the gains from trade fell substantially, and that this could have contributed to the productivity slowdown.

7. *Dynamism, Market Power, and Misallocation*

In recent years, there has been a growing concern that the decline in business dynamism, the increase in profits and concentration, and the increase in productivity dispersion are the symptoms of an underlying decline in competition and allocative efficiency.

We first review these facts, exploring some of the difficulties in methodologies and data that have led to contradictory results. We consider the case of the United States and also European countries, where the empirical evidence has been more mixed. To assess

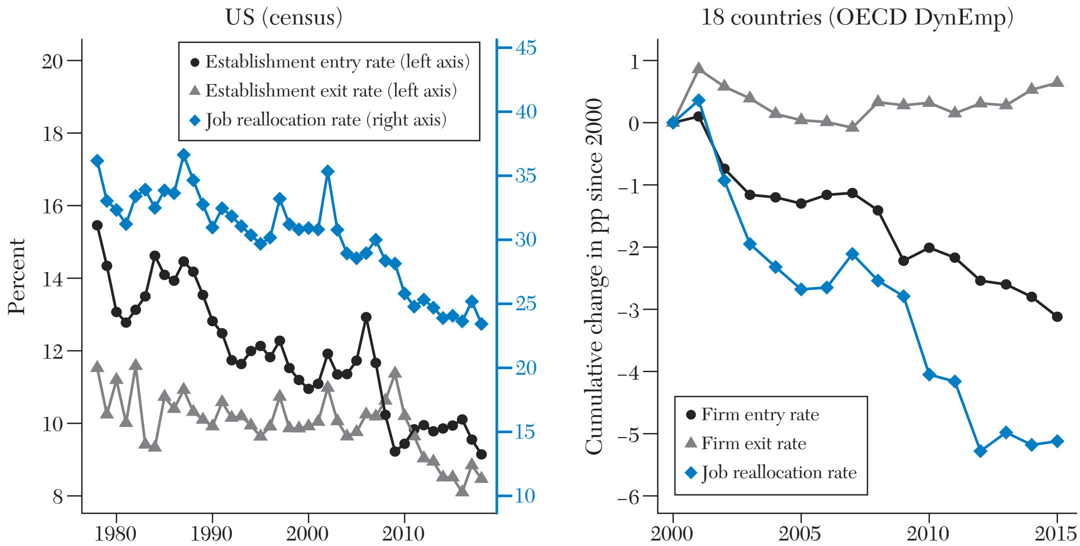

Figure 3. Business and Job Dynamism in the United States and 18 OECD Countries

Notes: Left: The US data is from the US Census Bureau "Business Dynamics Statistics" (Bureau of Labor Statistics 2021). The job creation (destruction) rates are computed as the number of jobs created (destroyed) in a given year t divided by total employment (averaged over t and $t-1$). The job reallocation rate is the sum of the job creation and destruction rates. Right: The OECD data is from the OECD's DynEmp3 database (OECD 2020). The entry and exit rates are for firms, not establishments. The data presented are the average within-country-sector trend of each variable, based on the year coefficients of within-country-sector regressions.

their quantitative impact on the productivity slowdown, we use a recently introduced decomposition of TFP growth into a residual and an allocative efficiency component that depends explicitly on estimates of the dynamics of firm-level markups and rates of profit (Baqaee and Farhi 2020).

7.1 *Business Dynamism*

In this section, we discuss the evidence for the two main indicators of business dynamism and reallocation: firm entry and exit rates, and job creation and destruction rates.

7.1.1 *Firms' Entry and Exit*

With the rising availability of micro datasets, a growing number of studies have pointed to a decline in business dynamism. Decker et al. (2014) first documented a decline in the share of employment in young firms.

Figure 3 (Left) shows the rates of (establishment) entry and exit, and the rates of job creation and destruction in the United States, showing a clear declining trend, although with a stagnation in the 2010s. Figure 3 also shows that at least before 2010, the exit rate was more or less constant, with the fall of net entry coming only from the fall of entry rates—a pattern also observed by Calvino, Criscuolo, and Verlhac (2020) across OECD countries (figure 3, right).

A slowing rate of entry could be an important element, as historically new firms have contributed disproportionately to growth. Using US administrative data (the Longitudinal Business Database data), Klenow and Li (2021) find that young firms (five years old or less) employ less than a fifth of the workforce but drive half of the total growth.

In terms of sectoral specificities, Decker et al. (2020) find that while the decline appears secular at an aggregate level since the late 1980s, it hides a substantial boom and bust in the high-tech sector in the period 1995–2005, which coincides with the labor productivity revival for the United States.

Calvino, Criscuolo, and Verlhac (2020) report similar results for other countries. Using the OECD DynEmp3 database[19] and, looking at the trends within each sector and each country, they find that entry rates and job reallocation rates have fallen by 3 to 5 pp during 2000–2015. Although there is some sectoral heterogeneity, the aggregate decline is driven by a decline within each sector, rather than by reallocation toward low-dynamism sectors (in fact, the "between" term tends to be positive). There is also substantial heterogeneity across countries; for the two countries on which we focus here and that are covered by DynEmp3 (France 2000–2012 and Japan 2000–2014), the decline in entry rate is at most 1 pp.

Several explanations for lower dynamism have been put forward. Calvino, Criscuolo, and Verlhac (2020) explicitly investigate the role of intangibles, and find that intangible intensive sectors are those with the largest fall in dynamism. A separate and fairly mechanical explanation is simply that population growth is slowing down (Hopenhayn, Neira, and Singhania 2022). During the baby boom, many firms were created as both supply and demand for labor grew. These firms grew and aged. Since population growth has slowed down, entry slowed down, and since large and old firms are less likely to exit, exit slowed down, explaining the lower dynamism.

7.1.2 *Job Creation and Destruction*

Another indicator of falling dynamism is the rate at which people change jobs. Hyatt and Spletzer (2013) document that in the United States, hires, separations, job creation, job destruction, and job-to-job flows have all declined since the late 1990s, in a staircase fashion (stable during normal time and falling during recessions). About half of this decline is due to the decline in single-quarter jobs and compositional effects (such as an aging population). Figure 3 shows the evolution of the job reallocation rates in the United States and in the countries covered by the OECD DynEmp3 database. The decline since 2000 is quantitatively substantial.

Lui et al. (2020) use administrative data to study business dynamism in the United Kingdom during the period 1999–2019. Their main result is that job creation and destruction rates have decreased, when comparing pre- and post-financial crisis periods. The strongest effect is from a decrease in job destruction from exiting firms, consistent with an increase in employment and with the idea that the financial crisis did not have a large "cleansing effect," as more firms were allowed to survive.

7.2 *Market Power*

Establishing an increase in market power or a decline of competitive pressure is always difficult, and often needs to rely on convergent evidence from three main indicators: rising concentration, rising markups, and rising profits. While there is evidence for each of these, there are also methodological

[19] Which covers 18 countries: Austria, Belgium, Brazil, Canada, Costa Rica, Denmark, Finland, France, Hungary, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, and Turkey.

debates. The evidence also does not appear to be as strong in all other advanced economies as it is in the United States. Beyond the methodological debates and the geographical heterogeneity, a key question is whether the trends in indicators of market power are good or bad for output and productivity. We next discuss the empirical evidence for each of the three sets of indicators, and then discuss how these trends fit together and what they imply for the productivity slowdown.

7.2.1 *Concentration*

All concentration metrics attempt to measure the weight of the largest players in a given market or industry. Implementing this in practice involves defining what the relevant market or industry is, in terms of competition. Another difficulty is to define the relevant entities, as cross-ownership between firms can lower competition while not visibly increasing concentration.

Industry-Level Patterns.—Using data on publicly listed firms from CRSP/Compustat, Grullon, Larkin, and Michaely (2019) document that over the period 1972–2014, concentration declined in the 1980s, reaching its lowest point in the mid-1990s, and subsequently increased by 70 percent. Census-based data is not available to confirm the 1970–80s decline, but for the period where it is available (1997–2012), Grullon, Larkin, and Michaely (2019) find that most industries featured an increase in concentration (measured by CR4, and often substantial). It is not clear whether the decline of the 1980s is also borne out by census data, as Covarrubias, Gutiérrez, and Philippon (2020) report relatively flat trends for CR8 the period 1984–92, which is based on SIC-4 industry codes instead of the North American Industry Classification System (NAICS) codes used after 1997. Ganapati (2021) reports increases in CR4 during the 1980s.

Outside of the United States, in a comprehensive recent study, Bajgar et al. (2019) use two different datasets. Their first dataset is representative, based on firm-level administrative data from participating OECD countries, but does not make it possible to aggregate firms based on ownership. They find that concentration, expressed as the share of sales by firms in the top decile, increased by about 2 pp between 2001 and 2012. These results are relatively robust, but the level of this measure of concentration is around 82 percent, so a change of 2 pp is not a very large change.

Their second dataset is an extended version of Orbis, which contains a large number of firms and, once merged with Zephyr, makes it possible to aggregate sales based on ownership links since 2000. The main issue is that because the coverage of the data increases over time, the largest firms are always in the data but smaller firms are added over time, so concentration will mechanically decrease when computing the size of the industry from the firm-level dataset. To deal with this issue, Bajgar et al. (2019) use industry-level data derived from national accounts (OECD STAN) as the denominator of their concentration metric, typically the sales of the 8 largest firms divided by the size of the industry (CR8). They find that the share of the top 8 firms is 4 pp higher in 2014 than in 2000 in Europe, and 8 pp in North America. This is substantial, amounting to between 16 to 28 percent of the initial concentration levels depending on the region (Europe and North America) and concentration metric (CR4, CR8 and CR20). Figure 4 (right) shows country-level concentration ratios obtained as unweighted averages of the (available) industry-level concentration ratios (CR8) computed by the OECD. The pattern of increasing concentration is

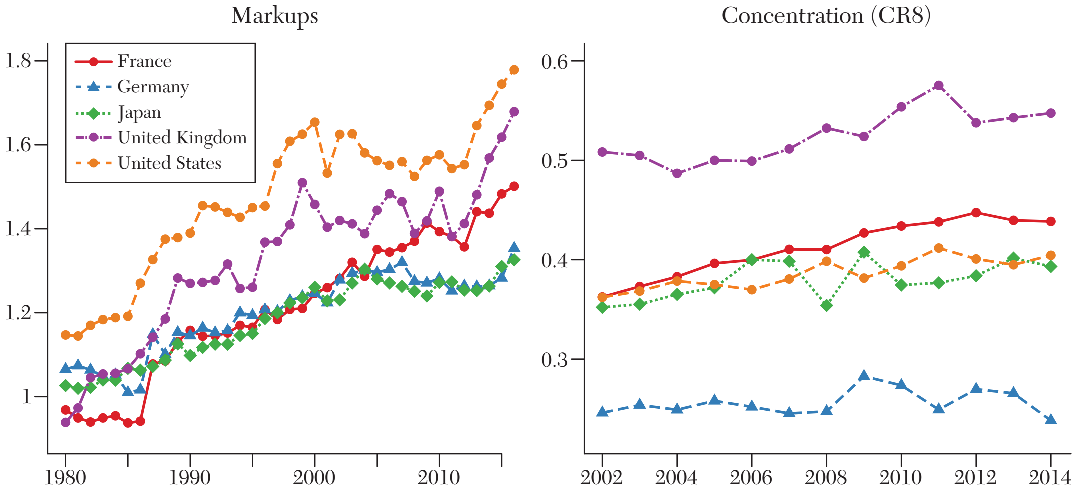

Figure 4.

Notes: Left: estimates of markups by De Loecker and Eeckhout (2018). Right: Country-level unweighted averages of available industry-level estimates of concentration (CR8), based on data from OECD (2021b).

clear and substantial, with the exception of Germany.

Bajgar's et al. (2019) results would have been different if they had used a measure of industry size derived from the (changing coverage) firm-level database, unconsolidated data, or data not cleaned manually (using, e.g., annual company reports), see for instance Cavalleri et al. (2019).

The Issue of Market Definition.—An issue with these studies is that they consider fairly large markets (often at best four-digit NAICS, nationally). What if we instead consider that competition takes place at the local level, so that this is the appropriate level at which we should compute concentration metrics? Rossi-Hansberg, Sarte, and Trachter (2020) use the National Establishment Time Series (NETS) database, which covers the universe of US firms and their establishments. They document that while concentration has increased nationally, it has *declined* locally, and the decline is stronger at narrower geographical definitions of markets. The divergence between national and local trends is stronger in industries where transport costs matter more (e.g., retail trade in contrast to manufacturing). Rossi-Hansberg, Sarte, and Trachter (2020) reconcile these diverging trends by documenting a pattern though which the largest firms open new establishments at the local level. However, Ganapati (2021), using census data, finds that concentration (CR4) at the county level increased, while it was almost flat at the zip code level. It remains unclear whether the concentration increase or decline at the local level is due to differences in datasets, but we can definitely conclude that looking at concentration at the subnational level substantially mitigates the strong results obtained at the national level.

Another recent study (Affeldt et al. 2021) addresses the issue of market definition, using data on 20,000 product and geography specific markets, as defined by the European Commission while investigating 2,000 mergers between 1995 and 2014. Affeldt et al. (2021) find that concentration has increased on average, and that it has increased more in broad than narrow markets and more in service than manufacturing sectors. Because the dataset is limited to markets that have been scrutinized, it is not obvious that the trends are representative of the whole economy, despite Affeldt et al.'s (2021) attempt to correct for the selection bias. However, it is interesting to note that within scrutinized markets, the positive correlation between intangible investment rates (intangible gross fixed capital formation/value added (GFCF/VA)) and concentration holds much more strongly for markets that the European Union has defined at the worldwide rather than national level, in services rather than manufacturing industries, and in the first rather than second decade of 1995–2014. These studies suggest that an aggregate relationship between an increase in concentration and an increase in intangible investment may be driven by specific markets. Other studies have reported sectoral heterogeneity. For instance, Bajgar et al. (2019) find that the increase in concentration is most pronounced in nonmanufacturing sectors, and Autor et al. (2020b) find that industries with an increase in concentration also tended to experience faster technical change, measured as an increase in patents per worker, but slower diffusion, measured as a drop in the speed of citations, that is, share of citations received within five years.

Good versus Bad Concentration.—We will repeatedly come back to the issue of determining whether observed trends in indicators of market power are good or bad for productivity. Covarrubias, Gutiérrez, and Philippon (2020) summarize two opposite views as follows. On the one hand, it is possible that thanks to "technology," more productive firms are getting a greater and greater market share. This can be because consumers are becoming price elastic (perhaps because online shopping makes price comparison easier), so lower-cost firms take on larger market shares (Autor et al. 2020b), or this could be because there exist increasing returns to scale, so larger firms keep growing and becoming more efficient. In this last case, productivity dispersion also increases. On the other hand, it is possible that successful firms are increasingly able to erect barriers to entry and extract rents, perhaps thanks to lobbying and regulation (Philippon 2019). Covarrubias, Gutiérrez, and Philippon (2020) list the opposite predictions of each theory and conclude that, while there may have been some "good" concentration in the 1990s, as is often reported for the positive productivity effects of consolidation in the retail trade industry, for the last 15 years the data suggest that concentration is "bad": most strikingly, they find that exit rates have not increased, the cross-sectional correlation of changes in concentration and TFP growth is negative, and investment rates have declined. Still, one piece of empirical evidence submitted by Autor et al. (2020b) in support of their theory is hard to ignore: when looking at firms within an industry, the change in the aggregate labor share is driven mostly by reallocation—competition driving concentration into superstar firms—rather than by a change in firm-level markups or labor shares.

We will discuss these issues below—for now, we note the reduced-form direct evidence for the United States provided by Ganapati (2021) using administrative data. Using industry-level estimates of concentration based on US census data, he finds that concentration increases are *positively* correlated to productivity, and that the strength of the relationship is not lower (or reversed) in recent years.

In summary, while there is evidence of an increase in concentration, the trend is less clear-cut if we consider local rather than global markets, and appears smaller in Europe than the United States. In the United States, there is a consensus that the increase in concentration has been associated with an *increase* in productivity during the 90s, but whether continued rising concentration has still been good after 2000 is a subject of debate.

7.2.2 *Profits*

If market power has increased, we should expect firms to extract more "pure profits," that is, above and beyond the "normal" cost of capital.

A simple approach is to look at the profit rates from national accounts. Figure 2 shows the capital share of income, as in Covarrubias, Gutiérrez, and Philippon (2020) and Philippon (2019), but using KLEMS. The post-1995 trend is clearly upward in the United States but rather flat in Europe and declining in Japan.

An issue with business or national accounts profit rates is that they do not distinguish between "pure profits," and "normal" payments to capital. If we can construct a reasonable measure of the cost of capital, then we can infer pure profits by substracting labor and capital costs from income. This is the approach followed by Barkai (2020), using National Accounts data for the United States coupled with estimates of the debt and equity costs of capital. Barkai (2020) found that the "pure profit" share of income rose from −5.6 percent in 1984 to 7.9 percent in 2014, a substantial increase that more than explains the fall of the labor share, so that the share of income attributed to "normal payments" to capital, in Barkai's estimates, is also falling.

Attempting to replicate Barkai's (2020) methodology for France, Germany, Italy and Spain, Salas-Fumás, San Juan, and Vallés (2018) find that, for 1995–2016, the pure profit share of value added rose only in Germany, while for other countries, the trend is flat or buried in substantial fluctuations—perhaps unsurprisingly since pure profit is computed as a residual, and evaluating the cost of capital requires using financial variables, which are notoriously volatile.

In fact, as pointed out by Karabarbounis and Neiman (2019), the income that cannot be traced directly to labor or capital costs, being a residual, is therefore not necessarily pure profit but also carries measurement errors from each of the terms. They write

$$\text{Factorless income} = Y - wL - rK,$$

where $rK = \sum_j r_j K_j$ and r_j and the rental rate of type j capital is computed using an extension of the classic formula of Hall and Jorgenson (1967) for the user cost of capital and is a function of depreciation, risk-free rates of return, capital prices, and tax rates on investment and capital.

A key finding of Karabarbounis and Neiman (2019) is that, while factorless income has increased in recent years, it is lower today than it was in the 1960s and 70s. This makes it difficult to link factorless income to the current productivity slowdown unless we can show that the source of factorless income has changed over time.

Karabarbounis and Neiman (2019) consider three sources for factorless income: pure profits, mismeasurement of what constitutes capital K_j (intangibles in particular may be missing), and misevaluation of rental rates r_j. Karabarbounis and Neiman (2019) assume that the labor share is well measured.[20] They then compute that, to account for all of the factorless income, unobserved capital would need to be around 30–60 percent of the entire capital stock, depending on the period. To explain all of the factorless income using alternative rental rates, the risk premia would have to have increased substantially since 1980. Overall, Karabarbounis and Neiman (2019) appear to favor the rental rates explanation, while acknowledging that mismeasured capital stocks may contribute significantly to factorless income. They remain critical of the pure profit interpretation, as factorless income is tightly negatively correlated with risk-free interest rates at both low and high frequency, which they find hard to explain theoretically.

Chen, Los, and Timmer (2018) consider factorless income in the international context, noting the difficulty of attributing income from intangibles to national income (even if profit shifting is not an issue). They start by computing the value-added contribution of each industry-country in a GVC. Using this decomposition, it is possible to deduce payments to unmeasured intangibles directly by assuming that payments to labor are correctly measured, profits are null, and payments to tangible capital can be retrieved using observed volume measures and a standard rental rate (e.g., 4 percent in their baseline results). Then, payments to intangibles are simply a residual. Using this method, Chen, Los, and Timmer (2018) found that the share of payments to intangibles in income is high (about twice that of payments to tangible capital, 30 versus 15 percent), and increased substantially during the period 2000–2007 (around 4 pp), remaining roughly stable after that. The increase in the share of intangibles in income is most pronounced for durable goods, perhaps because GVC fragmentation is easier and has been more intense than for nondurables. More generally, they conclude that the early 2000s were exceptional, with a decline of labor costs through offshoring, compensated by an increase in income to intangibles.

In sum, while there is evidence of an increase in the share of payments to capital, it appears stronger in the United States than in Europe, and the sources of this increase are likely to be both pure profits and also payments to unmeasured capital. Separating the two requires using fairly volatile financial variables and/or measuring "unmeasured" intangible capital stocks, so we can hardly expect precise estimates. This leads us to an alternative approach.

7.2.3 *Markups*

Before discussing measurement issues and empirical results, we provide simple theoretical relationships between markups and the other indicators of market power (profits, and concentration).

Markups, Profit Rates and Economies of Scale.—Markups, defined as price P over marginal cost MC and denoted μ, are directly related to profit rates (defined as total profits over revenues). For any technology where we can write a total cost function $C(Q)$, we have (De Loecker, Eeckhout, and Unger 2020, equation (15)).

[20] This assumption is in sharp contrast to the findings of Koh, Santaeulàlia-Llopis, and Zheng (2020), who argue that the labor share decline in the United States can be entirely accounted for by the accounting assumption about factor payments, in the case of ambiguous income from intangibles. Specifically, expenses in intellectual property products have been capitalized only recently, leading to an upward adjustment of GDP. To make up for this increase in GDP computed from the expenditure side ($GDP = C + I + G + X - M$), one must attribute new income to either labor or capital ($GDP = wL + rK$). The BEA attributes all income to capital, but Koh, Santaeulàlia-Llopis, and Zheng (2020) argue that it would have made sense to attribute some of it to labor, perhaps because R&D workers are paid with equity; reasonable choices for the proportion would have led to a non-declining labor share.

$$\pi = \frac{PQ - C(Q)}{PQ} = 1 - \frac{AC}{\mu MC}, \tag{5}$$

where AC denotes average unit cost and Q denotes the number of units sold. If we further write that the ratio of average to marginal cost, denoted γ, represents scale elasticity (that is, is greater than 1 if marginal cost is less than average cost), we have (Basu 2019, Syverson 2019, Barkai 2020).

$$\mu(1 - \pi) = \gamma. \tag{6}$$

Thus, under constant returns ($\gamma = 1$), we can deduce μ if we know π and the other way around. Our estimates of the contribution of allocative efficiency to the productivity slowdown will rely on this identity.

To understand the rise of market power in recent decades, however, one would prefer not to assume constant returns. Specifically, several recent papers have argued that intangible capital, and particularly information technologies, constitute a fixed cost that also makes it possible to reduce variable costs (De Ridder 2020). Using firm-level administrative data from France, Lashkari, Bauer, and Boussard (2019) find that larger firms have higher ICT intensity, suggesting that the marginal product of ICT investment rises with size.

If fixed costs rise and this implies greater economies of scale, firms need to charge a higher markup over *marginal* cost to be able to recover their total costs. Equation (6) reflects this: if economies of scale γ increase, an observed increase in the markup μ does not necessarily imply that the pure profits rate π has increased.

Markups and Concentration.—In models with oligopolistic competition, we expect markups and concentration to be positively related. Burstein, Carvalho, and Grassi (2020) validate such a prediction on firm-level administrative data from France.

Issues in Measuring Markups.—How can we then measure markups while allowing for nonconstant returns to scale? The key problem in measuring the ratio of price over marginal cost is that we observe neither prices nor marginal costs. The leading method, based on the cost approach introduced by Hall (1988) and developed for firm-level observations by De Loecker and Warzynski (2012), relies on first-order conditions for a single input, in a cost function with generally positive fixed costs. At the optimum, the markup μ_{it} of a cost-minimizing firm i at time t should satisfy

$$\mu_{it} = \frac{P_{it}}{MC_{it}} = \alpha_{it} \times \frac{P_{it}Q_{it}}{P_{it}^V X_{it}^V} \tag{7}$$

where P_{it} is unit price, MC_{it} is marginal cost, Q_{it} is the volume of output, P_{it}^V and X_{it}^V are unit price and quantities of variable inputs, and α_{it} is the elasticity of output (quantity) to variable input (quantity). Note that all quantities are indexed by i and t, but the parameter α_{it} is often estimated at the sectoral level.[21]

This approach, followed by De Loecker, Eeckhout, and Unger (2020) and De Loecker and Eeckhout (2018), requires a production function-based estimate of α, which is difficult to obtain in the absence of price information, and the ability to separate variable from fixed costs, which are difficult to derive from available financial statements. We will discuss each of these issues below. Figure 4 shows the time series obtained by De Loecker and Eeckhout (2018) for the countries on which we focus here. The increase since 1980 is quantitatively very large, with markups going from about 1 to 1.7 for the United Kingdom, for instance.

[21] We largely omit the discussion of sector-level estimates of markups, since the dynamics of the within-sector dispersion of markups is of crucial importance for determining the impact of allocative efficiency. We simply note here that Hall (2018) estimates that the aggregate markup grew from 1.12 in 1988 to 1.38 in 2015.

This methodology has attracted a number of criticisms. First, it requires firm-level data. For instance, the study of De Loecker and Eeckhout (2018), on which figure 4 is based, uses Worldscope, a database of harmonized financial statements for 70,000 (mostly publicly listed) firms, in 134 countries. In their paper focused on the United States, De Loecker, Eeckhout, and Unger (2020) use mostly Compustat, but show that using census data where this is possible (manufacturing, wholesale, and retail) leads to similar patterns.

A second issue is that financial accounting does not cleanly distinguish between fixed and variable costs. In Compustat, total costs are split between capital costs and operating expenses, which are themselves split into costs of goods sold (COGS) and selling, administrative, and general (SG&A) (and a small residual category). De Loecker, Eeckhout, and Unger (2020) use COGS, which typically comprises material costs and production workers' salaries as variable costs, and SG&A, which typically includes administrative, management marketing, and R&D as "overhead" cost. This choice has been debated. Traina (2018) and Karabarbounis and Neiman (2019) found that, using total operating costs instead of COGS only, markups have not increased over the long post–World War II period, although there is an increase between the low point of 1980 and today, from about 1.1 to 1.15 in Traina's (2018) study. In response, De Loecker, Eeckhout, and Unger (2020) maintain that COGS is a better measure of variable costs and SG&A represents overhead costs.

A third issue in implementing equation (7) concerns the estimation of α, the elasticity of output (quantity) to variable input (quantity). Firm-level financial statements provide data on revenues and expenses, but not on prices and quantities separately. Estimating a revenue production function identifies the elasticity of revenue to variable input expenses, not the elasticity of output to variable inputs. These issues have been widely discussed since Klette and Griliches (1996), and while De Loecker, Eeckhout, and Unger (2020) follow state-of-the-art approaches, identification rests on debatable assumptions (Doraszelski and Jaumandreu 2019, Bond et al. 2021).

Recent Empirical Results.—Leaving aside these limitations and taking markup estimates at face value, how do they relate to other macroeconomic patterns and what do they imply for the productivity slowdown? First, we return to the question of pure profits: De Loecker, Eeckhout, and Unger (2020) found that while part of the increase in markups is due to an increase in fixed cost—the increase in SG&A documented by Traina (2018)—there was also a rise in pure profits, which they take as conclusive evidence of rising market power. Furthermore, the aggregate increase in profits, which can be obtained by sales weighting the sum of equation (5) over all firms, produces an estimate that is roughly consistent with the independent estimates of the increase of pure profits from Barkai (2020).

Second, is this rise in aggregate markups due to a compositional effect or to an increase in markups in all firms? This is perhaps the most important question for understanding the consequences of the rise in markups on productivity. If all firms increase their markups, this might be a sign of a decline in competition; if instead the aggregate markup increases because the firms with a high markup are getting bigger, this could be a good sign. This is, in essence, the superstar firm theory of Autor et al. (2020b) and De Ridder (2020): high intangible-intensity firms have a high fixed cost and low variable cost. These high economies of scale lead them to have high markups, but also to be very competitive and gain market shares. To recall, Covarrubias, Gutiérrez, and Philippon

(2020) refer to this as the γ theory of "good" concentration: economies of scale imply that more concentration should increase industry-level productivity. They distinguish it from another theory of good concentration, which they call σ: recent developments in ICT, such as e-commerce, make it easier to compare prices and thus increase product substitutability σ. Firms that previously had some monopolistic power, perhaps because they were facing a captive local market, now compete on the global marketplace. As a result, the high-productivity, low -ariable cost, high-markup leaders of this market grow faster than the rest. We would observe increasing concentration, increasing markups, but perhaps not necessarily increasing pure profits, and in principle favorable effects on productivity.

For the United States, the evidence is relatively clear that aggregate markups have increased due to compositional effects: De Loecker, Eeckhout, and Unger (2020) and Baqaee and Farhi (2020) find that this is mostly driven by a reallocation toward high-markup firms, rather than an increase of markups within each firm; but there is also evidence that the increase in aggregate markups is due to individual firms increasing their markups, and De Loecker, Eeckhout, and Unger (2020) document that this part is concentrated among high-markup firms. In short, most of the increase in the aggregate markup is due to high-markup firms increasing their markups and also getting bigger.

Turning to international evidence, a number of other studies have found a rise in markups, albeit somewhat weaker than in De Loecker, Eeckhout, and Unger (2020). Using Orbis data for 26 countries, Calligaris, Criscuolo, and Marcolin (2018) found an increase in markups of around 4–6 percent over their sample period, 2001–14, with a substantial acceleration after 2005. The vast majority of the increase is due to firms in the top decile. In another study using Orbis for 20 countries, Díez, Fan, and Villegas-Sánchez (2021) also find an increase of around 6 percent between 2000 and 2015, mostly driven by advanced economies. Díez, Fan, and Villegas-Sánchez (2021) find that the overall increase in markups is driven by a within effect, mostly among the already-high-markup firms. Interestingly, while Díez, Fan, and Villegas-Sánchez (2021) can replicate, using Orbis data, the finding from De Loecker, Eeckhout, and Unger (2020) and Baqaee and Farhi (2020) that for US firms the rise in aggregate markups is largely due to reallocation, the reallocation component appears much weaker outside the United States, again with the within component at the top of the distribution being key. Similarly, Burstein, Carvalho, and Grassi (2020), using firm-level administrative data from France, decompose sector-level and aggregate markups into within and between components, finding that around two-thirds of the increase in markups is due to the within term.[22] An exception appears to be Japan, where Nakamura and Ohashi (2019) found little increase in markups between 2001 and 2015, and no evidence of superstar firms. This broadly agrees with the results from figure 4, which show only a small increase during this period.

This finding is of importance because the dynamics of the joint distributions of markups, size, and productivity are the main driver

[22] In contrast to De Loecker and Eeckhout (2018); Burstein, Carvalho, and Grassi (2020); and Baqaee and Farhi (2020) decompose the inverse of the markup, with the weights being sales share. Defining aggregate inverse markups as the sales share weighted sum of inverse firm-level markups maintains the relationship between profit rates and markups at all aggregation levels. Note also that Edmond, Midrigan, and Xu (2023) have found that defining aggregate markups as the cost-share weighted sum of markups reduces the estimate of the rise of aggregate markups, in comparison to De Loecker and Eeckhout (2018).

of the decomposition of TFP growth into allocative efficiency and technology that we use below. Because we have data only for the United States, we cannot conclude, just because markups are also rising outside the United States, that the decomposition would be similar there. But to get to our own estimate of the contribution of changes in markups to the productivity slowdown, we first need to discuss the literature on misallocation and the evolution of productivity dispersion.

7.3 *Dispersion and Misallocation*

Even within fine-grained industries producing relatively homogeneous products, productivity differences are large and persistent. Intuitively, if some firms are much more productive than others, reallocating production factors from low- to high-productivity firms, holding everything else constant, would improve productivity. In recent years, a growing number of studies seek to quantify allocative efficiency and shed light on the productivity slowdown directly.

7.3.1 *The Divergence of Superstar Firms*

Andrews, Criscuolo, and Gal (2019), using the Orbis data for 24 OECD countries between 1997 and 2014, compare productivity patterns in firms at the top (the 5 percent most productive in each year, that is, allowing the identity of firms at the frontier to change every year), and the rest, at the level of each two-digit NACE/ISIC industry. Firms at the top, which are 3 to 4 times more productive, are much more capital intensive and pay higher wages. They do not necessarily tend to have more employees; this depends on whether productivity is total factor or labor productivity, and whether the industries are in manufacturing or services.

Andrews, Criscuolo, and Gal's (2019) key finding is that dispersion has increased between 2001 and 2014. This divergence is stronger in services, and substantially stronger before the financial crisis than after. The divergence in labor productivity appears mostly driven by a divergence in TFP (rather than in capital intensity), particularly for manufacturing.

They further find, consistent with Autor et al. (2020b), that frontier firms increased their market share, and document that this pattern is stronger in ICT and data services. This is consistent with the idea that diverging productivity of superstar firms is due to an increase of the share of fixed costs, with economies of scale driven up by very low marginal costs for producing information goods and services, and network externalities typical of platform economies. However, an increase in the market share of top-productivity firms does not necessarily imply an increase in concentration, unless the most productive firms are also the largest.

Is the increase in dispersion surprising or worrying? After all, if firms' productivity follows a geometric random walk with drift, all with the same parameters, dispersion would increase naturally, without this reflecting a change in economic behavior. To address this concern, Andrews, Criscuolo, and Gal (2019) measure the speed of catch-up over time by regressing firm-level TFP growth of the non-frontier firms on their distance to the frontier (in terms of TFP), allowing the coefficient to vary across subperiods and including controls and fixed effects. They do find that there is a positive catch-up rate, and that these rates of catch-up have declined. Furthermore, industries with an increasing dispersion have had a substantially lower aggregate productivity growth. The estimated coefficient, applied to the average annual increase in the gap (2.3 pp), implies growth of TFP lower by 0.6 pp per year. However, the decline of catch-up rates took place mostly before the financial crisis, therefore it does not easily explain the aggregate slowdown between pre- and post-financial crisis.

Due to the negative relationship between dispersion and aggregate growth, coupled with sluggish dynamism (they document a decline in churn at the frontier), Andrews, Criscuolo, and Gal (2019) interpret their results as a sign of lower competition, showing evidence that TFP divergence was higher in industries with lower pro-competitive product market reforms. Overall, while the evidence in Andrews, Criscuolo, and Gal (2019) points to the superstar firms hypothesis, with high-productivity firms gaining market shares and additional competitive advantage, it also suggests that catching up has slowed down, making (sectoral) aggregate productivity suffer from increasing dispersion. In other words, there are no contradictions between a "good" process being at play leading to reallocation toward more efficient firms, and a simultaneously "bad" process, where catch-up is slowing down, weighing down on aggregate productivity growth more than reallocation boosts it.

Unfortunately, several issues with firm-level productivity statistics remain. First of all, when the goal is to understand aggregate productivity, it is preferable to compute value added rather than gross output. However, there are typically a few percent of firms with negative value added (Haldane 2017, Yang et al. 2022), particularly during downturns. This makes it impossible to study TFP for these firms, and typically biases measures of productivity dispersion based on log-transformed variables (Yang et al. 2022). Fortunately, there are also a few studies that focused on low-productivity firms specifically.

7.3.2 *Zombie Firms*

In general, we expect downturns to have a "cleansing effect," with the least productive firms exiting first, leading to an increase in aggregate productivity. In the United States, using the Longitudinal Business Database, Foster, Grim, and Haltiwanger (2016) found that the while crises are usually marked by stronger than usual productivity-enhancing reallocation, this was not the case during the financial crisis.

McGowan, Andrews, and Millot (2018) defined zombie firms as firms that are unable to generate enough operating income to pay their interest expenses (the interest coverage ratio, i.e., the ratio of operating income to interest expenses, is less than one for three consecutive years). They use Orbis, covering eight European countries and South Korea, and find that large and old firms are more likely to be zombies, which may be due to preferential government subsidies to large firms for protecting employment or bank forbearance. Since the financial crisis, quantitative easing and the associated exceptionally low interest rates may have made this worse. Over time (2003–13), the prevalence of zombie firms has increased and their share of capital has increased. This leads us to discuss productivity dispersion, business dynamism, and ultimately misallocation.

7.3.3 *Productivity Dispersion and Business Dynamism*

Decker et al. (2020) relate productivity dispersion and business dynamism. They contrast two possible explanations for the fall of job reallocation. On the one hand, it is possible that there is less reallocation because less reallocation is needed, that is, all firms face productivity shocks that are more and more similar, so the economic rationale for moving workers from low- to high-productivity firms would have become weaker. On the other hand, it is possible that the dispersion of shocks has not changed, but firms simply do not react to these shocks as much as they used to, leaving economy-wide reallocation opportunities unmet. Decker et al. (2020) found that the dispersion of TFP shocks has increased, rather than decreased, and thus conclude that the falling rates of job reallocation are due to a lower responsiveness.

7.4 *Contribution of Allocative Efficiency to the Productivity Slowdown*

There are two broad approaches for decomposing aggregate productivity growth into "pure" technological change and an "allocative efficiency" component. The first approach, often called statistical, basically comprises variations of the shift share or within-between decompositions, including the extensive margin (entry-exit) or not. The second approach is model-based. It derives a comparative static result that relates changes to individual firms' TFP or markups to changes of aggregate TFP. Because they are based on equilibrium relations, these results show how a technology shock (for instance) leads to an improvement in aggregate TFP directly and through a reallocation of factor and input shares.

Baqaee and Farhi (2020) introduce a general equilibrium model with a production network and markups, allowing them to quantify both misallocation (that is, the overall distance to an ideal situation) and the change in allocative efficiency (that is, the contribution of changes in resource allocation to TFP growth). They derive an equation that decomposes a distorted (i.e., markup-corrected) version of the Solow residual into an allocative efficiency component and a pure technology component (firm-level TFP growth). Baqaee and Farhi's (2020) model clarifies a key point about how the specific empirical pattern of markups relates to misallocation. To recall, aggregate markups have increased for two main reasons: the top markup firms have increased their markups, and the top markup firms have gained market shares. These two effects have different consequences. On the one hand, the increase of markups at the frontier has increased the dispersion in markups, making potential gains from removing markups higher—misallocation, in this sense, has increased. On the other hand, the reallocation of sales toward high-markup, high-productivity firms has increased allocative efficiency.

In a calibration to the US economy, Baqaee and Farhi (2020) find that between 1997 and 2014, changes in allocative efficiency contributed about half of the growth of TFP. Was this contribution constant? In other words, if half of cumulative TFP growth was due to contributions from allocative efficiency, how much of the *slowdown* of TFP growth was due to changes in the contributions of allocative efficiency? We next address this question.

Baqaee and Farhi (2020) assume a constant returns to scale cost function of the for $\frac{1}{\mathcal{A}_i}\mathcal{C}\big((1+\tau_{1i})p_1,(1+\tau_{2i})p_2,\dots\big)$, where $\mathcal{A}_i$ is a Hicks-neutral TFP growth factor, and the wedges τ_{ki} can be thought of as distortions in general (a tax or anything that prevents producer i from considering the actual price p_k, and forces it to consider the distorted prices $(1+\tau_{ki})p_k$ instead). They consider that the wedges come from markups from intermediate producers, allowing them to calibrate their model using data derived from the recent work on the evolution of markups reviewed above. Baqaee and Farhi (2020) derive that, under cost minimization, the following aggregate decomposition of TFP holds to first order:

$$(8)\qquad \underbrace{\Delta\log Y_t-\tilde{\Lambda}'_{t-1}\,\Delta\log\mathcal{L}_t}_{\Delta\text{Markup-corrected Solow residual}}$$

$$\approx \underbrace{\tilde{\lambda}'_{t-1}\,\Delta\log\mathcal{A}_t}_{\Delta\text{ Technology}}\underbrace{-\tilde{\lambda}'_{t-1}\,\Delta\log\mu_t-\tilde{\Lambda}'_{t-1}\,\Delta\log\Lambda_t}_{\Delta\text{ Allocative Efficiency}}$$

where Y_t is aggregate output, $\mathcal{A}$ and μ are vectors of producer-level TFP and markups, λ and $\tilde{\lambda}$ are vectors of revenue- and cost-based Domar weights of the producers, and Λ and $\tilde{\Lambda}$ are vectors of revenue-

TABLE 10
Contribution of Allocative Efficiency and Technology to the US Markup-Corrected Solow Residual, for the Two Periods and for the Slowdown, in Percentage Points

	Distorted TFP	Allocative efficiency	Technology
User cost of capital			
1997–2005	1.44	0.75	0.69
2006–14	0.33	0.09	0.24
Slowdown	1.11	0.66	0.44
Share of slowdown (percent)	100	60	40
Production function			
1997–2005	2.14	0.63	1.51
2006–14	0.58	0.22	0.37
Slowdown	1.56	0.41	1.15
Share of slowdown (percent)	100	26	74
Accounting profits			
1997–2005	1.74	0.37	1.37
2006–14	0.44	0.32	0.12
Slowdown	1.3	0.06	1.24
Share of slowdown (percent)	100	4	96

Note: Each block shows the results for a different approach to the computation of firm-level markups, see Baqaee and Farhi (2020).

and cost-based Domar weights for factors. $\mathcal{L}_t$ is a vector with the quantity of factors, in practice composition-adjusted labor and capital (see appendix D.2 for details). While the revenue-based Domar weights are defined as producer-level sales over GDP, the cost-based Domar weights need to be computed using information on the whole input-output network. Similarly for factors, while revenue-based Domar weights are factor shares, cost-based Domar weights, which are needed to compute the adjusted Solow residual, are distortion-corrected factor shares. Roughly speaking, the key insight here is that if all producers apply a markup along a supply chain, for a downstream producer the difference between price and "true cost" (i.e., as if all its upstream suppliers had no markups) depends on the depth of the supply chain.

Baqaee and Farhi (2020) compute each term of equation (8) for the period 1997–14 in the United States using input-output data from the BEA, output and input growth data from the Fed, and three estimates of firm-level markups using Compustat: an estimate based on the user cost of capital (from Gutiérrez 2017, following an approach similar to Karabarbounis and Neiman 2019 and Barkai 2020), an estimate based on production function estimates (following closely from De Loecker, Eeckhout, and Unger 2020), and an estimate based on accounting profits (Baqaee and Farhi 2020 assume constant returns to scale, so markups do not need to be estimated at the margin, and can be retrieved as revenue over total cost).

We retrieve the estimates from Baqaee and Farhi (2020), and use them to compute the contribution of each term to the *slowdown* in TFP growth between our two periods.

Table 10 shows the results. For each type of markup, the contribution of each term to TFP growth is reported for the two periods and for the slowdown. Perhaps unsurprisingly, it is difficult to arrive at a precise estimate for the contribution of allocative efficiency; this varies between almost nothing to more than half, depending on the kind of markups used. All considered, we conclude that a decline in the contribution of allocative efficiency to TFP growth has been a substantial reason behind the productivity slowdown.

There are two issues with the estimates in table 10. First, they were obtained using the aggregate input and output growth data from the original paper (Baqaee and Farhi 2020), taken from the Federal Reserve. However, we may have preferred to use our KLEMS data, or even inputs and output growth data that has been corrected for mismeasurement. Second, Baqaee and Farhi's (2020) decomposition is for the "distorted" Solow residual, rather than the Solow residual we have computed in section 2. It turns out that the allocative efficiency component does *not* depend on the aggregate output, capital, and labor growth data, but only on the input-output tables from the BEA and the estimates of markups. Thus, to explain the slowdown of TFP in our data, we propose to read the pp estimates for the column for allocative efficiency. These are 0.66, 0.41, and 0.06, which we average to give 0.38. In our summary table (table 11) at the end of the paper we will use 0.38 as our best estimate, and 0.06–0.66 for the range.

We do not have similar estimates for other countries. We do know, however, that the results for the United States are driven by the fact that markups are increasing and a substantial part of the increase in markups is due to a between-firm reallocation. We have discussed evidence that the increase in markups in other countries appears to have been driven less by reallocation (section 7.2.3), so perhaps the lower contribution of allocative efficiency to TFP growth as a source of the TFP slowdown is a less important channel outside the United States. Nevertheless, to offer an estimate for the other countries, we assume that allocative efficiency contributed to the same share of the slowdown as in the United States, that is about $0.38/0.91 \approx 41.5$ percent.

In all cases, our estimates come with considerable uncertainty. Two specific issues are that this framework assumes constant returns to scale and exogenous markups, which prevents us from engaging directly with the debate on good versus bad concentration and the nature of superstar firms. The results can nevertheless be taken as indicative of the fact that a large literature has documented interesting patterns of declining business dynamism, increasing concentration, and increasing divergence of top firms, with likely effects on productivity and its slowdown.

8. *Technological Progress*

In the previous sections, we made some progress in explaining part of the TFP slowdown: a decline in trade growth, a decline in spillover-generating investments, and a decline in the contribution of allocative efficiency. Can a slowdown in the quantity or quality of technological change explain the rest?

Indeed, the debate around the productivity slowdown is often presented as an argument between techno-optimists and techno-pessimists. Gordon (2016) argues that past waves of technological change, such as steam power, electricity, or the internal combustion engine, had a major but temporary impact on productivity. He argues that current new technologies, in particular digital, are unlikely to have such a significant impact, as they affect only specific aspects of human activity, such as communication and entertainment. Moreover, most of the productivity benefits of digitization may already have been harvested, through greater automation in manufacturing, retail, logistics and finance, in the late 1990s and early 2000s.

In contrast, Brynjolfsson and McAfee (2011, 2014) and Brynjolfsson, Rock, and Syverson (2019) argue that the ICT and AI revolutions are still in their infancy, and that it will take some time for their full potential to unfold. They argue that the technologies are still being developed, and that complementary investments, innovation, organizational changes and diffusion are needed before the full productivity potential of the ICT industrial revolution is realized. Mokyr's (2014) analysis, similar to Gordon's in that it is also rooted in extensive historical analysis, suggests that there are new technologies being currently developed that have the potential to become general purpose technologies (GPTs), enabling sustained productivity growth and welfare improvements arising, for example, from genomics. Pratt (2015) argues that the fusion of ICT with other new technological areas, notably robotics, will generate spectacular new gains in living standards.

In this section, we consider these arguments and investigate four sources of a potential decline of innovation or its effects on the real economy: the levels of investment in R&D and inventive activities, changes in research productivity, lags in the diffusion of innovations, and creative destruction.

8.1 *Research and Innovation Efforts*

R&D intensity (i.e., as a share of GDP) does not appear to have declined during 1995–2015. However, the composition of R&D has changed. We discuss the composition by source of funding and by research field. We briefly discuss whether changes to innovation policy or the concentration of R&D in specific countries or firms could have been relevant.

The OECD (2017) reports that aggregate R&D expenditures have not slowed dramatically across OECD countries after the recession, yet the level of funding by governments has plateaued since 2010. The decline in government investment has been offset by the increase in business R&D spending, accounting for more than 60 percent of total R&D expenditure in the OECD. While all types of research grew steadily in OECD countries both before and after the crisis, funding into basic science grew faster relative to applied and experimental research. This changing composition stems from a larger contribution from universities to R&D funding, although large variations persist between countries. Notably, expenses in basic science research performed by businesses in the United States has more than doubled between 2005 and 2015 (Mervis 2017).

What about the allocation of R&D by industry? Mervis (2017) uses data from the National Science Foundation to show that medical research funding by the US government has experienced the largest increase. This shift of funding toward the health sector may have impacts on productivity. On the one hand, a workforce in good health is more productive. In fact, to make this mechanism more explicit, it is arguable that we should extend national accounts so that public investment in the health system contributes to the growth of public intangible capital (Corrado, Haskel, and Jona-Lasinio 2017b). On the other hand, technological progress in health and pharmaceutical research is known to be increasingly costly and suffer from decreasing returns (DiMasi, Grabowski, and Hansen 2016), so this may not be the industry with the highest returns to R&D. In addition, improving TFP in one industry has a higher effect on aggregate TFP when the industry is upstream in the supply chain (Baqaee and Farhi 2019), but health and social work is one of the sectors with the lowest output multipliers (McNerney et al. 2022). In sum, it is possible that a dollar invested in health has both a lower direct impact (i.e., in terms of TFP in the industry where it is invested) and a lower indirect impact (i.e., in terms of how TFP in one industry leads to increase in aggregate TFP), but this warrants further research.

Policies play an important role in stimulating innovation. Edler et al. (2013) examined seven different sets of policy measures to stimulate the generation and dissemination of innovation by businesses and concluded that there are large differences in the effect of those policies. For example, policy measures can have different effects on the relative rate of "radical" versus "incremental" innovation. Meanwhile, some strategies like standardization and the introduction of production norms could have overall negative effects on innovation despite boosting productivity growth. Complicating matters further, the OECD (2017) finds substantial heterogeneity in the levels of tax incentives for R&D in different countries, and that the most innovative are not those with the highest tax incentives. However, changes in innovation do not appear to satisfy our sequencing or scope criteria, as no dramatic changes to innovation policy, common to our five countries, occurred prior to the slowdown.

The OECD (2017) revealed that commercial R&D is a highly concentrated activity, both across firms and across countries. Across countries, most of the high-impact research papers and patents are produced in only four or five countries, and within advanced economies the 50 businesses with the largest R&D expenditures on average account for around half of total business R&D spending. Veugelers (2018) points out that inequality in R&D expenditures has not increased in Europe and may have even slightly decreased before 2012. She notes that churn among the R&D leaders is low, yet whether this phenomenon is new is unclear.

An increasing share of global R&D is now performed in emerging economies. After the 1999 decision in China to accelerate economic development through innovation, R&D expenditures by firms located there rose from 0.5 percent to 1.5 percent of GDP between 2000 and 2013 (Boeing, Mueller, and Sandner 2016). According to the OECD (2017), China spends almost as much as the United States on R&D, in purchasing power parity terms.

Little is known about the impact of a changing composition of global R&D on productivity growth in advanced economies. Micro-level evidence for the United States suggests that firms enjoy spillovers from R&D done by other firms if they are close in the technological space, but suffer from R&D done by firms operating in similar markets (Bloom, Schankerman, and Van Reenen 2013). Thus, the effect of emerging economies R&D on advanced economies' productivity is unclear a priori.

Because both R&D and rates of adoption of specific technologies are procyclical, it has been suggested that lower technology adoption resulted from the financial crisis (Anzoategui et al. 2019), but this has not been demonstrated. Finally, Phelps (2013) argues that innovation started slowing down in the 1960s, after a period of mass flourishing. He attributes the slowdown in innovation to a change in values and institutions.

Overall, the growth in R&D expenditures has not slowed noticeably in the aggregate, although its composition may have changed. A larger share of R&D expenditure is being taken up by private businesses, and more is being allocated to the funding of basic science. There is also some evidence of reallocation in government research efforts to the health-care sector, with changes in the composition of innovation providing one potential source of a slowdown in aggregate productivity growth.

8.2 *Research Productivity*

While research efforts may not have declined noticeably, innovation rates could still be lower if research productivity declines. Here we discuss theoretical arguments regarding changes in research productivity as knowledge accumulates, and then turn to the empirical evidence.

One of the simplest arguments about research productivity is the fishing-out hypothesis: there is a fixed pond of ideas, and we are fishing the easiest out first. In other words, the low-hanging fruits have already been picked (Cowen 2011). Gordon (2016), for example, argues that many of the drivers of productivity in previous industrial revolutions were innovations that could only be made once and have a level effect, not a growth effect, on productivity. This argument applies to technological inventions such as steam and electricity, but also to non-technological drivers such as declining discrimination, urbanization, and the hygiene revolution.

In contrast, one can argue that knowledge should become easier to find as knowledge progresses because new ideas arise out of existing ideas. The rapidly rising global population of educated individuals, and the diversity of disciplines and perspectives, also creates the potential for more ideas to be generated. The more ideas there are, the more ideas can be found (Arthur 2009, Weitzman 1998). However, as the space of ideas expands, it may become increasingly hard to explore. Jones (2009) suggests that an expanding scientific frontier creates a "burden of knowledge," as generating original scientific contributions requires more and more knowledge. In support of this theory, empirical evidence suggests that (i) the age at which scientists and inventors make their most significant contributions has been increasing; (ii) the share of scientific papers and patents written by a team of multiple authors is increasing (Jones, Wuchty, and Uzzi 2008; Wuchty, Jones, and Uzzi 2007), suggesting that researchers cope with the increasing burden of knowledge by being more specialized and working in teams; and (iii) the likelihood of switching fields is decreasing, again suggesting that the burden of knowledge is creating higher barriers to entry into fields.

It has been argued that ICT, by making knowledge more accessible or by making science more automatable (see, for instance, King et al. 2009) could make research more productive. If we push the argument to the extreme, artificial intelligence could eventually lead to rising research productivity and an intelligence explosion (Bostrom 2017). Similarly, Mokyr, Vickers, and Ziebarth (2015) argue that the tools available for science and technology (especially ICT) can help search across information silos, store vast amounts of data, and analyze it at a fraction of the cost compared to a decade ago. These tools allow further combinations of existing resources and knowledge to be exploited in the future (Brynjolfsson and McAfee 2011). Yet, testing a number of macroeconomic implications of this "accelerationist" view, Nordhaus (2021) finds little evidence for it.

One method of determining research productivity is by using measures of research inputs per patent. Griliches (1994) is an early example, showing that the number of patents per researcher in the US economy has been on a more or less continuous decline for several decades. However, the OECD (2017) shows that research spending per patent is highly heterogeneous across countries. To test this hypothesis directly, endogenous growth models suggest that we need to determine whether a constant level of research effort leads to a constant growth in productivity (Bloom et al. 2020). Under this assumption, if research inputs stay constant, TFP should keep growing at the same rate. This hypothesis is overwhelmingly rejected, as is evident in the raw numbers: at best, TFP growth in the United States has been stable or even declining since 1930, whereas measured research input has increased by a factor of 23. In other words, while productivity keeps growing at a constant or even lower rate, the efforts to achieve this have been increasing. Anzoategui et al. (2019) suggest that a decrease in R&D productivity started in the early 2000s. Estimating a standard DSGE model extended to endogenize TFP growth as depending on innovation and adoption decisions, they find that the precrisis TFP slowdown starting around 2005 could be attributed to lags in the consequences of a decrease in R&D productivity.

The decline at the aggregate level could mask differences in research productivity trends at the micro level. The pharmaceutical sector is one area where declining research productivity has been emphasized. Research spending per drug has increased continuously and substantially, so much that it has been termed "Eroom's law," the letters reversing the large exponential increase in computing power termed Moore's law. Indeed, Bloom et al. (2020) confirm the decline in research productivity in medical research, and present similar evidence for agricultural yields and even for Moore's law itself, which was only upheld by a significant expansion in research effort. Repeating the exercise at the firm level and measuring research output as increases in sales, they find that research productivity increased only for a small fraction of firms. A large majority have seen their research productivity decline, sometimes substantially so.

Looking at new molecular entities specifically, Myers and Pauly (2019) put forward evidence for the low-hanging fruit hypothesis. Since the demand for medical products in increasing, the industry responds by increasing research effort; however, in a world where good ideas are researched first, the marginal productivity of R&D is declining so that increasing demand leads to lower average research productivity.

8.3 *Diffusion and Lags*

One explanation for the productivity paradox, by which productivity growth slows down despite accelerating innovation, is simply that it takes time for new technologies to diffuse, for companies and workers to adapt, and for complementary investments to take place.[23] For this explanation to meet our criteria, we first need to assume that an emerging GPT is underway and consider its impact to be associated with significant TFP growth.

This argument was put forward by David (1990), addressing Solow's observation that the benefits of computers were not yet evident in productivity numbers. David draws a historical parallel between the diffusion of the computer and the electrical dynamo during the electrification of the United States in the late nineteenth century. For both the dynamo and the computer, there were significant time lags between the first key inventions and their impacts on aggregate productivity. The key explanation is the prevalence of old technologies in the existing capital stock. First, old methods and capital remain more efficient during the initial phases of the GPT's development, so firms have no financial incentive to switch early to the new technology. Thus, investments to improve the GPT as well as complementary

[23] Improvements in technology can also have effects in the shorter run. Basu, Fernald, and Kimball (2006) argue that technological improvements are contractionary in the short run, due to a drop in utilization of existing capital and a reduction in investment. Inputs and investment recover with increases in output over the next few years.

innovations are needed before the new GPT becomes superior, while firms have little incentive to scrap existing capital. Such investments require time to make and are lumpy, so that improvements in the GPT itself can take decades, as was the case for the dynamo, which only superseded steam four decades after the first major inventions. Major productivity effects for firms occurred only when a complete reorganization of factories was realized. David (1990) also emphasizes inherent mismeasurement issues when new technologies are introduced.

The evidence for long lags is also documented in Gordon (2016), who argues that the revolutionary century following the US Civil War was made possible by the unique clustering of great inventions in the late nineteenth century, such as the railroad, the steamship, and the telegraph. These were followed by electricity, but also a range of inventions that changed lifestyles and improved the standard of living: canned food, electric refrigerators, sewing machines, public waterworks, X-rays, antibiotics, and others. For Gordon, the inventions since 1970 concern a narrow sphere of the economy having to do with entertainment, communication, and the collection and processing of information—by contrast to other goods and services like clothing, shelter, transportation, health, and working conditions, whose progress, he argues, slowed down after 1970.

While an assessment of the nature of technological change in different periods poses considerable challenges, many concur with Gordon in viewing productivity growth as successive adjustment of the levels ("one big wave" (Gordon 1999) or "the great leap forward" (Gordon 2016)), with each jump based on a different GPT. Are we in a new GPT?

Jovanovic and Rousseau (2005) review a number of patterns that are typically observed as a GPT emerges. Basically, we expect the economy to show signs of restructuring and innovative activity: firm dynamism increases, the number of patented inventions grows, initial public offerings take progressively younger firms to market, and investment by young firms increases relative to investment by old firms. Jovanovic and Rousseau (2005) also derive and test a number of other empirical predictions for the previous two GPT waves, which they mostly confirm for both waves: (i) the skill premium rises, since demand for skilled workers to enable the firms' transition increases; (ii) TFP growth slows at the beginning of the wave; (iii) entry, exit, and mergers of firms increase; (iv) stock prices fall initially as old capital depreciates in value; (v) younger and smaller firms do better than larger and older firms in terms of stock market performance and investment; and (vi) interest rates rise while the trade deficit worsens because of higher consumption. In considering these factors, they do not find that ICT technologies diffused faster than electricity, challenging arguments for current innovations having manifested themselves immediately.

What is the evidence for these facts currently? Regarding (i), the increase of wages at the very top has been linked to intangibles (Haskel and Westlake 2018), so perhaps the new economy does increase the skill premium for certain groups. Regarding (ii), TFP does slow down, but this is hardly evidence of the existence of a GPT by itself. Regarding (iii), as documented in section 7, there is little evidence for an increase in business dynamism currently; in fact there is considerable evidence of a decline of dynamism in the United States. Regarding (iv) the evidence rather points to high valuations, with market-to-book ratios (Tobin's Q) being higher than investment rates would suggest (Gutiérrez and Philippon 2017), although this may partly come from mismeasurement of investment and the book value of assets. Regarding (v), there is again some evidence against the idea that young firms are performing well; in section 7, we have seen that there is an increase in concentration, with large firms performing well. Regarding (vi), interest rates have been falling. All considered, if we are in a new GPT, its impact on firm dynamism is rather different from the impact of previous GPTs.

Bresnahan (2010) delivers an updated survey of the literature on GPTs, emphasising diffusion lags and the need for complementary innovation and investment. Furthermore, slow productivity growth in itself is not an unusual historical occurrence. Rather, periods of fast TFP growth are the exception. Without new technologies, TFP growth arguably comes from improved allocative efficiency, which by itself cannot sustain TFP growth rates indefinitely. Brynjolfsson, Rock, and Syverson (2019), reviewing existing explanations for the current productivity paradox, also conclude that lags in implementation are the most significant explanation. Similarly, Van Ark (2016b) supports the idea that the digital economy is still in its "installation phase," and productivity effects will occur once the technology enters the "deployment phase."

In sum, while we should expect long lags between the arrival of a GPT and its impact on productivity and digital technologies have the potential to revolutionize many aspects of economic life, it appears that other patterns associated with GPTs, business dynamism in particular, appear missing in recent years.

8.4 *Creative Destruction, Competition, and Faster Depreciation*

In addition to lags, there are reasons to believe that when a new technology is introduced, older capital depreciates faster. For instance, based on a few examples such as Amazon replacing brick-and-mortar bookshops, Komlos (2016) argues that creative destruction has accelerated. This suggests that one should use larger depreciation or scrapping rates, both in tangible and intangible capital, for technologies that are advancing more rapidly.

The review of the literature by Li and Hall (2020) suggests rates of depreciation of R&D capital ranging from negative rates to 100 percent a year. Their own methodology produces estimates ranging from 6 percent to 88 percent, depending on the sector and dataset. A recent study by de Rassenfosse and Jaffe (2018) examined the revenue stream associated with Australian patents, and estimated a rate of R&D depreciation between 2–7 percent. Overall, this suggests that there is a large degree of uncertainty regarding the stock of R&D capital, implying potentially large mismeasurement of TFP growth (for reference, the depreciation rate of R&D in table 6 is 0.2). Goodridge, Haskel and Wallis (2018), investigating the productivity puzzle in the United Kingdom using ONS data, compute an alternative series for various types of capital using alternate depreciation rates. Assuming higher post-2009 depreciation rates (multiplied by 1.5), they found that, under reasonable assumptions, this premature scrapping might explain up to 15 percent of their missing 13 pp of labor productivity growth in the United Kingdom.

While the argument for this in Goodridge, Haskel, and Wallis (2018) is motivated by the financial crisis, there is a more general theoretical argument: during phases of profound technological transformation, society as a whole has to adapt. During the previous industrial revolution, and again in the 1970s and '80s introduction of computing, it took a long time for firms and workers to adapt and for complementary innovations to develop (David 1990). As an example, consider AI and autonomous vehicles: not only may the education system need to be reformed to train people with the right skills, but other institutions such as contracts and the judiciary system need to be reformed, for instance to deal with the responsibility of autonomous nonhuman entities. Creative destruction makes entire branches of knowledge obsolete and requires new frameworks, as well as sets of institutions, including government regulations, but this is extremely hard to capture in the data.

An understanding of the role of creative destruction requires a deeper knowledge of what underpins the decisions to innovate and adopt new technology. A key consideration is the old debate regarding the relationship between competition and innovation, sometimes referred to as Schumpeter Mark I (where innovation is driven by creative destruction through new entrants and the key role of entrepreneurs) vs Schumpeter Mark II (where the large R&D labs of the incumbents are the main source of innovation), to reflect the evolution of Schumpeter's thinking on this question (Breschi, Malerba, and Orsenigo, 2000). Using firm-level panel data, Aghion et al. (2005) find evidence of an inverted U-shaped relationship between innovation (as measured by quality-adjusted patenting) and competition (as measured by one minus the Lerner index), suggesting an optimal level of competition for innovation. Studying the Intel and AMD duopoly, however, Goettler and Gordon (2011) argue that monopolies may have higher incentives to innovate, as they need to increase the quality of the existing stock to ensure the renewal of the market, but would be able to charge higher prices and harm consumer welfare. The link between innovation and competition may vary across industries, and in particular may depend on the degree of substitutability (Goettler and Gordon 2014).

More recent work has attempted to address the relationship between competition and innovation more specifically in the current context, as described in section 7, of lower business dynamism, higher concentration and markups, a shift to more intangible investment, and the divergence of superstar firms. A narrative that emerges across several papers is as follows. Because intangible investment changes the cost structure toward higher fixed and lower marginal costs, one should expect higher markups, to make up for higher fixed costs and because marginal costs are very low. Because this cost structure also implies larger economies of scale, we should expect higher concentration. Whether this generates higher aggregate productivity depends on whether catching up by low-productivity firms is muted, and whether large firms are able to erect barriers to entry and prefer rents over innovation investment once the market is concentrated.

In Aghion et al. (2023), the basic idea is that the United States experienced a wave of IT investment that lowered overhead costs, allowing firms to expand horizontally, increasing concentration, markups, and productivity in the process, but eventually leading to a situation where the resulting market structure deters innovation. Part of the shift toward intangible investment can be thought of as driven by exogenously falling IT prices. This is the case in Lashkari, Bauer, and Boussard's (2019) model, where, after documenting that IT *intensity* (i.e., the share of IT in all inputs) increases with firm size, they assume appropriately non-homothetic IT input demand, and show that the fall of IT price should then lead to a higher concentration, as large, high IT intensity firms become larger in equilibrium. In De Ridder's (2020) model, firms invest in R&D to improve on incumbents' quality, generating creative destruction and growth, but also invest in intangibles, which reduces their marginal cost. Together, these two forces are detrimental to productivity, as the cost of high-intangible firms becomes so low that it limits the incentives for new entrants trying to compete on higher quality. At this stage, R&D is not necessarily lower, but it is more concentrated, and thus less beneficial to aggregate productivity under a standard decreasing returns assumption. This issue of innovation concentration also features prominently in Akcigit and Ates

(2023), who attempt to explain recent patterns (dynamism, concentration, dispersion, etc.) using a general equilibrium model with competition and innovation at the sectoral level and four key parameters: taxes that limit incentives to being the leader, R&D subsidies, entry costs, and the ease of knowledge diffusion. Using counterfactual transition path analysis, they find that decreasing knowledge diffusion, modeled as a lower probability of leader-to-laggard spillovers, is the most important channel explaining the data. Akcigit and Ates (2023) document a dramatic rise in the concentration of the number of patents created and bought by the top 1 percent innovating firms, and suggest that the strategic use of patents may have been one of the reasons behind slower diffusion.

8.5 *Summary*

Ultimately, long-run aggregate labor productivity growth comes from innovation. Aggregate investment in R&D activities does not appear to have slowed significantly, but to some extent, shifted from public to corporate funding, where it is highly concentrated, as well as toward health and pharmaceuticals, which may not have spillovers as high as ICTs did. Nevertheless, a new wave of technological development is taking place, especially in digital technologies, that have the potential to be considered GPTs, although the current lack of business dynamism seems at odds with previous GPTs. The rewards from investment should not be expected to be reaped immediately. Historically, complementary investments are necessary, there are significant lags in diffusion, and replacing the existing capital stock can lead to the stranding of assets. Finally, while there are opposing theoretical arguments regarding the evolution of research productivity as knowledge increases, it appears that maintaining a steady rate of productivity growth has required an increasing number of researchers.

There remains the question of the intrinsic quality of new technologies, compared to older ones. This is very difficult to evaluate quantitatively. On the one hand, we do not see why recent technologies need be comparatively inferior to the ones that emerged during the nineteenth and the early twentieth centuries. After all, ICTs deal primarily with information, which is fundamental in every aspect of economic activity. It nevertheless remains the case that the techno-optimists have not produced evidence that productivity improvements will arrive with a lag, and the productivity enhancing effects from new technologies remain to be proven.

9. *Conclusion*

Comparing the period after 2005 to the 1996–2005 decade, there is a generalized slowdown in productivity in advanced economies, with labor productivity growth falling from around 2 percent to less than 1 percent. While part of this decline may be due to the end of convergence and a return to "normal" rates of growth at the frontier, it remains puzzling in view of its scale and considering the context of continued deployment of new digital and other technologies. The literature points to wide and varied reasons, which our review has sought to systematically evaluate. We identified a small set of forces and mechanisms that taken together explain most of the slowdown. Table 11 summarizes the results for the United States, although it is limited to the explanations that we have evaluated quantitatively.

Accelerated mismeasurement, which is mostly due the inherent difficulty of measuring aggregate price changes when creative destruction and quality change are important, contributed less than 15 percent of the slowdown in the United States, although

TABLE 11
Summary of Results for the United States

	US (pp)	US, percent of slowdown	Range, percent of slowdown	Section
Total slowdown	1.61	100		2
Capital: Financial crisis	0.35	22	[11,33][a]	4
Capital: Secular trends	0.35	22	[11,33][a]	4
Labor composition	−0.01	0	[−10,22][b]	5
TFP: Mismeasurement	0.21	13	[0,25][c]	3
TFP: Spillovers from intangibles	0.28	17	[0,25][d]	4.3
TFP: Trade	0.13	8	[0,16][e]	6.3
TFP: Allocative efficiency	0.38	23	[3,41][f]	7.4
Total “explained”	1.7	105	[15,195][g]	

Notes:
[a]Based on splitting between secular trends and financial crisis on a 25 percent–75 percent or 75 percent–25 percent basis, rather than on a 50 percent–50 percent basis.
[b]Based on cross-country variation in table 2.
[c]Based on our judgement.
[d]Based on judgement, considering cross-country variation from table 8 and results from other datasets and other studies.
[e]Range based on upper- and lower-bound estimates from table 9.
[f]Estimate based on the minimum and maximum estimates from table 10.
[g]Based on summing up lower and upper bounds. Note that this leaves some potential for under- or over-explanation of capital deepening.

there are large uncertainties associated with this estimate.

The reduction in the contribution of capital deepening contributed almost 45 percent of the slowdown in the United States. We did not evaluate the relative contributions of specific underlying causes quantitatively, but considering the literature on the slowdown of investment, we make a rough estimate that the two categories of factors contributed about equally. The first set of factors, which we call “financial crisis,” includes weak demand and credit constraints during, and to some extent after the financial crisis. The second set of factors, which we group under the name “secular trends,” recognizes that investment may have been weak due to more structural changes, such as the increasing share of intangibles and globalization, with additional hypotheses including changes to corporate governance and the weakening of competition.

There is also a recognition that intangible investment, due to its higher potential for spillovers, may affect labor productivity through TFP, that is, above and beyond its impact through capital deepening. Reusing published elasticities, we find that the slowdown in intangible assets accumulation may have had a substantial effect on the TFP slowdown.

Conventional growth accounting finds almost no role for a decline of human capital accumulation in the United States, and a weak role at best elsewhere. But several labor-related mechanisms may have affected TFP, including aging and labor market institutions.

A key feature of the last two decades is the fast growth of global trade after 1995, and its collapse during the financial crisis. Any positive effect of trade would therefore translate into a productivity slowdown, and we do indeed find substantial effects.

A large part of the current discussion on the productivity slowdown centers on business dynamism and competition, documenting trends such as declining entry-exit, increasing markups and concentration, and increasing divergence of the most productive firms. There is no consensus in the literature as to whether these trends are intrinsically good or bad for productivity and welfare, as concentration can reflect output-restricting dominant positions or a better allocation of resources to highly productive firms in an economy where firms are increasingly operating under increasing returns to scale, due in particular to the increasing prevalence of intangible investment. We do not attempt to settle this debate, but to reflect the potential importance of these trends we use recently developed estimates of the contribution of allocative efficiency to TFP growth that are calibrated on firm-level markup time series. We find that increasing allocative efficiency was a stronger contributor to TFP growth in the decade prior to 2006, implying that the lower contribution of increasing allocative efficiency to TFP growth explains a substantial part of the TFP slowdown.

Although technological change underlies many of the patterns discussed in sections 3–7, we have not presented an estimate of the contribution of technology on its own to the slowdown. It is possible that the new technologies being currently introduced are simply less transformative and less productivity enhancing than past innovations. But the opposite may also be the case: new technologies mean that our economies require far-reaching renewal, and higher levels of investment and institutional reforms are necessary before the productivity enhancing impact of the new technologies are widely observed.

Table 11 includes estimates of a plausible range of values for each of the explanation. While the methods to choose these ranges are debatable, of course, we have aimed to make transparent assumptions. Rather than being proper estimates of uncertainty, they should serve as a reminder that when producing these estimates we have found that different methods yielded different results, and that we sometimes observed cross-country variations that contradicts our scope criterion. Looking at the ranges, we see that we can easily over- or under-explain the slowdown by a large amount. This reflects the fact that we over- or under-explain TFP growth in the first place. “Slowdown” calculations are based on a difference between two means of noisy growth rates, each computed using around 10 observations, so we cannot expect much precision in our estimates. To further put these estimates in context, it is helpful to realize that while labor productivity estimates are fairly comparable across databases, the labor share and the contributions of TFP and capital deepening vary substantially; it is not unusual, for instance, that TFP estimates vary by up to 1 pp (Gouma and Inklaar 2021).

Keeping this mind, we report the summary results for our five countries in table 12. For mismeasurement, we assume that the same bias than the one we computed for the United States (0.21 pp) applies to all countries, reflecting our prior that all these countries have relatively similar economic structure and statistical systems. For allocative efficiency, we assume that, since it explains about 42 percent of the US TFP slowdown, it would explain 42 percent of the TFP slowdown of other countries. Both assumptions are again debatable, of course.

TABLE 12
Summary of Results for All Countries

	France	Germany	Japan	UK	US
Capital: financial crisis[a]	0.04	0.27	0.40	0.26	0.35
Capital: secular trends[a]	0.04	0.27	0.40	0.26	0.35
Labor composition[a]	−0.09	0.17	0.04	0.39	−0.01
TFP: mismeasurement[b]	0.21	0.21	0.21	0.21	0.21
TFP: spillovers from intangibles[c]	−0.07	0.06	0.48	−0.01	0.28
TFP: trade[d]	−0.00	0.30	0.52	0.46	0.13
TFP: allocative efficiency[e]	0.42	0.09	−0.01	0.35	0.38
TFP, to explain[a]	1.01	0.23	−0.02	0.84	0.91
TFP "explained"	0.56	0.67	1.20	1.02	1.00
Total slowdown	0.99	0.94	0.82	1.75	1.61
Total "explained"	0.54	1.38	2.05	1.93	1.70

Notes:
[a]Based on table 2.
[b]Assuming the same pp as in the United States.
[c]Based on table 8.
[d]Based on table 9.
[e]Assuming the same percent of the TFP slowdown as in the United States.

While the sum of explanations for the United States roughly matches what needs to be explained, table 12 shows a substantial under-explanation for France (and entirely from assuming similarity with the United States), and over-explanation for the other countries. We think that this reflects the original heterogeneity between countries, the uncertainty in the estimates that we have produced, and issues with the assumptions we made to extend US-centered calculations to other countries. Japan is the most extreme case, where despite no slowdown of measured TFP, we "explain" a slowdown of 1.2 pp. This over-explanation could partly be due to the labor productivity slowdown being under-attributed to TFP in KLEMS (for instance, the TFP slowdown for Japan is more substantial in the OECD productivity data, see table 15).

Table 12 can be considered in terms of the scope, scale, and sequencing criteria we established at the outset of this paper to evaluate the explanations for the productivity slowdown. The sequencing criterion is reflected in the design of our analysis, which compares the causes of changes in productivity growth in the decade up to 2005 with the subsequent period. In evaluating the scale and scope criteria, table 12 suggests that explanations that are strong in some countries may not be in others, although it is rare to find extreme differences. Overall, we find that all the effects listed are likely to explain at least some part of the slowdown in each country, but the relative contributions differ considerably and may be small in some cases.

There are two major caveats to our results. First, each of our quantitative evaluations is subject to a high degree of uncertainty, and we were not able to derive quantitative estimates for all the possible contributors to the slowdown. To the extent we have selected explanations that were already present in the literature and where we were able to derive quantitative estimates, our study suffers from sampling bias. Second, our explanations partly "overlap." They are not all computed within a single theoretical framework where it would be clear that these factors can be added up as straightforwardly as we do in table 11. This is particularly true for some of the factors behind TFP, which we derive using elasticities from published reduced-form estimates.

Finally, we have left unanswered a number of follow-up questions. First, is productivity still slowing down or are we in a prolonged period of low but stable productivity growth? There are few data points to evaluate this, and sorting out a trend in time series that includes the financial and the COVID-19 crises will be very challenging. Second, if we know why productivity is slowing down, can we do something about it? And if it is inevitable, what will be the consequences? While our review points to certain factors that are more easily addressed by policy than others, these questions require careful consideration. The interdependencies between the various factors we have identified highlight the need for further research, particularly with respect to measurement, competition, and the role of intangibles.

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