Aggregate Implications of Changing Sectoral Trends

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We describe how capital accumulation and the network structure of US production interact to amplify the effects of sectoral trend growth rates in total factor productivity and labor on trend GDP (gross domestic product) growth. We derive expressions that conveniently summarize this long-run amplification effect by way of sectoral multipliers. We

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estimate that sector-specific factors have historically accounted for approximately three-fourths of long-run changes in GDP growth. Trend GDP growth fell by nearly 3 percentage points over the postwar period, with especially significant contributions from the Construction sector in 1950–80 and the Durable Goods sector in 2000–2018. No sector has contributed any steady significant increase to the trend growth rate of GDP in the past 70 years.

I. Introduction

Following the so-called Great Recession of 2008–9, US GDP (gross domestic product) recovered only very gradually, resulting in a low average growth rate in the ensuing decade. Fernald et al. (2017) found that this weak recovery stemmed mainly from slow growth in total factor productivity (TFP) and a fall in labor input and note that these adverse forces preceded the Great Recession. Antolín-Díaz, Drechsel, and Petrella (2017) likewise document a slowdown in output growth that predates the Great Recession.[1] This paper studies what has in fact been a steady decline in trend GDP growth over the entire postwar period, 1950–2018. We explore the implications of TFP and labor input in accounting for this secular decline, but we do so at a disaggregated sectoral level. We document disparate trend variations in TFP and labor growth across sectors and estimate the extent to which these trends are driven by idiosyncratic rather than common factors. We then study the implications of our empirical findings for trend growth within a multisector framework with linkages that mimic those of the US economy, including, crucially, in the production of investment goods.

We first document that common trend factors play a relatively small role in explaining sectoral trends in labor and TFP growth. For example, in Durable Goods, only 3% of the overall trend variation in labor and TFP growth is explained by their respective common trend factors. These findings, therefore, highlight the quantitative importance of idiosyncratic forces not only for business cycle fluctuations (see Foerster, Sarte, and Watson 2011; Gabaix 2011; Atalay 2017) but also for variations in trends. There are, however, exceptions, in that in some service sectors, the trend variation in labor is explained to a greater degree by the common trend factor. Common trends explain a higher fraction of aggregate trend variation in labor and TFP growth because aggregation reduces the importance of sector-specific trends. We estimate that approximately one-third

[1] Cette, Fernald, and Mojon (2016) suggest that a slowdown in productivity growth that began before the Great Recession reflects in part the fading gains from the information technology (IT) revolution. This view is consistent with the long lags associated with the productivity effects of IT adoption found by Basu et al. (2004) and the collapse of the dot-com boom in the early 2000s. Decker et al. (2016) point to a decline in business dynamism that began in the 1980s as an additional force underlying slowing economic activity.

of the variation in the trend growth rate of aggregate TFP is common across sectors, while roughly two-thirds is common for labor. One cannot, however, infer from these findings the role that common and sectoral growth trends in labor and TFP play in the overall trend growth rate of GDP. The reason is that capital accumulation and the network structure of US production play a key role in translating those trends to the aggregate economy.

To explore the historical implications of changing sectoral trends for the long-run evolution of GDP growth, we derive balanced-growth accounting equations in a dynamic multisector framework where sectors use not only materials but also investment goods produced in other sectors. We then use these new growth accounting equations to assess the aggregate effects of observed sectoral changes in the trend growth rates of labor and TFP. Our analysis, therefore, generalizes the work of Greenwood, Hercowitz, and Krusell (1997) on investment-specific technical change (ISTC) to an environment with multiple investment and intermediate-goods sectors that are interconnected in production.[2] At the same time, our focus on estimating common and idiosyncratic sources of sectoral trends, and what their long-run aggregate implications are, differs from the literature building on Greenwood, Hercowitz, and Krusell (1997). Specifically, Fisher (2006), Justiniano, Primiceri, and Tambalotti (2010, 2011), and Basu et al. (2013) are primarily concerned with the business-cycle implications of sectoral shocks and, in particular, investment-specific shocks. More recently, vom Lehn and Winberry (2022) show that the input-output network of investment goods is critical in accounting for shifts in the cyclicality and relative volatilities of aggregate time series since the 1980s.[3]

We show that capital accumulation, together with the network structure of US production, markedly amplifies the aggregate long-run growth effects of sectoral changes in the trend growth rates of TFP and labor. This amplification mechanism can be conveniently summarized in the form of sectoral multipliers that reflect the knock-on effects of production linkages. Given observed US production linkages, the influence of individual sectors on

[2] Ngai and Pissarides (2007) provide a seminal study of balanced growth in a multisector environment. They consider both multiple intermediates and multiple capital-producing sectors, but not at the same time. Importantly, their analysis abstracts from pairwise linkages in both intermediates and capital-producing sectors that play a key role in this paper. Ngai and Samaniego (2009) generalizes the model in Greenwood, Hercowitz, and Krusell (1997) to three sectors, which allows for an input-output network in intermediate goods in carrying out growth accounting. Duarte and Restuccia (2020) include input-output linkages across sectors in a multisector environment abstracting from capital and study the implications of cross-country productivity differences in nontraditional service sectors.

[3] Basu et al. (2013) also construct a multisector extension of the Greenwood, Hercowitz, and Krusell (1997) environment, but they work with an aggregate capital stock and an aggregate labor endowment, with each factor being perfectly mobile across sectors. In contrast to our paper, the authors study short-run responses to TFP shocks.

GDP growth may be as large as 3 times their share in the economy, including in Durable Goods, Construction, and Professional and Business Services.

Combining our empirical findings with the amplification effects of sectoral multipliers, we find that sector-specific trends have accounted for roughly three-fourths of the trend variation in GDP growth over the postwar period, leaving aggregate or common factors to explain only one-fourth of those changes. The secular decline in US GDP growth since 1950, therefore, is a phenomenon largely driven by idiosyncratic rather than aggregate forces. These findings arise in part because of the knock-on effects of production linkages but also because sector-specific changes in TFP and labor have been historically large in some sectors. Thus, US trend GDP growth fell by nearly 3 percentage points between 1950 and 2018. The combination of large trend TFP growth variations in the Construction sector and its large sectoral multiplier means that it contributed roughly 1 percentage point of that decline between 1950 and 1980. The Durable Goods sector, after contributing significantly to an economic expansion in the 1990s, then contributed another 2 percentage point decline in trend GDP growth between 2000 and 2018. While Professional and Business Services stands out as having the second-largest sectoral multiplier, smaller trend TFP growth variations in that sector imply that its contributions to the secular decline in GDP growth have been more muted to this point. Remarkably, no sector has contributed any steady significant increase to the trend growth rate of GDP over the postwar period.

Our paper also falls within the literature on equilibrium models with sectoral production networks developed first by Long and Plosser (1983) and later by Horvath (1998, 2000) and Dupor (1999). Since then, a large body of work has explored important features of those models for generating aggregate fluctuations from idiosyncratic shocks. We maintain the original assumptions of competitive input and product markets as well as constant-returns-to-scale technologies. Even absent non–log linearities in production emphasized by Baqaee and Farhi (2019), for example, and beyond the role of idiosyncratic shocks in explaining aggregate cyclical variations, the analysis reveals that sector-specific changes also dominate long-run variations in US GDP growth.[4]

This paper is organized as follows. Section II gives an overview of the behavior of trend GDP growth over the past 70 years. Section III provides an empirical description of the trend growth rates of TFP and labor growth by industry and estimates the contributions of sector-specific

[4] See Foerster, Sarte, and Watson (2011), Gabaix (2011), and Atalay (2017) for assessments of the importance of idiosyncratic shocks in driving business-cycle fluctuations. We introduce explicit dynamic considerations into the work of Acemoglu et al. (2012), Baqaee and Farhi (2019), and Miranda-Pinto (2021), combined with an empirical model that parses out common and idiosyncratic components of sectoral trend input growth.

and common factors to these trends. Section IV develops the implications of these changes at the sector level in the context of a dynamic multisector model with production linkages in materials and investment. This model serves as the balanced-growth accounting framework that we use to determine the aggregate implications of changes in the sectoral trend growth rates of labor and TFP. Section V presents our quantitative findings. Section VI discusses salient implications of our work and outlines directions for future research. Section VII concludes. A detailed appendix contains a comprehensive description of the data, statistical methods, and economic model and discussions of departures from our benchmark assumptions and includes additional figures and tables referenced in the text.

II. The Long-Run Decline in US GDP Growth

Figure 1 shows the behavior of US GDP growth over the post–World War II period. Here, annual GDP growth is measured as the share-weighted value-added growth from 16 sectors comprising the private US economy; details are provided in the next section.

Figure 1*A* shows aggregate private-sector growth rates computed by chain-weighting the sectors and by using three alternative sets of fixed sectoral shares computed as averages over the entire sample (1950–2018), over the first 15 years of the sample (1950–64), and over the final 15 years (2004–18). This panel shows large variation in GDP growth rates—the standard deviation is 2.5% over the period 1950–2018—but much of this variation is relatively short-lived and is associated with business cycles and other relatively transitory phenomena. Moreover, to the extent that sectoral shares have changed slowly over time, these share shifts have little effect in figure 1*A*. In other words, changes in aggregate growth largely stem from changes within sectors rather than between them. Our interest, however, is in longer-run variation.

Figure 1*B*, therefore, plots centered 11-year moving averages of the annual growth rates. Here, too, there is variability. In the 1950s and early 1960s, average annual growth exceeded 4%. Average growth fell to 3% in the 1970s, rebounded to nearly 4% in the 1990s, but plummeted to less than 2% in the 2000s (see table 1). At these lower frequencies, the effects of slowly shifting shares over the sample become more visible, but they still play a relatively minor role.

Figures 1*C* and 1*D* refine these calculations by eliminating the cyclical variation, using an Okun's law regression as in Fernald et al. (2017). Thus, figure 1*C* plots the residuals from a regression of GDP growth rates onto a short distributed lead and lag of changes in the unemployment rate (Δu_{t+1}, Δu_t, Δu_{t-1}). This cyclical adjustment eliminates much of

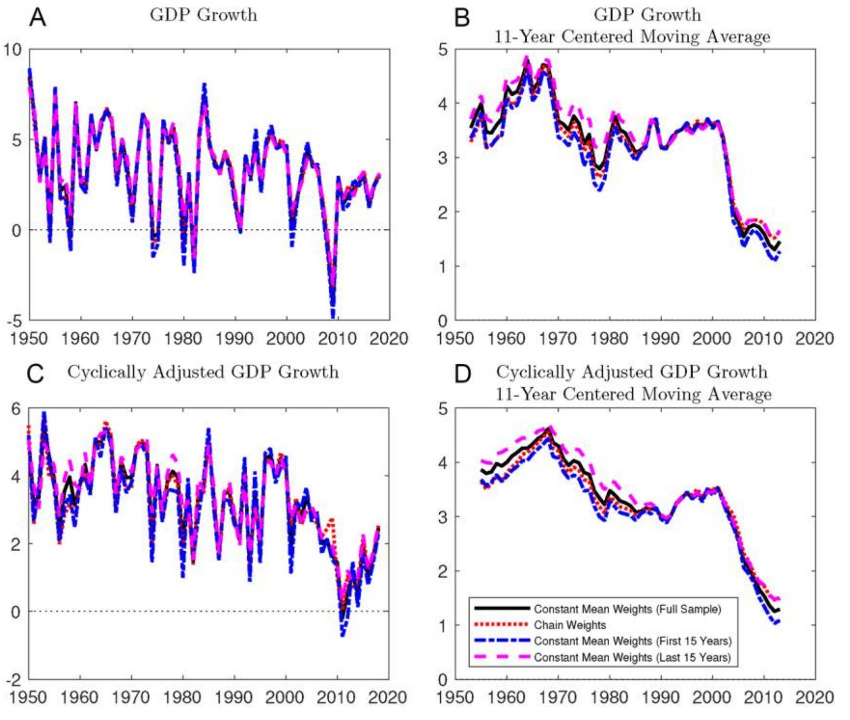

FIG. 1.—US GDP growth rates 1950–2018 (percentage points at an annual rate). Growth rates are share-weighted value-added growth rates from 16 sectors making up the private US economy. Cyclical adjustment uses a regression on leads and lags of the first difference in the unemployment rate.

TABLE 1
AVERAGE GDP GROWTH RATES

	CONSTANT MEAN WEIGHTS: FULL SAMPLE		TIME-VARYING WEIGHTS		CONSTANT MEAN WEIGHTS: FIRST 15 YEARS		CONSTANT MEAN WEIGHTS: LAST 15 YEARS	
DATES	Growth Rates	Cyclically Adjusted Rates	Growth Rates	Cyclically Adjusted Rates	Growth Rates	Cyclically Adjusted Rates	Growth Rates	Cyclically Adjusted Rates
1950–2018	3.3	3.2	3.3	3.2	3.2	3.1	3.4	3.4
1950–66	4.5	4.2	4.3	4.0	4.3	4.0	4.6	4.3
1967–83	3.1	3.6	3.0	3.5	2.8	3.4	3.4	3.9
1984–2000	3.9	3.4	3.9	3.4	4.0	3.4	3.8	3.4
2001–18	1.9	1.8	2.0	2.0	1.7	1.7	2.0	2.0

NOTE.—The values shown are averages of the series plotted in fig. 1 over the periods shown.

the cyclical variability evident in figure 1*A*. In addition, the 11-year moving average in figure 1*D* now produces a more focused picture of the trend variation in the growth rate of private GDP. Again, time-varying share weights have a discernible but relatively small effect on the aggregate growth rate or its 11-year moving average.

The numbers reported in table 1 frame the key question of this paper: why did the average growth rate of GDP fall from 4% per year in the 1950s to just over 3% in the 1980s and 1990s and then further decline precipitously in the 2000s? As the different columns of the table make clear, this question arises regardless of the shares used in constructing GDP. We look to inputs—specifically TFP and labor at the sectoral level—for the answer. That is, when long-run variations of the data are interpreted as a time-varying balanced-growth path (BGP), changes in trend GDP growth are in part determined by changes in the trend growth rates of those sectoral inputs. However, as the analysis in section IV makes clear, not all sectoral inputs are created equal. Sectors differ not only in their size or their value-added share in GDP but also in the share of materials or capital that they provide to other sectors.

Before investigating these input-output interactions, we begin by briefly describing the sectoral data and how sectoral value-added and labor and TFP inputs have evolved over the post-WWII period. In much of our analysis, we construct aggregates using constant weights computed from full-sample averages. As figure 1 and table 1 suggest, results using these constant shares are robust to alternative weighting schemes.

III. An Empirical Description of Trend Growth in TFP and Labor

As a first step, we estimate an empirical model of TFP and labor growth for different sectors of the US economy. Our paper applies as a benchmark the insights of Hulten (1978) on the interpretation of aggregate TFP changes as a weighted average of sector-specific value-added TFP changes. In particular, under constant returns to scale and perfect competition in product and input markets, the sectors' weights are the ratios of their valued added to GDP.[5]

We calculate standard TFP growth rates at the sectoral level, construct trend growth rates using a "low-pass" filter, and estimate a statistical model

[5] In the absence of constant returns to scale, perfect competition, or frictionless factor mobility, Basu and Fernald (1997, 2001) and Baqaee and Farhi (2018) show that aggregate TFP changes also incorporate reallocation effects. These effects reflect the movement of inputs between low- and high-return sectors in the absence of equalization of marginal rates of transformation and substitution.

to decompose these trend growth rates into common and sector-specific components.

A. Data

Sectoral TFP growth rates are calculated with KLEMS (capital, labor, energy, materials, services) data from of the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics integrated industry-level production accounts (ILPAs). These data are attractive for our purposes because they provide a unified approach to the construction of gross output and the primary inputs capital and labor, as well as intermediate inputs ("materials"), for a large number of industries. The KLEMS data are based on US national income and product accounts (NIPAs) and consistently integrate industry data with input-output tables and fixed-asset tables. The ILPA KLEMS data build on seminal work studying sectoral productivity accounting by Jorgenson and his collaborators and first summarized in Jorgenson, Gollop, and Fraumeni (1987).

Table 2 lists the 16 sectors we consider, along with the growth rates of value added, labor, and TFP for each sector. Section 7 of the appendix provides a detailed discussion of the data and the construction of labor and TFP from quantity and price indices available in KLEMS data. For each sector, the table shows average cyclically adjusted growth rates of value added, labor, and value-added TFP over 1950–2018, and it also shows their average shares in aggregate value added and labor input. The aggregate growth rates in the bottom row are the value-weighted averages of the sectoral growth rates, with average value added and labor shares used as fixed weights.

Clearly, sectors grow at different rates, and this disparity is hidden in studies that consider only aggregates. Average real value-added growth rates range from 1.4% in Mining to 4.9% in Information, bracketing the aggregate value-added growth rate of 3.3%. With the exception of the Durable Goods sector, most sectors with growth rates that exceed the aggregate growth rate provide services. Similarly, labor input growth rates range from −1.3% in Agriculture to 3.5% in Professional and Business Services (PBS), bracketing the average aggregate growth rate of 1.6%. Again, most sectors with labor input growth rates that exceed the aggregate growth rate provide services. Finally, TFP growth rates range from −0.4% in Utilities to 3.1% in Agriculture, bracketing the average aggregate TFP growth rate of 0.8%. Sectoral TFP growth rates are less aligned with either value-added or labor input growth rates. There are four sectors with TFP declines—namely, Utilities, Construction, FIRE (finance, insurance, and real estate, except for Housing [x-Housing]), and Education and Health—as well as a number of sectors with stagnant TFP levels. Negative TFP growth rates are a counterintuitive but known feature of disaggregated industry data. These are in

TABLE 2
16-Sector Decomposition of the US Private Economy (1950–2018)

Sectors	Average Growth Rate, Cyclically Adjusted Data (percentage points at an annual rate)			Average Share (percentage points)	
	Value Added	Labor	TFP	Value Added	Labor
1. Agriculture	2.41	−1.29	3.12	2.69	3.23
2. Mining	1.38	.37	.39	2.11	1.55
3. Utilities	2.09	1.00	−.42	2.37	1.04
4. Construction	1.69	1.76	−.23	4.99	7.62
5. Durable Goods	3.65	.54	2.10	13.32	15.5
6. Nondurable Goods	2.27	.14	.83	9.20	8.80
7. Wholesale Trade	4.61	1.67	1.81	7.15	6.63
8. Retail Trade	3.13	1.19	1.07	8.18	9.61
9. Transportation and Warehousing	2.58	.91	1.27	4.16	5.03
10. Information	4.93	1.35	1.04	4.97	3.74
11. FIRE (x-Housing)	3.88	2.77	−.03	9.97	7.53
12. PBS	4.45	3.51	.36	8.79	11.25
13. Education and Health	3.43	3.34	−.29	6.22	9.35
14. Arts, Entertainment, and Food Service	2.48	1.79	.36	3.74	4.56
15. Other Services (x-Government)	1.99	.52	1.04	2.94	4.37
16. Housing	3.45	.86	.24	9.20	.20
Aggregate	3.32	1.55	.82	100	100

Note.—The values shown are average annual growth rates for the 16 sectors. The row labeled "Aggregate" reports the constant share-weighted average of the 16 sectors.

part attributed to measurement issues with respect to output, though land and the regulatory environment are also factors in sectors such as Construction (see, e.g., Herkenhoff, Ohanian, and Prescott 2018).

To a first approximation, the contributions of the different sectors to aggregate outcomes are given by the nominal value-added and labor input shares in the last two columns of table 2. In those columns, two notable contributors to value added and TFP are Durable Goods and FIRE (x-Housing). The two largest contributors to labor payments are Durable Goods and PBS. Over time, the shares of goods-producing sectors have declined while the shares of services-producing sectors have increased. However, despite these changes, aggregating sectoral outputs and inputs using constant mean shares, as opposed to time-varying shares, has little effect on the measurement of aggregate outputs and inputs (fig. 1).

B. *Empirical Framework*

The empirical analysis used to characterize the long-run properties of the data proceeds in three steps. First, we carry out a cyclical adjustment of sectoral TFP and labor raw growth rates to eliminate some of their cyclical variability. Second, we make use of methods discussed in Müller and Watson (2020) to extract smooth trends capturing the long-run evolution of the data. Finally, we carry out a factor analysis that quantifies the relative importance of common and sector-specific factors in driving these smooth trend components.

1. Cyclical Adjustment

Let $\Delta\tilde{x}_{i,t}$ denote the growth rate (100 $\times$ the first difference of the logarithm) of annual measurements of labor or TFP in sector i at date t. These sectoral growth rates are volatile, and in many sectors, much of the variability is associated with the business cycle. Our interest is in trend (i.e., low-frequency) variation, which is more easily measured after cyclically adjusting the raw growth rates. Thus, as with the cyclically adjusted measure of GDP shown in figure 1, we follow Fernald et al. (2017) and cyclically adjust these growth rates, using the change in the unemployment rate, Δu_t, as a measure of cyclical resource utilization. That is, we estimate

$$\Delta\tilde{x}_{i,t} = \mu_i + \beta_i(L)\Delta u_t + e_{i,t},$$

where $\beta_i(L) = \beta_{i,1}L + \beta_{i,0} + \beta_{i,-1}L^{-1}$ and the leads and lags of Δu_t capture much of the business-cycle variability in the data. Throughout the remainder of the paper, we use $\Delta x_{i,t} = \Delta\tilde{x}_{i,t} - \hat{\beta}_i(L)\Delta u_t$, where $\hat{\beta}_i(L)$ denotes the OLS (ordinary least squares) estimator and $x_{i,t}$ represents the implied cyclically adjusted value of sectoral TFP (denoted $z_{i,t}$) or labor input (denoted $\ell_{i,t}$) growth rates.

2. Extracting Low-Frequency Trends

We begin by extracting low-frequency trends from the data, using a framework presented in Müller and Watson (2008). That framework is useful because, on the one hand, it yields smooth trends that capture the long-run evolution of the growth rate of GDP and the associated growth rates of sectoral labor and TFP and, on the other hand, it simultaneously provides a convenient framework for statistical analysis. We give an overview below of the approach here. Müller and Watson (2020) provide a detailed discussion of statistical analysis using this framework.[6]

To extract low-frequency trends in the growth rates of GDP, TFP, and labor input, generically denoted by Δx_t, we regress these series onto a constant and a set of low-frequency periodic functions. In particular, let

[6] The methods used are closely related to well-known spectral analysis methods using low-frequency Fourier transforms of the data. See Müller and Watson (2020) for a detailed discussion and references.

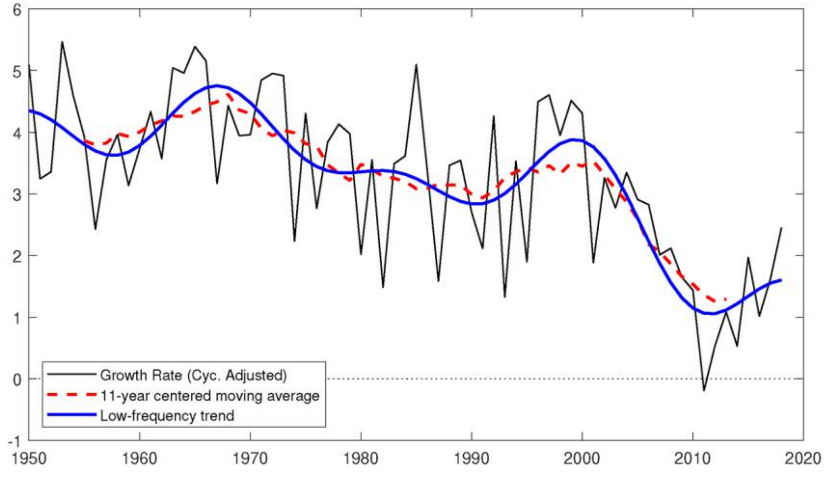

FIG. 2.—Trend rate of growth of GDP (percentage points at an annual rate). The low-frequency trend captures variability for periodicities longer than 17 years. Cyc. = cyclically.

$\Psi_j(s) = \sqrt{2}\cos(js\pi)$ denote a cosine function on $s \in [0, 1]$ with period $2/j$. The fitted values from the OLS regression of Δx_t onto a constant and $\Psi_j((t-1/2)/T)$ for $j = 1, \ldots, q$ and $t = 1, \ldots, T$ capture the low-frequency variability in the sample corresponding to periodicities longer than $2T/q$. Moreover, let $\boldsymbol{\Psi}(s)$ denote the vector of regressors $[\Psi_1(s), \ldots, \Psi_q(s)]'$ with periods 2 through $2/q$, $\boldsymbol{\Psi}_T$ the $T \times q$ matrix with tth row $\Psi((t-1/2)/T)'$, and $\Psi_T^0 = [\mathbf{1}_T, \boldsymbol{\Psi}_T]$, where $\mathbf{1}_T$ is a $T \times 1$ vector of 1s. The specific form used for the cosine weights implies that the columns of Ψ_T^0 are orthogonal with $T^{-1}\boldsymbol{\Psi}_T^{0\prime}\boldsymbol{\Psi}_T^0 = I_{q+1}$. Thus, the OLS coefficients from the regression of Δx_t onto $\boldsymbol{\Psi}_T^0$—that is, $(\boldsymbol{\Psi}_T^{0\prime}\boldsymbol{\Psi}_T^0)^{-1}\boldsymbol{\Psi}_T^{0\prime}\Delta x_{1:T}$—amount to $q+1$ weighted averages of the data, $T^{-1}\boldsymbol{\Psi}_T^{0\prime}\Delta x_{1:T}$, which we partition as $(\bar{x}, \mathbf{X})$, where $\bar{x}$ is the sample mean of Δx_t. In our application, $T = 69$, so that with $q = 8$, the regression captures long-run variation with periodicities longer than 17.25 ($= 2 \times 69/8$) years. These are the low-frequency growth rate trends analyzed in this paper.[7]

Figure 2 plots the growth rates of (cyclically adjusted) GDP, its centered 11-year moving average, and its trend computed as the fitted values from the low-frequency regression we have just described.[8] The

[7] Calculations presented in Müller and Watson (2008) show that these low-frequency projections approximate a low-pass filter for periods longer than $2T/q$. That said, there is some leakage from higher frequencies, and this makes the cyclical adjustment discussed above useful.

[8] An 11-year moving average is a crude low-pass filter, with more than half of its spectral gain associated with periods longer than 17 years.

low-frequency trend smooths out the higher-frequency variation in the 11-year moving average. While the aggregate importance of sectoral shocks is known for business cycles—generally, cycles with periods ranging from 2 to 8 years—our interest here is on the role of sectoral shocks for the aggregate trend variations shown in figure 2. Thus, we focus on cycles longer than 17 years, as captured by the Ψ-weighted averages of the data.

Figures 3 and 4 plot the cyclically adjusted growth rates of labor and TFP, respectively, for each of the 16 sectors, along with their low-frequency trends. The disparity in experiences across different sectors stands out. In particular, the trends show large variations across sectors and through time. For example, labor input was contracting at nearly 4% per year in Agriculture in the 1950s but stabilized near the end of the sample. In contrast, labor input in the Durable Goods and Nondurable Goods sectors was increasing in the 1950s but has been contracting since the mid-1980s. At the same time, the trend growth rates of labor in several service sectors exhibit large ups and downs over the sample. Similar disparities are apparent in the sectoral growth rates of TFP. Trend TFP growth in Construction, for

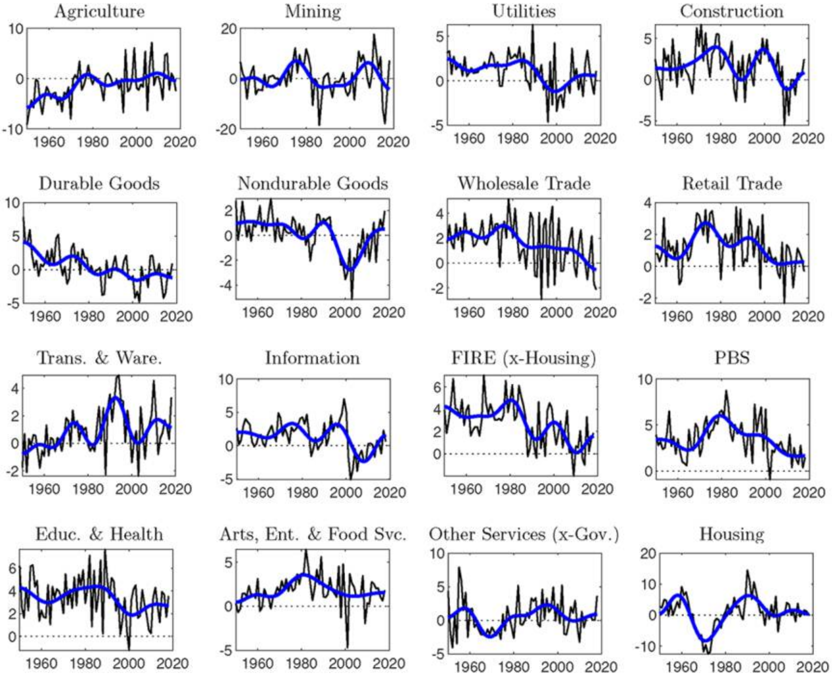

FIG. 3.—Labor growth rates and trends by sector (percentage points at an annual rate). Each panel shows the cyclically adjusted growth rate of labor for each sector in black, along with its low-frequency trend in blue. In figures 3, 4, 6–8, and 12, Trans. & Ware. = Transportation and Warehousing; Educ. = Education; Arts, Ent., & Food Svc. = Arts, Entertainment, and Food Service; Gov. = Government.

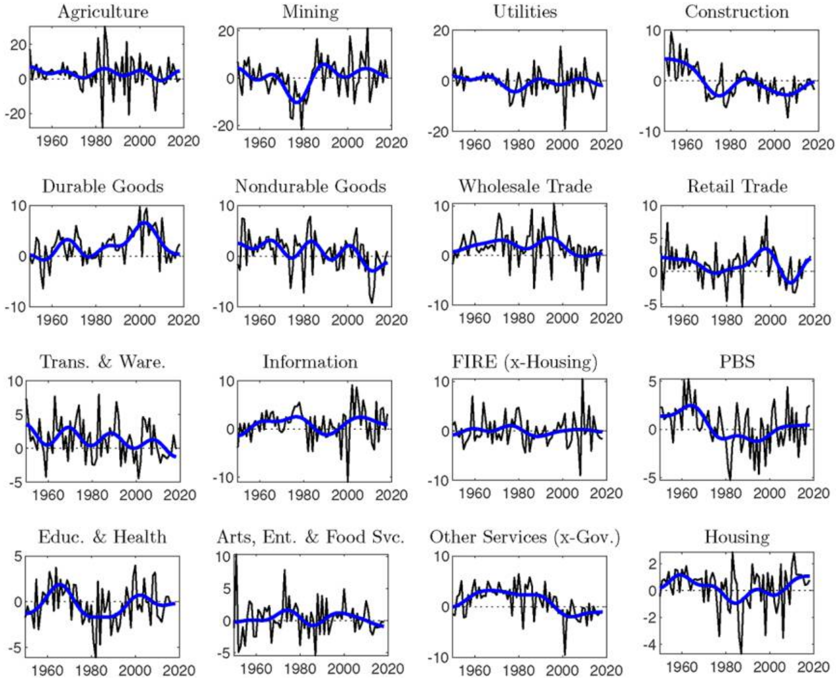

FIG. 4.—TFP growth rates and trends by sector (percentage points at annual rate). See figure 3 legend for further details.

example, was around 5% in the 1950s, declined over the next couple of decades, and flattened out thereafter. In contrast, TFP trend growth in Durable Goods increased somewhat steadily from the 1950s to 2000 but has since collapsed by more than 5 percentage points. In sections IV and V, we quantify the aggregate implications of these sectoral variations in labor and TFP inputs.

3. Decomposition of Trend Growth Rates into Common and Sector-Specific Factors

To fix notation, let g_t denote the trend growth rate constructed from our data on TFP or labor input, Δx_t. That is, g_t is the fitted value from the OLS regression of Δx_t onto a constant and the q periodic functions $\Psi_j((t-1/2)/T)$, and it is the low-frequency trend plotted in figures 2–4. We saw above that because the regressors are mutually orthogonal, the OLS regression coefficients are $(\bar{x}, \mathbf{X})$, where $\bar{x}$ is the sample mean of Δx_t and $\mathbf{X}$ is the $q \times 1$ vector of OLS regression coefficients from the regression of Δx_t onto $\Psi_j((t-1/2)/T)$ for $j = 1, \ldots, q$. Importantly, because the regressors are deterministic, the stochastic process for g_t is completely characterized by the probability distribution of the $q+1$ random variables $(\bar{x}, \mathbf{X})$, and variation in g_t over the sample is determined by the $q \times 1$ vector $\mathbf{X}$.[9]

A key implication of these results is that the original sample of T observations on Δx_t contains only q pieces of independent information on the long-run properties of Δx. In our context, the $T = 69$ annual observations contain only $q = 8$ observations describing the long-run variation for periods longer than 17 years. This makes precise the intuition that a statistical analysis of long-run growth is inherently a "small-sample" problem. Conveniently, however, this small-sample problem involves variables that are averages of the T observations—the elements of $\mathbf{X}$—and that are, therefore, (approximately) normally distributed and readily analyzed with standard statistical methods.

Examination of the trends plotted in figures 3 and 4 suggests that some of the trend variation may be common across sectors while some are sector specific. In addition, in some sectors, trend variation in labor appears to be correlated with trend variation in TFP (and, interestingly, this correlation generally appears to be negative). We now outline an empirical model that captures these features.

Let $\Delta \ln \ell_{i,t}$ denote the rate of growth of labor input in sector i in period t, and let $\Delta \ln z_{i,t}$ denote the rate of growth of TFP. Consider the factor model

$$\begin{bmatrix} \Delta \ln \ell_{i,t} \\ \Delta \ln z_{i,t} \end{bmatrix} = \begin{bmatrix} \lambda_i^{\ell} & 0 \\ 0 & \lambda_i^{z} \end{bmatrix} \begin{bmatrix} f_t^{\ell} \\ f_t^{z} \end{bmatrix} + \begin{bmatrix} u_{i,t}^{\ell} \\ u_{i,t}^{z} \end{bmatrix}, \tag{1}$$

where $f_t = (f_t^{\ell}\, f_t^{z})'$ are unobserved common factors, $\lambda_i = (\lambda_i^{\ell}\, \lambda_i^{z})'$ are factor loadings, and $u_{i,t} = (u_{i,t}^{\ell}\, u_{it}^{z})'$ are sector-specific disturbances. Denote the trend growth rates in $(\Delta \ln \ell_{i,t}, \Delta \ln z_{i,t}, f_t^{\ell}, f_t^{z}, u_{i,t}^{\ell}, u_{i,t}^{z})$ by, respectively, $(g_{i,t}^{\ell}, g_{i,t}^{z}, g_{f,t}^{\ell}, g_{f,t}^{z}, g_{u,i,t}^{\ell}, g_{u,i,t}^{z})$. Let $\mathbf{X}_i^{\ell}$ denote the $q \times 1$ vector of OLS coefficients associated with $\Psi_j((t-1/2)/T)$, $j = 1, \ldots, q$, in the regression of $\Delta \ln \ell_{i,t}$ on a constant and these periodic functions, and similarly for $\mathbf{X}_i^{z}$, $\mathbf{F}^{\ell}$, $\mathbf{F}^{z}$, $\mathbf{U}_i^{\ell}$ and $\mathbf{U}_i^{z}$. Premultiplying each element in equation (1) by $T^{-1}\psi_t'$, where $T^{-1}\psi_t'$ is the tth row of $\mathbf{\Psi}_T$, and summing yields a factor decomposition of the trends and cosine transforms of the form (abstracting from the constant),

$$\begin{bmatrix} \mathbf{X}_i^{\ell} \\ \mathbf{X}_i^{z} \end{bmatrix} = \begin{bmatrix} \lambda_i^{\ell} I_q & 0 \\ 0 & \lambda_i^{z} I_q \end{bmatrix} \begin{bmatrix} \mathbf{F}^{\ell} \\ \mathbf{F}^{z} \end{bmatrix} + \begin{bmatrix} \mathbf{U}_i^{\ell} \\ \mathbf{U}_i^{z} \end{bmatrix}, \tag{2}$$

which characterizes the low-frequency variation in the data. We estimate a version of equation (2) and use it to describe the common components,

[9] By construction, the low-frequency trends are highly serially correlated, and this must be accounted for in the statistical analysis. As it turns out, this is relatively straightforward, given the framework described above. We highlight a few key features of this framework in sec. 1 of the appendix and refer the reader to Müller and Watson (2020) and references therein for more detail.

$(g^\ell_{f,t}, g^z_{f,t})$, and sector-specific components, $(g^\ell_{u,i,t}, g^z_{u,i,t})$, of the trend growth rates in sectoral labor input and TFP.[10]

The model is estimated with Bayes methods. While large-sample Bayes and frequentist methods often coincide, the analysis of long-run trends is predicated on a small sample: in our application, the variation in each trend is characterized by only $q = 8$ observations. Hence, large-sample frequentist results are irrelevant for our "small-sample" empirical problem, and Bayes analysis will, in general, depend on the specifics of the chosen priors. Section 1 of the appendix contains details of the estimation method and empirical results for the low-frequency factor model.[11]

The priors we use are relatively uninformative except for the factor loadings. Let $\lambda^\ell = (\lambda^\ell_1, \ldots, \lambda^\ell_{16})'$, and note that the scales of λ^ℓ and $\mathbf{F}^\ell$ are not separately identified. Thus, we normalize $s'_\ell \lambda^\ell = 1$, where s_ℓ denotes the vector of average sectoral labor shares shown in table 2. This imposes a normalization where the growth of aggregate labor, say $\Delta \ln \ell_t = \Sigma_{i=1} s_{\ell,i} \Delta \ln \ell_{i,t}$, satisfies $\Delta \ln \ell_t = f^\ell_t + \Sigma_i s_{\ell,i} u^\ell_{i,t}$. That is, a 1-unit change in f^ℓ corresponds to a unit change in the long-run growth rate of aggregate labor.

The prior for λ^ℓ is $\lambda^\ell \sim N(\mathbf{1}, \mathbf{P}_\ell)$, where $\mathbf{1}$ is a vector of 1s and $\mathbf{P}_\ell = \eta^2 (I_{16} - s_\ell (s'_\ell s_\ell)^{-1} s'_\ell)$, which enforces the constraint that $s'_\ell \lambda^\ell = 1$. The parameter η governs how aggressively the estimates of λ^ℓ_i are shrunk toward their mean of unity. Our benchmark model uses $\eta = 1$, so the prior puts approximately two-thirds of its weight on values of λ^ℓ_i between 0 and 2. Smaller values of η tighten the constraint, making negative factor loadings less likely, while larger values of η loosen it. To gauge the robustness of our conclusions to the choice of η, we also show results with $\eta = 1/2$ and $\eta = 2$ in section V. We use an analogous prior for λ^z.

C. *Estimated Sectoral and Aggregate Trend Growth Rates in Labor and TFP*

For our purposes, the key results are summarized in a table and three figures. The table summarizes salient features of the stochastic process

[10] See Müller, Stock, and Watson (2022) for a related application studying long-run growth and long horizons forecasts for per capita GDP values of a panel of 113 countries. In eq. (1), the common factors affect all sectors without leads and lags, an unrealistic assumption made for expositional purposes. The low-frequency model in eq. (2) allows for lags in eq. (1) that are short relative to the sample size. That said, lags of a decade or longer, such as those associated with general-purpose technologies (e.g., semiconductors), will confound common and sector-specific sources of variation in the growth rates. See, e.g., Basu et al.'s (2004) discussion of the diffusion of information and communications technology (ICT) and its delayed effects on productivity growth in ICT-using industries in the United States and the United Kingdom.

[11] Frequentist methods for small-sample problems such as these are discussed, e.g., in Müller and Watson (2008, 2016, 2018). As a practical matter, these methods apply only to univariate and bivariate settings. Our application here involves 32 time series.

describing the long-run evolution of the sectoral growth rates. The figures summarize the historical evolution of the long-run growth rates over the sample period.

Table 3 reports the posterior medians for λ, along with 68% credible intervals.[12] Also reported is the fraction of the trend variability in each sector explained by the common trend factors, $(g^{\ell}_{f,t}, g^{z}_{f,t})$, denoted R^2_{ℓ} and R^2_z in the table. Finally, the table also reports the correlation between the sector-specific labor and TFP trends, $(g^{\ell}_{u,i,t}, g^{z}_{u,i,t})$, in each sector and the correlation between the common trends $(g^{\ell}_{f,t}, g^{z}_{f,t})$.

Looking first at the median values of the factor loadings, Agriculture, FIRE (x-Housing), and PBS have the largest factor loadings for labor, and Transportation and Warehousing, Durable Goods, and Nondurable Goods have the smallest. Utilities, Durable Goods, and Construction have the largest loadings for TFP, while FIRE (x-Housing) and Arts, Entertainment, and Food Services have the smallest. The 68% credible intervals are relatively wide and give a quantitative sense of how information about the long run is limited in our sample: the average width is 1.3 for λ^{ℓ} and 1.9 for λ^{z}. That said, for the majority of sectors, the posterior puts relatively little weight on negative values of the factor loadings. Detailed results for alternative priors are available in section 1 of the appendix.

The sectoral R^2 values are typically low, indicating that common trend factors play a relatively muted role in explaining overall sectoral trends. For example, in Durable Goods, only 3% of the overall trend variation in labor and TFP growth is explained by their respective common trend factors. Notable exceptions for R^2_{ℓ} arise in several service sectors, for example in FIRE (x-Housing), where 76% of the trend variation in labor is explained by the common trend factor. Interestingly, the posterior suggests that the sector-specific trends in labor and TFP are generally negatively correlated, rather dramatically so for PBS.

The final row of the table shows the results for aggregate values of labor and TFP. By construction, the share-weighted factor loadings sum to unity. The common trends, $(g^{\ell}_{f,t}, g^{z}_{f,t})$, are also negatively correlated. The R^2 values are higher for the aggregates because aggregation reduces the importance of the sector-specific trends. The point estimates suggest that roughly two-thirds of the variation in the trend growth rate of labor is common across sectors, while roughly one-third is common for TFP. However, one cannot directly infer from these findings the role that common growth trends in labor and TFP play in the overall trend growth rate of GDP. The reason is production linkages across sectors. In particular, the effective weight that

[12] Throughout the paper, we report equal-tail 68% credible intervals. Section 1 of the appendix also reports selected 90% credible intervals, which in some cases are markedly wider. We remind the reader that these long-run empirical results use only $q = 8$ independent observations on labor input and TFP for each of the 16 sectors.

TABLE 3
CHANGES IN TREND VALUE OF LABOR AND TFP GROWTH RATES

Sector	λ^{ℓ}	λ^{z}	R^2_{ℓ}	R^2_{z}	corr(ℓ, z)
1. Agriculture	2.01	.59	.21	.02	−.32
	(1.24, 2.71)	(−.59, 1.64)	(.06, .44)	(.00, .13)	(−.52, −.15)
2. Mining	.73	1.10	.01	.01	−.35
	(−.17, 1.64)	(.10, 2.09)	(.00, .07)	(.00, .04)	(−.63, −.06)
3. Utilities	1.13	1.36	.24	.05	.22
	(.41, 1.82)	(.36, 2.35)	(.04, .58)	(.00, .29)	(−.06, .58)
4. Construction	1.55	1.26	.33	.02	−.25
	(.95, 2.08)	(.21, 2.66)	(.10, .61)	(.00, .19)	(−.55, −.04)
5. Durable Goods	.40	1.31	.03	.03	−.35
	(−.23, 1.03)	(.44, 2.17)	(.00, .18)	(.00, .15)	(−.63, −.05)
6. Nondurable Goods	.59	1.22	.06	.04	−.36
	(−.20, 1.38)	(.36, 2.13)	(.01, .29)	(.00, .23)	(−.65, −.06)
7. Wholesale Trade	1.09	.88	.53	.04	.20
	(.62, 1.49)	(.06, 1.74)	(.17, .81)	(.00, .20)	(−.06, .53)
8. Retail Trade	.80	1.14	.26	.05	.06
	(.26, 1.29)	(.17, 2.82)	(.04, .60)	(.00, .85)	(−.25, .62)
9. Transportation and Warehousing	−.04	.88	.05	.06	.06
	(−.75, .72)	(−.02, 1.79)	(.00, .23)	(.00, .28)	(−.25, .36)
10. Information	1.34	.77	.22	.03	−.25
	(.69, 2.01)	(−.18, 1.81)	(.04, .51)	(.00, .19)	(−.56, −.00)
11. FIRE (x-Housing)	1.92	.35	.76	.08	.01
	(1.34, 2.48)	(−.42, 1.34)	(.35, .92)	(.01, .40)	(−.41, .40)
12. PBS	1.87	.90	.64	.06	−.92
	(1.48, 2.29)	(−.01, 1.80)	(.31, .87)	(.00, .39)	(−.98, −.67)
13. Education and Health	.59	1.36	.16	.10	−.63
	(−.06, 1.05)	(.24, 2.49)	(.01, .56)	(.01, .54)	(−.88, −.26)
14. Arts, Entertainment, and Food Service	1.19	.37	.37	.05	−.18
	(.69, 1.75)	(−.39, 1.31)	(.11, .67)	(.00, .26)	(−.51, .02)
15. Other Services (x-Government)	.68	.74	.06	.02	−.07
	(−.10, 1.48)	(−.10, 1.63)	(.01, .23)	(.00, .10)	(−.35, .17)
16. Housing	.82	.75	.01	.10	.07
	(−.13, 1.74)	(.08, 1.50)	(.00, .04)	(.01, .44)	(−.21, .40)
Aggregate	1.0	1.0	.67	.30	−.29
			(.48, .82)	(.10, .58)	(−.72, −.13)

NOTE.—The estimates are posterior medians, with 68% credible intervals shown in parentheses. The "corr(ℓ, z)" column reports the correlations between $g^{\ell}_{u,i,t}$ and $g^{z}_{u,i,t}$ for the rows corresponding to sectors, and correlations between $g^{\ell}_{f,t}$ and $g^{z}_{f,t}$ for the "Aggregate" row.

each sector has in the aggregate economy can differ considerably from its value-added share in GDP. Thus, as we show below, sectors such as Durable Goods, Construction, and PBS, with extensive linkages to other sectors as input suppliers, have an outsize influence on the aggregate trend.

Figure 5 shows a historical decomposition of the trends in aggregate labor and TFP growth rates arising from the common factors, $(g^{\ell}_{f}, g^{z}_{f})$, and sector-specific components, $\{g^{\ell}_{u,i}, g^{z}_{u,i}\}^{16}_{i=1}$. Figures 5*A* and 5*D* show the (demeaned) values of the aggregate growth rates with the associated

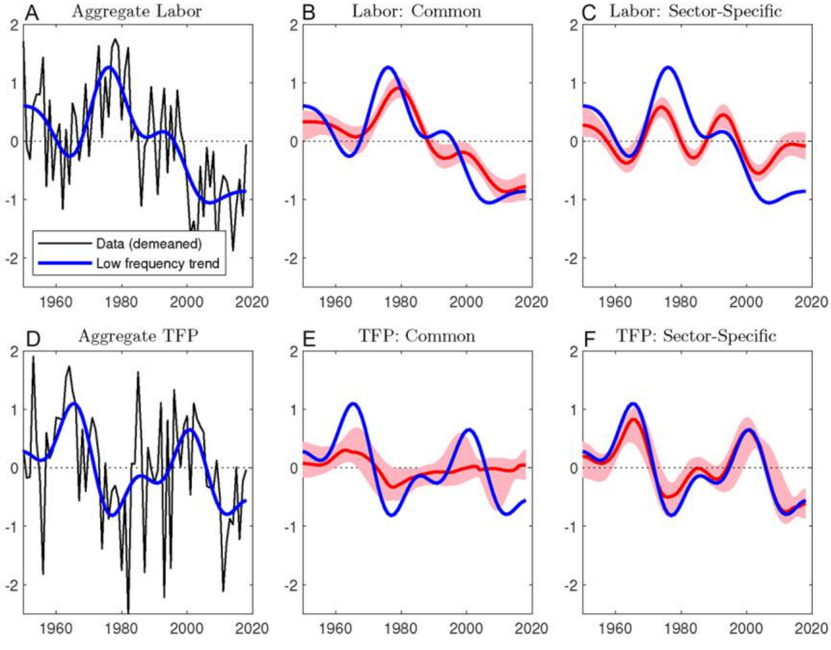

FIG. 5.—Aggregate trend growth rates in labor and TFP: common and sector-specific components (percentage points at annual rate). *A* and *D* show the growth rates (deviated from their sample mean) and the low-frequency trend. The other panels show the low-frequency trend and its decomposition into common and sector-specific components. The red lines denote the posterior median and the shaded areas the (pointwise) equal-tail 68% credible intervals.

low-frequency trend. The other panels decompose the trend into its common (figs. 5*B*, 5*E*) and sector-specific components (figs. 5*C*, 5*F*). This decomposition relies on standard signal extraction formulas to compute the posterior distribution of (**F**, **U**), given **X**, and the figure includes 68% (pointwise) credible intervals for the resulting common and sector-specific trends that incorporate uncertainty about the model's parameter values. Figure 5*B* suggests that much of the increase in the trend growth rate of aggregate labor in the 1960s and 1970s and the subsequent decline in the 1980s and 1990s (both typically associated with demographics) is captured by the model's common factor in labor. Sector-specific labor factors, for the most part, played a supporting role. In contrast, while the model's aggregate common factor played a role in the decline of trend TFP growth in the 1970s, the low-frequency variation in the series since then has been associated almost exclusively with sector-specific sources.

Figures 6 and 7 present the trend growth rates for each of the sectors (shown previously in fig. 5), along with the estimated sector-specific $(g^{\ell}_{u,i,t}, g^{z}_{u,i,t})$ components. Consistent with the R^2 values shown in table 3,

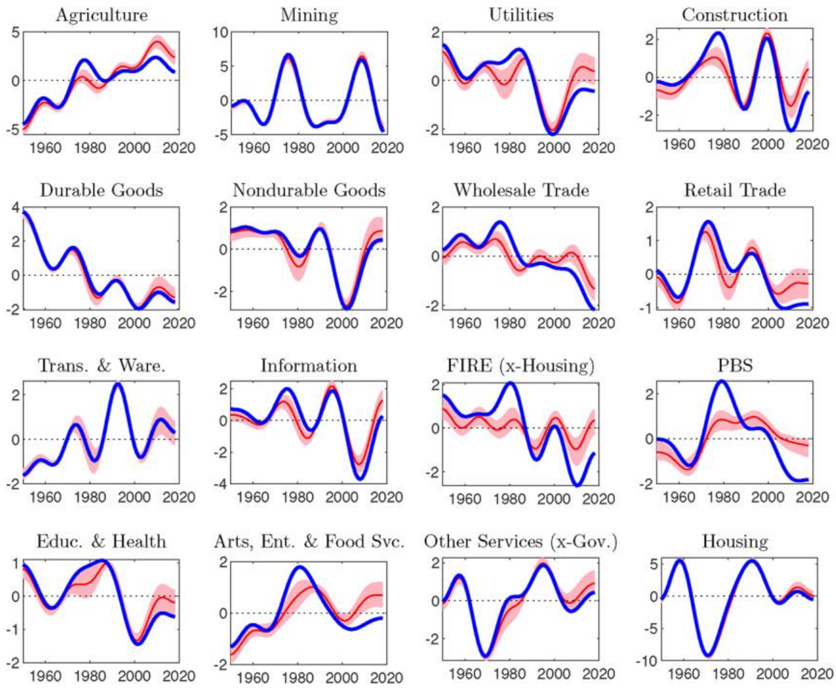

FIG. 6.—Labor trends and sector-specific components (percentage points at annual rate). Each panel shows the low-frequency trend for sectoral growth rate (in blue) and its sector-specific component (in red). The red lines denote the posterior median and the shaded areas the (pointwise) equal-tail 68% credible intervals.

much of the variation in the trend growth rates of sectoral TFP and labor is associated with sector-specific factors, and this is particularly true for TFP. Notable in figures 6 and 7 is the negative correlation between the low-frequency components of labor and TFP sectoral growth.[13]

IV. Sectoral Trends and the Aggregate Economy

Given the evolution of sectoral trend growth rates for labor and TFP over the past 70 years, this section explores their implications for long-run GDP growth. The key consideration here is that production sectors are linked because each sector uses capital goods and materials produced in other sectors. Therefore, we consider a multisector growth model that features

[13] One explanation for this negative correlation relies on complementarities in preferences (see Ngai and Pissarides 2007; Herrendorf, Rogerson, and Valentinyi 2013). Technological progress in a sector leads to reduced spending on that sector's consumption goods and, by implication, reduced employment in that sector as well.

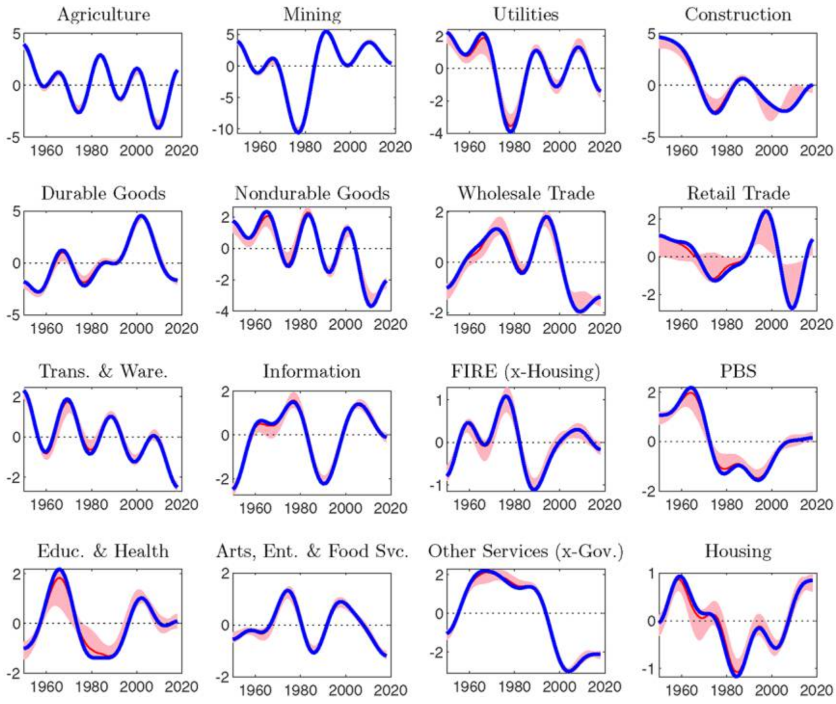

FIG. 7.—TFP trends and sector-specific components (percentage points at annual rate). See figure 6 legend for further details.

these interactions. Consistent with our TFP calculations in section III, the model also features competitive product and input markets.

We consider a structural framework with preferences and technologies that are unit elastic, so that the economy evolves along a BGP in the long run. Capital accumulation interacts with production linkages to amplify the effects of sector-specific sources of growth. In particular, changes in the growth rate of labor or TFP in one sector affect not only its own value-added growth but also that of all other sectors. We derive closed-form expressions for the long-run multipliers summarizing the aggregate growth implications of these network effects for each sector. The magnitude of the multiplier associated with a given sector depends on its role and importance as a supplier of capital and materials to other sectors.

We first outline a general n-sector model that we use in our quantitative analysis. After introducing the general model, we present several special cases using $n = 2$ sectors to highlight key mechanisms and their relationship to previous work. We then return to the general n-sector model.

A. *Economic Environment*

Consider an economy with n distinct sectors of production indexed by j (or i). A representative household derives utility from these n goods according to

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \prod_{j=1}^{n} \left(\frac{c_{j,t}}{\theta_j} \right)^{\theta_j}, \quad \sum_{j=1}^{n} \theta_j = 1, \quad \theta_j \geq 0,$$

where θ_j is the household's expenditure share on final good j.

Each sector produces a quantity, $y_{j,t}$, of good j at date t, using a value-added aggregate, $v_{j,t}$, and a materials aggregate, $m_{j,t}$, with the technology

$$y_{j,t} = \left(\frac{v_{j,t}}{\gamma_j} \right)^{\gamma_j} \left(\frac{m_{j,t}}{1 - \gamma_j} \right)^{1-\gamma_j}, \quad \gamma_j \in [0, 1]. \tag{3}$$

The quantity of materials aggregate, $m_{j,t}$, used in sector j is produced with the technology

$$m_{j,t} = \prod_{i=1}^{n} \left(\frac{m_{ij,t}}{\phi_{ij}} \right)^{\phi_{ij}}, \quad \sum_{i=1}^{n} \phi_{ij} = 1, \quad \phi_{ij} \geq 0, \tag{4}$$

where $m_{ij,t}$ denotes materials purchased from sector i by sector j. The notion that every sector potentially uses materials from every other sector introduces a first source of interconnectedness in the economy. An input-output matrix (IO matrix) is an $n \times n$ matrix Φ with typical element ϕ_{ij}. The columns of Φ add up to the degree of returns to scale in materials for each sector, in this case unity. The row sums of Φ summarize the importance of each sector as a supplier of materials to all other sectors. Thus, the rows and columns of Φ reflect "sell-to" and "buy-from" shares, respectively, for each sector.

The value-added aggregate, $v_{j,t}$, from sector j is produced using capital, $k_{j,t}$, and labor, $\ell_{j,t}$, according to

$$v_{j,t} = z_{j,t} \left(\frac{k_{j,t}}{\alpha_j} \right)^{\alpha_j} \left(\frac{\ell_{j,t}}{1 - \alpha_j} \right)^{1-\alpha_j}, \quad \alpha_j \in [0, 1]. \tag{5}$$

Capital accumulation in each sector follows

$$k_{j,t+1} = x_{j,t} + (1 - \delta_j) k_{j,t}, \tag{6}$$

where $x_{j,t}$ represents investment in new capital in sector j and $\delta_j \in (0, 1)$ is the depreciation rate specific to that sector. Investment in each sector j is produced using the quantity, $x_{ij,t}$, of sector i goods by way of the technology

$$x_{j,t} = \prod_{i=1}^{n} \left(\frac{x_{ij,t}}{\omega_{ij}} \right)^{\omega_{ij}}, \quad \sum_{i=1}^{n} \omega_{ij} = 1, \quad \omega_{ij} \geq 0. \tag{7}$$

Thus, there exists a second source of interconnectedness in this economy, in that new capital goods in every sector are potentially produced using the output of other sectors. This additional source of dynamic linkages in the economy, mostly absent from structural multisector studies, is shown to be a key propagation mechanism over the business cycle in vom Lehn and Winberry (2022). Similarly to the IO matrix, a capital flow matrix is an $n \times n$ matrix Ω with typical element ω_{ij}. The columns of Ω add up to the degree of returns to scale in investment for each sector which here is unity. The row sums of Ω indicate the importance of each sector as a supplier of new capital to all other sectors.

The resource constraint in each sector j is given by

$$c_{j,t} + \sum_{i=1}^{n} m_{ji,t} + \sum_{i=1}^{n} x_{ji,t} = y_{j,t}.$$

Sectoral change is defined by changes in the composite variable, $A_{j,t}$, that reflect the joint behavior of both TFP and labor growth. In particular, under the maintained assumptions, sectoral value added may be alternatively expressed as

$$v_{j,t} = A_{j,t}\left(\frac{k_{j,t}}{\alpha_j}\right)^{\alpha_j},$$

where

$$\Delta \ln A_{j,t} = \Delta \ln z_{j,t} + (1-\alpha_j)\Delta \ln \ell_{j,t}. \tag{8}$$

In this paper, we condition on the observed joint behavior of TFP and labor growth rates, $\{\Delta \ln z_{j,t}, \Delta \ln \ell_{j,t}\}$, in each sector j and derive their implications for aggregate value-added or GDP growth. In particular, we provide general growth accounting expressions that quantify the effects of changes in trend input growth in a given sector in light of its production linkages to all other sectors.

While we condition on observed labor growth rates, the growth accounting expressions we derive are largely unchanged in a model where the allocation of labor is endogenous. In particular, a conventional treatment of labor supply produces a growth expression that is isomorphic to that presented below. In that expression, the way in which capital accumulation and the network features of production determine the influence of different sectors on aggregate growth is unchanged, as are the effects of long-run changes in TFP growth on GDP growth. The key difference is that with endogenous labor supply, the common and idiosyncratic components of labor input now carry a structural interpretation. Specifically, the common component is associated with broad demographics such as population growth and how these demographics affect labor input in each sector. The idiosyncratic component reflects sector-specific factors such as those determining the disutility cost of working in different sectors, including a sector-specific Frisch elasticity, or sector-specific labor quality adjustments.[14]

For ease of presentation, we use the following notation throughout the paper: we denote the matrix summarizing value-added shares in gross output in different sectors $\Gamma_{\mathrm{d}} = \mathrm{diag}\{\gamma_j\}$, the IO matrix $\Phi = \{\phi_{ij}\}$, the capital flow matrix $\Omega = \{\omega_{ij}\}$, and the matrix summarizing capital shares in value added in different sectors $\alpha_{\mathrm{d}} = \mathrm{diag}\{\alpha_j\}$.

B. *Balanced Growth and Sectoral Multipliers*

We consider a BGP where the growth rates of TFP and labor in sector j are given by g_j^z and g_j^ℓ, respectively. From equation (8), it follows that along that path,

$$\Delta \ln A_{j,t} = g_j^a = g_j^z + (1 - \alpha_j) g_j^\ell.$$

We now show that because of production linkages, sources of change in an individual sector, g_j^a, help determine value-added growth in every other sector along the BGP. These linkages, therefore, amplify the effects of sector-specific change on GDP growth, and this amplification can be summarized by a multiplier for each sector. As we will see below, these multipliers scale the influence of some sectors on GDP growth by up to multiple times their share in the economy.

The sectoral multipliers are readily computed from the production linkages specified in the model. Along the BGP, gross output in sector j ($y_{j,t}$) and its uses ($c_{j,t}$, $m_{ji,t}$, and $x_{ji,t}$) grow at the same sector-specific rate. Thus, let g_j^y denote this common growth rate for y_j, c_j, m_{ji}, and x_{ji}. Let g_j^v, g_j^m, g_j^k, and g_j^x denote the BGP growth rates of sector j's inputs v_j, m_j, k_j, and x_j, respectively. Let $g^y = (g_1^y, \dots g_n^y)'$, and define the $n \times 1$ vectors g^v, g^m, and so on, analogously. From equation (4), note that $g_j^m = \Sigma_i \phi_{ij} g_i^y$ (because m_{ij} grows at rate g_i^y), so that $g^m = \Phi' g^y$. Similarly, from equations (6) and (7), $g_j^k = g_j^x = \Sigma_i \omega_{ij} g_i^y$ (because x_{ij} grows at rate g_i^y), so that $g^k = \Omega' g^y$. Equation (3) implies $g^y = \Gamma_{\mathrm{d}} g^v + (I - \Gamma_{\mathrm{d}}) g^m$, with $g^v = g^a + \alpha_{\mathrm{d}} g^k$ from equation (5). Collecting terms in g^y then yields $g^y = \Gamma_{\mathrm{d}} g^a + \Gamma_{\mathrm{d}} \alpha_{\mathrm{d}} \Omega' g^y + (I - \Gamma_{\mathrm{d}}) \Phi' g^y$, so that

[14] See sec. 4 of the appendix. The interpretation or identification of sources of labor growth will necessarily depend on the particular model of endogenous labor supply under consideration. Because our focus is on growth accounting (rather than counterfactuals), we take the observations on labor growth as given, whatever their underlying forces. Ngai and Pissarides (2007) explore an alternative framework where the reallocation of labor among consumption goods sectors is an outcome of unbalanced growth among those goods while, at the same time, preserving balanced growth at the aggregate level. Absent from their work, however, are the network considerations and the role of capital in determining network multipliers that are central to this paper. An interesting avenue for future work, therefore, is the study of growth and structural change with production networks.

$$g^y = \Xi' g^a, \tag{9}$$

where $\Xi' = [I - \Gamma_d \alpha_d \Omega' - (I - \Gamma_d)\Phi']^{-1}\Gamma_d$ is the generalized Leontief inverse.

Finally, with $g^v = g^a + \alpha_d g^k$ and $g^k = \Omega' g^y$, then

$$g^v = (I + \alpha_d \Omega' \Xi') g^a. \tag{10}$$

Observe that preference parameters are absent from equation (10), in that balanced-growth relationships are ultimately statements about technologies and resource constraints.

Equation (10) describes how the sources of growth in a given sector, g_j^a, affect value-added growth in all other sectors, g_i^v. This relationship involves the direct effects of sectors' TFP and labor growth on their own value-added growth, Ig^a, and the indirect effects that sectors have on other sectors through the economy's sectoral network of investment and materials, $\alpha_d \Omega' \Xi' g^a$. The general Leontief inverse, Ξ, is central and summarizes the knock-on effects of sectoral changes through linkages in investment, captured in Ω, and materials, captured in Φ.

Given the vector of sectoral value-added growth rates, g^v, the Divisia aggregate index of GDP growth is $g^V = s^{v\prime} g^v$, where $s^v = (s_1^v, \ldots, s_n^v)$ is a vector of sectoral value-added shares in GDP that are constant on the BGP. Thus,

$$g^V = s^{v\prime}(I + \alpha_d \Omega' \Xi') g^a, \tag{11}$$

so that, holding shares constant,

$$\frac{\partial g^V}{\partial g^a} = s^v + \Xi \Omega \alpha_d s^v. \tag{12}$$

The first term in equation (12) shows the direct effect of g^a on the growth rate of GDP, and the second term captures the network effects of g^a on GDP growth induced by production linkages.[15] Equation (12), therefore, defines the vector of *sectoral multipliers* for each of the j sectors.

When no sector uses capital in production, $\alpha_d = 0$, the drivers of growth in sector j, g_j^a, affect GDP growth only through that sector's share in the economy, $\partial g^V / \partial g_j^a = s_j^v$. More generally, equations (10) and (12) suggest the presence of a network multiplier effect that varies by sector and that depends not only on the importance of sectoral interactions

[15] In general, sectoral value-added shares in GDP, s^v, will also depend on the model's underlying parameters, including the vector of sources of sectoral growth, g^a. However, changes in sectoral shares induced by an exogenous change in a sector k, $\partial s_j^v / \partial g_k^a$, will be mostly inconsequential for overall growth, consistent with fig. 1 and the notion that since shares must sum to 1, $\Sigma_j (\partial s_j^v / \partial g_k^a) = 0$.

through the elements of Ξ but also on the extent to which sectors use capital produced by other sectors in their own production, that is, the elements in Ω and α_{d}. From equation (9), a change in input growth in sector j influences every other sector k through the network of production linkages summarized by all nonzero jk elements (i.e., from j to k) of Ξ. Induced changes in all sectors k, in turn, potentially affect investment in every other sector, i, through capital flows summarized by ω_{ki} in Ω (i.e., from k to i, including back to j). The net effect on GDP growth is the sum of all these interactions. Conveniently, the effects of sectoral changes, ∂g^a, on GDP growth may be thought of as a direct effect, s^v, and an additional indirect effect resulting from sectoral linkages, $\Xi\Omega\alpha_{\mathrm{d}}s^v$. Hence, we define the combined direct and indirect effects of structural change on GDP growth in terms of the vector of sectoral multipliers, $s^v + \Xi\Omega\alpha_{\mathrm{d}}s^v$.

To gain intuition, the next section discusses equations (10) and (11) in the context of special cases exemplified in previous work. In particular, we provide examples of sectoral multipliers in Greenwood, Hercowitz, and Krusell (1997) and variations thereof. The appendix discusses each example in detail, as well as the case studied by Ngai and Pissarides (2007). These examples highlight the role of capital accumulation in generating sectoral multipliers. They also underscore the fact that, given a network of intermediate goods, all sectors, even those that produce no capital goods, can have sectoral multipliers well in excess of their share in GDP. This last feature of sectoral influence is absent in Greenwood, Hercowitz, and Krusell (1997), which abstracts from intermediate inputs.

C. *Relationship to Greenwood, Hercowitz, and Krusell (1997)*

The one-sector environment featuring an aggregate production function in Greenwood, Hercowitz, and Krusell (1997) also has an interpretation as a two-sector economy (see their sec. V.A). Under that interpretation, one sector produces consumption goods (sector 1) and the other investment goods (sector 2), and each sector's production function has the same capital elasticity, α. For simplicity, we focus on the discussion in section III of Greenwood, Hercowitz, and Krusell (1997), which abstracts from the distinction between equipment and structures. Thus, consider a two-sector economy with production given by

$$\begin{aligned} c_t &= y_{1,t} = z_{1,t}k_{1,t}^{\alpha}\ell_{1,t}^{1-\alpha}, \\ x_t &= y_{2,t} = z_{2,t}k_{2,t}^{\alpha}\ell_{2,t}^{1-\alpha}, \\ k_{t+1} &= x_t + (1-\delta)k_t, \end{aligned}$$

where factors are freely mobile, $k_t = k_{1,t} + k_{2,t}$, $\ell_t = \ell_{1,t} + \ell_{2,t}$, and the constant scale factors in production (which simplify the algebra in the full model) have been dropped. Under the maintained assumptions, this two-sector environment reduces to the one-sector framework with aggregate production described in Greenwood, Hercowitz, and Krusell (1997). That is, there exists a one-sector interpretation of the two-sector economy with associated resource constraint,

$$c_t + q_t x_t = z_{1,t} k_t^{\alpha} \ell_t^{1-\alpha}, \tag{13}$$

where $q_t = z_{1,t}/z_{2,t}$ is the relative price of investment goods, and aggregate output (in units of consumption goods), $y_t = c_t + q_t x_t$, is a function of total factor endowment only, $z_{1,t} k_t^{\alpha} \ell_t^{1-\alpha}$. To the extent that technical progress in the investment sector, $z_{2,t}$, is generally more pronounced than that in the consumption sector, $z_{1,t}$, the relative price of investment goods will decline over time, as emphasized by Greenwood, Hercowitz, and Krusell (1997).

Along the BGP, all variables grow at constant but potentially different rates. Because Greenwood, Hercowitz, and Krusell (1997) do not consider materials, there is no distinction between gross output and value added. From the market-clearing conditions and the form of production technologies, it follows that sectoral output growth rates, $g_j^y = g_j^v$, are given by (in terms of the notation introduced above)

$$g_j^v = g_j^z + (1-\alpha) g^{\ell} + \alpha g^k = g_j^a + \alpha g^k, \quad j = 1, 2. \tag{14}$$

Equation (14) makes clear that any amplification of sectoral sources of growth, g_j^a, can take place only through capital accumulation. In this case, it follows from the capital accumulation equation that along the BGP, capital grows at the same rate as investment which, in sector 2 (the capital goods–producing sector), is also that of output. Thus, we have that

$$g_2^v = g^k = \frac{1}{1-\alpha} g_2^a \quad \text{and} \quad g_1^v = g_1^a + \frac{\alpha}{1-\alpha} g_2^a. \tag{15}$$

Note that the assumption of factor mobility across sectors has only minor implications for the characterization of the BGP. First, even with sector-specific investment, the resource constraint for investment implies that investment and capital grow at the same rate in each sector. Second, with sector-specific labor, the expression for output growth remains as in equation (14), with the only difference being that sector-specific labor growth rates, g_j^{ℓ}, now replace the aggregate labor growth rate, g^{ℓ}, so that $g_j^a = g_j^z + (1-\alpha) g_j^{\ell}$.

Aggregate GDP growth is defined as the Divisia index of sectoral value-added growth rates weighted by their respective value-added shares. Thus, from equation (15), aggregate GDP growth is

$$g^V = s_1^v\left(g_1^a + \frac{\alpha}{1-\alpha}g_2^a\right) + s_2^v\frac{1}{1-\alpha}g_2^a, \tag{16}$$

or alternatively,

$$g^V = s_1^v g_1^a + s_2^v g_2^a + \frac{\alpha}{1-\alpha}g_2^a. \tag{17}$$

In this economy, sector 2 is the sole producer of capital for both sectors 1 and 2 and has both a direct and an indirect effect on the aggregate economy. The indirect effect stems from the fact that capital accumulation amplifies the role of sectoral sources of growth. In equation (16), sector 2 contributes $[\alpha/(1-\alpha)]g_2^a > 0$ to value-added growth in sector 1 and scales its contributions from TFP and labor to its own value-added growth by $1/(1-\alpha) > 1$. Thus, in equation (17), the direct aggregate effect of an expansion in sector 2 by way of TFP or labor growth is its share, s_2^v, while its indirect aggregate effect is $\alpha/(1-\alpha) > 0$. It follows that sector 2's sectoral multiplier, $\partial g^V/\partial g_2^a$, is $s_2^v + \alpha/(1-\alpha)$. In contrast, because sector 1 produces goods that are fit only for consumption, it has a direct effect only on the aggregate economy. Its sectoral multiplier, $\partial g^V/\partial g_1^a$, is then simply its share in GDP, s_1^v.

A straightforward application of the general framework laid out in the previous section produces the same BGP and sectoral multipliers for sectors 1 and 2 that we have just discussed. In particular, the Greenwood, Hercowitz, and Krusell (1997) economy is a special case with $n = 2$ and, since sector 2 is the only sector producing investment goods, $\omega_{1j} = 0$ and $\omega_{2j} = 1$ for $j = 1, 2$. In addition, each good is produced without intermediate inputs, $\gamma_j = 1$, $j = 1, 2$, and the sectors use the same production functions, $\alpha_j = \alpha$, $j = 1, 2$. These yield the matrices

$$\Omega = \begin{pmatrix} 0 & 0 \\ 1 & 1 \end{pmatrix}, \quad \Gamma_{\mathrm{d}} = I, \quad \alpha_{\mathrm{d}} = \alpha I,$$

and

$$\Xi = (I - \Omega\alpha_{\mathrm{d}})^{-1} = \begin{pmatrix} 1 & 0 \\ \dfrac{\alpha}{1-\alpha} & \dfrac{1}{1-\alpha} \end{pmatrix}.$$

The associated sectoral multipliers are given by the elements of

$$\frac{\partial g^V}{\partial g_1^a} = s_1^v \quad \text{and}$$

$$\frac{\partial g^V}{\partial g_2^a} = s_2^v + \frac{\alpha}{1-\alpha}.$$

Actual production linkages are generally more involved than those just discussed. Importantly, even in the context of two sectors and no materials, the simple fact that factor income shares differ across sectors prohibits a one-sector interpretation of the economic environment with an aggregate production function. In this case, the amplification of sources of sectoral growth on GDP growth now depends on a value-added share-weighted average of capital elasticities.[16]

D. *Strictly Positive Multipliers for Sectors That Produce No Capital*

Moving beyond Greenwood, Hercowitz, and Krusell (1997), sectoral linkages also reflect a network of materials production. Thus, we now introduce intermediate goods into the Greenwood, Hercowitz, and Krusell (1997) environment. Crucially, when the consumption sector (sector 1) also produces materials for the investment-goods sector (sector 2), the growth rate of capital depends on both sectors 1 and 2. Therefore, both sectors 1 and 2 now have indirect effects on long-run GDP growth over and above their share in the economy.

We illustrate these points via a simple network of intermediate goods. Here, sector 1 produces not only consumption goods but also materials, $m_{1,t}$, used by sector 2. Similarly, sector 2 still produces capital goods for both sectors but also materials, $m_{2,t}$, used by sector 1. Since sector 1 now produces consumption goods and intermediate goods, we refer to sector 1 as the "Nondurable Goods" sector. Thus, in terms of our general notation, we have that $\gamma_j \neq 1, \omega_{1j} = 0$, and $\omega_{2j} = 1$ for $j = 1, 2$. Moreover, the relevant resource constraints in sectors 1 and 2 are now

$$c_t + m_{1,t} = y_{1,t} = \left(z_{1,t} k_{1,t}^{\alpha_1} \ell_{1,t}^{1-\alpha_1}\right)^{\gamma_1} m_{2,t}^{1-\gamma_1}$$

and

$$x_t + m_{2,t} = y_{2,t} = \left(z_{2,t} k_{2,t}^{\alpha_2} \ell_{2,t}^{1-\alpha_2}\right)^{\gamma_2} m_{1,t}^{1-\gamma_2},$$

while the rest of the production side of the economy is as in the previous examples.

In this case, a calculation shows that the BGP growth rate of capital is given by

$$g^k = \frac{(1-\gamma_2)\gamma_1 g_1^a + \gamma_2 g_2^a}{\Delta}, \tag{18}$$

where $\Delta = 1 - \gamma_2\alpha_2 - (1-\gamma_2)[\gamma_1\alpha_1 + (1-\gamma_1)]$. The growth rate of GDP is then

[16] See sec. 3 of the appendix for exact expressions.

$$g^V = s_1^v g_1^a + s_2^v g_2^a + (s_1^v \alpha_1 + s_2^v \alpha_2) g^k. \tag{19}$$

Two important observations emerge relative to the previous examples. First, because the Nondurable Goods sector now produces intermediate inputs for the investment sector, the growth rate of capital goods in equation (18) reflects sources of growth in both sectors, g_1^a and g_2^a. Hence, unlike in the previous section, both sectors 1 and 2 in equation (19) have an additional indirect effect on long-run GDP growth, $(s_1^v \alpha_1 + s_2^v \alpha_2)(\partial g^k / \partial g_1^a)$ and $(s_1^v \alpha_1 + s_2^v \alpha_2)(\partial g^k / \partial g_2^a)$, respectively, over and above their shares in the economy, s_1^v and s_2^v. Second, from equation (19), the indirect effect from sector 2 on GDP growth dominates that from sector 1 if and only if its contributions to overall capital growth, $\partial g^k / \partial g_2^a$, are larger than the corresponding contributions from sector 1, $\partial g^k / \partial g_1^a$. From equation (18), this condition holds if and only if

$$\gamma_2 > (1 - \gamma_2)\gamma_1.$$

This will not be true, for example, in economies where the value-added share in gross output of the capital sector, γ_2, is relatively small. In that case, the main inputs into the production of capital goods are intermediate inputs from the Nondurable Goods sector. That sector, therefore, ends up having more influence on aggregate growth.

Substituting equation (18) into equation (19) yields the sectoral multipliers:[17]

$$\frac{\partial g^V}{\partial g_1^a} = s_1^v + \frac{s_1^v \alpha_1 \gamma_1 (1 - \gamma_2) + s_2^v \alpha_2 \gamma_1 (1 - \gamma_2)}{\Delta} \quad \text{and}$$

$$\frac{\partial g^V}{\partial g_2^a} = s_2^v + \frac{s_1^v \alpha_1 \gamma_2 + s_2^v \alpha_2 \gamma_2}{\Delta}.$$

Generally, the main lesson from these examples is that network production linkages and capital accumulation are the key components that lead to sectoral multipliers along the BGP. Furthermore, the implied amplification of idiosyncratic sources of growth on GDP growth can arise in any sector, including those producing only Nondurable Goods.

Finally, we note a caveat to our results: they all pertain to a closed economy. Cavallo and Landry (2010) argue that imports are also a source of equipment capital accumulation, and more generally Basu et al. (2013)

[17] Equivalently, these multipliers can be computed from the general formula in eq. (12) using the matrices for this model:

$$\Omega = \begin{pmatrix} 0 & 0 \\ 1 & 1 \end{pmatrix}, \; \alpha_d = \begin{pmatrix} \alpha_1 & 0 \\ 0 & \alpha_2 \end{pmatrix}, \; \Gamma_d = \begin{pmatrix} \gamma_1 & 0 \\ 0 & \gamma_2 \end{pmatrix}, \text{ and } \Phi = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}.$$

argue for including trade when studying ISTC with production networks. In section 3.5 of the appendix, we introduce traded investment goods into the Greenwood, Hercowitz, and Krusell (1997) framework along the lines of Basu et al. (2013). In that case, the amplification effects of production networks and capital accumulation also reflect variations in the terms of trade, scaled by the share of foreign investment goods in total investment. In this example, the quantitative implications of traded capital goods remain limited, though they have increased over time.

V. Quantitative Findings

This section puts together the empirical findings from section III and model insights from section IV. It shows that sector-specific trends have played a dominant role in driving the trend rate of growth in GDP over the postwar period. We estimate that this aggregate trend rate of growth has fallen by almost 3 percentage points between 1950 and today.

A. Model Parameters

We first outline the construction of model parameters, a procedure that follows mostly Foerster, Sarte, and Watson (2011) and is governed by the BEA input-output and capital flow accounts.[18]

In our benchmark economy, value-added shares in gross output, $\{\gamma_j\}$, capital shares in value added, $\{\alpha_j\}$, and material bundle shares, $\{\phi_{ij}\}$, are obtained from the 2015 BEA make and use tables. The make table tracks the value of production of commodities by sector, while the use table measures the value of commodities used by each sector. We combine the make and use tables to yield, for each sector, a table whose rows show the value of a sector's production going to other sectors (materials) and households (consumption) and whose columns show payments to other sectors (materials) as well as labor and capital. Thus, a column sum represents total payments from a given sector to all other sectors, while a row sum gives the importance of a sector as a supplier to other sectors. We then calculate material bundle shares, $\{\phi_{ij}\}$, which constitute the IO matrix, as the fraction of all material payments from sector j that goes to sector i. Similarly, value-added shares in gross output, $\{\gamma_j\}$, are calculated as payments to capital and labor as a fraction of total expenditures by sector j, while capital shares in value added, $\{\alpha_j\}$, are payments to capital as a fraction of total payments to labor and capital.

[18] Section 8 of the appendix contains a more detailed description of the procedure, and for the 16 sectors considered in this paper it displays the capital flow matrix, table A10; the IO matrix, table A11; and the associated generalized Leontief inverse, table A12.

The parameters that determine the production of investment goods, $\{\omega_{ij}\}$, are chosen similarly in accordance with the BEA capital flow table from 1997, the most recent year for which this flow table is available. The capital flow table shows the flow of new investment in equipment, software, and structures toward sectors that purchase or lease it. By matching commodity codes to sectors, we obtain a table that has entries showing the value of investment purchased by each sector from every other sector. A column sum represents total payments from a given sector for investment goods to all other sectors, while a row sum shows the importance of a sector as a supplier of investment goods to other sectors. Hence, the investment bundle shares, $\{\omega_{ij}\}$, that constitute the capital flow matrix are estimated as the fraction of payments for investment goods from sector j to sector i, expressed as a fraction of total investment expenditures made by sector j.

Conditional on these parameters, equation (10) gives sectoral value-added growth along the BGP. In constructing aggregate GDP growth from these sectoral value-added growth rates, we rely on the full-sample mean value-added shares from the KLEMS data that were used in our empirical analysis. Recall also that in figure 1, we explored using different definitions of value-added shares in calculating GDP growth. While this did not lead to meaningful differences in aggregate growth, to the extent that these shares are changing over time, as do input-output relationships, the model might nevertheless yield more material differences in the implied sectoral multipliers. Thus, in section 9 of the appendix, we show that our benchmark sectoral multipliers are robust to versions of the model informed by mean value-added shares for the first and last 15 years and the 1960 and 1997 make and use tables.

B. *Production Linkages in the US Economy*

The production of investment goods in the United States turns out to be concentrated in relatively few sectors. Construction and Durable Goods produce close to 80% of the capital in almost every sector. Put another way, as shown in figure 8, we can think of the Construction and Durable Goods sectors as investment hubs in the production network. Construction comprises residential and nonresidential structures, including infrastructure. The bulk of capital produced by the Durable Goods sector resides in motor vehicles, machinery, and computer and electronic products. Other sectors recorded as producing capital goods for the US economy include Wholesale Trade, Retail Trade, and PBS. In the PBS sector, the notion of capital produced for other sectors is overwhelmingly composed of computer system designs and related services. The BEA distinguishes between materials and capital goods by estimating the service life of different commodities, and, consistent with the annual time period used in this paper, commodities expected to be used in production within the year are defined as materials.

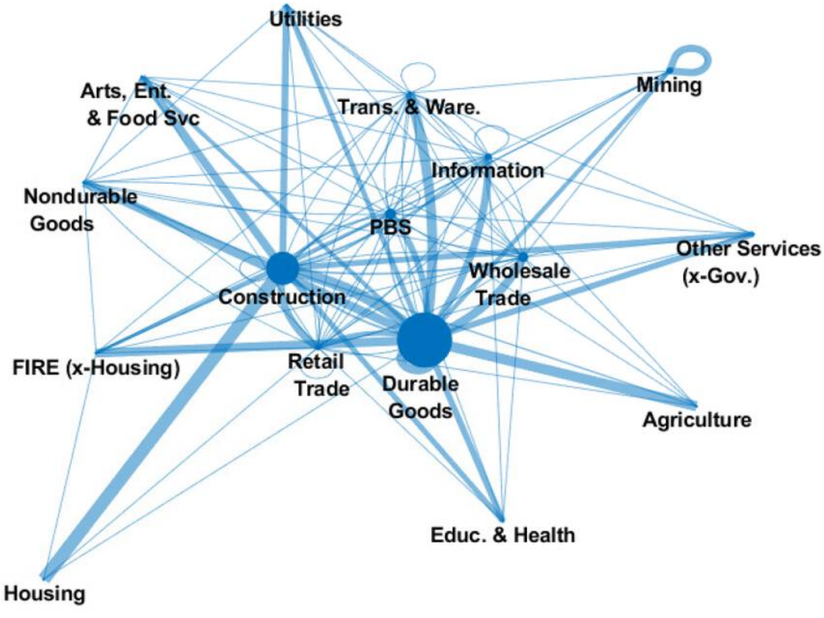

FIG. 8.—Investment network. This figure shows the investment network as a graph, where capital flows are represented by edges between nodes representing sectors. A sector with a larger node indicates that other sectors spend a larger share of their capital expenditures, on average, in that sector. A wider edge between two nodes reflects larger bidirectional capital flows relative to all other capital flows. See the capital flow table (A10) in section 8 of the appendix.

As a practical matter, however, the distinction between materials and investment goods is not always straightforward. We address measurement issues separately in section VI.[19]

Compared to the capital flow matrix, the production of intermediate goods is somewhat less concentrated, as all sectors produce materials for

[19] Major revisions of the NIPAs broadened the concept of capital by including expenditures on software in 1999 and expenditures on R&D and entertainment, literary, and artistic originals in 2013. These investments now come under the heading of "intellectual property products" (IPPs). While the KLEMS data include a broad measure of IPP capital, the 1997 capital flow tables include software investment but not all IPP investment categories. The share of missing investment is less than 10% in 1960 and about 15% today. As also noted in Foerster, Sarte, and Watson (2011), capital flow tables do not account for an industry's purchases of used capital goods and likely miss a portion of maintenance and repair using within-sector resources. Results presented here are robust to adjustments that assume up to an additional 25% of capital expenditures within sectors. Finally, we abstract from land and inventories in the production structure. Including inventories and land is conceptually straightforward, but data quality at the sector level remains an issue. The online appendix of Fernald (2014) includes land and inventories into a Greenwood, Hercowitz, and Krusell (1997) growth accounting framework and finds only a marginal effect.

all other sectors to varying degrees. However, from the IO matrix, PBS and FIRE stand out as suppliers of materials. These two sectors are the largest suppliers of intermediate goods in the US production network, making up roughly 20% of materials expenditures across sectors. A key difference, however, is that intermediate inputs produced by FIRE are used extensively in Housing, which is consumed mostly as a final good. In contrast, PBS is the largest supplier of intermediate goods to Durable Goods (other than those Durable Goods purchases from itself). After FIRE and PBS, the next-largest suppliers of materials are Durable Goods and Nondurable Goods, which make up around 11% of materials expenditures across sectors on average, or half of those spent on PBS.

In contrast to the sectors that play a key role in the US production network, output produced in sectors such as Agriculture, Forestry, Fishing and Hunting, Housing, and Arts, Entertainment, and Food Services is mostly consumed as final goods.

C. Sectoral Multipliers

Table 4 shows the direct and combined effects of sectoral sources of growth on GDP growth. The importance of Durable Goods, PBS, and Construction means not only that their value-added shares in GDP are large—13%, 9%, and 5%, respectively—but also that they have large spillover effects on other sectors. In particular, Durable Goods and PBS have the two largest sectoral multipliers, 0.42 and 0.25, respectively, while Construction's multiplier exceeds 3 times its value-added share in GDP at 0.17, given its central role

TABLE 4
SECTORAL MULTIPLIERS

Sector	s^v (1)	$\Xi\Omega\alpha_d s^v$ (2)	$(I + \Xi\Omega\alpha_d)s^v$ (3)
Agriculture	.03	.01	.03
Mining	.02	.03	.05
Utilities	.02	.01	.03
Construction	.05	.12	.17
Durable Goods	.13	.28	.42
Nondurable Goods	.09	.03	.13
Wholesale Trade	.07	.08	.15
Retail Trade	.08	.02	.11
Transportation and Warehousing	.04	.03	.07
Information	.05	.03	.08
FIRE (x-Housing)	.10	.03	.14
PBS	.09	.16	.25
Education and Health	.06	.00	.06
Arts, Entertainment, and Food Service	.04	.01	.04
Other Services (x-Government)	.03	.01	.04
Housing	.09	.00	.09

NOTE.—This table decomposes each sector's total multiplier (col. 3) into a direct effect (col. 1) and an indirect effect (col. 2). The sums do not necessarily add up because of rounding.

in the investment network. Considering that trend TFP growth in Construction fell by almost 5 percentage points between 1950 and 1980 in figure 4, this gives us, all else equal, a roughly 0.85 percentage point decline in trend GDP growth from that sector alone during that period. Similarly, the over 6 percentage point collapse in the trend growth rate of TFP in Durable Goods since 2000 would have, on its own, contributed roughly a 2.5 percentage point decline in trend GDP growth.

It is also apparent from table 4 that the effects of sectoral change on GDP growth are always at least as large as sectors' value-added shares in GDP. Sectoral network multipliers almost triple the share of PBS, from 0.09 to 0.25, and double that of Wholesale Trade, from 0.07 to 0.15. In other sectors, such as Agriculture, Forestry, Fishing and Hunting, or Housing, the network multipliers are smaller, since these sectors produce mainly final consumption goods. Because the same network relationships embodied in the capital flow matrix, Ω, and the IO matrix, Φ, determine the importance that sectors have in the economy both as a share of value added and through their spillover effects, sectors with relatively larger shares in GDP will also tend to be associated with large network multipliers.

A key implication of table 4 is that the effects of sectoral change on GDP growth arise in part through a composition effect. Therefore, secular changes in GDP growth can take place without observable changes in aggregate TFP growth. For example, consider purely idiosyncratic changes in TFP growth, $\partial g_{u,j}^{u,z}$, that leave aggregate TFP growth unchanged, $\sum_{j=1}^{n} s_j^v \partial g_{u,j}^z = 0$. In other words, the direct effect of sectoral TFP growth in this case is zero. Despite aggregate TFP growth not changing, these idiosyncratic changes will nevertheless have an (indirect) effect on GDP growth, since the sum of sectoral multipliers is larger than 1.

D. Historical Decomposition of the Trend Growth Rate of GDP

The various sectoral multiplier calculations we have just carried out depend on the balanced-growth equations (10) and (11). These equations hold only in steady state and ignore endogenous transitional dynamics that are potentially important in explaining variations over the business cycle. However, because our empirical focus is on variations in growth rates with periodicities longer than 17 years, we abstract from these transitional dynamics and apply the formulas (10) and (11) directly to the trend growth rates of TFP and labor extracted in section III, $g_{i,t}^z$ and $g_{i,t}^\ell$, as an approximation.[20] In addition, we then explore how our estimates

[20] Our results then reflect the long-run amplifying effects of production linkages by way of capital accumulation. Despite abstracting from the transition dynamics, sec. 9 of the appendix shows that the model's implied trend sectoral capital growth rates match their

of common ($\lambda_i^z g_{i,t}^z$, $\lambda_i^\ell g_{i,t}^\ell$) and sector-specific ($g_{u,i,t}^z$, $g_{u,i,t}^\ell$) trend input growth have historically contributed to the trend growth rates of sectoral value-added and GDP. Thus, we compute the trend growth rates of sectoral value added as

$$g_t^v = (I + \alpha_d \Omega' \Xi')\left[\lambda^z g_{f,t}^z + g_{u,t}^z + (I - \alpha_d)\left(\lambda^\ell g_{f,t}^\ell + g_{u,t}^\ell\right)\right],$$

where $g_t^v = (g_{1,t}^v, \ldots, g_{n,t}^v)$, and $(\lambda^z, \lambda^\ell)$ are vectors containing the factor loadings from equation (1). GDP trend growth is then

$$g_t^V = s^{v\prime} g_t^v.$$

Figure 9 depicts the annual growth rate of GDP and its trend in black (previously shown in fig. 2), together with the corresponding trend growth rate computed from the balanced-growth multipliers (solid blue line) and its contribution from the direct effect using sectors' value-added shares only (dashed blue line), $s^{v\prime} I[g_t^z + (I - \alpha_d) g_t^\ell]$. In all, trend GDP growth fell by nearly 3 percentage points over the postwar period. Importantly, the sizable gap between the trend with direct effects only and the full-model trend implies that the indirect effects stemming from network production linkages constitute a significant component of trend GDP growth. There is a notable discrepancy between model and data in the 1970s, when the balanced-growth multipliers suggest a larger decline in trend GDP growth rates than in the data. In that period, periodicities longer that 17 years may not be adequate to capture the required adjustment to capital implied by the model.

Figure 10 decomposes the trend growth rate of GDP implied by the model into its components derived from common factors and sector-specific factors. The model indicates that sector-specific or unique factors in trend labor and TFP growth (fig. 10*B*) have historically accounted for roughly three-fourths of the long-run changes in GDP growth. Conversely, only about one-fourth of the variation in trend GDP growth since 1950 has come from common sources of input growth (fig. 10*A*). This is despite common factors explaining roughly two-thirds of the variation in the trend growth rate of aggregate labor, noted in section III. To understand this finding, recall that some sectors that have large sectoral multipliers, such as Durable Goods or Construction (table 3), also have large variations in trend input growth that are almost entirely driven by idiosyncratic factors (figs. 6, 7).

Figure 10*C* plots the posterior density for R_f^2, the fraction of the variance in trend GDP growth explained by common sources. The median of the posterior for R_f^2 is 0.26, the mode is less than 0.20, and 70% of the

counterparts in the data well, with the exception of Mining, which carries a small sectoral multiplier.

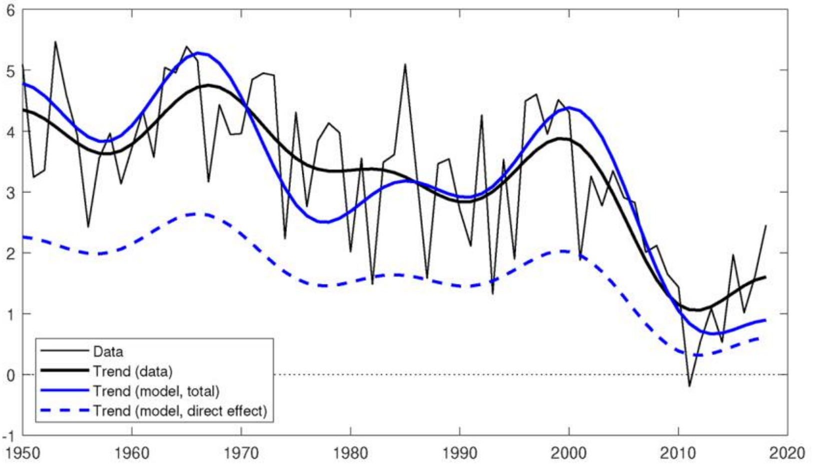

FIG. 9.—Trend growth rate in GDP: data and model (percentage points at annual rate). The figure shows the cyclically adjusted GDP growth rate (thin black line), along with its low-frequency trend (thick black line). Also shown are the model-implied trend using the low-frequency trends of labor and TFP growth (solid blue line) and the trend implied by only the direct effects of labor and TFP based solely on value-added shares (dashed blue line).

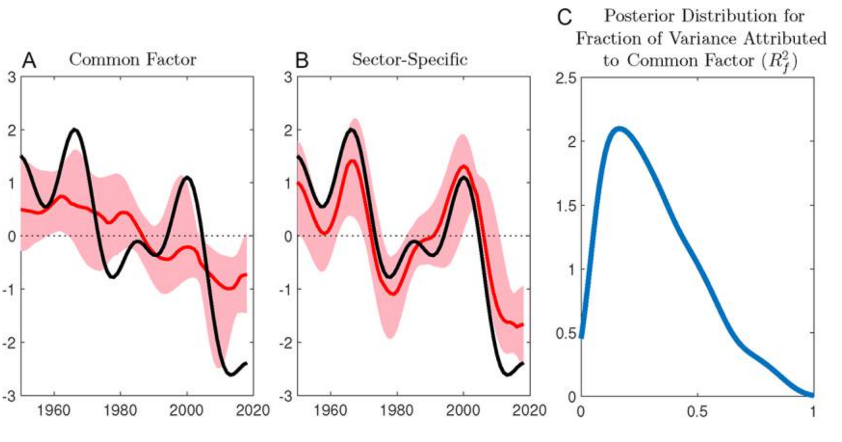

FIG. 10.—Decomposition of the trend growth rate in GDP (percentage points at annual rate). *A*, *B*, The (demeaned) model-implied trend GDP growth (black line) and its decomposition into changes due to the common factor and sector-specific factors (red lines). The overall trend in black is $s^{v\prime}(I + \alpha_{\mathrm{d}}\Omega'\Xi')[g_t^z + (I - \alpha_{\mathrm{d}})g_t^\ell]$. The posterior median estimates of common and sector-specific components, along with their 68% credible intervals red lines, shaded areas) are, respectively, $s^{v\prime}(I + \alpha_{\mathrm{d}}\Omega'\Xi')[\lambda^z g_{f,t}^z + (I - \alpha_{\mathrm{d}})\lambda^\ell g_{f,t}^\ell]$ and $s^{v\prime}(I + \alpha_{\mathrm{d}}\Omega'\Xi')[g_{u,t}^z + (I - \alpha_{\mathrm{d}})g_{u,t}^\ell]$. *C*, Posterior distribution for the fraction of the variance in trend GDP growth attributed to the common factor.

posterior mass is associated with values of R_f^2 that are less than 0.40. Thus, these results suggest that most of the long-run evolution of GDP growth has historically stemmed from sector-specific factors.

The results reported thus far use the benchmark priors. Recall from section III that these priors were relatively uninformative, except for the factor loadings. In particular, the prior for λ^ℓ was $\lambda^\ell \sim N(\mathbf{1}, \mathbf{P}_\ell)$, where $\mathbf{P}_\ell = \eta^2[I_{16} - s_\ell(s_\ell' s_\ell)^{-1} s_\ell']$, and an analogous prior was used for λ^z. These priors enforced the normalization that $s_\ell'\lambda^\ell = s_v'\lambda^z = 1$, so that unit changes in f_t^ℓ and f_t^z lead to unit changes in the long-run growth rate of aggregate labor and TFP. The parameter η then governed how aggressively the estimates of λ_i^ℓ or λ_i^z are shrunk toward their mean of unity. The benchmark results use $\eta = 1$. Smaller values of η shrink the estimates closer to 1, while larger values of η allow them to deviate from 1 more than the baseline model. Thus, we now explore the robustness of our findings to alternative priors, $\eta = 1/2$ and $\eta = 2$. In addition, we also run the model using $q = 6$, which captures long-run variations with periodicities longer than $2 \times 69/6 = 23$ years.

Figure 11 summarizes the findings from these robustness exercises by reproducing figure 10 for each of these alternative models. It is clear from the figure that across all cases, contributions from common sources of trend input growth to the long-run evolution of GDP growth remain limited. Median estimates of R_f^2 range from 0.28 to 0.37, with posterior distributions that place the bulk of their mass between 0 and 0.5. We thus conclude that the result that sector-specific forces are the primary driver of trend GDP growth is robust to changes in the priors for the factor loadings and to increasing the periodicity used that defines long-run trends.

Given that sector-specific (rather than common) trends have played a dominant role in driving trend GDP growth over the postwar period, figure 12 gives the historical trend contributions to aggregate GDP growth from the sector-specific components for each sector. Two sectors stand out, Construction and Durable Goods. Recall that US trend GDP growth fell by approximately 3 percentage points between 1950 and 2018. Comparing the beginning and the end of the sample, figure 12 indicates that Durable Goods alone contributed around 1 percentage point of that decline and Construction 0.75 percentage points. However, there are also important differences in the timing and variation of those sectoral contributions. Construction contributed roughly a 1 percentage point decline in trend GDP growth between 1950 and 1980 and was essentially flat thereafter. In contrast, Durable Goods played a key role in raising trend GDP growth in the 1980s and 1990s before contributing an almost 2 percentage point decline in trend GDP growth after 2000. Nondurable Goods also notably contributed to the postwar decline in trend GDP growth, at roughly 0.5 percentage points over the entire sample period, though offset somewhat by Mining after 1980. Strikingly, many other sectors show relatively

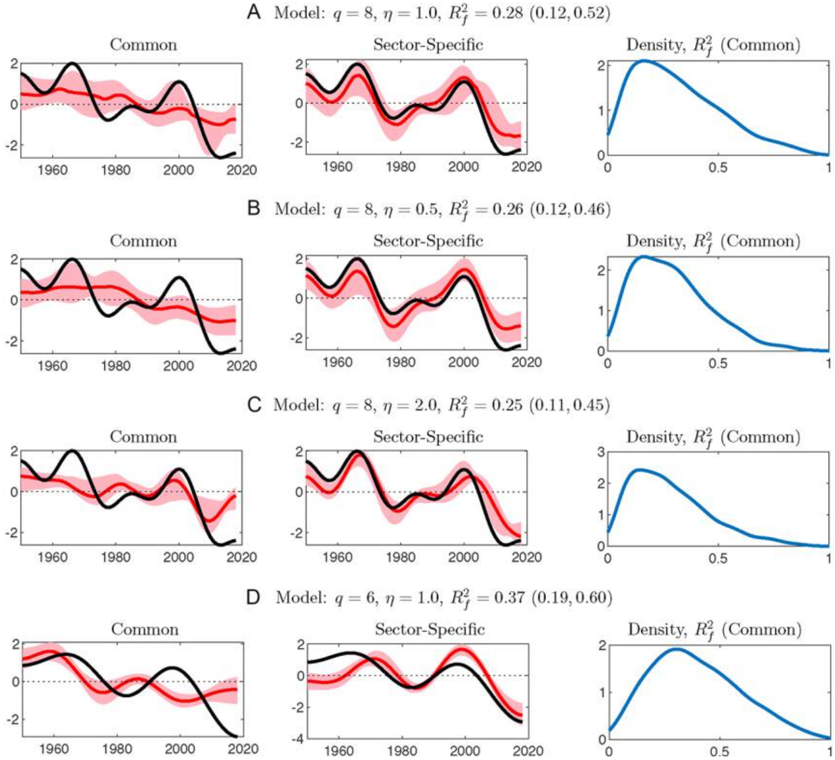

FIG. 11.—Robustness to changes in statistical model. See figure 10 legend. Each vertical panel of the figure shows results for a different specification of the prior distribution, η, or long-run periodicities, q.

flat contributions to aggregate trend growth over 1950 to 2018, between -0.1 and 0.1 percentage points. Perhaps even more surprising, no sector has contributed any steady significant increase to the trend growth rate of GDP over that period.

VI. Discussion and Implications for Future Research

The findings we have just described result from two key notions explored above. One is largely empirical and relates to the size of variations in trend TFP and labor growth in each sector. The other is more theoretical and relates to the size of a sector's multiplier, given its place in the production network. The paper then brings together two related, though so far mostly distinct, literatures. One addresses ISTC, explored by Greenwood, Hercowitz, and Krusell (1997) and others, and the other studies the effects of production networks, underscored, for example, by Acemoglu

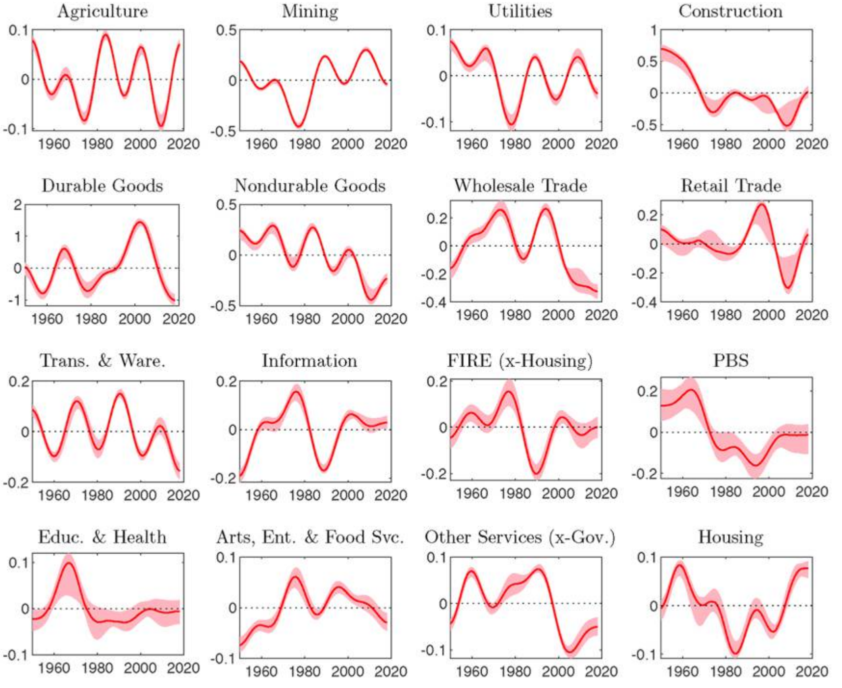

Fig. 12.—Sector-specific contributions to the trend growth rate of GDP (percentage points at annual rate). Each panel shows the implications of sector-specific trends for the trend growth rate of GDP using the model-based multipliers. The solid lines denote the posterior median and the shaded areas the (pointwise) equal-tail 68% credible intervals.

et al. (2012) and Baqaee and Farhi (2019). We extend Greenwood, Hercowitz, and Krusell (1997) by considering the full set of materials and investment linkages that characterize US sectoral production. At the same time, we introduce their emphasis on dynamics and capital accumulation into the static production network environments of Acemoglu et al. (2012). The analysis then provides new results and more general insights into each of these literatures separately. Importantly, these results, combined with our empirical trend analysis, provide the basis for a more complete and accurate picture of the drivers of the secular decline in GDP growth.

A. Production Networks and ISTC

The literature on ISTC has relied for the most part on a particular set of key simplifying assumptions. One is a direct relationship between the relative price of investment goods and the relative productivity of the capital-producing sector. Another is that there is no distinction between producer prices and final demand prices. Finally, abstracting from sectoral linkages in materials means that only the capital-producing sector can have a sectoral multiplier that exceeds its value-added share. In practice, however, as illustrated in the two-sector example of section IV, even sectors that produce only services will have a multiplier effect when those services are used by capital-producing sectors.

Sectoral linkages break down the one-to-one relationship between relative productivity and relative price. In Greenwood, Hercowitz, and Krusell (1997), this would mean that investment-specific productivity, $1/q_t$, is no longer the relative price of investment goods, q_t, as in equation (13) above.[21] In section 2 of the appendix, we show a more general mapping where productivity growth in any one sector potentially contributes to changes in producer prices in all other sectors. Analogous to equation (10), this more complex mapping reflects the influence of production linkages, Ω and Φ, through the general Leontief inverse, Ξ'. The appendix then further shows that the model's quantitative implications for producer prices generally matches well their data counterparts across sectors.[22] That said, as in most previous work, we continue to abstract from the distinction between producer prices and final demand prices. To make that distinction, including for investment prices, one needs to model the allocation of the cost components from intermediation industries, which include Retail Trade, Wholesale Trade, and Transportation, to final goods. For now, we leave exploring these relationships to future work.[23]

With only two sectors and no intermediate inputs, the last key limitation of Greenwood, Hercowitz, and Krusell (1997) is that the effects of TFP increases in a sector that produces mainly intermediate goods or services cannot be easily traced. In particular, these would show up partly as a decline in the relative price of investment goods when those services are purchased by capital-producing sectors. Therefore, without a more structural description of the sectoral production network, any effects on growth risk

[21] It should be noted, though, that even in the absence of sectoral linkages, unequal capital income shares across sectors alone introduce a wedge between relative prices and relative productivities. See Hornstein and Krusell (1996).

[22] Let p^y denote the $n \times 1$ vector of prices for sectoral output and g^{p^y} the associated long-run growth rate. With multiple sectors and the full set of production linkages, $g^{p^y} = (\mathbf{1}\Theta - I)\Xi' g^a$. See sec. 9 of the appendix for a comparison of the model's implied sectoral trend growth rates in producer prices and the data. Closer to the ISTC literature, Basu et al. (2013), in a similar framework but imposing that capital and labor are homogeneous and mobile across sectors, obtain an analogous relationship that relates the relative price of capital to a weighted average of all sectoral productivities off the BGP.

[23] The construction of input-output tables and gross product by industry separates intermediation industries' contributions to final demand and their contributions to the direct provision of goods. Therefore, commodity transactions are valued at producers' prices that exclude final purchasers' payments for trade services and transportation costs to obtain the commodities. A useful survey on the treatment of intermediation industries is Yuskavage (2007).

being attributed to capital sectors rather than the original service sector. In contrast, while PBS plays a notably less prominent role in the investment network than does Construction in figure 8, table 4 shows that PBS nevertheless has a larger overall sectoral multiplier than Construction, 0.25 versus 0.17. Moreover, while the ratio of Construction's sectoral multiplier to its value-added share exceeds that of PBS, both are around 3. The reason is that while PBS's role in the investment network is small, it is a key supplier of materials, including to Durable Goods. Figure 12 shows that the contributions from PBS to trend variations in GDP growth are smaller than those from Construction. However, this finding arises not because PBS is less influential in the overall production network but because variations in trend TFP growth in PBS have been historically less important (recall fig. 4). Evidently, as an empirical matter, this can change going forward in a way that could not be captured in a starker model.

B. Measurement

While explicitly modeling the production network helps address shortcomings implied by a starker sectoral setup, one challenge with more detailed multisector models is that output is more easily measured in some sectors, for example, Durable Goods, than in others, such as PBS. In the case of PBS, this matters for at least two reasons. One is that PBS is a large supplier of intermediate inputs to other sectors. The other is that, after the Information sector, PBS is the second-largest producer of IPPs.

Measurement error in PBS then potentially arises in mainly two ways. First, service price deflators that account for quality changes in IPP industries are notoriously difficult to obtain. It is possible, therefore, that our benchmark results incorrectly attribute sources of productivity growth across sectors by understating output in PBS. Second, the distinction between materials and investment goods is sometimes ambiguous, and goods can be misclassified. Over time, the BEA has in several instances come to recognize expenditures on goods as investment rather than as payments for intermediate inputs. This is the case, for example, in the comprehensive revisions to the NIPAs in 2013 regarding expenditures on R&D and entertainment originals. Our analysis relies on capital flow tables from 1997 to determine the sources of investment goods in different sectors. While these tables already include software as an investment good, they do not line up exactly with the broader IPP definition used in the construction of capital stocks in KLEMS. Our capital requirements matrix, Ω, therefore, likely does not capture all of the investment contributions from PBS, in particular those of its IPP industries.

In the environment we study, the mismeasurement of output growth in one sector, say PBS, will generally affect measured TFP in other sectors. Thus, suppose that sectoral output growth, g^y, is measured with some error, ϵ, so that measured sectoral output growth is $g^{y,m} = g^{y} + \epsilon$. Then, given production linkages, measured sectoral TFP, $g^{z,m}$, is given by

$$g^{z,m} = g^{z} + \Xi'^{-1}\epsilon.$$

Therefore, measurement error in any sector's output growth rate, ϵ, is generally reflected in all sectors' measured TFP growth, $g^{z,m}$, through Ξ'.[24] In particular, to the degree that output growth in PBS is undermeasured ($\epsilon_j < 0$ in PBS), so is its TFP growth rate, while TFP growth in other sectors tends to be overstated (because the off-diagonal elements of Ξ'^{-1} are generally negative). This last expression then allows us to carry out counterfactuals exploring the implications of measurement error in sectoral gross output growth. In particular, removing the measurement error changes GDP growth by

$$-s^{v\prime}(I + \alpha_{\mathrm{d}}\Omega'\Xi')\Xi'^{-1}\epsilon = -s^{v\prime}\Xi'^{-1}\epsilon - s^{v\prime}\alpha_{\mathrm{d}}\Omega'\epsilon. \tag{20}$$

In other words, correcting for downward bias in the measurement of PBS output ($\epsilon_j < 0$), the first term on the right-hand side of the above expression, $-s^{v\prime}\Xi'^{-1}\epsilon$, increases the contributions to GDP growth from PBS and lowers the contributions from other sectors (TFP growth is now higher in PBS and lower in other sectors). The second term, $-s^{v\prime}\alpha_{\mathrm{d}}\Omega'\epsilon$, generally increases all other sectors' contributions to GDP growth to the extent that PBS sells some investment goods to these sectors. The net effect of correcting for understated output growth in PBS, therefore, is an increase in its contributions to GDP growth, and either an increase or a decrease in the contributions from other sectors.

To explore the role of possible output mismeasurement in PBS, we consider the possibility that price growth in its two IPP-related subsectors, namely, Computer System Design (BEA industry code 5415) and Miscellaneous Professional, Scientific, and Technical Services (BEA industry code 5412OP), is overstated in KLEMS. Alternatively, gross output growth in those sectors would be understated. In particular, in a manner comparable to Byrne, Fernald, and Reinsdorf (2016), we modify observed price measures in the two IPP-related subsectors of PBS to be more closely aligned with price measures of IPPs (which cover commodities similar to those in BEA industry codes 5415 and 5412OP) in the NIPAs. The NIPA price indices indicate less rapid price growth and, therefore, imply higher productivity (see sec. 6 of the appendix). By using closely related NIPA price indices, we interpret this exercise as a reasonable first pass at correcting for suspected bias in the KLEMS prices, or at least providing a sense of robustness with respect to measurement. In this case, the adjustment produces a

[24] See sec. 6 of the appendix for derivations.

price index for PBS that increases at a rate that is 1 percentage point lower than KLEMS prices.

The dashed line in figure 13 shows, relative to the contributions to GDP growth originally shown in figure 12, the effects of higher productivity in PBS implied by the more rapidly declining prices of its IPPs in the NIPAs. As explained above, higher measured productivity growth in PBS affects all sectors, including Construction and Durable Goods, highlighted here. The contributions from PBS to trend GDP growth are noticeably higher both because of the direct effect of higher measured TFP in that sector, through the corresponding element of $-s^{v\prime}\Xi'^{-1}\epsilon$ in equation (20), and because the production of other capital goods in PBS benefits from its more productive IPP sectors (and thus lower prices), captured by the corresponding element of $-s^{v\prime}\alpha_d\Omega'\epsilon$ in equation (20). In contrast, the quantitative contributions from Construction and Durable Goods to the trend growth rate of GDP do not change appreciably, relative to their baseline. On the one hand, measured TFP growth is now smaller in those sectors (i.e., the corresponding elements of $-s^{v\prime}\Xi'^{-1}\epsilon$ are negative). On the other hand, those sectors also benefit from employing more productive IPP sectors in PBS in producing their own output ($-s^{v\prime}\alpha_d\Omega'\epsilon > 0$).

The other key potential source of mismeasurement in multisector models is the misclassification of goods. Specifically, while the 1997 capital flow tables include software as investment, they do not line up exactly with the broader definition of IPPs used in KLEMS for capital. Thus, they likely miss contributions from PBS to investment stemming from its IPP industries. To explore the implications of this misclassification problem, we separate out

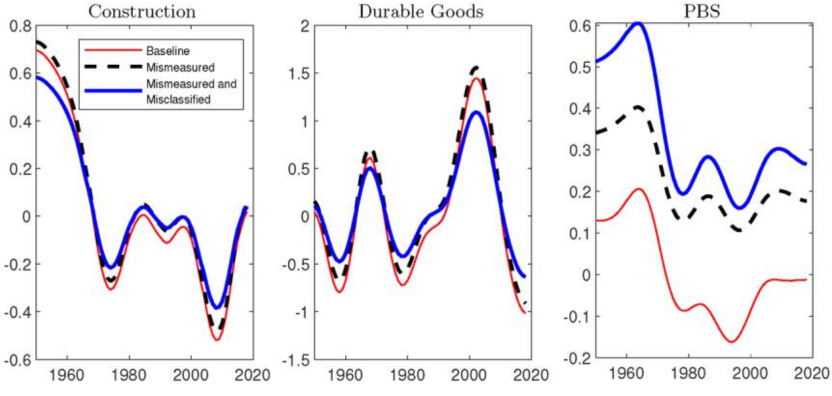

FIG. 13.—Mismeasurement and misclassification in PBS. The red solid lines depict the baseline contributions to trend GDP growth from the different sectors. The black dashed lines reflect the effects of higher productivity in PBS, implied by the price indices of its IPP industries in the NIPAs, on those contributions. The solid blue lines illustrate sectoral contributions to trend GDP growth when, in addition, the capital requirement matrix allows for investment contributions from IPP industries within PBS.

the two sectors producing IPPs within PBS, BEA industry codes 5415 and 5412OP defined above, from other PBS industries producing more clearly defined intermediate inputs.[25] We then construct a modified capital requirement matrix, Ω, that accounts for the possible omission of IPP contributions from PBS to the production of new capital. In particular, as an upper bound for possible mismeasurement in Ω, we reclassify 50% of the value of IPPs produced by industries 5415 and 5412OP in PBS as final investment demand for IPP. This reclassification implies a new capital requirement matrix, Ω, that results in a sectoral multiplier for PBS of 0.36, as compared to our baseline of 0.25.

The solid blue line in figure 13 shows the combined effects of the new capital requirement matrix with those correcting for possible bias in KLEMS prices of IPPs in PBS. The partial reclassification of Computer System Designs and Miscellaneous Professional, Scientific, and Technical Services in PBS from materials to capital raises its sectoral multiplier and lowers those of Construction and Durable Goods. The net effect is that contributions from PBS to trend GDP growth are now higher overall than those from Construction. While the reapportioning of 50% of the production value of PBS's main IPPs may be an upper bound on missing contributions from IPP capital in Ω, the exercise nevertheless underscores the importance of classifying goods appropriately. Moreover, this section also highlights the importance of continuing efforts to address challenges associated with the measurement of IPP indices.

C. Production Networks and Capital Accumulation

In seminal work, Hulten (1978) showed that when different sectors employ inputs produced in multiple other sectors, aggregate TFP is a weighted average of sectoral TFP, with weights given by the ratio of sectoral gross output to GDP, or Domar weights. This result hinges in part on interpreting TFP as scaling gross output. When TFP is instead interpreted as scaling value added, as we do here, the relevant weights become value-added shares in GDP.[26] Building on Long and Plosser (1983), a number of papers over the past decade have studied the different ways in which sectoral productivity changes influence aggregate value added.

[25] These are Legal Services, Management of Companies and Enterprises, Administrative and Support Services, and Waste Management and Remediation Services.

[26] These results are evidently related. When sectoral TFP, z_j, is measured as scaling value added, $\tilde{z}_{j,t} = z_{j,t}^{\gamma_j}$ becomes the relevant scalar for sectoral gross output, where γ_j is j's value-added share in gross output, $p_j^v v_j / p_j^y y_j$. In Hulten (1978), $\partial \ln V_t / \partial \ln \tilde{z}_{j,t} = \mathcal{D}_j$, where $\mathcal{D}_j$ is sector j's Domar weight or ratio of gross output to GDP, $p_j^y y_j / V$. It immediately follows from the definition of $\tilde{z}_j$ that $\partial \ln V_t / \partial \ln z_{j,t} = \gamma_j \mathcal{D}_j$, where $\gamma_j \mathcal{D}_j$ is then simply sector j's value-added share in GDP, s_j^v.

Acemoglu et al. (2012) note that in a static multisector environment abstracting from the production of capital, the same sectoral value-added shares also capture the effects of sectoral productivity changes on GDP. They interpret this observation, therefore, in terms of Hulten's (1978) work on aggregation and refer to the vector of value-added shares as the "influence vector." They show that when some sectors serve as hubs in the production network, the distribution of these shares is such that sectoral shocks do not generally cancel out in aggregation. These insights are used in Gabaix (2011) to highlight the importance of shocks to large firms for aggregate variations. Baqaee and Farhi (2019) then explore in a similar environment the role of nonlinearities in production for generating GDP effects from sectoral shocks that go beyond what they refer to as Hulten's theorem.

Our work recognizes that a key aspect of an economy's production network arises through sectoral linkages in the production of investment goods, in addition to those in materials. The presence of capital, in particular, means that the effects of sectoral changes on GDP reflect the interactions between sectoral linkages and the dynamics of capital accumulation. These features then amplify the aggregate effects of disturbances in different sectors beyond their value-added shares. Moreover, they do so under otherwise standard neoclassical assumptions, log-linear technologies, and competitive input and product markets. Importantly, unlike the aforementioned papers on production networks, sectoral multipliers here apply to the effects of changes in sectoral input growth on GDP growth, $\partial\Delta \ln V/\partial\Delta \ln A$, rather than levels, $\partial \ln V/\partial \ln A$. This complements the empirical macroeconomics literature's emphasis on the characterization and behavior of growth rates, including at different frequencies, rather than levels. In this case, the new formulas we derive make it possible to explore empirically the secular decline in GDP growth, as highlighted in figure 9.[27]

Beyond our focus on long-run growth, our work highlights the importance of capital accumulation within the production network. Because the investment network plays a key role in amplifying the aggregate effects of sectoral changes, it is reasonable to conjecture that other features related to investment or other sources of dynamics could also play a role. While we allow for sectoral technologies that differ in their input shares, features such as time to build, investment adjustment costs, or the cost of holding

[27] Section 5 of the appendix shows that the findings and insights in Acemoglu et al. (2012) and subsequent work remain nested in a static version of our economic environment without capital and where the focus is on levels rather than growth rates. However, it also shows that this "levels" result changes somewhat in the steady state of a dynamic economy with capital. In particular, the effect of a productivity change in a sector on the level of GDP is given by its value-added share (or Domar weight) scaled by the inverse of the average labor income share.

investment goods in inventories likely differ across sectors. Aside from affecting the long-run amplification mechanisms highlighted here, these features likely also help shape how sectoral disturbances play out at business-cycle or medium-run frequencies. Therefore, more accurately modeling the technologies used in different sectors, and how these technologies affect dynamics at different frequencies, is an important next step.

VII. Concluding Remarks

In this paper, we study how trends in TFP and labor growth across major US production sectors have helped shape the secular behavior of GDP growth. We find that sectoral trends in TFP and labor growth have generally decreased across a majority of sectors since 1950. Common trends in sectoral TFP growth contributed around one-third of the secular decline in aggregate TFP growth. Common trends in sectoral labor growth contributed about two-thirds of the secular decline in aggregate labor growth.

We embed these findings into a dynamic multisector framework in which materials and capital used by different sectors are produced by other sectors. These production linkages, along with capital accumulation, mean that changes in the growth rate of labor or TFP in one sector affect not only its own value-added growth but also that of all other sectors. In particular, capital induces network effects that amplify the repercussions of sector-specific sources of growth on the aggregate economy and that we summarize in terms of sectoral multipliers. Quantitatively, these multipliers scale up the influence of some sectors by multiple times their value-added share in the economy.

Ultimately, we find that sector-specific factors in TFP and labor growth historically explain three-fourths of low-frequency variations in US GDP growth, leaving common or aggregate factors to explain only one-fourth of these variations. Changing sectoral trends in the past 7 decades, translated through the economy's production network, have on net lowered trend GDP growth by close to 3 percentage points. The Construction and Durable Goods sectors, more than any other sector, stand out for their contribution to the trend decline in GDP growth over the postwar period, though other sectors with large multipliers, such as PBS, could also have an outsize influence on the aggregate economy going forward. Remarkably, no sector has contributed any steady or significant increase to the trend growth rate of GDP in the past 70 years.

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