Technology, Long-Term Growth, and Economic Measurement

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Abstract

Growth dynamics of the developed economies experience significant variation over long periods. With recognition of such variation, measurement can better assess long-term growth, more readily adapt to structural shifts, and exploit general-purpose technology – where appropriate – to create new measurement capabilities.

To explore the economic logic of long-term growth variation an industrial revolution framework is developed and provides a point-in-time reference for placing current events in the context of sustained, multidecade periods of faster or slower GDP and productivity growth. Political, social, and economic metamorphoses have accompanied each revolution. In the context of extended decades, industrial revolutions provide a unique frame to measure and assess global economic transformation with implications for public policy and business strategy.

Recent measurement innovations have added intangible capital spending to tangible capital investment reflecting management and technology advances impacting business sectors and labor markets. In addition, improved income distribution data are available. However, innovations in measuring the value of new and free goods, the use of web-based search to estimate and predict economic activity, the integration of administrative and survey data, and the value of data remain in early stages of development.

Recent advances in artificial intelligence have opened new measurement approaches. Nonetheless, much work remains and there are substantial challenges to be addressed. In the context of industrial revolution, there are behaviors whose progression is important but where data are either limited or non-existent. Such topics include new worker tasks, knowledge diffusion and absorptive capacity, transformation by enterprise size, and technology adoption.

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I. Introduction

The growth dynamics of the developed nations experience significant variation over long periods. To explore the economic logic of such variation, the Fourth Industrial Revolution is a unique frame to assess global economic transformation. The industrial revolution framework provides a point-in-time reference for placing current events in the context of sustained, multidecade periods of faster or slower GDP and productivity growth. Political, social, and economic metamorphoses have accompanied each revolution.

Industrial revolution is the economic and social transformation occurring as a result of the lengthy and complex interaction of capital investment and technological change, along with the redefinition of how work gets done and how businesses are organized. Investment in machinery and equipment can shift from substituting for the skill of workers to complementing the skill of workers and vice versa. Industrial revolution creates the need for (1) new intangible capital, intellectual property, and worker skills to build, use, and maintain the new technology, as well as (2) time to adjust to the new social norms implied by the revolutionary transformation. Industrial revolution is about shifting the nature of the competition for wealth among nations.

Each industrial revolution has also brought amazing and previously inconceivable technology advances that drive unimagined innovation in businesses, work, and life. Industrial revolution brings new less expensive energy sources—from water, to steam, to coal, to oil, and to renewables. In each revolution, a new general-purpose technology (GPT), such as information technology, initially gives rise to "mushroom" growth with scattered success popping up, while latter "yeasty" growth takes hold (See Harberger 1998). Economic activity is leavened by increased capital investment, education, skills, knowledge transfer, technology diffusion, and labor income share.

The intersection of technological innovation and creative destruction is at the heart of industrial revolution. Schumpeter (1950) coined the term "creative destruction," which is the continuous process of product and service creation, business process improvement, and business model innovation. Through creative destruction new, innovative capabilities replace existing processes that are rendered obsolete over time. The restructuring process runs through major aspects of macroeconomic performance, not only long-run growth but also economic fluctuations, structural adjustment, and the functioning of factor markets. Over the long run, Caballero (2010) estimates the process of creative destruction accounts for over 50 percent of productivity growth.

Section II outlines the dynamics of long-term growth variation. Building on longstanding work of scholars as well as recent innovations, the approximate timing of four industrial revolutions is provided. The major underlying features of each industrial revolution are discussed – the investment, depreciation, and age of technology-embedded capital; the role of intangible capital; the pace of knowledge diffusion and, conversely, the capacity for absorption; and shifting income shares of capital and labor (See Fleming 2022 for a detailed discussion).

If the Fourth Industrial Revolution is to deliver benefits similar to earlier periods, substantial transformation of business and work activities as well as public policies actions will be required. Section III provides a discussion of measurement program changes and innovation that might be required. There are a number of important efforts already underway, including greater focus and improved measurement of intangible assets and income distribution. However, there are other innovations still required, including data and measurement of new tasks, knowledge diffusion and absorptive capacity, activity by enterprise size, and technology adoption. Section IV concludes.

II. Technology, Capital, and Long-Term Growth

In 1983, Rosenberg and Frischtak wrote: "No one who has examined the dynamics of capitalist economies over long historical periods can doubt that they experience significant long-term variations in their aggregate performance" (Rosenberg and Frischtak 1983, 146). The interest of Rosenberg and Frischtak was to "examine the economic logic" of such variation and whether such long-term movement is the result of exogenous events or whether the observed behavior is endogenous. While much of the systemic behavior contributing to long-term variation in aggregate performance has an internal cause—the behavior is endogenous—a meaningful portion of variation develops from external factors—exogenous events. The challenge is to parse underlying causes between those that arise from within the system and those responding to external shocks.

Rosenberg and Frischtak were seeking a "coherent explanation" for poor economic performance and propose four requirements that such an explanation must meet—causality, timing, economywide repercussions, and recurrence.[1]

In contrast to Rosenberg and Frischtak, the economics literature commonly considers long-term aggregate performance as trend growth. Such focus is aligned with the sources of growth analytics that has provided deep insight in the shift in importance of factor inputs.[2] Figure 1A shows US nonresidential investment spending and its trend. As an alternative view, Figure 1B shows US nonresidential net investment spending as a percent of the stock of nonresidential capital, depicting periods of variation in long-term investment spending growth.

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[1] Rosenberg and Frischtak cite the work of four scholars—Schumpeter (1939), Freeman (1982), Kondratiev (1979), and Forrester (1981)—each of which they find wanting.
[2] Fernald (2015), for example, is a well-done and frequently cited reference. See also CBO (2022) https://www.cbo.gov/system/files/2022-07/57971-LTBO.pdf

Figure 1A

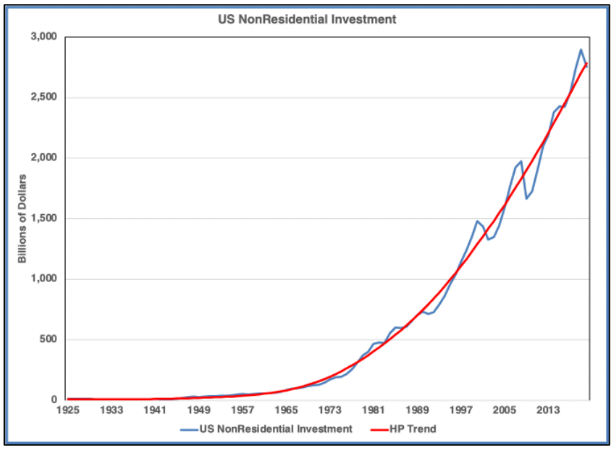
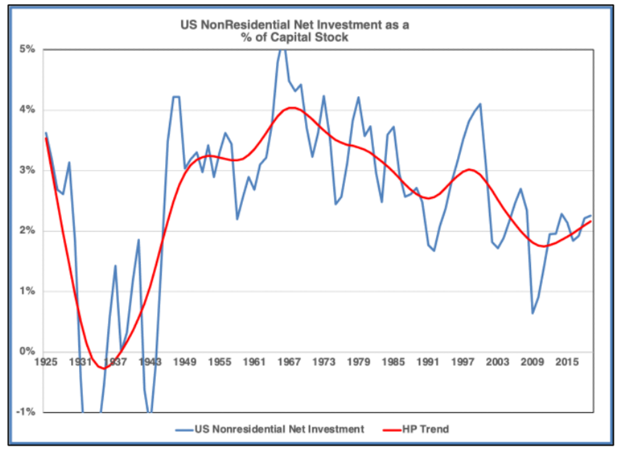


Figure 1B



Source: US Bureau of Economic Analysis and Author's Calculations

Figure 2
US Per Capita GDP Growth Rates
With Intervals and Growth Rates as Presented by Romer

	Romer's U.S. Per Capita GDP Growth Rates			
	Years	**Per Capita GDP Growth**	**Years**	**Per Capita GDP Growth**
1st	1800-1840	0.58%	1840-1880	1.44%
2nd	1840-1880	1.44%	1880-1920	1.78%
3rd	1920-1960	1.68%	1960-1978	2.47%

Source: Romer (1986, p. 1009).See Romer's Table 2. Original source data from Maddisson (1979).

Recognizing such variation is not new. For the US, Romer (1986) showed per capita GDP growth rates increasing steadily over five subperiods between 1800 and 1978 with alternating periods of faster and slower growth (see Figure 2). Maddisson (1982) argues each era is different and should be considered on its own merits. He recognized that while random events can influence outcomes, endogenous behavior is also at work. Maddisson concludes:

> It is clear that major changes in growth momentum have occurred since 1820, and some explanation is needed….Major system shocks change the momentum of capitalist development at certain points. (Maddisson, 1982, p. 17)

Harberger (1998) was among the first to recognize the distinction in the underlying economics between such periods, his American Economic Association presidential address cited complementary inputs as necessary ingredients, for example, physical infrastructure, energy technology, and engineering talent.[3] One, with focused creative destruction is characterized as "mushroom" growth with "real cost reduction stemming from 1001 different causes" with a limited number of sectors, industries, or firms experiencing much-improved productivity. The second type of growth is what Harberger called "yeasty" growth "with very broad and general externalities, like externalities linked to the growth of the total stock of knowledge or of human capital, or bought about by economies of scale tied to the scale of the economy as a whole." Once productivity improvement spreads widely across the economy, "yeasty" growth responds to the adoption of a general-purpose technology (GPT) with substantial creative destruction and business process transformation (see van Ark, de Vries, and Erumban 2020).

In formalizing the work of earlier scholars, Perez (2002) uses the industrial revolution as a frame of reference and focuses on the issue of the timing as well as the nonlinear nature of the process in which modest improvement in an early period is followed by a more robust latter

[3] Rostow (1960) postulated growth occurs in five stages of varying length: traditional society, preconditions for takeoff, takeoff, drive to maturity, and age of high mass-consumption. He argued that growth is initially led by a few industrial sectors.

Figure 3
Industrial Revolution Dates and Eras

Era	Industrial Revolution	Years	Technology Innovation	Installation		Major Financial Crisis	Deployment	
				Irruption	Frenzy		Synergy	Maturity
1st	Age of Steam and Railways	1829-1873	"Rocket" Steam Engine (1829)	1830s	1840s	1848-1850	1850-1857	1857-1873
2nd	Age of Steel, Electricity and Heavy Engineering	1875-1918	Carnegie Bessemer Steel Plant (1875)	1875-1884	1884-1893	1893-1895	1895-1907	1908-1918*
3rd	Age of Oil, Automobiles and Mass Production	1908-1974	Model-T Mass Production (1908)	1908-1920*	1920-1929	Europe 1929-1933 US 1929-1943	1943-1959	1960-1974*
4th	Age of Information and Telecommunications	1971-2019	Intel Microprocessor Announced (1971)	1971-1987*	1987-2007	2007-2010	2010-	

Source: Perez (2002), p.78. (*Phase overlaps between successive surges)

stage in which the resolution of high uncertainty results in broad diffusion and adoption (See Figure 3).[4]

Industrial revolutions, as defined by Perez, consist of two periods—an installation period and a deployment period with a major financial crisis intervening. Romer's growth rate internals, as shown in Figure 2, approximately align with the Perez model. In each period, state dependence plays a role as perceived market and price effects anticipate future income opportunities.

Like Harberger's "mushroom" growth, the installation period is a period of experimentation and learning when the new technology finds early, albeit somewhat primitive, applications. While the new technology provides early benefits, innovation in management practices, business models, and new products and services lag. The installation period also carries the legacy of the prior era's long-lived capital, and its embodied technology. With vast

[4] In the spirit of Rostow (1960) and Harberger (1998), Perez (2002) proposes each industrial revolution consists of five stages across two periods.

wealth having been created in the prior era, the inclination is to defend and grow existing accumulated wealth and resist fundamental transformation (see Gordon 2016 and Mokyr 1998).

The installation period leads to a frenzy of investment in the new technology—for example, the 1990s dot.com bubble and mortgage securitization contribution to the 2008–2009 financial crisis. Financial bubbles arise as investors, eager for returns, overcommit to a new technology that business processes are not yet prepared to exploit at scale (Janeway 2012 and Perez 2002). Value creation is not yet sustainable (see Minsky 1975 and Minsky 1986). On the one hand, existing business models and practices cannot support the fundamental change needed to make the new technology fully effective. On the other hand, the value creation capability of the legacy capital and technology of the prior era begins to fade. The frenzy of new investment fails to persist.

The deployment period-like Harberger's "yeasty" growth-is one in which the new technology, along with new business models, social acceptance, and political support are sufficiently in place to deploy, or put in place, the new capital, and its embedded, now general purpose, technology, at a vast scale. Investors now have a deeper understanding of the technology, its rate and pace of diffusion, and the extended time horizon necessary for expected financial return. State dependence is now such that aggregate demand grows at an increased pace and factor demand grows in a complementary fashion.

Recent advances in artificial intelligence have helped to define periods of faster and slower growth. Kelly, Papanikolaou, Seru, and Taddy (2021) apply natural language processing (NLP) to data from U.S. patent documents to build indices of breakthrough innovations (See Figure 4). Kelly et al. define breakthrough innovations as distinct improvements in the technological frontier that become the foundation on which subsequent innovations are built.

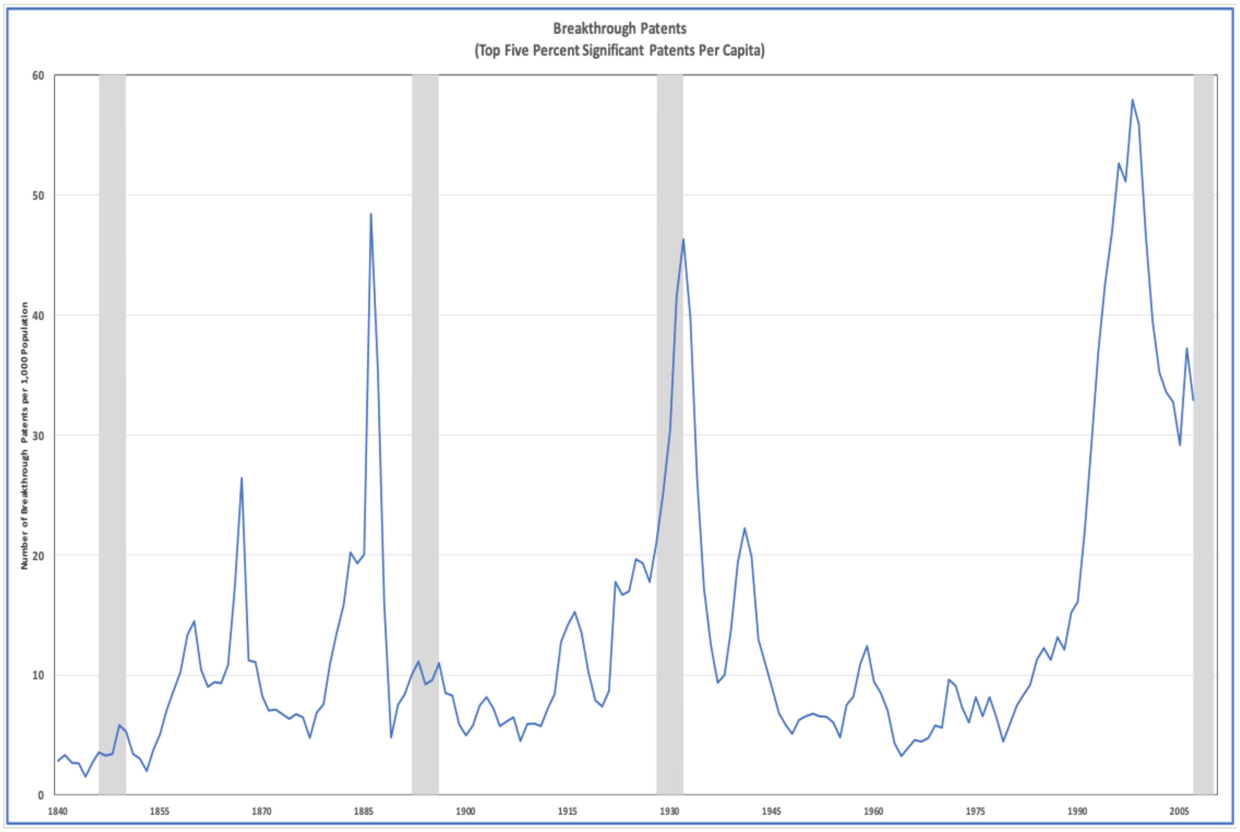
These breakthroughs include watershed inventions such as the telegraph, the elevator, the typewriter, the telephone, electric light, the airplane, frozen foods, television, plastics, electronics, computers, and advances in modern genetics (see Gordon 2016 for detailed discussion).

The resulting Kelly et al. aggregate innovation index shows three technology surges—mid- to late-19th century, the 1920s and 1930s, and the post-1980 period. Advances in electricity and transportation in the 1880s; agriculture in the 1900s; chemicals and electricity in the 1920s and 1930s; and computers and communication in the post-1960s all contribute to high-value innovation.

The innovation index is also a strong predictor of aggregate total factor productivity (TFP) for which a one-standard deviation increase in the index is associated with a 0.5 to 2 percentage point higher annual productivity growth over the subsequent 5 to 10 years. By mapping technology to industries, sectoral technological breakthrough indexes span the entire sample. Sectors that have breakthrough innovations experience faster growth in productivity than sectors that do not.

These breakthrough innovations are of the nature of the advances that Romer had in mind when suggesting that many such ideas, because they are protected by patents or as trade secrets, are nonrival and nonexcludable. Indeed, the Kelly et al. innovation index in Figure 4 shows periodic surges of very significant ideas have spread repeatedly, widely, and rapidly over nearly two centuries, suggesting the presence of increasing returns to scale at the industry and national levels.

Figure 4



Source: Kelly et. al. (2020). (Kelly et. al. Figure 4, Panel A shows Top 10 Percent Significant Patents Per Capital. Additional data are available from online data.) Gray bars are major financial crises.

As shown in Figure 4 and asserted by Perez, periodic technology and innovation surges have been frequently followed by major financial crises. Among the most well-known are the events of the 20th and early 21st century—the Great Depression of the 1930s and the Great Recession and Global Financial Crisis of 2007 to 2009. Scholars, who have carefully tracked such events, agree that both downturns qualify as major financial crises. Aliber and Kindleberger (2015), Reinhart and Rogoff (2009), and Perez (2002), all identify the Great Depression and the Global Financial Crisis as financial crises that are among the historically largest.

Building on the work of Minsky (1975) and Minsky (1986), Aliber and Kindleberger identify crises that follow an exogenous shock that sets off a mania. The mania involves a specific object of speculation, such as commodities, real estate, bonds, and equities as well as a source of monetary expansion. Perez builds on the work of Minsky, Aliber, and Kindleberger.

Reinhart and Rogoff (2009), famously, develop a quantitative history of financial crisis. Between 1800 and 2009, Reinhart and Rogoff identify 250 external sovereign debt default episodes, 68 domestic debt defaults, and 270 banking crises. Reinhart and Rogoff also highlight inflation and currency crises. However, they label four episodes as global financial crises. Reinhart and Rogoff define global financial crises as having four main elements: (1) a global financial center is involved in a systemic crisis, (2) two or more global regions are involved, (3) the number of countries involved in each region is three or more, and (4) the Reinhart and Rogoff composite GDP-weighted average global financial turbulence index is at least one standard deviation above average.[5] In Reinhart and Rogoff's view, such financial crises share three characteristics—a deep and pro-longed asset market crash, a banking crisis that is followed by profound declines in output and employment, and a vast expansion in the value of government debt. As shown in Figure 3, four such major financial crises have occurred over the recent two centuries.

As measured by Reinhart and Rogoff, financial crises bring declines in real housing prices averaging 35 percent, a three-and-a-half-year equity price decline averaging 56 percent, peak to trough output declines averaging 9 percent, and an increase in the value of government debt rising to 86 percent of GDP in the major post-World War II episodes.

While detailed data are limited to more recent periods across the Third and Fourth Industrial Revoltions, three empirical regularities stand out. Figure 5 provides a view of tangible and intangible capital investment. As shown across the figure's bottom row, capital deepening

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[5] See Reinhart and Rogoff. 2009. Box 16.1, pp. 260–261.

increases more rapidly during the Third Industrial Revolution deployment period during which the stock of capital grew at a 2.0 percent annual rate. Growth slowed in the Fourth Industrial Revolution to 1.2 percent annual rate during the installation period. While the technology irrupts and eventually creates a frenzy, capital investment slows as the capital stock deployed in the earlier era continues to provide service and generate income. In the current period, capital deepening has failed, thus far, to fully capture the recovery experienced in previous deployment periods. The lag in capital deepening is one manifestation of what has been labeled "secular stagnation" (Summers 2014).

Figure 6 shows the well-known productivity slowdown across the table's bottom row. The robust 2.6 percent productivity growth in the Third Industrial Revolution deployment slowed to 2.0 percent per year in the installation period in the Fourth Industrial Revolution. In the current period, productivity growth has slowed even further to an annual rate of 0.9 percent. Again, another sign of failure of the deployment period to launch.

Consistent with Figure 6, recent work by Gordon and Sayed (2022) show that their examination of historic data suggests there were three eras of cyclical productivity growth changes between 1950 and 2019. Gordon and Sayed write:

> The first [era] extending from 1950 to 1985 marks the regular procyclical response of roughly 0.3 in virtually every expansion and recession episode. The second [era] covering 1986-2006 witnessed a more muted and inconsistent procyclical response. And the third [era] from 2007 to 2019 combined the strong excess adjustment of hours during the 2008-09 recession with the reappearance of a regular procyclical productivity response after 2009. (Gordon and Sayed 2022, p. 16)

Figure 5
Capital Deepening by Industrial Revolution

	Capital Deeping Capital-Labor Ratios (Thousands of 2012 Dollars per Worker) And Growth Rates							
Industrial Revolution	3rd Era Age of Oil, Automobiles and Mass Production 1945-1974			4th Era Age of Information and Telecommunications 1971-2010			4th Era Age of Information and Telecommunications 2010-2019	
	Deployment Period			Installation Period			Deployment Period	
	1943	1959	1974	1971	1987	2007	2010	2019
Capital-Labor Ratio	141.0	197.5	261.1	273.1	308.0	414.9	424.2	474.1
Annual Growth Rate	--	--	2.0%	--	--	1.2%		1.2%

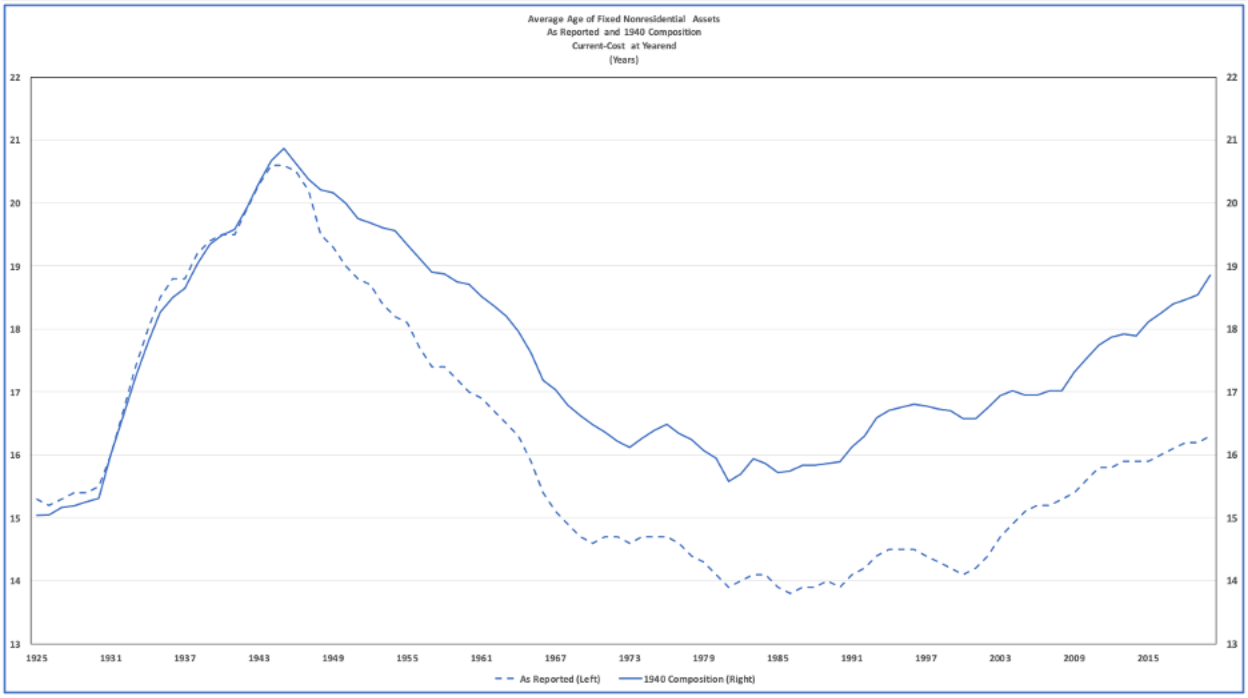
Source: U.S. Bureau of Economic Analysis. Fixed Assets Accounts Table. Table 1.1 Current-Cost Net Stock of Fixed Assets and Consumer Durable Goods, row 1, U.S. Bureau of Labor Statistics, All Employees: Total Nonfarm Payrolls, Thousands of Persons, Annual, Seasonally Adjusted and Producer Price Index by Commodity: All Commodities.

Figure 6
Labor Productivity Growth by Industrial Revolution

	Labor Productivity Nonfarm Sector Output per Hour (Base Year 2009 = 100)							
Industrial Revolution	3rd Era Age of Oil, Automobiles and Mass Production 1945-1974			4th Era Age of Information and Telecommunications 1971-2010			4th Era Age of Information and Telecommunications 2010-2019	
	Deployment Period			Installation Period			Deployment Period	
	1947	1959	1974	1971	1987	2007	2010	2019
Index	23.5	32..6	47.4	45.2	58.6	91.6	99.2	107.9
Annual Growth Rate	--	--	2.6%	--	--	2.0%	--	0.9%

Source: U.S. Bureau of Labor Statistics, Nonfarm Labor Productivity, Major Sector Productivity and Costs, Index, 2009 Base Year = 100.

Figure 7



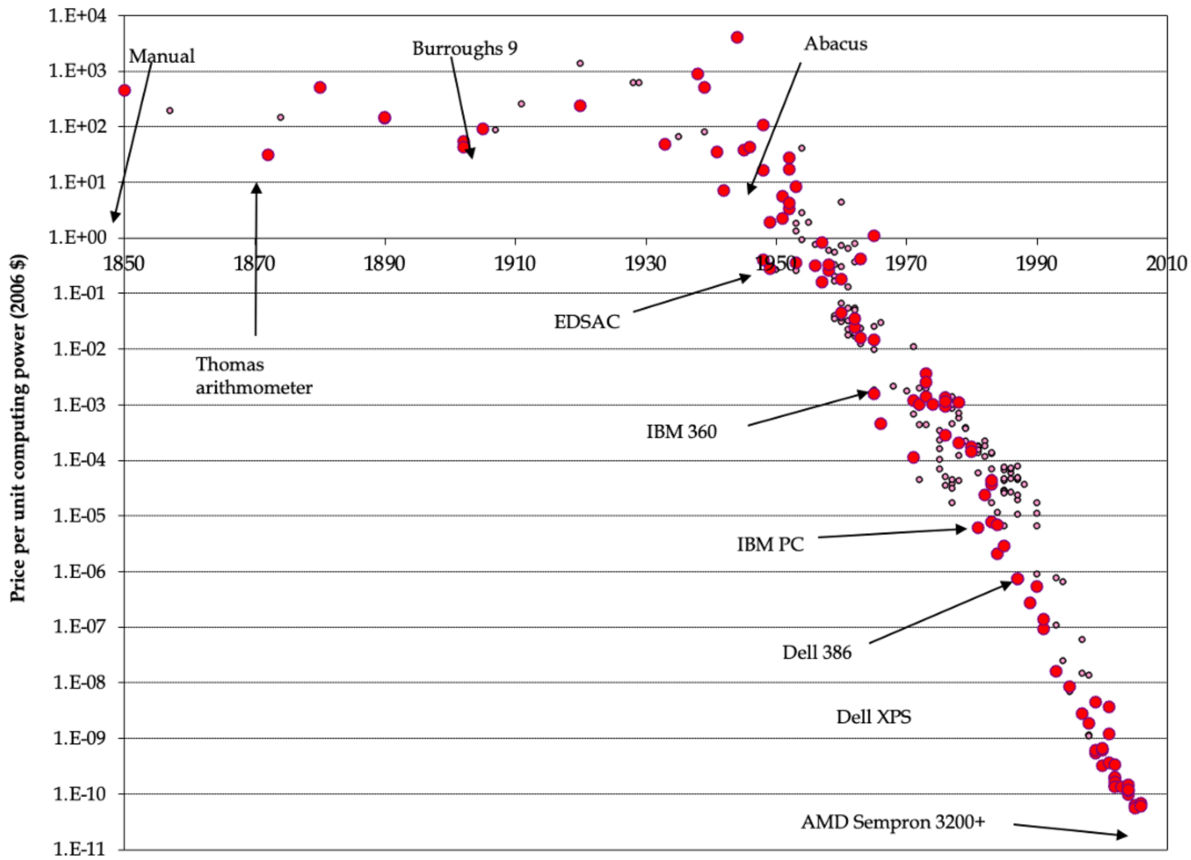
Source: U.S. Bureau of Economic Analysis. Fixed Assets Accounts Table. Table 1.9. Current-Cost Average Age at Yearend of Fixed Assets and Consumer Durable Goods, rows 4, 5, 6, and 7 with author's calculations.

Figure 7 also shows that as a result of the dramatic slowing of investment spending growth in the 1930s, the capital stock aged. From an average age of 15.3 years in 1925, the stock grew progressively older to 20.6 years in 1945 and 1946. Clearly, some of the aging could have been a result of neglect while production was focused on the 1941–1945 war effort. However, the average age of the capital stock had already reached 19.5 years in 1940 and 1941 with only one added year of age over the ensuing five years.

Compared with the prewar capital stock age of 19.5 years in 1940, shown in Figure 7, the 16.3-year age in 2020 is largely accounted for by the shift in the composition of capital investment spending, which reflects the increased importance of equipment and IPP in 2020. Figure 7 shows the trend in the age of nonresidential net capital investment with the 1940 weights applied. In the absence of the composition shift, the 2020 average capital age would have been 18.9 years, only slightly below its 1940 value. Controlling for the compositional shift, the capital stock in 2020 is about as aged as it was in 1940. While Gordon and Sayed (2022) find some evidence of capital deepening in 2017-2019-consistent with the deployment period of the Fourth Industrial Revolution-such investment is yet to be reflected in the age of the capital stock.

Finally, not only is capital long lived, but technology cycles are lengthy as well. Intel was launched in 1971. However, it was not until the mid-1990s when microprocessor technology provided meaningful economic value, as reflected in increased productivity growth (Jorgenson and Stiroh 2000 and Gordon and Sayed 2022). By 1995, microprocessor innovation resulted in the cost per million computations (CMC) falling by six orders of magnitude over a quarter of a century (See Figure 8). An additional 20 years passed, with additional CMC reduction of two further orders of magnitude, before a GPT was available and the global cloud infrastructure was deployed at scale. The realization of a global technology revolution required mobile device innovation as well as a fundamental redesign of the worldwide computing and communication infrastructure across 40 years. To revolutionize economic value, the steam engine required approximately 80 years, while electric power and mass production each required approximately 40 years (Crafts 2004 and David 1990).

Figure 8



Source: Nordhaus (2021)

III. Knowledge Transfer and Labor Income Share

Industrial revolutions are characterized by investment and depreciation of tangible and intangible capital that embodies new and legacy technology whose ability to add value is dependent on creative destruction across business organizations, worker cohorts, and governments as new products and services are launched, new business models are created, and existing business processes are transformed.

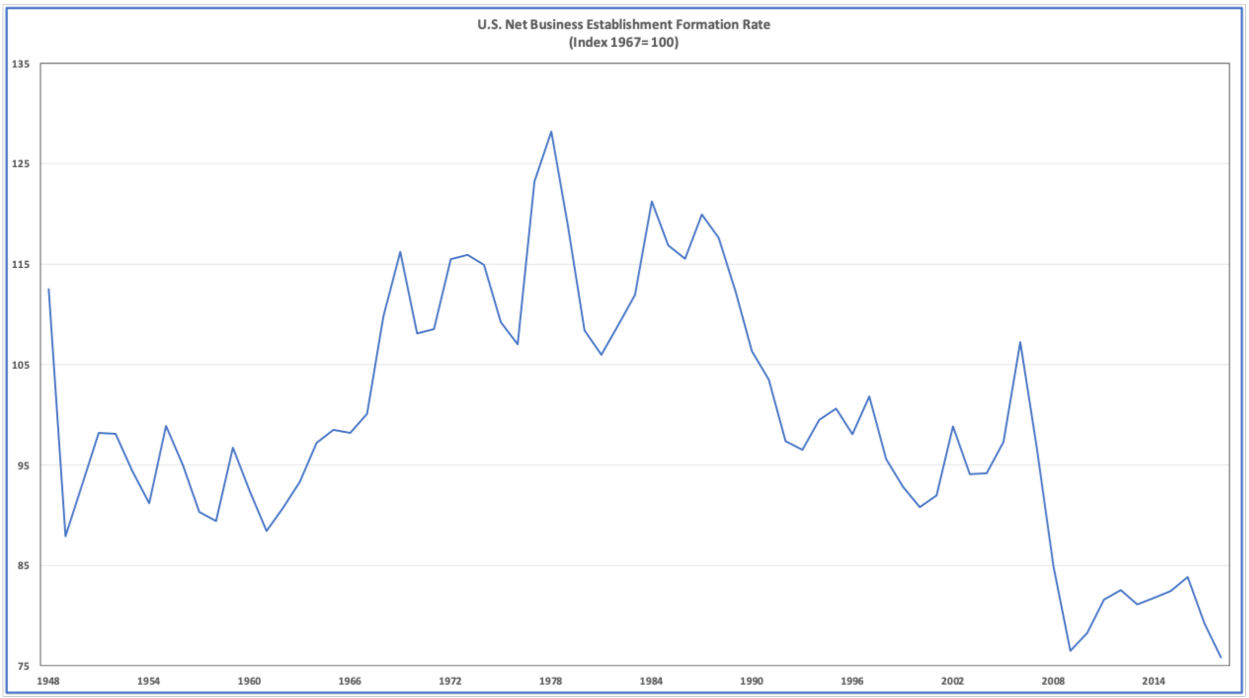
Two critical features of industrial revolutions are—(1) knowledge transfers and absorptive capacity and (2) changing capital and labor income shares with a shifting income distribution. Both differ fundamentally over the course of each industrial revolution and define the dynamics of systemic change. In the installation period of each industrial revolution, high productivity, leading-edge firms absorb knowledge effectively and find new applications for the new technology, resulting in market share gains, increased industry concentration, and reduced labor expense as a percent of revenue. Income is skewed toward capital owners and away from labor. The high productivity, leading-edge firms are labeled superstar firms. But the star-lit nature of the leaders implies there are laggards. The laggards and the opportunities they offer for productivity improvement is highly variable and widely disbursed across industry firms. While the determinants of productivity are unsettled, worker engagement has received less than needed attention, especially in a services-driven economy. The contribution of workers to productivity growth and the conditions under which labor effort is automated or augmented remains a subject of debate.

In the deployment era-in the aftermath of the financial crisis-cleansed balance sheets and available cash are positioned to invest in the now mature and inexpensive new technology with the replacement of then-aged tangible and intangible capital. However, even more intense creative destruction produces fundamental change, establishing a new order, cutting across labor and product markets with widespread adoption of new business models, processes, products, and services. Because such deep and profound change is resisted by entrenched interests—wealth holders, business organizations, workers, and governments—often major external events such as wars, depressions, and pandemics are required to cause new social and economic regimes to emerge. However, if creative destruction and the ensuing regime transformation are successful, robust output and productivity growth are expected-eventually-in a low inflation environment.

If organizations are to fully benefit from the renewal of tangible and intangible capital, an ability to absorb knowledge is critical. Industry productivity leaders, by their nature and organizational culture, understand how to learn, transform, and grow. The absorptive capacity of organizations and the rate of knowledge diffusion—"two sides of the same coin"—depend on the nature and extent of capital and labor interaction. The diffusion of knowledge only creates economic value if organizations can absorb such knowledge and create productive improvements. Indeed, successful creative destruction—launching innovation, creating new firms, and finding new job roles—requires knowledge diffusion and absorptive capacity.

Figure 9 provides a view of business establishment formation from 1948 to 2018. After an increasing business formation rate from 1960 to 1978, business formation declined from 1980 to 2010. The 1948–1980 period approximately coincides with the years that have been identified as the deployment period of the Third Industrial Revolution. With the fossil-fuel, mass production era having reached maturity and tangible and intangible capital in a period of rapid accumulation, including government sector infrastructure and intellectual capital, business formation began a period of rapid increase. Interestingly, more than a decade was required for the formation rate improvement to begin. By the later portion of the period, business formation

Figure 9



Source: Historic Data Colonial Times to Present, Part 2, Business Enterprise, Series V 20-30 Business Formation and Business Failures 1857 to 1970; Statistical Abstract, Various Issues, 1980 – 1990; and U.S. Census Bureau, 2018 Business Dynamics Statistics 1979 – 2018.

accelerated to a very high rate. Once underway, the formation rate remained elevated for three decades.

By contrast, the 1980–2018 period approximately aligns with the installation period of the Fourth Industrial Revolution. With the aging capital of the previous period and the nascent technology of the new electronics and IT era, business formation slowed, industry concentration increased. The leadership of IBM in the computer industry and later by Intel, Corp. in the semiconductor industry are examples of concentration in the newly formed technology industry. Eventually, of course, newly formed highly innovative industries, such as keyword search, social media, and browser software, also showed new business formation and high concentration.

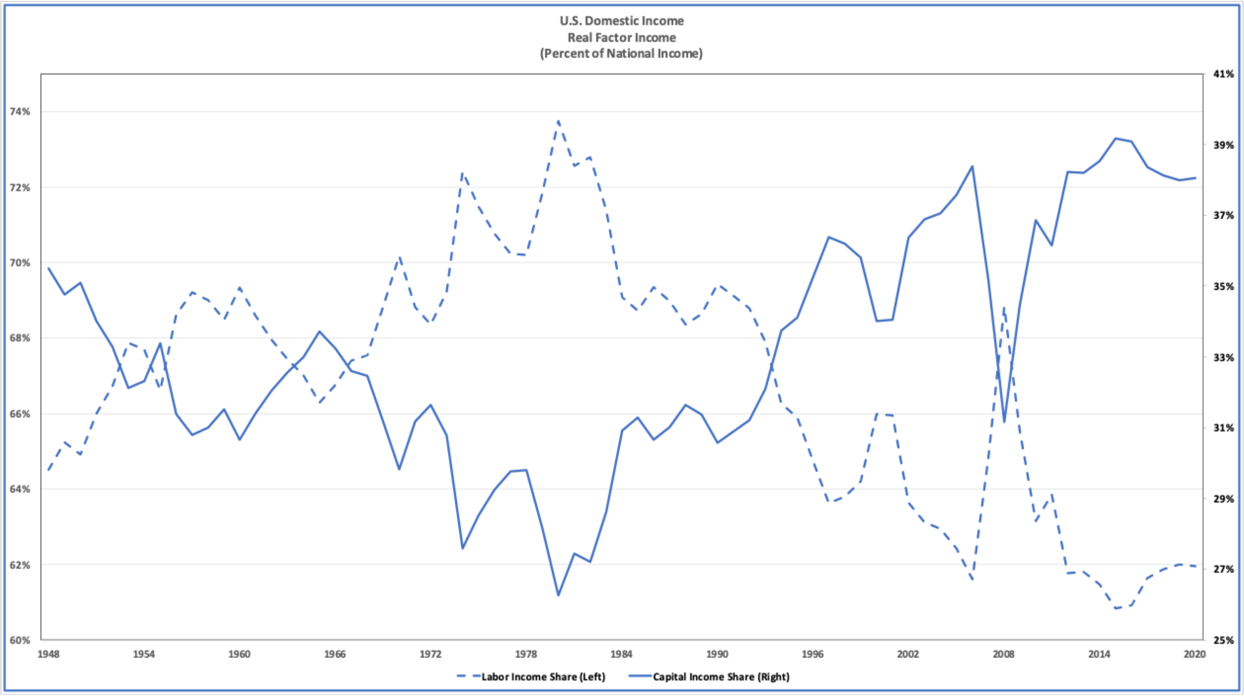
Autor, Dorn, Katz, Patterson, and Reenen (2020) find industries that have become more concentrated are those with faster productivity growth. Each industry's productivity-leading firms—superstar firms—are not only more innovative but also are larger firms and getting larger while realizing higher markups. As a result, those industries with increased product market concentration, more rapid productivity growth, and enhanced innovation have experienced larger declines in the labor share. Innovation combined with economies of scale has reduced labor expense as a percent of revenue. Because labor shares tend to be lower in larger firms, reallocation of market share to larger firms has tended to depress aggregate labor share.

Autor et al. find there has been a "rise in sales concentration … across the vast bulk of the U.S. private sector, reflecting the increased specialization of leading firms on core competencies" (p. 650). In labeling such industry-leading, high-productivity firms "superstar firms," Autor et. al. call to mind the current small set of well-known technology firms. However, their data cover 676 four-digit industries, suggesting that the phenomena are widespread across industry sectors. To the extent that the advent of new technology increases automation, lowers marginal costs, and increases markups, labor's income share rises at the firm level among productivity-leading firms (See Figure 10).

The existence of superstar firms as shown by Autor et al. follows a growing body of research and scholarship that has established "enormous and persistent productivity differences across producers even within naturally defined industries" (Syverson 2011). These differences are not fleeting with higher productivity firms more likely to survive over long periods (Foster, Haltiwanger, and Syverson 2008). While such persistence is often attributed to technological diffusion, the literature suggests that productivity differentials appear to be the result of investments in intangible capital—the business know-how embodied in capabilities across organizations.

While determinants of productivity at the firm level remain unsettled, much is known about a broad set of influences. Building on a growing body of work, Bloom, Brynjolfsson,

Figure 10



Source: U.S. Bureau of Economic Analysis. National Income and Product Accounts. Table 1.13. National Income by Sector, Legal Form of Organization, and Type of Income Goods, rows 4, 5, 6, and 7 with author's calculations.

Foster, Jarmin, Patnaik, Saporta, and Van Reenen (2019) find enormous dispersion of management practices across plants, with 40 percent of the variation across plants within the same firm. Talent and human resource management, more generally, have also been shown to impact productivity. While establishing causality for the role of talent and management practices remains a difficult issue, Fleming (2022) shows with the increased importance of services sectors in the global economy, there is a growing literature identifying the casual influences on firm-level productivity improvement.

Further, the growth of the services sectors alters firm-level economics, in which worker skill and commitment, intangible assets, and information technology rise in importance in comparison to the economics of manufacturing and agriculture. In services sectors, above-average productivity growth is achieved with high rates of repeat business that generate high-profit margins, requiring strong customer loyalty and sustained customer relationships. The important insight is that customer loyalty is earned with high internal service quality achieved with a focus on job and workplace design, employee selection and development, employee rewards and recognition, and the technology employees utilize to serve customers. The skill, quality, and satisfaction of the workforce, often referred to as worker engagement, is a critical element of service success. As a result, the economics of services requires innovative measurement.

With an aged capital stock, limited knowledge diffusion and absorptive capacity, and declining labor income share, the deployment era of the Fourth Industrial Revolution is not assured to deliver robust and rapid growth, capital deepening, and improved living standards. Clearly, the future is uncertain. A breakthrough is not guaranteed. The concern is well founded. Both in the United States and Europe, periods following economic shocks have often experienced limited growth. In the United States, between 2007 and 2020 after the Great Recession and financial crisis, U.S. real GDP growth averaged only 1.3 percent per year. The slowdown is often referred to as hysteresis—the persistence of negative effects after the initial cause is removed (Summers 2014).

As Landes (1969) and Lazonick (1998) observed, the success of each industrial revolution depends, in part, on the interest and ability of workers and businesses to transform behavior and engage in creative destruction. For example, as the Second Industrial Revolution moved from installation to deployment in the last quarter of the 19th century, American, German, and Swiss firms moved rapidly to adopt the new technology and make the needed capital investments, while British business leaders and workers guarded the status quo, living off existing income-producing capital.

Similarly, the UK, Germany, and U.S. transformation from the installation period to the deployment period of the Third Industrial Revolution in the second quarter of the 20th century, as Landes (1969) and Gordon (2016) observed, was in part a result of the shock to economic activity in support of the war effort; an unwillingness to return to old, prewar ways; the economic rescue after the war; and substantial infrastructure spending as part of the strategic competition with the Soviet Union. Now, if the global economy, especially the developed world, is to move into the deployment phase of the Fourth Industrial Revolution, the shock and dislocation of the 1990s dot-com bubble and the 2008–2009 Great Recession and financial crisis appears to have been insufficient to create the needed pressure for change. However, much as the conclusion of the Second World War appears to have created circumstances for the Third Industrial Revolution's deployment period, perhaps the combined effect of the Great Recession and the 2020–2021 pandemic will create conditions for the Fourth Industrial Revolution's deployment period.

Over recent decades, a wide array of fiscal, tax, and monetary policies have been deployed to support growth, but unsatisfactory outcomes remain. While finding the best and most effective government policy and programs configurations is important, it seems unlikely there is a silver bullet yet to be found. More likely, a new social contract is required in which workers, business leaders, and elected public officials can come to together, as a result of the pressure and dislocation from unsatisfactory economic outcomes and the 2020–2021 pandemic (See Fleming 2022, Chapter 6). A new social psychology, recovering from the recent decade's trauma, is very likely necessary. While pessimism abounds, rising expectations, high hopes, and anticipation of a brighter future ahead seem unrealistic. Nonetheless, it will be in the individual and collective interest of workers, businesses, and governments to transform economic activity, if the the benefits of a period of more robust growth and a more equal distribution of incomes are to be realized.

IV. The Transformation of Measurement for the Period Ahead

If the Fourth Industrial Revolution is to deliver social and economic benefits comparable to earlier periods, new measurement concepts, tools, and capabilities will be required, just as other aspects of business and work life will be required to transform. It is not coincidental amid the Third Industrial Revolution that the pain wrought by the Great Depression launched a historic effort to create an entirely new measurement system. The 3rd and 15th Nobel Prizes in economic science were awarded largely for contributions to the development of national income accounts - in 1969 to Simon Kuznets for work in the U.S. and in 1984 to Richard Stone for work in the U.K. While many innovations and improvements have been introduced over the years, the early design remains the foundation of national income measurement (See Landefeld, Seskin and Fraumeni 2008).

IV.1. Recent Measurement Innovations

Recognizing that radical change must occur to technology, economic activity, and ways of working for the benefits of industrial revolution to be realized, measurement transformation is needed as well. However, several measurement innovations have already occurred and have taken hold to some degree.

Intangible Capital

The work of Carol Corrado, Jonathan Haskel, and others has provided detailed development of both the measurement of intangible capital investment spending and the economics of such assets, including knowledge based-asset investment, the relationship of intangible assets to growth theory, growth accounting expansion, and the manner in which growth and ownership of intangible assets alters the competitive environment across firms (See Corrado, Haskel, Jona-Lasinio, and Iommi 2022).[6]

Importantly in the context of the Fourth Industrial Revolution, Crouzet, Eberly, Eisfeldt and Papanikolauo (2022) write:

> The key finding is that rents associated with intangible assets have contributed to a sharply rising share in the growth of total enterprise value of US businesses since the early 1990s, accounting for approximately 15 percent in the mid-1980s and to up to 40 percent in 2015, depending on how broadly intangibles are measured. (Crouzet, Eberly, Eisfeldt and Papanikolauo 2022, p. 48).

In related work, Crouzet and Eberly (2020) find that tangible capital investment has responded to (1) earned excess profit—rents earned by tangible capital, (2) the value of intangible capital, and (3) the interaction between the two. However, when Crouzet and Eberly expand the definition of intangibles to include research, development, organizational capital, innovation, and transformation, the combined contribution of growth in the intangible capital stock and rents generated by intangible capital increases to about two-thirds. Crouzet and Eberly's work suggests that the growth of investment has become much more dependent on the availability of a skilled workforce and somewhat less dependent on the cost of physical capital, even in a low interest rate environment. One implication of Crouzet and Eberly's work is that the pressure on capital owners to share rents with a skilled workforce might contribute to slower investment spending growth.

[6] The Journal of Economic Perspective, Summer 2022, published an intangible capital symposium.

Income Distribution

The important role played by changing capital and labor income shares over the course of each industrial revolution point to the obvious need for income distribution data. Two decades of work by Anthony Atkinson, Thomas Piketty and Emmanuel Saez, as is well known, has provided detailed data. Indeed, in a recent innovation, high frequency data have recently appeared. Blanchet, Saez, and Zucman (2022) provide quarterly estimates of economic group by income groups, finding in the post-pandemic period all income groups recovered to pre-crisis pretax income levels within 20 months of the March 2020 pandemic onset. While employment resumption primarily drove the recovery, wage gains at the bottom of the distribution were significant as labor markets tightened. Including taxes and cash transfers, real disposable income for the bottom 50% was 20% higher in 2021 than in 2019 but fell in the first half of 2022 as fiscal measures receded.

IV.2. Tools in Early Development

The ubiquitous availability internet service and the world-wide-web as well as the near universal digitization of information has set the stage of a continuing expansion of the global cloud computing infrastructure and the growing adoption of machine learning, deep-learning, and neutral network models. These information technology and artificial intelligence capabilities raise a variety of measurement questions and opportunities. While not intended to be comprehensive, here is survey of a few in the early stages of development - the value of new and free goods, the use of web-based search to estimate and predict economic activity, the integration of administrative and survey data, and the value of data.

Brynjolfsson, Collis, Diewert, Eggers, and Fox (2019) assert that the welfare contributions of the digital economy, characterized by the proliferation of new and free goods – such as online search, email, social networks, and retail banking - are not well-measured in the national accounts. Consequently, Brynjolfsson et. al. have introduced a new metric, GDP-B, which quantifies benefits, rather than costs. Two illustrations are considered – Facebook and smart phone cameras. With the use of incentive compatible choice experiments, the welfare gains from Facebook, for example, would have added between 0.05 and 0.11 percentage points to GDP-B growth per year in the US.

Hal Varian in a series of exercises shows the ability of online search data to provide estimates of the unemployment rate and initial claims for unemployment benefits. Choi and Varian (2019) show that Google Trends data can help predict initial claims for unemployment benefits in the U.S. Choi and Varian also find, using Google Trends, significant improvements in forecasting accuracy for German and Israeli unemployment data.

Koenecke and Varian observe increasing volumes of data and analytics produced with firm-level data, which is sensitive, proprietary, or private. To address the resulting reproducibility issues, Koenecke and Varian propose researchers release synthetic datasets based on true data, allowing external parties to replicate methodology. Koenecke and Varian explore synthetic data generation for economic analyses.

Despite these recent advances, the use of large-scale digitized information for the purpose of estimating prices and quantities by national statistical agencies to improve economic statistics remains in an early stage of development. In the U.S., statistical agencies have begun to make use of such data to augment traditional data sources with an opportunity to redesign the underlying architecture of official statistics. In March 2019, the NBER Conference on Income and Wealth explored progress in the use of large-scale digitized information and the challenges remaining. Abraham, Jarmin, Moyer, and Shapiro (2022) document the conference and find that the use of large-scale digitized information is “ripe” for incorporation into the production of official statistics. However, much “hard work and significant investment is necessary”.

Notwithstanding the challenges faced by national income accountants, large-scale digitized information is finding new applications as unstructured text data are converted to structure data. As outlined in Section II, Kelly et al. (2021) use natural language processing (NLP) to define breakthrough innovations as distinct improvements in the technological frontier that become the foundation on which subsequent innovations are built. They develop “measures of textual similarity to quantify commonality in the topical content of each pair of patents.” Significant, high-quality patents whose content is novel and impactful on future patents are identified. As a “ground truth” data set, Kelly et al. identify major technological breakthroughs across the 19th and 20th centuries. The measures of patent significance, developed with the NLP patent citation method, perform substantially better than citation counts in identifying the “ground truth” of major technological breakthroughs (See Figure 4). Validation shows the relationship of the measures to market value. With novel contributions adopted by subsequent technologies, the measures are capturing the scientific value of a patent (see also Bloom, Hassan, Kalyani, Lerner, and Tahoun 2021).

If the economic, productivity, and income distribution benefits of the Fourth Industrial Revolution are to be realized, understanding the interaction of technology and the labor market will be important. In the context of increased services sector activity, especially among SMBs, improved worker engagement is necessary. Workers and business leaders will need to transform their behavior and engage in creative destruction. To address worker engagement, a novel U.S.

program has been created over two decades. The Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program combining federal, state and Census Bureau data on employers and employees. As part of the program, states agree to share Unemployment Insurance earnings data and the Quarterly Census of Employment and Wages (QCEW) data with the Census Bureau. The program combines these administrative data with additional administrative data and data from censuses and surveys. From these data, the program creates statistics on employment, earnings, and job flows at detailed levels of geography and industry and for different demographic groups. In addition, the program uses these data to create partially synthetic data on workers' residential patterns (See Abowd, Haltiwanger and Lane 2004 and Lane 2020).

Finally, the nearly universal digitization of information has raised the question of the value of data. The valuation theory, process, and empirical estimates are in the early stages of development, addressing a nebulous issue. Indeed, a vast proportion of existing digitized information is sensitive, proprietary, and private. Led by the Laura Veldkamp, Farboodi, Singal, Veldkamp, and Venkateswaran, (2021) outline a model that provide sufficient statistics, making an investor's private value of data measurable. Farboodi et. al. find, first, investor characteristics always matter. Second, despite the heterogeneity, market illiquidity is a significant determinant in how investors value data. When price moving trades occur, the value of data falls, especially for the investors who value data most. The high sensitivity of the value of data to market liquidity, for high value data, suggests that modest fluctuations in market liquidity can eviscerate the value of financial firms whose main asset is financial data.

IV.3. Needs for the 21st Century

In the context of industrial revolution, there are behaviors whose progression is important but where data are either limited or non-existent. Such topics include new tasks, knowledge diffusion and absorptive capacity, transformation by enterprise size, and technology adoption.

New Tasks

Industrial revolutions bring with them new business models and new ways of working. In the second half of the 20th century and into the 21st century, Acemoglu and Restrepo have shown labor augmentation, approximately aligned with the deployment period of the Third Industrial Revolution, increased labor income. By contrast, Acemoglu and Restrepo also show labor automation, approximately aligned with the installation period of the Fourth Industrial Revolution, decreased labor income. The notion is that occupations are a collection of tasks with the expectation that tasks evolve with greater frequency than occupations and the pace of new task creation is much faster in the deployment period than in the installation period, increasing labor income share. While data on occupations are well established, data on tasks and a supporting taxonomy is limited.

Recent work by Autor, Chin, Salomons and Seegmiller (2022), with 80 years of data, construct a novel database of new job titles linked both to U.S. Census microdata and to patent-based measures of occupations' exposure to labor-augmenting and labor-automating innovations. They find that most current employment is in job specialties introduced after 1940. However, new work creation has shifted from mid-wage production and clerical occupations over 1940–1980, approximately the deployment period of the Third Industrial Revolution, to high-wage professional occupations and low-wage services since 1980, approximately the installation period of the Fourth Industrial Revolution. New work appears in response to technology innovation that complement occupations and demand shocks that raise occupational demand. Conversely, innovation that automate tasks, or reduces occupational demand, slows new work emergence. Augmentation and automation innovation are positively correlated across occupations with augmentation increasing labor demand and automation decreasing labor demand.

Autor et. al. find causality from new work augmentation and automation, spurred by breakthrough innovations two decades earlier, on occupational labor demand. Consistent with the view that the deployment period of the Fourth Industrial Revolution remains in an early stage, Autor et. al. suggest that demand-eroding effects of automation innovations have intensified in the last four decades while the demand-increasing effects of augmentation innovations have not.

Knowledge Diffusion and Absorptive Capacity

By definition, knowledge diffusion is unobservable and difficult to measure. However, the advent of artificial intelligence, deep-learning models have the potential to create a service category which is currently unmeasured. In the existing national accounts framework, software and the associated deployment services that are licensed for on-premise use are included in spending for intellectual property. Spending for software-as-as-service (SaaS) is an intermediate purchase. While the appropriate treatment of SaaS spending can be debated, knowledge diffusion measures can be captured, in part, with as-a-service spending. In research at the MIT-IBM

Watson AI Lab, two recently compiled business cases demonstrate knowledge diffusion as-a-service.[7]

Building safe and reliable AI models for Autonomous Vehicles (AVs) requires enormous compute power and training data, along with skill, resource, and expertise at scale. Under such conditions, large platforms are emerging that pool data from multiple participants, aggregate demand to justify the large investments required, and enable new business models where AV software can be offered as-a-service to carmakers and fleet operators. NVIDIA is addressing these challenges with a service provide to auto manufacturers.

A common data platform across multiple customers allows for pooling data among several companies that increases the data available for training and enable greater model performance, particularly with edge cases. Hundreds of millions of driving scenarios can be simulated to supplement real-world data and help bootstrap models for silent on-street testing and iteration. NVIDIA is able to minimize the compute required by jointly training multiple tasks on a single model architecture. Once the full model is trained, the model is optimized for each task, without the need to re-train the model.

Participating auto makers can either lease AV hardware to train their own models based on a larger dataset or use pre-trained AV models from NVIDIA. In either case, instead of making significant capital investments in hardware and development capability, the AV technology becomes a service and an operating expense with benefits from hardware and software improvement. The offering also represents the beginning of a new market dynamic. On one side are vertically integrated auto makers (e.g., Tesla), that co-design their software and hardware for more seamless experiences. On the other side are increasingly modularized auto makers who

[7] https://www.ibm.com/thought-leadership/institute-business-value/en-us/report/ai-examples

compete on the quality of their hardware and buy their software from centralized players such as NVIDIA.

While the NVIDA offering is intended to service large enterprise buyers, more intriguing are similar offerings for small and medium businesses (SMBs) who often find large scale development projects unprofitable. Such limitations are increasingly true for machine-learning, particularly where the tasks being automated are perception-based with the use of image recognition. These applications can require significant data and compute resources to develop and maintain. Navtech identified an opportunity to bring advanced computer vision to individual diamond retailers across the globe, by creating a model and delivering it as-a-service.

India alone has an estimated 300,000 diamond jewelry retailers. Many are smaller companies, with limited inventory capacity who typically increase their offerings through custom-made jewelry. Visual catalogs are an important element of the sales process. Each retailer maintains such a catalogue for their own inventory and supplements it with images of other jewelry as inspiration for customers looking for bespoke pieces. Digital catalogs remove physical catalog constraints but introduce other challenges. Staff compile images from various sources and categorize them manually into folders. The process is slow, prone to error, and results in only very high-level categorization.

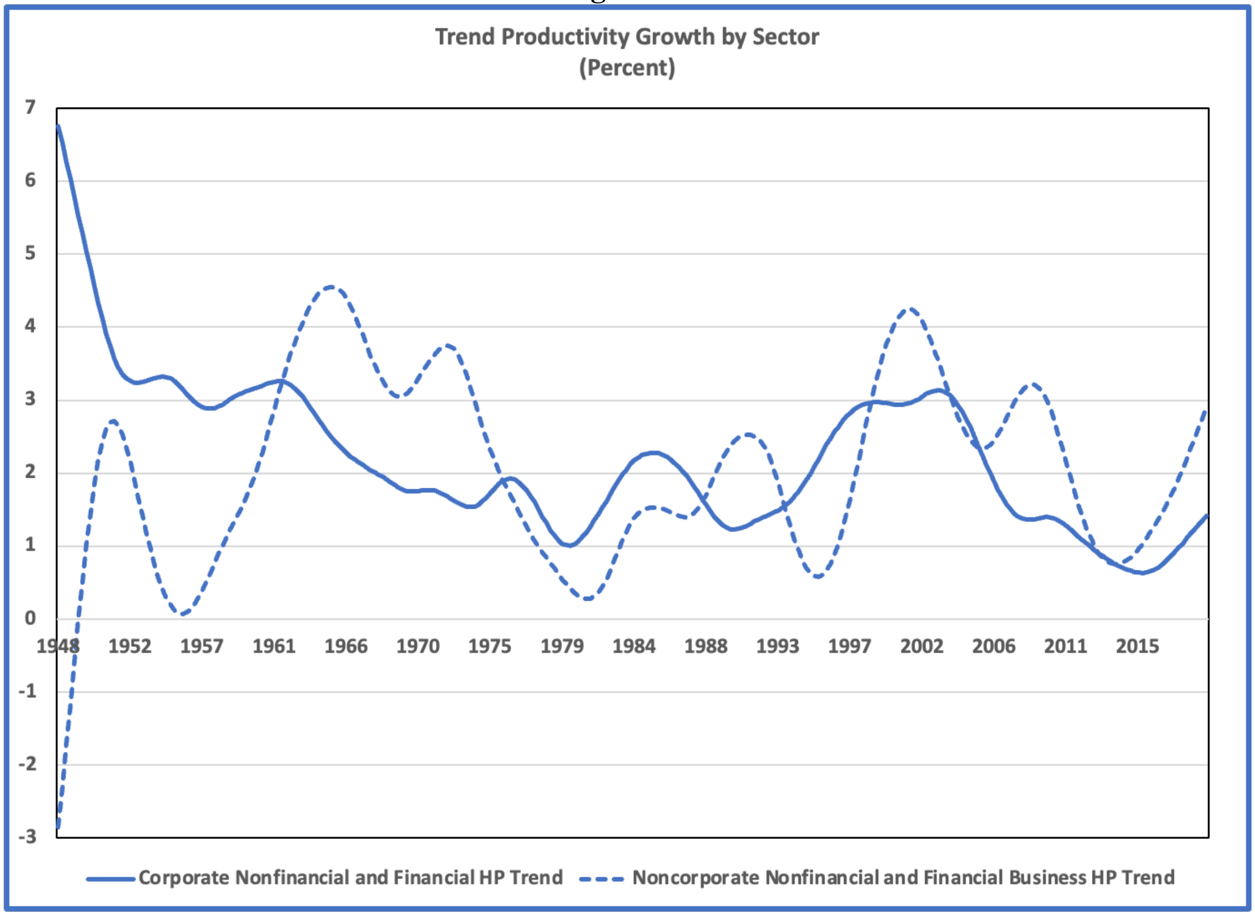
Computer vision systems that leverage deep learning to classify images improves speed and accuracy, but the reality is that they are out of reach for most retailers. As a result, Navtech built a computer vision system and offered it as-a-service. The system enables retailers to rapidly build large digital catalogs, classifying up to 100 images per minute at an accuracy of 90-93% for product category and style and 85-86% for diamond cut. The model is built with a relatively small data set of only 3000 labelled images for each jewelry item. Navtech performs postprocessing, where the results of one model – style - are used to increase the confidence of predictions for another model - diamond cut. The service illustrates the cost-benefit tradeoffs of deep learning, where some use cases can only be enabled by larger, centralized providers with the ability to serve a broad market. Such systems, because they are delivered at scale, must be delivered as part of as-a-service architecture, underpinned by traditional cost-effective software development.

Enterprise Size

Small and Medium Businesses (SMBs) play an important role in value add, employment, and productivity (See Fleming 2022, Chapter 4). For example, Berlingeri, Calligaris and Criscuolo (2018) find that productivity and wages increase significantly with firm size in the manufacturing sector while the distribution is much flatter in the nonfinancial market services sector. However, wages increase with productivity in both the manufacturing and nonfinancial market services sector with the increase especially large in services firms. For the most productive manufacturing and nonfinancial market services firms – those above the 90th percentile – wages are generally higher in the services firms than in manufacturing firms. Further, if aggregate economic and productivity growth are expected to grow at a more robust rate in the future, SBMs will be required to contribute to the stronger growth environment.

Surprisingly with SMBs providing a substantial proportion of employment across most developed nations, detailed, and regularly reported data by enterprise size are limited. As an illustration, the U.S. Bureau of Labor Statistics (BLS) publishes productivity data for the nonfarm business sector and the nonfinancial corporate sector, leaving the nonfinancial noncorporate sector and the financial sector unreported. It is in the nonfinancial noncorporate

Figure 11



Source: Author's Calculations

and the financial sectors where many SMBs are found. In the second quarter of 2022, productivity in the nonfarm business sector fell 4.1% from a year earlier and productivity in the nonfinancial corporate sector fell 0.7% from a year earlier. From flow-of-funds data, the nonfinancial corporate sector delivers 65% of private nonfarm business sector value add, implying that productivity in the nonfinancial noncorporate and financial sectors fell 10.5% from a year earlier. While such a calculation is a poor substitute for a well-developed data program, the estimate – consistent with Figure 11 – increased productivity growth volatility in the sector, perhaps reflecting a time lag in knowledge diffusion.

AI Technology Adoption

Finally, along with the transformation of labor markets and business models and process of enterprises of all sizes, the adoption of artificial technology adoption will be an important element of growth prospects. While data are limited early work by the U.S. Census Bureau provides some early insight.

Zolas, Kroff, Brynjolfsson, McElheran, Beede, Buffington, Goldschlag, Foster, and Dinlersoz (2020) provide the most extensive estimate of AI technology usage. They found in 2017, across AI-related technologies, for all firms in the U.S. the aggregate adoption rate was 6.6 percent.[8] Zolas et al. introduced a survey module that complemented and expanded research on the causes and consequences of advanced technology adoption. The 2018 Annual Business Survey (ABS), conducted by the U.S. Census Bureau in partnership with the National Science Foundation, provided a comprehensive view of advanced tech-nology diffusion among U.S. firms. The technologies included were AI, cloud computing, and the digitization of business information. The survey was a large, nationally representative sample of over 570,000 respond-ing firms covering all private, nonfarm sectors of the economy.

Zolas et al. also finds adoption was skewed. While the heaviest concentration was among a small subset of older and larger firms, an increasing number of new, young, born-on-the-web, still quite small firms, are also adopters. The smallest firms had the lowest use rates. Even among firms of the same age, the usage rates tended to increase with size. For small firms (less than 50 employees) usage rates tended to decline with age with the oldest small firms having the lowest adoption rates. Overall, size was an important predictor of AI technology use and the connection between age and the use of these technologies depended on size. Scale appeared to be important

[8] Unpublished estimates provided by a global technology provider found 4 per-cent of global large enterprises were operating AI solutions in 2016, 5 percent were operating such solutions in 2018, and 9 percent in 2020.

for AI usage, likely due to requirements for large quantities of data, copious computing power, experienced software developers, and skilled data scientists fully exploiting AI capabilities.

Cloud services adoption displayed modest adoption in 2017, with a large share of firms hosting at least one IT function in the cloud. But cloud usage was significantly lower than the adoption rates of digital business information, which is nearly universal. Zolas et al. also found that technology adoption exhibits a hierarchical pattern, with the most-sophisticated technologies adopted most often only when more-basic applications were as well. For instance, digitization of business information was very widely adopted. The vast majority of firms who utilize the cloud for their IT services also digitize their information. Similarly, the vast majority of firms that adopt at least one AI technology, almost always purchase cloud services.

V. Conclusion

The deployment era of the Fourth Industrial Revolution is not assured to deliver robust and rapid growth, capital deepening, and improved living standards. Clearly, the future is uncertain. A breakthrough is not guaranteed. If robust and rapid growth is forthcoming, it is likely that economic, social, and political transformation is required. Economic and social measurement will not escape the transformation.

For the United States, United Kingdom, and other developed nations, benefit from a period of stronger economic and productivity growth with a more equal distribution of incomes will require a new social contract among workers, business leaders, and government officials, both elected and appointed. Tradition and culture are important, but the willingness of productivity-lagging but surviving businesses to embrace lower-cost technology that will continue to be easier to deploy will be necessary. Likewise, a substantial proportion of the workforce will also need to be willing to transform job roles and take on new tasks. Government leaders will need to show a willingness to comprise and adapt to the new economic environment. Political leaders will need to be willing to compromise, recognize the importance of new measurement programs – along with many other – and reallocate funding as necessary.

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