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Industry Concentration and Technological Progress in U.S. Industries

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ABSTRACT:

This paper analyzes the impact of increasing concentration on the pace of technological progress in the U.S. economy. Since the beginning of the 2000s, the U.S. economy has been in a period of slower capital accumulation marked by lower aggregate productivity growth, while concentration ratio in most industries has increased. Studies analyzing the consequences of increasing concentration provide firm-level evidence that new-technology-induced productivity gains are an important driver behind increasing market power. Motivated by the lack of macro-level evidence for such productivity gains, this paper investigates the relation between new technologies and increasing concentration by focusing on industry-level measures of technological progress: labor and capital productivity, intangible asset intensity, and skilled labor ratio. The results show the impact of concentration on labor and capital productivity to be positive from the late 1990s and early 2000s, yet gradually turning negative through 2000s. While there is a significantly negative relationship between changes in skilled labor use and concentration, there does not seem to be any evidence that industries with increasing concentration are those with higher intangible capital ratio.

Keywords: market power, concentration, labor productivity, capital productivity, skilled labor

JEL CODES: L1, D2, E2, J2, O3, O4

1. Introduction

Since the beginning of the 2000s, the U.S. economy has been in a period of slower capital accumulation marked by weak investment, declining labor share and lower aggregate productivity growth. At roughly the same time, a considerable rise of market concentration has occurred in most U.S. industries. These facts have led to an interest in the potential macroeconomic consequences of rising market power, with a handful of empirical studies exploring the connections among these trends. While the findings of these studies about the impact of rising concentration on the declining labor share and weak investment seem more conclusive (Autor et al. 2017, Barkai 2017, Phillippon and Gutierrez 2018), evidence of the underlying mechanisms has been lacking.

In this paper, I explore the impact of industry concentration on measures of technological progress, such as capital and labor productivity, and the increase in the use of intangible capital, and skilled labor. The importance of technological progress for growth and distribution is well recognized, yet various studies on the slowdown in productivity of the U.S. economy have not considered rising market power as a potential contributor to the "puzzle." Studies on the consequences of market power, on the other hand, are remarkably ambiguous on the relationship between technological progress and increasing concentration. A good number focus on new-technology-induced productivity gains as an important driver behind increasing market share of firms (Autor et al 2017). While that might be the case in certain industries or with top firms within industries, this view does not help explain the aggregate trends in productivity. Building on the insights from these two strands of literature, I provide evidence that increasing market concentration is another attenuating factor for the slowdown in technological progress and productivity in the U.S. economy.

Industry level, regression-based analyses in this paper show a significantly changing impact of concentration on capital and labor productivity over the last two decades. While the impact is positive during the late 1990s and early 2000s, it gradually turns negative through the mid-late 2000s, and follows a pattern close to aggregate productivity trends. Further consideration of various industries reveals retail trade, petroleum and coal products manufacturing, and chemical manufacturing to be prominent drivers of these trends at the

aggregate level.

This paper is organized as follows: In Section 2, I review the aggregate indicators of technological progress for the U.S. economy, and identify the periods during which changes occur. In Section 3, I briefly discuss the recent literature on the impacts of concentration to identify the common threads, potential problems, and lacking areas. Section 4 primarily presents the sources of data used, a discussion of estimation framework, and results from industry level regressions. Additionally, in the last part of Section 4, I provide a closer look at industries leading in changes in concentration, labor, and capital productivity, as well as the use of intangible capital and skilled labor. Section 5 contains a summary of findings, and a discussion of implications.

2. Technological Progress in the U.S. Economy From the 1990s to 2000s

The pace and nature of technological progress in a capitalist economy is important for both growth prospects and distributional issues. The distribution-growth framework developed within the tradition of Marxian political economy[1] shows how distributional conflicts and technical change have an impact on the accumulation process via changes in the rate of profit. When the pace of technical change slows down, for instance, causing labor productivity to slow down or decline, capital accumulation slows down, compelling capitalists to increase pressure on the working class to maintain profitability.

Aggregate investment and productivity are the main indicators to assess whether technological progress is taking place in an economy. Technical change follows as a result of investment in new machines and equipment, and is expected to bring productivity growth. Recognizing the weak investment performance of the U.S. economy since early 2000s, a number of studies have offered explanations for the phenomenon of "profits without accumulation." Among them, many emphasized how the process of financialization changes the incentives and constraints faced by non-financial corporations (Stockhammer 2006, Orhangazi 2008, for example). Others focused on a globalized nature of production, whereby outsourcing

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[1] The framework has been widely used to study medium- to long-run capitalist evolution involving structural changes and crises—see Foley and Michl (1999), Mohun (2009), Dumenil and Levy (2011), Basu and Vasudevan (2013).

and offshoring reduce the need for U.S. domestic investment (Milberg and Winkler, 2013). The issue of intangibles has drawn recent attention, framing the problem of weak investment as a matter of mismeasurement (Haskel and Westlake 2017). While a survey of this considerable literature lies well beyond the boundaries of this paper, I return to the issue of intangibles below, as it relates to the process of technological progress.

Turning our attention to productivity measures, Figure 1 shows the trends in labor productivity and capital productivity in the U.S. economy.[2]

< Insert Figure 1>

The figure displays a trend of increase in capital productivity from 1982 onwards, indicating the relative importance of technological progress in recovering from the crisis period of the 1970s. While volatile, this trend continues until 2006, when capital productivity in real terms reaches the same level as its peak in the 1970s. After 2006, the trend turns downward, and in 2009, capital productivity drops to the same level seen in 1991, after which it settles into a stagnation pattern. Labor productivity, on the other hand, exhibits a relatively steady-looking increase compared to capital productivity, hinting at the possible labor-saving nature of technical change.

Any choice of technique in production is a choice of capital-labor ratio (capital intensity), which results in a change in labor productivity. The relative changes in capital intensity and labor productivity, then, jointly determine the changes in capital productivity.[3] In classical theory, technical change is meant to be biased: labor-saving, capital-using, and leading to increases in capital intensity and labor productivity. Biased technical change implies that labor and capital productivity do not grow symmetrically over time. If the change in capital-labor ratio is greater than the change in labor productivity, capital productivity might decline. Basu and Vasudevan (2013) report this has been the case for a large group of capitalist countries

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[2] For a long-term review of the pattern of labor productivity in the U.S. economy, see Gordon (2016). For long-term patterns of change in capital productivity see Mohun (2009), and Basu and Vasudevan (2013).
[3] Logarithmic differentiation of the real capital productivity ratio tells us that the growth in capital productivity = growth in labor productivity - growth in capital-labor ratio.

over long periods of time; labor productivity has increased even as the capital productivity ratio has declined or stagnated.[4]

Looking at the growth rates of both series would give us a clearer picture of the changes over time. Figure 2 shows, in two panels, labor and capital productivity growth and their trends, beginning from 1983 (the immediate aftermath of the early 1980s recession). For most years during this period, labor productivity growth was higher than the growth in capital productivity, bringing an increase in capital intensity in line with the concept of biased technical change. While both capital and labor productivity exhibit declining trends over the entirety of 1983-2017 (black dashed trend lines in both panels), there are also exceptions, such as 1995-2005's period of relatively high labor productivity growth.

<Insert Figure 2>

Many economists consider the relatively higher productivity growth of the late 1990s as resulting from the economy-wide adoption of Information-Communication-Technologies (ICT). To some, Solow's paradox seems long resolved, including the productivity statistics.[5]

While agreeing with the initial gains from the "Internet revolution," Gordon (2016) has been more skeptical about the continuing contribution of new technologies to productivity growth. In his seminal work, *the Rise and Fall of American Growth* (2016), he notes that "the changes created by the Internet revolution were sweeping but were largely completed by 2005." (2016:529). As can be seen in the shorter red trend line of labor productivity growth over 2004-2017 period in Panel A of Figure 2, the last decade has brought a remarkable slowdown in labor productivity growth, with the exception of 2009-10, which was likely caused by aggressive cuts to employment hours during the crisis. Panel B shows that capital

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[4] This pattern of labor-saving and capital-using technical change is labeled as Marx-biased technical change by Foley and Michl (1999). For an empirical test of the existence of Marx-biased technical change in capitalist economies, see De Souza (2017).

[5] In his 1987 New York Times Book Review article, Robert Solow commented on computers: "... what everyone feels to have been a technological revolution, a drastic change in our productive lives, has been accompanied everywhere, including Japan, by a slowing-down of productivity growth, not by a step up. You can see the computer age everywhere but in the productivity statistics."

productivity stagnated over the same period, and displayed a similar decline (red trend line for 2010-2017).

　　While there is no clear answer in the literature to this productivity slowdown "puzzle," there seems to be an agreement that mismeasurement of productivity and GDP growth is an issue, especially for products associated with the digital revolution and health care. Sichel (2019) discusses the increasing prevalence of free goods (such as Facebook's and Google's search and mapping tools) that are not counted as final output in GDP calculations, and how these free goods and other pricing-related mismeasurement issues lead to an underestimation of GDP. Having reviewed various compensation calculations for such omissions, Sichel (2019) also concludes that mismeasurement cannot completely explain the slowdown in U.S. productivity growth. Syverson (2011) similarly makes the case that even the largest estimates of consumer surplus arising from digitalized "free goods" are too small to offset the magnitude of the productivity slowdown.

　　Related to these debates on mismeasurement is the issue of the changing composition of various types of capital and labor inputs. Disaggregating labor and capital inputs into components and highlighting the relative changes in these components has been a way to assess the nature of technological progress and distributional patterns. Acemoglu and Autor (2010) describe a production process which features two distinct skill groups—typically college and high school workers—which perform two distinct and imperfectly substitutable occupations, or produce two imperfectly substitutable goods. Technology, in this "canonical model," is assumed to take a factor-augmenting form, meaning that it complements either high- or low-skill workers. The consensus view is that the post 1980s' increase in skill demand in the U.S. labor markets has been closely linked to technological progress especially in the form of computerization. Although the details of various skill-biased technical change stories vary, the general idea is that new technology is a complement to the skills necessary to perform complex cognitive tasks, and a substitute for more routine skills (Autor, et al 2001). In this context, information technology and intellectual property (intangibles), types of capital inputs, have received specific attention to assess skill-biased technological change. Indeed, as it relates to the focus of this paper, the story of the top firms is that of "the canonical superstar firms

such as Google and Facebook [which] employ relatively few workers compared to revenue, as their market value is based on intellectual property and a cadre of highly-skilled workers" (Autor et al 2017).

<center><Insert Figure 3></center>

A cursory look at the macro data confirms the rising importance of skilled labor in the U.S. economy. Considering educational attainment as a proxy for skill level—which is widely done in the recent literature on skill levels—Figure 3 shows the percentage of employees with bachelor's and advanced degrees has increased from 28 to 41 percent over the last 25 years, making this group the largest portion of U.S. employment. The increase in the share of skilled labor in employment is almost exactly matched by the declining shares of those with high school or lesser degrees. This increase in the economy-wide use of skilled labor could provide evidence for a skill-biased technical change. However, considering the sluggishness in both labor and capital productivity over the last decade, during which the share of skilled labor has kept increasing, it is not clear how a steady increase in the use of skilled labor relates to productivity patterns.

Since the "canonical model" of skill-induced technical change suggests that new technologies are complementary to high-skill labor use, it is essential to examine the indicators of such new technologies as they relate to changes in the composition of capital stock. The intensity of the use of intangible capital is considered a pertinent indicator for this purpose. The category of intangibles corresponds to intangible fixed assets (without the goodwill) on firm balance sheets. Since intangible assets are treated as a form of fixed assets for firms, the initial motivation of the literature on intangibles was to explain the weak investment performance of the U.S. economy since the 2000s—see Orhangazi (2018), Crouzet and Eberly (2018), Gutiérrez and Philippon (2017). These studies suggest the weak investment performance observable in firm-level investment is partly the result of a mismeasurement problem with intangibles. Firm-level accounting data on investment and capital stock only include expenditures in plant, property, and equipment, and leave out intangibles which contribute to production and profits. These studies note that the values of intangible assets are difficult to measure and prone to

<center>7</center>

underestimation. Even when they are included in the capital stock of the firms, this would result in the underestimation of capital stock.[6]

Macro level data for intangibles come from BEA, which focuses on intellectual property products (IPP), defined as a new category of investment, consisting of software, research and development (R&D), and entertainment, literary, and artistic originals.[7] Figure 4 shows that the share of IPP in private non-residential capital stock has indeed increased from 5 percent in 1982 to above 13 percent in 2017. Shares of R&D capital and software capital, main components of IPP, also increased over this period, and R&D capital share continually stayed above that of software capital.

<Insert Figure 4>

While an increase in these ratios could indeed signal an economy-wide adoption of ICT and the increasing importance of R&D activities, there seems to be a break in the growth rates of these new technology indicators around the early 2000s. Specifically, from 2000-2008, both the shares of IPP and R&D have declining trends while the share of software capital remained stagnant. The slowdown in growth of IPP intensity seems to concur with the view that the 2000s was not a decade of intensified technological progress with respect to the adoption of new technologies.

Gordon (2010) shows that the productivity growth of the early 2000s was primarily driven by an upsurge of productivity growth in non-ICT industries, not ICT industries. He suggests instead that a sharp decline in both profits and the stock market in 2000-01 motivated

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[6] To my knowledge, there is not yet any systematic evidence of underestimation problems for reported intangibles in firm-level balance sheets. To measure the missing intangibles and resulting missing investment, Gutiérrez and Philippon (2017), for instance, provide a framework which assumes "that intangible investment is consistently under-estimated across all industries." Their conclusion that "the rise of intangibles appears to explain a quarter to a third of the observed investment gap" is based on this assumption. The underlying reason for the prevalence of this assumption seems the be the potential gap between the cost and market value approaches to valuation of intangibles, a notion inevitably influenced by the degree of confidence in markets.

[7] Software and R&D purchases are captured with receipts from sales data from the Census Bureau. However, a large part of IPP is produced in-house and not sold in the market. For these, the BEA estimates the own-account production of software and R&D as the sum of costs plus a markup. As different from BEA's treatment, at the firm level, ICT systems-related expenditures typically are not included in this category, and are treated as a part of tangible fixed assets.

firms to aggressively cut all costs, but particularly labor costs. As Gordon (2010) notes, cutting labor costs was mostly done by cutting employment hours, translating into higher labor productivity.

All in all, the main macro indicators of technological progress in the U.S. economy show a slowdown in the pace of the adoption and/or innovation of new technologies after the early-to mid-2000s. Existing literature focuses more on explaining the productivity "puzzle," rather than placing this issue in a larger context of technology. The variety of explanations include the aging workforce (Eggertsson & Mehrota 2014) and a slowdown in business dynamism—the process of business birth, growth, decline and exit (Decker et al 2018). One missing component in this literature is an exploration into causes of industry-wide variation in productivity trends. Recently emerging literature on the macroeconomic consequences of market power provides an alternative perspective allowing us to investigate such industry level differences. In the next section, I present a selective review of this recent literature to broadly illustrate how market structure might relate to technological progress and other important dimensions of capital accumulation process.

3. The Recent Literature on Rising Market Power

The last two decades has seen a substantial increase in concentration, measured as the revenue share of top firms, in most U.S. industries (CEA 2016, De Loecker and Eeckhout 2017, and Grullon et al. 2018). As the period partially coincided with slower capital accumulation in the U.S. economy, which was marked by weak investment, declining labor share, and a volatile-yet-increasing-trend in profitability, empirical studies on consequences of rising concentration followed. Grullon et al (2018), for instance, find a strong, positive correlation between firm-level profitability and changes in the Herfindahl-Hirschman index (HHI), specifically for the period of 2001-2014. When they decompose profits into two components, they find that firms in concentrated industries have become profitable due to higher profit margins rather than through higher efficiency. Gutierrez and Philippon (2017) provide firm-level evidence that an increase in market power is an important factor behind low investment rates in the U.S. Their findings show the rise of intangibles can statistically explain one third of low investment rates in

the U.S., while the change in corporate ownership structure and an increase in industry concentration explain the rest. Another study interested in profitability and market power, Barkai (2017), finds the increase in concentration is strongly associated with an increase in profit share and the decline in the labor share of income. Different from the previous studies, Barkai (2017) derives his conclusions from macro-level and industry-level data. At this point, the empirical evidence of the correlation between increasing industry concentration and declining labor shares or investment rates seems conclusive in this recent literature. The same cannot be said, however, of how concentration is related to technological progress and productivity changes at the macro level, and that is the focus of this paper.

One issue arising from this empirical literature is whether increasing concentration is informative regarding the state of competition and/or market power of the firms in an industry. This issue determines what type of measure of market power different studies use: Those who are not convinced of the positive link between concentration and market power use mark-up ratios to measure market power, instead of firm- or industry-level concentration ratios. De Loecker and Eeckhout (2017), for example, document the evolution of markups based on firm-level data for the U.S. economy, and show that average markups rise from 21 percent above marginal cost in 1980, to 61 percent in 2017. They explain the increase partly as the result of technological change, and partly due to sheer increase in market power. Their measure of markup, following Hall (1988), is the ratio of [elasticity of output to a variable input/share of revenue for that variable input]. They consider the "Cost of Goods Sold" item in firm financial statements as variable input and argue that the variable input share of revenue has decreased substantially, while overhead costs—measured as "Selling, General and Administrative Expenses"—have increased. They interpret this increase in overhead costs as the result of technological change, where marketing and advertising expenses are meant to be expenses on intangible capital. Traina (2018), on the other hand, criticizes De Loecker and Eeckhout (2017) for treating marketing and advertising costs as overhead and argues that, once the cost definitions change, there is no evidence of an aggregate-level increase in market power. As Syverson (2019) notes, the use of firm-level financial statements in this recent market power literature to identify economic inputs has been problematic. Accounting standards in different

industries allow firms to record various expenses under different cost categories, turning the same expense into the cost of either fixed or variable inputs depending on the production process adopted by firms.

Beyond the empirical issue of how to measure market power, whether increasing market power is indicative of less competition, is also a theoretically ambiguous matter. While the empirical studies mentioned above point at the negative consequences of rising market power, a few other papers strike a more optimistic stance, generally seeing rising market power as the inevitable result of top firms gaining market share by adopting new technologies. Perhaps the most-cited study among those emphasizing the performance of top firms is by Autor et al (2017), which presents a model in which a higher degree of competition helps the most productive "superstar firms" capture market share, thereby increasing industry concentration. The suggestion is that firms gain high market shares by competing either on the merits of their innovations or superior efficiency. These firms tend to have lower labor share and they dominate industries, causing the aggregate labor share to decline. Autor et al (2017) argue that the growth of concentration is disproportionately apparent in industries experiencing faster technical change as measured by the growth of patent intensity or total factor productivity, suggesting that technological dynamism is an important driver of this trend, "not anti-competitive forces." Bessen (2017) supports this observation, finding that sales concentration is strongly correlated with the use of ICT. In this vein, Crouzet and Eberly (2018) suggest industry leaders might be particularly efficient at using intangible assets. Their study on the U.S. retail industry shows that an increase in intangible capital use is associated with higher productivity. Their interpretation is that the intangible capital reflects the adoption of more efficient business practices, as well as the growing value of brands, which improve business performance without the addition of new physical capital. The use of intangibles is considered to be beneficial to firms specifically for two reasons: 1) Intangible capital tends to be scalable without substantial increase in marginal cost. 2) Intangible capital comes with the protection of patents, copyrights and trademarks, which excludes competitors. These efficiency gains associated with intangible investments may drive greater industry concentration.

The theoretical ambiguity about how competition is related to concentration can be

better articulated within the Marxist framework, which characterizes capitalism as a dynamic process of capital accumulation. According to Marx, it is the competitive process that drives investment in new technologies leading to the centralization and concentration of capital. Marx tells us how competition increases the economies of scale: "The battle of competition is fought by cheapening of commodities. The cheapness of commodities demands, ceteris paribus, on the productiveness of labour, and this again on the scale of production. Therefore, the larger capital beats the smaller." (Marx, Capital, Volume 1, chapter 25, Section 2:441).

Technical change and market structure can be related in multiple ways. If the optimal scale of production increases with new technology (due to higher fixed costs and lower variable costs), there will be a tendency for the industry to become more concentrated. If technological change takes the form of new innovations, innovating firms would gain monopoly rents from patents and increase their profitability, leading to more market power. How easily these profits are dissipated (the process of diffusion of technology) would change how long such advantages last. Through these mechanisms, we would observe a positive relationship, running from technological change to concentration. On the other hand, one should consider the possibility of reverse causality in the relationship, whereby market structure might have consequences for the pace of technological change in an industry. Highly concentrated markets with very large companies might imply less incentive to innovate or invest in new technologies. This would have resulted in a negative correlation between two variables. Alternatively, large companies in concentrated markets might have enough funding to undertake R&D to innovate or adopt new technologies, which, in turn, would imply a positive correlation. To summarize, technology and market structure are endogenously related, with complex underlying mechanisms which cannot be summed in negative or positive correlations—even when using appropriate empirical techniques to control for endogeneity.

As seen in this brief review, the studies on the consequences of market power do not specifically focus on whether market power could be detrimental to the technological progress. Arguments suggesting that highly concentrated markets are dominated by relatively more productive, large firms which are investing in new technologies are hard to reconcile with the economy-wide trends in productivity of the last decade presented in Section 2. While the

empirical investigation in the next section in no way claims to unearth complex mechanisms underlying the relationship between increased concentration and technological progress, it departs from the existing studies in two ways: 1) To tie the discussion of concentration to aggregate trends in technological progress, I undertake an empirical analysis by constructing industry-level indicators of the level of technology (as discussed in Section 2). The existing empirical evidence typically relies on firm-level financial data from publicly traded firms, based on a firm-level model of how top firms gain market power via new technologies.[8] Since there is enough evidence of rising productivity dispersion between top firms and the rest of the firms within industries in the U.S. (Decker et al. 2018), it is not clear how any impact of market power translates to the aggregate level, which is important to assess the role of technological progress in an aggregate growth-distribution framework. 2) I also test whether the relationship between concentration and the indicators of technology varies over the last two decades, in order to shed light on the productivity puzzle in the U.S. economy.

4. Empirical Evidence on the Impact of Rising Concentration on Technological Progress

    4.a. Data and Variables

The empirical examination in this section is pursued at the industry level to better tie the issue of industry concentration to macroeconomic changes. The industry-level data comes from four databases: the Census Bureau's Economic Censuses, BEA's NIPA and Fixed Asset Tables, BEA's Integrated Production Accounts (KLEMS) and the Bureau of Labor Statistics' employment database.[9]

    The source of industry concentration data is the Census Bureau's Economic Censuses, which are conducted every five years. Concentration figures are provided by North American Industry Classification System (NAICS) codes[10] as the total shares of the sales of the top 4, top 8,

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[8] These studies do use industry-level concentration ratios as a measure of market power, yet they match it with firm-level measures of investment, labor share, intangible intensity, etc. to analyze the impact of the concentration on these variables. The exception is Barkai (2017), which uses macro and industry-level measures of labor share.

[9] See the Data Appendix for matching procedures used for industries across four databases.

[10] NAICS identifies each industry by a 6-digit code, where the first two digits indicate the sector; the third digit indicates the subsector; and the fourth digit indicates the narrower industry group. For instance,

top 20, and top 50 firms. I use the data from the 1997, 2002, 2007 and 2012 censuses, since the data from previous years are arranged by SIC codes, and data from the 2017 survey is not yet available. One advantage of using this database is the fact that the Economic Census covers both public and private enterprises. Another advantage—compared to firm-specific HHI types of measures used in studies utilizing firm-level Compustat data—is its ability to account for the activities of conglomerates. Specifically, the census constructs measures of concentration based on NAICS classification of each individual facility rather than assigning NAICS codes at a firm level. As a result, sales of conglomerate firms are decomposed by divisions sharing the same NAICS code, then grouped with the sales of stand-alone firms sharing the same NAICS code. I conduct an industry analysis at the NAICS 3-digit level because, although a 4-digit NAICS definition potentially captures industries in a more detailed way, it may be too narrow to reflect market power when firms operate in closely-related but separate markets. Using data at the 3-digit level increases the probability that large corporations are grouped together as competing firms in the same industry.

Industry-level data on value added, capital stock, and intellectual property products, as well as their chain-type quantity and price indices, are from BEA, whose industry classification more or less corresponds to the NAICS 3-digit level.[11] These are used to construct industry-level labor productivity, capital productivity, and IPP intensity variables, as explained in the data appendix. The data on industry-level employment hours, used for constructing labor productivity, are from the BLS.[12] Quantity indices for college educated and non-college educated workers, which are used to construct the variable for skilled-to-unskilled labor ratio come from BEA KLEMS database.

NAICS 31-33 is used for the manufacturing sector, NAICS 333 is for the machinery manufacturing subsector, and NAICS 3336 represents the Engine, Turbine, and Power Transmission Equipment Manufacturing industry. Adopting a more colloquial style, I use the term industry to refer to both industry and sub-sector classifications while using the accurate NAICS codes.

[11] Another reason for choosing the NAICS 3-digit industry level as the unit of analysis is the fact that BEA data are not available at a more granular level.

[12] BLS issues a labor productivity index for most industries, however the index data are missing for certain industries at NAICS 3-digit level, hence I calculate labor productivity myself.

Figure 5 shows the distribution of change in C4 for 46 industries from 1997-2012. The distribution is heavily skewed to the right, indicating an increase in C4 for most industries. The results are similar for other measures of concentration.

<Insert Figure 5>

Having established that concentration did indeed increase across most U.S. industries since 1997, I investigate the empirical impact of the change in industry concentration on the changes in the four indicators of technological progress: labor productivity (computed as the ratio of real value added to employment hours), capital productivity (computed as the ratio of real value added to real capital stock), IPP intensity (computed as the ratio of real IPP to real capital stock) and skilled labor ratio (the ratio of quantity indices for skilled-to-unskilled labor).

The data set constructed is a panel of 46 industries for four years (1997, 2002, 2007 and 2012). Table 1 presents the descriptive statistics of the changes in these variables from 1997-2012. Since we are interested in how increasing concentration is related to changes in the technology indicators, it is more meaningful to describe the data in terms of changes than levels.

<Insert Table 1>

As expected, change in all measures of concentration has positive means and medians, indicating an increase in concentration in most of these industries. We also see positive mean and median values for the change in labor productivity, which implies an increase in average while displaying a distribution skewed to the right. In addition, the period shows a decline in capital productivity, and a slight increase in IPP intensity and skilled labor ratio for the sample group of industries. Trends over the period in this sample appear comparable to trends in macro level indicators.

4.b. Industry-level Estimation Framework and Results

The period in consideration (1997-2012) has been one of macroeconomic volatility, signs of which are visible in the macro indicators of technological progress presented in Section 2. Therefore, it is important to keep the time dimension in and examine if the relationship

changes over time through 1997, 2002, 2007 and 2012. For this, I estimate the following

reduced form empirical specification:

$$\Delta Y_{jt} = \alpha_t + \beta \, \Delta C_{jt} + \; \varepsilon_{jt} \qquad\qquad (1)$$

where dependent variable Y_{jt} denotes various measures of technology in industry j at time t

and C_{jt} stands for measures of revenue concentration in industry j at time t. Since variables are

expressed in changes, the time (t) is three periods of changes from (1997-2002), (2002-2007)

and (2007-2012); α_t is a full set of time dummies for these three periods and ε_{jt} is an error

term. Note that there is no common intercept in this model, instead intercept is allowed to

change for each period via time dummies. The estimation method is OLS; the standard errors

are clustered by industry, making them robust to correlation between error terms for the same

industry and heteroskedasticity over time.[13] In equation (1), coefficient β represents the impact

of the change in concentration on the change in the technology indicator. Technology

indicators are L-productivity, K-productivity, IPP intensity, and skilled labor ratio; measures for

concentration are C4, C8, C20 and C50. Table 2 reports the results from the regressions based

on equation (1).[14]

<center><Insert Table 2></center>

Each column presents results from the regression of a technology indicator on

concentration: column (a) with C4 and column (b) with C20. The values in parenthesis are

clustered standard errors. The last two rows show the results of joint significance tests for time

dummies and for the whole regression (F-test). All observations in levels, except the skilled

labor ratio, are weighted by the industry shares of relevant variables.[15]

Regressions with L-productivity, K-productivity and IPP intensity do not produce a

statistically significant estimate of β, so we can infer that for most indicators of technological

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[13] Equation (1) and its estimation method is structurally the same as in Barkai (2017) and Autor et al (2017), while using different variables of interest. Expressing the variables in change over time is equivalent to a regression in first differences, where industry fixed effects are eliminated.

[14] The results are only reported with C4 and C20 and do not qualitatively change with the use of C8 and C50.

[15] The weight used in these calculations is the denominator of the relevant variable. Specifically, concentration measures (C4, C8, C20 and C50) are weighted by the industry share of revenue; K-productivity and IPP intensity are weighted by industry share of real capital stock; L-productivity is weighted by industry share of employment.

change, increasing concentration does not have a significant impact observable across industries for the whole period. One regression, of the skilled labor ratio, stands out with a strongly significant and negative estimate for the coefficient of the change in concentration regardless of whether C4 or C20 is used. This regression (including time dummies, which are significantly positive) can explain almost half of the variation in skilled labor ratio across 46 U.S. industries. This result strongly contradicts the expectation that industries with increasing concentration are those that are making more intense use of skilled labor while adopting new technologies complementary to skilled labor. If we take this complementarity assumption as given—as in the canonical model of Acemoglu and Autor (2011)—then we can infer there is no evidence of the skill-biased technological change in industries with increasing concentration over the period of 1997-2012.

The significance of time dummies in all regressions coupled with insignificant estimates of β impels us to further examine these period effects on technology indicators. It is possible that the concentration ratio has a different effect on technology in different periods, and, in turn, these different effects are captured by time dummies. In order to separately analyze the changing effect of concentration over different periods from its effect for the whole period, I introduce interaction variables into Equation (1) as follows:

$$\Delta Y_{jt} = \alpha_t + \beta \Delta C_{jt} + \gamma \, \Delta C_{jt} \alpha_t \, + \, \varepsilon_{jt} \qquad\qquad (2)$$

The coefficient of the interaction variable (γ) represents the differentiated effect of change in concentration on technological progress over three different periods: 1997-2002, 2002-2007 and 2007-2012. To prevent dummy trap, only two interaction terms for Period 2 (2002-2007) and Period 3 (2007-2012) are included. Since there is no common constant term in this equation, but only intercepts for each period representing time effects, the overall effect of change in concentration can be determined as the sum of the estimated coefficients ($\beta + \gamma$) for these two periods, and as (β) only for the first period (1997-2002). Table 3 presents the results from the regressions based on equation (2). As before, regression with C4 is in column (a), with C20 in column (b). Values in parenthesis are clustered standard errors.

<Insert Table 3>

The overall results in Table 3 show the importance of periodization in analyzing the effect of changing concentration on technological change. Except for IPP intensity, the impact of change in concentration varies significantly across the three periods under examination. The differences between the results in Tables 2 and 3 are quite striking, especially for labor and capital productivity: while regressions in Table 2 show no significant impact of concentration, regressions in Table 3, with periodization, indicate significant, yet changing impact. The impact on IPP intensity, on the other hand, does not change at all and stays insignificant, even after allowing for changing period effects. There seems to be no evidence that industries with higher concentration on average are those with increasing IPP intensity, measured as the share of IPP in their capital stock. Finally, the impact on skilled labor ratio stays significantly negative across all three time periods, in agreement with the results in Table 2.

To summarize and compare the magnitudes of these significant variations across time, Table 4 reports the estimated coefficients of (β) for 1997-2002, and ($\beta + \gamma$) for 2002-2007 and 2007-2012 for L-productivity, K-productivity and skilled labor ratio.

<center><Insert Table 4></center>

The figures in Table 4 tells us that changes in both labor and capital productivity are positively impacted by the increase in concentration during 1997-2002. From 2002-2007, this impact turns small—yet negative—for labor productivity, and zero for capital productivity. From 2007-2012, increase in concentration has a relatively large, negative impact on both labor and capital productivity. For skilled labor ratio, the impact is negative in all three periods, but grows significantly in the last period.

Overall, these results pose a serious challenge to the presumption that the increasing concentration of the last two decades has been driven by highly productive "superstar" firms, their adoption of new technologies, and increased use of skilled labor (Autor et al 2017; Bessen 2017). When we consider 1997-2012 as a whole, we see no significant impact of concentration on technological progress. Yet, when we consider how the impact varies over different time periods, we do see a pattern which fits the macro trends in productivity reviewed in Section 2. The relatively high aggregate labor productivity growth of the late 1990s and early 2000s corresponds to the first period in our analysis, during which increasing industry concentration

<center>18</center>

had a positive impact on the change in labor productivity. The slowdown in aggregate L-productivity and relative stagnation in capital productivity, which began around the mid 2000s, corresponds to the last two periods during which industries with higher concentration have experienced slower labor productivity change or stagnating capital productivity. Overall, the evidence tells us that changing concentration plays at least a partial role in explaining the aggregate trends in productivity and technological progress.

4. c. A Closer Look at Industries

The debate surrounding productivity slowdown and recent literature on the consequences of market power have both paid particular attention to the changes in a couple of sectors of the economy. Crouzet and Eberly (2018) suggest that the rise in concentration in the retail industry was primarily driven by productivity, which was highly correlated with intangible investment. In this context, retail is claimed to be a prominent example of an industry in which efficiency gains associated with ICT systems could account for both the on-going weakness of physical capital investment, and the rise in concentration. Likewise, information is said to be another sector where new technologies are associated with the creation of market power and increasing concentration (Autor et. al 2017).

In this section, I first group industries based on change in concentration and changes in IPP intensity and skilled labor ratio, to discover where retail, information, and other industries in our sample fit with respect to these indicators of technological progress. The first column in Table 5 lists the top 15 industries based on the change in concentration ratio, C4, over the entirety of 1997-2012. As focusing on unweighted concentration values would give us a misleading picture of the degree of change in concentration in industries with a changing share of output, the grouping here is based on weighted values.[16] Using weighted observations makes our analysis more relevant to understanding the aggregate level changes.

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[16] For example, the change in concentration in the paper manufacturing industry from 1997-2012 seems substantial at a glance (an increase in C4 by 11 percentage points), but revenue share of paper manufacturing declines significantly over the same period (from 1.1 to 0.6 percent of total revenue of all industries). When we use this information to adjust the concentration ratios, the change in concentration in paper manufacturing proves to be a decline, rather than the substantial increase seemingly represented.

<Insert Table 5 here>

Table 5 also lists the top 15 industries with changes in IPP intensity and skilled labor ratio from our sample of 46. This information is useful not only for matching industries across these categories, but also to assess which industries are becoming more technologically intensive. The second and third columns of the table display only four industries, which have experienced increases in both skilled labor and IPP capital intensity over the period (highlighted in green). Not surprisingly, two of these (Computers & Electronics, and Electrical Equipment) are manufacturing industries typically classified as technology-intensive production areas.[17] The other two (Publishing, and Motion Picture & Sound Recording) are industries in the Information Sector. For these two manufacturing industries, the IPP category tends to include software and R&D-related inputs, whereas in Information industries the category is more for copyrights for literary, artistic, and entertainment originals, as well as software.

To see how these relatively high-tech industries fare in terms of change in concentration, we turn to the first column of Table 5 and find the Publishing industry among those that experienced a substantial increase in concentration. The increase in concentration within Publishing mostly comes from its software publishing segment—rather than print-publishing of books, newspapers, and magazines—which possibly confirms the view that an increase in concentration is likely driven by advanced technology, as indicated by Publishing's higher IPP intensity and skilled labor ratio.

Table 5 also shows how other industries with higher concentration fare in IPP or skilled labor use. Among those with both higher concentration and higher IPP intensity (highlighted in green), Chemical Manufacturing is particularly notable. The largest components of Chemical Manufacturing are "Pharmaceuticals," and "Soaps, Detergents and Cosmetics" (which include major companies like Novartis, Biogen, Colgate-Palmolive, and Estee Lauder). In 2012, the revenue share of the top 50 companies in these two components of Chemical Manufacturing ranges around 80%. Pharmaceuticals specifically are classified as a "high technology industry"

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[17] According to OECD's ISIC Rev. 3. Technology Intensity classification of manufacturing industries, Computers and Electronics" is classified as high-tech, while "Electrical Equipment" is a medium-high tech industry.

based on its R&D intensity, which is easily observable in the high increase in IPP intensity.[18] Among those with both higher concentration and higher skilled labor ratio (highlighted in orange), the Information sector stands out again with "Broadcasting & Telecommunications," "Data Processing, Hosting and Other Information Services." What's interesting about these Information industries is that they are not in the top 15 industries achieving the higher increase in IPP intensity expected alongside the prevalence of ICT- and IPP-related assets seen in these industries.

What we learn from Table 5 is that the Information sector and certain industries of Manufacturing indeed display signs of more intangible and/or skilled-labor intensive technological change, as well as higher concentration. This pattern exists across most segments of the Information sector, and only in the Chemical Manufacturing segment of the Manufacturing sector. Among the other industries with a substantial increase in concentration, retail does not show any evidence of an increase in IPP intensity or skilled labor ratio. Crouzet and Eberly (2018), among others, emphasized that market power in the retail industry is being driven by a more intensive use of intangible assets, but that claim is not supported by data at the sectoral level.[19]

The next step is to see how these differences across industries in the changes in concentration and technology translate to productivity differences. For productivity changes, I focus specifically on the changes in the last two periods of the study to identify the industries that are likely to contribute to the aggregate productivity slowdown "puzzle" of the period since the mid-2000s. Table 6 shows three groups of industries in three columns: column one displays the top 15 industries based on the change in concentration ratio, C4, over the entirety of 1997-2012 (same as in Table 5). The second column shows the bottom 15 industries based on change in L-productivity between 2002-2012; The third shows change in K-Productivity

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[18] According to OECD's ISIC Rev. 3. Technology Intensity classification of manufacturing industries, together with Pharmaceuticals; Aircraft and Spacecraft; Office, Accounting and Computing Machinery; Radio, TV and Communications Equipment; Medical, Precision and Optical Instruments, are all high-tech industries.
[19] As noted before with other studies in recent market power literature, Crouzet and Eberly (2018)'s measure of intangibles intensity for retail is a firm-level variable.

during the same period. All groupings are based on weighted observations in an attempt to reflect the importance of industries in the overall economy.

<Insert Table 6 here>

A quick look at the second and third columns of Table 6 show most industries that experienced a productivity slowdown in both labor and capital productivity are in the Manufacturing sector (marked with *). Out of these, only two have gone through an above-average increase in concentration: "Petroleum and Coal Products," and "Chemical Manufacturing." The former contains refineries of crude oil and major global companies like Chevron, and Exxon Mobil; it is typically classified as a low-to-medium technology industry, and considering the lack of evidence of an above-average increase in skilled labor ratio or IPP intensity, is also an example of highly-concentrated industry within which companies with a lot of market power are failing to achieve an increase in capital and labor productivity. Chemical Manufacturing, on the other hand, has achieved an increasing IPP intensity, as discussed above, yet fails to attain any corresponding labor and capital productivity increases. In fact, according BLS data, the labor productivity index for Pharmaceutical and Medicine Manufacturing (the largest components of Chemical Manufacturing) decreased from 98% in 2004 to 74% in 2018 (2007 being the base year).[20] Despite its high-tech category, Pharmaceuticals presents a case where intangible assets like R&D does not translate into higher productivity, and instead contributes to an increase in concentration and market power—most likely by erecting barriers to entry via patents and the high cost of R&D.

Table 6 also shows us that Retail is another sector that underwent a large increase in concentration, yet achieved a below-average performance in labor and capital productivity in the last two periods. This, again, does not quite fit with the optimistic suggestion that a rise in concentration in the retail industry is primarily driven by productivity and retailers' efficient use of their intangible capital (Crouzet and Eberly 2018). As shown above, at the industry level, Retail is not among those with a higher increase in IPP intensity or skilled labor ratio. The

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[20] BLS provides data on capital and labor productivity for all manufacturing industries at a high level of detail, however the data are not available for multiple non-manufacturing industries, hence could not be used in as the main labor productivity measure in this study. Capital productivity index for this industry, provided by BLS, also shows a very similar decline, although it is only available since 2007.

driving force behind the concentration increase in this sector is more likely to be the result of mergers and acquisitions, not technological progress and productivity increases.

Lastly, it should be noted that none of the Information sector industries (marked with ♦) in the first column of Table 6 is listed in the groups of low labor or capital productivity change. It seems that in the case of the Information sector, an above average increase in concentration is indeed associated with an above-average increase in productivity; "Broadcasting and Telecommunications" and "Data Processing, Hosting and Other Information" are specific industries with high labor and capital productivity growth over the last two periods. This suggests that the Information sector is possibly one in which increasing concentration is associated with a higher pace of technological progress and productivity.

5. Conclusion

Recent studies on the macroeconomic impacts of market concentration remain ambiguous about how the increase in concentration might be related to technological progress. One strand of this literature suggests that concentration is the inevitable result of competition, whereby large, productive firms gain market share due to intensified use of intangible and human capital (Autor et al 2017). Motivated by the lack of macro-level evidence for such productivity gains, this paper investigates the relation between new technologies and increasing concentration by focusing on industry-level measures of technological progress: labor and capital productivity, intangible asset intensity, and skilled labor ratio.

This paper presents econometric evidence that increasing market concentration has had a negative impact on technological progress across 46 industries the U.S. economy for the period of 2002-2012. Specifically, I find the impact of concentration on labor and capital productivity to be positive from the late 1990s and early 2000s, yet it gradually turns negative through mid-to-late 2000s. This variation follows a pattern close to aggregate productivity trends for the productivity "puzzle" within the U.S. economy. My findings also show that there is no evidence, across all industries, that those with an increasing concentration tend to also have higher intangible capital or a skilled labor ratio, as suggested by Autor et al (2017) and Crouzet and Eberly (2019). Further consideration of specific industries reveal only industries in

the Information sector fit into this model, where relatively higher intangible capital and skilled labor use lead to higher productivity increases, which, in turn, lead to the growth of top firms and higher concentration. However, Information sector industries have a relatively small share of output and employment in the economy. Instead, retail trade, petroleum and coal products manufacturing, and chemical manufacturing are the primary industries driving the slowdown in labor and capital productivity, despite experiencing increasing concentration.

The strongly negative relationship between increasing concentration and a skilled labor ratio throughout the entirety of the period examined is particularly reminiscent of the debates on the labor process and the question of skill change. Braverman's (1974) position that deskilling is the fundamental tendency of the capitalist accumulation process has been challenged by many, yet it seems necessary to reconsider the relevance of his arguments, mainly because one of the continuing premises of the capitalist accumulation process is the control of labor. The recent research on the labor process indeed finds evidence of deskilling especially in service industries: Ikeler (2016), for instance, undertakes a qualitative examination of the deskilling argument in the New York City area retail industry's expansion into discount stores, and finds a strong decline in the complexity and autonomy of salespersons' labor. Ritzer's (1998) McDonaldization thesis focuses on the fast-food industry, where automation and routinization lead to deskilling of the labor force. This paper's evidence shows that firms in industries with increasing concentration are gaining market power by reorganizing the labor process and deskilling their labor force.

Considering the firm-level evidence provided by Crouzet and Eberly (2019) about the positive correlation between concentration and intangibles, the lack of any significant relationship in this study, between changes in IPP ratio and concentration calls for explanations. The first is that intangibles at firm level are a much broader category than the BEA's definition of intellectual property products. As mentioned earlier, BEA measures are expenditure based, and only include purchases of software and development of intellectual property, while firm level measures are balance sheet valuations of computerized information, innovative property, and economic competencies, which may or may not be capitalized properly. Second difference comes from the fact that IPP ratio in this study is an industry level indicator. While top firms in

more concentrated industries might be more intangible-intensive, within industry discrepancies across firms could lead to no change in IPP ratio at the industry level. Lastly, Crouzet and Eberly (2019)'s results rely on simple correlation coefficients, between the levels of intangible intensity and concentration rather than the regression framework of this paper, which controls for industry and time effects. The presumed correlation disappears once these effects are controlled for.

A crucial question is why the relationship between concentration and productivity turned negative throughout the 2000s. A possible explanation is that firms did gain market power in the late 1990s due to productive investments in technology; once they grew large and well-established, they relied on their market power, monopoly rents, and practices rather than productive investments to keep their superior positions. In the growth-distribution framework of a capitalist economy, this also tells us, by putting downward pressure on capital and labor productivity, that increasing market concentration has, in turn, contributed to the downward pressure on profit rate. If this pressure on the profit rate coming from the technological structure of the economy continues, it is likely to intensify the effort of capitalists to further increase profit share as their main source of profitability.

As a cautious remark, the findings of this paper are not implying that the increase in concentration is the only driver of a slowdown in aggregate productivity or technological progress. Indeed, these trends might have their own leading factors, which may be different than what I am suggesting. Rather, these results stress the importance of future research to understand the underlying reasons for slowdown in technological progress and productivity.

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Figure 1: Labor and Capital Productivity

Labor Productivity = Net value added in 2012 $/hour

Capital Productivity = Value added in 2012 $/capital stock
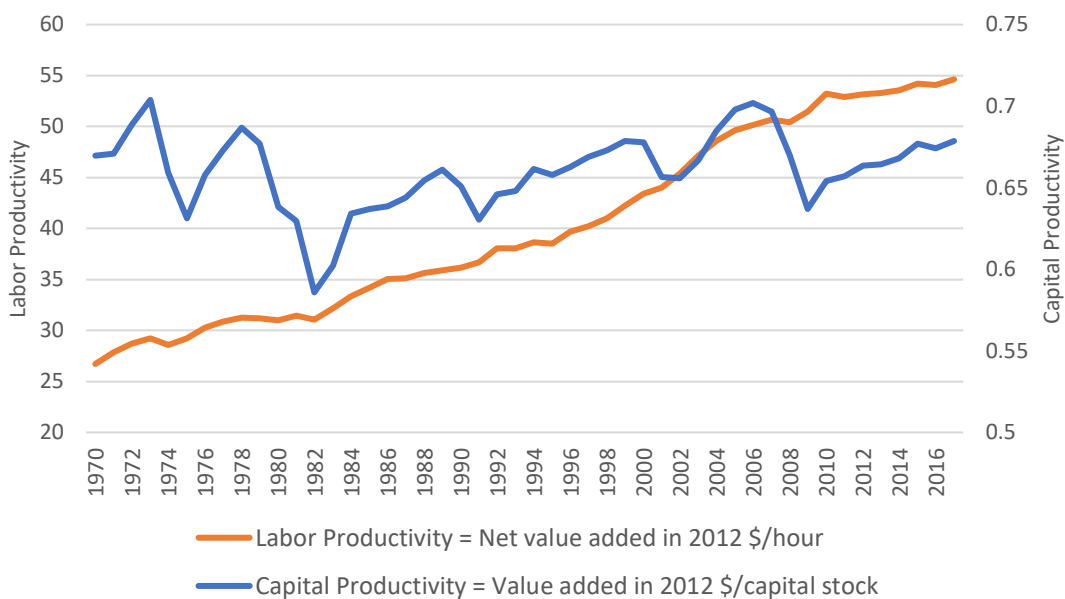
Sources and definitions:

Labor Productivity = Real net value added for business (from BEA NIPA Table 1.9.6.) / Hours Worked by Full-Time and Part-Time Employees for Private Industries (NIPA Table 6.9).

Capital Productivity = Real net value added for business (from BEA NIPA Table 1.9.6.)/real capital stock.

Real capital stock = chained $ value of capital stock = chain-type quantity index for capital stock (from BEA Fixed Assets Table 6.2)/Current cost net stock of private fixed assets for corporations in year 2012 (from BEA Fixed Asset Table 6.1)/100, where the base year is 2012.
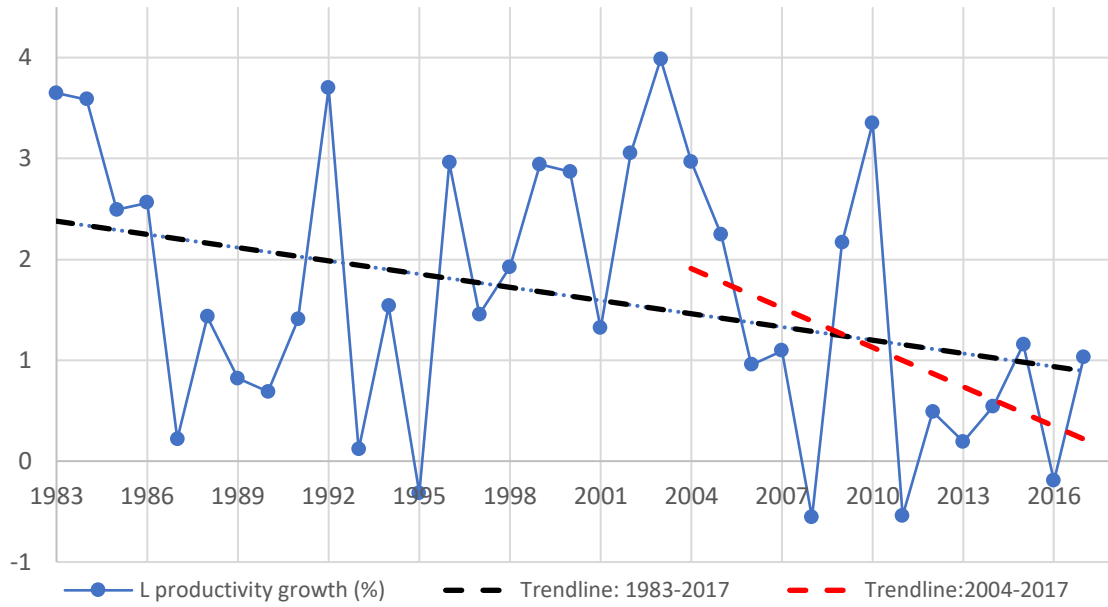
Figure 2: Panel A - L productivity growth

Figure 2: Panel B - Capital Productivity Growth
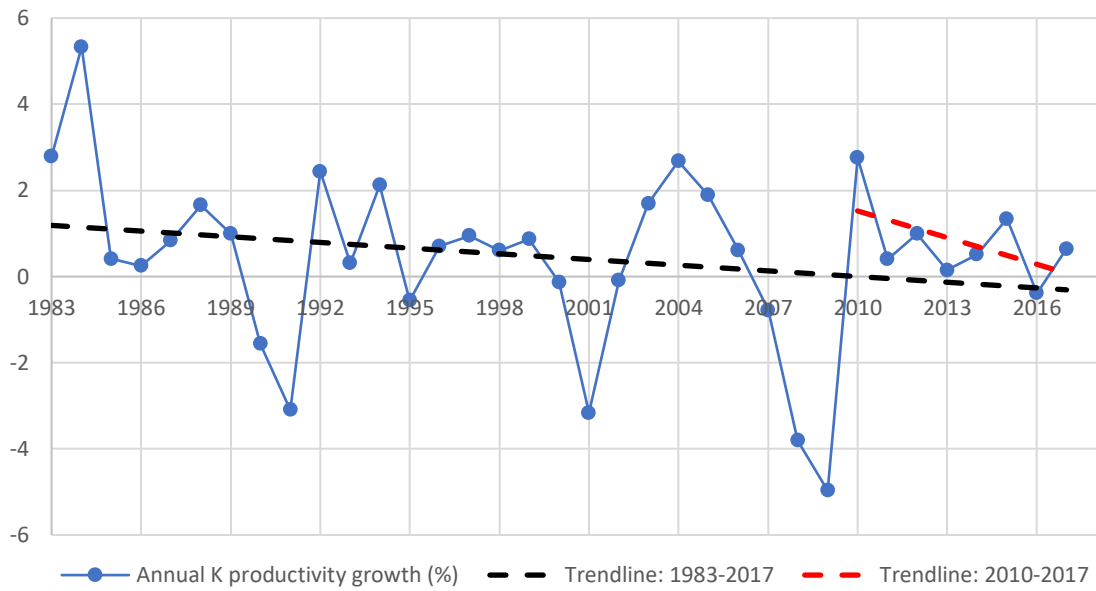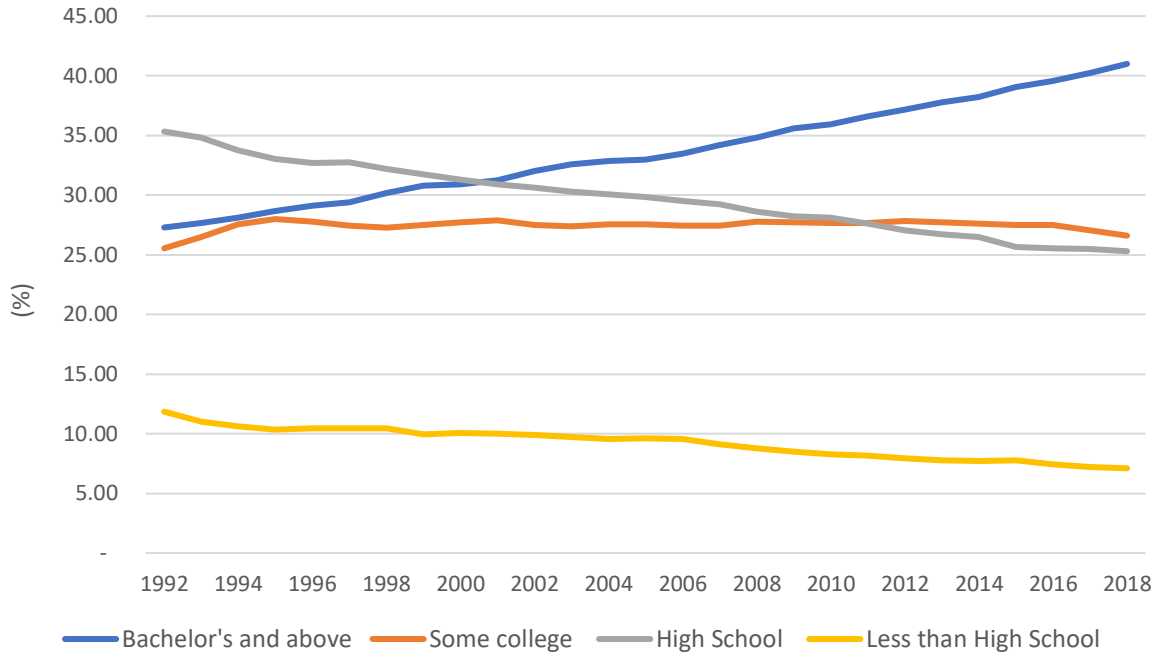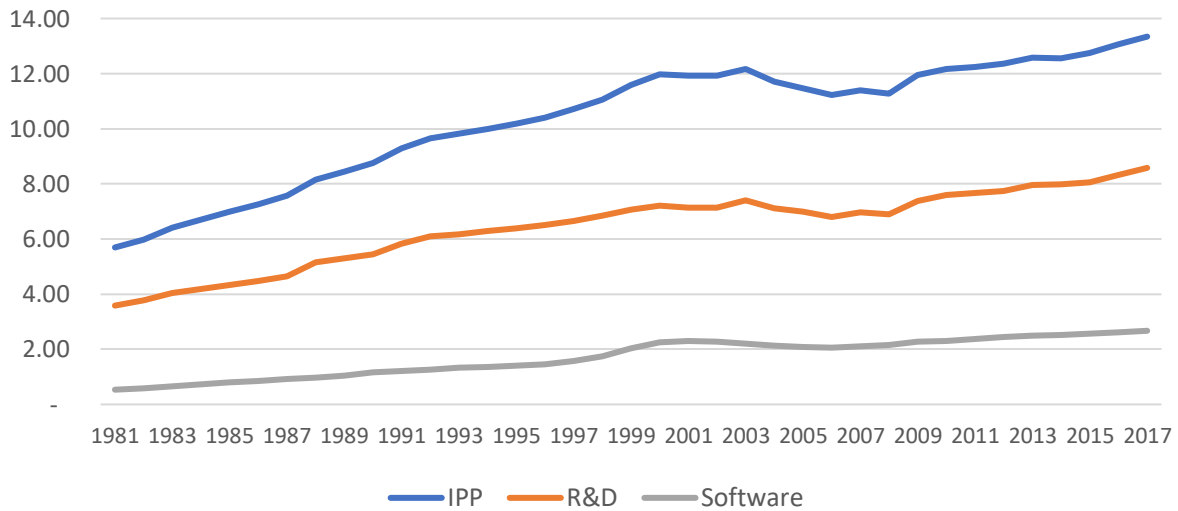
Sources and Definitions: Same as Figure 1

Figure 3: Share of Annual Employment by Educational Attainment (25⁺ years)

Source: U.S. Bureau of Labor Statistics

Figure 4: Percentage of non-residential capital stock by IPP and its components

Source: BEA Fixed Assets Table 2.1

Figure 5: Distribution of Change in Industry Concentration

46 industries - Change from 1997-2012
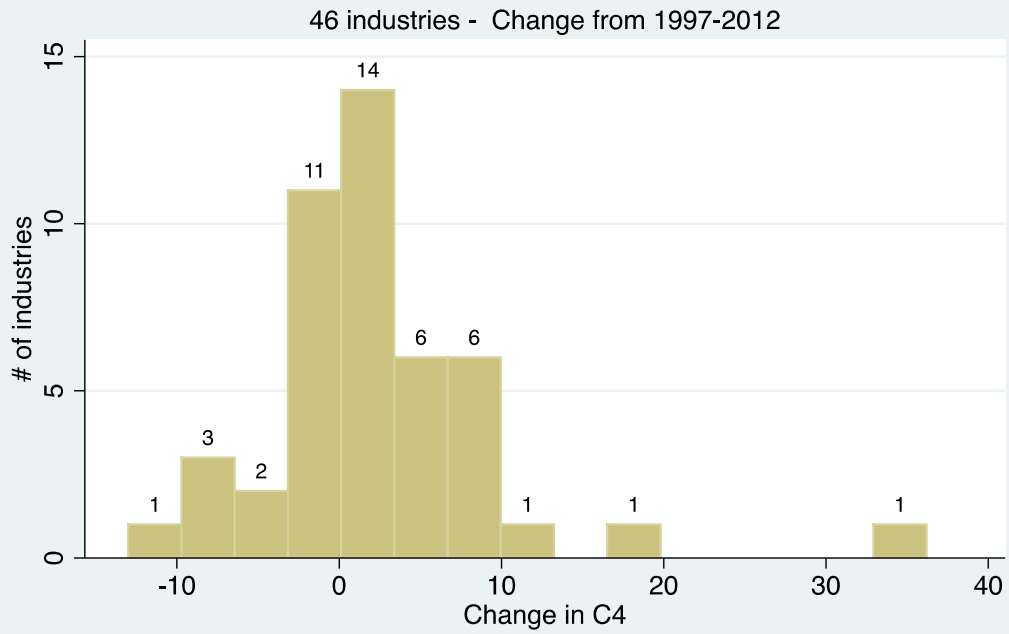
TABLE 1: Descriptive Statistics for Changes in Variables					
46 industries (1997-2012) – unweighted observations					
	Mean	Median	St.dev.	Minimum	Maximum
Δ in C4	2.15	0.75	7.49	-13.00	36.20
Δ in C8	2.99	1.65	8.20	-9.60	42.20
Δ in C20	3.63	3.17	7.23	-7.90	38.30
Δ in C50	3.66	2.65	5.70	-7.10	27.10
Δ in L-productivity	33.71	19.43	41.90	-13.60	176.77
Δ in K-productivity	-0.29	-0.07	0.72	-3.92	0.38
Δ in IPP intensity	0.02	0.01	0.05	-0.14	0.20
Δ in skilled-labor ratio	0.28	0.28	0.16	-0.14	0.61

	Dependent Variable (ΔY_{jt})							
	Δ L-Productivity		Δ K-Productivity		Δ IPP Intensity		Δ Skilled Labor ratio	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Δ C4	0.131		-0.0001		-0.0002		-0.199***	
	(0.391)		(0.001)		(0.0003)		(0.064)	
Δ C20		0.1835		-0.0003		-0.00004		-0.100***
		(0.159)		(0.0007)		(0.0002)		(0.037)
R^2	0.190	0.202	0.055	0.058	0.115	0.113	0.498	0.498
Joint significance of time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Significance of F-test	Yes	Yes	No	No	Yes	Yes	Yes	Yes

TABLE 2: The Impact of Change in Concentration on Change in Technology Indicators
1997-2012 (46 industries)

*p<0.1;   **p<0.05;   ***p<0.01

	Δ L-Productivity		Δ K-Productivity		Δ IPP Intensity		Δ Skilled Labor ratio	
TABLE 3: The Impact of Change in Concentration on Change in Technology Indicators with Interactions								
1997-2012 (46 industries)								
Dependent Variable (ΔY_{jt})								
	Δ L-Productivity		Δ K-Productivity		Δ IPP Intensity		Δ Skilled Labor ratio	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
ΔC4	1.793***		0.005**		-0.001		-0.103**	
	(0.406)		(0.002)		(0.001)		(0.050)	
Period 2 x ΔC4	-2.067***		-0.005*		0.001		-0.055	
	(0.691)		(0.003)		(0.001)		(0.082)	
Period 3 x ΔC4	-2.979***		-0.011***		0.000		-0.531***	
	(0.520)		(0.004)		(0.001)		(0.1521)	
ΔC20		0.837***		0.001		-0.000		-0.021
		(0.168)		(0.001)		(0.001)		(0.026)
Period 2 x ΔC20		-0.967***		-0.001		0.000		-0.105**
		(0.217)		(0.001)		(0.001)		(0.050)
Period 3 x ΔC20		-1.242***		-0.004**		-0.000		-0.194*
		(0.313)		(0.002)		(0.000)		(0.105)
R²	0.302	0.316	0.173	0.143	0.118	0.114	0.523	0.511
Joint significance of time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Significance of F-test	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 4: Overall Impact of ΔC4 in three periods			
	on Δ L-productivity	on ΔK-productivity	on Δ skilled labor ratio
($\hat{\beta}$) for 1997-2002	+1.793	+0.005	-0.103
($\hat{\beta} + \hat{\gamma}$) for 2002-2007	-0.274	0	-0.158
($\hat{\beta} + \hat{\gamma}$) for 2007-2012	-1.186	-0.006	-0.634

Source: Computed from regression results in Table 3.

TABLE 5: TOP 15 INDUSTRIES WITH HIGHEST CHANGES IN C4, IPP AND SKILLED LABOR INTENSITY over 1997-2012		
Δ in C4	Δ in IPP intensity	Δ in skilled labor ratio
Petroleum and Coal Manufacturing	Chemical Manufacturing	Investment Banking
Retail Trade	Administrative and Support Services	Computers and Electronics
Air Transportation	Publishing	Publishing
Administrative and Support Services	Computers and Electronics	Electrical Equipment Manufacturing
Broadcasting and Telecommunications	Insurance	Social Assistance
Chemical Manufacturing	Electrical Equipment Manufacturing	Wood Products
Data Processing, Hosting and Other Inform.	Investment Banking	Nonmetallic Mineral Products
Ambulatory Healthcare	Apparel and Leather Manufacturing	Furniture and Related
Primary Metal Manufacturing	Wholesale Trade	Broadcasting and Telecommunications
Professional, Scientific, Technical services	Printing and related*	Motion Picture and Sound Recording
Rental, Leasing, Lessors of Intangible Assets	Motion Picture and Sound Recording	Data Processing, Hosting and Other Inform.
Real Estate	Furniture Manufacturing	Machinery Manufacturing
Warehousing and Storage	Textile Mills and Products	Miscellaneous Manufacturing
Miscellaneous Manufacturing	Education	Fabricated Metal Products
Publishing	Plastics and Rubber Manufacturing	Rental, Leasing, Lessors of Intangible Assets

Green Highlight: Industries with increases in skilled labor ratio and IPP intensity (but no substantial increase in C4, except Publishing)
Blue Highlight: Industries with increases in C4 and IPP intensity, but no substantial increase in skilled labor ratio.
Orange Highlight: Industries with increases in C4 and skilled labor ratio, but no substantial increase in IPP intensity.

TABLE 6: Groups of Industries with Highest Δ in C4 and Lowest Δ in L-Productivity and K-productivity		
Top 15 industries for Δ in C4 (1997-2012)	Bottom 15 Industries Δ in L-productivity (2002-2012)	Bottom 15 Industries Δ in K-productivity (2002-2012)
Petroleum and Coal Manufacturing*	Petroleum and Coal Manufacturing*	Retail Trade
Retail Trade	Rental, Leasing, Lessors of Intangible Assets	Petroleum and Coal Manufacturing*
Air Transportation	Furniture and Related Products*	Chemical Manufacturing*
Administrative and Support Services	Paper Manufacturing*	Rental, Leasing, Lessors of Intangible Assets
Broadcasting and Telecommunications♦	Textile mills and products*	Food, Beverage, Tobacco Products*
Chemical Manufacturing*	Chemical Manufacturing*	Accommodations
Data Processing, Hosting and Other Inform.♦	Apparel and Leather manufacturing*	Investment Banking
Ambulatory Healthcare	Nonmetallic Mineral Products*	Food Services
Primary Metal Manufacturing*	Plastics and Rubber Products*	Paper Manufacturing*
Professional, Scientific, Technical services	Food Services	Furniture and Related Products*
Rental, Leasing, Lessors of Intangible Assets	Printing and related activities*	Plastics and Rubber Products*
Real Estate	Retail Trade	Fabricated Metal Products*
Warehousing and Storage	Food, Beverage, Tobacco Products*	Nonmetallic Mineral Products*
Miscellaneous Manufacturing*	Electrical Equipment *	Textile mills and products*
Publishing♦	Wood Products*	Truck Transportation

Industries marked with (*) are in Manufacturing sector (NAICS 31-33), those marked with (♦) are in Information sector (NAICS 51)
Industries that appear in all three columns are highlighted in orange.

DATA APPENDIX

In the process of matching BEA, Census and BLS data, following adjustments were made:

- Census does not report data on Agriculture (NAICS 11), Mining (NAICS 21), Construction (NAICS 23) and Management of Companies and Enterprises (NAICS 55), rail transportation (NAICS 482); hence these were excluded from the analysis.

- Within Information sector (NAICS 51), concentration ratios are reported based on a different 3-digit classification for 1997, hence concentration data for three 3-digit industries within this sector begin with 2002 Census.

- Certain 3-digit industries are reported together in BEA tables. e.g. Food Manufacturing (NAICS 311) is combined with Beverage and Tobacco Product Manufacturing (NAICS 312). For these, I compute the weighted average of concentration ratios (weighted by the revenue share of that industry in total sales of all those industries) and take the sum of employment hours, output and capital stock measures. NAICS codes for these industries are the following: (311 + 312), (313+314), (315+316), (515+517=515), (518+519=518), (532+533), (711+712)

- 'Other transportation' industry was reported as the sum of three 3-digit industries (487+488+492) in BEA, hence was dropped.

- Transportation equipment industry (NAICS 336) figures from BEA are reported in two parts, with 6 different 4-digit industry categories. Instead of taking weighted averages I drop transportation equipment industry.

- BEA does not report complete 3-digit level of data on industries of wholesale and retail trade. For these, I used NAICS 2-digit level sectoral data.

- Industries NAICS-521 and NAICS-522 under finance were dropped, as BEA report these as a combined industry in value added tables.

- KLEMS database report NAICS 622 and 623 as combined. For skill measures, I use the same data for both industries. KLEMS database report NAICS 541 values in three different 4-digit categories that make up NAICS 541. For skill measures, I take average of these and use it for NAICS 541.

Industry-level variables computed:

Labor Productivity = Y_r/L

Capital Productivity = Y_r/K_r

IPP instensity = $\dfrac{IPP_r}{K_r}$

Skilled labor intensity = $\left(\dfrac{L_c}{L_{nc}}\right)$ = Quantity Index for Labor Input of College educated Workers /

Quantity Index for Labor Input of Non-college educated Workers

Y_r is the real value added by industry from BEA industry accounts,

L is measured as "annual number of hours" worked in each industry from BLS employment statistics.

Real capital stock (K_r) is calculated by using the chain-type quantity index as explained in notes to Figure 1.

(IPP) Intellectual Property Products is the series of "Current-Cost Net Stock of Intellectual Property Products by Industry" from BEA Fixed Assets Table 3.1. Since the price index for IPP series is also not available at industry level, real IPP is computed similar to real capital stock above, by using the series of "Chain-Type Quantity Index for Net Stock of Intellectual Property Products by Industry" from BEA Fixed Assets Table 3.2.

Both quantity index series in skilled labor intensity are from BEA/BLS Integrated Industry-level Production Accounts, known as KLEMS.