

## PRODUCTIVITY GAINS AND ITS LINKAGE WITH COMPENSATION AND CAPITAL – A

### SECTORAL ANALYSIS

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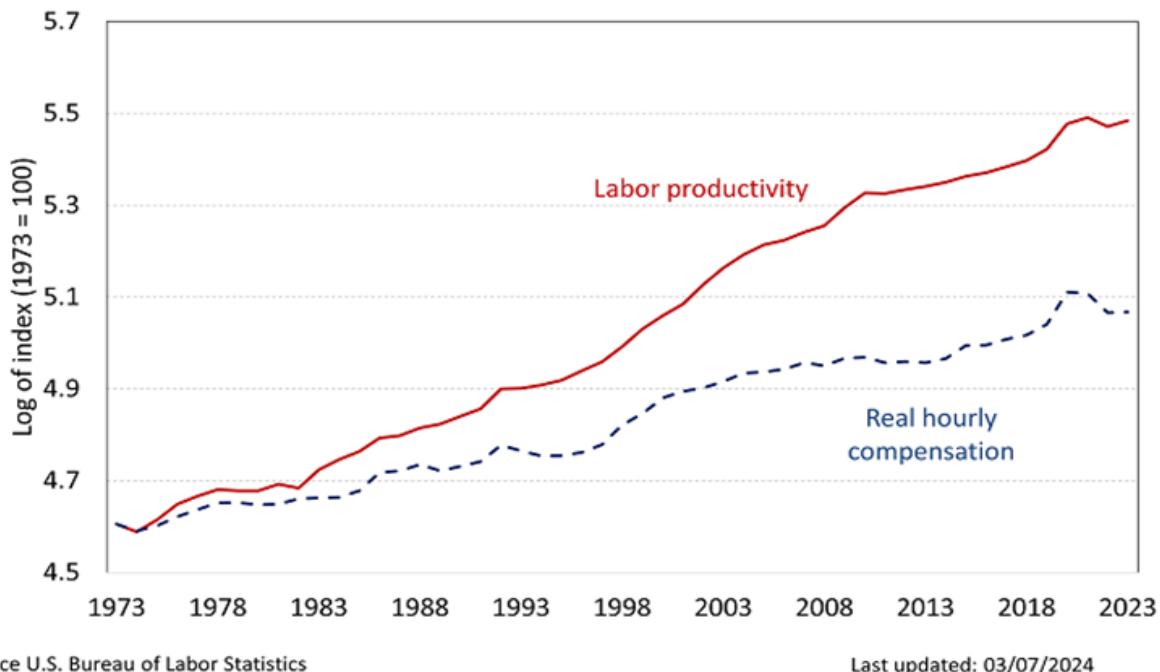
#### **Introduction**

Economic growth reflects how people in the economy are benefiting and increasing their standards of living. Labor productivity is a key economic indicator, closely linked to economic growth, competitiveness, and living standards within an economy (International Labor Organization, 2024). While economic growth and living standards are associated with labor productivity (hereafter also referred to as productivity), productivity growth has failed to translate into rising wages and benefits to the employees. In other words, productivity gains are not translating completely into income and benefits to the workers. This raises important question about channels to which productivity gains are being distributed – particularly, raising the question whether productivity gains are flowing into capital investment instead of compensation. Brill et al. (2017) also raise the same question to discuss that industries divide their revenues amongst capital, labor compensation, and intermediate purchases (Brill et al., 2017). In this paper, I establish the linkages between productivity and compensation and productivity and capital intensity to study the flow of productivity gains into compensation and capital.

The US Bureau of Labor Statistics (BLS) publishes the widening gap between labor productivity and real hourly compensation in the non-farm business sector over the years. Figure 1 from BLS provides evidence of the widening gap on average in the US for non-farm business sectors for the years 1973 to 2023 (US Bureau of Labor Statistics, 2024). Since the 1970s, it has been observed that a divergence between productivity and compensation exists, suggesting that compensation has failed to keep pace with productivity. This divergence, commonly referred to as productivity-compensation gap, signals that the employees are not benefitting from the increasing economic growth. The divergence also reflects a declining labor share of income, which is also measured as “ how much revenue is going to workers as opposed to the other components of production – intermediate purchases and capital” (Brill et al., 2017, pg. 5). With rapidly evolving technology, productivity gains could be channeled towards capital investment instead of benefiting the workers through wages and compensation. A recent article in *Business Insider* supports the argument reporting that productivity is increasing and inspiring firms to invest in basic equipment to increase the speed of work (Dutta, 2024).

Technological progress or increase in capital has been traced through declining labor's share of income or productivity-compensation gap. However, there are debates in the existing literature on attributing declining labor share of income to technological changes (Elsby et al. (2013), Glover and Short (2020)). Moreover, literature including Wolff (1991) and Basri et al. (2020) show the association between capital intensity and productivity gains demonstrating how capital investments are increasing outputs in future. In this paper I assess the technological changes by demonstrating the divergence of productivity gains towards capital by analyzing the

### Labor Productivity and Real Hourly Compensation, Nonfarm Business Sector, 1973-2023



*Figure 1: Demonstrates the widening gap between labor productivity and real hourly compensation on average in US for nonfarm business sectors over the years 1973 to 2023*

linkage between productivity and capital intensity. I adopt the linkage-delinkage spectrum model proposed by Stansbury and Summers (2017) to establish the linkages between (i) productivity and compensation and (ii) productivity and capital in (i) manufacturing sector and (ii) transportation and warehousing sector. These linkages display the flow of productivity gains into compensation and capital respectively in each sector. The productivity- capital linkage reflects

technological progress through capital intensity growth (or capital deepening) and productivity-compensation linkage reflects declining labor share of income.

The linkage-delinkage spectrum model introduced by Stansbury and Summers (2017) is a framework to assess how strongly productivity growth translates into compensation growth by looking at the coefficient associated with productivity. A coefficient of 1 implies a complete linkage – productivity gains are completely transmitted to compensation – while a coefficient of 0 implies a complete delinkage. A value between 0 and 1 shows a transmission of productivity into compensation to certain extent with other factors blocking the transmission. Their empirical analysis for the years 1990 to 2016 estimates the coefficient between 0.4 and 0.8, suggesting that productivity gains are transmitted to compensation to certain extent with other factors like capital investment blocking this transmission. I extend this idea of linkage between productivity and compensation to establish the linkage between productivity and capital. I analyze these two linkages to gain new insights into channels through which productivity gains are distributed amongst compensation and capital.

## Literature Review

Since 1970s, the divergence between productivity and compensation has been observed with more focus on nonfarm business sectors. Brill et al. (2017) discuss productivity-compensation gap at industry level rather than nonfarm business sectors. They study the trends in the widening gap between productivity and compensation in 183 industries from 1987 to 2015. Part of their analysis demonstrated that largest gap between productivity and compensation is

found in industries with largest productivity gains like the IT industry. Brill et al. (2017) attribute the divergence of productivity and compensation to two components – difference between two deflators and labor's share of income. The difference between two deflators is the difference between compensation adjusted by Consumer Price Index (CPI) and compensation adjusted by the output deflator specific to each industry. They point to the fact that compensation adjusted by the output deflator better aligns with productivity compared to compensation adjusted by CPI. Furthermore, they found that the gap between productivity compensation decreased for 87% of industries, which had shown productivity was rising faster than compensation (Brill et al., 2017). The second component, labor's share of income measures the part of revenue going to workers compared to other factors of production including capital and intermediate goods. They conclude that after accounting for the difference in CPI and output deflator, the productivity-compensation gap came from labor's share of income. In other words, when the same deflator was used, they found that the gap between productivity and compensation was explained by labor's share of income.

Extending on their work, Fofack and Temkeng (2021) assess and compare the link between productivity and pay in four industries in the European Union including air transport, electronics, finance, and telecommunication using the Autoregressive Distributive Lag (ARDL) model. They analyzed these four industries in 25 member states of the European Union from 2000 to 2014. Fofack and Temkeng (2021) conduct an in-depth analysis of the heterogeneous relationship between productivity and compensation using pooled mean group estimation, mean group estimation, and dynamic fixed effect estimators (Fofack & Temkeng, 2021). They also conduct their estimation by using value-added per hour worked as the proxy for productivity.

Their analysis of the heterogeneity of the gap between productivity and compensation confirms the existence of the gap as well as confirming that the link between productivity and compensation is not broken. Fofack and Temkeng (2021) claim that their results support the results from Stansbury and Summers (2017) suggesting that there are other factors that “prevent productivity gains to be reflected on paycheck” (Fofack & Temkeng, 2021).

Fofack and Temkeng (2021) compare their results with Stansbury and Summers (2017) to confirm the existence of productivity-compensation gap. Stansbury and Summers (2017) investigate the extent to which productivity growth translates into compensation growth for the typical American. They find substantial evidence of linkage between productivity and compensation over 1973 – 2016. Stansbury and Summers (2017) approach the question through the linkage-delinkage spectrum, where they view that at the simplest level, the estimate associated with productivity shows where the relationship falls on the spectrum. If the estimate equals 1, the relationship between productivity and compensation is viewed as the “strongest linkage”, while if the estimate equals 0 it is seen as the “strongest delinkage” (Stansbury & Summers, 2017). The value of the estimate between 0 and 1 is viewed as a point on the linkage-delinkage spectrum. They look at three concepts of compensation – typical compensation, average production/nonsupervisory compensation, and average compensation to test their hypothesis (Stansbury & Summers, 2017). Their baseline specification regresses the three-year moving average of change in the log of compensation on three-year moving average of change in productivity and current and lagged three-year moving average of the unemployment rate (Stansbury & Summers, 2017).

Expanding on the work from Stansbury and Summers (2017), Greenspon et al. (2021) study the productivity-pay relationship in the United States and Canada to understand the divergence and delinkage of productivity and compensation. They compare the degree of divergence with the degree of linkage and delinkage between compensation and productivity across the United States and Canada along different metrics and different time periods (Greenspon et al., 2021). They describe divergence as “the degree to which levels of productivity and pay have diverged” and delinkage as “the degree to which incremental increase in the rate of productivity growth translate into incremental increases in the rate of growth of pay, holding all else equal” (Greenspon et al., 2021). They find that in both countries, the pay of typical workers diverged substantially from average labor productivity, which they attribute to three trends – decline in labor’s share of income, rise in labor inequality, and decline in labor’s term of trade in both countries. They define decline in labor’s share of income as “divergence between labor productivity and average compensation, deflated by the same price deflator”, rise in labor income inequality as “divergence between average compensation and the compensation of typical workers”, and decline in labor’s term of trade as “divergence between consumer and producer price deflators” (Greenspon et al., 2021). They also suggest that in the US the decline in labor share is further attributed to technological changes, globalization and labor offshoring, reduction in worker bargaining power, higher firm concentration, increased markups, and housing market dynamics.

To study the productivity-pay relationship Greenspon et al. (2021) estimate the linkage-delinkage spectrum model by running a regression of the three-year moving average of the change in log compensation on the change in log productivity while controlling for

unemployment. Their findings show that “over recent decades a one percentage point increase in the rate of productivity growth in the US has been associated with a 0.6-0.8 percentage point faster average compensation growth, a 0.5-0.7 percentage points faster median compensation growth, and a 0.3-0.9 percentage points faster growth in the compensation of production and nonsupervisory workers” (Greenspon et al., 2021). Furthermore, they find evidence suggesting that in both countries higher productivity growth rate is associated with significant increases in compensation growth rate, with higher linkage in the United States (US) as opposed to Canada. Their further exploration suggests that international factors such as global commodity prices could play a role in explaining the gap between productivity and pay.

Diving deeper into the productivity-compensation gap and exploring falling labor’s share of income, Stansbury and Summers (2017) argue that from the perspective of technology-focused theory, if the primary cause of productivity-divergence is technological progress then the periods with faster productivity growth should coincide with faster growth in divergence of productivity and compensation. To test this theory, Stansbury and Summers (2017) examine the co-movement of labor productivity with labor share and with mean-median compensation ratio. Against the technology-focused theory, they find “little evidence of a significant relationship between productivity growth and changes in the labor share for any period except 2000” (Stansbury & Summers, 2017). Elsby et al. (2013) did not find the timing of capital deepening aligning straightforwardly with the timing of movements in labor’s share in their data.

Elsby et al. (2013) test five hypotheses that focus on detailed examination of magnitude, determinants, and implications tested decline in labor share. Aside from statistical procedures used to impute labor income of self-employed, they attribute decline in labor’s share of income

to movement of labor shares within the industry dominated by trade and manufacturing sector, supply chain, offshoring labor-intensive components, and capital deepening. Focusing on capital deepening, they explore the relation between productivity-compensation gap and capital intensity through neoclassical theory. When the elasticity of substitution is greater than 1 ( $\sigma > 1$ ), the shrinking labor's share of income must be traced through capital deepening. They find that to exploit technological change in new capital goods unskilled labor is replaced by capital when capital gets cheaper. They further explain that for a given growth rate of labor augmenting technological progress, the decline in labor's share of income is consistent with the additional growth in output outstripping additional growth in real wages. While testing the theory, they find that decline in labor share from 1980s to mid-1990s was characterized by rising growth in the 1980s, which was characterized by average labor productivity growth surpassing hourly compensation growth. However, they did not find the timing of capital deepening aligning straightforwardly with the timing of movements in labor's share in their data. They conclude from their analysis that "either neoclassical theory is unable to provide a coherent account of the decline in labor's share, or a simple aggregate production function is too crude to capture the relevant economic forces" (Elsby et al., 2013).

Supporting the idea of capital deepening not aligning with labor's share of income, Glover and Short (2020) estimate the aggregate elasticity of substitution between labor and capital. Glover and Short (2020) highlight that one of the potential reasons for declining labor's share of income is capital intensity, which is defined as capital to labor ratio. Glover and Short (2020) analyze the declining trend of labor's share of income from the perspective of capital deepening, which is defined as increasing capital intensity. They look at the aggregate elasticity

of substitution between capital and labor to test if capital deepening can explain the global decline in labor share. Glover and Short (2020) conduct a cross-country analysis of declining labor share to argue that as investment goods become cheaper, countries accumulate more capital relative to labor, hence increasing capital intensity. They theoretically derive a proxy for the rental rates which is dependent on investment prices and consumption growth. They use the inter-temporal Euler equation for investment and a transitional term that reflects gradual rise in consumption as a response to lower investment prices. Their results conclude that the estimate of aggregate elasticity of substitution between labor and capital is near or below one which implies that capital deepening cannot explain the global decline in labor's share. But their estimation provides support for explanations such as falling labor share along with rising product-market concentration. It also supports Elsby et al. (2013) who estimate a strong correlation between inter-industry trends in labor share and import competition.

While labor productivity and compensation have been widely studied, capital deepening is another factor studied to understand productivity gains. Basri et al. (2020) examine how shocks in wage, capital intensity and human capital affect labor productivity in Malaysian manufacturing sector. They adopted a Panel Vector Autoregressive (PVAR) Model to examine the impact of these shocks on labor productivity growth. The main finding, labor productivity growth, shows an expected positive and significant response to one standard deviation in shock in the change of wage, capital intensity and human capital. Moreover, they find that capital intensity and wage have the largest explanatory power for labor productivity. The forecast variance decomposition (FEVD) proves that the weighting of capital against labor and wage has a large explaining power over labor productivity over ten years.

Analyzing labor productivity and capital intensity, Wolff (1991) presents estimates of labor productivity and total factor productivity (TFP) growth at three different levels over the years 1948 – 86: (1) US insurance industry, (2) whole economy and (3) selected subsectors. They explain that despite the rapid growth of capital intensity in the insurance industry, poor productivity performance had been noticed during the postwar period. In their analysis they use the sum of total factor productivity (TFP) growth and growth in capital-labor ratio to measure labor productivity growth. They find that in 1948 – 86 there was a strong growth in capital intensity in insurance industry which led to relatively modest growth in labor productivity. Wolff (1991) further conclude that it was only through capital intensity that the insurance industry was able to achieve its relatively modest growth in labor productivity for the year 1948 – 86.

Overall, Stansbury and Summers (2017) establish a linkage between productivity and compensation to draw conclusion that productivity gains are not completely translating to compensation. This has been verified by Fofack and Temkeng (2021), but Greenspon et al. (2021) dive deeper into the linkage between productivity and compensation attributing the gap to falling labor's share of income. They suggest that in the US declining labor share is further attributed to technological changes, globalization and labor offshoring, reduction in worker bargaining power, higher firm concentration, increased markups, and housing market dynamics. Stansbury and Summers (2017) hypothesize the primary cause of productivity- pay divergence is technological progress. They address their hypothesis by examining the co-movement of labor productivity with labor share and with mean-median compensation ratio. However, past literature has found that declining labor's share of income could not be attributed to capital by checking for elasticity of substitution and co-movements of declining labor's share of income and

technological progress. This explains that capital deepening may not be accurately traced through productivity-compensation gap and declining labor's share of income. However, a linkage between productivity and capital could explain the divergence of productivity gains towards capital instead of compensation. Literature including Wolff (1991) and Basri et al. (2020) show the association between capital intensity and productivity gains demonstrating how capital investments are increasing outputs in future but fail to showcase the divergence of productivity gains towards capital to discuss technology advances. Hence, there's a potential to analyze the divergence of productivity gains towards capital by analyzing the linkage between productivity growth and capital deepening (or capital intensity growth).

## Data

The Office of Productivity and Technology (OPT) data from the Bureau of Labor Statistics (BLS) comprises detailed industry-level data for the years 1987 – 2022. The output is the sectoral output which is constructed from the annual-weighted (Fisher-Ideal) index by the Bureau of Economic Analysis (BEA) from GDP. BLS excludes output from general government, non-profit institutions, paid employees of private households, rental value of owner-occupied dwellings, and farm output. The sectoral output is constructed by removing intra-industry transactions. The output data is used to compute labor productivity, which is defined as the efficiency of producing goods and services through labor hours. For labor productivity, the BLS Current Employment Statistics (CES) program collected data for 83 three-digit-level industries under the North America Industry Classification System (NAICS) in the private nonfarm sector. Employment of non-production and non-supervisory workers in each industry is computed by

taking a difference between employment of all employees and employment of production workers. The CES program collected average weekly hours on an hour-paid basis including the time when employees are not at work. These hours are then adjusted to ensure that changes in vacation, holiday, and sick pay do not affect growth in hours (*Productivity Glossary*, 2023).

In this paper I am focusing my analysis on 2 sectors – manufacturing sector and transportation and warehousing sector for the years 1989 to 2019. The data for all variables is measured annually to evaluate the percentage changes from year to year. Table 1 presents the description of the variables used in the models. BLS defines labor productivity as the efficiency with which goods and services are produced via labor hours or as output per hour and hourly compensation as the sum of wage and benefits paid per hour of work. Capital Intensity, as defined by BLS, is the ratio of the amount of capital input used relative to the amount of labor hours used to produce output of goods and services (*Productivity Glossary*, 2023). The lag of productivity is created for the percentage change in labor productivity from previous year for year prior to the referred year. Furthermore, productivity data is at sectoral level which is constructed by BLS using sectoral output. As opposed to using the aggregate measures, like GDP and value-added output, used in past literature using sectoral data provides better insight for sector-wise analysis.

Table 2 provides detailed summary statistics for percentage change in labor productivity, percentage change in compensation, percentage change in capital intensity, and percentage change in lag of labor productivity in manufacturing sector and transportation and warehousing sector. Productivity, compensation and capital intensity are measured annually, and the lagged values of productivity are computed at yearly level.

**Table 1***Description of Variables*

<b>Variable Name</b>	<b>Description of variables</b>
LProductivity	Percentage change in labor productivity from previous year.
Compensation	Percentage change in hourly compensation from previous year.
KIntensity	Percentage change in capital intensity from previous year.
LProductivity_lag1	Percentage change in labor productivity from previous year lagged 1 period
LProductivity Level	Labor Productivity indexed at 2012
Compensation Level	Hourly compensation indexed at 2012
Capital Intensity Level	Capital Intensity indexed at 2012

**Table 2***Summary Statistics*

VARIABLES	n	mean	sd	median	min	max	range	se
LProductivity	6,586	1.781	7.957	1.300	-40.000	105.600	145.600	0.098
Compensation	6,586	2.830	5.978	2.700	-44.500	55.200	99.700	0.074
KIntensity	4,278	1.781	6.576	1.300	-33.700	40.900	74.600	0.101
LProductivity Level	6,601	89.485	23.345	92.621	0.623	218.037	217.414	0.287
Compensation Level	6,601	84.337	22.372	85.729	27.391	170.509	143.118	0.275
Capital Intensity Level	4,278	84.080	20.297	87.080	18.247	161.593	143.346	0.310
LProductivity_lag1	6,577	1.860	7.929	1.400	-40.000	105.600	145.600	0.098

## Theoretical Model

### a. Background: Linkage-Delinkage Spectrum Model

Stansbury and Summers (2017) introduced a linkage-delinkage spectrum model to understand the widening disparity between productivity and compensation. They develop this framework to assess how strongly productivity growth translates into compensation growth by looking at the coefficient associated with productivity. They follow the approach similar to Feldstein (2008) who investigated linkage between productivity and average compensation by regressing change in log of average compensation on current and lagged change in log of productivity to find a strong and close to one-to-one relation (Stansbury & Summers, 2017, pg. 12). On one end of the spectrum is the possibility of productivity growth delinking from compensation and other factors may be blocking the transmission. This suggests that increases in productivity growth do not systematically translate into increases in compensation with other factors blocking the transmission. Stansbury and Summers (2017) refer to this as “strong delinkage”. The other end of spectrum shows while other factors may have severed the connection between productivity and compensation, an increase in productivity growth translates directly into compensation. Stansbury and Summers (2017) refer to this as “strong linkage”. The strong linkage implies that when productivity growth raises compensation, productivity-compensation gap can be explained by other orthogonal factors that could be reducing compensation growth. While these two are the extreme ends of the spectrum, there are a range of possibilities on the spectrum in between that show some degree of linkage exists between productivity and compensation. Stansbury and Summers (2017) use a simple linear model to project the linkage between productivity and compensation which they base on (1).

$$\text{compensation growth}_t = \alpha + \beta \text{productivity growth}_t \quad (1)$$

The foundation for the linkage-delinkage spectrum for productivity and compensation and productivity and capital can be expressed using Cobb-Douglas production function. The Cobb-Douglas production function ensures constant returns to scale and linear homogeneity, which ensures a proportional relationship between inputs and output. Labor productivity is defined as the output per labor hour which is the average output per unit of labor. Cobb Douglas production function ensures that marginal product of labor is proportional to the average product of labor, in which case the wages paid by the competitive firm should increase at the same pace as productivity growth (Feldstein, 2008).

### b. Framework

Consider a simple two-input one output production function which takes the form of Cobb Douglas production function as shown in (2). Let  $Y$  represent the output,  $K$  represents capital,  $L$  represents labor input and  $A$  represents the total factor productivity. In the Cobb-Douglas function  $\alpha$  is the market share of capital and  $\beta$  is the market share of capital.

$$Y = AK^\alpha L^\beta \quad (2)$$

A firm's profit maximization problem is the difference between the firm's revenue and cost, hence the difference between the output and sum of the value of its inputs.  $w$  is the wage rate (or hourly compensation) given to the workers per labor hour worked.  $r$  is the rent (or investment) paid towards the capital assets. Hence, the maximization problem for the firm is

$$\begin{aligned} & \max_{L,K} Y_t - wL_t - rK_t \\ & \text{s.t. } Y_t = A_t K_t^\alpha L_t^\beta \end{aligned} \quad (3)$$

The first order derivative with respect to  $L$  from the maximization problem shows the relation between productivity and compensation as shown in (4).

$$\beta \left( \frac{Y_t}{L_t} \right) = w \quad (4)$$

The first order derivative with respect to  $K$  from the maximization problem shows the relation between output and capital as shown in (5)

$$\gamma Y_t = K_t \quad (5)$$

where  $\gamma = \frac{\alpha}{r}$ . Capital intensity is the capital to labor ratio, so (5) is modified to show the relation between productivity and capital intensity.

$$\gamma \frac{Y_t}{L_t} = \frac{K_t}{L_t} \quad (6)$$

Equations (4) and (6) build the foundation for linkage-delinkage spectrum for productivity-compensation and productivity-capital. (4) represents the foundation for linkage-delinkage spectrum for productivity and compensation and (6) represents the foundation for linkage-delinkage spectrum for productivity and capital intensity.

## Empirical Model

### a. Linkage-Delinkage Spectrum Model for Productivity and Compensation

Linkage-Delinkage Spectrum Model for productivity and compensation shows the linkage (or delinkage) between productivity and compensation. The linkage-delinkage spectrum model for Productivity and Compensation assumes that there exists a gap between productivity

and compensation. A simple regression model in (7) estimates the location of the point on linkage-delinkage spectrum that explains the relation between productivity and compensation. To avoid running into a spurious regression, I consider growth in productivity and growth in compensation. (7) represents the productivity and compensation growth using a simple linear model (Stansbury & Summers, 2017) for industry  $i$  at time  $t$  in sector  $s = \{\text{Manufacturing}, \text{Transportation and Warehousing}\}$ .

$$\Delta\text{compensation}_{ist} = \beta_0 + \beta_1 \Delta\text{productivity}_{ist} + \epsilon_t \quad (7)$$

The estimate of  $\beta$  associated with productivity growth ( $\beta_1$ ) demonstrates the transmission of productivity into compensation, explaining the contribution of productivity gains into compensation. The value of  $\beta$  ranges between 0 and 1. When  $\beta = 1$ , there's "strong linkage" which shows that increase in productivity growth completely translates into compensation; for a value of 0, there is a "strong delinkage" which shows that increase in productivity growth is not translating into compensation (Stansbury & Summers, 2017). Strong linkage and delinkage are defined as the two extreme ends, there are a range of possibilities between the two ends where  $\beta$  ranges between 0 and 1 (excluding 0 and 1). These possibilities explain that certain degree of linkage exists between productivity and compensation (Stansbury & Summers, 2017).

### **b. Linkage-Delinkage Spectrum Model for Productivity and Capital.**

From the linkage-delinkage spectrum model for productivity and compensation, I build the linkage-delinkage spectrum model for productivity and capital. Equation (8) demonstrates the simple linear model that projects the location of linkage between productivity and capital

intensity on linkage-delinkage spectrum. To avoid running into a spurious regression, I analyze the growth in productivity and growth in capital intensity (or capital deepening). (9) represents the linkage-delinkage spectrum model for capital deepening and productivity growth in industry  $i$  at time  $t$  in sector  $s = \{Manufacturing, Transportation and Warehousing\}$

$$\text{capital deepening}_t = \alpha + \beta \text{productivity growth}_t \quad (8)$$

$$\Delta \text{capital}_{ist} = \beta_0 + \beta_1 \Delta \text{productivity}_{ist} + \epsilon_t \quad (9)$$

The estimate of  $\beta$  associated with productivity growth ( $\beta_1$ ) demonstrates the transmission of productivity into capital intensity, explaining the contribution of productivity gains into capital intensity. The value of 1 for  $\beta$  determines a “strong linkage” between productivity and capital intensity and a value of 0 determines a “strong delinkage” between productivity and capital intensity. Strong linkage and delinkage are on the two extreme ends of the spectrum and there is a range of possibilities between the two ends where  $\beta$  ranges between 0 and 1 (excluding 0 and 1). These possibilities reflect the transmission of productivity growth into capital deepening (or growth of capital intensity) with other factors blocking the transmission.

## Results

### a. Unit Root Test

Before proceeding with the empirical analysis, I examine whether there exists an underlying trend within the variables. For checking underlying trends and stationarity within a variable, I employ Augmented Dickey Fuller (ADF) test to check for underlying trends and stationarity within productivity growth, compensation growth, and growth of capital intensity (or

capital deepening). Augmented Dickey Fuller (ADF) test is a unit-root test useful in checking for underlying trends and stationarity. The ADF test evaluates the null hypothesis that non-stationarity exists in the data against the alternative hypothesis of stationarity. The results from ADF test in Column (1) of Table 3 confirm stationarity in productivity growth, compensation growth, and capital deepening in manufacturing sector and results in Columns (2) of Table 3 confirm stationarity in transportation and warehousing sector. The lag length for ADF tests in Table 3 is automatically selected according to Akaike Information Criteria (AIC).

**Table 3**

*Augmented Dickey Fuller for Percentage Changes in Labor Productivity, Compensation and Capital Intensity in Manufacturing Sector (1) and Transportation and Warehousing Sector (2).*

	$\Delta$ Labor Productivity		$\Delta$ Compensation		Capital Deepening	
	(1)	(2)	(1)	(2)	(1)	(2)
z.lag.1	-0.491 *** (0.013)	-0.486 *** (0.037)	-0.530 *** (0.013)	-0.387 *** (0.035)	-0.455 *** (0.014)	-0.547 *** (0.148)
z.diff.la g	-0.001 (0.013)	0.065 (0.039)	-0.002 (0.013)	-0.054 (0.039)	0.078 *** (0.015)	-0.134 (0.132)
N	5919	663	5919	663	4214	60

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

### **b. Linkage-Delinkage for Productivity and Compensation**

A simple regression model in (7) projects the location of the point on linkage-delinkage spectrum that explains the relation between productivity and compensation. To avoid running into a spurious regression, I analyze the growth in productivity and compensation in the OLS models investigating the strength of linkage between productivity and compensation. To account for autocorrelation and heteroskedasticity in the error term, I report the Newey-West heteroskedastic and autocorrelation robust standard error. The results from these OLS models in Table 4 show the existence of the linkage between productivity and compensation, with the estimates being in the range of 0.32 and 0.46 for the years 1989 to 2019. Estimates for manufacturing sector in columns (1) and (2) are consistent with the range of 0.4 to 0.79 suggested by Stansbury and Summers (2017) who report this range for the years 1990 to 2016. However, estimates for transportation and warehousing sector in columns (3) and (4) are slightly lower than this range. This indicates that the linkage between productivity and compensation in manufacturing sector is stronger than the linkage in transportation and warehousing sector, suggesting workers benefit more in the manufacturing sector than in the transportation and warehousing sector. Moreover, the estimates confirm the existence of linkage, but the linkage is not a one-to-one translation of productivity gains into compensation. This implies that workers (or employees) are not enjoying all the benefits coming from the productivity gains, instead the productivity gains are redirected towards other factors of production, more likely towards capital.

**Table 4**

*OLS Models for Productivity growth and Compensation growth in Manufacturing Sector and Transportation and Warehousing Sector (1989 – 2019)*

	<i>Manufacturing Sector</i>		<i>Transportation and Warehousing Sector</i>	
	(1)	(2)	(3)	(4)
(Intercept)	2.072 *** (0.085)	2.141 *** (0.091)	2.155 *** (0.206)	2.168 *** (0.206)
LProductivity	0.427 *** (0.047)	0.459 *** (0.040)	0.330 *** (0.047)	0.321 *** (0.051)
LProductivity_lag1		-0.066 ** (0.025)		0.018 (0.036)
N	5921	5921	665	656
R2	0.323	0.329	0.188	0.186
AIC	36076.088	36026.073	3474.110	3434.452

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

*Note: The standard errors reported are Newey-West heteroskedasticity and autocorrelation robust standard errors (Newey-West HAC robust standard errors)*

### c. Linkage-Delinkage for Productivity and Capital

From the linkage between productivity and compensation, I observe that there is no one-to-one transmission of productivity gains into compensation. Thus, there are other factors

blocking the transmission, including capital. To understand this blockage, I look at the linkage between productivity growth and growth in capital-to-labor ratio (or capital intensity). A simple regression model in (9) projects the location of the point on linkage-delinkage spectrum that explains the relation between productivity and capital intensity. To avoid running into a spurious regression, I analyze the growth in productivity and capital deepening in the OLS models investigating the strength of linkage between productivity and capital intensity. Capital deepening is defined as growth in capital intensity, which is used to define capital-to-labor ratio. To account for autocorrelation and heteroskedasticity in the error term, I report the Newey-West heteroskedastic robust standard error.

The results from the OLS models in Table 5 show the existence of the linkage between productivity gains and capital intensity. For the years 1989 to 2019, the linkage is within the range of 0.26 and 0.43, reported in Table 5. Although the linkage seems to be slightly weaker than the linkage between productivity and compensation, it reflects that there is a linkage between productivity and capital intensity and the productivity gains have diverted towards capital. In the manufacturing sector, the estimate value is around in the range of 0.26 to 0.28 while the estimates in the transportation and warehousing sector are in the range of 0.40 and 0.43. This shows that the linkage is stronger in the transportation and warehousing sector compared to the manufacturing sector. However, there is no one-to-one transmission of productivity gains into capital intensity meaning that not all productivity gains are transmitted to capital. This implies that the productivity gains are distributed amongst capital and workers. A one-to-one translation with  $\beta = 1$  would have demonstrated a complete translation of productivity gains into capital.

**Table 5**

*OLS Models for Productivity and Capital Intensity in Manufacturing Sector and Transportation and Warehousing Sector (1989 – 2019).*

	Manufacturing Sector		Transportation and Warehousing Sector	
	(1)	(2)	(3)	(4)
(Intercept)	1.257 *** (0.161)	1.289 *** (0.196)	1.841 * (0.836)	2.467 ** (0.879)
LProductivity	0.262 *** (0.033)	0.280 *** (0.033)	0.404 * (0.175)	0.424 * (0.169)
LProductivity_lag1		-0.033 * (0.015)		-0.206 (0.136)
N	4216	4216	62	62
R2	0.115	0.116	0.142	0.180
AIC	27357.729	27353.572	377.011	376.236

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.

*Note: The standard errors reported are the Newey-West heteroskedasticity and Autocorrelation robust standard errors*

The results from productivity-compensation linkage and productivity-capital linkage show a 42.7% contribution of productivity gains towards compensation and a 26.2% contribution of productivity gains towards capital in manufacturing sector. Moreover, there is 33% contribution of productivity gains towards compensation and 40.4% contribution of productivity gains towards capital in transportation sector. These results demonstrate that stronger linkage in

productivity and compensation coincides with weaker linkage in productivity and capital and vice-versa. As observed in the results, the productivity-compensation linkage is stronger in the manufacturing sector compared to transportation and warehousing sector, which coincides with the weaker linkage in productivity and capital. Opposingly, in the transportation and warehousing sector the productivity-compensation linkage is weaker compared to manufacturing sector which coincides with stronger linkage in productivity and capital. This implies that while productivity gains are distributed amongst labor and capital, workers are benefiting more through compensation in the manufacturing sector while more is invested in capital in the transportation and warehousing sector.

## Conclusion

Since 1970s productivity compensation gap, on average in the US, has been on the rise. Productivity-compensation gap has been studied widely with debates on the gap being attributed to technological change. Although, from the perspective of technology-focused theory, declining labor share of income can be attributed to technological progress, there is little to no evidence found to support theory. A key indicator of economic growth is labor productivity which is closely linked to competitiveness and living standards within an economy (International Labor Organization, 2024). The gap between productivity and compensation indicates that compensation is not growing at the same pace as productivity, hence economic growth does not completely benefit the workers. This raises the question that if not to the workers, what factors is economic growth in terms of productivity is being channeled towards? The fast-growing technology indicates that economic growth is being diverted towards capital instead of labor.

Stansbury and Summers (2017) conclude that the primary cause of productivity-pay divergence is technological progress. However, there is a debate in the literature on declining labor share of income and capital suggesting that capital deepening may not be accurately traced through productivity-compensation gap or declining labor share of income. This creates potential to trace down the divergence of economic growth towards capital through the linkage-delinkage spectrum for productivity and capital. The linkage-delinkage spectrum for productivity and pay was introduced by Stansbury and Summers (2017) to assess the transmission of productivity gains towards compensation.

In this paper I assess the technological changes by establishing the linkage between productivity and capital intensity and use BLS data from their Office of Productivity and Technology (OPT). The advantage of using the BLS data is that they compute labor productivity using sectoral output instead of GDP. Past literature has analyzed productivity-compensation gap using the aggregate measure including GDP and value-added output which could cause aggregation bias. Building upon the work of Stansbury and Summers (2017) to examine the linkage between productivity and capital intensity, I find that the sector that invested more in capital diverted the productivity gains from workers, while the sector that paid more to workers invested less in capital. This implies that the productivity gains that are not going towards compensation to the workers have been diverted towards capital. Moreover, the results show that 42.7% of productivity gains contributed to compensation growth while 26.2% of productivity contributed to capital deepening in manufacturing sector. Moreover, in the transportation and warehousing sector 33% of productivity gains contributed to compensation growth while 40.4% of productivity gains contributed to capital deepening. This implies that there exists a stronger

linkage between productivity and compensation in manufacturing sector as compared to transportation and warehousing sector, while the linkage between productivity and capital is stronger in transportation and warehousing sector as compared to manufacturing sector.

The analysis in this paper shows that economic growth is contributing to technological growth when it is not benefiting the workers. The linkage between productivity and capital is based on the assumption that productivity and compensation do not show a one-to-one translation, meaning productivity gains are not completely going to the workers and are distributed amongst workers and capital. Due to limitations in data availability this paper only found insights from two sectors – manufacturing sector and transportation and warehousing sector. Future research can contribute by including more sectors for better insights. Furthermore, research into different factors of production like intermediate inputs could add more insight into the channels that productivity gains are being transmitted to. Furthermore, accounting for high-skill and low-skill workers could provide a better insight into technological changes. This research can be further extended to forecast the contribution of productivity gains to different factors of production, which could be helpful in looking at reallocation of resources including capital and labor. Furthermore, this analysis can contribute to the literature for artificial intelligence (AI) by looking at how productivity gains could be influencing investments into AI.

## References

- Brill, M., Holman, C., Morris, C., Raichoudhary, R., & Yosif, N. (2017). Understanding the labor productivity and compensation gap. *Beyond the Numbers: Productivity, Vol. 6/No. 6.* [https://www.bls.gov/opub\(btn/volume-6/understanding-the-labor-productivity-and-compensation-gap.htm](https://www.bls.gov/opub(btn/volume-6/understanding-the-labor-productivity-and-compensation-gap.htm)
- Dutta, N. (2024, March 21). *The secret weapon behind America's soaring productivity*. Business Insider. <https://www.businessinsider.com/employee-productivity-booming-workers-jobs-ai-stock-market-gdp-2024-3>
- Elsby, M. W. L., Hobijn, B., & Şahin, A. (2013). The Decline of the U.S. Labor Share. *Brookings Papers on Economic Activity, 2013(2)*, 1–63. <https://doi.org/10.1353/eca.2013.0016>
- Feldstein, M. (2008). Did wages reflect growth in productivity? *Journal of Policy Modeling, 30*(4), 591–594. <https://doi.org/10.1016/j.jpolmod.2008.04.003>
- Fofack, A. D., & Temkeng, S. D. (2021). A cross-sectoral analysis of the relation between labor productivity and labor compensation in the European Union. *Applied Econometrics, 62*, 54–65. <https://doi.org/10.22394/1993-7601-2021-62-54-65>
- Greenspon, J., Stansbury, A. M., & Summers, L. H. (2021). *Productivity and Pay in the US and Canada* (Working Paper No. 29548). National Bureau of Economic Research. <https://doi.org/10.3386/w29548>
- International Labor Organization. (2024, January 15). *Statistics on labour productivity*. ILOSTAT. <https://ilo.stat.ilo.org/topics/labour-productivity/>
- Mohd Basri, N., Abdul Karim, Z., & Sulaiman, N. (2020). The Effects of Factors of Production Shocks on Labor Productivity: New Evidence Using Panel VAR Analysis. *Sustainability, 12*(20), 8710. <https://doi.org/10.3390/su12208710>
- Productivity glossary: U.S. Bureau of Labor Statistics.* (2023). Bureau of Labor Statistics. <https://www.bls.gov/productivity/glossary.htm>
- Stansbury, A. M., & Summers, L. H. (2017). PRODUCTIVITY AND PAY: IS THE LINK BROKEN? *NBER WORKING PAPER SERIES, No. 24165*. <http://www.nber.org/papers/w24165>

US Bureau of Labor Statistics. (2024, March 7). *Labor-compensation-labor-productivity-gap.png* (720×522). <https://www.bls.gov/productivity/images/labor-compensation-labor-productivity-gap.png>

Wolff, E. N. (1991). Productivity Growth, Capital Intensity, and Skill Levels, in the U. S. Insurance Industry, 1948–86. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 16(2), 173–190. <https://doi.org/10.1057/gpp.1991.15>

## **APPENDIX A**

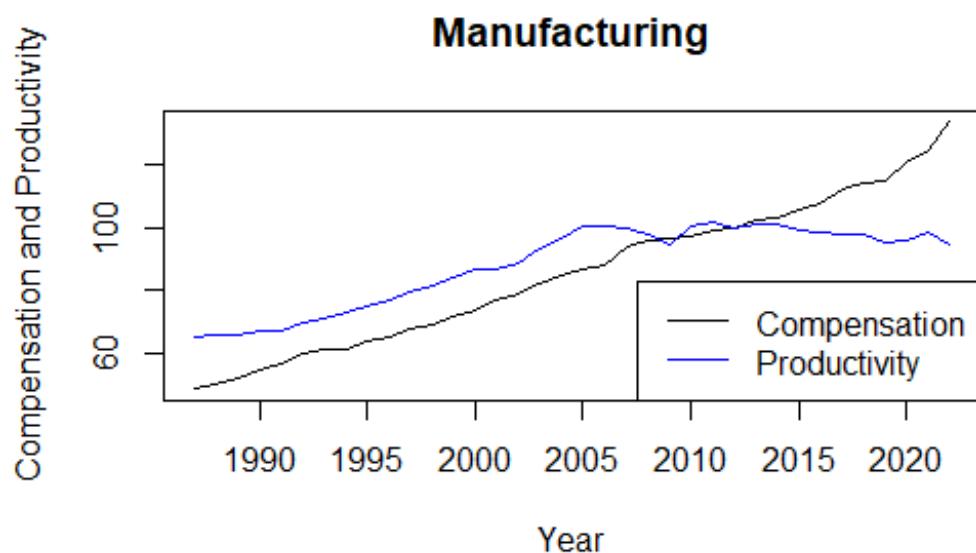


Figure 2: Gap between productivity and compensation in manufacturing sector indexed at 2012  
(2012 = 100)

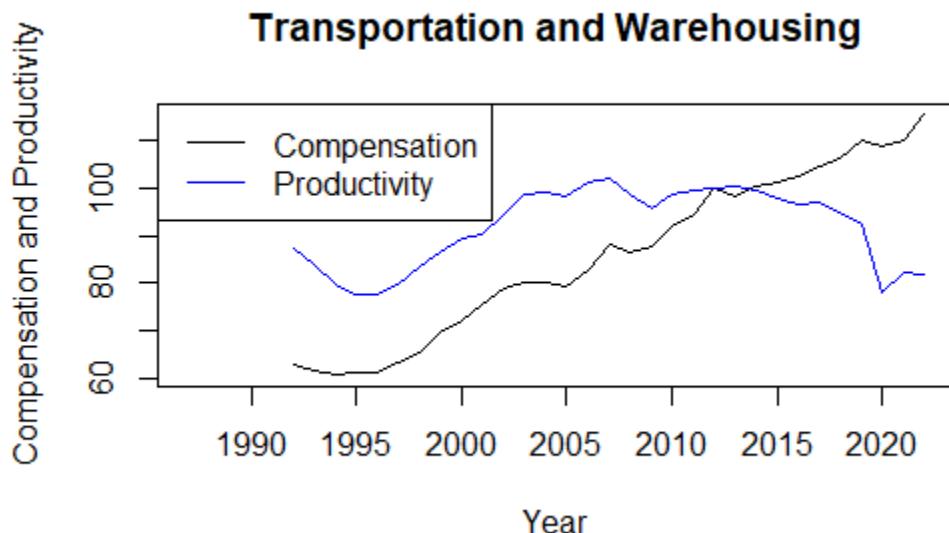


Figure 3: Gap between productivity and compensation in transportation and warehousing sector indexed at 2012 (2012=100)

## **APPENDIX B**

*Table 6: Augmented Dickey Fuller Test for Labor Productivity, Compensation and Capital Intensity Indexed at 2012=100*

	Labor Productivity		Compensation		Capital Intensity	
	Manufacturing	Transportation and Warehousing	Manufacturing	Transportation and Warehousing	Manufacturing	Transportation and Warehousing
z.lag.1	-0.004 *** (0.001)	-0.002 (0.003)	-0.007 *** (0.002)	-0.004 (0.004)	-0.004 ** (0.001)	0.013 (0.011)
z.diff.1 ag	-0.009 (0.013)	0.029 (0.038)	-0.034 ** (0.013)	-0.006 (0.038)	0.007 (0.015)	0.064 (0.134)
N	5919	678	5919	678	4214	60

\*\*\* p < 0.001; \*\* p < 0.01; \* p < 0.05.