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The Effects of Labor-Saving Technological Progress on Capital Accumulation: Evidence from NASDAQ-100 Firms

Necip BULUT*, Naci İbrahim KELEŞ**

Abstract

This study delves into the impact of labor-saving technological progress on the capital accumulation of technology companies that have a substantial workforce consisting of highly skilled workers over the sample period from 2000/Q2 to 2021/Q3. To begin with, we estimate a three-equation system of the normalized-CES production function to derive labor-saving technical progress and the elasticity of substitution between capital and labor for NASDAQ-100 firms. Secondly, two linear regression models are estimated by using parameters acquired in the initial step to assess the impacts of labor-saving technological progress on capital accumulation. Based on the estimation results, labor-saving technological progress and the elasticity of substitution between capital and labor mitigate the upward trend of capital accumulation despite their stimulating impacts on economic value added in the NASDAQ-100 firms. These two adverse results are consistent with the concept of skill intensity in technology firms, referring to the difficulties of replacing automation with non-routine tasks and highly skilled workers. In this sense, along with the insufficient replacement of technological progress with labor, the detrimental effects of technological progress on capital accumulation widen the gap between labor productivity and labor compensation during profit expansion periods. These negative consequences are mitigated by worker layoffs during profit-downsizing periods, despite its accelerating impact on economic value added.

Keywords: Labor-Saving Technological Progress, Capital Accumulation, Technology Firms, Labor Compensation, CES Production Function

Emek Tasarruflu Teknolojik İlerlemenin Sermaye Birikimine Etkileri: NASDAQ-100 Firmaları Üzerine Bir Çalışma

Öz

Bu çalışma, 2020 yılının ikinci çeyreğinden 2021 yılının üçüncü çeyreğine kadar olan örnekleme döneminde, nispeten fazla sayıda yüksek vasıflı işçi çalıştıran teknoloji firmalarında emek tasarrufu sağlayan teknolojik ilerlemenin sermaye birikimi üzerindeki

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etkilerini araştırmaktadır. İlk olarak, NASDAQ-100 firmaları için emek tasarruflu teknolojik ilerleme ve sermaye ve emek arasındaki ikame esnekliğini elde etmek için normalleştirilmiş CES üretim fonksiyonunun üç denklemli bir sistemi tahmin edilmiştir. İkinci olarak, emek tasarruflu teknolojik ilerlemenin teknoloji firmalarının sermaye birikimi üzerindeki etkilerini değerlendirmek adına ilk adımda elde edilen parametreler kullanılarak doğrusal bir regresyon modeli tahmin edilmiştir. Tahmin sonuçlarına göre, emek tasarruflu teknolojik ilerleme ve sermaye ile emek arasındaki ikame esnekliği, onların ekonomik katma değeri hızlandırıcı etkilerine ragmen, NASDAQ-100 firmalarının sermaye birikimlerindeki artış eğilimini yavaşlatmaktadır. Bu iki zıt sonuç, teknoloji firmalarında, otomasyonun rutin olmayan işlerin ve yüksek vasıflı çalışanların yerini almasındaki yetersizliğine işaret eden vasıf yoğunluğu konseptine uygundur. Bu bağlamda, emek tasarruflu teknolojik ilerleme, otomasyonun işgücünü yerinden etmedeki yetersizliğiyle birlikte, kar genişlemesi dönemlerinde, işgücü üretkenliği ve işgücü ödemeleri arasındaki uçurumu genişletmektedir. Teknolojik ilerlemenin ekonomik katma değere olan pozitif katkısına ragmen, bu negative sonuçlar kar daralması dönemlerinde, işten çıkarmalar ile yatıştırılmaktadır.

Anahtar Kelimeler: Emek Tasarrufulu Teknolojik İlerleme, Sermaye Birikimi, Teknoloji Firmaları, İşgücü Ödemeleri, CES Üretim Fonksiyonu

Introduction

A capitalist economy relies on capital accumulation. In theory, especially in Marxian economic theory, the tendency of the profit rate to fall due to perfect competition impedes the capital accumulation needed by the capitalist to reproduce capitalism. This process eventually ends up with a decrease in labor share (labor exploitation in Marxian theory). However, this particular model does not take into account any technological progress. Technological advancements have multiple dimensions that could impact both capital accumulation and the labor market in diverse ways. Capital, labor, and technological progress are intricately linked and have a complex interdependent structure.

To understand the impact of technological progress on the share of production inputs in value-added, it is crucial to distinguish between the types or functions of technology and labor. The key question is, "what type of technological progress has affected which skilled workers, and in what way?" The literature categorizes technological progress into two groups: labor-saving and capital-saving. Similarly, workers can be divided into three groups based on their skill level: low, middle, and high-skilled.

Input-saving technological progress has led to an increase in labor productivity and a decrease in labor compensation. These two consequences of technological progress ended up with a decrease in the labor share in value-added as well as an increase in the capital share in value-added produced by capital and labor together. Consequently, this process has sped up the capital accumulation for firms due to the upward trend in labor productivity and the downward trend in the share of labor force.

However, the impact of input-saving technological progress has not affected every worker equally. These foregone consequences of technological progress could be more pronounced for middle-skilled workers than for low-skilled and high-skilled ones. In other words, while technological progress has increased the productivity of almost every worker, this progress has not sufficiently raised the compensation of middle-skilled workers compared to low-skilled and high-skilled workers. Considering the main determinants of capital accumulation, along with the upward trend in profit of firms, the downward trend in compensation of middle-skilled workers could contribute more to the capital accumulation of firms compared to those of low-skilled and high-skilled ones. In other words, the contribution of high-skilled and low-skilled workers to capital accumulation could be different than the contribution of middle-skilled workers.

This study focuses on differences in the contribution of different skilled workers to the capital accumulation of firms. Since there is no data on the qualifications of the workers employed by the firms, the focus of this study is on the NASDAQ-100 firms that employed relatively more high-skilled workers. At the same time, these firms are separated into sectors in terms of their operations. Due to a lack of comprehensive data on the qualifications and education levels of workers within companies, researchers have been unable to investigate how technological progress and the elasticity of substitution between labor and capital affect highly skilled workers at the firm level. To address this gap, we aim to explore the impact of labor-saving technological progress and the elasticity of substitution between labor and capital on technology firms that employ a higher proportion of highly skilled workers. Our study focuses on NASDAQ-100 companies, which are technology firms with a different employment structure and elasticity of substitution than firms with lower levels of technological sophistication. The main contribution of this study is to analyze the effect of these two factors on NASDAQ-100 firms.

To this end, in the empirical research of this study, first of all, three equation system of normalized CES production function is estimated at firm level, sector level, and aggregate level over the sample period from 2000/Q2 to 2021/Q3. In this stage of empirical investigation, labor-saving technological progress is obtained for each firm. Secondly, an investigation of the effects of labor-saving technological progress, which is obtained in the first stage, on the capital accumulation of NASDAQ-100 listed firms is conducted by estimating a linear regression model via the Estimated Generalized Least Square (EGLS) estimation method to avoid implication of possible heteroskedasticity or autocorrelation problems. Besides, dummy variables representing operation sectors of firms, labor productivity, substitution rate between labor and capital, and the unemployment rate are added to this linear regression model as explanatory variables in the second stage of empirical investigation.

The most important finding in this study is that the coefficient for labor-saving technological growth has been found as negative for technology firms that employ relatively more high-skilled workers. It means that the capital accumulation of these firms has been arrested mainly from other sources such as capital-saving technological progress, profit, the upward trend of productivity rather than labor-saving technological growth, and the downward trend of labor compensation.

The subsequent sections of this paper are structured as follows: A review of the relevant literature is provided in the literature review section, which outlines existing research on the effects of technological progress on labor compensation, labor productivity, and capital accumulation. Section 3 outlines the methodology employed in this study, including a three-equation system based on the normalized CES production function, two different linear regression models, and summary statistics for the sample data used in the analysis. In Section 4, the results of the production function are presented at the aggregate, sector, and firm levels, as well as the outcomes of the two linear regression models. Finally, the concluding section summarizes the findings of this study.

Literature Review

The effects of ongoing technological progress on the demand side and supply side of the economy are being increasingly felt especially in countries that caught up with the latest production technology. With technological progress, the replacement of workers with machines has been increasing rapidly. Frey and Osborn (2017) estimate that 47% of total employment in the US is "potentially automatable over some unspecified number of years, perhaps a decade or two". McKinsey Global Institute Report (2017) estimates that approximately half of 2,000 work activities across 800 occupations have the potential to be automated by adapting current technology. It can be expected that this ratio would increase with development in technology in the future.

The World Bank (2016) points out that about 60% of total employment is susceptible to automation in OECD countries. According to the same report of the World Bank, wages become have become more stable since workers face strong competition arising from automation. Even though these studies offer insight into the general interaction between labor and automation, they do not provide evidence regarding skill-biased or task-biased discussions in the literature.

Goldin and Katz (2007) show that educated workers' real wages have remained the same from 1915 to 2005 in the US due to the competition between skilled workers and dramatically increase in the supply of educated workers arising mainly from the high school movement starting around 1910s. Acemoglu and Autor (2011) found that technological growth has decreased middle-skilled workers' real wages rather than those of low-skilled and high-skilled workers due to an increase in the demand for high-skilled and low-skilled occupations compared to middle-skilled occupations. They emphasize the rapid diffusion of new technology along with job polarization as a significant reason for this situation. According to the findings of Autor and Dorn (2013), there is an upward trend in employment and real wages in services occupations whereas real wages of low-skilled workers have remained the same.

On the one hand, wages remain stagnant due to the replacement of labor with machines and a dramatic increase in the supply of educated labor, on the other hand, the productivity of labor that cannot be replaced by machines has been soaring. According to an OECD report (2015), since 1990, labor productivity has increased by 28.4 in emerging countries, 3.7 in OECD countries, and 7.5 in the US. The reason for this dramatic increase in labor productivity is to ability to use current technology. Battisti, Belloc and Del Gatto (2020) investigate technological dimension of productivity in OECD countries at sector level. They found that the main determinant of labor productivity measured as residual of estimated sector-specific production function is technological progress.

Chansarn (2010) investigates determinant factors of labor productivity in G7 countries, western developed countries, eastern developed countries, and eastern developing countries. According to her semination result, labor productivity in 30 countries classified into above four groups is determined by education and technological progress. As well as technological progress as the main factor to increase labor productivity, life expectancy is another determinant for labor productivity as a proxy for health conditions (Chadha, 2008) (Hazan, 2006) (Knapp, 2007) (Leroux, Rizzo, & Sickles, 2004). In addition, many studies such as Duryea (2002), Razzak (2010), and Yunhua, Beng and Wenzhi (1998) suggest that education level is a significant determinant of labor productivity.

Along with both increase in labor productivity and the decrease or stagnancy in wages as mentioned in their empirical evidence above, the capital accumulation of firms has continuously expanded over the years. Several theoretical studies investigate the dynamics of capital accumulation at aggregate and firm levels in the literature. The widely used Solow (1956) growth model has a given capital accumulation in general (Solow, Tobin, von Weizsacker, & Yaari, 1966).

In Marx’s (1977) theory of capital accumulation, capital accumulation is determined by technical progress, an increase in labor productivity, and the rate of surplus value. In this sense, the capitalists invest the previous surplus in order to increase their production capacity. It means capital is the main source of capital accumulation in the short run. According to Marx (Marx, 1977), the reserve army of unemployed labor is another significant factor for capital accumulation due to the falling tendency profit rate in the long run.

On the contrary, Tsaliki (2009) argues that full employment is not necessary for the use of capital stock. This finding indicates that the capital stock can be used normally without the reserve army of unemployed labor from the Marxist perspective. However, without this army, the economic system cannot normally maintain its usual operation (Tsaliki, 2009) (Shaikh, 2016) (Charzarakis & Tsalki, 2021).

In the literature, as can be seen above, since researchers have very limited access to data containing the qualifications and education level of workers employed by firms, they cannot focus on the impacts of technological progress and elasticity of substitution between capital and labor on only educated and high-skilled workers at the firm-level. In this context, we attempt to show the effect of labor-saving technological progress along with elasticity of substitution between labor and capital for technology firms that employ relatively more educated and high-skilled workers. The main contribution of this study is to focus on the impact of these two main factor on NASDAQ-100 firms as technology firms that have relatively different elasticity of substitution and employment structure compared to other firms that produce low technology.

Empirical Investigation

In this section, empirical investigation consists of two steps. In the first step, the three-equation system of normalized CES production function has been fitted at firm, sector, and aggregate levels in order to obtain labor-saving technological progress and the elasticity of substitution between labor and capital. In the second step, the effects of labor-saving technological progress and the elasticity of substitution between labor and capital on capital accumulation of sample firms are investigated by estimating a linear regression model. The rest of this section is organized as follows. Firstly, our sample data and descriptive statistics are introduced. In section 3.2, the three-equation normalized CES production function is derived and its parameters are introduced. Finally, section 3.3 consists of estimation of linear regression model and dependent, independent, and dummy variables.

Sample Data and Descriptive Statistics

The quarterly sample data used in this study are collected from Bloomberg and OECD Database over 2002/Q2 - 2021/Q4. The NASDAQ 100 firms are classified as 8 sectors in terms of their operation. Table 1 shows descriptive statistics of our unbalanced panel dataset. In Table 1, K represents invested capital, L represents the number of workers, wL represents compensation, Y represents economic value-added and r represents long-term interest rate.

Variable	Observation	Mean	Std. Dev.	Min	Max
K	7,057	380641.7	3.10e+07	-8630	2.60e+09
L	6,623	36877.98	73918.45	99	1600000
wL	5,202	134.1612	405.2333	-957	3954
Y	7,107	60501.17	447507.3	-3300000	7800000
r	8,772	0.03207868	0.01295681	0.0065	0.06176

Table 1: Descriptive Statistics

In order to compute labor share, economic value added can be calculated as follows:

$$EVA = NOPAT - [Invested\ Capital * WACC] \\ = Invested\ Capital * WACC\ EVA\ SPREAD$$

where EVA represents economic value-added, NOPAT is Net Operation Profit After Tax, and WACC stands for Weighted Average Capital Cost.

Econometric Models

A standard CES production function can be shown as follows;

$$Y_t = \left[(\alpha(A_t^K K_t)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(A_t^L L_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{1-\sigma}}$$

where A_t^K and A_t^L stand for capital-saving and labor-saving technological progress, respectively. This CES production function can be normalized for a given baseline time (t_0) as follows:

$$Y_t = A\tilde{Y}\left[\bar{\alpha}\left(A_t^K \frac{K_t}{\tilde{K}}\right)^{\frac{\sigma-1}{\sigma}} + (1-\bar{\alpha})\left(A_t^L \frac{L_t}{\tilde{L}}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{1-\sigma}}$$

$$\alpha_0 = \frac{r_0 K_0}{r_0 K_0 + w_0 L_0}$$

where $\bar{\alpha}$ is calculated as the simple average of α. Labor and capital share are represented by $(1-\bar{\alpha})$ and $\bar{\alpha}$, respectively. $\tilde{K}$ and $\tilde{L}$ are geometric means of capital and labor, respectively. We can normalize labor-saving and capital saving parameters as $A_t^K = e^{\gamma K}$ and $A_t^L = e^{\gamma L}$. Where, γK and γL stand for growth rates of capital-saving and labor-saving technology, respectively. If we rearrange the normalized CES production function;

$$Y_t = A\tilde{Y}\left[(\bar{\alpha}\left(e^{\gamma K} \frac{K_t}{\tilde{K}}\right)^{\frac{\sigma-1}{\sigma}} + (1-\bar{\alpha})\left(e^{\gamma L} \frac{L_t}{\tilde{L}}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{1-\sigma}}$$

In the normalized CES production function presented by Specification 4, the rate of technological progress does not depend on time. In other words, this specification assumes that the growth rates of capital-saving and labor-saving technologies are constant. Finally, the three-equation system of the normalized CES production function can be shown as follows:

$$log\left(\frac{Y_t}{\tilde{Y}}\right) = lnA_t + \frac{\sigma}{1-\sigma} ln\left[\bar{a}\left(\frac{K_t}{\tilde{K}}\right)^{\frac{\sigma-1}{\sigma}} + (1-\bar{a})\left(e^{\gamma_L}\frac{L_t}{\tilde{L}}\right)^{\frac{\sigma-1}{\sigma}}\right]$$

$$log\left(\frac{r_t K_t}{P_t Y_t}\right) = ln\left(\frac{\bar{a}}{1+\mu}\right) + \frac{\sigma}{1-\sigma}\left[ln\left(\frac{Y_t\tilde{K}}{K_t\tilde{Y}}\right) - lnA_t\right]$$

$$log\left(\frac{w_t L_t}{P_t Y_t}\right) = ln\left(\frac{1-\bar{a}}{1+\mu}\right) + \frac{1-\sigma}{\sigma}\left[ln\left(\frac{Y_t\tilde{L}}{L_t\tilde{Y}}\right) - lnA_t - \gamma_L\right]$$

In this three-equation system of the normalized CES production function, there are three tough assumptions:

• There is a normal profit for each firm under perfect competition (markup (μ) = 0).

• There is only labor-saving technological progress (γ_K = 0, γ_L > 0).

• The growth rate of labor-saving technological progress is not time-varying (γ_L is constant).

In the second step of empirical investigation, two different regression models are estimated by using the EGLS method, which is not suffered from heteroskedasticity and autocorrelation problems, over the sample period in order to evaluate the effects of labor-saving technological progress on the workers in NASDAQ 100 firms. As can be seen in table 2, our balanced panel data used in this step includes 2 dependent variables, 3 independent variables and 8 dummy variables which refer to sub-sector of NASDAQ 100 firms. The technological growth variable that refers labor saving technological progress is obtained from estimation of a three-equation system of the normalized CES production function in the first step and this variable varies across firms but not the time. In this sense, the technological growth variable is a firm-specific variable and its estimated coefficient represents the effects of technological differences among firms on their capital accumulation and economic value added.

Model 1:

$$\log(cap\_accm) = \delta_0 + \delta_1 \log(techgrow) + \delta_2 log(subs) + \delta_3 \log(prod) + \delta_4 D_2 + \delta_5 D_3 + \delta_6 D_4 + \delta_7 D_5 + \delta_8 D_6 + \delta_9 D_7 + \delta_{10} D_8 + \delta_{11} D_9$$

Model 2:

$$\log(EVA) = \delta_0 + \delta_1 \log(techgrow) + \delta_2 log(subs) + \delta_3 \log(prod) + \delta_4 D_2 + \delta_5 D_3 + \delta_6 D_4 + \delta_7 D_5 + \delta_8 D_6 + \delta_9 D_7 + \delta_{10} D_8 + \delta_{11} D_9$$

Variable	Explanation	Type
cap_accm	Capital Accumulation	Dep. Var.
EVA	Economic Value Added	Dep. Var.
L	Labor (the number of workers)	Indep. Var.
compens	Compensation per employee	Indep. Var.
prod	Labor productivity	Indep. Var.
subs	Elasticity of substitution between capital and labor	Indep. Var.
unemp	Unemployment rate	Indep. Var.
D_1	1 if sector = Producer Manufacturing	Dummy, Base Group
D_2	1 if sector = Retail Trade	Dummy
D_3	1 if sector = Consumer Durables / Non-Durables	Dummy
D_4	1 if sector = Consumer Services	Dummy

D_5	1 if sector = Electronic Technology	Dummy
D_6	1 if sector = Health Technology	Dummy
D_7	1 if sector = Technology Services	Dummy
D_8	1 if sector = Other	Dummy

Table 2: Variables

Estimation Method

In order to achieve coefficients for explanatory variables in model 1 and model 2 along with their unbiased variances, Generalized Least Square (GLS) is used in this study. The general form of GLS method can be demonstrated as follow;

$$\hat{\beta}_{GLS} = (\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X})^{-1}\mathbf{X}'\hat{\Omega}^{-1}y$$

$$\widehat{Var}(\hat{\beta}_{GLS}) = (\mathbf{X}'\hat{\Omega}^{-1}\mathbf{X})^{-1}$$

where Ω matrix can be written in terms of Kronecker product;

$$\Omega = \Sigma_{m\times m} \otimes I_{T_i\times T_i}$$

The estimated variance matrix is derived by replacing Σ with its estimator ($\hat{\Sigma}$), as demonstrated in the following equation:

$$\hat{\Sigma}_{i\times j} = \frac{\hat{\epsilon}_i'\hat{\epsilon}_j}{T}$$

Estimation Results

This section includes estimation results of three equation systems of normalized CES production function at sector level and aggregate level, and those of two linear regression models as introduced in the previous section. First of all, Table 3 shows the estimation results of normalized CES production function at the aggregate level. According to these results, quarterly labor-saving technological progress in NASDAQ-100 firms has been estimated at 0.023 percent over the sample period at the aggregate level. The elasticity of substitution between capital and labor has been estimated at 0.52 percent. As can be seen in Table 3, all parameters of normalized CES production function are statistically significant.

Similarly, Table 4 shows the estimation results of normalized CES production function at the sector level. As can be seen from the first column, the highest labor-saving technological progress has taken place in the technology services sector. According to estimation results, labor-saving technological progress parameters of technology sectors have been estimated relatively greater than those of other sectors such as production/manufacturing, retail trade, and consumer durable/non-durable sectors.

Equation	**Obs.**	**Parms**	**RMSE**	**R-sq**
Log_gm_Y	2077	4	2.767787	-1.4764
Log_rK_PY	2077	3	0.4834833	0.9937
Log_wL_PY	2077	4	1.676791	0.9488
Parameter	**Coef.**	**Std. Err.**	**z**	**P Val.**
A	0.02318***	0.001184	19.58	0.0000
σ	0.5233299***	0.002436	21.48	0.0000

α	0.0653839***	0.0024161	27.06	0.0000
γ_L	-4.290118***	0.0547486	-78.36	0.0000
** p < 0.05, ** p < 0.01, *** p < 0.001*				

Table 3: Estimation Results of Three Equation System Normalized CES Production Function at Aggregate Level

As can be expected, the parameters of elasticity of substitution in technology firms have been relatively lower estimated than in other sectors except for the retail sector. The reason for this situation is that technology firms employ relatively more high-skilled workers such as engineers whereas other sectors such as manufacturing employ relatively more middle-skilled and low-skilled workers. Since middle-skilled workers conduct relatively more routine production processes, the elasticity of substitution between middle-skilled and capital can be greater than the elasticity of substitution between high-skilled labor and capital.

Similarly, low-skilled workers just like high-skilled workers conduct non-routine production processes. It is expected that the elasticity of substitution between low-skilled labor and capital is less than the elasticity of substitution between middle-skilled labor and capital. In the empirical investigation of this study, consistent with these reasonable expectations, the elasticity of substitution between labor and capital in manufacturing and consumer durable/ non-durable sectors has been found as relatively high compared to technology sectors.

Parameter / Sector	**A**	**σ**	**α**	γ_L	**Obs.**
Producer Manufacturing	0.00601*** (4.26)	0.604*** (63.57)	0.0701*** (10.23)	-6.961*** (-23.19)	79
Retail Trade	0.0230*** (5.84)	0.492*** (88.88)	0.0937*** (5.58)	-4.397*** (-26.37)	121
Consumer Durables / Non-Durable	0.0167*** (7.15)	0.570*** (93.05)	0.0435*** (12.80)	-6.765*** (-28.28)	130
Consumer Services	0.0197*** (5.28)	0.572*** (65.32)	0.0370*** (12.15)	-6.274*** (-25.69)	153
Electronic Technology	0.0274*** (10.45)	0.504*** (133.74)	0.0710*** (11.28)	-3.671*** (-41.47)	465
Health Technology	0.0250*** (10.40)	0.516*** (114.13)	0.0649*** (12.75)	-3.228*** (-33.12)	364
Technology Services	0.0299*** (9.84)	0.525*** (107.19)	0.0544*** (13.15)	-4.004*** (-41.66)	574
Other	0.0989*** (5.81)	0.502*** (56.55)	0.216*** (10.10)	-4.556*** (-23.25)	191
** p < 0.05, ** p < 0.01, *** p < 0.001* *t statistics in parentheses*					

Table 4: Estimation Results of Three Equation System Normalized CES Production Function at Sector Level

Table 5 shows the estimation results of Model 1 linear regression. According to these estimation results, there is a negative relationship between labor-saving technological growth and capital accumulation in NASDAQ-100 firms that employ relatively more high-skilled workers. As can be seen in the estimation results, the coefficient for productivity has been signed as positive while the coefficients for labor-saving technological growth and the elasticity of substitution have been signed as negative.

Dependent Variable: Log (Capital Accumulation)				
	Coef.	**Std. Err. (Robust)**	**t**	**P Value**
log(techgrow)	-0.0730874***	0.0176784	-4.13	0.000
log(subst)	-1.01936*	0.4022653	-2.53	0.011
log(unemp)	0.0841776	0.0727127	1.16	0.247
log(prod)	0.1211759***	0.0175988	6.89	0.000
D_2	0.9139291***	0.1703257	5.37	0.000
D_3	0.2551691	0.1530232	1.67	0.096
D_4	0.4050328*	0.1653311	2.45	0.014
D_5	0.3362178*	0.1429027	2.35	0.019
D_6	0.4365955**	0.1423316	3.07	0.002
D_7	0.3455227*	0.1380653	2.5	0.012
D_8	-0.0830778	0.1444265	-0.58	0.565
constant	-4.242989***	0.3960933	-10.71	0.000
Number of Obs	2317			
F (11, 2305)	14.27			
Prob> F	0.0000			
R-squared	0,07			
Root MSE	1,109			
** p < 0.05, ** p < 0.01, *** p < 0.001*				

Table 5: Estimation Results of Model 1

The labor-saving technological growth mitigates capital accumulation in these firms. In these firms, the majority of which are in the technology sector, the sources of capital accumulation seem to be capital-saving technological progress, operating / non-operating profit, and the upward trend of productivity instead of labor-saving technological growth and the elasticity of substitution between labor and capital. In addition, p-values of dummy variables indicate that the difference in capital accumulation between sub-sectors is statistically significant.

Dependent Variable: Log (Economic Value-Added)				
	Coef.	**Std. Err. (Robust)**	**t**	**P Value**
log(techgrow)	0.6691425***	0.0153272	43.66	0.000
log(subst)	6.963918***	0.3326262	20.94	0.000
log(unemp)	-0.2295155***	0.0590604	-3.89	0.000
log(prod)	0.6180898***	0.0155550	39.74	0.000
D_2	-0.2172985	0.1338715	-1.62	0.105
D_3	-0.5664937***	0.1487816	-3.81	0.000
D_4	-0.2055552***	0.1211624	-1.70	0.000
D_5	-0.5974592***	0.1093635	-5.46	0.000
D_6	-1.226017***	0.1113203	-11.01	0.000
D_7	-0.7318411***	0.1064963	-6.87	0.000
D_8	0.1743686	0.1136715	1.53	0.125
constant	17.08807***	0.3168435	53.93	0.000
Number of Obs.	3289			
F (11, 2305)	474.90			
Prob> F	0.0000			
R-squared	0,6226			
Root MSE	1,1422			
** p < 0.05, ** p < 0.01, *** p < 0.001*				

Table 6: Estimation Results of Model 2

Table 6 shows the estimation results of Model 2. According to these results, even though an increase in labor-saving technological growth leads to a decrease in capital accumulation, it positively contributes to economic value-added. Actually, it seems that there is a conflict regarding the effects of labor-saving technological growth on capital accumulation and economic value-added. Since economic value-added is recognized as a function of capital accumulation, it is expected that the variable that accelerates economic value-added must accelerate capital accumulation. However, an increase in labor-saving technological progress could have accelerated not only economic value-added produced by firms but operating costs also. Therefore, operation costs arising mainly from an increase in labor-saving technological progress might have pressured capital accumulation accelerated by labor-saving technological progress.

Another main finding is that an increase in the elasticity of substitution between capital and labor leads to an increase in the economic value-added of firms. As can be expected, there is a positive relationship between productivity and economic value-added. As can be seen from the coefficients for dummy variables, there is a significant difference in economic value-added among firms operating in different sectors.

Robustness Check

Our panel data analysis can be broken down into three main parts after estimation of three equation system of normalized CES production function to obtain labor saving technological progress and elasticity of substitution between capital and labor. The first part investigates presence of unit roots in the panels through the application of two distinct unit root tests. As can be seen in Table 7, null hypothesis, which indicates panels contain unit roots, has been rejected according to both Dickey-Fuller and Phillips-Perron approaches. Since labor-saving technological growth and elasticity of substitution variables have been obtained by fitted production function, their test statistics could not be generated.

	Dickey Fuller				Phillips Perron			
Variables	**Inv. χ^2**	**Inv. Normal**	**Inv. Logit**	**Mdf. Inv. χ^2**	**Inv. χ^2**	**Inv. Normal**	**Inv. Logit**	**Mdf. Inv. χ^2**
ln(productivity)	924.93*	-21.71*	-27.07*	40.59*	716.94*	-12.50*	-18.42*	29.11*
ln(economic VA)	881.70*	-20.15*	-25.57*	38.26*	756.74*	-10.97*	-18.58*	31.23*
ln(unemp)	1036.07*	-25.23*	-28.27*	41.19*	464.22*	-12.78*	-12.07*	12.88*
ln (cap. accm.)	901.15*	-17.06*	-22.96*	35.33*	2307.01*	-38.31*	-63.23*	105.3*
ln(tech. growth)	-	-	-	-	-	-	-	-
ln(subst. elast.)	-	-	-	-	-	-	-	-
**: p-value <0.01, **: p-value <0.05, null hypothesis: panels contain unit roots*								

Table 7: Unit Root Tests

In the subsequent part of panel data analysis in this study, Hausman test has been conducted to ascertain whether random or fixed effect model is statistically appropriate. Table 8 presents the coefficients for unemployment and productivity derived from both fixed and random effect methods. Since technological growth and elasticity of substitution variables are firm-specific but not time-varying variables, the results of the Hausman test do not include the coefficients for these two variables. According to the results of Hausman test we implement, the null hypothesis, which indicates the random effect model is appropriate, cannot be rejected for both models. Since we cannot reject the null hypothesis against the alternative one that indicates fixed effect method is appropriate, we have implemented random effect model in this study.

Models →	**Model 1**		**Model 2**	
Variables →	**log_unemp**	**log_prod**	**log_unemp**	**log_prod**
Fixed Effect	0.773399	0. 098083	-0.2456467	0.6182765
Random Effect	0.0841776	0. 1211759	-0.2295155	0.6180898
Difference	-0.0068377	-0.023093	-0.0161312	0.0001867
Diag² Std. Error	0.0078632	0.0147484	0.0038086	0.0007141
χ^2	2.37		17.12	
Prob.	0.3062		0.1044	
null hypothesis: the random effect model is appropriate				

Table 8: Hausman Test

In the third part of analysis, Wooldridge serial correlation test has been carried out due to the absence of a strictly balanced panel data set. Table 9 shows the autocorrelation test results of random effect models estimated by generalized least squared (GLS) method. The results show there are strong evidence that random effect model involve heteroskedasticity.

In order to address to autocorrelation problem in random effect model estimated by GLS, we have conducted a similar test for first difference random effect model. However, the findings presented in Table 10 indicate that employing the first difference of variables may not be a sufficient approach for mitigating potential statistical errors that mostly arise due to the presence of autocorrelation.

Models →	**Model 1**		**Model 2**	
Variables →	**Var.**	**Std. Dev.**	**Var.**	**Std. Dev.**
Dependent Variable	1.305233	1.142468	3.44543	1.856187
e	1.058888	1.0290228	0.551471	0.742611
u	0.386406	0.6216159	0.416540	0.645399
Random Effects, Two Sided† (~χ^2)	510.11	0.0000	20724.74	0.0000
Random Effects, One Sided† (~N)	22.59	0.0000	143.96	0.0000
Serial Corr. ⁑ (~χ^2)	35.79	0.0000	495.76	0.0000
Joint Test†⁑ (~χ^2)	635.48	0.0000	23239.35	0.0000
$y_{i,t} = \boldsymbol{X}\beta + u_i + v_{i,t}$ $v_{i,t} = \lambda v_{i,t-1} + e_{i,t}$				
†:ALM(Var(u)=0), ⁑:ALM(λ=0) , †⁑:LM(Var(u)=0, λ=0)				
null hypothesis: no first-order autocorrelation				

Table 9: Wooldridge Autocorrelation Test

Models →	**Model 1**		**Model 2**	
Variables →	**log_unemp(-1)**	**log_prod(-1)**	**log_unemp(-1)**	**log_prod(-1)**
Coefficient	0.217494	0.0272321	-0.0012856	0.9704916
Robust St. Error	0.1433575	0.0592452	0.0088933	0.0103583
P-value	0.134	0.647	0.885	0.000
F (1, 66), F(1, 69)	4.981		862.010	
Prob. > F	0.029		0.0000	
null hypothesis: no first-order autocorrelation				

Table 10: The First-differenced Regression Results and Wooldridge Autocorrelation Test

Furthermore, within the context of panel data analysis, the Breusch-Pagan Lagrange Multiplier (LM) test has been employed to examine random effect models. The findings presented in Table 11 provide compelling evidence about the presence of heteroskedasticity.

Hence, the presence of both autocorrelation and heteroskedasticity can lead to discrepancies between the estimated variances of variables and their actual values, resulting in type I or type II errors, despite the statistical appropriateness of estimating a random effect model using GLS.

Models →	**Model 1**		**Model 2**	
Variables →	**Var.**	**Std. Dev.**	**Var.**	**Std. Dev.**
Dependent Variable	1.305233	1.142468	3.44543	1.856187
e	1.058888	1.029023	0.551471	0.742611
u	.3864064	.6216159	0.416540	0.645399
$\bar{\boldsymbol{X}}^2(\mathbf{01})$	599.69		22743.59	
$\mathbf{Prob.} > \bar{\boldsymbol{X}}^2$	0.0000		0.0000	
$y_{i,t} = \boldsymbol{X}\beta + u_i + e_{i,t}$				
null hypothesis: no heteroskedasticity				

Table 11: Breusch and Pagan LM Test for Random Effects

When we obtain coefficient for explanatory variables with their robust variance, we have adopted special version of GLS method to avoid implications arising mainly from heteroskedasticity and autocorrelation and to obtain correct inferences about consistency and unbiasedness. Under the concepts of autocorrelation and heteroskedasticity, the variance structures can be illustrated as follows;

Under correlation across panels (cross-sectional correlation);

$$\Omega = \begin{bmatrix} \sigma_{1,1}^2 I & \sigma_{1,2}^2 I & \cdots & \sigma_{1,m}^2 I \\ \sigma_{2,1}^2 I & \sigma_{2,2}^2 I & \cdots & \sigma_{2,m}^2 I \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m,1}^2 I & \sigma_{m,2}^2 I & \cdots & \sigma_{m,m}^2 I \end{bmatrix}$$

Under heteroskedasticity:

$$\Omega = \begin{bmatrix} \sigma_1^2 I & 0 & \cdots & 0 \\ 0 & \sigma_2^2 I & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_m^2 I \end{bmatrix}$$

However, since autocorrelation parameter (ρ) is not available, instead of random effects model by using GLS estimator, the GLS method with the "Estimated" type (EGLS) has been used in this study to address implications arising from heteroskedasticity and autocorrelation. Thus, we have successfully implemented above variance structure with estimated ρ value into GLS method as described in the previous subsection under "estimation method". This implementation has resulted in the attainment of unbiased and consistent variances for explanatory variables.

Conclusions

The advent of labor-saving technological advancements has resulted in a dual effect of stagnant labor compensation and heightened labor productivity. The impact of technology advancements on capital accumulation is substantial, as evidenced by these two outcomes. This study aims to examine whether there are variations in the capital accumulations of firms resulting from technical advancements based on their respective operational sectors.

In order to obtain labor-saving progress for NASDAQ-100 firms that employ a higher proportion of high-skilled workers, the normalized CES production function with three equations has been estimated for the sample period from 2000/Q2 to 2021/Q3. After obtaining labor-saving technological progress of these firms, a comprehensive investigation offering insight into the impact of labor-technological progress on the capital accumulations of the NASDAQ-100 firms has been conducted by using linear regression models. Furthermore, the estimation outcomes have been assessed with respect to the operational sub-sectors of these companies by incorporating eight distinct dummy variables that reflect the sectors into the models.

Based on the findings of the estimation results, it can be observed that the labor-saving technical advancements have a detrimental impact on the capital accumulation inside technology firms that have a higher proportion of highly skilled employees, as opposed to firms operating in sectors such as services, consumer durables, and non-durables. This implies that the advancement of labor-saving technology serves to alleviate the growth of capital accumulation within technology firms. Another notable finding is that in technological firms, an increase in the elasticity of substitution between capital and labor leads to a decrease in capital growth. Nevertheless, both variables have a positively effects on economic value added despite their negative effects on capital accumulation.

When considering these two notable findings collectively, they aligns with the notion of skill intensity in the technology firms. The labor-saving technologies have the potential to efficiently automate routine and low-skilled tasks that need lower levels of competence. However, their effectiveness in replacing highly-skilled workers may be limited due to costs of its implementation. During periods of profit expansion, the adverse impact of technological progress and insufficient automation on the accumulation of capital in technology firms leads to a progressive widening of the gap between labor productivity and labor compensation. During periods characterized by downsizing, this negative consequences on capital accumulation are mitigated by worker layoffs, notwithstanding the considerable effect it has on the overall economic value added.

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Özet

Kapitalist ekonominin en temel yapı taşlarından biri olan sermaye birikimi, Marksist iktisat teorisine göre emek sömürüsüne neden olmaktadır. Günümüz çalışmalarında klasik modellerin kullanılması, sermaye birikimini ve işgücü piyasasını doğrudan etkilediği varsayılan teknolojik ilerlemenin etkilerini göz ardı edebilmektedir. Tam bu noktada, teknolojik ilerlemeyi ekonometrik modellemelere eklemek tek başına yeterli olmamakta, aynı zamanda bu modelleri türlerine veya işlevlerine göre ayırt etmek de önem arz etmektedir. Kritik nokta, ne tür bir teknolojik ilerlemenin hangi vasıflı işçiyi ne şekilde etkilediğini bulmaktır.

Teknoloji, emek tasarrufu sağlayan ve sermaye tasarrufu sağlayan teknolojik ilerleme olarak ikiye ayrılabilir. İş gücü ise niteliklerine göre düşük, orta ve yüksek vasıflı işçi olarak üç ana gruba ayrılabilmektedir. Girdi tasarrufu sağlayan teknolojik ilerlemenin emek verimliliğinde artışa ve emeğin bedelinde azalmaya yol açması, emeğin katma değer içindeki payının azalmasına ve katma değer içindeki sermayenin payının artmasına neden olmuştur. Bununla birlikte, girdi tasarrufu sağlayan teknolojik ilerlemenin etkisi her işçiyi eşit şekilde etkilememektedir. Teknolojik ilerleme hemen hemen her işçinin üretkenliğini artırmış olsa da, bu ilerlemenin orta vasıflı işçilerin emek bedelinin düşük vasıflı ve yüksek vasıflı işçilere göre yeterince artırmadığı görülmektedir.

Bu çalışma, farklı vasıflı işçilerin firmaların sermaye birikimine katkılarındaki farklılıklara odaklanmayı amaçlamaktadır. Ekonomide bulunan diğer firmalara göre görece daha yüksek vasıflı işçi çalıştırdığını kabul ettiğimiz NASDAQ-100 firmaları çalışmamızın temelini oluşturmaktadır. Çalışmanın ampirik kısmında, 2000/Ç2'den 2021/Ç3'e kadar olan örnekleme döneminde NASDAQ-100 firmalarının sektörel düzeyde ve toplam düzeyde normalleştirilmiş CES üretim fonksiyonunun üç denklemli sistemi tahmin edilmiştir. Elde edilen emek tasarrufu sağlayan teknolojik ilerleme, daha sonrasında doğrusal bir regresyon modeli kullanılarak EGLS tahmin yöntemi ile bu firmaların sermaye birikimi üzerindeki etkilerini tahmin etmek için kullanılmıştır. Ayrıca ikinci aşamada, açıklayıcı değişkenler olarak bu lineer regresyon modeline firmaların faaliyet sektörlerini temsil eden kukla değişkenler, işgücü verimliliği, emek ve sermaye arasındaki ikame oranı ve işsizlik oranı eklenmiştir.

Elde edilen sonuçlara göre, teknoloji firmalarında emek tasarrufu sağlayan teknolojik ilerlemenin sermaye birikimindeki artışı azalttığı ve bu teknoloji firmalarında sermaye ve emek arasındaki ikame esnekliği arttıkça sermaye birikiminin azaldığı gözlemlenmiştir. Ayrıca emek tasarrufu sağlayan teknolojik ilerlemenin sermaye birikimine etkisi açısından sektörler arasında önemli farklılıklar bulunmuştur. Emek tasarrufu sağlayan teknolojik ilerlemenin hem emek bedelinde bir durgunluğa yol açtığı gözlemlenmiş ancak diğer bir yandan emek verimliliğinde artışa neden olduğu sonucuna varılmıştır.