

The Economics of Human Capital Misallocation and Long-Run Value Destruction

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Abstract: - In modern organizations, human capital is not merely an operational resource but a strategic asset, and its misallocation results in value destruction. This paper examines human capital misallocation as a structural source of economic inefficiency. The paper assesses the long-term effects on organizational value by integrating perspectives from labor economics and corporate finance using econometric analysis. The theoretical framework is based on the perception of human capital as a semi-fixed production factor, in which structural mismatches reduce marginal productivity and distort the use of resources, resulting in negative organizational outcomes. The article develops a dynamic conceptual model that captures the mechanisms through which human capital misallocation leads to productivity losses. In conclusion, the findings indicate that inefficient human capital allocation constitutes a structural economic problem that limits the potential of organizational growth and systematically destabilizes long-term financial sustainability.

Key-Words: - Human Capital Misallocation, Organizational Frictions, SG&A Intensity, Return on Assets, Corporate Profitability

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1 Introduction

In modern organizations, human capital is more than an operational factor, an investable and strategic-oriented asset whose value depends on skills, tasks, and organizational structure. The theoretical basis of human capital views the resources “embedded” in people as an investment that affects productivity and income progressions over time, thus creating a basis for assessing the allocation of human capital not only in terms of employment status but also in terms of value creation dynamics [1]. From this perspective, human capital misallocation represents a structural economic problem: it creates a systematic mismatch between skills and job demands and leads not to one-time damage, but to cumulative consequences over time – reduced productivity, distortions in internal labor markets, suboptimal use of managerial resources, and long-term value erosion. The literature on skills mismatch views this process as multidimensional, distinguishing macro-level imbalances, shortages, and job incompatibility, each having distinct effects on productivity [2]. Yet, the analysis of misallocation often becomes a discussion of measurement, where the main question is “how much” the imbalance is, rather than “how it works” within the organization. Moreover, measured misallocation is not always a reliable analogue of

welfare loss: if recorded deviations result from market failures rather than policy distortions, standard benchmarks may mislead, and second-best solutions may appear suboptimal [3]. Consequently, a framework is needed that simultaneously provides (a) conceptual clarity, (b) discipline for causal interpretation, and (c) openness to organizational mechanisms [4].

The literature often divides the discussion of this problem into two parallel strands. The first, macro misallocation framework connects resource distortions to overdispersion of marginal products and aggregate productivity losses [5]. Second, it is mismatch studies that provide important empirical indicators, but regularly remain at the level of „accounting“ for mismatches, yet do little to establish an integrated mechanism that would link organizational decisions to the long-term value [6]. Because of this gap, it is often unclear when observed imbalances are a result of organizational constraints/market failures and when of policy distortions, which directly defines the limits of interpretation [7].

A terminological distinction is critical for this paper. Mismatch typically describes a mismatch between skills/qualifications and job requirements and includes macro mismatch, shortages, and on-the-

job mismatch [8]. Misallocation, on the other hand, forms a broader condition: it refers to the distribution of labor (and other factors) in such a way that marginal outputs (or price-weighted marginal revenue) differ systematically across units, indicating distortions, constraints, or incomplete markets [9]. Therefore, mismatch is considered in this paper as a micro-manifestation/signal, while misallocation is considered as a structural basis that is transformed into long-term outcomes through specific channels within an organization.

Building on the preceding terminological distinction, the macro logic of misallocation provides a clear intuition: when distortions create excessive dispersion of marginal outcomes across units, aggregate productivity falls. Operational expressions of this idea often use measures such as $\log(\text{TFPR})$ dispersion to capture the severity of these distortions. Our task is to transfer this logic to human capital so that the outcome does not remain just an abstract indicator, but is explained in the language of internal organizational decisions [10].

To move beyond abstraction, it is important to recognize that, without considering internal decisions, misallocation is still a “black box”. Labor allocation often occurs not only in the market but also within firms through processes such as appointments, transfers, promotions, and training allocation [11]. By this logic, internal labor markets are the spaces where the market price mechanism is often replaced by managerial coordination and internal rules in the allocation of assets. Accordingly, explaining human capital misallocation only in terms of “skills shortages” or “education systems” is insufficient – we need to understand how mismatches influence internal allocative decisions.

Within this context, managerial decisions in labor allocation are especially important: internal appointments, transfers, and job adjustments create a channel through which skill mismatches may be reinforced or, conversely, reduced. It should be noted that internal transfers can also be a practical mechanism for reducing misallocation.

The approach of this paper combines operational indicators of mismatch with a structural interpretation of misallocation, while strictly considering the risks associated with the measurements [12]. Variance-based measures are sensitive to data quality and measurement errors; therefore, any assessment of misallocation must rely on a clear identification logic so that the “noise” in the variance does not turn into a real distortion. At the same time, the multidimensionality of mismatch obliges us not to link productivity outcomes to a general “mismatch”

but to consider which dimension is connected to organizational dynamics [13].

On this basis, the main research question of the paper is: How and through which channels does human capital misallocation cause productivity losses at the organizational level and ultimately long-term value erosion? As sub-questions we consider the followings: (i) which dimensions of mismatch are most closely related to the trajectory of productivity/organizational outcomes; (ii) how the architecture of internal labor markets and managerial decisions affect the allocation of labor; (iii) how to construct an assessment so that interpretation does not go beyond its limits and does not introduce the effect of measurement error.

Accordingly, the contribution of the paper can be read in three parts. First, we propose a dynamic conceptual model in which mismatch is the initial signal, and misallocation is a structural condition that, through a chain of internal decisions, leads to accumulated losses and value decline over time. Second, we connect the macro logic of misallocation (the dispersion of marginal outcomes) to certain organizational channels, so that the idea of “wedges” is not just indicative. Third, we identify internal labor markets as a central channel through which internal movements can reduce gaps in the marginal income productivity of labor across units, therefore providing a practically interpretable basis for the dynamics of misallocation.

2 Conceptual framework and model

First, we interpret mismatch as a process signal: when a person’s competence and job requirements do not match, the cost of error increases, and output per asset declines. Similar connections are also seen in studies of skill mismatch [14]. The problem can become persistent if internal assignment rules, allocation flexibility, and managerial quality do not allow the system to correct itself. In such cases, the quality of matching and management becomes a key determinant of productivity [15]. These mechanisms directly affect return on assets (ROA): asset utilization becomes less profitable, and the costs associated with coordination and supervision often increase. Interest Coverage is pressured because of operating results, while the financial burden, such as interest expenses, remains the same or increases, especially if the firm tries to “cover” problems with debt. We empirically test this relationship using a panel model, in which $\text{Outcome}_{\{i,t+1\}}$ is explained by $\text{Misallocation}_{\{i,t\}}$, with controls and fixed effects.

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The Interest Coverage channel is more sensitive and often produces a “heavier” result. If operating income (EBIT/EBITDA) weakens, while interest expense is fixed or rising, the coverage ratio falls significantly. This is especially true when the firm is trying to finance internal problems with debt or is already operating with high leverage.

The impact of human capital misallocation on financial performance is not immediate; it typically works through intermediate organizational and operational channels. When employees’ skills or roles do not match job requirements, performance errors, coordination delays, rework, and supervision costs increase. As a result, assets are used less productively, linking misallocation to lower operating efficiency and, subsequently, to lower ROA and weaker solvency indicators.

The role of controls in this model is pragmatic: if we do not take into account size, industry, asset structure, and leverage, misallocation may simply become a “shadow” of other factors. For example, return on assets (ROA) behaves differently in capital-intensive industries compared to the service sector, and Interest Coverage is more sensitive to the debt structure than to the operational effect. Accordingly, theoretically, we rely on a comparable framework: misallocation is an independent source that affects productivity and subsequently financial indicators. However, the magnitude of the effect depends on the context of the industry [16]. Thereby, identical shock or mismatch may be dangerous for one company but not for another [17].

In this conceptual model, two related but analytically distinct channels are distinguished. The first channel reflects the impact on operational performance and ultimately on ROA: internal misallocation reduces the combined efficiency of labor and assets, which reduces the financial result obtained per unit of assets. The second channel relates to Interest Coverage: when misallocation weakens EBIT/EBITDA while interest expense remains unchanged or increases, the firm’s ability to service its debt significantly declines. Accordingly, ROA and Interest Coverage do not express the same financial response – the former more clearly reflects the efficiency of asset use, while the latter is more sensitive to the combined impact of operational weakness and financial burden.

The most important danger in the identification logic is the confusion of cause and effect. Weak ROA may lead to misallocations, as firms lack resources for proper selection, retraining, or restructuring. For this reason, we use lagged results ($t+1$) and fixed effects as “guards” to avoid overstating causal interpretations [18]. In addition, measurement error is another

concern. If the misallocation index is noisy, the effect can either be reduced or, conversely, amplified [19]. Standard errors are computed conservatively; the empirical strategy is presented stepwise, from baseline OLS to Year FE and Firm FE specifications to assess how stable the main relationship remains under progressively stricter controls.

Figure 1 summarizes the two main channels examined in this study: misallocation to operating performance and ROA, and misallocation to weaker operating income, ultimately leading to lower Interest Coverage. Conceptually, the figure connects the macroeconomic logic of misallocation as a source of productivity loss with the micro-level perspective of job matching and managerial coordination. In this way, the model links internal organizational frictions to observable financial outcomes

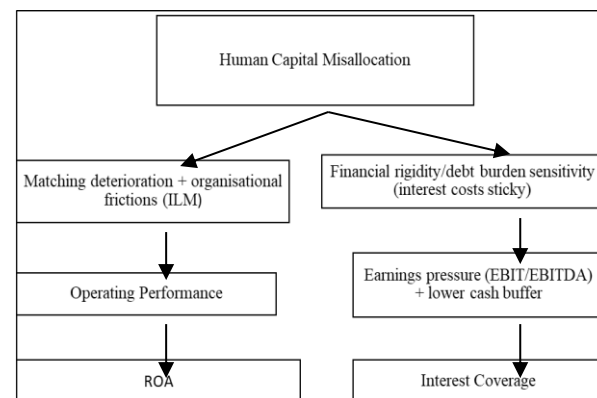


Fig. 1: Conceptual model: Human misallocation > ROA and Interest Coverage

Source: designed by authors

The left side of the figure shows that the misallocation of human capital primarily impairs the matching of work, role, and competence, which creates organizational friction in the internal labor market. Under such conditions, operational performance decreases: coordination time increases, the need for rework appears, decision quality weakens, and the use of assets becomes less productive. The final financial expression of this process is a decrease in ROA, as the firm produces relatively less output from the same assets. The right side of the figure illustrates the second channel, which is related to solvency and financial stability. Under misallocation conditions, weakening operating income directly reduces EBIT/EBITDA, while interest expense is typically less responsive in the short term. If a firm is already highly leveraged or is trying to cover internal problems with debt, this asymmetry is even more pronounced. As a result, Interest Coverage deteriorates more quickly and sharply than some other profitability indicators. This

is why Figure 1 presents ROA and Interest Coverage as two distinct, yet related, financial outcomes of misallocation. To illustrate, such a mechanism is particularly easy to imagine when a firm allocates employees not based on skills but on administrative convenience, internal inertia, or weak managerial judgment. In such an environment, a critical function may end up in the hands of an employee with less appropriate competence, while a better-suited resource is unused or placed in the wrong position. In the short term, this often manifests itself not in an immediate collapse but in a deterioration in performance, a slowdown in processes, increased supervision, and the need for rework. As a result, the firm's operating results weaken, and if this is accompanied by a persistent debt service burden, the negative effect on Interest Coverage is particularly severe.

On this basis, the following hypotheses are proposed. H1: Higher misallocation is associated with lower ROA in the subsequent period, as asset utilization loses productive connections and operational friction increases. H2: Higher misallocation is associated with lower Interest Coverage, as operating income declines, and the interest burden becomes more pronounced in the coverage ratio.

The strength of these two relationships will not be the same in all firms. For example, in highly leveraged companies, Interest Coverage reacts faster because interest expense persists and has the ability to amplify even minor operating losses. On the other hand, ROA is more sensitive to asset structure and business model. In the capital-intensive industries, asset turnover and operating cycle are significant factors, while in service industries, the dynamics are different. Therefore, we expect the misallocation effect to be stronger where the possibility of correction is low (internal allocation is difficult, management quality is poor, or market shocks are frequent) and to be relatively weaker where matching improves quickly.

3 Results and Discussion

The data come from annual financial records of the largest U.S. public companies from 2014 to 2024. Each record represents one company per year, so we can track financial results and internal factors, organizational friction, and efficiency losses [20], [21], [22], [23], [24]. The sample includes firms from various industries, which is important because profitability, asset structure, and debt sensitivity differ across sectors. This diversity highlights the need for control variables and fixed effects to ensure the

misallocation effect does not merely reflect structural differences between industries.

We use return on assets (ROA) as our main outcome variable, calculating it with average assets to avoid the effects of one-time changes in the balance sheet.

$$AvgAssets_{it} = \frac{Assets_{it} + Assets_{i,t-1}}{2}$$

$$ROA_{it} = \frac{NetIncome_{it}}{AvgAssets_{it}}$$

We take SG&A intensity (SG&A/Revenue) as the main definition/proxy for misallocation, because this indicator practically reflects overhead, coordination costs, and excessive administrative burden in relation to sales.

$$Misalloc_{it} = \frac{SGA_{it}}{Revenues_{it}}$$

Using this approach, we test whether increasing internal frictions lowers profitability [25].

Along with the explanatory variable, we added control variables commonly used in financial research: company size (log assets), financial leverage (leverage=total_debt/assets), capital intensity (cap_intensity=ppe/assets), and sales growth (sales growth). These controls help ensure that the effect of SG&A intensity is not just due to differences in size, debt structure, or growth cycles (Table 1).

Table 1. Descriptive statistics (Main Variables)

Variable	N	Mean	StdDev	Min	Median	Max	Missing%
ROA_w1	1759	0,04855303	0,07127054	-0,1806115	0,03103769	0,28251039	0
log_assets	1759	24,259438	1,32577142	19,2530723	24,3427148	28,8132142	0
leverage	1759	0,28408172	0,22852691	0	0,27136665	2,44116223	0
cap_intensity	1759	0,25317349	0,25700507	0,00093027	0,13140405	0,95809309	0
sales_growth	1759	0,41241036	1,84334805	-6,9704307	0,07070187	45,0898452	0
misalloc_A_w1	1043	0,39222116	0,41673795	0,01406452	0,24419078	2,46373583	0,40704946

Source: designed by authors

Table 1. shows the distribution of the main variables, their central tendencies, and ranges, which are necessary for the correct interpretation of the subsequent regression estimates. First, the mean value of ROA_w1 is positive, but the difference between the minimum and maximum indicates that the sample combines both relatively weak and significantly better financial results. On the other hand, the difference between the mean and median values of misalloc_A_w1, as well as its high maximum, indicates that the intensity of administrative costs in some firms significantly exceeds the typical level of the sample. This is important as it provides a dispersion that allows us to check whether an increase in misallocation is associated with a deterioration in ROA. Table 1 also justifies the use of controls in the subsequent model. Log_assets, leverage, cap

intensity, and sales growth show distinctly different magnitudes and variances, indicating that firms are not homogeneous in size, capital structure, and growth dynamics. Therefore, estimating the effect of misallocation without controlling for these factors would be inadequate. At the same time, the Missing% of misalloc_A_w1 shows that this variable is not available for all observations, which is why the final sample used in Table 2 is smaller than the full initial array

We test whether the misallocation proxy (misalloc_A_w1) is linked to a decrease in ROA, while controlling for other factors.

$$ROA_{it} = \alpha + \beta * Misalloc_{it} + \gamma' * X_{it} + \delta_t + \varepsilon_{it}$$

X_{it} - is a vector of controls (log_assets, leverage, cap_intensity, sales_growth)

δ_t = denotes year fixed effects capturing common macroeconomic shocks

i = firm

t = fiscal year

β = captures the association between the misallocation proxy and profitability, holding the control variables constant

ε_{it} = is the idiosyncratic error term; standard errors are computed conservatively

As a robustness check, we also estimate a lagged specification where $ROA_{\{i,t+1\}}$ is explained by $Misalloc_{\{it\}}$, to reduce concerns about contemporaneous reverse causality.

The econometric analysis follows a stepwise logic. In the first step, a baseline OLS specification is estimated, providing an initial indication of the sign and strength of the association between the misallocation proxy and ROA. In the next step, year fixed effects are introduced into the model to control for common time-related shocks that may affect all firms simultaneously – for example, macroeconomic cycles, changes in the interest rate environment, or broader market fluctuations. This sequence is important because it shows how stable the misallocation effect is under stringent specifications.

First, we show the baseline OLS (ordinary least squares) estimate, followed by the year fixed effects. This helps ensure that common macroeconomic changes and shocks, which can affect many companies at once, do not distort the results. In addition, an important step in the econometric extension is to account for unobserved heterogeneity across firms. The same ROA can be partially explained by stable characteristics such as managerial culture, business model, sectoral positioning, or the historically established structure of internal processes. If these factors are not controlled in the model, the misallocation coefficient may partially capture their effects. Accordingly, additional fixed effects

specifications are needed to make the estimate rely more on within-firm variability over time and less on stable differences between firms. It is best to present these results in a single table with both specifications, so we can clearly see how the effect holds up after adding controls. Thus, the estimation strategy can be interpreted as a sequential expansion of specifications. At the initial stage, the OLS model provides a general associative picture, while year fixed effects reduce the impact of common time shocks. Further fixed-effects specifications are especially important when the study aims to control for the impact of unobservable, firm-specific characteristics. In such a case, the misallocation coefficient already reflects more clearly how changes in internal organizational friction are related to changes in profitability over time.

Table 2. presents the main results of the regression analysis, while subsequent tables and additional statistical tests – including ANOVA – expand the empirical evidence and provide the reader with a more complete connection of the identified relationship

Table 2. Regression results (Ordinary Least Squares vs Year Fixed Effects)

Variable	OLS	Year FE
misalloc_A_w1	-0,0579	-0,0425
	-3,29E-29	-3,80E-16
log_assets	-0,0019	-0,0038
	(-0,2353784970533	-0,015764006
leverage	-0,0046	-0,0051
	-0,652776885	-0,608191935
cap_intensity	-0,0476	-0,0335
	-6,17E-07	-0,000335513
sales_growth	-0,0020	-0,0028
	-0,031031359	-0,002039335
Year fixed effects	No	Yes
Observations	1043	1043
R-squared	0,1251	0,1921

Source: designed by authors

It presents the main empirical results of the study and shows the relationship between misalloc_A_w1 and ROA across three specifications – the baseline OLS model, the Year FE model, and the Firm FE model. In all three specifications, the coefficient on misalloc_A_w1 is negative, consistent with the study's main hypothesis: an increase in administrative intensity, as a proxy for internal misallocation, is associated with lower profitability. Of particular importance is the fact that the coefficient remains negative across the expanded set of specifications, including both Year FE and Firm FE models. This indicates that the result is not simply a subject of the general macroeconomic or sectoral background of specific years.

At the same time, Table 2 shows that the model's explanatory power increases after adding year fixed effects, confirming that accounting for time factors is important. Nevertheless, the effect of `misalloc_A_w1` remains negative and statistically significant, which increases confidence that the observed relationship is not explained solely by differences in size, leverage, capital intensity, or sales growth. In other words, the obtained result is consistent with the argument that SG&A/Revenue intensity may reflect internal organizational frictions that are independently associated with the deterioration of ROA.

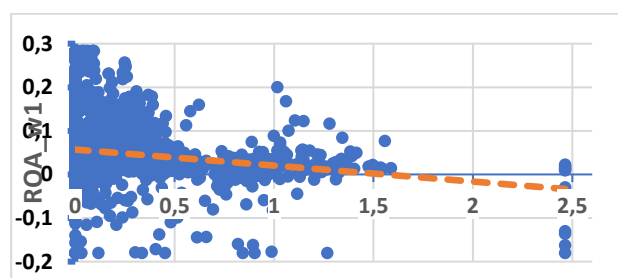


Fig. 2: ROA and misallocation proxy (SG&A/Revenue)

Source: designed by authors

Figure 2 is a scatter plot that shows the direction of the relationship between `misalloc_A_w1` and `ROA_w1` at a descriptive level. Although the observations are heterogeneous and there is a sharp scatter in the data, the overall picture is consistent with the basic expectation: higher misallocation values are, on average, associated with lower ROA. Such visual evidence should not be interpreted as a causal inference; its function is more intuitive: to show the reader that, at the descriptive level, the data also point in the same direction as is captured in the subsequent regression estimates.

A descriptive image gives us a quick look at the sample size and the typical ranges of the variables before discussing causal interpretation. The distributions of ROA and SG&A/Revenue proxies have some extreme values, so we use winsorization as a practical way to prevent a few outliers from distorting the overall results (see Table 1).

While a correlation matrix is not strictly necessary, it can be valuable when applied briefly and with clear intent. It shows us whether the misallocation proxy moves in the expected direction with ROA and whether it has such a high correlation with the controls that it creates a risk of multicollinearity. At this point, we are not establishing definitive proof with the correlation matrix; rather, we are checking that the data show logical signs, then proving this with regression specifications (see Table 3).

Table 3. Pairwise Correlations Between Main Variables

Column1	ROA_w1	log_assets	leverage	cap_intensity	sales_growth	misalloc_A_w1
ROA_w1	1	-0,04891225	0,04209591	-0,061973913	-0,013788984	-0,308493324
log_assets	-0,0489123	1	-0,167022	0,067453913	-0,022551033	-0,112769856
leverage	0,04209591	-0,16702197	1	0,154552103	0,032094001	-0,07139306
cap_intensity	-0,0619739	0,067453913	0,1545521	1	0,01312004	-0,190382581
sales_growth	-0,013789	-0,02255103	0,032094	0,01312004	1	-0,029782974
misalloc_A_w1	-0,3084933	-0,11276986	-0,0713931	-0,190382581	-0,029782974	1

Source: designed by authors

Table 3. further shows that the pairwise correlation between `misalloc_A_w1` and `ROA_w1` is negative, which is still consistent with the research hypothesis in its primary descriptive sense. At the same time, the associations of `misalloc_A_w1` with other control variables are moderate and do not indicate a degree of apparent collinearity that would substantially weaken the regression interpretation. In this sense, Table 3 is important not as definitive evidence, but as an interim check that the sign and direction in the data make economic sense

The correlation matrix shows that the correlation between `misalloc_A_w1` and `ROA_w1` is -0.308 (see Table 3). This result means that our SG&A/Revenue – based proxy for misallocation is higher in companies with lower ROA, which matches the direction of our hypothesis. However, at this point, this is only an association, not proof of causation. The conclusion is made with regression specifications with controls and year effects (see Table 2).

It is also important to note that the correlation between `misalloc_A_w1` and the control variables is not particularly high, suggesting that its effect is not simply a reflection of size, leverage, or capital intensity. This does not eliminate the risk of omitted-variable bias or endogeneity, but it does reduce the risk that the main result is simply due to a simple covariate. Accordingly, the correlation matrix functions as an auxiliary diagnostic step at this stage, and the final assessment should still be based on the controlled specifications in Table 2.

Table 4. presents a comparison of firm characteristics by misallocation terciles

Table 4. Comparison of firm characteristics by misallocation terciles

Variable	Low Misallocation	Medium Misallocation	High Misallocation
N	348	347	348
Mean ROA_w1	0,065	0,066	0,017
Median ROA_w1	0,051	0,058	0,018
Mean log_assets	24,213	24,193	23,925
Mean leverage	0,295	0,263	0,293
Mean cap_intensity	0,323	0,170	0,193
Mean sales_growth	0,514	0,614	0,301
Mean misalloc_A_w1	0,080	0,248	0,849

Source: designed by authors

Table 4. supplements the main results with a comparative analysis across groups and shows how financial characteristics vary with the intensity of misallocation. The most important result is that in the high misallocation group, both the mean and median ROA are significantly lower than in the low and medium misallocation groups. This indicates that the negative relationship between misallocation and profitability is not just a subject of regression estimation; it is also observed at the descriptive level when firms are divided according to a proxy for internal organizational friction. At the same time, the table shows that the difference between the low and medium misallocation groups is relatively small, and the sharp deterioration is especially shown under conditions of high misallocation.

This result is particularly important for the research argument as it points to a possible nonlinearity: the effect of misallocation may appear relatively weak at low and medium levels, but becomes significantly stronger at high levels of administrative intensity. Accordingly, Table 4 does not replace the regression evidence, but rather reinforces it and provides the reader with a clearer idea of this relationship within the sample. The difference identified in Table 4 was further tested by comparing the two-step means between the low- and high-misallocation groups. The t-test results show that the mean ROA in the low misallocation group is statistically and significantly higher than in the high misallocation group. Specifically, the mean ROA in the low misallocation group is 0.065, while in the high misallocation group it is 0.017; the difference is statistically significant ($p < 0.01$). This additional result reinforces the main argument that high levels of misallocation are associated with significantly lower profitability.

To test for overall differences between groups, a single-factor ANOVA was also conducted, comparing ROA with the low, medium, and high misallocation groups. The results showed that the average ROA across the three groups differed significantly ($F = 62.858$; $p < 0.01$). This means that as misallocation intensity increases, the difference in profitability is not only observed between the two extreme groups but also across the entire sample. Thus, the ANOVA further strengthens both the comparative picture in Table 4 and the regression evidence presented in Table 2.

Figure 2 shows that the proxy for misallocation ($\text{misalloc_A_w1} = \text{SG\&A/Revenue}$) is negatively associated with ROA_w1 at the descriptive level. In the baseline OLS estimate, the coefficient on misalloc_A_w1 is -0.0579 and is statistically significant ($p < 0.01$), indicating that companies with higher administrative intensity tend to have lower

profitability on average. When we add year fixed effects to the model, the direction of the effect does not change and the coefficient remains negative (-0.0425 , $p < 0.01$), while the explanatory power of the model increases ($R^2: 0.125 \rightarrow 0.192$; $N = 1043$), indicating that the result is not simply a product of the influence of common time shocks (see Table 2).

Importantly, the negative relationship is visible not only in the regression estimates, but also in the supporting descriptive evidence. The correlation matrix shows a negative association between misalloc_A_w1 and ROA_w1 (Table 3), while the scatter plot points in the same general direction despite the heterogeneity of observations (Figure 2). This visual pattern does not constitute proof of causality, but it gives the reader an intuitive sense of the direction of the relationship, which is then confirmed more formally in Table 2.

The results also indicate that the relationship between misalloc_A_w1 and ROA_w1 is not merely a reflection of other standard firm characteristics. The inclusion of controls ($\log_assets$, $leverage$, $cap_intensity$, $sales_growth$) in Table 2 is necessary for this very reason: to ensure that the effect of misallocation is not explained by company size, debt structure, or different phases of growth. Under these conditions, the coefficient of misalloc_A_w1 remains negative and highly significant across all three main specifications, indicating that SG&A/Revenue intensity is related to ROA through an independent channel.

4 Conclusion

This paper aimed to assess, using a practical misallocation proxy (SG&A/Revenue), whether an increase in organizational “frictions” is associated with a deterioration in a company’s financial performance. The results are unambiguous in the direction: misalloc_A_w1 is negatively related to ROA_w1 , and this relationship remains stable in both the basic OLS and Year FE specifications. This paper thus supports the argument that the intensity of coordination costs relative to sales can be considered an important signal of organizational inefficiency, which is systematically associated with a decrease in return on assets. However, two limitations should be noted when interpreting the findings: first, SG&A/Revenue is a “frictional” proxy for misallocation and cannot capture all forms of inefficiency, especially those components that are directly related to worker-level mismatch; its

advantages remain its transparent interpretation and firm-year comparability. On the other hand, although the Year FE and Firm FE specifications significantly strengthen the econometric framework and reduce the impact of common time shocks and firm-specific immutable characteristics, the results should still be interpreted with caution in terms of causality, as measurement error, omitted variables, and the limitations of the proxy itself cannot be completely excluded. Further research could be strengthened by testing alternative proxies for misallocation, incorporating additional financial outcomes, and employing broader robustness checks, which would further enhance the reliability and practical applicability of the findings. From a practical perspective, the results provide a simple message: when SG&A is consistently increasing relative to sales, it may indicate not only “increasing costs,” but also deteriorating internal process efficiency – excessive administrative burden, increased coordination costs, and unproductive resource allocation. In such circumstances, a decline in ROA is often a consequence, not a cause, so it is useful for management to use a proxy for misallocation as an early warning: monitoring overhead dynamics, breaking down the SG&A structure, streamlining processes, and clearly delineating responsibilities can be practical directions that reduce organizational frictions.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Velga Vevere carried out the overall planning of the research and created the conceptual framework. David Alimbarashvili did the literature review and performed actual calculations. Iveta Linina and Rosita Zvirgzdina interpreted the research results and formulated overall conclusions.

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