Estimating the Value of CEOs in Privately Held Businesses*

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Abstract

We develop a framework to estimate CEO value in private firms using administrative data, overcoming traditional measurement challenges. Our theoretical model assumes managers differ in skills that directly affect total factor productivity, with firms retaining rents accruing to fixed factors like organizational capital. Applied to comprehensive Hungarian data spanning 1992-2022, we find substantial CEO heterogeneity: replacing a CEO at the 25th percentile of the skill distribution with that at the 75th percentile would increase firm productivity by 9.7-26.6 percent. Manager skills explain about a quarter of the within-firm variation and 5–9 percent of the cross-firm variation in outcomes.

Keywords: CEO value, private firms, productivity
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1 Introduction

Managers play a crucial role in determining firm performance, as documented across various institutional settings (Bertrand & Schoar, 2003; Fisman et al., 2014; Bandiera et al., 2020; Bennedsen et al., 2020). Most existing studies in this literature focus on publicly listed firms in developed markets such as the United States. Evidence from developing countries suggests that management practices are equally important for firm performance in these contexts (Bloom et al., 2014). However, the relevance of existing evidence on CEO value remains limited for developing markets for two key reasons. First, in developing markets, most firms are privately held and do not have publicly traded shares or readily available information about executive compensation of the sort surveyed in Frydman & Saks (2010). This creates a fundamental measurement challenge for researchers. Second, in private businesses, owners typically retain direct control over the firm, which may generate different incentive structures and performance outcomes compared to publicly listed firms with dispersed ownership.

In this paper, we develop a framework to estimate the value of CEOs in privately held businesses using standard financial statement data and administrative registers, data sources that are commonly collected by governments in developing countries. This approach enables the measurement of CEO value in settings where traditional methods based on stock market valuations or executive compensation data are not feasible.

Our theoretical model builds on Lucas (1978) and assumes that managers differ in their skills, which directly affect the total factor productivity of the firm. Following Atkeson & Kehoe (2005); McGrattan (2012), we assume that firms retain economic rents due to decreasing returns to scale in the presence of manager skills, organizational capital, and intangible assets. This framework allows us to identify the marginal contribution of CEO skills to firm surplus while controlling for other sources of firm heterogeneity.

We apply this framework to comprehensive administrative data from Hungary covering the period 1992-2022. The dataset enables us to track CEO changes across firms and measure their impact on firm performance, specifically on the economic surplus generated by the firm. This empirical strategy allows us to identify CEO value through variation in managerial appointments while controlling for firm-specific and time-varying factors that might otherwise confound the analysis.

Our analysis yields three main findings. First, CEO skills exhibit substantial heterogeneity both within firms over time and across the broader managerial labor market. Within firms, replacing a 25th percentile manager with a 75th percentile manager increases productivity by 9.8 percent, translating to a 118 percent increase in surplus. Second, this heterogeneity is even more pronounced when examining the connected component of managers who move between firms: the same percentile replacement increases productivity by 25.6 percent and surplus by 461 percent. Third, manager skills account for meaningful variation in firm outcomes, with regression analysis revealing significant relationships between estimated managerial ability and revenue, profitability, and employment across Hungarian firms.

2 Modeling Framework

Firms produce output using a Cobb-Douglas production function that incorporates both fixed and variable inputs. Owing to the presence of fixed inputs, technology exhibits decreasing returns to scale. This will pin down the scale of the firm even when markets are perfectly competitive and the firm is a price taker in both input and output markets (Atkeson & Kehoe, 2005; McGrattan, 2012).[1]

The production function for firm i with manager m at time t is:

$$Q_{imt} = \Omega_{it} A_i Z_m K_{it}^{\alpha} L_{imt}^{\beta} M_{imt}^{\gamma} \tag{1}$$

where Ω_{it} is residual total factor productivity, A_i represents time-invariant organizational capital and immaterial assets (location, brand value), Z_m captures manager skill, K_{it} is physical capital, L_{imt} is labor input, M_{imt} is intermediate input usage. The parameters α, β and γ represent the elasticities with respect to physical capital, labor and material inputs, respectively. We denote $\chi := 1 - \beta - \gamma$. Conditional on productivity, organizational capital and manager skill, the production function exhibits decreasing returns to scale, $\alpha + \beta + \gamma < 1$. In a traditional production function with only capital, labor and material as inputs, Ω, A and Z would all be lumped together as *total factor productivity.*

We assume managers optimize variable inputs L_{imt} and M_{imt} while taking fixed inputs A_i and Z_m and physical capital K_{it} as given. In private businesses, owners typically have direct control over fixed inputs, including large-scale investments in organizational and physical capital (Barba Navaretti et al., 2010). Managers, on the other hand, are responsible for day-to-day operations and variable input choices.

Output is sold at sector-specific price P_{st}, making the revenue of the firm $R_{imst} = P_{st} Q_{imt}$. The firm faces a wage rate W_{st} for labor input, price ϱ_{st} for intermediate inputs. After straightforward algebra solving for the optimal labor and intermediate input choices, the firm's revenue can be expressed as:

$$R_{imst} = (P_{st} \Omega_{it} A_i Z_m)^{1/\chi} K_{it}^{\alpha/\chi} W_{st}^{-\beta/\chi} \varrho_{st}^{-\gamma/\chi} (1-\chi)^{(1-\chi)/\chi}. \tag{2}$$

Revenue is increasing in fixed inputs A_i and Z_m, physical capital K_{it}, and decreasing in the wage rate W_{st} and material input price ϱ_{st}. Higher prices P_{st} and productivity Ω_{it} also increase revenue. Note that because $\chi < 1$, the elasticity of revenue with respect to fixed inputs is greater than the elasticity in the production function, i.e. $\alpha/\chi > \alpha$. This is because the firm can leverage its fixed inputs to increase revenue more than proportionally by hiring more variable inputs.

As is usual under Cobb-Douglas production functions, the share of revenue accruing to each input is constant over time and across firms, equal to their elasticity in the production function.

[1]Alternatively, we could assume that firms face downward sloping residual demand curves, which would make the *revenue production function* decreasing returns to scale. As long as residual demand is isoelastic, the analytical derivation of the model remains unchanged. The only difference is that the parameters have a different interpretation: the revenue elasticity of an input is the product of the input's share in revenue and $1 - 1/\sigma$, where σ is the elasticity of residual demand (De Loecker, 2011).

We define the rent accruing to fixed factors (including physical capital)

$$S_{imst} = R_{imst} - W_{st}L_{imt} - \varrho_{st}M_{imt} = \chi R_{imst}. \tag{3}$$

Taking logarithms of equations (2) and (3), we can express the log surplus as:

$$s_{imst} = C + \frac{\alpha}{\chi}k_{it} + \frac{1}{\chi}z_m + \frac{1}{\chi}p_{st} + \frac{1}{\chi}\omega_{it} + \frac{1}{\chi}a_i - \frac{\beta}{\chi}w_{st} - \frac{\gamma}{\chi}\rho_{st}, \tag{4}$$

where C is a constant only depending on fixed parameters, $k_{it} = \ln K_{it}$, $z_m = \ln Z_m$, $p_{st} = \ln P_{st}$, $\omega_{it} = \ln \Omega_{it}$, $a_i = \ln A_i$, and $w_{st} = \ln W_{st}$, $\rho_{st} = \ln \varrho_{st}$.

Equation (4) shows how surplus depends on manager skills, holding fixed the inputs chosen by the owner and the input and output prices prevailing in the sector. Taking two managers m and m' with skills z_m and $z_{m'}$ at the same firm, the change in surplus attributable to the new manager is:

$$s_{im'st} - s_{imst} = \frac{1}{\chi}(z_{m'} - z_m). \tag{5}$$

The *value* of the new manager to the owners of the firm is the change in surplus. This value is proportional to the difference in manager skills, scaled by the inverse of the elasticity of revenue with respect to fixed inputs χ. In what follows, we aim to measure this value by estimating the change in surplus following a manager change.

Estimable equation. In absence of observing organization capital and input prices, we can substitute these out with fixed effects, leading to the following estimable equation:

$$s_{imst} = \frac{\alpha}{\chi}k_{it} + \frac{1}{\chi}\tilde{z}_m + \lambda_i + \mu_{st} + \tilde{\omega}_{it} \tag{6}$$

where $\lambda_i = a_i/\chi$ is a firm fixed effect capturing time-invariant organizational capital, $\mu_{st} = C + p_{st}/\chi - \beta w_{st}/\chi - \gamma\rho_{st}/\chi$ is an industry-time fixed effect capturing sector-specific prices and wages, and $\tilde{\omega}_{it} = \omega_{it}/\chi$ is a rescaled time-varying firm productivity shock.

Assuming that residual productivity $\tilde{\omega}_{it}$ is uncorrelated with manager skills and physical capital, we can estimate the model using ordinary least squares with fixed effects (OLSFE). Note that we do *not* assume that manager skills are uncorrelated with physical capital, organizational capital or sectoral prices. It may well be the case that better firms with good price conditions hire better managers and invest more.

Given our estimated parameters and fixed effects, we can recover manager skills as:

$$\hat{\chi}s_{imst} - \hat{\alpha}k_{it} - \hat{\chi}\lambda_i - \hat{\chi}\mu_{st} := \tilde{s}_{imst} = \hat{z}_m + \hat{\omega}_{it}. \tag{7}$$

We remove the contribution of physical capital, firm and industry-year fixed effects from log surplus to obtain a *residualized surplus* $\tilde{s}_{imst}$. Because ω_{it} is assumed to be mean zero independent of m, we can estimate $\hat{z}_m$ as the average of $\tilde{s}_{imst}$ across all observations for manager m. This gives us a consistent estimate of manager skill, $\hat{z}_m = \frac{1}{N_m}\sum_{i,t}\tilde{s}_{imst}$, where N_m is the number of observations for manager m.[2]

[2] This is equivalent to including a manager fixed effect in the regression, similar in spirit to Abowd et al. (1999)

3 Data and Measurement

Main data sources. Our analysis uses comprehensive administrative data on Hungarian firms during 1992-2022, created by merging balance sheet and financial statement data with firm registry information. The balance sheet data come from HUN-REN KRTK (2024b) and contains financial information for essentially all Hungarian firms required to file annual reports. The firm registry data come from HUN-REN KRTK (2024a) and includes information on firm registration, ownership structure, and director appointments. Both datasets are distributed by HUN-REN KRTK and originally published by Opten Zrt.[3]

The balance sheet data include all firms required to file financial statements with Hungarian authorities, covering essentially the entire formal business sector except for the smallest corporations not engaged in double-entry bookkeeping and individual entrepreneurs. The dataset contains detailed financial information including sales revenue, export revenue, employment, tangible and intangible assets, raw material and intermediate input costs, personnel expenses, and ownership indicators for state and foreign control.

Registry information is collected by the Hungarian Corporate Court, which maintains legally mandated public records on firms (*Cégtörvény*, 1997). These records include information on company representatives—individuals authorized to act on behalf of the firm in legal and business matters. Representatives may include CEOs and other executives, but also lower-level employees with signatory rights. We exclude the rare instances where the representative is a legal entity. The dataset is structured as a temporal database: each entry has an effective date interval and reflects the state of representation at a given time. Updates occur not only when positions change but also when personal identifiers (e.g., address) are modified or when reporting standards evolve. Start and end dates are often missing, and prior to 2010, the data does not contain unique numerical identifiers for individuals.

We resolve individual identities by linking records based on name, birth date, mother's name, and home address, creating a unique identifier for each person. This entity resolution step enables tracking of representatives over time and across firms. To construct an annual panel of top managers, we infer the period of service for each representative using available date bounds and sequential information. A representative is considered active in a given year if their tenure includes June 21 of each year.

Because job titles are not standardized, identifying the CEO requires heuristic rules. When an explicit title such as *managing director* is available, we classify the individual accordingly. For firms lacking such labels, we assume that all representatives are CEOs if the number of representatives is three or fewer. If there are more than three and one of them was previously identified as a CEO, we assign the CEO role based on continuity. This approach allows us to systematically identify the firm's top executive across years.

Sample construction. We construct our analytical sample through several filtering steps. We restrict our analysis to the period 1992 to 2022 to focus on the post-transition Hungarian

and Card et al. (2018). This notation emphasizes that manager effects estimated from fewer observations are noisier.

[3]The data cannot be publicly shared due to privacy and licensing restrictions. The replication package available at https://github.com/korenmiklos/ceo-value describes how to get access to the data.

economy. This removes 136,141 observations from years prior to 1992, when the economic and institutional environment was fundamentally different. Our sample contains 10,214,120 firm-year observations spanning 31 years. Table 1 shows the temporal distribution of observations in our final sample. The sample exhibits steady growth from 98,780 observations in 1992 to 454,106 in 2022. This expansion reflects the growth of entrepreneurship in Hungary following the transition to a market economy.

Table 1: Sample Distribution by Year

Year	Observations	Year	Observations	Year	Observations
1992	98,780	2002	301,278	2012	397,131
1993	122,677	2003	305,947	2013	437,692
1994	153,639	2004	319,750	2014	427,494
1995	171,759	2005	326,905	2015	433,371
1996	198,558	2006	334,498	2016	431,041
1997	219,751	2007	345,134	2017	424,184
1998	246,660	2008	362,920	2018	425,601
1999	256,992	2009	370,788	2019	419,883
2000	280,386	2010	384,570	2020	424,501
2001	302,894	2011	402,636	2021	432,594
				2022	454,106
Total: 10,214,120					

Notes: Sample distribution after applying time period restrictions (1992-2022) and data quality filters.

CEO panel construction. We construct a panel of chief executive officers from the firm registry data, restricting the sample to the same 1992-2022 time period. The initial CEO panel contains information on 996,387 observations that are excluded due to the time restriction. The final CEO panel includes variables identifying the firm (frame_id_numeric), person (person_id), year, as well as CEO characteristics including gender (male), birth year, manager category, and ownership status.

The CEO data reveals substantial variation in the number of CEOs per firm-year. Among the 12,726,597 firm-year observations with CEO information, the vast majority (82.24%) have a single CEO. However, 15.32% of firm-years have two CEOs, 1.98% have three CEOs, and small fractions have even larger numbers of CEOs, with some firms reporting up to 52 CEOs in a single year. This distribution reflects the complexity of executive structures in Hungarian firms, including cases where firms may have multiple managing directors or where CEO transitions occur within a year.

Sample merging and match rates. We merge the CEO panel with the balance sheet data using firm identifiers and year. The merge process reveals important patterns in data availability across sources. Of the 15,980,738 total observations from both datasets, 11,886,636 observations (74.4%) successfully match between CEO and balance sheet data. The remaining observations consist of 3,507,466 CEO observations without corresponding balance sheet data and 586,636 balance sheet observations without CEO information.

At the firm level, the match rates are more favorable. Among the 1,200,145 unique firms in our combined dataset, 942,684 firms (78.55%) have information in both datasets. The remaining firms are split between 238,852 firms (19.90%) that appear only in the CEO registry and 18,609 firms (1.55%) that appear only in the balance sheet data. This pattern suggests that CEO information is available for most active firms but may be missing for very small firms or those with simplified reporting requirements.

Industry composition. We classify firms into broad industry sectors using the TEAOR08 classification system. The final analytical sample spans diverse industries, with notable concentration in service sectors. Wholesale, retail, and transportation activities account for the largest share at 28.86% of observations. Nontradable services represent 26.72%, while telecom and business services contribute 18.92%. Manufacturing firms account for 10.56%, construction for 9.25%, and agriculture for 3.46%. Mining and finance sectors are excluded from the final analytical sample due to their distinct production characteristics and regulatory environments.

CEO turnover and tenure patterns. The data reveals substantial heterogeneity in CEO turnover across firms. We construct CEO spell variables to track the sequence of different CEO appointments within each firm. Among firm-year observations, 66.72% represent the first CEO spell, meaning these are either firms with their original CEO or the first year of data for that CEO. Second CEO spells account for 22.90% of observations, while 6.88% represent third spells. The distribution has a long tail, with some firms experiencing up to 25 different CEO spells during the observation period.

At the firm level, 62.97% of the 1,012,113 firms in our sample experience only one CEO spell during the observation window. However, 24.07% of firms have exactly two CEO spells, indicating at least one CEO change. The remaining 12.96% of firms experience multiple CEO changes, with some firms having up to 25 CEO transitions. This pattern suggests that while many firms maintain stable CEO leadership, a substantial minority experience frequent executive turnover.

Sample restrictions and final dataset. We apply several filters to focus on firms most suitable for productivity analysis. First, we exclude firms that ever have more than two CEOs in a single year, removing 1,519,524 observations. This filter eliminates firms with potentially complex or unstable governance structures that may confound productivity estimates. Second, we drop firms with more than six CEO spells over the observation period, removing an additional 45,216 observations to focus on firms with more stable executive structures.

We also exclude certain industries and ownership types that may have different production functions or regulatory environments. Mining and finance sectors are dropped due to their unique operational characteristics: mining operations face resource constraints and depletion effects that differ from standard production functions, while financial services operate under distinct regulatory frameworks that affect standard productivity measures. Additionally, we exclude all firms that were ever state-owned during the observation period, as state ownership introduces different objective functions and constraints that may confound our productivity analysis of private firm management.

Variable construction.

Measurement of Model Variables. We measure the key variables from the theoretical framework as follows:

Physical capital (K_{it}): Tangible assets from balance sheet data, including machinery, equipment, and buildings, measured in logarithmic form as $k_{it} = \ln K_{it}$.

Surplus (S_{imst}): EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortization), calculated as sales revenue minus personnel expenses minus material costs, measured in logarithmic form as $s_{imst} = \ln S_{imst}$.

Manager skill (Z_m): CEO fixed effects $\tilde{z}_m$ estimated from the regression in equation (5), capturing time-invariant managerial ability.

Labor input (L_{imt}): Employment measured as the number of employees, transformed to logarithmic form as $l_{imt} = \ln L_{imt}$.

Manager compensation (W_{imst}): CEO wages including base salary and bonuses from administrative records (not yet available in current analysis).

Organizational capital (A_i): Time-invariant firm characteristics including location, brand value, and market position, captured by firm fixed effects λ_i and not directly observed.

Sector-time variation: Industry-specific prices and wages controlled through industry-time fixed effects μ_{st} using TEAOR08 sector classifications.

Missing values in financial variables are systematically recoded to zero, following standard practice in administrative data analysis where missing values typically indicate zero rather than unknown values. The extent of missing data varies considerably across variables, reflecting different reporting requirements and business activities. Export data has the highest rate of missing values, with 5,456,815 observations recoded, reflecting that many firms do not engage in export activities. Employment data required recoding for 1,138,791 observations, while sales revenue had relatively few missing values with only 486,197 observations recoded.

For employment, we make an additional adjustment by setting values below one to equal one. This transformation affects 3,655,899 observations and acknowledges that active firms filing administrative reports must have positive employment. Zero or negative employment values likely reflect administrative reporting inconsistencies rather than true zero employment.

We also address issues with wage bill and personnel expense variables, where 3,931,270 and 1,117,283 observations respectively are recoded from missing to zero. For asset variables, tangible assets required recoding for 1,014,331 observations while intangible assets had 4,299,589 missing values recoded, reflecting that many firms do not report significant intangible assets.

We construct several derived variables for the analysis. EBITDA is calculated as sales minus personnel expenses minus materials. Log transformations are applied to key variables including sales (lnR), EBITDA (lnEBITDA), employment (lnL), and tangible assets (lnK). CEO tenure is measured as years since first appointment, while CEO age and firm age are calculated from birth year and founding year respectively. We also create indicator variables for expatriate CEOs (those with missing gender information, suggesting non-Hungarian names) and ownership status.

The final analytical sample contains 8,872,039 firm-year observations representing 960,464 unique firms over the 1992-2022 period. This sample focuses on manufacturing, wholesale/retail/transportation, telecom/business services, and other nontradable services sectors, with firms having relatively stable CEO structures suitable for productivity analysis.

4 Methodology

[Methodology to be written]

Table 2: Industry Composition of Final Sample

Industry Sector	Observations	Percent
Wholesale, Retail, Transportation	3,430,342	28.86
Nontradable Services	3,176,339	26.72
Telecom and Business Services	2,249,271	18.92
Manufacturing	1,254,792	10.56
Construction	1,100,022	9.25
Agriculture	411,226	3.46
Finance*	247,718	2.08
Mining*	16,926	0.14
Total (before restrictions)	11,886,636	100.00
Final analytical sample	8,872,039	–

Notes: *Industries excluded from final analytical sample. Additional restrictions exclude firms that were ever state-owned. Industry classification based on TEAOR08 system.

Table 3: CEO Structure and Turnover Patterns

Panel A: Number of CEOs per Firm-Year

Number of CEOs	Observations	Percent
1	10,466,412	82.24
2	1,949,370	15.32
3	251,882	1.98
4+	58,933	0.46
Total	12,726,597	100.00

Panel B: CEO Spells per Firm-Year

CEO Spell	Observations	Percent
1 (First CEO)	6,423,429	66.72
2	2,204,806	22.90
3	662,846	6.88
4	205,665	2.14
5+	130,738	1.36
Total	9,627,484	100.00

Panel C: Maximum CEO Spells per Firm

Max CEO Spells	Firms	Percent
1	637,287	62.97
2	243,609	24.07
3	84,184	8.32
4-6	42,788	4.23
7+	4,245	0.42
Total	1,012,113	100.00

Notes: Panel A shows distribution of concurrent CEOs per firm-year. Panel B shows CEO spell distribution among successfully matched firm-years. Panel C shows maximum number of CEO changes per firm over entire observation period.

5 Results

Because we are estimating manager skills conditional on firm and industry-year fixed effects, we can only obtain a *relative* skill measure of different managers within the same firm and industry-year, relative to a suitably chosen baseline. With the right baseline, however, we can interpret the estimated skills.

Within-firm manager changes. First we study the impact of within-firm manager changes on firm surplus. If there are n managers in a firm, we can estimate $n-1$ manager fixed effects. We normalize the log skill of the first manager of the firm to zero. The remaining $n-1$ manager fixed effects are then interpreted as the difference in skills relative to the first manager. Naturally, this calculation only makes sense for $n > 1$, i.e. for firms that have at least two managers in the sample. The relative manager skills are estimated as the average of the residualized surplus $\tilde{s}_{imst}$ across all observations for that manager, as described in equation (7).

Figure 1 Panel A shows the distribution of relative manager skills in the sample with at least two managers. The distribution is centered a bit higher than zero, with a mean of 0.16. This means that, on average, second and subsequent managers are 16 percent more skilled than the first manager of the firm. This is expected if under-performing managers are more likely to be replaced, leading to a positive selection bias in the sample of second and subsequent managers.

There is, however, substantial variation around this mean, with some managers being significantly more skilled than the first manager and others being less skilled. The interquartile range of relative skills corresponds to a 9.8 percent difference in firm productivity. Because higher productivity can be leveraged by buying more variable inputs, this would lead to a larger increase in revenue and surplus. The counterfactual manager change mentioned above would increase revenue and surplus by 118 percent.

Table **??** shows the relationship between manager skills and firm outcomes. The regression coefficients indicate how manager skills correlate with revenue, EBITDA, and employment within the connected component of managers.

Largest connected component. Managers that lead mutiple firms (even at different times) help identify the skills of other managers. To consider a specific example, suppose manager B replaces manager A at firm 1 with a measured skill increase of 0.2, and manager B is replaced by manager C at firm 2 with a measured skill drop of 0.05. We can then infer the relative skill of manager C compared to manager A as +0.15. This process can be repeated for all managers that are connected through a chain of replacements, leading to a large connected component of managers.

Using standard graph analysis, we find the largest connected component of managers in our sample, which contains 180,421 managers. These managers account for 27.1 percent of all firm-year observations.[4] For these managers, their skills can be estimated by two-way firm and manager fixed effects (Abowd et al., 1999; Correia, 2023). We normalize log manager skills to

[4]The second largest connected component contains only a small fraction of managers, so the largest connected component is overwhelmingly dominant, as is often the case in real-world networks.

zero, so the estimated skills can be interpreted as deviation from the average manager in the largest connected component.

Figure 1 Panel B shows the distribution of relative manager skills in the largest connected component. The distribution is centered around zero by construction. The interquartile range of relative skills corresponds to a 25.6 percent difference in firm productivity. Because higher productivity can be leveraged by buying more variable inputs, this would lead to a 461 percent increase in revenue and surplus. This larger variation compared to within-firm estimates suggests that good managers tend to be replaced by other good managers within the firm.

In the cross section, the contribution of manager skills is less important relative to other fixed factors (captured by firm fixed effects). Manager skills explain 5 to 9 percent of within-industry variation in log revenue, log surplus and log employment.

6 Conclusion

[Conclusion to be written]

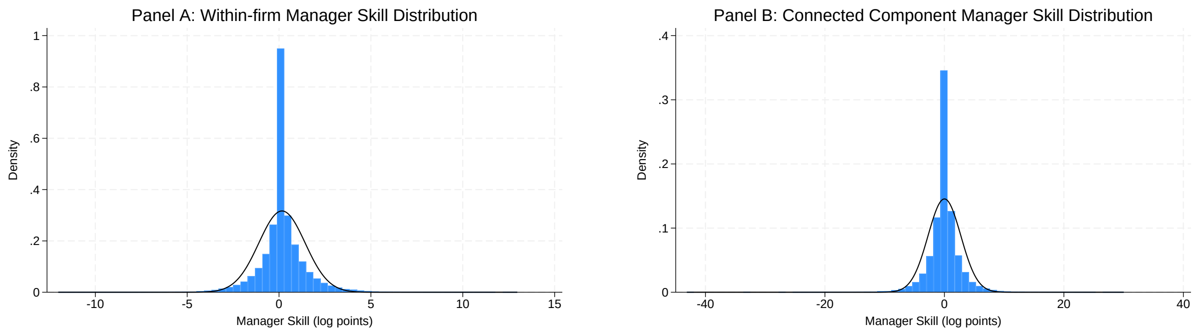

Figure 1: Manager Skill Distributions
Notes: Panel A shows the distribution of within-firm manager skill variation for firms with multiple CEOs. Panel B shows the distribution of manager skills in the largest connected component of managers. Both distributions show manager skills in log points after normalization and scaling.

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Table 4: Manager Skill Effects on Firm Outcomes

	(1) Revenue	(2) EBITDA	(3) Employment
Sales (log)	0.086***		
	(0.004)		
EBITDA (log)		0.055***	
		(0.004)	
Employment (log)			0.090***
			(0.007)
Constant	-0.861***	-0.431***	-0.085***
	(0.039)	(0.035)	(0.011)
Observations	1856674	1398280	1856674
Adjusted R-squared	0.005	0.003	0.003

Standard errors in parentheses

Standard errors clustered at firm level.

All regressions include industry-year fixed effects.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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A Robustness Checks

Table 5: The revenue function in various samples

	(1)	(2)	(3)	(4)	(5
	Full	sample	First CEO spell	Single CEO spell	Multiple C
Tangible and intangible assets (log)	0.254***	0.255***	0.256***	0.249***	0.325
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0
Intangible assets share	-0.028***	-0.027***	-0.038***	-0.016*	-0.02
	(0.007)	(0.009)	(0.011)	(0.010)	(0.0
Foreign owned	0.012	0.012	-0.004	0.018*	0.02
	(0.008)	(0.011)	(0.014)	(0.010)	(0.0
Observations	6634335	4404163	3073377	3560899	2956

Controls: firm-CEO-spell fixed effects; industry-year fixed effects.

Table 6: The revenue function by sector

	(1)	(2)	(3)	
	Agriculture	Manufacturing	Wholesale, Retail, Transportation	Tele
Tangible and intangible assets (log)	0.322***	0.302***	0.262***	
	(0.005)	(0.003)	(0.002)	
Intangible assets share	0.100*	0.013	-0.009	
	(0.058)	(0.025)	(0.014)	
Foreign owned	-0.075*	0.043*	0.010	
	(0.043)	(0.024)	(0.015)	
Observations	213719	769740	1961088	

Controls: firm-CEO-spell fixed effects; industry-year fixed effects.