Firm Organization and Spillovers

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Abstract

This paper studies whether the organizational decisions of new entrants in a market are influenced by the hierarchical structure of their incumbent peers. Using matched employer-employee data from Brazil, we classify establishments into one to four-layer entities and examine how a new entrant's decision to add an organizational layer varies with the average number of layers of other establishments in their industry and location. To address the potential endogeneity of peers' layers, we construct an instrument based on layers of other establishments in peers' firms that operate in different markets. We find that new entrants are twice as likely to add a layer within five years if their average peer has one more layer at the time of entry. Our results suggest that organizational structure spillovers can provide a new source of agglomeration advantages. We also find that the influence of peers is stronger in industries that are more similar. Additionally, we show that new entrants with high-layer peers hire more workers from within the market in the newly created layers, indicating personnel exchanges as a mechanism for organizational spillovers.

Keywords: spillovers, agglomeration, economic growth, labor pooling
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I Introduction

Organizations make decisions regarding the number and characteristics of their employees and their roles in the organization. Choices concerning the organization of production can have significant impacts on a firm's productivity. A substantial body of economic literature has examined spillover effects among firms and how they contribute to the concentration of economic activity. [1] In this paper, we investigate whether and to what extent an establishment's organizational decisions are influenced by the internal organizational structure of its peers.

Specifically, we study whether the hierarchical structure of incumbent product market peers in a location influences how new entrants organize their production. We use matched employer-employee data from Brazil to measure hierarchical layers based on workers' occupations and classify establishments into one-layer, two-layer, three-layer, and four-layer entities following Caliendo et al. (2015).[2] We then study how a new entrant's decision to add an organizational layer in the first five years varies with the number of layers of other establishments in their industry and location a year before entry.

To disentangle the effects of peer firms' organizational structure from industry-location-specific advantages, we employ an instrumental variable (IV) approach. Specifically, we construct an instrument for peers' layers by using the number of layers of other establishments in peers' firms that operate in different markets. By doing so, we aim to identify the causal effect of peer firms' organizational structure on the decisions of new entrants to add organizational layers.

Our IV estimates indicate that the presence of an additional layer in the average peer's organization increases a new entrant's likelihood of adding a layer by 0.29 percentage

[1]For instance, Henderson (2003) documents that a higher count of own-industry plants in a location is positively correlated with productivity in high-tech sectors. Similarly, Ellison et al. (2010) shows that co-agglomeration rates are higher between economically similar industries. Greenstone et al. (2010) quantify total factor productivity spillovers in manufacturing using exogenous variation in the entry of new plants.

[2]The concept of organizational layers originates from the theory of management hierarchies as in Rosen (1982), Garicano (2000), and Caliendo and Rossi-Hansberg (2012). Layers consist of employees with similar knowledge and tasks. Higher layers have fewer but more knowledgeable employees who oversee those in lower layers.

points. Since 40% of new entrants add a layer within the first five years in our sample, an extra layer in the average peer's organization nearly doubles the likelihood of a new entrant adding a layer. Our main specification includes location, industry, and entry-year fixed effects, in addition to controls for the entrant's initial characteristics. Furthermore, our results remain robust even after controlling for peers' initial size. Hence, we conclude that there are notable spillover effects in organizational structure across establishments.

We then delve deeper into the drivers of the spillovers and examine the relative significance of locational proximity and industry similarity. By repeating our analysis using 2-digit industries instead of 3-digit industries, we find weaker effects, suggesting that peers in more similar industries play a larger role. We also investigate whether the availability of workers in the upper hierarchy of the organizational structure in markets with high-layer peers could be a source of these spillovers. Our results indicate that entrants in markets with a significant number of high-layer peers tend to hire more workers in the newly created layers from within the market rather than outside the market. This suggests that the cost of adding a new layer is lower for entrants in markets with peers who have more layers. Another potential channel for these spillovers could be through learning about organizational structure from peers. Since organizational structure may be more visible than technology, it is plausible that firms in the same market would learn from each other. However, we are unable to test this hypothesis in our data directly.

We also present additional robustness checks and heterogeneity analyses in the paper. Specifically, we explore whether peers impact the likelihood of survival for entrants in our sample. We also investigate whether our mapping of layers, and our estimates are consistent with the models of knowledge-based hierarchies. Further, we test the robustness of our results to alternative definitions of layers and perform sensitivity tests by varying the time frame. Finally, we explore the heterogeneity of spillover effects across entrants with different numbers of initial layers and the impacts of high-wage versus low-wage paying peers.

Our findings indicate that spillovers in organizational structure can provide a new source of agglomeration advantages. Previous research on agglomeration economies has demonstrated that firms located near similar firms experience increased productivity and that larger cities tend to have more productive firms.[3] This implies that market size can enhance firm productivity through spillovers. However, there are relatively few causal estimates of spatial spillovers. A notable exception is Baum-Snow et al. (2022), which uses data on high-skilled services firms in three large Canadian cities and provides causal estimates of productivity spillovers. While our paper is complementary to theirs, we do not measure productivity spillovers, but instead, spillovers operating through organizational structure. Our approach has two advantages. Firstly, the organizational structure is a more easily observable and measurable characteristic of firms compared to productivity, which can be challenging to quantify accurately. Secondly, since internal organization impacts the productivity of the firm, organization structure spillovers can be seen as a source of productivity spillovers.

The approach in Caliendo et al. (2015) to measure organizational layers has been followed by several recent papers.[4] Most related to our paper is Spanos (2019), who studies the effect of market size on layers and finds that firms in larger markets organize into more layers. The paper develops a theoretical model and shows that the mechanism for large markets leading to greater layers is that larger markets increase competition between firms, lower markups, force firms with low product demand to exit the market, and the remaining firms to restructure their organization. In contrast, our paper focuses on the effect of peers even after controlling for market size. Thus, we propose another mechanism for larger markets leading to more layers — high-layer peers in larger markets.

The rest of the article is organized as follows. In the next section, we describe the data, our construction of layers, and our instrument and provide basic characteristics of our sample of entrants. Section III details our empirical specification and the identifying assumption behind our instrument for peers' layers. The main results are presented in Section IV, while additional robustness tests and extensions are presented in Section VI.

[3]Greenstone et al. (2010), Ellison et al. (2010), Bloom et al. (2013), Faggio et al. (2017), Hanlon and Miscio (2017), and others all provide evidence that firm and worker productivity are increasing in the prevalence of nearby firms to which they are connected, with connectivity measured through input-output relationships, patent citations or occupational similarity.

[4]For example, Gumpert et al. (2022) study multi-establishment firms, and Bias et al. (2020) show that firms that go public become more hierarchical in nature. Tåg et al. (2016) show that employees in firms with more layers are less mobile and less likely to enter entrepreneurship, become self-employed, or switch to another employer. Friedrich (2022) shows that adding a layer increases within-firm wage inequality.

Section VII concludes. We present additional data descriptives and results in Appendix A and Appendix B, respectively.

II Data

We use data from Relação Anual de Informações Sociais (RAIS) for the years 2002–2014. RAIS is an employer-employee matched dataset that covers nearly all formal sector jobs in Brazil. Firms report annual information to RAIS on all employees who were on the payroll in the previous year, including their monthly earnings, contracted hours, education, and occupation. In addition, the data also contains the location and industry of employment. For now, we restrict the sample to the southeast region of Brazil.[5]

Following Caliendo et al. (2015), we define four hierarchical layers to measure organizational change. These layers are defined as follows: layer 1 corresponds to directors, layer 2 to managers, layer 3 to professionals and supervisors, and layer 4 to workers. We use Brazil's occupational classification system, Classificação Brasileira de Ocupações (CBO) 2002 to divide employees at each establishment into these layers. The CBO system classifies occupations into 10 main groups described in Table 1. We exclude group 0, which includes armed forces, police, and firefighters. Group 1 consists of directors and managers, and we distinguish between the two and place directors in layer 1 and managers in layer 2. While group 2 consists of professionals and is classified into layer 3, mid-level technicians that comprise group 4 are placed in layer 4. Lastly, groups 4-9 consist of supervisors and blue- and white-collar workers. For this group, we classify supervisors as layer 3 and all other workers as layer 4. See Appendix A.1 for further details on the mapping between occupations and our definition of layers.

Our goal is to classify employees based not on the characteristics of the tasks they perform but on their hierarchical position within the organization. To validate our classification, we present Table A1, which illustrates that our definition of layers aligns with

[5]The southeast region includes the states of Espírito Santo, Minas Gerais, Rio de Janeiro, and São Paulo, and is the largest and richest region of the country. We follow Gerard et al. (2021) in imposing this restriction who argue that minimum wage is an important consideration in Brazil and the ratio of the minimum wage to the median wage in the southeast region is comparable to other developing and developed countries.

TABLE 1: CBO 2002 OCCUPATIONAL CLASSIFICATION

CBO Group	Layer(s)	CBO Occupations
0	–	Armed forces, police and firefighters
1	1, 2	Senior members of public authorities, directors of public interest organizations and companies, and managers
2	3	Professionals (e.g., researchers, engineers, architects, doctors, lawyers, accountants, etc.)
3	4	Mid-level technicians (e.g., industrial lab technicians, optometrists, dental technicians)
4	3, 4	Administrative service workers (office workers)
5	3, 4	Service workers, salespeople in shops and markets
6	3, 4	Agricultural, forestry, hunting and fishing workers
7, 8, 9	3, 4	Workers who manufacture goods, or operate and maintain equipment

a hierarchical structure, as indicated by the higher average wages and fewer workers in higher layers. Following the classification of workers into layers, we can define the total number of hierarchical layers in each establishment as the number of levels in which it reports employees in a given year. Additional characteristics of layers are presented in Table A2.

We identify new entrants as establishments that first entered the data in any year after 2002.[6] We exclude entrants with establishment size and employment growth values in the bottom 1 or top 99 percentile, as well as those with fewer than four employees at the time of entry. Since we are interested in the impact of peers on the organizational decisions of new entrants during the first five years after their entry, we restrict our sample to entrants who survived over this period. Hence, our main sample of entrants includes establishments that entered the data between 2003–2009 and were observed for at least six years in total.[7]

[6]It is not possible to distinguish between new entrants and incumbent establishments in 2002 as it is the first year for which data is available.

[7]This restriction could lead to an additional selection bias in our sample. For instance, if it is harder

Our primary goal in this paper is to study the influence of peers on the organizational decisions of new entrants. We define peers as other establishments operating in the same three-digit industry and micro-region as the entrant.[8] To construct an instrument for peers' layers, we use the information on other establishments that are part of the same firm as the entrant's peers. Specifically, we consider establishments that operate in different markets than the entrant's establishment but are part of the same firm as the entrant's peers. However, not all entrants have multi-establishment peers, which leads to a smaller sample size for our instrumental variable analysis. Table 2 displays the summary statistics for our sample of entrants relative to all entrants between 2003–2009. As we can see from this table, entrants in our sample are similar to other entrant over this period.

In addition to our primary definition of peers, we also consider an alternative definition that includes firms in the same two-digit industry as the entrant. This alternative definition allows us to explore whether industry similarities play a larger role in influencing organizational decisions compared to locational proximity. Table 3 presents summary statistics of our peer groups at the industry-location level.[9] The entrants in our sample are distributed across 7042 markets, with an average of 18.68 new entrants per market over a seven-year period, belonging to 15.68 unique firms. On average, each market has 138.53 peers, of which 11.36 are multi-establishment peers.[10] The average number of layers of peers is 1.50, and the average number of layers for other establishments of peer firms is 1.92. If we define peer groups using the 2-digit industry, the number of entrants in each market and the peer group becomes nearly twice as large as compared to using the 3-digit industry.

to survive in high-layer markets, the surviving entrants in these markets may be positively selected in comparison to entrants in other markets.

[8]There are 220 three-digit industries and 160 micro-regions in the data.

[9]Note that in our analysis, peer groups also vary by year of entry. However, the variation across time is not significant. Therefore, we deemed it more meaningful to present summary statistics at the market level rather than at the market-year level.

[10]Due to a vast majority of establishments in the dataset being individual entrepreneurs, there exists a considerably larger number of peers in comparison to multi-establishment peers.

TABLE 2: DESCRIPTIVE STATISTICS

	Sample	All Entrants
Panel A: Baseline outcomes		
Number of layers	1.57	1.54
Log establishment size	2.12	2.09
Number of occupations	4.24	4.12
Log wages	1.45	1.43
Log total hours	7.35	7.32
Survived at least 6 years	1.00	0.58
Observations	131541	247924
Panel B: Changes over six years conditional on survival		
Added layer	0.40	0.40
Added occupation	0.75	0.75
Change in log-employment	0.14	0.16
Change in log-wages	0.24	0.24
Change in log-total hours	0.14	0.16
Observations	131541	143204

Note: The first column of the table displays the summary statistics for our analytical sample, while the second column shows the summary statistics for all establishments that entered between 2003 and 2009. Panel B presents the statistics for entrants who survived for at least six years since their entry. For both columns, we only consider establishments with establishment size and employment growth values not in the bottom 1 or top 99 percentile, and those with at least four employees at the time of entry.

III EMPIRICAL FRAMEWORK

Our goal is to assess how the organizational structure of incumbent peers at the time of entry affects the likelihood of a new entrant adding a layer to its organization within the first five years. Before we present our estimating equation, we define some notation. Specifically, we define a market as an industry-location combination, which we denote as m. Additionally, we define two sets: $P_{-f,m}(i)$, which comprises all establishments in establishment i's market that do not belong to i's firm, and $P_{f,-m}(i)$, which includes all establishments belonging to i's firm but not in i's market.[11] For our analysis, $P_{-f,m}(i)$

[11]Assuming that $f(i)$ is the set of establishments that belong to the same firm as i, and $m(i)$ is the set of establishments that operate in the same market as i, we can define $P_{-f,m}(i) = f(i)^C \cap m(i)$ and $P_{f,-m}(i) = f(i) \cap m(i)^C$.

Table 3: Descriptives by Market

Market definition: Micro × 3 Digit Industry	
Number of markets	7042
Number of establishments	18.68
Number of firms	15.68
Number of peer establishments	138.53
Number of multi-establishment peers	11.36
Peers' number of layers	1.50
Peers' other establishment layers (instrument)	1.92
Market definition: Micro × 2 Digit Industry	
Number of markets	3478
Number of establishments	37.82
Number of firms	31.75
Number of peer establishments	294.21
Number of multi-establishment peers	23.50
Peers' number of layers	1.45
Peers' other establishment layers (instrument)	1.93

represents the peer group of establishment i, and we are interested in examining the effect of having a high proportion of peers with many layers in this group on establishment i's organizational decisions.

We postulate that for a new entrant i that enters market m in year e, the decision to add a layer to its organization in the first five years depends linearly on the average number of layers of its peers in year e. This gives us the following linear-in-means model:

$$Add\ Layer_{i,m,e+5} = \alpha + \beta \cdot \left(\frac{1}{|P_{-f,m}(i)|} \sum_{j \in P_{-f,m}(i)} Layers_{j,m,e} \right) + \boldsymbol{X_{i,e,m}} \gamma + \varepsilon_{i,e,m} \qquad (1)$$

The variable $Add\ Layer_{i,m,e+5}$ is a binary indicator that equals 1 if establishment i that entered market m in year e added a layer in any year between $e+1$ and $e+5$. Thus it indicates if the establishment reported an employee in an additional layer compared to the previous year at any point during the five years.[12] $Layers_{j,m,e}$ represents the number of layers for establishment j in market m in year e, and $\boldsymbol{X_{i,e,m}}$ represents other observable characteristics of new entrant i or i's market at the time of entry. The error term $\varepsilon_{i,e,m}$ captures unobservable factors that affect the decision of establishment i to add a layer to its organizational structure.

We are primarily interested in the coefficient β, which reflects how an entrant's decision to add a layer varies with the average number of layers of its peers. To obtain a consistent estimate of β, we require that any unobserved factors that affect an entrant i's decision to add a layer should not be systematically related to the average number of layers of its peers in $P_{-f,m}(i)$, conditional on observables.

Since Manski (1993), researchers have been aware of the challenges associated with identifying spillovers or peer effects, which are primarily related to two issues: reflection and endogeneity. Reflection is not a concern in our study, as we use peers' lagged outcomes before entry. However, endogeneity concerns may still arise from two sources. First, certain markets may experience common unobserved shocks or share common fundamentals. For example, a technology startup in São Paulo would benefit from the same ecosystem that has helped other technology firms thrive in the area, such as access to skilled labor due to the presence of universities and research institutes or government initiatives focused on promoting technology and innovation in the area. Second, sorting or endogenous group formation may also be a concern. For example, if larger, more productive startups tend to locate closer to larger, more productive firms, we may erroneously attribute the effects of sorting to peer effects.

To address the issue of correlated effects across markets, we employ an instrumental variable (IV) approach. We instrument peers' average layers with the average layers of other establishments in peer firms that are not in the same market as the entrant. In particular, our instrument is given by:

$$Z_{i,m,e} = \sum_{j \in P_{-f,m}(i)} \left(\sum_{k \in P_{f,-m}(j)} Layers_{k,m',e} \right) \tag{2}$$

[12]In some cases, establishments may add and then remove a layer within this period. However, our definition of $Add\ Layer_{i,m,e+5}$ would still take a value of 1 in such cases, even if the total number of layers remains unchanged. Therefore, we also provide results using an alternative definition of the dependent variable, which is an indicator of whether the number of layers increased over a period of five years.

Our instrument will be relevant as long as layers across establishments of the same firm are correlated.[13] For instrument validity, in addition to relevance, we also need that our instrument is uncorrelated with unobserved factors that affect an entrant's organizational decisions. Since our instrument is based on layers of establishments outside of *i*'s market, it attenuates the concern regarding unobserved factors resulting from market-specific fundamentals or shocks.[14] This approach is akin to using network structures to identify peer effects, as proposed by Bramoullé et al. (2009). However, there remains a concern about new entrants sorting into markets with high-layer peers. To address this concern, we control for the entrant's initial size, number of layers, and average log wages, as well as the market size at the time of entry. Additionally, we include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects across all specifications.

IV Impact of Peers on New Entrants

In this section, we present our key finding on the impact of the organizational structure of incumbent product market peers on the organizational decisions of new entrants.

The main results are presented in Table 4, where column (1) shows the OLS estimates. The results indicate a positive correlation between the likelihood of new entrants adding a layer within the first five years and the average number of layers of its peers. Peers are defined as other incumbent establishments in the entrant's industry and location at the time of entry who do not belong to the entrant's firm. The estimation controls for industry and entry-year fixed effects, as well as micro area and entry-year fixed effects. This suggests that the observed correlation cannot be attributed to industry- or location-specific factors that might affect both the incumbents and the entrants directly or indirectly through selective entry.

However, it is possible that this observed correlation is driven by market-specific fac-

[13] Gumpert et al. (2022) show that managerial organization is interdependent across establishments within a firm. This is true in our data as well, as evidenced by a strong first stage.

[14] Although a shock in a market could affect other establishments of peer firms, our use of lagged values for our independent variable and instrument mitigates this concern. Persistent shocks at or before entry could still result in $Cov(Z_{i,m,e}, \varepsilon_{i,e,m}) \neq 0$, but our instrument remains valid as long as the shocks do not immediately transmit to establishments of other firms and do not persist for a significant period of time.

TABLE 4: IMPACT OF PEERS ON ENTRANTS' ORGANIZATIONAL STRUCTURE

	OLS (1)	IV (2)	IV (3)	IV (4)
Dependent variable		Add layer		
Peers' average layers	0.087***	0.202*	0.290***	0.298**
	(0.013)	(0.109)	(0.111)	(0.120)
Additional controls			X	X
Peer size quartile dummies				X
First-stage dependent variable		Peers' average layers		
Instrument for peers' layers		0.044***	0.044***	0.040***
		(0.003)	(0.003)	(0.003)
KP Wald F-Stat		210.12	209.24	219.30
Observations	131541	131541	131541	131541

Note: The table presents the estimated coefficients from a regression of the binary indicator for adding a layer in the first five years on the average number of peers' layers. Column (1) presents OLS estimates, while columns (2)–(4) present IV estimates. The instrument for peers' layers is constructed using other establishments that belong to the peer's firm but are not in the same micro area and 3-digit industry. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

tors. Here, a market is defined as a combination of industry and location. For instance, there could be unique characteristics of the technology sector in São Paulo that differentiate it from technology sectors elsewhere, as well as from other sectors in São Paulo. If such factors impact both entrants and incumbents, then the observed correlation may not reflect a causal impact of peers on entrants. To account for this, we employ an instrumental variables strategy. We instrument average peers' layers using the layers of other establishments belonging to the same firm as the peer but operating in a different market. The instrument is specified in eq. (2).[15]

[15] Note that for constructing the instrument, we allow establishments operating in the same micro but different industry and those operating in the same industry but different micro. In section V.A, we also present results from an alternative instrument, where we only allow other establishments of the peer's

We report IV estimates across three specifications in columns (2)–(4). Column (2) doesn't include any additional controls, and we find a positive impact of peers' layers on the probability of adding a layer. While IV helps account for market-specific factors, we are still concerned about reverse causality, in particular, through entrants systematically entering markets with high- or low-layer peers. To address this issue, we control for several characteristics of entrants at the time of entry, including log wages, number of layers, establishment size, and market size. The resulting specification presented in column (3) is our preferred specification. Our empirical results indicate that an additional layer in the average peer's organization increases a new entrant's likelihood of adding a layer by 0.29 percentage points. Given that 40% of new entrants add a layer within the first five years in our sample, an extra layer in the average peer's organization nearly doubles the likelihood of a new entrant adding a layer.

In column (4), we further investigate whether our estimates are primarily driven by larger peers by including indicators for quartiles of average peer size as controls. We find that the coefficient on this specification is somewhat larger, implying that layers play a role independently of peer size.

Overall, the IV estimates are stable across all three specifications mitigating concerns about endogeneity due to unobserved factors. Taken together, our findings suggest that the internal organizational structure of peers has a significant impact on the organizational decisions of new entrants.

V Mechanisms Behind Spillovers

In this section, we explore the mechanisms underlying the spillovers documented in the previous section. Specifically, in Section V.A, we examine the role of industry similarity, while in Section V.B, we explore the potential contribution of availability of upper-hierarchy workers in markets with high-layer peers.

firm that do not operate in the same micro *or* industry.

V.A Locational Proximity vs. Industry Similarity

So far, we have documented that high-layer peers in the entrant's three-digit industry and location causally affect the entrant's likelihood of adding a layer. We now investigate whether being in the same three-digit industry is a crucial factor in determining the likelihood of adding a layer for entrants or whether the proximity between establishments is the most significant determinant. Specifically, we redefine peers as establishments in the same two-digit industry and micro area and compare the impact of this alternative peer group to the impact of peers in the same three-digit industry and micro area.[16]

Table 5 displays the outcomes of this analysis, indicating that the impact of two-digit peers is less significant than that of three-digit peers, underscoring the relevance of peers in similar industries.[17]

V.B Hiring in New Layers: Internal vs External Hires

In this section, we investigate whether establishments in markets with more high-layer peers find it easier to hire workers with management or supervisory experience, which could be a potential explanation for the observed spillover effects. To examine this hypothesis, we begin by considering all entrants in our sample who added a layer, and we analyze the hires in newly created layers over five years.

We start by examining the share of entrants that added layers exclusively through internal promotions. Then, we shift our focus to establishments that added a layer and hired at least one worker externally. We construct variables to capture the share of external hires from within the three-digit industry and micro, two-digit industry and micro, and micro area. Our results are presented in Table 6. From column (1), we can see that the probability of exclusively hiring internally in newly added layers does not

[16] We do not consider peers in the entrant's micro-area as this would preclude us from incorporating micro-area fixed effects. Relying on such locational variation is more susceptible to omitted variable bias, which is why we don't rely on it. Consequently, estimates for micro area peers, available on request, are actually larger.

[17] Note that we exclude other establishments in the micro area of peers' firms for both instruments here, whereas these were allowed in our baseline instrument. With this alternative approach to defining the instrument, we find that the influence of three-digit industry peers is slightly greater.

TABLE 5: RESULTS WITH ALTERNATIVE PEER GROUPS DEFINITIONS

	(1)	(2)
Dependent variable	Add layer	
3-digit industry X micro peers	0.337***	
	(0.045)	
2-digit industry X micro peers		0.274**
		(0.128)
First stage dependent variable	Peers' average layers	
3-digit X micro instrument	0.103***	
	(0.004)	
2-digit X micro instrument		0.059***
		(0.004)
KP Wald F-stat.	564.99	249.72
Observations	128368	128368

Note: The table displays the results of an instrumental variables regression of a binary indicator for adding a layer in the first five years on the average number of peers' layers. For column (1), the entrant's peers are defined as other establishments in the entrant's micro area and 3-digit industry, while for column (2), peers are defined as other establishments in the entrant's micro area and 2-digit industry. The instrument for peers' layers is constructed using other establishments that belong to the peer's firm but are not in the same micro area. All columns include 2-digit industry interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

vary significantly with the number of layers in peers' establishments. Further columns (2)-(3) demonstrate that entrants operating in markets where peers have more layers are more likely to hire employees from within the market, as defined at different levels.

Taken together, our findings suggest that one potential source of spillovers is the reduced cost of hiring workers in managerial or supervisory positions who are already available in these markets. By hiring locally, establishments can benefit from a pool of workers with relevant experience, which can reduce the costs and time associated with finding and training new workers.

TABLE 6: HIRES IN NEWLY CREATED LAYERS

	Only Internal Promotions (1)	Within 3-Digit Ind × Micro (2)	Within 2-Digit Ind × Micro (3)	Within Micro (4)
Peers' average layers	0.097	0.122**	0.152**	0.191**
	(0.139)	(0.060)	(0.066)	(0.093)
KP Wald F-Stat	157.80	144.77	144.77	144.77
Observations	52694	41147	41147	41147

Note: In column (1), the sample consists of all entrants in our analytical sample who added a layer. The dependent variable in column (1) is a binary variable that equals 1 if all hires in the newly created layers were internal promotions. Columns (2) to (4) further exclude from the sample entrants for whom all new hires in newly created layers were internal promotions. The dependent variable in columns (2) to (4) is the proportion of external hires (excluding internal promotions) that were from within the specified reference category. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

VI ADDITIONAL RESULTS AND ROBUSTNESS TESTS

In this section, we discuss robustness checks and additional results. All tables are presented in the appendix.

VI.A Timing of Adding Layers

In our baseline analysis, we examined cumulative outcomes over a period of five years. Specifically, our dependent variable takes on a value of 1 if an entrant reports an employee in a new layer that was not present in the previous year, at any point during the first five years. We now shift our focus to the timing of adding a layer. For each of the first five years since entry, we investigate how the cumulative probability of adding a layer varies with the number of peer layers. The top panel of Table A5 presents these estimates. The estimate presented in column (5) of this panel, is the same as our baseline estimate in column (3) of Table 4.

Furthermore, we also define an alternative add layer indicator, which takes on a value of 1 if there is an increase in the number of layers from entry year to the reference year. The estimates with this alternative indicator are presented in the bottom panel of Table A5. The coefficient for the cumulative probability of adding a layer in five years is lower for the alternative definition, suggesting that a significant number of establishments also drop a layer over this period.

By examining the estimates for all years in both panels, it becomes clear that the majority of the impact occurs within the first two years. Specifically, the impact of peers' layers on the cumulative probability of adding a layer does not increase after the first two years, with most of the impact occurring in the year following entry. It is important to note that entrants do not solely add layers in the first year since entry, as the raw cumulative probability of adding a layer actually increases over time. However, our findings suggest that the impact of peers is only significant for the first two years after entry.

VI.B Impact on Exit Probability

We now examine how the probability of exit is affected by the average layers of peers. Our sample for this analysis consists of all establishments that entered the data between 2003–2009. As we did for our baseline sample, we exclude entrants with extreme values on establishment size and employment growth, as well as those without multi-establishment peers. However, unlike our baseline sample, we do not require entrants to survive for at least six years. We investigate the probability of exit in any given year, conditional on having survived thus far, and explore whether this probability varies with the average layers of peers.

The results of this analysis are presented in Table A3. We observe negative but statistically insignificant impacts of peers' average layers in the first two years. In year three, we find a large negative coefficient that is statistically significant. In particular, one additional layer in the average peer's organization reduces the likelihood of exiting in year three by 15 percentage points. We interpret this as suggestive evidence that peers can impact entrant productivity through organizational change spillovers. In high-layer markets, entrants are more likely to add layers in the first two years, which likely aids in their survival.

The null effects in years four and five reiterate that the impact of peers only matters during the initial years after entry. The lack of impact on the initial probability of exit is reassuring as it implies that the effect on exit rates is likely due to peers, rather than the result of initial sorting of more productive businesses in high-layer markets.

VI.C Wages, Employment, and Hours

Next, we look at the impact of peers on wages and employment of new entrants. We have shown that establishments operating in high-layer markets tend to increase the number of layers within their organization. The theory of production hierarchies in Caliendo and Rossi-Hansberg (2012) suggests that by adding layers, businesses economize on the cost of knowledge by having highly knowledgeable managers at the top and less knowledgeable employees at the bottom. Based on this theory, we expect to see a decline in wages for employees in pre-existing layers among establishments operating in high-layer markets since these establishments are more likely to add layers. To test this hypothesis, we use IV estimation to regress log changes in wages for pre-existing layers over five years on peers' average layers. The results reported in Table A4 validate our initial hypothesis, as evidenced by the negative coefficient in column (1). So, we find evidence of a decline in wages for pre-existing layers in high-layer markets.

Furthermore, we also present IV estimates for log changes in employment and total hours over five years in Table A4. We observe positive but statistically insignificant impacts on employment and hours. This suggests that the impact of peers on employment is not entirely clear. We interpret this as evidence that it is not necessarily that entrants in high-layer markets are expanding more, but they are more likely to expand by adding layers rather than just expanding without reorganizing.

VI.D Alternative Definition of Layers

For our baseline analysis, we defined four layers to measure organizational structure. These were defined hierarchically, with directors at the top, followed by managers, supervisors, and workers at the bottom. We now want to test if our results are sensitive to the definition of layers. So, in addition to the baseline definition of layers, we use two alternative definitions of layers and repeat the analysis. In the first alternative definition, the third and fourth layers from the baseline are combined, with supervisors and workers grouped together as one category. The second alternative definition combines the second and third layers, with supervisors and managers classified as a single category.

The results presented in Table A6 show that the impact of peers on organizational change is similar across all three layer definitions. While the estimated coefficients vary slightly between the different definitions, the overall pattern of results remains consistent. Overall, these findings suggest that the definition of layers used in the analysis has a limited impact on the results and that the main conclusions of our study are robust to different layer definitions.

VI.E Heterogeneity Analysis

Finally, we examine whether there are any heterogeneous impacts based on the initial layer of the entrant. Our findings, presented in Table A7, indicate that the role of peers is most significant for entrants who begin with a single layer at the time of entry.

In addition, we also investigate heterogeneous impacts based on peers' productivity. Given that we do not have a direct measure of productivity, we use the average wage as a proxy for it. Specifically, we divide peers into four groups based on quartiles of the average wage distribution and create separate measures for the average peers' layers, our independent variable, and the corresponding instrument for each group. The results of this analysis, presented in Table A8, demonstrate that entrants do not seem to respond to peers in the lowest wage quartile.

VII Conclusion

Our paper investigates the extent to which a firm's organizational decisions are influenced by the internal organizational structure of its peers. Using matched employer-employee data from Brazil, we show that the presence of an additional layer in the average peer's organization nearly doubles a new entrant's likelihood of adding a layer. Our study highlights several potential channels for these spillovers, including learning from peers and the availability of workers with the requisite skills in markets with high-layer peers. Further research could also investigate the impact of spillovers in organizational structure on other aspects of firm performance, such as innovation and profitability.

The paper contributes to the literature by proposing organizational structure spillovers as a potential source for agglomeration economies. By providing evidence of the causal effect of peer firms' hierarchical structure on the decisions of new entrants to add organizational layers, we also add to our understanding of how firms interact and shape each other's behavior.

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Appendix A Data and Additional Descriptives

A.1 Construction of Layers

We define four hierarchical layers to measure organizational change using Brazil's occupational classification system, Classificação Brasileira de Ocupações (CBO) 2002. The table below presents the mapping of CBO occupation groups to our definition of layers.

Layer	CBO Occupation Group
1: Directors	12: Officers of companies and organizations (except of public interest), 13: Directors and managers in health services company, education, or cultural, social or personal services
2: Managers	14: Managers
3: Professionals & Supervisors	2: Professionals in arts and sciences 410: Administrative services supervisors 420: Public service supervisors 510: Service supervisors 520: Sales supervisors 620: Supervisors in agricultural exploration 630: Supervisors in forest exploration and fishing 710: Supervisors of mineral extraction and civil construction 770: Supervisors in the wood, furniture, etc. 780: Packaging and labeling workers supervisors 810: Production supervisors in chemical, petrochemical, etc. 820: Production supervisors in steel industry 830: Pulp and paper manufacturing supervisors 840: Food, beverage, and smoke manufacturing supervisors 860: Utility production supervisors
4: Workers	3: Mid-level technicians 4-9: all workers except supervisors identified above

TABLE A1: WAGES, EMPLOYMENT, AND HOURS BY NUMBER OF LAYERS

Layer	4	3	2	1
Log wages	1.44	2.16	2.19	3.03
Workforce size	11.14	5.95	2.28	2.04
Total hours	2072.79	1026.43	427.33	372.49
Observations	13598622	2733832	2802197	288042

Note: This table displays the average log wages, employment, and total hours for each hierarchical layer aggregated across the years 2002-2014. The layers are denoted as follows: (4) workers, (3) professionals/supervisors, (2) managers, and (1) directors.

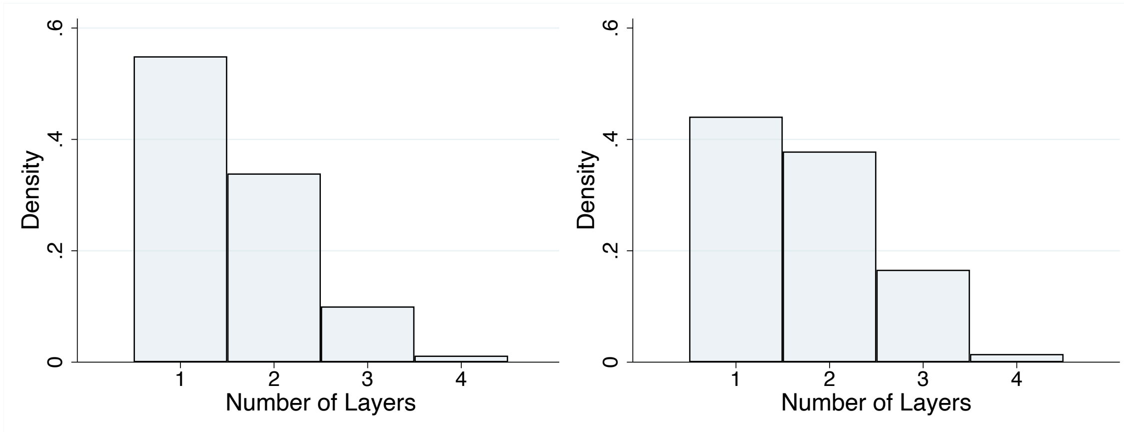
Table A1 presents the characteristics of layers in our data. As we can see from this table, our definition of layers does capture hierarchy within organizations, as lower-level layers, on average, have more number employees and lower wages.

A.2 Additional Descriptives of the Sample

Figure A1 displays the distribution of the number of layers among entrants in our sample at the time of entry and five years after. Similarly, Figure A2 shows the distribution of establishment size for entrants in our sample at the two time points. As shown in these figures, both distributions shift towards the right over time, indicating that the entrants have experienced growth.

Finally, Table A2 presents additional details on layers and transitions between them for our sample. Panel A of Table A2 presents counts and shares of establishments with each particular layer by the number of layers. From panel A, we can see that most establishments with a single layer have workers as their only layer. For establishments with two layers, one of the layers is almost always workers, while the other layer is half the time supervisors and half the time managers. Panel B of Table A2 displays the transition matrix by the number of layers, indicating that most establishments tend to add or remove only one layer at a time, and a significant percentage of establishments remove a layer over time. Lastly, panel C of Table A2 displays the probability of adding a specific layer conditional on the initial layer and the establishment adding exactly one layer in the following year. From this panel, we can see that if an establishment starts with workers and adds exactly one layer, it is 44% likely to be supervisors and 55% likely

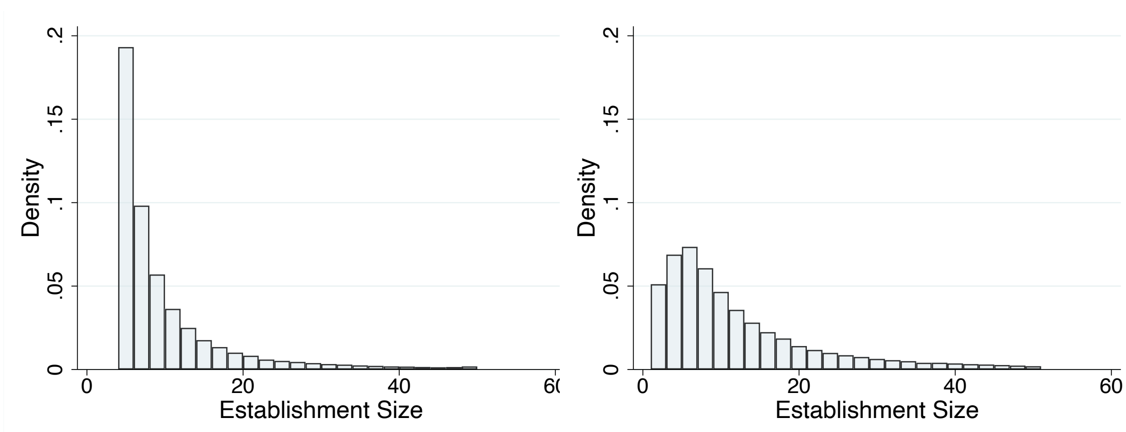
FIGURE A1: DISTRIBUTION OF NUMBER OF LAYERS FOR ENTRANTS



(A) T (B) T+5

Note: The figure displays the distribution of hierarchical layers for new entrants in our sample, with panel A representing the distribution at the time of entry and panel B showing the distribution five years later.

FIGURE A2: ESTABLISHMENT SIZE DISTRIBUTION



(A) T (B) T+5

Note: The figure displays the distribution of establishment size for new entrants in our sample, with panel A representing the distribution at the time of entry and panel B showing the distribution five years later.

to be managers.[18] Finally, if an establishment starts with workers and supervisors, it is 90% likely to add managers instead of directors.

Table A2: Level of Layers and Transition Across Layers

Panel A: Level of Layer by Number of Layers

L	Observations	Workers	Supervisors	Middle Management	Top Management
1	374382	0.98	0.01	0.01	0.00
2	292419	0.99	0.47	0.52	0.02
3	112610	1.00	0.98	0.93	0.09
4	9835	1.00	1.00	1.00	1.00

Panel B: Transitions by Number of Layers

L	1	2	3	4
1	0.83	0.16	0.01	0.00
2	0.15	0.75	0.10	0.00
3	0.03	0.18	0.76	0.03
4	0.01	0.04	0.29	0.66

Panel C: Transitions by Level of Layers

Base Layer/Layer Added	Supervisors	Middle Management	Top Management
Workers	0.44	0.55	0.02
Workers and Supervisors		0.90	0.10

Note: This table provides information on layers and transitions between them for our sample. Panel A displays the counts of establishments with 1, 2, 3, or 4 layers over the sample period. Additionally, it shows the shares of establishments that had any particular layer, conditional on the number of layers. Panel B presents the transition matrix for the number of layers, where each cell represents the share of establishments that started with the number of layers indicated by the row and had the number of layers indicated by the column in the next year. Panel C consists of two rows that condition on the initial layer and the establishment adding exactly one layer in the following year. The first row displays the probability of adding one of the three upper layers after starting with workers only. The second row shows the probability of adding one of the top two layers after starting with workers and supervisors.

[18] This hierarchy pattern is different from other papers that use data from other countries, so we also use an alternative definition of layers where we combine layers 2 and 3.

Appendix B Additional Results

Table A3: Impact on Likelihood of Exiting

Dependent variable	Indicator for exiting conditional on survival				
	Year 1	Year 2	Year 3	Year 4	Year 5
Peers' average layers	-0.05	-0.10	-0.15***	0.04	0.06
	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
KP Wald F-Stat	286.7	270.7	262.3	246.3	232.5
Observations	231333	209915	187739	168381	150992

Note: The table presents IV estimates for the impact of peers' average layers on the likelihood of exiting in any given year since entry, conditional on survival. The sample includes all establishments that entered between 2003–2009. We exclude entrants with extreme values and entrants with no multi-establishment peers. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A4: IMPACT ON WAGES IN PRE-EXISTING LAYERS, EMPLOYMENT, AND HOURS

Dependent variable	Δ Wages (1)	Δ Employment (2)	Δ Total Hours (3)
Peers' average layers	-0.165*** (0.053)	0.130 (0.195)	0.137 (0.197)
Own layers at entry	-0.028*** (0.001)	-0.060*** (0.004)	-0.073*** (0.004)
Number of peers at entry	-0.002 (0.002)	0.006 (0.006)	0.005 (0.006)
Employment at entry	-0.007*** (0.001)		
Log wages at entry		0.126*** (0.007)	0.175*** (0.008)
Observations	109940	131541	131541

Note: The table presents the estimated coefficients from an instrumental variables regression for entrants in our sample. The dependent variable in column (1) is the change in the log of average wages in pre-existing layers over five years since entry. In columns (2) and (3), the dependent variable is the change in the log of employment and total hours over the same time frame. Establishments with missing average wage growth are excluded from column (1). All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A5: TIMING OF ADDING A LAYER

Reference Year	1	2	3	4	5
Dependent variable	Indicator for adding a layer up to the reference year				
Peers' average layers	0.235***	0.299***	0.284***	0.288***	0.290***
	(0.080)	(0.096)	(0.104)	(0.108)	(0.111)
Dependent variable	Indicator for increase in number of layers				
Peers' average layers	0.235***	0.254***	0.226**	0.203**	0.185*
	(0.080)	(0.090)	(0.094)	(0.097)	(0.100)
Observations	131541	131541	131541	131541	131541

Note: The top panel of this table shows the IV estimates with the dependent variable being the indicator for adding a layer at any year up to the reference year. The bottom panel has the dependent variable as the indicator for the number of layers in the reference year being greater than the number of layers at entry. The reference years represent the number of years since entry. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A6: ALTERNATIVE DEFINITION OF LAYERS

Dependent variable	Add layer		
	(1)	(2)	(3)
Peers' average layers	0.290***	0.258*	0.325**
	(0.111)	(0.143)	(0.130)
First-stage dependent variable	Peers' average layers		
Instrument for peers' layers	0.044***	0.046***	0.048***
	(0.003)	(0.003)	(0.003)
KP Wald F-Stat	209.24	291.17	249.68
Observations	131541	131541	131541

Note: Column (1) presents instrumental variable estimates using the baseline definition of layers, which has four levels. However, columns (2) and (3) use different definitions with only three levels. Specifically, in column (2), the 3rd and 4th layers from the baseline are combined, i.e., supervisors and workers are considered as one category. In column (3), the 2nd and 3rd layers are combined, i.e., supervisors and managers are considered as one category. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A7: HETEROGENEITY BY INITIAL NUMBER OF LAYERS

Number of Layers at entry	1	2	3
Dependent variable	Add layer		
Peers' average layers	0.357**	0.163	0.040
	(0.159)	(0.176)	(0.278)
KP Wald F-Stat	158.03	126.92	28.23
Observations	72138	44404	12741

Note: The table presents IV estimates separately for entrants with 1, 2, or 3 layers at entry. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

TABLE A8: HETEROGENEITY BY QUARTILES OF WAGE DISTRIBUTION

	(1)	(2)	(3)	(4)
Dependent variable		Add layer		
Q4 peers' layers	0.143**			
	(0.059)			
Q3 peers' layers		0.125**		
		(0.060)		
Q2 peers' layers			0.165*	
			(0.099)	
Q1 peers' layers				-0.004
				(0.118)
KP Wald F-Stat	232.93	239.49	163.55	122.72
Observations	125843	112553	104690	94643

Note: The table presents estimates from separate instrumental variables regressions, with each column corresponding to a specific independent variable and IV constructed using peers in particular quartiles of the wage distribution. All columns include 3-digit industry interacted with entry-year fixed effects, as well as micro-area interacted with entry-year fixed effects. Additionally, all columns include controls for log wages, number of layers, establishment size, and the number of peers at the time of entry. Robust standard errors clustered at the level of peer groups are presented in the parenthesis. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.