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Workplace Design: The Good, the Bad, and the Productive

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Working Paper 16-147

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Abstract

We study the effects of performance spillover in the workplace—both positive and negative–on several dimensions, and find that it is pervasive and decreasing in the physical distance between workers. We also find that workers have different strengths, and that while spillover is minimal for a worker when it occurs in an area of strength, the same worker can be greatly affected if the spillover occurs in her area of weakness. We find this feature allows for a symbiotic pairing of workers in physical space that can improve performance by some 15%. Overall, workplace space appears to be a resource that firms can use to design more effective organizations.

Keywords: strategic human resource management, peer effects, productivity, spillovers, toxic worker

1 Introduction

Fundamental to organizational performance is its human capital (Koch and McGrath [1996] and Hitt et al. [2001]); both specific (Hatch and Dyer [2004] and Kambourov and Manovskii [2009]) and general (Becker [1993]) forms of human cap- ital are crucial. We know that this capital can be increased through selective hiring and effective education and training (Lazear and Oyer [2012]). We also know that the social structure of the workplace can strongly influence that capital: supervisors, co-workers, and toxic employees all have an impact on our performance. In spite of these strong social effects, there is a dearth of knowledge surrounding how the return to human capital is affected by the physical location of those individuals within an organization. While some have studied the effect of workers stationed at entirely different locations from one another (Cramton [2001] and Bloom et al. [2015]), little is known about varying levels of proximity within the same location. Investing in selection and training can be extremely costly; simply re-arranging desks may be one of the lowest cost ways to affect the returns to human capital. In this paper, we explore the returns to the physical location of workers.

We call the pursuit of how to best physically locate workers within an organization spatial management. To explore spatial management across physical space and time, we follow the performance of nearly 3,000 workers within a large technology firm. Taking advantage of quasi-exogenous placement of workers, we are able to identify how the colocation of workers affects their performance outcomes on several dimensions of performance.

Using both a simple measure of physical distance (e.g. the radius around a worker) and a parametric distance weighting function, we find that physical location has large performance effects on workers. All three of our measures of positive performance–productivity, effectiveness, and quality–exhibit strong positive spillovers as a function of how closely situated one type of worker is to another. In terms of magnitudes, increasing the density of exposure to productivity by one standard deviation increases the productivity of the focal worker by roughly 8%. A similar increase in exposure to other effective workers increases effectiveness of the focal worker by some 16%. Finally, a similar increase in the density of exposure to other quality workers increases the focal workers quality by some 3%.

There has been some important work on peer effects that shows that productivity (Falk and Ichino [2006], Mas and Moretti [2009], and Bandiera et al. [2010]) and quality (Jackson and Bruegmann [2009] and Azoulay et al. [2010]) often spill over to fellow workers. However, when considering spillover as multi-dimensional–encompassing more than just productivity–a richer story emerges. In such a setting, we find three types of workers, which we dub Productive, Generalist, and Quality workers. Productive workers are very productive but lack in quality. In contrast, Quality workers produce superior quality but lack in productivity. All the while, the Generalists are average on both dimensions. This presents an interesting and important organizational question: which types of workers should be paired together? We find that matching Productive and Quality workers together and matching Generalists separately generates up to 15% of increased organizational performance. In short, symbiotic relationships are created from pairing those with opposite strengths. It turns out that those strong on one dimension are not very affected by spillover on that dimension; however, they are very sensitive to spillover on their weak dimension. In total, based on our empirical estimates, for an organization of 2,000 workers, symbiotic spatial management could add an estimated $1 million per annum to profit.

In terms of a mechanism driving these results, it appears that these spillover effects do not stem from peer-to-peer learning (Foster and Rosenzweig [1995]), as effects occur almost immediately and vanish within two months of exposure. Instead, it appears that some combination of inspiration and peer pressure (Kandel and Lazear [1992] and Mas and Moretti [2009]) spurs workers on to higher levels of multi-dimensional performance.

We also consider whether these spillover effects extend to negative performance through misconduct and unethical behavior spillovers (Robinson et al. [1998], Ichino and Maggi [2000], Pierce and Snyder [2008], and Gino et al. [2009]). In particular, we measure the extent to which a toxic worker–i.e. a worker that harms a firm's people and/or property (Housman and Minor [2016])–induces spillover from their behavior. We find that the negative performance of these workers spills over to fellow workers in a process similar to the positive worker spillover outlined above. The bad news is that negative spillover effects happen almost immediately. The good news is that the effects vanish within a month of no longer being exposed to the toxic worker.

In total, we see the contribution of this paper as threefold. First, we essentially generalize past work that only studied one type of spillover, often productivity, among workers. We document pervasive spillover across multiple types of performance, positive and negative, simultaneously within one organization. This multi-dimensional analysis leads to our next contribution of finding that various workers with diverse strengths are affected differently by spillovers, and that workers tend to have different strengths across dimensions. Consequently, symbiotic relationships can be created to improve organizational performance. This suggests that optimal organizational design should include the physical design of worker space. Finally, we identify that spillover among workers is not simply a matter of exposure or not, but also the magnitude of exposure, which is captured by the physical distance between workers within a given location.

The organization of the paper is as follows. The next section describes our data. Section Three reports our empirical analysis. Our final section concludes with a discussion.

2 Data

To answer these questions, our study utilized data from a large technology company with several locations in the U.S. and Europe. Included in the sample were over 2,000 employees engaged in technology-based services, along with their direct supervisors. The study period consisted of an approximately two-year period from June 2013 through May 2015.

The data that we used to examine this population emerged from five different sources that were merged on the basis of a single universal identifier for each worker:

1. The central data source was a master employee file that was pulled from the company's Human Resource Information System (HRIS). This file contained historical data related to the employees: their hire and termination dates, and their

position, compensation, and direct managers.

2. Data emerged from two engagement surveys that had been conducted across the organization: one in fall of 2013 and one in fall of 2014. The engagement survey achieved a 95% response rate. However, no individual employee-level data was provided, so it was aggregated at the manager level when there were at least three responses available.

3. Each employee's location and their assigned cubicle over time were provided by the company's facilities team. The unit of observation for this data was the employee-month, as the data indicated where each employee was sitting on the first of the month (although not on any dates in between). This data was provided for all of the direct supervisors as well.

4. Building maps were also provided by the facilities team. These were architectural diagrams in which the location of each cubicle was drawn out on the blueprint along with a cubicle label. Figure 1 shows a sample of a floor layout. We used architectural AutoCAD software to plot the x- and y-coordinates of every cubicle and were then able to calculate the distance from each cubicle to every other cubicle on the floor. It should be noted that the walls surrounding actually vary across buildings and locations, but there was no systematic way to capture this data.

5. Performance data was available for a variety of different metrics that are tracked for this employee population. However, in the course of interviews, we discovered three that were considered most important to the company when evaluating employee performance. Based on this, we used these following metrics:

a. Productivity - Measured the average length of time it takes a worker to complete a task. For any given worker, tasks are fairly similar and occur regularly.

b. Effectiveness - Measured the average daily rate at which a worker needed to refer a task to a different worker to solve. This occurred when the employee couldn't resolve the task on their own.

c. Quality - Measured the satisfaction of the beneficiary of the completed task. In essence, this a net promoter score in which a satisfactory score is represented by selecting a 4 or 5 on a 5-point scale. Due to the fact that this data was more sparse, these were measured weekly for each employee and then averaged by month.

These five primary sources of data were all merged through unique IDs and on the basis of the time period that they covered. Data sources (1) and (3) were measured monthly whereas data source (2) was an annual measurement, and the source:(4) did not change over time. The performance measured in (5) either utilized daily or weekly measurements, depending on the metric of interest, and were then averaged by month.

We achieved match percentages in the $95-97\%$ range across every type of merge, which attests to the high level of quality with which this company maintains its data, and the level of data cleansing that they had done in the years prior. In sum, we ended up with a total of 2,454 employees and 342 managers within our sample across the roughly two-year study period. Figure 2 shows a heat map which illustrates the combination of workers' physical location and their respective performance outcomes, showing how it can vary across space. This data is for a single month for a group of workers on a single floor engaging in similar tasks.

Through interviews, we learned that worker placement occurs in a quasi-random manner. In particular, the manager of a given business location regularly transfers workers to different locations due to the demand for needed types of positions and the supply of workers for a given position . It was explained that the exact location of any given worker is "pretty random." To the extent that the supply and demand shocks driving the matching of workers and location are uncorrelated, this claim is true. Although we cannot directly test this claim, Housman and Minor (2015) find when they can test for exogenous placement into different workgroups in a similar human resource setting that placement is indeed essentially random.

2.1 Measuring Spillover

To measure spillover, we develop a weighting of workers to measure the potential impact on a focal worker as a function of how close they are in terms of physical distance. We then use this "distance weighting" to obtain a measure for the overall spillover that a focal worker receives on a given performance dimension.

Our distance weighting metric for any given focal worker is

$$w_i = \frac{d_{\max} - d_i}{d_{\max}}, \tag{1}$$

where $d_{\max}$ is the Euclidian distance between the focal worker and the worker located the farthest from her. The value d_i is the Euclidian distance between the focal worker and the worker producing any spillover. Thus, the workers closed to the focal employee gets weight $w_i \simeq 1$ and the employee farthest away gets weight $w_i = 0$. A worker half of the maximum distance away receives weight $w_i = \frac{1}{2}$.

The overall spillover is then obtained from essentially integrating up the performance of those around the focal worker i with density weight w_i at time t. Formally, we then calculate spillover density as

$$s_{i,t} = \sum_{i \neq j} p_{j,t} w_{i,t}, \tag{2}$$

where $p_{j,t}$ is the performance outcome of worker j at time t and $w_{i,t}$ is the weighting function (1) at time t. For example, for simplicity, assume a focal worker has just three worker peers: one next to her, one 25 feet away, and another 50 feet away. Assume that the nearest worker produces at the rate of 3 units per hour, the middle distance one produces 2 units per hour, and the farthest worker produces 3 units per hour. The spillover is then $3\frac{50-0}{50} + 2\frac{50-25}{50} + 3\ \frac{50-50}{50} = 4$. If instead, the nearest worker only produces at the rate of 2 units per hour and the middle worker at 3 units per hour, spillover falls to 3.5. Though regression analysis, we then estimate a coefficient of spillover, which tells us the effect of varying levels of spillover on a focal worker's own performance. Table 1 reports summary statistics for these density measures, as well as our primary measures discussed in the previous section.

We also tried a much coarser measure of distance by constructing the weighting function as an indicator of whether or not a worker is within a 25 foot radius of the focal worker. Whether we summed worker performance or averaged it within the 25 food radius, we found similar results to our more fine grained density measure found in (2).

3 Empirical Analysis

We begin by studying positive performance spillovers and how these can inform optimal organization design. We then turn to identifying negative spillover.

3.1 Positive Performance Spillover: Productivity, Effectiveness, and Quality

To estimate the spillover effect of our three positive performance outcomes ■ productivity, effectiveness, and quality ■ we use a linear panel model with manager fixed effects. A manager is the direct supervisor of a worker, where a direct supervisor typically oversees 6 to 8 workers. Controls include time fixed effects, a cubic function of job position experience, and job position. Standard errors are clustered at the manager level.

Table 2 reports the results from estimating productivity spillovers (i.e., when $p_{j,t}$ is a measure of productivity). Each column adds successive controls. We find that the spillover effects of productivity are significant at the 1% level and are large in magnitude. An increase of one standard deviation in productivity density results in a 7.86% increase in the productivity measure of the average focal employee.

Tables 3 and 4 report analogous results for effectiveness and quality spillovers. The coefficient on the density of effectiveness spillover is significant at the 1% level; an increase of one standard deviation in effectiveness density results in a 15.81% increase in the effectiveness of the focal employee. Quality spillovers are also significant at the 1% level. An increase of one standard deviation in quality density results in a 2.62% increase in one's own quality. Anecdotally, managers claim that quality is harder to change. That is, they explain that people have a given level of quality that stays relatively constant across time, regardless of the environment.

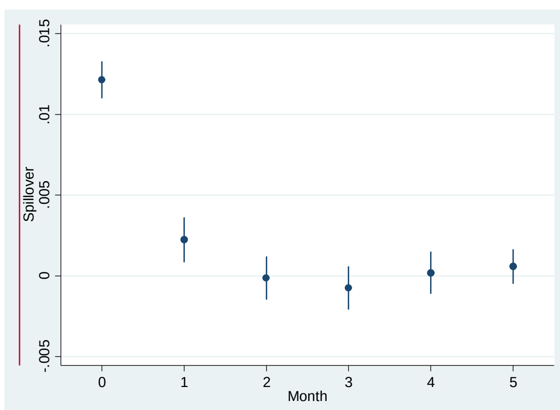
Taken together, these results suggest that positive spillover of performance, measured in three different ways, is pervasive. Now we consider how spillover evolves dynamically.

3.2 Positive Spillover Dynamics

Two leading mechanisms that could be driving the performance spillover found in the last section are learning and some version of peer pressure or inspiration. If the spillover mechanism is learning, we should see the effects of spillover taking some time to generate the maximum effect and the effect should persist, or at least decay slowly due to forgetting, over time. In contrast, if the spillover mechanism is some sort of peer pressure, we should witness immediate effects and then the effects should dissipate relatively quickly once the worker is no longer exposed to the spillover.

To distinguish between these two mechanisms, we estimate our effect over six months, beginning with the contemporaneous month of exposure and then allowing for an additional five months of effect of the current month's exposure . We find the positive spillover effects are immediate and are dissipated by the second month of exposure.

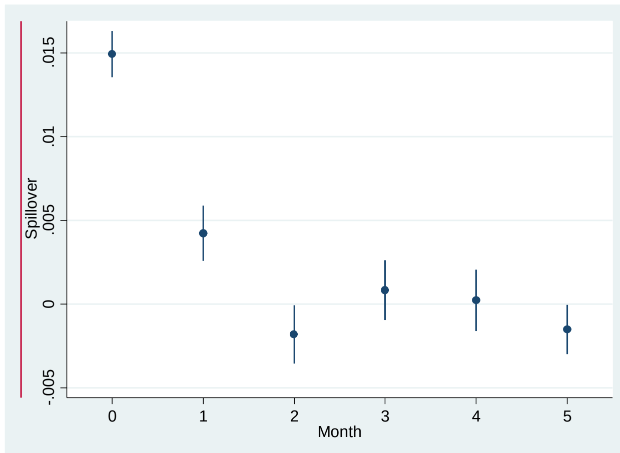
The results for productivity spillovers are as follows:



Productivity Spillover Across Time

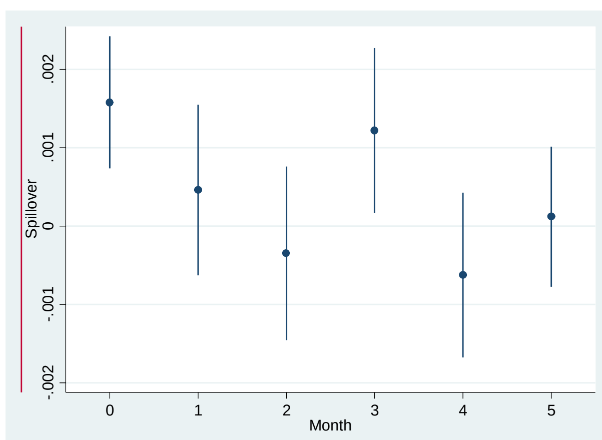
Each bar represents the 95% confidence interval of estimates for the given time frame of the coefficient and the dot is the point estimate. After two months from initial exposure, spillover effects are statistically no different from zero.

We find similar results for the dynamics of effectiveness spillover:



Effectiveness Spillover Across Time

Finally, we find for quality that the effects are very noisy as evidenced by the large bars and most of the effect is in the first month:



Quality Spillover Across Time

In sum, it seems spillover is more of the form of peer pressure than learning. In speaking with managers, we were told that a team of workers meet weekly to discuss performance goals and review past performance, and that they are aware of each other's performance. Interestingly, direct compensation is based on individual performance. However, to the extent workers are creating a history of high performance to increase the chances of promotion, relative performance should still have some incentive effects. Whatever the case, it does seem likely peer pressure effects are at least partially driven by social pressure. We cannot, however, distinguish if the effects are from negative peer pressure or positive peer inspiration (or some combination).

3.3 Spillover Effects as a Function of Worker Type

Thus far, all of our spillover effects have been estimated in terms of average effects. However, it is quite possible that different types of workers are affected differently, and that some workers affect others differently . To explore these possibilities, we create a productivity worker fixed effect. In particular, we regress time to complete a unit of work (i .e., productivity) on a cubic function of experience and controls for job position and the floor that they work on.

We then categorize those in the top quartile as high-productivity and those in the bottom 25% productivity as low productivity. By design, high-productivity workers are 38% faster than the average worker, and low-productivity workers are 33% slower. In terms of effectiveness, these same high-productivity workers escalate a task to another worker 28% less often than the average worker, whereas low-productivity workers are 17% more likely to need to escalate a task to another worker to solve. However, these high-productivity workers seem to need to trade off some work quality; they 14% lower quality work versus the average worker, whereas the low-productivity workers produce 7% higher quality work.

Next, we consider how these two types of workers might be affected differently by spillover. Table 5 reports the results from recreating the specifications reported in the final columns from Table 2 through Table 4, and then adding additional regressors for High and Low productivity types and an interaction between productivity type and spillover. For example, the results in column 1 of Table 5 are simply those found in column 4 of Table 2, but then the results of column 2 come from the same specification creating the results of column 1 when also adding indicator variables for High and Low types and an interaction between types and productivity spillover.

We see from column 2 that the effect of spillover is four times that for a Low type worker versus the average (i.e., $\frac{.0003+\ .0009}{.0003} = 4$). In contrast, although statistically no different from zero, the point estimate suggests that, if anything, High types are less sensitive to productivity spillovers than the average worker.

Column 4 reveals that in terms of effectiveness spillovers, Low types are again much affected—roughly four time the rate as the average worker. In contrast, High types are almost not affected at all (i.e., $.0016 - .0012 = .0004$).

Column 6 reveals the opposite trend compared to the other two types of spillovers: High types are more sensitive to quality spillover (almost three times the average rate (i.e., $\frac{.0003+.0005}{.0003} \simeq 2.67$)) and Low types are very little affected by quality spillover (i.e., $.0003 - .0002 = .0001$).

Taken together, these results show that those that are strong on a given dimension are less sensitive to spillover on that dimension. However, those that are weak on a given dimension are much more sensitive to spillover on that dimension, compared to the average. This suggests an opportunity to pair together complementary workers—those strong and weak on differing dimensions—to produce greater overall organizational performance.

3.4 Optimal Organizational Design

Our previous results suggest that there are gains to be made by pairing complementary workers. We now estimate these potential worker synergies form our data. To ease exposition, we will give worker types different names. In particular, a high-productivity worker will be called a Productive worker; these workers are in the top quartile of productivity and are more effective than the average worker. A low-productivity worker is on average a higher quality worker: we will call this worker a

Quality worker : they produce greater quality but at lower productivity and effectiveness than the average worker. Meanwhile, the balance of workers are average on both dimensions and we call them Generalists.

A simple way to explore organizational design is to estimate the overall organizational performance from all of the possible symbiotic pairings of the above three types of workers: Productive, Quality, and Generalist workers. The table below does just this with an organization of eight workers. H denotes a Productive worker, L denotes a Quality worker, and M denotes a Generalist worker. The first column shows the overall organization performance of pairing the two H workers together (recall that H and L are top and bottom Productive workers, respectively), two L workers, and the remaining M workers. We index the first column as performance of 100. As can be seen, the optimal paring is the complementary one: H's with L's and then M's together. This configuration increases quality by just under 1%, increases the speed of work (i.e., decreases the time to produce a unit on average) by 13%, and reduces the frequency of unsolved tasks by almost 17%.

	HH MM MM LL	HH MM ML ML	HM HM MM LL	HM HM ML ML	HL HL MM MM
Quality	100.00	99.83	100.12	99.94	100.79
Productivity (time)	100.00	98.24	95.50	93.74	87.07
Effectiveness (not solved)	100.00	97.79	93.34	91.12	83.25

Performance from Pairing Different Worker Types

Of course, we do not claim this to be the optimal configuration for all firms. However, it illustrates that the potential performance differences from different physical organizational designs could be substantial. And here the only lever of improving performance is simply co-locating workers differently.

Homophily is a well-known force that draws common types to work together. However, at least for our empirical setting, this is the lowest-performing organizational configuration. Neither is the best performing organization that which pairs only diverse workers. Instead, our setting calls for some types of workers to be in similar pairings and others to be in opposite types of pairings. That is, some diversity and some lack of diversity is together the best.

3.5 Negative Performance Spillover: Toxic Workers

Housman and Minor (2015) find that so-called Toxic Workers—those that harm an organization through hurting its people or property—can have an enormous impact on organizational performance. In fact, they find that the magnitude of effect of a Toxic Worker versus a superstar worker is much greater. Motivated by these findings, we explore to what extent does the presence of a Toxic Worker spillover to other workers as a function of physical proximity.

We proceeds analogously as when we measured positive performance spillovers. In particular, we use a linear model with supervisor fixed effects to measure the hazard of toxicity of a worker as a function of the density of their exposure to other toxic workers. To do so we construct a measure of toxic density as we did with equation (2) for performance spillover density. However, here performance $p_{j,t}$ is an indicator of whether or not worker j is a Toxic Worker. We define a toxic worker as a worker that is ultimately terminated in our data from misconduct related to harming a person or firm property. This definition results in our data containing 45 toxic workers, which represents roughly 2% of our 2,454 workers. Ideally, we would like to have a continuous measure that captures all levels of toxicity. However, this is not possible in our setting. Thus, our measure of toxicity can be viewed as indicating the more extreme cases of toxicity that warrant a termination. Whatever the case, this type of behavior that we measure is harmful for an organization and identifying its spillovers to other workers seems valuable to understand.

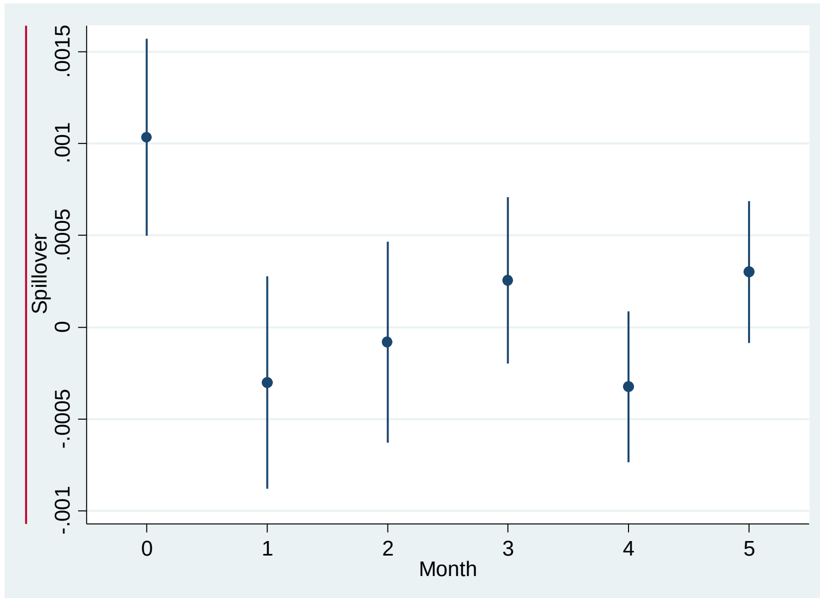
Table 6 reports the results of our analysis. Each column records the estimates obtained from using successive controls. Column 2 adds controls for positions and column 3 additionally include controls for time and experience. The coefficient estimate from column 3 suggests that a one standard deviation in toxic density increases the probability of the focal worker themselves being terminated for toxicity by over

150%.

The final column adds a regressor that has a measure of how much the worker trusts her manager. As discussed in the Data Section, this measure was obtained from the voluntary employee engagement survey; employees rated on a scale of 0 (worst) to 100 (best) how much they trust their. The survey also asked the employee how positive they felt that their work environment is. However, these two measures are highly co-linear (i.e., correlation of .8525) so we only use the first measure, as both provide nearly identical results.

As seen from column 4, adding this regressor reduces the estimated effect of toxic density, as it seems toxic density proxies for a sense of worker trust and sense of a positive work environment. Nonetheless, the coefficient on toxic density is still significant at the 1% level and an increase of one standard deviation in toxic density, even after controlling for a workers sense of the work environment, increases the chance of a toxic termination by roughly 27%. Meanwhile, a one standard deviation of increased sense of trust in one's manager reduces the likelihood of termination for toxic behavior by roughly 22%. This suggests that employee engagement surveys that capture how workers feel about their work environment and manager can be an important first line of defense to rooting out toxicity by providing an early warning to intervene in such a team.

Next, we consider the dynamic nature of toxic spillover. One could imagine once a worker becomes contaminated from toxic exposure they remain toxic. One could also imagine it may take a while to become toxic. These two features would suggest a mechanism of changing culture. In contrast, if a worker quickly has increased likelihood of toxicity upon exposure and then reverts back to their original propensity before exposure, this suggests a more episodic type of toxicity. To differentiate these two possibilities we estimate the analog of those charts found in Section (3.2) where we identify the effect of toxic density the month of exposure and then for an additional 5 months after. The chart below reports these dynamic coefficient estimates on toxic density:



Toxic Worker Spillover Across Time

As can be seen, the entire effect of toxic exposure occurs in the month of exposure. This means that bad news is the effect of toxic exposure is essentially immediate. However, the good news is that the exposure dissipates even faster than the positive performance spillover estimated in section (3.2). This suggests that it is urgent for management to address toxicity once discovered.

4 Conclusion

We studied how worker performance on several dimensions–both positive and negative–spills over to other workers. We found that spillover is pervasive on all of these dimensions and increases in magnitude as workers move physically closer within the office. We also found that there is generally not one type of worker who is best on all dimensions of performance; different workers have different strengths. Moreover, a worker who is stronger on a particular dimension tends to be less affected by spillover on this dimension, whereas they tend to be very sensitive to spillover on their weaker performance dimension(s).

These results taken together suggest that firms can develop a framework to maximize organizational performance simply through the physical placement of workers. To be sure, different organizations will have different kinds of tasks and different kinds of spillover. However, once an organization identifies which spillovers exist and how they spillover to different kinds of workers, management can plan the space of the organization to produce better outcomes. In this way, physical space, which all firms have and can relatively inexpensively manage, can be an important firm resource. We hope that this paper is the first of many to better understand and advance this potentially important, but little understood tool for management.

References

[1] Azoulay, P., Zivin, J. S., & Wang, J. (2010). Superstar Extinction. Quarterly Journal of Economics, 125(2), 549-589.Bandiera, O., Barankay, I., & Rasul, I. (2010). Social incentives in the workplace. The Review of Economic Studies, 77(2), 417-458.

[2] Becker, G. S. (1993). Human capital: A theoretical and empirical analysis, with special reference to education. University of Chicago Press.

[3] Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does Working from Home Work? Evidence from a Chinese Experiment. The Quarterly Journal of Economics, 165, 218.

[4] Cramton, C. D. (2001). The mutual knowledge problem and its consequences for dispersed collaboration. Organization science, 12(3), 346-371.

[5] Falk, A., & Ichino, A. (2006). Clean evidence on peer effects. Journal of Labor Economics, 24(1), 39-57.

[6] Foster, A. D., & Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. Journal of political Economy, 1176-1209.

[7] Gino, F., Gu, J., & Zhong, C. B. (2009). Contagion or restitution? When bad apples can motivate ethical behavior. Journal of Experimental Social Psychology, 45(6), 1299-1302.

[8] Hatch, N. W., & Dyer, J. H. (2004). Human capital and learning as a source of sustainable competitive advantage. Strategic management journal,25(12), 1155-1178.

[9] Hitt, M. A., Biermant, L., Shimizu, K., & Kochhar, R. (2001). Direct and moderating effects of human capital on strategy and performance in professional

service firms: A resource-based perspective. Academy of Management journal, 44(1), 13-28.

[10] Housman, M. and D. Minor. 2015. "Toxic Workers." Harvard Business School Working Paper No. 16-057

[11] Ichino, A., & Maggi, G. (2000). Work Environment and Individual Background: Explaining Regional Shirking Differentials in a Large Italian Firm. The Quarterly Journal of Economics, 115(3), 1057-1090.

[12] Jackson, C. K., & Bruegmann, E. (2009). Teaching Students and Teaching Each Other: The Importance of Peer Learning for Teachers. American Economic Journal: Applied Economics, 85-108.

[13] Kambourov, G., & Manovskii, I. (2009). Occupational specificity of human capital. International Economic Review, 50(1), 63-115.

[14] Kandel, E., & Lazear, E. P. (1992). Peer pressure and partnerships. Journal of political Economy, 801-817.

[15] Koch, M. J., & McGrath, R. G. (1996). Improving labor productivity: Human resource management policies do matter. Strategic management journal,17(5), 335-354.

[16] Lazear, E. P., & Oyer, P. (2012). Personnel Economics. The Handbook of Organizational Economics, 479.

[17] Mas, A., & Moretti, E. (2009). Peers at Work. The American Economic Review, 99(1), 112-145.

[18] Pierce, L., & Snyder, J. (2008). Ethical spillovers in firms: Evidence from vehicle emissions testing. Management Science, 54(11), 1891-1903.

[19] Robinson, S. L., & O'Leary-Kelly, A. M. (1998). Monkey see, monkey do: The influence of work groups on the antisocial behavior of employees. Academy of Management Journal, 41(6), 658-672

Figure 1: Mapping Seat Positions to Space Coordinates

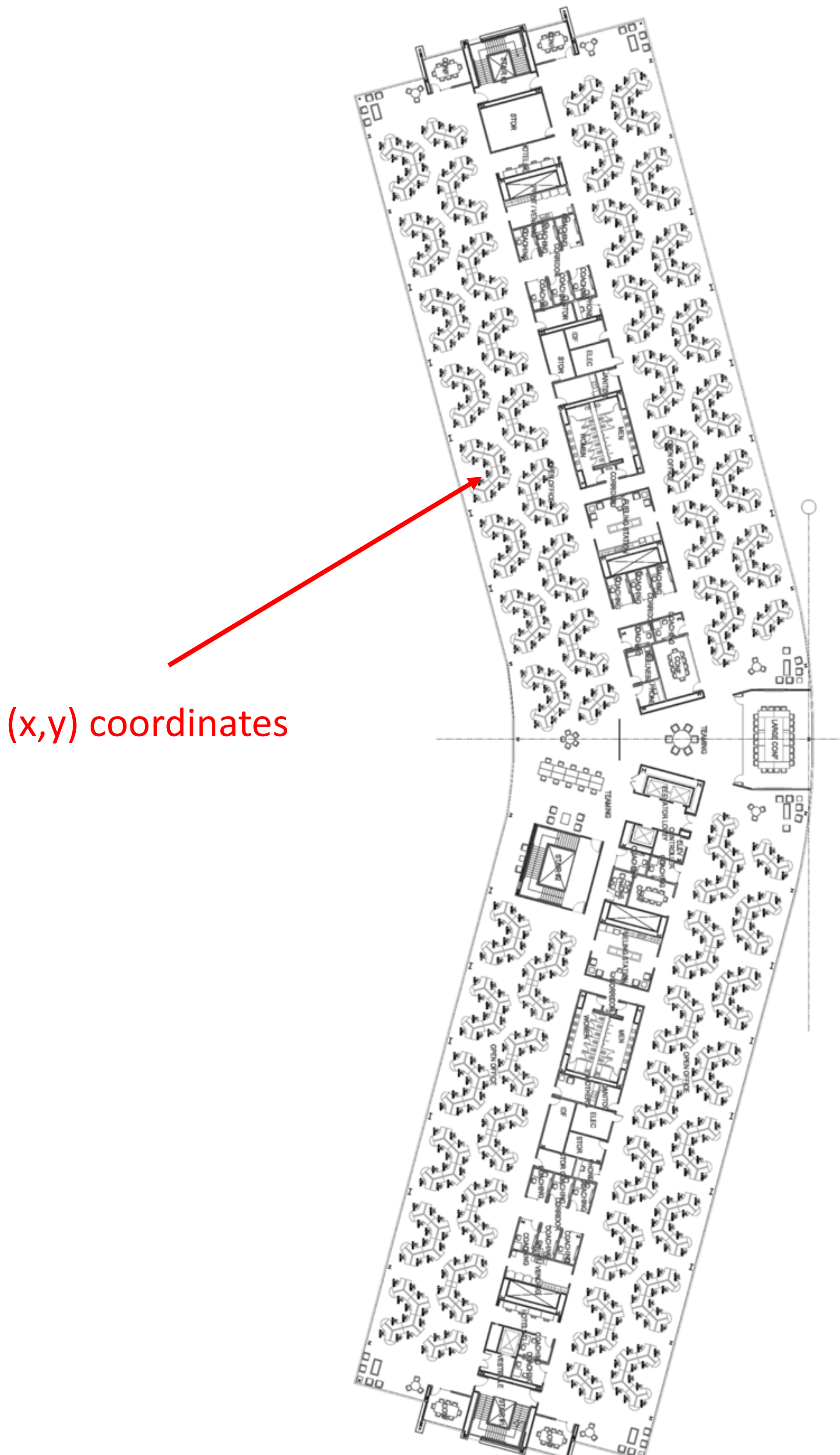


Figure 2: Heatmap of Productivity Across Space

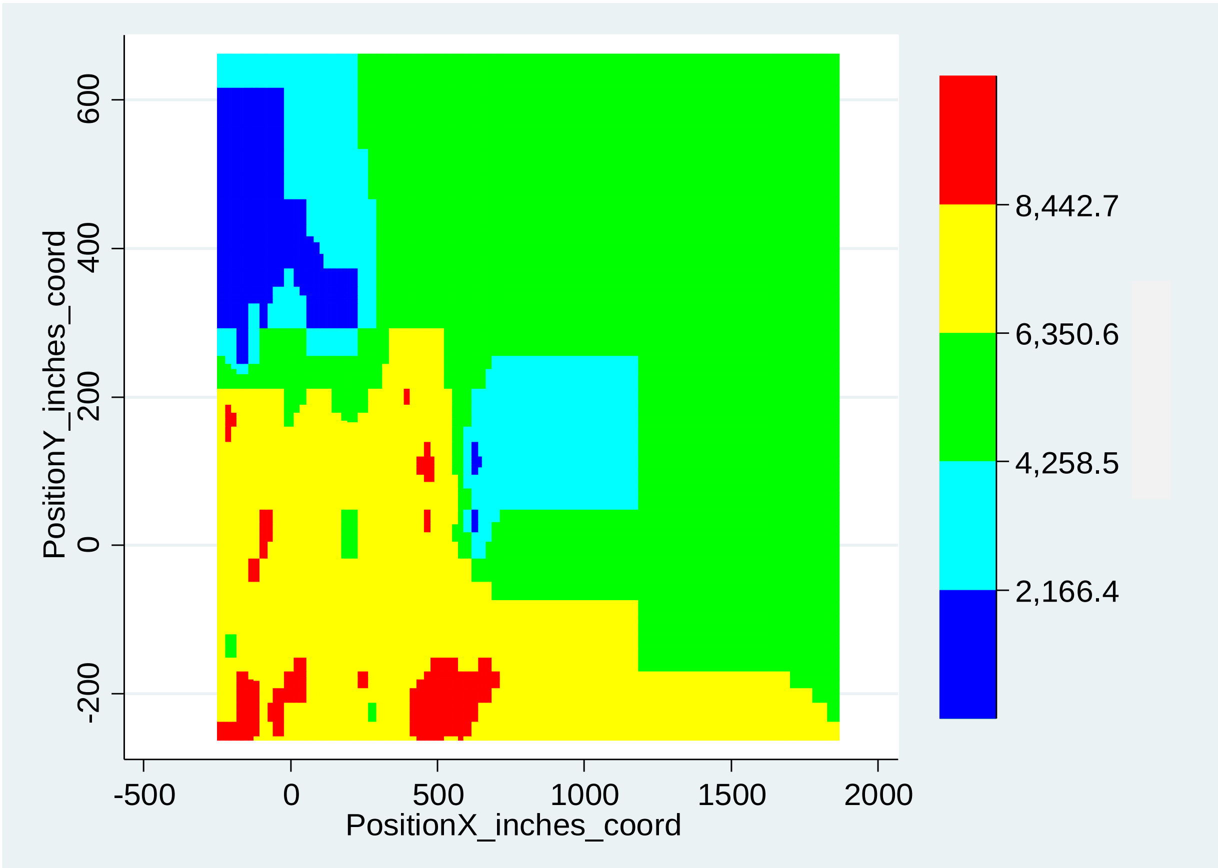


Table 1: Summary Statistics

Variable	Obs #	Mean	Std. Dev.	Min	Max
Productivity (time per task completed)	33,071	4199.98	2937.71	0	21450
Effectiveness (number of tasks referred to others)	33,071	0.82	0.85	0	11.50
Quality (rating of task quality)	33,052	70.43	25.20	0	100
Toxic (indicator of termination for toxicity at time t)	59,487	0.0008	0.03	0	1
Productivity Density	59,477	515751.80	367016.90	0	1442816
Effectiveness Density	59,477	109.03	80.94	0	312.0827
Quality Density	59,477	9216.67	6140.75	0	19670.33
Toxic Density	59,477	1.84	2.00	0	9.75
Trust Level in Manager	59,409	83.49	10.00	20	100
Experience (Days)	56,354	1376.00	1266.44	0	6414

Table 2: Productivity Spillover

	Outcome: Individual Productivity			
	(1)	(2)	(3)	(4)
Productivity Density	0.0005***	0.0006***	0.0008***	0.0009***
	(6.05)	(7.33)	(9.26)	(10.80)
Experience				-1.7541***
				(-21.76)
Experience^2				0.0005***
				(13.10)
Experience^3				-0.0000***
				(-9.16)
Intercept	3930.1435***	1839.5798***	3311.9100***	4184.9818***
	(69.61)	(4.59)	(7.96)	(6.54)
Fixed Effects				
Position	*No*	*Yes*	*Yes*	*Yes*
Time	*No*	*No*	*Yes*	*Yes*
Supervisor	*Yes*	*Yes*	*Yes*	*Yes*
Observations	28335	28335	28335	28302
R-Squared	0.474	0.487	0.518	0.536
Adjusted R-Squared	0.470	0.483	0.514	0.532

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<.01

Standard errors clustered at the supervisor level

Table 3: Effectiveness Spillover

	Outcome: Individual Effectiveness			
	(1)	(2)	(3)	(4)
Effectiveness Density	0.0020***	0.0021***	0.0015***	0.0016***
	(21.04)	(22.02)	(13.50)	(14.55)
Experience				-0.0004***
				(-15.36)
Experience^2				0.0000***
				(9.13)
Experience^3				-0.0000***
				(-5.62)
Intercept	0.5258***	0.4125***	0.7882***	0.9804***
	(40.79)	(4.84)	(10.06)	(11.59)
Fixed Effects				
Position	*No*	*Yes*	*Yes*	*Yes*
Time	*No*	*No*	*Yes*	*Yes*
Supervisor	*Yes*	*Yes*	*Yes*	*Yes*
Observations	28335	28335	28335	28302
R-Squared	0.457	0.469	0.483	0.494
Adjusted R-Squared	0.453	0.465	0.479	0.490

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<.01

Standard errors clustered at the supervisor level

Table 4: Quality Spillover

	Outcome: Quality Effectiveness			
	(1)	(2)	(3)	(4)
Quality Density	0.0003***	0.0003***	0.0003***	0.0003***
	(4.39)	(4.71)	(3.91)	(4.25)
Experience				-0.0013
				(-1.48)
Experience^2				-0.0000
				(-1.18)
Experience^3				0.0000**
				(2.47)
Intercept	67.6586***	73.9188***	76.6457***	77.8815***
	(95.71)	(15.77)	(15.23)	(14.38)
Fixed Effects				
Position	*No*	*Yes*	*Yes*	*Yes*
Time	*No*	*No*	*Yes*	*Yes*
Supervisor	*Yes*	*Yes*	*Yes*	*Yes*
Observations	28356	28356	28356	28321
R-Squared	0.257	0.263	0.270	0.272
Adjusted R-Squared	0.253	0.258	0.264	0.266

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<.01

Standard errors clustered at the supervisor level

Table 5: Worker Type and Spillover Effects

Outcome: Individual Performance

Regressors:	Productivity		Effectiveness		Quality	
	(1)	(2)	(3)	(4)	(5)	(6)
Productivity Density	0.0009***	0.0003**				
	(10.80)	(2.57)				
Effectiveness Density			0.0016***	0.0016***		
			(14.55)	(11.42)		
Quality Density					0.0003***	0.0003***
					(4.25)	(3.30)
High Type		-1611.4853***		-0.1812***		-9.4699***
		(-15.48)		(-8.40)		(-4.73)
Low Type		1388.4810***		0.1479***		4.9021***
		(15.04)		(5.58)		(4.68)
High Type Interaction		-0.0000		-0.0012***		0.0005***
		(-0.01)		(-7.34)		(3.31)
Low Type Interaction		0.0009***		0.0006***		-0.0002**
		(7.33)		(3.29)		(-2.41)
Intercept	4184.9818***	7220.2585***	0.9804***	0.9781***	77.8815***	73.3576***
	(6.54)	(34.05)	(11.59)	(19.33)	(14.38)	(25.15)
Cubic Experience Controls	Yes	Yes	Yes	Yes	Yes	Yes
			Fixed Effects			
Position	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Supervisor	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	28302	18773	28302	18773	28321	17120
R-Squared	0.536	0.633	0.494	0.534	0.272	0.277
Adjusted R-Squared	0.532	0.628	0.490	0.528	0.266	0.268

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<.01

Standard errors clustered at the supervisor level

Table 6: Toxic Worker Spillover

	Outcome: Terminated for Toxic Behavior			
	(1)	(2)	(3)	(4)
Toxic Density	0.000500***	0.000512***	0.000577***	0.000101**
	(3.55)	(3.60)	(3.95)	(2.41)
Experience			-0.000000	-0.000000
			(-0.42)	(-0.61)
Experience^2			0.000000	0.000000
			(0.33)	(0.84)
Experience^3			-0.000000	-0.000000
			(-0.38)	(-1.06)
Trust Level in Manager				-0.000017**
				(-2.20)
Intercept	-0.000261	-0.000258	-0.001344**	0.001104*
	(-1.07)	(-1.12)	(-2.17)	(1.72)
Fixed Effects				
Position	*No*	*Yes*	*Yes*	*Yes*
Time	*No*	*No*	*Yes*	*Yes*
Supervisor	*Yes*	*Yes*	*Yes*	*Yes*
Observations	50286	50286	50085	44794
R-Squared	0.006	0.006	0.007	0.009
Adjusted R-Squared	-0.000	-0.001	-0.001	0.000

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<.01

Standard errors clustered at the supervisor level