The Management of Knowledge Work*

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Abstract

We explore the role of management in knowledge-intensive work. Our theory posits that the function of the manager mainly consists of (i) ex ante coordination in terms of specifying and delegating tasks to her team and (ii) ex post coordination of the team's execution of those tasks as unexpected events unfold. Consistent with the predictions generated from this view, and using microlevel data from architectural design teams, we find that the manager's involvement in a project is high in the beginning but decreases as the project progresses. However, when the manager has better ex ante information, she decreases her involvement ex ante. We also find a higher workload of the manager not only strains her involvement but also the team's time spent on the project. Our analysis on workload shows that the manager and the team synchronize their involvement in proportion under shifting workloads. Finally, both over- and under- involvement by the manager from our predicted involvement correlates with higher team hours and hence lower profitability. Our

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study highlights the importance of managerial coordination and rational inattention in organizing knowledge workers in modern economies.

1 Introduction

Knowledge firms are a staple of the modern economy (Drucker 1999). Those firms often organize teams of specialized workers led by higher-level managers to carry out multiple projects and tasks concurrently. Senior managers coordinate the knowledge and time of their subordinates to complete work (Bolton and Dewatripont 1994) and leverage their own knowledge (Garicano and Hubbard 2016). However, the intangible nature of knowledge causes the tasks of and the collaboration among knowledge workers to be less well-specified than for workers in traditional industrial firms. This raises a number of important research questions.

First, what is the role of management and its economic impact in knowledge work? In traditional industries, the literature has emphasized the role of monitoring and motivating employees (Alchian and Demsetz 1972, Holmstrom 1982, Hermalin 1988). However, it is not clear how the non-repetitive and intangible nature of knowledge work affects this role. Second, knowledge work is typically project-based, with each project presenting unique requirements, having a start and completion date, and workers often involved in multiple projects. How do senior managers - as team leaders - and their teams allocate time across different projects and across different stages of a given project? Arguably, the allocation of managerial time under limited attention plays a crucial role in organizing team work in knowledge firms (Dessein, Galeotti, Santos 2016).

In this paper, we provide a theory of how the manager and her team allocate time on knowledge-intensive work. We posit that the role of the manager in a project - known as "a job" in our context - mainly consists of (i) ex ante coordination - that is, specifying which tasks must be completed as well as how and by whom, and (ii) ex post coordination of her team's execution of those tasks as events such as a change in project specifications unfold. Our theoretical model predicts that the allocation of managerial attention to jobs changes over the life span of a project. The majority of the manager's time is spent on ex ante coordination in terms of the delegation and specification of tasks to workers and, as a result, her involvement in the job decreases over time. The decrease in job involvement is more pronounced when the manager has better ex ante information about the job. However, the manager is more involved in larger projects due to the fact that larger projects, involving bigger teams, require more managerial attention devoted to (ex post) coordination. Because of additional staff support, the more senior the manager is, the less time she spends on a job. Finally, the heavier the workload the manager has, the less time she spends in a job. Together, these theoretical results shed light on the issues of coordination and organizational attention among knowledge workers.

To test our theory, we obtained micro-level data on the time spent by employees and the characteristics of architectural design jobs in one of the largest architectural firms in Japan. The firm hires hundreds of architects and our data covers the firm's design jobs recorded from 2004-2016. This context is appealing to test our theory for the following reasons. First, knowledge workers such as architects tend to be more autonomous and rewarded based on outputs (e.g., project completion) rather than effort provision, and monitoring of task execution is a small part of the manager's time. Second, architects are involved in many design tasks that are not well-specified at the time of formal contracting due to both the tacit nature of knowledge and clients' idiosyncratic requirements. This requires substantial communication with clients and coordination among team members, particularly in the early stages of a design job. For example, developing initial concepts requires design imagination and creativity while paying attention to cost calculations. In this process, architects are required to think outside of the box, link previously unlinked concepts, or viewing things in fresh ways in order to give form to client requirements (Pressman 2014). Third, although parametric modeling using computer-aided-design (CAD) systems allows for many changes to be made quickly, there is still substantial need for ex-post coordination in a design job due to specification changes made by clients, schedule changes in response to human resource constraints, or the discovery of design defects. Fourth, the manager mostly assumes the coordination role whereas her team focuses on the execution of an architectural job. This clear and distinctive division of labor facilitates our interpretation of the empirical results.

Our empirical results in general support our theory. On the one hand, the manager and her team spend more time initially at a job but decrease their time involvement as the job progresses toward completion. The manager and the team log more hours on new clients and jobs that are farther away from their offices during the initial phases than the later stages. A larger architectural job, and hence a bigger design team, receive more attention. More knowledge-intensive jobs ask for more involvements as well. These results are consistent with the notion that information acquisition is important in organizational coordination. On the other hand, heavier workload on the manager leads to less involvement by the manager and her team in a given job. Interestingly, the elasticities of the manager's workload on manager hours and team hours at a given job stage are the same. Our main results are robust to alternative specifications or measures.

Finally, we analyze the economic significance of managerial attention. Assuming our predicted time spent by managers is at the optimum, our analysis shows that higher variable costs (i.e., wages and traveling expenses) positively correlate with the absolute value of the deviation of the actual number of hours from the optimal time spent. In fact, spending more (”over-run”) or less (”under-run”) time by the manager than the predicted one prolongs team hours and is detrimental to company profit as well.[1]

In sum, our paper investigates the span and evolution of manager and team involvement in knowledge work. We consider the management of those jobs as a production function in which the quality of work depends on ex-ante coordination of the manager, task execution, and ex-post coordination. The empirical analysis supports our theoretical predictions. In this way, our study integrates key organizational architecture and managerial attention into a novel, coherent framework.

Related literature. TBC

2 Institutional Context

Our data is obtained from a large architectural and engineering consultancy firm in Japan (”the firm”). The firm maintains an exemplar reputation in the industry, and has its own sales team to reach clients who seek consulting work on their buildings, structures, and construction sites. The firm has headquarters in Tokyo but has several regional offices in the country. A complete architectural design project encompasses several phases, including initial planning, schematic design, design development, construction documentation, and the supervision of the construction process.[2] It is not un-

[1]The difference between revenue and variable cost is known as the contribution margin, a measure of short term profit. In our institutioanl context, revenue of a job is pre-determined when the contract is signed.

[2]As a secondary source of revenue, the firm also provides consulting services for the specific problems that the client want to solve. For example, a client might want to explore the possibility of enhancing the

common that the design and construction supervising work required by clients only include a subset of such phases. For instance, for standard buildings like a small factory, the requirement for creativity is low and the first stages may be skipped. The firm views a phase as the basic unit of its design jobs and organizes teams around different phases. We follow the firm's practice by calling a phase as a "job" and treat it as our unit of analysis.

When a client contacts the firm and the negotiation process starts, an executive panel consisting of the most senior executives assign "the job" to an employee who is at the rank of "Manager" as "the job manager." Factors affecting a job assignment include expertise, tenure, and current workload. Job revenue is largely predetermined at the beginning of the job and written in the contract. Therefore, once the job starts, the manager's goal is to minimize cost, especially its major components of labor and incidental costs, while maintaining quality work.[3]

Once the contract of a job is decided, the job manager organizes a design team to work on their buildings and structures. A design team typically consists of up to ten members, all of whom are architectural specialists at lower ranks (i.e., Senior and Junior Architect) than the manager.[4] Since each architect has different skills and experience, the manager attempts to optimize the talent mix in order to achieve a high-quality output with reasonable labor cost. Moreover, the size and composition of the design team may adapt to evolving needs as the job progresses. As mentioned earlier, the manager typically performs coordination functions. Her coordination work includes, but is not limited to, determining designs and material with clients, scheduling progress, assigning tasks to team members, solving conflicts and quality problems, negotiating with clients on specification changes, adjusting for delays, and mentoring team members. She often delegates to her team members the implementation of the plan and task execution. The firm has a formal structure and reporting lines along which every employee is evaluated by their direct supervisor at the Manager rank. At the same time, with the

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strength against potential risk of earthquakes or other natural disasters.

[3]An exception to cost minimization is when a job participates in an industry competition that awards the design of, for instance, a monumental building. In this case, cost minimization may affect the chance of awards or its reputation so other metrics are involved.

[4]The firm classifies its employees into Manager, Senior Architect, and Junior Architect. There are multiple grades within each rank. In our data, job managers who are at the rank of Manager make up more than 99.6% of the jobs.

approval of the executive panel, the job manager can invite to her team employees reporting to other managers.[5] As a common practice in Japan, this is partly to encourage employees accumulate experience with various managers and clients (Aoki 1990).

Most managers we interviewed informed us that understanding client needs and their decision-making process as well as conscientious planning and coordination are essential to ensure smooth operations and on-schedule job completion. Our initial analysis revealed that most project managers are specialized in a certain client industry, implying that industry-specific knowledge is important. A manager at the firm has to manage multiple jobs, ranging from a few to over 100. Given that all managers face time constraint, the attention each manager pays to each job varies substantially depending on the workload and the size of the other jobs on hand. Usually, a manager pays more attention to jobs that generate higher revenue because there are more parameters to decide on and there is more scrutiny into decision-making. A manager also pays more attention to jobs that need more planning and coordination such as those with new clients or those that involve more creativity. The attention a manager pays may depend on the experience of the leader and the members as well. For instance, more senior managers are more likely to delegate developmental job assignments in order to advance team members' careers in the firm .

Notably, we do not view moral hazard as a major concern in our context because of the following three reasons: First, division of labor in such close-knit relationships facilitates observable and measurable contributions of each team member to the job. Any architect can easily show and prove the part of the design and documentation they crafted. Second, architects in reputable firms are intrinsically motivated to strive for quality work. Winning external awards from one's work further provides a strong extrinsic motivation as well (MacLeamy 2020). Third, time pressure to meet a deadline is often present. An architect's shirking and other malfeasances are easily detected by professional team members and would adversely impact the architect's career in the

[5]Related to the issue of reporting lines and internal hierarchy, the firm's compensation policy has two components: fixed salary and bonus. Salary is adjusted every year depending on the merit evaluation by his supervisor within the range set for each rank grade. The bonus pool is proportional to the firm's profit and divided based on the salary. No part of the compensation is directly linked with the individual performance.

firm.[6]

3 Management in a production function, with an application to project management

3.1 Model

Since moral hazard is not a major concern in the architectural firm, we consider a team-theoretic model in which production depends in a multiplicative way on (i) the quality of ex ante coordination/delegation of tasks, Q^D, by a manager and a team of workers (ii) the quality of task execution by workers, Q^E, and (iii) the quality of ex post coordination of tasks, Q^C, by a manager an a team of workers. Concretely, total output is given by

$$Q = \mu^{1-(\alpha+\beta+\gamma)} \cdot \left(Q^D\right)^{\alpha} \left(Q^E\right)^{\beta} \left(Q^C\right)^{\gamma} \tag{1}$$

where μ is the size of the project and $\alpha + \beta + \gamma < 1$.

(1) **Quality of ex ante coordination & task delegation**: As noted in Section 2, understanding client needs as well as conscientious planning and coordination are essential to ensure smooth operations and on-schedule job completion. The manager has to specify which tasks must be completed as well as how and by whom. Workers need to know "what to do" and "what to do" must correspond to client needs.

Whereas the manager is essential in the process of ex ante coordination, she can use a team of workers to assist her in this effort (e.g. collecting information, writing out instructions, filling in details etc.).[7] We further posit that the quality of ex ante coordination, Q^D, depends on the time the manager spends in the early stages of the project, as well as the familiarity of the manager with the project.

[6] This is not to say that the interests of the firm and the employee are perfectly aligned. Some employees might spend more time on the job than the company would like, for example, in order to win an external award. Another employee might design from scratch instead of using an existing blueprint in the archives to gain experience. These can result in some loss to the firm, at least in the short run. However, these issues are minor compared to the coordination problem we focus on in this paper.

[7] This work is different from delegation in that the work of the manager and subordinates are complements and not substitutes.

Formally,

$$Q^D = A^D \left(\frac{t_M^D}{\rho}\right)^{\rho} \left(\frac{t_T^D}{1-\rho}\right)^{1-\rho} + \mu \cdot s \cdot (1 + k_c x_c + k_d x_d) \tag{2}$$

where t_M^D and t_T^D are the time devoted to ex ante coordination and task-specification by respectively the manager and a team of workers that supports her.

The parameter ρ captures how essential the role (and time) of the manager is in this process. The larger the value of ρ, the less the manager is able to rely on workers (or assistant managers) to support her in this process.

The parameter x_c reflects how many projects with common clients are under the supervision of the same manager. We assume $k_c > 0$, so that less time is required to achieve the same level of ex ante coordination for projects that have a common client. The parameter x_d reflects the distance of the project from headquarters. We assume $k_d < 0$, so that more time is required for projects that are more remote.

(2) **Quality of task execution.** How well do employees execute the delegated tasks and task instructions? We posit that

$$Q^E = A^E \cdot t_T^E$$

where t_T^E is the effort/time put in by employees. Note that execution of tasks is by definition only a function of worker input. Anything that requires the involvement by the manager ex post will be captured by the quality of ex post coordination.

(3) **Quality of task coordination (ex post coordination)**. Unforeseen circumstances arise and new client needs may emerge, which requires a re-juggling or re-organizing of tasks. In other words, ex post coordination may be needed. Again, the manager plays a key role in this "ex post" coordination, though he may be assisted by a team of workers. In particular,

$$Q^C = A^C \left(\frac{t_M^C}{\rho}\right)^{\rho} \left(\frac{t_T^C}{1-\rho}\right)^{1-\rho}$$

where t_M^C and t_T^C are the time devoted to ex post coordination.

Labor cost: Finally, while total output is given by (**??**), the total cost of production equals

$$L = t_M^D \lambda_M + t_M^C \lambda_M + t_T^D \lambda_T + t_T^E \lambda_T + t_T^C \lambda_T$$

where λ_M and λ_T are the wages of managers and workers (or, alternatively, opportunity cost). Intuitively, both the manager and the workers are involved with multiple project and λ_M and λ_T are the marginal value of one unit of attention, which we take as exogenous for now.

Timing: We assume there are 2 periods. In period 1, there is ex ante coordination. In period 2, there is task execution and ex post task coordination.

In period 1, we denote

$$t^1 = t_M^1 + t_T^1 = t_M^D + t_T^D$$

In period 2, we denote

$$t^2 = t_M^2 + t_T^2 = t_M^C + t_T^E + t_T^C$$

We further denote $t = t^1 + t^2$ and $t_l = t_l^1 + t_l^2$ for $l = M, T$.

3.2 Optimal Time Allocation

The firm chooses $t_M^D, t_M^C, t_T^D, t_T^E$ and t_T^C in order to maximize

$$Q - L = \mu^{1-(\alpha+\beta+\gamma)} \cdot \left(Q^D\right)^\alpha \left(Q^E\right)^\beta \left(Q^C\right)^\gamma - (t_M^D + t_M^C)\lambda_M - (t_T^D + t_T^E + t_T^C)\lambda_T$$

As we show in the Mathematical Appendix, the first order conditions with respect to t_T^k and t_D^k for $k = D, C$ imply that

$$\frac{t_T^{k^*}}{t_M^{k^*}} = \frac{(1-\rho)\lambda_M}{\rho\lambda_T} \equiv \kappa$$

Intuitively, the larger is ρ, that is the more essential is the manager in the process of ex ante or ex post coordination, the lower is the span of control of the manager κ. Similarly, the larger is the wage premium of the manager, λ_M/λ_T, the larger is the span of control κ. It follows that

$$\frac{\left(t_M^{k*}\right)^\rho \left(t_T^{k*}\right)^{1-\rho}}{\rho^\rho (1-\rho)^{1-\rho}} = \frac{t_M^{k*}}{\rho} \left(\frac{\lambda_M}{\lambda_T}\right)^{1-\rho}$$

In the Mathematical Appendix, we further show that

$$
\begin{aligned}
Q^{D^*} &= \alpha A^D \left(\frac{\lambda_T}{\lambda_M}\right)^{\rho} \left(\frac{1}{\lambda_T}\right) Q^* \\
Q^{C^*} &= \gamma A^C \left(\frac{\lambda_T}{\lambda_M}\right)^{\rho} \left(\frac{1}{\lambda_T}\right) Q^* \\
Q^{E^*} &= \beta A^E \left(\frac{1}{\lambda_T}\right) Q^*
\end{aligned}
$$

and

$$
\begin{aligned}
Q^* &= \mu \cdot \left(\alpha A^D\right)^{\frac{\alpha}{1-(\alpha+\beta+\gamma)}} \cdot \left(\gamma A^C\right)^{\frac{\gamma}{1-(\alpha+\beta+\gamma)}} \cdot \left(\beta A^E\right)^{\frac{\beta}{1-(\alpha+\beta+\gamma)}} \\
&\cdot \left(\left(\frac{1}{\lambda_M}\right)^{\rho} \left(\frac{1}{\lambda_T}\right)^{1-\rho}\right)^{\frac{\alpha+\gamma}{1-(\alpha+\beta+\gamma)}} \left(\frac{1}{\lambda_T}\right)^{\frac{\beta}{1-(\alpha+\beta+\gamma)}}
\end{aligned}
$$

It follows that the optimal time allocation of the manager and his team are given by

$$
\begin{aligned}
t_M^{D^*} &= \rho \frac{\mu}{A^D} \left(\frac{\lambda_T}{\lambda_M}\right)^{1-\rho} \left[\frac{Q^{D^*}}{\mu} - s \cdot (1 + k_c x_c + k_d x_d)\right] \\
t_T^{D^*} &= \frac{(1-\rho)\lambda_M}{\rho \lambda_T} \cdot t_M^{D^*}
\end{aligned}
$$

and

$$
\begin{aligned}
t_M^{C^*} &= \rho \frac{\mu}{A^C} \left(\frac{\lambda_T}{\lambda_M}\right)^{1-\rho} \frac{Q^{C^*}}{\mu} \\
t_T^{C^*} &= \frac{(1-\rho)\lambda_M}{\rho \lambda_T} \cdot t_M^{C^*}
\end{aligned}
$$

We can further show that[8]

$$
t_T^{E^*} = \frac{\beta}{(1-\rho)\gamma} t_T^{C^*}
$$

[8]Indeed, $t_T^{E^*} = \frac{Q^{E^*}}{A^E} = \beta \left(\frac{1}{\lambda_T}\right) Q^*$ and $t_T^{C^*} = \frac{(1-\rho)}{A^C} \left(\frac{\lambda_T}{\lambda_M}\right)^{-\rho} Q^{C^*} = (1-\rho)\gamma \left(\frac{1}{\lambda_T}\right) Q^*$.

3.3 Comparative Statics

Note that Q^*, Q^{D^*}, Q^{E^*} and Q^{C^*} are (i) independent of x_c and x_d and (ii) linear in μ. The following lemma is now direct:

Lemma 1.
- *$t_M^D, t_T^D, t^1/t$ and t_M^D/t_M are decreasing in x_c (and $-x_d$). On the other hand t_M^D/t_T^D is unaffected*
- *The ratios $Q^{D^*}/Q, Q^{C^*}/Q$ and Q^{E^*}/Q are independent of x_c, x_d, and μ.*

Using the fact that ex ante coordination occurs in period 1, whereas execution and ex post coordination occurs in period 2, we obtain the following comparative static results:

Proposition 1.
1. *The share of the manager's time is larger in period 1 (t_M^1/t^1) than that in period 2 (t_M^2/t^2).*
2. *The more jobs come from a common client (x_c) in the manager's portfolio, the less time the manager and the team spend in period 1 (t_M^1, t_T^1), and proportionally more time the manager and the team spend in period 2 (t_M^2/t_M and t_T^2/t_T).*
3. *The smaller the distance of the site of a job is (x_d), the less time the manager (t_M^1) and her team (t_T^1) spend in period 1 but the proportionally more time in period 2 (t_M^2/t_M and t_T^2/t_T).*
4. *In a larger job (μ), the manager and the team spend more time both in period 1 (t_M^1, and t_T^1) and period 2 (t_M^2 and t_T^2).*

The intuition of the hypotheses in Proposition 1 is explained as follows. The first hypothesis means that the manager decreases her relative involvement as the job progresses. Intuitively, in both Period 1 and 2, the manager and her team are involved in coordinating work (ex ante coordination in period 1, ex post coordination in period 2). While managerial attention devoted to ex ante coordination may be higher (or lower) when compared to ex post coordination, the ratio of managerial-to-worker attention devoted to coordination will be identical in both periods as it is solely determined by the parameters ρ, λ_M,and λ_T. In Period 2, however, the team must also execute the tasks specified and delegated in period 1, whereas the manager is not involved in task execution. Hence, the manager's relative involvement drops in period 2 when compared to period 1.

The next two hypotheses are about the effect of the availability of ex ante information on attention. When the manager has already had more ex ante information about a job (i.e., a nearby job) or a client (i.e., a common client), then she is more efficient in ex ante coordination and task delegation. In the fourth hypothesis, the manager and the team spend more hours both *ex ante* and *ex post* in larger jobs because of their higher returns to (or need for) attention.

3.4 Multiple projects and changes in workload

In our analysis above, we have assumed that the attention dedicated by managers and workers to a project is optimized given their wages λ_M and λ_T. In the short run, however, the number of managers and workers (and the hours they work) may be fixed but the workload may vary over time. Hence, in the short run, when managers are involved in multiple projects, λ_M and λ_T can also be interpreted as the opportunity cost of a unit of attention. This opportunity cost of attention, in turn, will be affected by the portfolio of projects assigned to a manager and their team.

Let us therefore denote by $\lambda_M(S)$ and $\lambda_T(S)$ the opportunity cost of attention when the manager and their workers are involved in projects $j \in S = \{1, 2, ..., m\}$. At the optimum, the marginal value of attention must be equalized across all projects, and the manager and their workers must be working full-time. In the Mathematical Appendix, we prove the following result:

Proposition 2. *Assume total available managerial and worker attention is fixed in the short run and optimized for a set of project S. Consider now an increase in workload from S to S' where $S \subset S'$. Then for any project $j \in S$, the increase in workload to S'*

- *reduces period 1 worker and managerial attention by the same (percentage) amount.*
- *reduces period 2 worker and managerial attention by the same (percentage) amount.*

Proof: Let us denote by $t^k_{j,M}(S)$ with $k = D, C$ and $t^k_{j,T}(S)$ with $k = D, E, T$ the optimal attention allocations for project j. From our analysis above, we have that for all projects $j \in S$

$$\frac{t^{D*}_{j,T}(S)}{t^{D*}_{j,M}(S)} = \frac{t^{C*}_{j,T}(S)}{t^{C*}_{j,M}(S)} = \frac{(1-\rho)}{\rho}\frac{\lambda_M(S)}{\lambda_T(S)}$$

and

$$\frac{t^{E*}_{T}(S)}{t^{C*}_{j,M}(S)} = \frac{\beta}{(1-\rho)\gamma}\frac{t^{C*}_{j,T}}{t^{C*}_{j,M}} = \frac{\beta}{\rho\gamma}\frac{\lambda_M(S)}{\lambda_T(S)}$$

Hence, in period 1, the relative involvement of the manager is given by

$$\frac{t^{D*}_{j,M}}{t^{D*}_{j,T}} = \frac{\lambda_T(S)}{\lambda_M(S)}\frac{\rho}{(1-\rho)} \tag{3}$$

Similarly, in period 2, the relative involvement of the manager is given by

$$\frac{t^{C*}_{j,M}}{t^{C*}_{j,T} + t^{E*}_{j,T}} = \frac{\lambda_T(S)}{\lambda_M(S)}\left[\frac{1}{\frac{(1-\rho)}{\rho} + \frac{\beta}{\gamma}\frac{1}{\rho}}\right] \tag{4}$$

Assume now that $\lambda_T(S) = w_T$ and $\lambda_T(S) = w_M$, that is managers and workers are hired assuming a workload of S. Assume further that the total attention of each worker and manager is fixed. Consider now a shock to the workload of managers, in that the portfolio of assigned project to is S' instead of S where $S \subset S'$, with at least one project k that belongs to S' but not to S. Then, at the optimum, we must have that

$$\frac{\lambda_T(S')}{\lambda_M(S')} = \frac{\lambda_T(S)}{\lambda_M(S)} = \frac{w_M}{w_T} \tag{5}$$

Indeed, assume not. For example, assume that

$$\frac{\lambda_T(S')}{\lambda_M(S')} > \frac{\lambda_T(S)}{\lambda_M(S)} = \frac{w_M}{w_T}$$

At the optimum, the managers and workers must be working full time both under S and S'. But if the above inequality holds, and the managers work the same amount of time under S as under S', then workers would be working longer hours under S' than under S, which is not possible. Proposition **??** follows directly from (**??**), (**??**) and (**??**).

QED

3.5 Senior and junior managers

We now incorporate senior and junior managers in our analysis. We assume that by working with an assistant manager on a project, a senior manager can save time and be involved in more projects. Junior manager, in contrast, can only work independently.

Abusing notation, let t_M be labor output of a senior manager when assisted by an assistant manager. We posit that

$$t_M = \left(\frac{t_{sM}}{\phi}\right)^{\phi} \left(\frac{t_{aM}}{1-\phi}\right)^{1-\phi} \tag{6}$$

where t_{sM} is the time contributed by the senior manager and t_{aM} the time contributed by the assistant manager.[9] In contrast, the labor output of a junior manager simply equals

$$t_M = t_{jM}$$

where t_{jM} is the time contributed by the junior manager. Finally, Q^D and Q^C are a function of t_M as in our base-line mode. We denote the wages of junior managers, senior manager, and assistant managers respectively by λ_{jM}, λ_{sM}, and λ_{aM}, where we posit that

$$\lambda_{aM} < \lambda_{jM} \equiv \lambda_M$$

The wage of the senior manager λ_{sM} will be determined in equilibrium such that the wage cost of t_M is identical when provided by a junior manager or by a team of a senior and an assistant manager (see Assumption 2 below).

Optimal managerial time allocation implies that

$$t_{aM} = \frac{(1-\phi)\lambda_{sM}}{\phi\lambda_{aM}} t_{sM}$$

[9] As we will show below, this production function is such that if another senior manager were to take the role of an assistant manager, then the firm would be indifferent to having a senior manager working by himself or in a team with another senior manager (both managers are paid the same hourly wage λ_{sM} in the latter case).

Substituting t_{aM} in (**??**), we obtain that

$$t_M = \frac{1}{\phi}\left(\frac{\lambda_{sM}}{\lambda_{aM}}\right)^{\mathbf{1-\phi}} t_{sM}$$

Hence, for a given managerial labor output t_M, the optimal labor input from the senior and assistant manager equal

$$t^*_{sM} \equiv \phi\left(\frac{\lambda_{aM}}{\lambda_{sM}}\right)^{\mathbf{1-\phi}} t_M$$

and

$$t^*_{aM} \equiv (1-\phi)\left(\frac{\lambda_{sM}}{\lambda_{aM}}\right)^{\boldsymbol{\phi}} t_M$$

Assumption 2 The wage of the senior manager, λ_{sM}, is such the managerial wage cost of a project led by a senior and assistant manager is identical to the wage cost of a project led by a junior manager:

$$\lambda_{sM}t^*_{sM} + \lambda_{aM}t^*_{aM} = \lambda_{jM}t_M$$

Substitution t^*_{sM} and t^*_{aM}, it follows

$$\lambda_{jM} = \lambda_{aM}^{1-\phi}\lambda_{sM}^{\phi}$$

Hence, $\lambda_{aM} < \lambda_{jM}$ implies that

$$\lambda_{jM} < \lambda_{sM}$$

Without loss of generality, let $\lambda_{jM} \equiv \lambda_M$. Then t_M^{C*} and t_M^{D*} will be exactly as before – regardless of whether a team is led by a junior or a senior manager – but with the time devoted by the senior manager satisfying

$$t^{k*}_{sM} = \phi\left(\frac{\lambda_{aM}}{\lambda_{sM}}\right)^{\mathbf{1-\phi}} t^{k*}_M < t^{k*}_M \text{ for } k = D, C$$

and the time devoted by a junior manager satisfying

$$t_{sM}^{k*} = t_{M}^{k*} \text{ for } k = D, C.$$

We summarize in the following proposition:

Proposition 3. *Compared to the junior manager, the senior manager spends less time on both ex ante and ex post coordination, both in absolute terms ($t_{sM}^{1*} < t_{jM}^{1*}$, $t_{sM}^{2*} < t_{jM}^{2*}$) and as a share of the team's time ($t_{sM}^{1*}/t^1 < t_{jM}^{1*}/t^1$, $t_{sM}^{2*}/t^2 < t_{jM}^{2*}/t^2$).*

This result captures the ideas that the senior manager has more responsibilities by being assigned with larger teams and that she also delegates part of her coordination role to the junior manager.

4 Data and Measures

4.1 Data

The data used in our analysis includes project management data, personnel data, and labor inputs data. In the project management data, contract terms for each phase of projects - that is, a job - during 2004 to 2016 are observed. A project may consist of several phases and some related jobs. For example, designing a large sports stadium involves at least five jobs: (i) planning, (ii) schematic design, (iii) design development, (iv) construction documentation, and (v) construction supervision. There will be more jobs if it also involved the construction of , for instance, a connected shopping arcade, its peripheral roads and parking structure. Many times, however, a project is composed of a single job. Our unit of analysis is the job. For each job, we know its revenue, costs, and detailed categorical classification such as the client industry and building type. As we stated earlier, job revenue is largely predetermined at the beginning of production. Personnel records are available from 2011 to 2016. It includes each worker's basic information such as the year of birth, the year of entering the firm, etc.

The labor inputs data contain detailed records of working hours for each worker on each job in each month. We index job and month by j,and t respectively. Instead of using the time records to bill the client, they are mainly for cost control purposes. Although workers self report number of hours, the records are closely monitored by the manager and the firm to ensure compliance. After the client signs the contract, each job is assigned to a job manager as the team leader who is responsible for all the subsequent actions. Manager typically manage multiple jobs concurrently. How managers allocate their limited time is therefore a key decision for the success of the firm. In our analysis, jobs that receive zero attention from their chief manager throughout the job period are excluded. For those jobs, the manager's coordination role is fully delegated to a seasoned senior architect in a second-in-command role.[10] We also exclude jobs with revenue less than one million Japanese Yen (about US$9000 during our data period). This restriction is essentially to exclude failed jobs that do not generate any meaningful revenue to the firm.

4.2 Variables and measurement

This section introduces and describes the notations of the variables used in our empirical analysis.

- $ManagerHour_{jt}$ ("manager hours") is the number of hours recorded for the manager of job j in month t. We use "the manager" and "the team leader" interchangeably in the text.
- $TeamHour_{jt}$ ("team hours") is the total working hours of all team members of job j in month t, excluding the manager.
- $ManagerHourShare_{jt}$ is the ratio in percentage of manager hours to total hours spent on job j month t, namely

$$ManagerHourShare_{jt} = ManagerHour_{jt}/(ManagerHour_{jt} + TeamHour_{jt})\,.$$

- $t\_progress_{jt} \in [0.1]$, or "job progress," is the ratio of the cumulative days from the start of job j to the first day of next month $t+1$, to the total day length of the total

[10] Even for the selected jobs, managers need not spend positive time in every month during the project period. Zero hours may happen because the manager has higher priority in other jobs, or because the team is waiting for the client decide on the choice of design details.

duration of job j. It value ranges from 0 (job start) to 1 (job completion), measuring the progress of the current job.

- $C_{jt} \in [0, 1]$ (”common client”) is defined as follows. For each job j in the job portfolio of manager i in month t, count the number of other jobs in the portfolio having the same client as job j, and then divide the count by the total number of jobs under manager i minus 1. The more jobs from the same client is under the manager's responsibility, the more the manager's understanding of the client business. This is one of our two measures on (lack of) information friction.
  - An example of C_{jt} : there are 10 jobs in month t for the manager. Suppose, 5 are with the same client, and the other 5 are all different clients. For job j sharing clients with other 4 jobs, C_{jt} is 4/9. For job j not sharing clients with other jobs, C_{jt} is 0.
- $Prox_j \in [0, 1]$ (”proximity”) is how close the site of job j is to the firm. It is measured as $1/(Dist_j + 1)$, where $Dist_j$ is the geographical distance between the job site and the firm's responsible office in kilometers. $Dist_j$ is calculated as follows. For the job sites that are located in Japan, we calculate the distance between the responsible regional office (in four prefectures) and the job site prefecture, using data from Geospatial Information Authority of Japan [11]. For jobs outside Japan, we use country level distance measure from CEPII [12]. The longer the distance, the more the information asymmetry is between the manager and the headquarter office (Kalnins and Lafontaine 2013; Huang et al. 2017). This is our second measure of (lack of) information friction.
- $NoJob_{jt}$ (”workload”) is the number of jobs of which the manager in charge in month t.
- $NoReC_{jt}$ (”repeat client”) is the number of *new* jobs assigned to the manager of job j in month t from those repeat clients other than the focal client. Repeat clients are identified from the contract type being “continued client” in our data set. In other words, we exclude observations to count $NoReC_{jt}$ in which the focal client is the

[11] https://www.gsi.go.jp/KOKUJYOHO/kenchokan.html
[12] http://www.cepii.fr/CEPII/en/publications/wp/abstract.asp?NoDoc=3877

same as the client that makes the new order. This variable is used as an instrument for $NoJob_{jt}$.

- An example of $NoReC_{jt}$: there are two clients, A and B, in month t for manager j. Client A is a repeat client that had worked with the manager before. In month t, a new job arrived from client A. We exclude all the observations of client A in this month. For client B, $NoReC_{jt}$ equals to 1, and $NoJob_{jt}$ is increased by 1. This ensures the relevance condition. Removing client A's observations in the month eliminates unobserved client-specific factors (e.g., client A's preference for working with the manager) that may affect both $NoReC_{jt}$ for the focal client and the outcome variables of job j. This helps to satisfy the exclusion condition.

- Rev_j ("job revenue") is the revenue of job j. It is determined before the start of production. We use its standardized logarithm values with mean zero and unit standard deviation in our regressions.

- $Tenure_{jt}$ ("tenure") is the number of years since the manager of job j, at the year indicated by time t, joined the firm. We use its standardized logarithm values in our regressions.

- $TeamSize_{jt}$ ("team size") is the number of workers contributing positive hours to job j in month t, excluding the manager. Team size varies with time due to the changing need of labor as a job progresses.

- $JobType_j$ ("job type") denotes a categorical variable (with 22 categories) that controls for the type of service in each job j. [13]

- $Industry_j$ denotes a vector of 39 dummies indicating the industry that a job is classified. Industries include real-estate, education, finance/insurance, transportation, municipal government, and others.

[13] The top 10 categories of $JobType_j$ cover 92.4% of the number of jobs and 97.1% of revenue in the sample. Ordered in terms of revenue, they are: Construction documentation (32.2%), Design/Construction supervision (24.9%), Construction supervision (14.0%), Design development (13.4%), Other (3.2%), Schematic design (2.9%), Planning management (2.0%), Other planning (2.0%), Basic planning (1.4%), Planning and development management (1.1%).

Table 1 provides the summary statistics for these variables. We note that the monthly average hours spent on a job are 9.6 for the manager and 278.1 for the team. With the average team has 6.9 members, a team member spends on average 40 hours per month on a job. The mean value of the manager's share of hours to that of her full team is 9.4%. A typical manager has worked for the firm for about 25 years and carries a workload of about 17 jobs per month. Finally, the average revenue of a job is 88 million Japanese Yen (=USD748,000 at the exchange rate recorded at the year end in 2016).

<insert Table 1 about here>

4.3 Stylized Facts

Before we examine our regression analysis, we document a couple of stylized facts about the allocation of managerial attention. Our data from the architectural firm show strong evidence of selective attention of knowledge workers. The general pattern corroborates to the "rational inattention" phenomenon in which managers often choose to pay no or little attention to a significant number of tasks at any selected time (Dessein et al. 2016). Both panels in Figure 1 show that a positive correlation exists between the number of jobs on which a manager spends positive time and the number of jobs under her management. However, the increase in jobs to which the manager devotes positive attention is much smaller than the increase in the number of jobs assigned to her portfolio. When we limit the number of assigned jobs to 40, the left panel shows a ratio of approximately 1/4: only 1 out of 4 jobs receives positive managerial attention in a given month. As the samples in our data for managers who have more than 40 jobs become fewer, the standard errors increase. Still, the right panel that uses our full samples shows the average between the number of jobs with positive attention to that of inattentive ones decreases to about only 1/8. [14]

<Insert Figure 1 about here>

[14]Note that we restrict our sample to those with positive hour from either the manager or the team, so if a job stop completey for some reason (i.e. waiting for the client'sdecision, etc.), it is excluded from our analysis because that is not relevant to the choice of manegerial inattention.

In Figure 2, we plot the average number of hours that managers spend on a job against the rank of the job in terms of hours. For instance, the jobs to which the managers allocate the most attention (rank=1) occupy about 20 hours of their time per month and the 2nd jobs are about 12 hours, and so on. This figure displays that managerial hours allocated to jobs exponentially decrease in the hour rank of jobs. Only jobs that are ranked sixth or higher receive meaningful hours spent by managers in the firm.

<Insert Figure 2 about here>

5 Econometric Specifications

To recall, the main goal of our empirical analysis is to examine the effect of job progress, information friction, and manager's workload on outcome variables, namely manager hours, team hours, team size, and manager's hours as a share of team hours. We describe the econometric setup for each of those three analyses below.

5.1 Effect of job progress

On the effect of job progress on team size of and its manager and team members' hours spent on job j in a given month t, we use the following regression as our baseline setup:

$$y_{jt} = \beta_0 + \beta_1 t\_progress_{jt-1} + \beta_2 t\_progress^2_{jt-1} + \gamma_1 \text{ln}(Tenure_{jt}) + \gamma_2 \text{ln } Rev_j + \phi_j + \epsilon_{jt}, \quad (7)$$

where y_{jt} is the outcome variable, $\ln(ManagerHour_{jt}+1)$, $\ln(TeamHour_{jt}+1)$, $\ln(TeamSize_{jt}+1)$, or $\ln(ManagerHourShare_{jt} + 1)$. ϕ_j is a vector of manager, industry, and job-type fixed effects, and ϵ_{jt} is the error term that is clustered by job type and year. Using $t\_progress_{jt-1}$, our regression amounts to examine the effect of the job progress accomplished in the previous month on the outcome variables. The pre-determined $t\_progress_{jt-1}$ also helps to avoid contemporaneous correlations between the error term and job progress. We add a value of 1 to raw value of those variables with logarithm because their raw value may involve zeros. Regression (**??**) enables us to see the evolution of time spent by the manager, her team, and time size as a job progresses. In this and other regressions, we treat ln$(Tenure_{jt})$ and ln Rev_j as control variables.

By industry practice, the contract pre-specifies the starting date of a job before a design team is compiled because that is often determined by client needs. However, the ending date of a job is correlated with the characteristics of manager and/or his team; hence $t\_progress_{jt-1}$ and its squared term in (**??**) are endogenous. For instance, omitted variables such as the changing composition and quality of the team members may affect both the time of job completion (and hence $t\_progress_{jt-1}$) and our outcome variables. To correct the endogeneity of $t\_progress_{jt-1}$ and its squared term, we follow the procedure proposed by Wooldridge (2010, p. 939). Specifically, we use an "extended" version two-stage-least-square (2SLS) regression to estimate (**??**). The procedure outlined in Wooldridge (2010) requires the generation of predicted values of $t\_progress_{jt-1}$ and the squared term of the predicted values as the instrumental variables for the original variables as the first step. To accomplish it, we obtain the predicted values of $t_progress_{jt-1}$by estimating the fractional probit function (Wooldridge 2010, pp.750-751):

$$E(t\_progress_{jt-1}|\mathbf{x}, \mathbf{z}) = \Phi[\alpha_1 ln(Tenure_{jt}) + \alpha_2 lnRev_j + \boldsymbol{\lambda}\mathbf{z}], \tag{8}$$

where $\mathbf{x}$ is the vector of the included variables in (**??**), ln$(Tenure_{jt})$,ln Rev_j, and $\mathbf{z}$ are the excluded variables. The second step is simply to use the standard 2SLS to estimate (**??**) by treating the predicted values of $t\_progress_{jt-1}$ and its squared term as instruments for $t\_progress_{jt-1}$ and $t\_progress^2_{jt-1}$ respectively in the base-line regression (**??**).

The excluded variables, $\mathbf{z}$, in the fractional probit model (**??**) take advantage of the exogenous nature of the starting date of job j. They are:

- $InactiveFirstThree_j$: a categorical variable representing the number of inactive month (identified in data as no labor input from anyone) in the first three months after job j's start date. The inactivity is typically caused by unanticipated situations of the client, licensing, or other administrative issues. The longer the initially inactive period is, the more likely there are idiosyncratic problems and issues that may slow down the job progress.

- $StartYear_j$, $StartMonth_j$: two dummy variables representing the start year and start month of job j. Certain years may experience external shocks (e.g., government policy, occurrence of natural disasters) while certain months may have fewer working days because of national and regional holidays. These percularities may impact the formation of the team and the manager's initial, important tasks of delegation and coordination effort.

- For each job in each month except the first month, we calculate $DayStart_{jt-1}$ - the number of days to the end of the previous month since start - by using the first day in the next month minus the start date (e.g., if a job starts in June 15th, then the $DayStart_{jt-1}$ in June is calculated as 15 days). Other things (e.g., job size, manager's experience) constant, a job that has an earlier starting date logged more days of working ought to have an earlier ending date as well.

Notice that our data unfortunately lacks a job's completion date stipulated in the original contract - if any - that the firm signed with its clients. The fractional probit in (**??**), nonetheless, provides an useful way to estimate the expected job progress and thus the date of job completion.

As discussed in Wooldridge (2010), it is incorrect to directly use the excluded variables in estimating (**??**) by conventional 2SLS. This is because the endogenously variable $t\_progress_{jt-1}$ is not linear but has a range of $[0, 1]$. As such, the step of generating its predicted values as an instrumental variable becomes necessary.

5.2 Effect of information friction

We add C_{jt} and $Prox_j$ to the base-line regression (**??**) to examine the effect of information friction:

$$\begin{aligned} y_{jt} = \beta_0 + \beta_1 t\_progress_{jt-1} + \beta_2 t\_progress^2_{jt-1} \\ + \beta_3 C_{jt} + \beta_4 C_{jt} \cdot t\_progress_{jt-1} + \beta_5 Prox_j + \beta_6 Prox_j \cdot t\_progress_{jt-1} \\ + \gamma_1 \ln(Tenure_{jt}) + \gamma_2 \ln Rev_j + \phi_j + \epsilon_{jt}, \end{aligned} \quad (9)$$

To estimate (**??**) by 2SLS, all terms involving $t\_progress_{jt-1}$ are instrumented by its predicted value from estimating (**??**) and its derived terms in the information friction regression. We again follow the procedure proposed by Wooldridge (2010, p. 939) as in the previous subsection.

5.3 Effect of managerial workload

To examine the effect of managerial workload, we add $NoJob_{jt}$ to the base-line regression (**??**) above:

$$
\begin{aligned}
y_{jt} = \beta_0 + \beta_1 t\_progress_{jt-1} + \beta_2 t\_progress^2_{jt-1} \\
+ \beta_7 \ln(NoJob_{jt}) + \beta_8 \ln(NoJob_{jt}) \cdot t\_progress_{jt-1} \\
+ \gamma_1 \ln(Tenure_{jt}) + \gamma_2 \ln\, Rev_j + \phi_j + \epsilon_{jt}, \quad (10)
\end{aligned}
$$

In addition to $t\_progress_{jt}$ and its squared term, $NoJob_{jt}$ in (**??**) is also endogenous. To see this, the manager's workload may be affected by unobserved firm-specific or job-specific factors (e.g., availability of certain type of specialists) that impact the outcome variables of time spent and team size as well. To correct this, we use $NoReC_{jt}$ ("repeat client") and its previous month's counterpart, $NoReC_{jt-1}$, as the two instrumental variable for $NoJob_{jt}$ in the 2SLS regression to estimate (**??**). We explain our rationale as follows. The firm implements the policy of assigning the return clients to the same manager, whenever possible. The number of jobs coming from repeat customers increases a manager's workload and hence satisfies the relevant condition. At the same time, this pre-determined rule of job assignment removes the concern over the correlation between $NoReC_{jt}$ and $NoReC_{jt-1}$ and unobserved firm-side factors embedded in ϵ_{jt}.[15] Endogeneity concerns can also arise due to unobserved client-specific factors. For

[15]To verify the assignment policy in our data set, for each repeat client that has positive revenue, we calculate the share of revenue assigned to the manager that gets assigned the most. Across the 2392 repeat clients, the average revenue share of the most assigned manager is 77.9%. We believe the actual number should be higher because we do not have information on the identity of clients earlier than our data period. This implies that some of the clients in our data set may be repeat clients as well but we do not have the information. In any case, the high percentage of re-assignment shows the strong tendendy

instance, a client may have a preference toward working with the manager who previously worked with him. Such client preference not only leads the client to re-order but may also affect manager and team hours. To mitigate this problem, we exclude the observations of the repeat client in the month when the client re-orders a job(s) in that month. This ensures the excluded restriction is satisfied. Its operationalization and example are described in the data and measurement subsection above.

To estimate (**??**) by 2SLS as prescribed in the Wooldridge procedure (2010, p. 939), we obtain the predicted values from the fractional probit model but with ln($NoReC_{jt}+1$),ln($NoReC_{jt-1}+1$) as the additional variables in (**??**). Then the endogenous variables are instrumented by ln($NoReC_{jt}+1$), ln($NoReC_{jt-1}+1$), the predicted $t\_progress_{jt-1}$, its squared term, and its interactions with ln($NoReC_{jt}+1$) and $ln(NoReC_{jt-1}+1)$.

6 Main Result

In this section, we review in turn the results on time trend of job progress, the effect of information friction and workload, and their robustness checks.

6.1 Time trend of job progress

Table 2 shows the result of predicting job progress obtained from the fractional probit regression in (**??**). Despite the effect of an inactivity for the first month after the starting date is positive (estimate=0.037) on job progress, the further delay in a job's starting leads to increasingly slower job progress (estimates are -0.052 and -0.082 for two and three months delay respectively). Jobs starting earlier, having smaller revenue, or managed by more senior managers show faster progress. A majority of the start year (7 out of 13) and start month (6 out of 12) dummies are statistically significant at 10% or smaller.

<insert Table 2 about here>

of following the assignment policy. We also find that exceptions to this policy are more likely when the revenue of a job from a repeat client become higher. A simple regression shows that an unit increase in log revenue decreases the average revenue to the most assigned manager by 2.7%. Another exception is when the manager who handled a previous client is about to retire.

Table 3 shows the key results of estimating (**??**) on time trend in terms of job progress. [16] Columns 1 and 2 look at manager and team hours while columns 3 and 4 look at team size and manager's time as a share of team hours, respectively. The positive coefficients of $t\_progress_{jt-1}$ and the negative coefficients of $t\_progress^2_{jt-1}$ in columns 1 and 2 on manager and team hours imply their inverted U-shape relation with job progress. That is, their hours initially increase but decrease after reaching a peak. In other words, the manager and the team concentrate their effort ex ante on coordinating and organizing tasks. Ex post, the manager the team decrease their involvement in the execution stage. The result on team size in column 3 shows a similar pattern. Interestingly, and in contrast to the first three columns, the result in the last column shows that the manager's share of involvement has an U-shape relation with job progress. This implies that the manager spends more effort relative to her team both ex ante and during the final stage of the job. Task coordination and delegation by the manager when the job starts is obviously important. The manager's share of time also goes up toward the time when the job concludes; however, it has little economic significance during the job conclusion stage in our architectural context. This is because the team and the manager *both* spend very little time at the final stage. The manager's increasing time share closer to its completion merely shows her formal role in terms of signing off the job.[17]

<insert Table 3 about here>

Using the results obtained from Table 3, we plot their time-trend graphs by assuming the control variables at their mean values. Figure 3 visually shows how the four outcome variables evolve as a job progresses from its start to its completion. The first graph shows that a typical managers starts a job with relatively plenty of time - 4.5 hours in a month. Their time increases to the peak at about 20% into the job, but then it monotonically decreases to only 0.5 hour when the job concludes. The second graph shows a similar

[16] Column 1 in Table A1 in the Empirical Appendix A shows the corresponding first-stage results. The coefficients of the predicted values of job progress and its squared term show high statistically signficance. Tables A2 to A8 in the Empirical Appendix include the results of first-stage regressions of other analyses in this section on Main Results.

[17] Table A9 in the Empirical Appendix in the appendix has the results on time trend with the inclusion of only $t\_progress_{jt-1}$ but not its squared term. Those results show that the marginal effect of job progress on all the four outcome variables is negative. Unlike the main regression in (**??**) that also includes with the squared term of job progress, the coefficient of the linear term of job progress on the manager's hour share in column 4 is not statistically signficant.

time trend of her architect teams: team hours start with about 100 hours per month, peak at over 135 hours just before the 40% mark, and then monotonically decreases to about 20 hours when the job completes. Similar to team hours, team size in the third graph follows a similar inverted-U shape with the maximum size of just under six members at the 40% job mark. The fourth graph shows the managers's share of time are the highest in the initial stage to organize tasks and the conclusion stage to sign off of jobs. The overall patterns in Figure 3 reaffirm the view that, managers generally devote most of their work time on architectural jobs to ex ante coordination and task delegation whereas their teams focus on execution during the middle stage.[18]

$<$insert Figure 3 about here$>$

On our two control variables. First, larger jobs - measured by pre-determined revenue Rev_j - have a large positive scale effect on the manager's (estimate=0.477) and team hours (estimate=0.969). That larger jobs have bigger teams is intuitive too. Due to more team hours and larger size, the share of the manager hours to team hours inadvertently decreases as jobs become larger. Second, the seniority of the managers has opposite effects on managerial and team involvement. Column 1 shows that more senior managers spend less time on their jobs (estimate=-0.177) by having larger teams that spend more hours. These may be explained by the facts that more senior managers have other internal administrative tasks such as committee work and/or a bigger role to prepare future managers through delegation.

6.1.1 Time trend of knowledge intensive jobs

As we mentioned in our introduction, the key features of knowledge-intensive work is its non-repetitive, intangible nature. In architectural jobs that require high creativity, one would expect that the involvement of the manager and the team should be higher, especially in the beginning. The more creative types of jobs in our contexts are planning and development, schematic design, and design development, whereas the less

[18] Table A1 in the Empirical Appendix in the appendix has the results on time trend using the observations where $ManagerHour_{jt}$ is positive. The results show that the decreasing time trend is holds as well as that when the samples include the months when the manager does not spend any time.

creative types are construction documentation and construction supervision. We classify the jobs in the first category as "knowledge-intensive" jobs and the second category as "less knowledge-intensive" jobs. To examine the difference in job progress, the baseline model includes a dummy variable $KnowInten_j$ of the two job categories, where $KnowInten_j = 1$ for knowledge-intensive jobs and 0 otherwise, and its interaction with $t\_progress_{jt-1}$ as the following:

$$\begin{aligned} y_{jt} = \beta_0 + \beta_1 t\_progress_{jt-1} + \beta_2 t\_progress^2_{jt-1} + \\ KnowInten_j + KnowInten_j \times t\_progress_{jt-1} + \\ \gamma_1 \ln(Tenure_{jt}) + \gamma_2 \ln Rev_j + \phi_j + \epsilon_{jt}, \end{aligned} \tag{11}$$

Table 4 shows the regression results of (**??**). The positive coefficients of the dummy variable $KnowInten_j$ in columns 1, 2 and 3 imply that manager hours, team hours, and team size are all increasing in knowledge intensive jobs when they start. The negative coefficients of the interaction term in the first three columns means the value of the three dependent variables decreases after reaching a peak as jobs progress. These two results support the view that both the manager and the team concentrate their attention in the initial stages on task definition, coordination, and assignment for highly creative jobs. The fourth column shows the difference between the two categories of jobs is not statistically significant for the manager's share of hour spent. Other explanatory variables in (**??**) have the same directional effects as those in the base line model in (**??**).

<insert Table 4 and Figure 4 about here>

Figure 4 plots the respective four graphs. The first one shows that the typical manager actually spends more time on knowledge-intensive work throughout the job. Her team, on the other hand, spends more time for the first half of jobs on knowledge-intensive jobs than on the less knowledge intensive ones. This implies that knowledge-intensive jobs are generally more effort demanding and coordination intensive. These provide evidence showing the importance of ex ante managerial coordination and task assignment among a team of specialists when work involve less well-defined tasks but more imagination (Drucker 1999). That the first graph shows the convergence of manager time across the two categories of jobs further confirms the nominal role of signing off at the end by managers, as we indicated in Figure 1.

6.2 Time trend of information friction - common clients and proximity of job sites

This subsection covers the results of using common clients and job proximity as measures of (lack of) information friction. With two additional explanatory variables - C_{jt} and $Prox_j$ - in the outcome regression in (**??**), the Wooldridge procedure requires their inclusion in the fractional probit model in (**??**) as well. Table 5 shows the results. Nearby job sites correlate with slower progress (estimate=-0.004) whereas common clients who have multiple concurrent jobs under the supervision of the same manager correlate with faster progress (estimate=0.014). The counter-intuitive effect of proximity on job progress, however, disappears once we use quarterly averages in the next subsection.

Table 6 shows the results of the outcome regression of the 2SLS specified in (**??**). As the two measures of (lack of) information friction, it is soothing to see common client and proximity show the same directional effects. Both variables yield negative main effects but positive interaction effects in the first three columns on manager hours, team hours, and team size, but positive and negative main and interaction effects in the last column on manager time share. These results are intuitive. As information friction becomes smaller when the client has more jobs being handled by the manager or when the job site is closer to the firm, employees in the firm can economize their effort and labor ex ante. In other words, only when the client is new or the job is faraway, the manager and the larger team spend their limited attention on ex ante information acquisition, coordination, and task delegation. With same range of $[0, 1]$ of the two variables, we note that common client has larger main effects while job proximity has larger interaction effect (except that the magnitudes on manager hours' interaction are very close). On the manager's time share, except the negative interaction effect of proximity is statistically significant, the other three coefficients on information friction are not.

$<$Insert Tables 5 and 6 about here$>$

Using the results in Table 6, we plot the corresponding graphs in figure 6 by distinguishing between jobs that have higher versus low information friction. High and low information friction is constructed by letting C_{jt} and $Prox_j$, respectively, one standard deviations below and higher than their means. The first three graphs show, respectively, more manager and team hours and larger team size occur in the first half of those jobs for whose information friction is high. This supports the view that more ex ante work is needed due to a lack of information. Although the last graph shows a difference on manager hour share, the difference between the two curves are not statistically significant.

<Insert Figure 5 about here>

6.2.1 Robustness check - quarterly average and job fixed effects

We conduct two sets of robustness checks. First, by replacing ϕ_j, job fixed effects are used. This eliminates any endogeneity caused by correlations between time-invariant job, manager, or team characteristics and the error term. Table 7 shows the fractional probit regression where the effects of the remaining time varying variables are qualitatively the same as in Table 6. On our outcome regressions in Table 8, The main and interaction effects of common client in the second stage are also similar as those obtained from the original regression in (**??**). The two coefficients in the last column on common client turn out to be statistically significant: the manager spends more time in ex ante coordination when there are more jobs coming from repeat customers.

<Insert Tables 7 and 8 about here>

Second, given rational inattention, manager and team hours may not be smooth moving from one month to another during a job's duration. If so, it is more suitable to use a quarterly average of the outcome variables. Tables 9 and 10 show the job progress prediction and the second stage results respectively. Again, the results are qualitatively similar to those obtained from the monthly regressions in Tables 9 and 10. Notice that the negative effect of job proximity in Table 9 becomes tiny and is no longer statistically significant.

<Insert Tables 9 and 10 about here>

6.3 Time trend of workload

We turn to our results on the effect of the manager's workload in this subsection. Table 11 shows the results of using the fractional probit model to generate the predicted value of $t\_progress_{j,t-1}$.The negative estimates of ln($NoReC_{jt}+1$) and ln($NoReC_{jt-1}+1$) mean that the more jobs the manager received from repeat clients in recent months, the slower the job progress is. This is because jobs from repeat clients assigned by the company rule increases the manager's workload which in turn hampers job progress.

The first stage results of estimating the workload regression in (**??**) are shown in Table A4 in the Empirical Appendix. The estimates of the two variables on repeat clients yield high statistical significance and hence their relevance. The second stage results in Table 12 show negative main effects on ln($NoJob_{jt}$) across the first three columns. This indicates that the manager and the team spend less time ex ante under heavier workload. The positive interaction effects show the manager and her team only make up their time as the job progresses toward its completion. The main and interaction effects of manager hour share in the last column are positive and negative respectively, but the coefficients are not statistically significant.

Figure 6 plots the graphs using the 2SLS workload results. High and low levels are constructed by letting ln($NoJob_{jt}$) one standard deviations higher and below than their means respectively. The first three graphs show that the curves of manager hours, team hours, and team size in higher workload managers under the low workload scenario are all dominated by the curves drawn under the high workload scenario. As such, high workload inevitably slows down job progress in general.

<Insert Tables 11, 12, and Figure 6 about here>

6.3.1 Remarks on the synchronization of manager and team hours

We have seen the general pattern of the concentrated effort of managers and their teams ex ante and the decreasing involvement of both the manager and the team afterward.

This similarity is particularly notable on the effect of workload in Table 12. With the log-log formulation of our regressions there, the marginal effect of ln($NoJob_{jt}$),or workload, on manager hours is essentially the elasticity of workload on manager hours:

$$\frac{\partial \ln(MH_{jt}+1)}{\partial ln(NoJob_{jt})} = \eta_{MH} = -0.262 + 0.310 \cdot t\_progress_{jt-1}.$$

Similarly the marginal effect, or elasticity of, workload, on team hours can be expressed as:

$$\frac{\partial \ln(TH_{jt}+1)}{\partial ln(NoJob_{jt})} = \eta_{TH} = -0.283 + 0.352 \cdot t\_progress_{jt-1}.$$

The estimates of the main and interaction effects between manager and team hours are very close. Indeed, the t-statistics obtained from the tests on whether the main effect and interaction effect of workload are the same between manager and team hours yield p-values of 0.076 and -0.136 respectively. As such, we cannot reject the null hypotheses at the 5% level. Then statistically speaking, $\eta_{MH} = \eta_{TH}$ at any given moment in the job process. That is, a change in managerial workload leads to the *same* proportional changes in *both* manager hours and team hours. This synchronization of hours adjustment shows that managers' inputs on coordination and task allocation are essential for the team members to work on their tasks. The manager's workload not only strains her attention but also prevents her team from making progress. This finding matches our institutional setting in which internal or external labor supply of architects is rigid, at least in the short run. As a result, a shock of increased workload to the manager causes the same proportional increase of workload to the team, which in turn forces the design team and its leader to adjust their attention in a synchronized manner.

6.3.2 Robustness check - relative workload, quarterly average, and job fixed effects

We conduct three sets of robustness checks for the workload regressions using (i) relative workload as an alternative measure of workload, (ii) job fixed effects, and (iii) quarterly average of the outcome variables.

First, we construct the ratio of between number of jobs and the average number of jobs across months in last year as "relative workload" or Rel$NoJob_{jt}$. Using the same approach for $NoJob_{jt}$, the logarithm of relative workload variable, ln(Rel$NoJob_{jt}$), is instrumented by the two "relative repeat client" variables, ln($RelNoReC_{jt}$+1) and ln($RelNoReC_{jt-1}$+1). The relative repeat client variable is the ratio between the number of jobs from repeat clients, $NoReC_{jt}$, and the average monthly number of jobs in the previous year. Results in Tables 13 and 14 on the prediction of job progress and the 2SLS for the main regression respectively are all qualitatively similar to those obtained in the original workload regression in (**??**).

<Insert Tables 13 and 14 about here>

Second, using job fixed effects yields similar results on the effect of workload on predicting job progress and the four outcome variables. Tables 15 and 16 show the results. Lastly, quarterly averages also continue to generate robust results, as seen in Tables 17 and 18.

<Insert Tables 15, 16, 17, and 18 about here>

7 Economic significance

Our theoretical model predicts that managerial attention optimally balances ex ante and ex post coordination. Deviations - both upward or downward - from optimal time spent reduces profitability. Labor cost and related incidental costs (e.g., travel expenses) are arguably the most significant portion of variable cost in knowledge work in modern companies. The difference between gross revenue of a job, which is predetermined, and its variable cost is known as the contribution margin. The contribution margin is an important measure of short-term profits for the firm. If the model successfully captures a significant part of the desired balance in manager's time allocation, time deviations by the manager should reduce the contribution margin of the design jobs under her supervision.

We use model 1 in Table 6 to calculate predicted hours, $Manag\hat{e}rHour_{jt}$. We then define the difference between the observed and the predicted hour as

$$HourDiff_j = \sum_t \left(ManagerHour_{jt} - Manag\hat{e}rHour_{jt} \right).$$

We transform $HourDiff_j$ by using the following logarithm function to reduce its dispersion so as to fit into an affable figure:

$$g(x) = \begin{cases} \ln x + 1 & x \geq 1 \\ x & -1 < x < 1 \\ -(\ln(-x) + 1) & x \leq -1 \end{cases},$$

where $g(x)$ is continuous at $x = \pm 1$. Denote $FlatHourDiff_j = g(HourDiff_j)$ .We then run the following regression, including quadratic and cubic terms of $FlatHourDiff_j$, to estimate the nonlinear effects of hour difference:

$$\ln Cost_j = \beta_0 + \sum_{k=1}^{3} \beta_{1,k} FlatHourDiff_j^k + \beta_2 \ln Rev_j + Industry_j + JobType_j + \epsilon_j,$$

where $Cost_j$ is the variable cost of job j. Figure 8 plots the implied polynomial curve using the estimated values of $\beta_{1,k}$. It shows that *both* ”under-run” and ”over-spending” of time with respect to our predicted manager hours are associated with higher cost-revenue ratio (and hence short-run profit) than under our predicted hours.

<Insert Figure 8 about here>

To calculate absolute value of hour deviations from prediction at job level, we use the following formula:

$$HourDeviation_j = \sum_t |ManagerHour_{jt} - \hat{ManagerHour}_{jt}|.$$

Moreover, we differentiate between over-run (i.e., when the observed number of hours is higher than the predicted number of hours) and under-run (i.e., when the observed hours are smaller than the predicted ones) respectively as:

$$HourDeviationOver_j = \sum_t \max\left(ManagerHour_{jt} - \hat{ManagerHour}_{jt}, 0\right),$$

and

$$HourDeviationUnder_j = \sum_t \max\left(\hat{ManagerHour}_{jt} - ManagerHour_{jt}, 0\right).$$

Then we estimate the regression in which the cost-to-revenue ratio is a primary measure of job performance:

$$\ln\left(\frac{Cost_j}{Rev_j}\right) = \alpha_0 + \alpha_1 \ln\ HourDeviation_j + \alpha_2 \ln Rev_j + \phi_j + e_j.$$

We also use the logarithm value of the original cost, $\ln(Cost_j)$, as an alternative dependent variable. Using the OLS regressions, Tables 19 shows the correlation between hour deviation and profits. Both columns show high *positive* correlation between manager hour deviations and costs. We repeat the regressions including both $HourDeviationOver_j$ and $HourDeviationUnder_j$ as independent variables in Table 20, which show the detrimental effects of of over-run and under-run. In unreported regressions, we further confirm that hour deviations are correlated with higher cost and cost-to-revenue ratios even when we exclude manager's costs from the total costs incurred by the team.

To investigate how hour deviations affect team hours, we run two OLS regressions. Table 21 reports the results. We find that higher team hours correlate with both under- and over- deviations. On the one hand, it is intuitive to understand over-runs by both the manager and the team. On the other hand, the under-run result implies that a lack of manager involvement is substituted by higher team involvement. Note that our previous finding on the synchronization between manager and team hours is caused by the rigidity of labor supply at a *given point* of the job progress. In contrast, the analysis about hour-deviations can be considered as a "total" effect because monthly hours are aggregated to the job level. The under-run result implies that a lack of the manager's involvement to coordinate aggravates the progression of the job; hence, the team has to compensate more hours for its manager's under-run.

<Insert Tables 19, 20, and 21 about here>

Since the above analysis is conducted at the job level, one concern is that job-level shocks may drive both hour deviations and variable costs. To alleviate this concern by averaging out job-level shocks, we further aggregate revenue, costs, and hour deviations across jobs for each manager-year pair. For those jobs spreading across years, we use the proportion of days that within each year to split their revenue and variable cost. For example, if a job starts in the middle of a year and ends in the middle of the next year, then its revenue and costs are split half and half in each year. The results of those regressions are reported in Tables 22 and 23. Although some estimates are weaker due to the smaller sample size, the overall patterns are similar. For instance, absolute hour deviations, and over-run and under-run are still statistically relate to higher cost (columns 2 in both tables).

<Insert Tables 22 and 23 about here>

8 Conclusion

TBC.

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9 Mathematical Appendix

9.1 Optimal time allocation.

[To be cleaned up a bit] Denote $h^D(t_M, t_T) = A\frac{t_M^\rho t_T^{1-\rho}}{\rho^\rho(1-\rho)^{1-\rho}}$ and $h^C(t_M, t_T) = A\frac{t_M^\upsilon t_T^{1-\upsilon}}{\upsilon^\upsilon(1-\upsilon)^{1-\upsilon}}$. Optimizing $Q - L$ over t_M^D, t_M^C we have that

$$\begin{aligned}
\mu^{1-(\alpha+\beta+\gamma)}\alpha h_1(t_M^{D*}, t_T^{D*})\frac{Q}{Q^D} &= \lambda_M \\
\mu^{1-(\alpha+\beta+\gamma)}\gamma h_1(t_M^{C*}, t_T^{C*})\frac{Q}{Q^C} &= \lambda_M
\end{aligned}$$

Similarly, optimizing $Q - L$ over t_T^D, t_T^E and t_T^C, we have that

$$\begin{aligned}
\mu^{1-(\alpha+\beta+\gamma)}\alpha h_2(t_M^{D*}, t_T^{D*})\frac{Q}{Q^D} &= \lambda_T \\
\mu^{1-(\alpha+\beta+\gamma)}\gamma h_2(t_M^{C*}, t_T^{C*})\frac{Q}{Q^C} &= \lambda_T \\
\mu^{1-(\alpha+\beta+\gamma)}\beta h_2^E\frac{Q}{Q^E} &= \lambda_T
\end{aligned}$$

We further have that

$$h_1^D(t_M, t_T) = \frac{1}{\rho^\rho(1-\rho)^{1-\rho}}\frac{\rho A t_M^\rho t_T^{1-\rho}}{t_M} \tag{12}$$

$$h_1^C(t_M, t_T) = \frac{1}{\upsilon^\upsilon(1-\upsilon)^{1-\upsilon}}\frac{\upsilon A t_M^\upsilon t_T^{1-\upsilon}}{t_M} \tag{13}$$

and

$$h_2^D(t_M, t_T) = \frac{1}{\rho^\rho(1-\rho)^{1-\rho}}\frac{(1-\rho) A t_M^\rho t_T^{1-\rho}}{t_T} \tag{14}$$

from which

$$\frac{h_1^D(t_M, t_T)}{h_2^D(t_M, t_T)} = \frac{\rho}{1-\rho}\frac{t_T}{t_M}$$

$$\frac{h_1^C(t_M, t_T)}{h_2^C(t_M, t_T)} = \frac{\upsilon}{1-\upsilon}\frac{t_T}{t_M}$$

From the FOC wrt to t_M^k and t_T^k, $k = C, D$, we must also have that

$$\frac{h_1^k(t_M^k, t_T^k)}{h_2^k(t_M^k, t_T^k)} = \frac{\lambda_M}{\lambda_T}$$

it follows that at the optimum

$$\frac{t_T^{D*}}{t_M^{D*}} = \frac{(1-\rho)\lambda_M}{\rho\lambda_T} \equiv \kappa_D$$

and

$$\frac{t_T^{C*}}{t_M^{C*}} = \frac{(1-\upsilon)\lambda_M}{\upsilon\lambda_T} \equiv \kappa_C$$

Substituting $t_T^{k*} = \kappa_l t_M^{k*}$, $l = C, D$, in (**??**) and (**??**), we obtain

$$\begin{aligned} h_1^D(t_M^{D*}, t_T^{D*}) &= A^D \frac{\rho}{\rho^\rho(1-\rho)^{1-\rho}}(\kappa_D)^{1-\rho} = A^D \left(\frac{\lambda_M}{\lambda_T}\right)^\rho \\ h_1^C(t_M^{C*}, t_T^{C*}) &= A^C \frac{\upsilon}{\upsilon^\upsilon(1-\upsilon)^{1-\upsilon}}(\kappa_C)^{1-\upsilon} = A^C \left(\frac{\lambda_M}{\lambda_T}\right)^\upsilon \end{aligned}$$

and

$$h_2^D(t_M^{D*}, t_T^{D*}) = A^D \frac{1}{\rho^\rho(1-\rho)^{1-\rho}} \frac{1-\rho}{\kappa_D^\rho} = A^D \frac{(1-\rho)}{\rho^\rho(1-\rho)^{1-\rho}} \left(\frac{\rho\lambda_T}{(1-\rho)\lambda_M}\right)^\rho = A^D \left(\frac{\lambda_T}{\lambda_M}\right)^\rho$$

From the FOC wrt to t_M^D and t_M^C, we further have that

$$\frac{h_1^D(t_M^{D*}, t_T^{D*})}{h_1^C(t_M^{C*}, t_T^{C*})} = \frac{\gamma}{\alpha}\frac{Q^D}{Q^C}$$

from which

$$\frac{Q^D}{Q^C} = \frac{\alpha A^D}{\gamma A^C}\left(\frac{\lambda_M}{\lambda_T}\right)^{\rho-\upsilon}$$

From the FOC wrt to t_E^T and t_C^T, we have that

$$\gamma h_2^C(t_M^{C*}, t_T^{C*})\frac{Q}{Q^C} = \beta h_2^E \frac{Q}{Q^E}$$

or still

$$\gamma A^C \frac{(1-\upsilon)}{s_C^{\upsilon}} \frac{Q}{Q^C} = \beta A^E \frac{Q}{Q^E}$$

or still

$$\frac{\gamma A^C \left(\frac{\lambda_T}{\lambda_M}\right)^{\upsilon}}{\beta A^E} = \frac{Q^C}{Q^E}$$

Moreover, from the FOC, we know that

$$\gamma h_1^C(t_M^{C*}, t_T^{C*}) \frac{Q}{Q^C} = \lambda_M$$

from which

$$\begin{aligned} Q_C &= \frac{1}{\upsilon^{\upsilon}(1-\upsilon)^{1-\upsilon}} \frac{\gamma A^C \upsilon (s_C)^{1-\upsilon}}{\lambda_M} = \frac{1}{\upsilon^{\upsilon}(1-\upsilon)^{1-\upsilon}} \frac{\gamma A^C \upsilon}{\lambda_M} \left(\frac{(1-\upsilon)\lambda_M}{\upsilon \lambda_T}\right)^{1-\upsilon} \\ &= \gamma A^C \left(\frac{1}{\lambda_M}\right)^{\upsilon} \left(\frac{1}{\lambda_T}\right)^{1-\upsilon} Q \end{aligned}$$

or still

$$\begin{aligned} Q_C &= \gamma A^C \left(\frac{1}{\lambda_M}\right)^{\upsilon} \left(\frac{1}{\lambda_T}\right)^{1-\upsilon} Q \\ Q_D &= \alpha A^D \left(\frac{1}{\lambda_M}\right)^{\rho} \left(\frac{1}{\lambda_T}\right)^{1-\rho} Q \end{aligned}$$

and

$$\begin{aligned} Q^E &= \frac{\beta A^E \gamma A^C}{\gamma A^C \left(\frac{\lambda_T}{\lambda_M}\right)^{\upsilon}} \left(\frac{1}{\lambda_M}\right)^{\upsilon} \left(\frac{1}{\lambda_T}\right)^{1-\upsilon} Q \\ &= \frac{\beta A^E}{\lambda_T} Q \end{aligned}$$

Hence,

$$\begin{aligned} Q &= \mu^{1-(\alpha+\beta+\gamma)} \cdot \left(Q^D\right)^{\alpha} \left(Q^E\right)^{\beta} \left(Q^C\right)^{\gamma} \\ &= \mu^{1-(\alpha+\beta+\gamma)} \cdot \left(\alpha A^D \left(\frac{1}{\lambda_M}\right)^{\rho} \left(\frac{1}{\lambda_T}\right)^{1-\rho}\right)^{\alpha} Q^{\alpha} \left(\frac{\beta A^E}{\lambda_T}\right)^{\beta} Q^{\beta} \left(\gamma A^C \left(\frac{1}{\lambda_M}\right)^{\upsilon} \left(\frac{1}{\lambda_T}\right)^{1-\upsilon}\right)^{\gamma} Q^{\gamma} \end{aligned}$$

or still

$$Q^* = \mu \cdot \left(\alpha A^D \left(\frac{1}{\lambda_M} \right)^\rho \left(\frac{1}{\lambda_T} \right)^{1-\rho} \right)^{\frac{\alpha}{1-(\alpha+\beta+\gamma)}} \left(\beta A^E \frac{1}{\lambda_T} \right)^{\frac{\beta}{1-(\alpha+\beta+\gamma)}} \left(\gamma A^C \left(\frac{1}{\lambda_M} \right)^\upsilon \left(\frac{1}{\lambda_T} \right)^{1-\upsilon} \right)^{\frac{\gamma}{1-(\alpha+\beta+\gamma)}}$$

Note that if $\rho = \upsilon$, then this is equal to

$$Q^* = \mu \cdot \left(\left(\frac{1}{\lambda_M} \right)^\rho \left(\frac{1}{\lambda_T} \right)^{1-\rho} \right)^{\frac{\alpha+\gamma}{1-(\alpha+\beta+\gamma)}} \left(\alpha A^D \right)^{\frac{\alpha}{1-(\alpha+\beta+\gamma)}} \left(\beta A^E \frac{1}{\lambda_T} \right)^{\frac{\beta}{1-(\alpha+\beta+\gamma)}} \left(\gamma A^C \right)^{\frac{\gamma}{1-(\alpha+\beta+\gamma)}}$$

And

$$\begin{aligned}
Q_C &= \gamma A^C \left(\left(\frac{1}{\lambda_M} \right)^\rho \left(\frac{1}{\lambda_T} \right)^{1-\rho} \right)^{\frac{1-\beta}{1-(\alpha+\beta+\gamma)}} \mu \left(\alpha A^D \right)^{\frac{\alpha}{1-(\alpha+\beta+\gamma)}} \left(\beta A^E \frac{1}{\lambda_T} \right)^{\frac{\beta}{1-(\alpha+\beta+\gamma)}} \left(\gamma A^C \right)^{\frac{\gamma}{1-(\alpha+\beta+\gamma)}} \\
Q_D &= \alpha A^D \left(\left(\frac{1}{\lambda_M} \right)^\rho \left(\frac{1}{\lambda_T} \right)^{1-\rho} \right)^{\frac{1-\beta}{1-(\alpha+\beta+\gamma)}} \mu \left(\alpha A^D \right)^{\frac{\alpha}{1-(\alpha+\beta+\gamma)}} \left(\beta A^E \frac{1}{\lambda_T} \right)^{\frac{\beta}{1-(\alpha+\beta+\gamma)}} \left(\gamma A^C \right)^{\frac{\gamma}{1-(\alpha+\beta+\gamma)}} \\
Q_E &= \frac{\beta A^E}{\lambda_T} \mu \cdot \left(\left(\frac{1}{\lambda_M} \right)^\rho \left(\frac{1}{\lambda_T} \right)^{1-\rho} \right)^{\frac{1-\beta}{1-(\alpha+\beta+\gamma)}-1} \left(\alpha A^D \right)^{\frac{\alpha}{1-(\alpha+\beta+\gamma)}} \left(\beta A^E \frac{1}{\lambda_T} \right)^{\frac{\beta}{1-(\alpha+\beta+\gamma)}} \left(\gamma A^C \right)^{\frac{\gamma}{1-(\alpha+\beta+\gamma)}}
\end{aligned}$$

9.2 Project-dependent delegation ratio ρ

In our set-up, the manager is assisted by a team of workers in coordinating tasks both ex ante (in the early stages of the production process, specifying and delegating tasks, and planning their coordinated execution) and ex post (responding to unforeseen contingencies and changing circumstances), using the production function

$$A_k \left(\frac{t_M^k}{\rho} \right)^\rho \left(\frac{t_T^k}{1-\rho} \right)^{1-\rho} \text{ with } k = D, C$$

Intuitively, the ability of the manager to "delegate" part of her managerial responsibilities may depend on a number of circumstances. In our empirical contest, we are particularly concerned with the role of "common projects" and "distance". While proposition 1 assumes that ρ is independent of both x_c (the variable capturing common projects), the manager may be less able to do so when projects involve common clients. Intuitively, the relational nature of multilateral contracts (Argyres et al. 2020) and the increased need of centralized coordination (Dessein et al. 2022) may make it more difficult for the manager to delegate such coordination activities to senior workers. Thus, it seems reasonable to assume that ρ is increasing in x_c implying that

$$\kappa \equiv \frac{t_T^{k*}}{t_M^{k*}} = \frac{(1-\rho)\lambda_M}{\rho\lambda_T}$$

is decreasing in x_c.

Similarly, for larger projects, it may be easier for a manager to delegate a larger fraction of ex ante and ex post coordination (e.g. it may become feasible to have an assistant manager, or senior worker, who becomes second in command). So one might conjecture that ρ is decreasing in project size μ.

Assumption 1 It is more difficult for a manager to delegate ex ante and ex post coordination to subordinates when projects have (i) common clients (ii) projects are smaller:

$$\frac{\partial \rho}{\partial x_c} > 0 \text{ and } \frac{\partial \rho}{\partial \mu} < 0$$

To differentiate our results from Proposition 1, we will further assume that s is small, so that

$$Q_k \approx A_k \left(\frac{t_M^k}{\rho}\right)^{\rho} \left(\frac{t_T^k}{1-\rho}\right)^{1-\rho} \text{ with } k = D, C$$

Note that for $s = 0$, the comparative statics in Proposition 1, (2)-(4) disappear. Proposition 2 should therefore be seen as complimentary to Proposition 1:

Proposition 4. *Assume s is small and Assumption 1 holds. Then an increase in x_c or $-\mu$ increases the relative involvement of the manager but more so ex ante than ex post: t_M^1/t^1, t_M^2/t^2 and $t_M^1/t_T^1 - t_M^2/t^2$ are increasing in x_C and $-\mu$.*

Proof: We know that

$$t_M^1/t_T^1 = \frac{\rho}{(1-\rho)}\frac{\lambda_T}{\lambda_M}$$

When $s = 0$, we further have that

$$t_M^2/t_T^2 = \frac{\rho \frac{1}{A^C} \left(\frac{\lambda_T}{\lambda_M}\right)^{1-\rho} Q^{C^*}}{(1-\rho)\frac{1}{A^C}\left(\frac{\lambda_M}{\lambda_T}\right)^{\rho} Q^{C^*} + \frac{1}{A^E} Q^{E^*}}$$

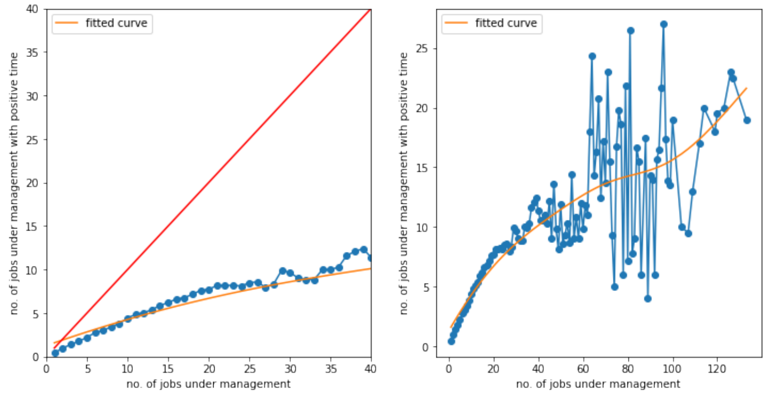
which can be simplified to

$$t_M^2/t_T^2 = \frac{\rho\gamma}{(1-\rho)\gamma + \beta} \frac{\lambda_T}{\lambda_M},$$

which is increasing ρ and otherwise independent of x_s, x_d or μ. Finally, we have that

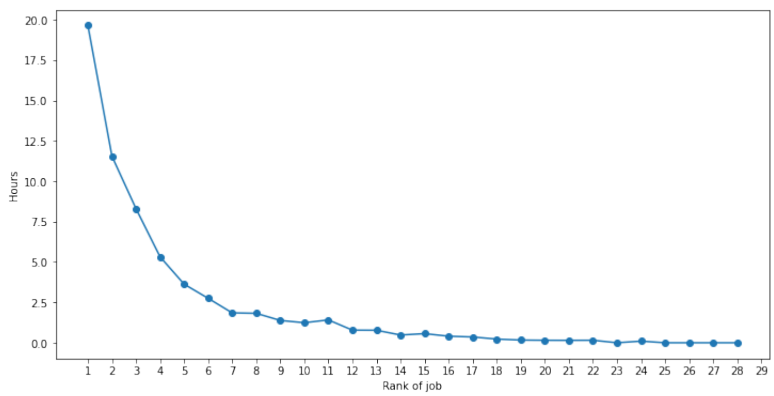
$$\begin{aligned} t_M^1/t_T^1 - t_M^2/t_T^2 &= \frac{\rho\left((1-\rho)\gamma + \beta\right) - (1-\rho)\rho\gamma}{(1-\rho)\left((1-\rho)\gamma + \beta\right)} \frac{\lambda_T}{\lambda_M} \\ &= \frac{\rho\beta}{(1-\rho)\left((1-\rho)\gamma + \beta\right)} \frac{\lambda_T}{\lambda_M} \end{aligned}$$

which is also increasing in ρ, and otherwise independent of x_s, x_d or μ.



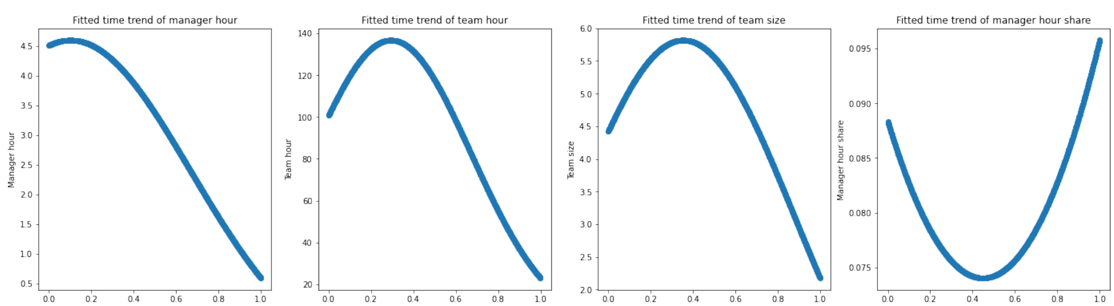
Note: The figure plots average number of jobs allocated positive time, conditional on number of jobs under management. The fitted curve is estimated from a nonparametric kernel regression.

Figure 1 – Number of jobs with positive attention and number of jobs assigned



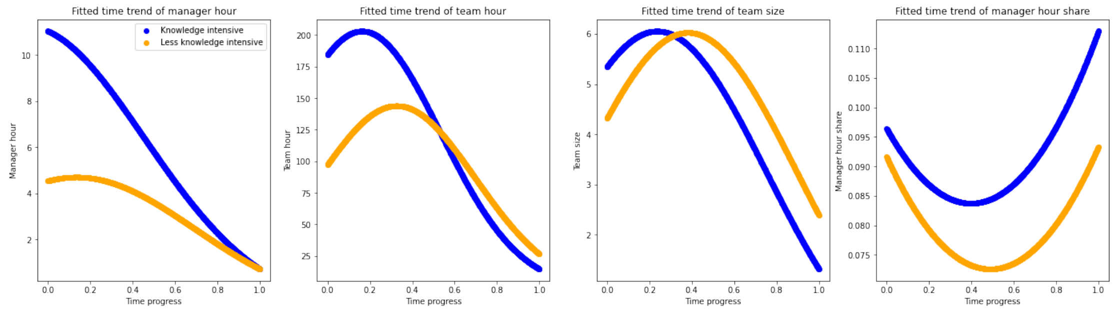
Note: The figure plots average number of hours spent on each job, conditional on rank in terms of hours.

Figure 2 – Average attention conditional on rank of job



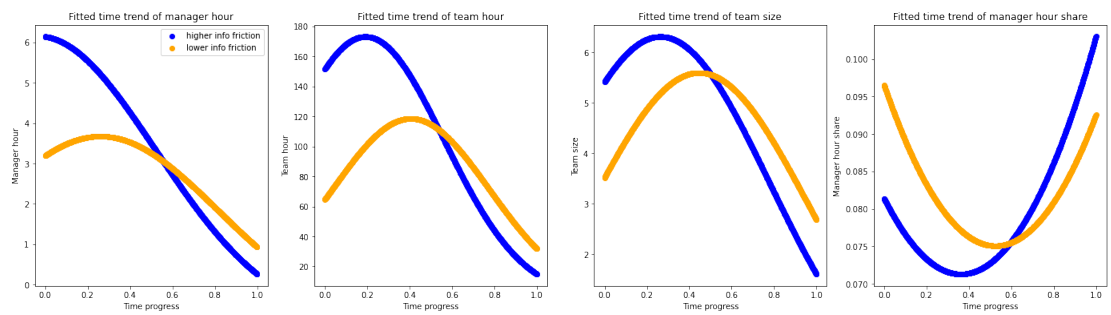
Fitted curves against $t\_progress_{jt-1}$. Control variables are taken at mean.

Figure 3 – Time trend of hours



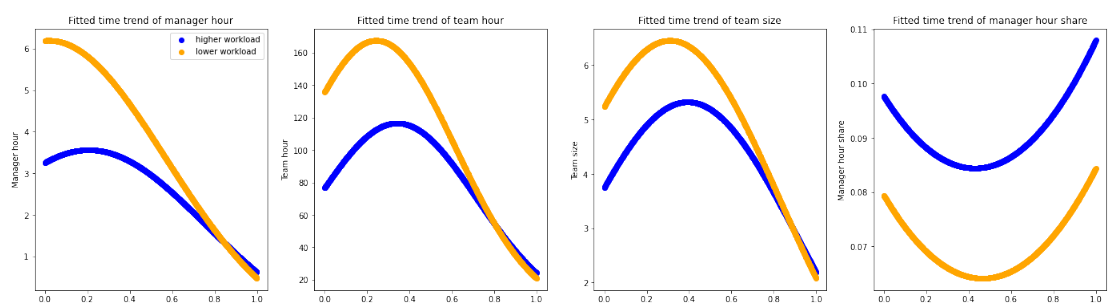
Note: Classification by job types. Knowledge intensive types include Planning & develop management, Schematic design, and Design development. Less knowledge intensive types include Construction documentation and Construction supervision. Controls are taken at mean.

Figure 4 – Time trend of hours by job types



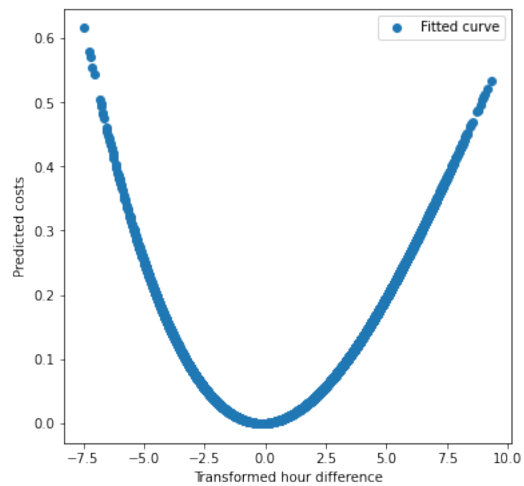
Curves of high (low) information friction are calculated by letting C_{jt} and $Prox_j$ one standard deviation lower (higher) than their means. Controls are held at mean values.

Figure 5 – Time trend of hours by information barriers



Curves of high (low) workload are calculated by letting $\ln NoJob_{jt}$ one standard deviation higher (lower) than then its mean. Controls are held at mean values.

Figure 6 – Time trend of hours by workload



Note: The figure plots the polynomial implied by the estimated values of $\beta_{1,k}$.
Benchmark hours are predicted from 2SLS model.

Figure 7 – Fitted curve between cost-revenue ratio and flatted hour difference, 2SLS model

	count	mean	std	min	25%	50%	75%	max
$ManagerHour_{jt}$	61873.000	9.616	18.588	0.000	0.000	3.000	11.000	304.500
$TeamHour_{jt}$	61873.000	278.079	427.217	0.000	35.000	126.500	345.000	9832.000
$TeamSize_{jt}$	61873.000	6.875	6.133	0.000	2.000	5.000	10.000	76.000
$ManagerHourShare_{jt}$	61873.000	0.094	0.211	0.000	0.000	0.015	0.070	1.000
$t\_progress_{jt}$	61873.000	0.537	0.257	0.011	0.324	0.542	0.755	1.000
C_{jt}	61873.000	0.066	0.124	0.000	0.000	0.000	0.077	1.000
$Prox_j$	61873.000	0.534	0.493	0.000	0.006	1.000	1.000	1.000
$NoJob_{jt}$	61873.000	16.947	11.779	1.000	9.000	14.000	22.000	87.000
Rev_j	61873.000	88101312.342	132611844.829	1000000.000	12800000.000	38200000.000	98800000.000	1148320000.000
$Tenure_{jt}$	61873.000	24.576	5.954	2.000	21.000	24.000	28.000	43.000

Table 1 – Summary statistics

	$t\_progress_{jt-1}$	t-value
$InactiveFirstThree_j = 1$	0.037	3.475
$InactiveFirstThree_j = 2$	-0.052	-4.380
$InactiveFirstThree_j = 3$	-0.082	-6.882
$\ln DayStart_{jt-1}$	0.688	291.888
$\ln Rev_j$	-0.237	-95.815
$\ln Tenure_{jt}$	0.210	16.187
Model	Fractional Probit	
No. Obs	61873	
Pseudo R^2	0.196	
Fixed Effect	W+I+J+Y+M	
No. of Start Years	13	
No. of Significant Start Year Effects	7	
No. of Start Months	12	
No. of Significant Start Month Effects	6	

Note: Start year or start month effects are regarded as significant if p-value is lower than 0.1. $\ln Rev_j$, $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 2 – Predict job progress

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$t\_progress_{jt-1}$	0.315	1.776	2.062	10.363	1.297	14.771	-0.059	-3.236
$t\_progress^2_{jt-1}$	-1.559	-7.596	-3.510	-14.988	-1.834	-17.642	0.066	3.071
$\ln Rev_j$	0.477	31.178	0.969	62.281	0.398	54.822	-0.025	-14.564
$\ln Tenure_{jt}$	-0.177	-5.447	0.254	7.747	0.169	11.902	-0.031	-8.821
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	61873.000		61873.000		61873.000		61873.000	
Adj. R^2	0.202		0.438		0.491		0.239	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln Rev_j$ and $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 3 – Time trend of hours

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$t\_progress_{jt-1}$	0.434	2.318	2.386	11.123	1.457	15.476	-0.072	-3.701
$t\_progress^2_{jt-1}$	-1.606	-7.561	-3.660	-14.761	-1.908	-17.498	0.073	3.278
$KnowInten_j$	0.776	11.206	0.634	8.346	0.176	5.101	0.004	0.650
$KnowInten_j \times t\_progress_{jt-1}$	-0.776	-5.366	-1.198	-6.904	-0.556	-7.125	0.013	0.914
$\ln Rev_j$	0.429	30.977	1.043	73.164	0.442	65.959	-0.034	-21.361
$\ln Tenure_{jt}$	-0.129	-4.004	0.216	6.634	0.144	10.062	-0.024	-6.978
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I		W+I		W+I		W+I	
No. Obs	61873.000		61873.000		61873.000		61873.000	
Adj. R^2	0.188		0.422		0.475		0.215	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. The table shows linear time trend. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln Rev_j$ and $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error. Knowledge intensive types include Planning & develop management, Schematic design, and Design development. Less knowledge intensive types include Construction documentation and Construction supervision.

Table 4 – Time trend of hours, knowledge intensity

	$t\_progress_{jt-1}$	t-value
$InactiveFirstThree_j = 1$	0.035	3.326
$InactiveFirstThree_j = 2$	-0.055	-4.597
$InactiveFirstThree_j = 3$	-0.084	-7.094
$\ln DayStart_{jt-1}$	0.688	291.431
C_{jt}	0.014	6.333
$\ln Prox_j$	-0.004	-2.028
$\ln Rev_j$	-0.236	-95.685
$\ln Tenure_{jt}$	0.211	16.248
Model	Fractional Probit	
No. Obs	61873	
Pseudo R^2	0.196	
Fixed Effect	W+I+J+Y+M	
No. of Start Years	13	
No. of Significant Start Year Effects	7	
No. of Start Months	12	
No. of Significant Start Month Effects	6	

Note: Start year or start month effects are regarded as significant if p-value is lower than 0.1. C_{jt}, $\ln Prox_j$,$\ln Rev_j$, $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 5 – Predict job progress for information friction regression

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
C_{jt}	-0.160	-6.865	-0.248	-9.299	-0.108	-9.466	0.004	1.448
$C_{jt} \times t\_progress_{jt-1}$	0.242	5.712	0.322	6.406	0.146	6.772	-0.001	-0.197
$\ln Prox_j$	-0.106	-4.362	-0.174	-6.664	-0.066	-5.708	0.003	1.156
$\ln Prox_j \times t\_progress_{jt-1}$	0.237	5.137	0.462	8.864	0.202	8.706	-0.011	-2.314
$t\_progress_{jt-1}$	0.359	2.044	2.180	11.104	1.349	15.522	-0.064	-3.483
$t\_progress^2_{jt-1}$	-1.616	-7.930	-3.663	-15.824	-1.903	-18.473	0.072	3.337
$\ln Rev_j$	0.475	31.156	0.965	62.296	0.396	54.937	-0.024	-14.498
$\ln(Tenure_{jt})$	-0.181	-5.538	0.250	7.653	0.169	11.911	-0.031	-8.832
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	61873.000		61873.000		61873.000		61873.000	
Adj. R^2	0.203		0.443		0.496		0.239	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln Rev_j$, $\ln Tenure_{jt}$, C_{jt}, $\ln Prox_j$ are standardized to have zero mean and unit standard error. $Prox_j = 1/(Dist_j + 1)$ is a proximity measure.

Table 6 – Time trend of hours, information friction

	$t\_progress_{jt-1}$	t-value
$\ln DayStart_{jt-1}$	0.924	281.379
C_{jt}	0.009	3.323
$\ln Tenure_{jt}$	1.017	57.688
Model	Fractional Probit	
No. Obs	37955	
Fixed Effect	Job	

Note: Due to computational reason, only jobs that have more than 12 observations across time are included. C_{jt}, $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 7 – Predict job progress for information friction regression, job fixed effect

	$\ln(ManagerHour_{jt}+1)$	t-value	$\ln(TeamHour_{jt}+1)$	t-value	$\ln(TeamSize_{jt}+1)$	t-value	$\ln(ManagerHourShare_{jt}+1)$	t-value
C_{jt}	-0.233	-7.056	-0.325	-8.851	-0.137	-8.730	0.007	2.004
$C_{jt} \times t\_progress_{jt-1}$	0.185	4.836	0.355	7.962	0.143	7.264	-0.010	-2.269
$t\_progress_{jt-1}$	-0.192	-1.371	1.800	10.507	1.183	15.756	-0.067	-5.216
$t\_progress^2_{jt-1}$	-0.334	-2.384	-2.063	-12.046	-1.244	-16.378	0.060	4.336
$\ln(Tenure_{jt})$	0.048	0.286	0.228	1.400	0.203	2.888	-0.030	-1.284
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	Job		Job		Job		Job	
No. Obs	37955		37955		37955		37955	
Adj. R^2	0.533		0.588		0.647		0.528	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

Due to computational reason, only jobs that have more than 12 observations across time are included. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln Tenure_{jt}$, C_{jt} are standardized to have zero mean and unit standard error.

Table 8 – Time trend and information friction, job fixed effects

	$t\_progress_{jt-1}$	t-value
$InactiveFirstThree_j = 1$	0.029	1.692
$InactiveFirstThree_j = 2$	-0.079	-4.137
$InactiveFirstThree_j = 3$	-0.112	-5.814
$\ln DayStart_{jt-1}$	0.682	189.398
C_{jt}	0.011	3.106
$\ln Prox_j$	-0.003	-0.750
$\ln Rev_j$	-0.239	-59.483
$\ln Tenure_{jt}$	0.234	10.976
Model	Fractional Probit	
No. Obs	24876	
Fixed Effect	W+I+J+Y+M	
No. of Start Years	13	
No. of Significant Start Year Effects	4	
No. of Start Months	12	
No. of Significant Start Month Effects	6	

Note: Start year or start month effects are regarded as significant if p-value is lower than 0.1. C_{jt}, $\ln Prox_j$,$\ln Rev_j$, $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 9 – Predict job progress for information friction regression, quarterly average

	$\ln(ManagerHour_{jt}+1)$	t-value	$\ln(TeamHour_{jt}+1)$	t-value	$\ln(TeamSize_{jt}+1)$	t-value	$\ln(ManagerHourShare_{jt}+1)$	t-value
C_{jt}	-0.168	-7.582	-0.260	-9.557	-0.116	-10.133	0.005	1.622
$C_{jt} \times t\_progress_{jt-1}$	0.256	6.365	0.346	6.826	0.158	7.347	-0.002	-0.314
$\ln Prox_j$	-0.123	-5.289	-0.184	-6.799	-0.068	-5.827	0.003	1.055
$\ln Prox_j \times t\_progress_{jt-1}$	0.250	5.555	0.494	9.167	0.211	9.053	-0.013	-2.498
$t\_progress_{jt-1}$	0.910	4.910	2.565	11.816	1.445	15.344	-0.076	-3.449
$t\_progress^2_{jt-1}$	-2.168	-10.208	-4.058	-16.138	-1.992	-18.181	0.086	3.402
$\ln Rev_j$	0.469	31.806	0.981	60.895	0.406	55.461	-0.028	-15.426
$\ln(Tenure_{jt})$	-0.188	-5.940	0.241	7.214	0.166	11.370	-0.031	-8.500
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	24876		24876		24876		24876	
Adj. R^2	0.220		0.454		0.509		0.259	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln Rev_j$, $\ln Tenure_{jt}$, C_{jt}, $\ln Prox_j$ are standardized to have zero mean and unit standard error.

Table 10 – Time trend and information friction, quarterly average

	$t\_progress_{jt-1}$	t-value
$InactiveFirstThree_j = 1$	0.038	3.539
$InactiveFirstThree_j = 2$	-0.050	-4.184
$InactiveFirstThree_j = 3$	-0.079	-6.547
$\ln DayStart_{jt-1}$	0.687	287.298
$\ln(NoReC_{jt} + 1)$	-0.010	-1.839
$\ln(NoReC_{jt-1} + 1)$	-0.002	-0.424
$\ln Rev_j$	-0.237	-95.011
$\ln Tenure_{jt}$	0.210	16.056
Model	Fractional Probit	
No. Obs	60624	
Pseudo R^2	0.196	
Fixed Effect	W+I+J+Y+M	
No. of Start Years	13	
No. of Significant Start Year Effects	7	
No. of Start Months	12	
No. of Significant Start Month Effects	6	

Note: Start year or start month effects are regarded as significant if p-value is lower than 0.1. $\ln Rev_j$, $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 11 – Predict job progress for workload regression

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$\ln NoJob_{jt}$	-0.262	-4.317	-0.283	-4.107	-0.136	-4.429	0.008	1.230
$\ln NoJob_{jt} \times t\_progress_{jt-1}$	0.310	4.142	0.352	3.928	0.154	3.905	0.002	0.268
$t\_progress_{jt-1}$	0.365	2.033	2.080	10.279	1.308	14.695	-0.059	-3.176
$t\_progress^2_{jt-1}$	-1.643	-7.886	-3.564	-14.939	-1.861	-17.654	0.066	3.017
$\ln Rev_j$	0.471	30.346	0.963	60.096	0.394	52.923	-0.024	-14.085
$\ln(Tenure_{jt})$	-0.128	-3.689	0.303	8.394	0.194	12.425	-0.032	-8.558
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	60624		60624		60624		60624	
Adj. R^2	0.199		0.435		0.489		0.236	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln NoJob_{jt}$ is instrumented by $\ln(NoReC_{jt}+1)$ and $\ln(NoReC_{jt-1}+1)$. The interaction term is instrumented by the interaction term of corresponding instruments. Standard errors are clustered by job-year. $\ln Rev_j$, $\ln Tenure_{jt}$, $\ln NoJob_{jt}$ are standardized to have zero mean and unit standard error.

Table 12 – Workload and time allocation

	$t\_progress_{jt-1}$	t-value
$InactiveFirstThree_j = 1$	0.028	2.532
$InactiveFirstThree_j = 2$	-0.062	-5.055
$InactiveFirstThree_j = 3$	-0.089	-7.289
$\ln DayStart_{jt-1}$	0.687	287.696
$\ln (RelNoReC_{jt} + 1)$	-0.051	-1.523
$\ln (RelNoReC_{jt-1} + 1)$	-0.026	-0.860
$\ln Rev_j$	-0.237	-94.952
$\ln Tenure_{jt}$	0.210	16.070
Model	Fractional Probit	
No. Obs	60624	
Fixed Effect	W+I+J+Y+M	
No. of Start Years	13	
No. of Significant Start Year Effects	7	
No. of Start Months	12	
No. of Significant Start Month Effects	6	

Note: Start year or start month effects are regarded as significant if p-value is lower than 0.1. $\ln Rev_j$, $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error. $RelNoReC_{jt}$ is the ratio between the number of repeat client in month t and the average number of jobs in the previous year.

Table 13 – Predict job progress for relative workload regression

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$\ln RelNoJob_{jt}$	-0.083	-3.155	-0.199	-3.019	-0.083	-3.155	0.023	2.808
$\ln RelNoJob_{jt} \times t\_progress_{jt-1}$	0.115	2.199	0.205	1.618	0.115	2.199	-0.007	-0.448
$t\_progress_{jt-1}$	1.194	11.945	1.867	8.180	1.194	11.945	-0.046	-2.077
$t\_progress^2_{jt-1}$	-1.736	-14.791	-3.346	-12.555	-1.736	-14.791	0.058	2.261
$\ln Rev_j$	0.398	54.357	0.970	61.770	0.398	54.357	-0.025	-14.582
$\ln(Tenure_{jt})$	0.142	7.645	0.166	3.847	0.142	7.645	-0.015	-3.171
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	60624.000		60624.000		60624.000		60624.000	
Adj. R^2	0.492		0.438		0.492		0.234	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln RelNoJob_{jt}$ is instrumented by $\ln(RelNoReC_{jt}+1)$ and $\ln(RelNoReC_{jt-1}+1)$. $RelNoJob_{jt}$ is the ratio between the number of jobs in month t and the average number of jobs in the previous year. The interaction term is instrumented by the interaction term of corresponding instruments. Standard errors are clustered by job-year. $\ln Rev_j$, $\ln Tenure_{jt}$, $\ln NoJob_{jt}$ are standardized to have zero mean and unit standard error.

Table 14 – Workload and time allocation

	$t\_progress_{jt-1}$	t-value
$\ln DayStart_{jt-1}$	0.923	277.498
$\ln(NoReC_{jt}+1)$	-0.019	-5.979
$\ln(NoReC_{jt-1}+1)$	-0.009	-3.015
$\ln Tenure_{jt}$	0.935	57.313
Model	Fractional Probit	
No. Obs	37211	
Fixed Effect	Job	

Note: To include job fixed effects, only jobs that have more than 12 observations across time are included. $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 15 – Predict job progress for workload regression, job fixed effect

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$\ln NoJob_{jt}$	-0.043	-0.464	-0.141	-1.192	-0.069	-1.334	0.007	0.772
$\ln NoJob_{jt} \times t\_progress_{jt-1}$	0.230	3.597	0.304	3.681	0.135	3.612	-0.001	-0.108
$t\_progress_{jt-1}$	-0.221	-1.522	1.727	9.863	1.154	15.080	-0.066	-5.078
$t\_progress^2_{jt-1}$	-0.356	-2.462	-2.087	-11.734	-1.261	-16.060	0.061	4.260
$\ln(Tenure_{jt})$	0.134	0.753	0.393	2.089	0.275	3.449	-0.031	-1.332
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	Job		Job		Job		Job	
No. Obs	37211		37211		37211		37211	
Adj. R^2	0.527		0.583		0.645		0.527	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. To include job fixed effects, only jobs that have more than 12 observations across time are included. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln NoJob_{jt}$ is instrumented by $\ln(NoReC_{jt}+1)$ and $\ln(NoReC_{jt-1}+1)$. The interaction term is instrumented by the interaction term of corresponding instruments. $\ln Tenure_{jt}$, $\ln NoJob_{jt}$ are standardized to have zero mean and unit standard error.

Table 16 – Time trend and workload, job fixed effects

	$t\_progress_{jt-1}$	t-value
$InactiveFirstThree_j = 1$	0.034	1.990
$InactiveFirstThree_j = 2$	-0.073	-3.830
$InactiveFirstThree_j = 3$	-0.105	-5.471
$\ln DayStart_{jt-1}$	0.681	187.238
$\ln (NoReC_{jt} + 1)$	-0.029	-2.076
$\ln (NoReC_{jt-1} + 1)$	-0.009	-0.713
$\ln Rev_j$	-0.239	-59.412
$\ln Tenure_{jt}$	0.238	11.112
Model	Fractional Probit	
No. Obs	24742	
Fixed Effect	W+I+J+Y+M	
No. of Start Years	13	
No. of Significant Start Year Effects	4	
No. of Start Months	12	
No. of Significant Start Month Effects	6	

Note: Start year or start month effects are regarded as significant if p-value is lower than 0.1. $\ln Rev_j$, $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table 17 – Predict job progress for workload regression, quarterly average

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$\ln NoJob_{jt}$	-0.134	-3.855	-0.262	-3.322	-0.134	-3.855	0.005	0.562
$\ln NoJob_{jt} \times t\_progress_{jt-1}$	0.157	3.883	0.380	4.044	0.157	3.883	0.001	0.059
$t\_progress_{jt-1}$	1.426	14.715	2.515	11.200	1.426	14.715	-0.075	-3.359
$t\_progress^2_{jt-1}$	-1.967	-17.433	-3.994	-15.342	-1.967	-17.433	0.084	3.250
$\ln Rev_j$	0.405	53.759	0.979	59.336	0.405	53.759	-0.028	-15.186
$\ln(Tenure_{jt})$	0.189	11.753	0.289	7.798	0.189	11.753	-0.032	-7.885
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	24742		24742		24742		24742	
Adj. R^2	0.500		0.444		0.500		0.256	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln NoJob_{jt}$ is instrumented by $\ln(NoReC_{jt}+1)$ and $\ln(NoReC_{jt-1}+1)$. The interaction term is instrumented by the interaction term of corresponding instruments. $\ln Tenure_{jt}$, $\ln NoJob_{jt}$ are standardized to have zero mean and unit standard error.

Table 18 – Time trend and workload, quarterly average

	$\ln \frac{Cost_j}{Rev_j}$	t-value	$\ln Cost_j$	t-value
$\ln(HourDeviation_j + 1)$	0.041	6.469	0.128	15.613
$\ln Rev_j$			0.866	104.027
Fixed Effects	W+I+J		W+I+J	
No. Obs	5480		5480	
Adj. R^2	0.177		0.899	

Table 19 – Profit and predicted attention, 2SLS model

	$\ln \frac{Cost_j}{Rev_j}$	t-value	$\ln Cost_j$	t-value
$\ln(HourDeviationOver_j + 1)$	0.028	6.070	0.075	13.676
$\ln(HourDeviationUnder_j + 1)$	0.017	3.066	0.069	10.798
$\ln Rev_j$			0.875	106.556
Fixed Effects	W+I+J		W+I+J	
No. Obs	5480		5480	
Adj. R^2	0.177		0.898	

Table 20 – Profit and predicted attention, over and under, 2SLS model

	$\ln(TeamHour_j + 1)$	t-value	$\ln(TeamHour_j + 1)$	t-value
$\ln(HourDeviation_{it} + 1)$	0.226	13.019		
$\ln(HourDeviationOver_j + 1)$			0.142	12.314
$\ln(HourDeviationUnder_j + 1)$			0.220	16.351
$\ln Rev_j$	0.831	47.095	0.796	46.414
Fixed Effects	W+I+J		W+I+J	
No. Obs	5480		5480	
Adj. R^2	0.731		0.738	

Table 21 – Team hour and predicted attention, over and under, 2SLS model

	$\ln \frac{Cost_{it}}{Rev_{it}}$	t-value	$\ln Cost_{it}$	t-value
$\ln(HourDeviation_{it} + 1)$	0.011	1.026	0.062	3.993
$\ln Rev_{it}$			0.933	62.331
Fixed Effects	W+Y		W+Y	
No. Obs	1082		1082	
Adj. R^2	0.481		0.980	

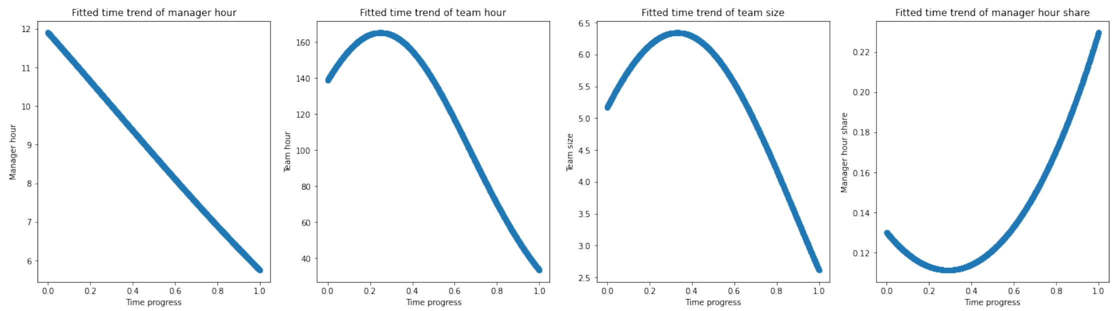
Manager and year fixed effects are controlled.

Table 22 – Profit and predicted attention, manager-year level

	$\ln \frac{Cost_{it}}{Rev_{it}}$	t-value	$\ln Cost_{it}$	t-value
$\ln(HourDeviationOver_{it} + 1)$	0.003	0.386	0.026	2.676
$\ln(HourDeviationUnder_{it} + 1)$	-0.003	-0.376	0.024	2.300
$\ln Rev_{it}$			0.935	54.383
Fixed Effects	W+Y		W+Y	
No. Obs	1082		1082	
Adj. R^2	0.480		0.980	

Table 23 – Profit and predicted attention, over and under, manager-year level

A Empirical Appendix



Fitted curves against $t\_progress_{jt-1}$. Control variables are taken at mean.

Figure A1 – Time trend of hours, positive observations

	$t\_progress_{jt-1}$	t-value	$t\_progress^2_{jt-1}$	t-value
$t\_pro\hat{gre}ss_{jt-1}$	0.966	57.132	0.126	6.410
$t\_pro\hat{gre}ss^2_{jt-1}$	0.054	2.451	0.890	33.531
$\ln Rev_j$	-0.000	-0.087	0.004	1.802
$\ln Tenure_{jt}$	-0.002	-0.453	-0.000	-0.090
Fixed Effect	W+I+J		W+I+J	
No. Obs	61873.000		61873.000	
Adj. R^2	0.723		0.637	
Standard error	Cluster by job-year		Cluster by job-year	
Partial F stat	47167.481		23996.118	

Table A1 – First stage results of job progress

	$t\_progress_{jt-1}$	t-value
$t\_progr\hat{e}ss_{jt-1}$	0.993	58.251
$t\_progr\hat{e}ss^2_{jt-1}$	0.047	2.171
$\ln Rev_j$	0.000	0.004
$\ln Tenure_{jt}$	-0.003	-0.690
$KnowInten_j$	0.057	9.694
$KnowInten_j \times t\_progr\hat{e}ss_{jt-1}$	-0.131	-9.741
Fixed Effect	W+I+J	
No. Obs	61873.000	
Adj. R^2	0.724	
Standard error	Cluster by job-year	
Partial F stat	50378.202	

Table A2 – First stage results of job progress, knowledge-intensity

	$t\_progress_{jt-1}$	t-value	$t\_progress_{jt-1}$	t-value	$t\_progress_{jt-1}$	t-value
$t\_progr\hat{e}ss_{jt-1}$	0.966	57.066	0.419	78.078	0.967	55.558
$t\_progr\hat{e}ss^2_{jt-1}$	0.054	2.487	0.863	89.215	0.053	2.373
$\ln Rev_j$	-0.000	-0.098			-0.000	-0.109
$\ln Tenure_{jt}$	-0.002	-0.445	-0.271	-22.416	-0.002	-0.425
C_{jt}	-0.010	-4.510	-0.003	-3.537	-0.012	-5.359
$C_{jt} \times t\_progr\hat{e}ss_{jt-1}$	0.022	4.735	-0.001	-0.825	0.026	5.698
$\ln Prox_j$	-0.007	-3.019			-0.008	-3.706
$\ln Prox_j \times t\_progr\hat{e}ss_{jt-1}$	0.015	3.056			0.018	3.743
Fixed Effect	W+I+J		Job		W+I+J	
No. Obs	61873.000		37955.000		24876.000	
Adj. R^2	0.723		0.989		0.730	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year	
Partial F stat	47299.743		73628.310		47407.299	

The table shows the first stage results related to information friction. The first column corresponds to the main result. The second set of results control for job fixed effects. The third set of results use quarterly average.

Table A3 – First stage results of job progress, information friction

	$t\_progress_{jt-1}$	t-value	$t\_progress_{jt-1}$	t-value	$t\_progress_{jt-1}$	t-value
$t\_pro\hat{g}ress_{jt-1}$	0.963	56.493	0.417	76.351	0.966	55.295
$t\_pro\hat{g}ress^2_{jt-1}$	0.057	2.595	0.862	89.570	0.053	2.399
$\ln Rev_j$	-0.000	-0.089			-0.000	-0.098
$\ln Tenure_{jt}$	-0.002	-0.460	-0.248	-22.598	-0.002	-0.426
$\ln(NoReC_{jt}+1)$	0.000	0.092	0.005	4.776	0.000	0.074
$\ln(NoReC_{jt-1}+1)$	-0.000	-0.053	-0.005	-4.377	0.000	0.109
Fixed Effect	W+I+J		Job		W+I+J	
No. Obs	60624.000		37211.000		24742.000	
Adj. R^2	0.692		0.989		0.729	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year	
Partial F stat	46465.437		82327.014		46924.837	

The table shows the first stage results related to workload. The first column corresponds to the main result. The second set of results control for job fixed effects. The third set of results use quarterly average.

Table A4 – First stage results of job progress, workload

First Stage	$\ln NoJob_{jt}$	t-value
$\ln(NoReC_{jt}+1)$	0.292	37.283
$\ln(NoReC_{jt-1}+1)$	0.271	36.189
$t\_pro\hat{g}ress_{jt-1}$	0.389	4.852
$t\_pro\hat{g}ress^2_{jt-1}$	-0.470	-4.708
$\ln Rev_j$	-0.049	-6.557
$\ln(Tenure_{jt})$	0.217	9.728
Fixed Effect	W+I+J	
No. Obs	60624	
Adj. R^2	0.692	
Partial F stat	1486.111	

Table A5 – First stage of workload regression

First Stage	$\ln RelNoJob_{jt}$	t-value
$\ln(RelNoReC_{jt}+1)$	2.749	28.852
$\ln(RelNoReC_{jt-1}+1)$	2.362	28.726
$\hat{t\_progress}_{jt}$	-0.067	-0.662
$\hat{t\_progress}^2_{jt}$	-0.281	-2.301
$\ln Rev_j$	-0.002	-0.159
$\ln(Tenure_{jt})$	-0.742	-30.950
Fixed Effect	W+I+J	
No. Obs	60624	
Adj. R^2	0.330	
Partial F stat	1486.111	

Table A6 – First stage of relative workload regression

First Stage	$\ln NoJob_{jt}$	t-value
$\ln(NoReC_{jt}+1)$	0.157	11.108
$\ln(NoReC_{jt-1}+1)$	0.156	11.978
$\hat{t\_progress}_{jt-1}$	0.189	2.564
$\hat{t\_progress}^2_{jt-1}$	-0.559	-6.166
$\ln(Tenure_{jt})$	0.896	11.638
Fixed Effect	Job	
No. Obs	37211.000	
Adj. R^2	0.853	
Partial F stat	676.571	

Table A7 – First stage of workload regression, job fixed effect

First Stage	$\ln NoJob_{jt}$	t-value
$\ln(NoReC_{jt}+1)$	0.326	24.841
$\ln(NoReC_{jt-1}+1)$	0.352	28.568
$t\_pro\hat{g}ress_{jt}$	0.465	5.897
$t\_pro\hat{g}ress_{jt}^2$	-0.515	-5.365
$\ln Rev_j$	-0.046	-6.458
$\ln(Tenure_{jt})$	0.199	9.312
Fixed Effect	W+I+J	
No. Obs	24742.000	
Adj. R^2	0.714	
Partial F stat	1381.046	

Table A8 – First stage of workload regression, quarterly average

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$t\_progress_{jt-1}$	-1.058	-22.870	-1.027	-20.294	-0.317	-13.899	-0.001	-0.213
$\ln Rev_j$	0.471	30.963	0.956	62.064	0.391	54.287	-0.024	-14.517
$\ln Tenure_{jt}$	-0.192	-5.964	0.219	6.734	0.151	10.710	-0.030	-8.661
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	61873.000		61873.000		61873.000		61873.000	
Adj. R^2	0.207		0.442		0.493		0.239	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. The table shows linear time trend. $t\_progress_{jt}$ is instrumented. $\ln Rev_j$ and $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table A9 – Time trend of hours, linear term only

	$\ln(MH_{jt}+1)$	t-value	$\ln(TH_{jt}+1)$	t-value	$\ln(TS_{jt}+1)$	t-value	$\ln(MHS_{jt}+1)$	t-value
$t\_progress_{jt-1}$	-0.480	-3.855	1.398	6.131	1.051	10.303	-0.116	-4.603
$t\_progress^2_{jt-1}$	-0.168	-1.155	-2.805	-10.323	-1.588	-12.938	0.201	6.595
$\ln Rev_j$	0.455	41.101	1.045	53.561	0.439	50.328	-0.054	-22.325
$\ln Tenure_{jt}$	-0.279	-12.383	0.267	6.782	0.180	10.716	-0.046	-10.353
Model	2SLS		2SLS		2SLS		2SLS	
Fixed Effect	W+I+J		W+I+J		W+I+J		W+I+J	
No. Obs	37899.000		37899.000		37899.000		37899.000	
Adj. R^2	0.384		0.522		0.575		0.336	
Standard error	Cluster by job-year		Cluster by job-year		Cluster by job-year		Cluster by job-year	

$MH_{jt} = ManagerHour_{jt}$, $TH_{jt} = TeamHour_{jt}$, $TS_{jt} = TeamSize_{jt}$, $MHS_{jt} = ManagerHourShare_{jt}$. $t\_progress_{jt-1}$ is instrumented by the predicted value. $t\_progress^2_{jt-1}$ is instrumented by the squared predicted value. $\ln Rev_j$ and $\ln Tenure_{jt}$ are standardized to have zero mean and unit standard error.

Table A10 – Time trend of hours, positive observations