Productivity and Working Hours Within Teams of Knowledge Workers*

Ruo Shangguan

Jinan University, China

Jed DeVaro

California State University, East Bay, USA

Hideo Owan[1]

Waseda University, Japan

March 22, 2025

Abstract

Modern workplaces extensively use teams of white-collar knowledge workers to complete complex projects. Data on architects designing construction projects in a Japanese firm reveal that a five-person team's highest contributor invests over 60% of the team's working hours. Following the financial crisis of 2008, the average team productivity increased by 8.9%, while hours became more concentrated within teams. A theoretical model of team productivity is used to explain the changes. The counterfactual exercise finds that 40.3% of the team productivity increase is attributed to an increase in individual worker productivity, and 59.7% of the increase is due to hours reallocation.

Keywords: team production, labor productivity, working hours, allocation of labor

JEL classification: J23, J24, M50, M54

*Manuscript received December 21, 2021; revised June 16, 2023 and December 10, 2024.

[1]This study is conducted as a part of the Project "Productivity Effects of HRM Policies and Changing Employment Systems" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This work was also supported by JSPS KAKENHI Grant Numbers 18H03632 and 23H00056. Helpful comments from the editor (Iourii Manovskii), three anonymous reviewers, Sachiko Kuroda, John Pencavel, Guangyu Pei, Kathryn Shaw, Katsuya Takii, Kensuke Teshima, Yuta Toyama, Daniel Xu and seminar participants at various workshops and conferences are gratefully acknowledged.

1 Introduction

Teamwork is an engrained feature of the modern workplace and has increased in complexity over time, as the nature of work has become more global, virtual, project focused, and enmeshed in new technologies. Understanding how to manage teams for optimal productivity in increasingly complex environments is essential for business managers. A central question managers face is how to assign working hours across a team's members, to maximize team productivity. If an increase in demand for the firm's product or service necessitates adding more worker hours, which team member(s) should work more? In the reverse case of a negative demand shock, which team member(s) should work less? What are the implications of these decisions for team productivity?

Daunting data demands have hampered academicians' ability to provide much guidance or insight on these questions, particularly for white-collar teams of knowledge workers. Empirical research on teams and productivity focuses heavily on manual laborers (e.g., Hamilton et al. 2003, Bandiera et al. 2013). The dearth of research on knowledge workers leaves unanswered, for example, the question of how important "stars" are as drivers of team productivity except for limited research on teams of scientists and inventors (Azoulay et al., 2010; Zacchia, 2018). A wealth of anecdotal information suggests that stars effectively carry their teams. That idea is encapsulated in the Pareto Principle of business management, which states that 80% of a team's work is completed by only 20% of the team's membership.

This study empirically investigates the determinants of team productivity in construction project design teams, exploiting unique data on construction projects in a Japanese architectural and engineering consultancy firm during the years 2004 to 2016. That timespan includes the Great Recession, which affords a source of plausibly exogenous variation in demand for the firm's services (and in particular a reduction in the demand for the firm's working hours). From a single firm's perspective, the economic crisis is an exogenous event that provides the hours variation necessary to identify the productivity effect of within-team labor reallocation. Focusing on a particular firm and industry holds constant the considerable heterogeneity that would otherwise complicate the interpretation of results from a broader sample. Our setting offers an attractive laboratory for studying how team productivity responds to a recession-induced hours reduction because the construction industry is strongly sensitive to the business cycle, which makes the recession a particularly effective treatment.

We find that team productivity increased in this firm following the economic crisis. The question is, why? We focus on two possible mechanisms that, ex ante, might be important. First, team members may become individually more productive following the crisis. This could happen, for example, because shorter work schedules may imbue workers with greater energy and focus per hour, and less exhaustion and fatigue. Alternatively, fewer projects demanding each worker's attention imply fewer disruptions (Coviello et al., 2014). Second, the labor hours of workers with heterogeneous productivities may be reallocated within the team so that a greater fraction of the team's total hours are contributed by high-productivity workers than before the crisis. The marginal productivity of an additional hour that is assigned to a team of a given size depends on which team member is assigned that hour. As assigned hours increase to meet demand for the firm's output, the time constraints of the team's most productive workers start binding, which requires the employer to assign further hours to less productive team members.

After describing the data and production setting in section 2, section 3 presents descriptive empirical evidence of three types. First, we show that within-team labor allocation is highly concentrated, with a small number of team members contributing the bulk of the working hours. A higher within-team concentration of hours is also found to be associated with higher team productivity, which is consistent with our theory. Second, we document that the downward adjustment in the labor input during the crisis occurred more for working hours than for employment and that average team productivity increased by nearly 8.9% after the crisis. Third, we present evidence suggesting that within-team labor reallocation may contribute to explaining the post-crisis increase in team productivity. Specifically, following the crisis, each worker became more focused on fewer jobs, teams became smaller, and working hours became more concentrated on the top hours contributors.

Section 4 presents a theoretical model that explains the within-team allocation of working hours. The model's workers, who differ in their productivities and time endowments, are assigned working hours based on their productivity and time constraints. The most productive workers are assigned hours first. When product demand overwhelms those workers' capacities, additional hours are assigned to less productive workers, which decreases average team productivity. We then compute a "pre-crisis" and a "post-crisis" calibration of the model's parameters with data and use it in section 5 to simulate outcomes in both regimes.

The model simulation replicates well the observed empirical patterns. The calibrated model generates an average team-level productivity increase of 8.8% after the crisis, which is statistically indistinguishable from the increase found in the data. Additionally, the calibrated model successfully generates several patterns that are qualitatively similar to those in the data, including: (1) after the crisis, the fraction of the team's time accounted for by the team's top hours contributor increases, and team size decreases; (2) the within-team concentration of working hours is positively correlated with team productivity. The calibration allows us to simulate the production of pre-crisis jobs using the post-crisis work force and to decompose the total productivity effect into parts due to increased worker-level productivity and within-team hours reallocation. We find that worker-level productivity increases explain 40.3% of the team-level productivity increase, while hours reallocation explains the remaining 59.7%. Therefore, the results suggest that hours reallocation plays an important role in explaining team-level productivity changes.

Given that team production is widely used in the professional services industries around the world, we expect our results from the Japanese firm we study to apply to the

U.S. and other economies. Section 6 elaborates and discusses the managerial implications of our study.

Whereas the teams literature often studies the manufacturing sector (e.g., Hamilton et al. 2003), this study provides new evidence from the knowledge-intensive, white-collar professional jobs where teamwork has become the norm--design, R&D, consulting, accounting, auditing, academic research, etc. Within-team heterogeneity in hours arises in such occupations because team members can work in different places, at different times, and for different durations.[1] But the outputs are idiosyncratic in those occupations, which has complicated economists' efforts to study team productivity. Our setting and unique data facilitate productivity measurement and analysis because the production process is sufficiently standardized that the total labor required to complete each job is predictable. Moreover, the value of the output is fixed on each project before teamwork commences. Consequently, productivity depends only on total inputs.

Our approach to endogenous team formation and task assignment and our focus on within-team heterogeneity in working hours are new. The theoretical model highlights that heterogeneity in working hours is a consequence of heterogeneity in team members' individual productivities and time endowments, where the employer assigns the most productive workers to tasks first, followed by the less productive ones. Complementarities imply that, as individual skill levels improve, the marginal effect on team productivity of concentrating working hours on the most productive workers increases. Although team composition is endogenous in our model, the available talent pool of candidates is randomly drawn, which implies significant variation in the distribution of available skill levels. The model's team formation process creates a negative correlation between heterogeneity in skills and productivity because less productive teams tend to add more workers from the lower part of the skill distribution. The result is also amplified by com-

[1] In contrast, manufacturing jobs often require workers to be physically and temporally proximate. On an assembly line, for example, complementarities are achieved only when the team members are physically present at the same time, so within-team heterogeneity in working hours (regardless of heterogeneity in abilities) is limited or nonexistent.

plementarities in production, which make homogeneous teams more productive (Prat, 2002).

There is a related literature on team diversity and productivity. Hamilton et al. (2012) theoretically and empirically show that teams with more heterogeneous worker abilities are more productive. In their setup, the positive effect of heterogeneous abilities comes from task heterogeneity, which generates gains from assortative matching between worker and task, and peer learning.[2] Productivity improves when workers' skill levels and task difficulties are optimally matched or when more experienced workers share their knowledge with less experienced ones. Those factors found in teams of unskilled workers do not seem to play a dominant role in our teams of knowledge workers. Studying 24 million research articles and 3.9 million US patents, Ahmadpoor and Jones (2019) also find a substantially greater effect of teamwork over solo work when teams of scientists or inventors are formed by individuals with similar citation impact. Although many other dimensions of heterogeneity have been explored, no other studies investigate the implications of demand shocks for team productivity. When workers' individual productivities and time endowment increase as a result of fewer assigned projects, within-team working hours become more concentrated among fewer workers, average team size decreases, and team productivity increases.

A study in a similar spirit to ours is Anderson and Richards-Shubik (2022). Their model of the strategic formation of teams of researchers describes the production function of research outcomes, with the goal of understanding what factors affect researchers' selection of project collaborators. Estimating the model parameters of the recently developed regression tree model, they find that an increase in the number of collaborators raises the chance of producing high-impact papers without increasing communication and coordination costs. Similarly, using a Cobb-Douglas technology, we estimate our model's parameters, with workers' individual productivities and time endownments

[2] Similar empirical results are obtained in Hamilton et al. (2003) and Chan et al. (2014).

represented as random draws, to demonstrate how team formation and task allocation patterns change after a demand shock. Bonhomme (2021) proposes a way to estimate individual productivity when only team output is observed. While his method allows for complementarity in the production function under some conditions, the method is infeasible for us, given the larger teams in our sample.

2 Production setting, data, and measures

The data are from a large, Japanese, architectural and engineering consultancy firm. They include personnel records (from 2011 to 2016), labor hours records (from years 2004 to 2016), and project management data (from fiscal years 2004 to 2016). The analysis is also informed by our in-person interviews with seven of the firm's managers[3] and by our informal communication with the firm's human resource managers. The personnel records cover all employees, including dispatched or contract workers who may be included in the project management data, and include salary and hierarchical ranks that are classified into three levels (junior architect, senior architect, and manager).

Projects consist of multiple phases, called jobs. The job is the unit of observation.[4] Contracts are negotiated separately for each job in a project, with contract terms set before the job begins. Each job is performed by a team of varying size depending on the phase of the project, type of the building, etc. Teams have an average size of 13 and are assigned to a chief manager, who is the person fully responsible for the job and who is penalized for quality problems. The chief manager's responsibilities include selecting one team leader, usually a senior architect, to lead daily operations. The chief manager also selects the junior architects who execute tasks (e.g., drawing pictures after the design details are confirmed).

[3]The seven managers were selected on the basis of the manager effects estimated in Shangguan et al. (2024), which also contains further details about the data.

[4]Usage of the word "job" here differs from that in either the personnel economics literature or the forthcoming theoretical model. A job is a phase of a longer-term project.

An example of the sequence of jobs in a project is: initial planning, schematic design, design development, construction documentation, and supervision of the construction process. In the initial stages, the architects work with the client to discuss broad specifications, including the building's size and shape. After the basic design is decided, the project team interacts with the client concerning the project's details (e.g., selection of interior finishes). Much of the architectural work is construction documentation, where architects produce drawings containing the details for approval and construction. Finally, the architects work with both clients and contractors at the supervision stage, to ensure that the construction aligns with the design, making design changes when necessary.

The labor hour records include two kinds of jobs. External jobs are profit-center jobs that generate revenue. Internal jobs are cost-center jobs that mainly entail administrative responsibilities. In the project management data, revenue and costs (both labor and non-labor) are observed for each external job. Finer components of nonlabor costs are also observed, including material/traveling costs and three types of outsourcing costs. The project management data also include information on the client's identity and industry, type and size of the building being designed, location of the work, phase of work, contractor selection method, etc. Information about the client industry comes from the Current Survey on Orders Received for Construction, conducted by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT).

Our analysis focuses on the productivity changes before and after the crisis. We regard the years 2008 to 2010 as the crisis period and begin by considering three years on either side of the crisis. This definition of the crisis is consistent with the time trend of industrial demand plotted in Figure D1 in section D of the online appendix, where we show that external demand declines from 2008 to 2010. However, since many jobs last more than one year, jobs that started in 2007 are likely to continue into the crisis period. We therefore exclude year 2007 and define the pre-crisis period as the years 2005 and 2006. The post-crisis period is defined as the years 2011, 2012, and 2013. We consider the sensitivity of our estimate of the productivity change to variations in the definitions of the pre and post-crisis periods. Based on our communication with the firm, the firm's management practices did not change in response to the crisis.

2.1 Team productivity

Let j index jobs. A natural measure of team productivity is the ratio of job j's revenue, denoted Rev_j, to job j's total working hours. However, the numerator is broader than the denominator because typically some of the work is outsourced to third parties, whose working hours are unobserved in the data. Outsourced work mostly includes routine tasks that are more efficiently done by a subcontractor and highly specialized tasks that cannot be completed within the firm (e.g., special inspections that require a specialized license). To render the input and output measures compatible, Rev_j is adjusted downward using job j's outsourcing costs. Let O_j be the outsource ratio for job j, which is calculated as the ratio of outsourcing costs, $OutsourceCost_j$, to job-level total costs, $Cost_j$. "Adjusted revenue" for job j is then $AdjRev_j \equiv Rev_j \left(1 - O_j\right) = Rev_j - \frac{Rev_j}{Cost_j} OutsourceCost_j$. In Figure D2 of the online appendix, we show that adjusted revenue is similar to the value-added of each job.

The job-level team productivity measure that serves as the main dependent variable is $\ln \frac{AdjRev_j}{h_j}$, i.e., the natural logarithm of the ratio of job j's adjusted revenue to job j's total working hours, h_j, which are defined in the next subsection. In Figure D3 of the online appendix, we plot the distribution of $\ln \frac{AdjRev_j}{h_j}$ and compare it with a normal random variable with the same mean and standard deviation as those for the distribution of $\ln \frac{AdjRev_j}{h_j}$. The productivity exhibits substantial variation across teams, and the normal distribution approximates the data reasonably well.

2.2 Working hours and other variables

Our interviews with managers revealed that working hours are assigned to workers by the chief manager rather than chosen by the worker. The managers allocate tasks across workers and plan and monitor how many hours are spent on each task to control labor costs, providing advice and support when there are delays. They also conduct regular internal meetings to communicate about the status of each worker on each project, to improve subsequent labor allocation decisions. The labor hours records, which are reported by the workers for internal accounting purposes, are available at the worker-job-month level. Managers strongly discourage the misreporting of hours. The productivity measure's denominator, h_j, denotes total working hours on job j. Let h_{kj} denote the total working hours on job j of the worker who ranks k^{th} in terms of total hours within the team. For example, h_{1j} denotes the working hours of job j's rank-1 worker, who is the team member who supplies the most hours. The term rank-1 worker refers to the worker who contributes the most hours.

Similarly, l_{kj} denotes the fraction of job j's hours contributed by the rank-k worker. An alternative measure, l_j^q, is the q^{th} percentile of the distribution of hours fractions. For example, l_j^{90} is defined as follows. We first order the hours contributions of team j's members. The fraction of team j's hours contributed by the rank-1 worker is on the far right, the fraction contributed by the rank-2 worker (who is the second highest hours contributor) is second from the right, and so on. The fractions on the far left and right are attributed to the 0^{th} and 100^{th} percentiles, respectively. Using a linear interpolation rule, l_j^{90} is calculated as a weighted average of the hours fractions of the two workers whose hours fractions straddle the 90^{th} percentile.[5]

[5] Suppose team j has n_j workers. If the 90^{th} percentile falls between the rank-i and rank-$(i+1)$ workers, i.e., $n_j - (i+1) \leq 0.9(n_j - 1) \leq n_j - i$, the 90^{th} percentile is calculated as the weighted average of the hours shares of the rank-i and rank-$(i+1)$ workers, with the weight for the rank-i worker being $n_j - i - 0.9(n_j - 1) = 0.1n_j + 0.9 - i$. By this definition, 90 percent of the interval $[1, n_j]$ lies to the left of l_j^{90}. This is the standard interpolation rule, as shown in method 7 of Hyndman and Fan (1996). When $2 \leq n_j \leq 10$, the 90^{th} percentile is the weighted average of the hours shares of the rank-1 and rank-2 workers.

Let $TeamSize_j$ denote the number of workers engaged on job j, calculated as the number of unique worker identifiers appearing on job j over the entire production period. In our analysis sample, half the teams have fewer than ten workers. Fewer than thirty percent have more than 14 workers. The distribution of team size appears in the top row of Table 4. The other rows of that table are discussed in section 3.2. Let $JobContent_j$ denote a categorical variable (with 22 categories) that we use to control for the type of service in each job j.[6] Let Ind_j denote a vector of 39 dummies indicating the client's industry.[7] Let $AfterCrisis_j$ denote a dummy equaling 1 if job j's starting year occurred in the post-crisis period and 0 otherwise. Let i and t index workers and months. $NumJob_{it}$ denotes the number of unique jobs in which worker i participates in month t. Age_{it} denotes the age (in years) of worker i as of month t. $Focus_{ijt}$ denotes the share of hours that worker i spent on job j among all jobs she reported having worked on in month t. $IsTop1_{ij}$ is a dummy equaling one if worker i is the top contributor in terms of total working hours, and zero otherwise.

2.3 Sample selection and summary statistics

Given our use of a revenue-based productivity measure, we focus on external jobs, which are the revenue-generating profit-center jobs. We only include jobs with revenue of at least one million Japanese yen. Jobs for which the floor area is zero are excluded. These tend to be consulting jobs that differ in nature from design jobs. The analysis is restricted to the sample of jobs with $O_j \leq 0.8$ to reduce the noise introduced by jobs with substantial

[6] The top 10 categories of $JobContent_j$ cover 95.9% of the number of jobs and 97.5% of revenue in the sample. In decreasing order of revenue, they are: construction documentation (32.9%), design/construction supervision (23.9%), design development (15.1%), construction supervision (12.5%), other (5.4%), schematic design (3.4%), planning & development management (1.5%), other planning (1.1%), construction supervision consulting (1.0%), design/construction supervision consulting (0.8%).

[7] The top 10 client industries cover 66.1% of the number of jobs and 68.6% of the revenue in the sample. In decreasing order of revenue, they are: Real-estate (17.1%), Financial/insurance (9.8%), Education (9.6%), Municipal government (5.8%), Electronics (5.4%), Transportation (5.1%), Other public interest organizations (5.0%), Medical related organizations (3.7%), Commercial industry (3.7%), and Prefectural government (3.3%).

outsourcing, though using alternative cutoffs yields similar estimates of the team productivity change reported in section 3.1. We require jobs to be completed so that the labor hours records are complete. The data are right-censored because some jobs that started in 2014 or later were not completed by 2016, the end of our observation period. Consequently, our analyses are limited to jobs that started by 2013. Figure D4 of the online appendix plots the average job duration over the period from 2004 to 2016, showing a decrease in job duration since 2014. The excluded jobs that started before 2004 are expected to be longer jobs. We drop two observations due to invalid values for total working hours and job duration. Finally, to mitigate the influence of outliers, we exclude jobs whose values of $\frac{AdjRev_j}{h_j}$ or h_{1j} are at or above the 98^{th} percentile . Results without such right trimming are similar and are available upon request. Table 1 reports summary statistics for all job-level variables used in the analysis.

3 Empirical evidence on teams and productivity

Section 3.1 documents the post-crisis increase in team productivity. Section 3.2 provides evidence on within-team labor allocation of working hours and the determinants of team productivity. Section 3.3 provides evidence suggesting mechanisms to explain the post-crisis productivity increase.

3.1 Productivity changes surrounding the crisis

The crisis coincided with a drop in demand for both the firm and the industry. As shown in the solid line in Figure 1, the total adjusted revenue for jobs that started in 2008 substantially declines, and the trend continues in 2009. Since the total adjusted revenue for jobs that started in 2007 is unusually high, we also plot the two-year moving average as the dotted line in Figure 1, which indicates a decline in 2009 and a recovery starting in 2011. Figure 2 plots the number of workers participating in revenue-generating jobs in each year. It shows that the number of workers increased until 2009, then decreased until 2013, providing further evidence that the prospect of future demand had changed dramatically for this firm during the crisis. Figures D1, Figures D5, and D6 in the online appendix further confirm the same trend using plots of industrial orders, total revenue, and the total number of jobs that started in each year. Figure 3 plots the average $\frac{AdjRev_j}{h_j}$ for jobs that were started in the year indicated on the horizontal axis and completed by the end of the sample period (i.e., 2013). The plot reveals a trend that decreases until 2007 and then increases from 2009 to 2012. This downward trend is likely due, at least partially, to the replacement of experienced senior managers by less experienced junior managers, as baby boomers retire or are promoted to management positions. The pre-trend preceding 2008 disappears when accounting for workforce composition changes. We demonstrate in Figures D7 and D8 in the online appendix that the average age of rank-1 workers decreases from 2004 to 2007, and after purging this effect, the declining trend of team productivity from 2004 to 2007 largely disappears.[8]

Table 2 reports the magnitude of the productivity change following the crisis. Column 1 reports the estimate of a simple regression of $\ln \frac{AdjRev_j}{h_j}$ on $AfterCrisis_j$. The estimated value of δ in column 1 is 8.9 percent. To mitigate the concern that the productivity increase is driven by the project composition change in terms of client industry and job content, we include dummies indicating client industry and job content in the following regression:

$$\ln \frac{AdjRev_j}{h_j} = \beta_0 + \delta AfterCrisis_j + \phi_j^{Ind} + \phi_j^{JC} + \varepsilon_j, \tag{1}$$

The estimated δ is reported in column 2 of Table 2, i.e., 8.3 percent. The modest and statistically insignificant decrease in the estimated δ between columns 1 and 2 shows that

[8]For two reasons, we do not purge the age effect when analyzing the team productivity change. First, doing so would require us to extrapolate the trend of team productivity before the crisis to the period after the crisis. Second, if the rank-1 worker's age captures the compositional changes of worker productivity, our subsequent analysis captures this by estimating the parameters of the individual productivity distribution.

productivity improvement within job categories (rather than a change in the composition of jobs) is driving the team productivity increase.[9] In Table D1 in the online appendix, we show that the estimates are robust to restricting the sample to jobs that end within two years to mitigate the concern that jobs started in 2006 may continue until the crisis period. In Table D2 in the online appendix, we show that the estimates are qualitatively similar using value added per hour as the measure of team productivity.

With any revenue-based productivity measure, revenue might incorporate price changes that obscure productivity changes. This is a well-known and widespread concern in productivity analysis, as discussed in Syverson (2011). In our case, the markup, i.e., the spread between the selling price and the production cost, likely decreased following the drop in demand. That decrease may at least partly explain why revenue per hour decreased in 2009. By the same logic, the post-crisis increase in revenue per hour may at least partly reflect a recovering markup instead of an improving production technology.

To mitigate this concern, we use the floor area in square meters, divided by working hours, as another measure of job-level productivity that is independent of price. We adjust the measure for outsourcing in the same manner as for revenue, estimating the same regression as in Equation (1) to examine the effect of the crisis while eliminating the impact of changes in markup. The first column of Table 3 shows that the adjusted floor size per hour increased by 21.8% after the crisis. Controlling for industry and job content reduces the estimate to 8.1%, about the same size as the second column in Table 2, although the large variance of the floor area renders it statistically insignificant. The similarity in the patterns of Table 2 and Table 3 suggests that the cyclical change in the markup is not

[9]If the pre-crisis and post-crisis definitions are both shortened by a year (i.e., 2006 instead of 2005-2006, and 2011-2012 instead of 2011-2013), column 1 of Table 2 changes to 13.7 percent with standard error 0.034, and column 2 changes to 11.8 percent with standard error 0.034. If the pre-crisis period is lengthened by a year (i.e., 2004-2006 instead of 2005-2006), column 1 changes to 5.1 percent with standard error 0.023, and column 2 changes to 4.5 percent with standard error 0.022. The tradeoff is that shorter bandwidths for time periods reduce the sample size, whereas longer ones increase the risk that events unrelated to the crisis may cloud the picture. We do not lengthen the post-crisis period by a year because including 2014 is problematic for the reason discussed in the data section.

driving our result.[10] Despite the advantage of offering a physical measure of productivity, floor area is a less comprehensive measure of output, as it may not capture quality differences across buildings. For example, a factory may have a large floor area but low design complexity. Therefore, henceforth we use revenue per hour.

Regression (1) lacks a control group, so identification comes from temporal variation (i.e., the difference before and after the crisis). Given the nearly universal reach of this crisis, it is unclear that a valid control group could be defined. Nonetheless, temporal variation alone is interesting because of the magnitude, nature, and abrupt onset of the crisis. A single firm's experience following this plausibly exogenous major shock is informative, particularly in a highly cyclical industry like construction.

3.2 Within-team allocation of working hours and the determinants of team productivity

Table 4 illustrates the within-team allocation of working hours, showing the distribution of team size at the top. For example, 24.7 percent of the sample is comprised of teams with 6 to 10 people. The rows are listed in descending order by the team members' hours contributions, with the highest-ranked worker listed first.[11] A striking concentration of within-team allocation of working hours is revealed. In a five-person team, the top team member contributes more hours than the four others combined. Although the top worker's contribution share of the team's total hours naturally decreases with team size, it remains substantial even in teams as large as 20 or more.

Table 5 reports the results from a regression of team productivity on the fraction of

[10] The reason is as follows. Clients who are under increased pressure to reduce costs may be more demanding in price negotiations, or they may seek to reduce costs by choosing simpler designs with less complexity. The former should reduce adjusted revenue per hour, while the latter should increase the floor area per hour. Thus, they exhibit opposite-signed correlations with the business cycle. However, the two measures produce similar results, suggesting that the correlation with the business cycle is limited and that the post-crisis productivity increaseis not driven by an increase in the markup.

[11] For example, in the third column, over 61 percent of a team's hours with four or five people are contributed by the rank-1 worker, whereas 25 percent are contributed by the rank-2 worker. The rank-3 and rank-4 workers contribute only around 10 percent and 5 percent of total working hours, respectively.

the team's hours contributed by the rank-1 worker. The fraction has strong explanatory power. A 10-percentage-point increase in the fraction is associated with a 4.7% increase in team productivity.[12] The second column of Table 5 controls for team size. The coefficient of the rank-1 worker's hours fraction drops to 0.263 but remains precisely estimated. The coefficient of team size reveals that adding a worker to the team is associated with a 1.5 percent reduction in team productivity. This relationship reveals the relevance of within-team labor allocation for understanding team productivity.

3.3 Channels of influence for post-crisis increase in team productivity

We next show evidence suggesting changes in workers' time allocation, discussing the implications for changes in team productivity. Table 6 decomposes the changes in team productivity, measured by output per hour, into changes in output per day and team hours per day. The estimates reveal that output per day increases by 21.8 percent. Recalling that both job revenue and job duration are determined before production starts, this result suggests an important change in the time constraints faced by production teams after the crisis. An implication is that the work is completed faster. Consistent with this, the second column in Table 6 shows that the average team hours per day increases by 13.4 percent. The difference between the two numbers is the increase in team productivity as reported in the second column of Table 2.

Figure 4 reveals a decline in the average monthly working hours (of workers), which was likely driven by a drop in demand. The variable does not return to its pre-crisis level even when total revenue recovers in 2013. Figure 5 plots a scatter in which each point is the average (across workers for a given month) number of jobs on which a worker spends time. Each point on the solid line gives the annual average across all months in that year. That line decreases around 2007 to 2010 and never rebounds to its 2006 level.

[12] The correlation between team productivity and the fraction of the team's hours contributed by the rank-1 worker is not confounded by output size. The estimated coefficient is even larger when controlling for output size.

The reduction in working hours and in the number of jobs per worker is consistent with an increase in individual productivity via reduced fatigue and higher focus. Specifically, with larger but fewer jobs to do and less need for multitasking, the attention of the team's top hours contributor is less likely to be diverted to other jobs, thereby increasing their productivity. That is consistent with Coviello et al. (2014, 2015), which show that multitasking reduces worker productivity via task juggling.

To provide further evidence, Table 7's first column reports results from the following regression:

$$\ln NumJob_{it} = \beta_0 + \beta_1 AfterCrisis_t + \beta_2 \ln Age_{it} + \phi_t^{Month} + \varepsilon_{it}, \tag{2}$$

where $NumJob_{it}$ is the number of jobs on which worker i participates in month t, $AfterCrisis_t$ is a dummy equaling one if the time period is after 2010 (and zero otherwise), Age_{it} is worker i's age (in years) as of month t, and ϕ_t^{Month} is a month fixed effect. We restrict the sample to years from 2005 to 2007 and from 2011 to 2014. Including the years 2007 and 2014 allows for inclusion of workers who participate in any jobs that started before 2007 or 2014 but that last until or beyond those years. Such workers' observations are included up to those two years. Standard errors are clustered at the worker level. On average, the number of jobs decreased by 16.9% after the crisis. The coefficient of $\ln Age_{it}$ shows that senior worker are assigned more jobs.

In the second column of Table 7, we report the estimates from the following regression:

$$\ln Focus_{ijt} = \beta_0 + \beta_1 AfterCrisis_t + \beta_2 \ln Age_{it} + \beta_3 \ln AdjRev_j \tag{3}$$

$$+\beta_4 IsTop1_{ij} + \beta_5 AfterCrisis_t \times IsTop1_{ij} + \phi_t^{Month} + \varepsilon_{it},$$

where $Focus_{ijt}$ is the share of hours that each worker i spends on job j in month t across all jobs in which she participates in that month, $IsTop1_{ij}$ is a dummy equaling one if worker i is the top hours contributor (and zero otherwise). The estimated coefficient of $AfterCrisis_t$ shows that, on average, workers spend 4.2 percent more attention on jobs after the crisis. The estimated coefficient of $IsTop1_{ij}$ shows that rank-1 workers spend a much higher share of attention on the focal job. Interestingly, the estimated coefficient of the interaction term indicates that the high attention of rank-1 workers further increased by 9.1 percent after the crisis. The coefficients of $\ln Age_{it}$ also show that more senior workers spend less time on a job. We revisit that point later in section 5.1. The positive coefficient of $\ln AdjRev_j$ shows that workers tend to allocate more attention to larger jobs.

Recall from section 3.2 that there is a high within-team concentration of working hours and that the contribution of the team's highest hours contributor relates positively to team productivity. This suggests that within-team reallocation of working hours to more productive workers may have contributed to the post-crisis increase in team productivity. To explore this possibility, the first two rows of Table 8 report estimation results from regressions of the form:

$$Outcome_j = \beta_0 + \beta_1 AfterCrisis_j + \beta_2 \ln AdjRev_j + \phi_j^{Ind} + \phi_j^{JC} + \varepsilon_j, \tag{4}$$

where the first measure of $Outcome_j$ is $\ln TeamSize_j$, and the second is l_{1j}, which is the fraction of hours contributed by the rank-1 worker.[13] A limitation of l_{1j} is that it represents a different position within the team when the team size changes. For example, the rank-1 worker represents 100 percent of the labor in a one-person team but only represents the top 20 percent of labor in a five-person team. To mitigate this effect, we also include l_j^{90}, i.e., the 90^{th} sample percentile of the within-team hours fraction, as defined in section 2.2. Finally, the fourth dependent variable is $\ln h_{1j}$, i.e., the the rank-1 worker's total working hours supplied by . For the estimations using the latter three dependent variables, we restrict the sample to jobs with team sizes of at least three, which renders

[13] See Figure D9 in the online appendix for the histogram of l_{1j}.

the labor allocation decision interesting.

The first row of Table 8 shows that team size decreases after the crisis, whereas the second and the third show that the hours fraction for the right tail increases, with the estimate for l_j^{90} larger than l_{1j}. Both patterns are consistent with labor reallocation contributing to the increase in team productivity. The fourth row shows that the rank-1 worker's hours decreased after the crisis, suggesting a worker-level increase in efficiency. Unreported regression estimates also reveal decreases in working hours for the team's workers ranked 2 through 5.

In sum, following the crisis, on average, working hours became more concentrated on fewer days, each worker was assigned fewer working hours and became more focused on fewer jobs, while teams became smaller and more heavily reliant on the top hours contributors. Theoretically, both the increase in the productivities of individual team members and a within-team reallocation of working hours may have contributed to the post-crisis increase in team productivity. The next two sections develop a theoretical model of labor assignment within teams and apply it to quantify the relative magnitudes of the preceding two channels.

4 A theoretical model of labor assignment within teams

The theoretical model provides both an interpretation of the empirical patterns revealed in section 3 and an analytical framework for quantifying two potential contributors to the post-crisis increase in team productivity. The model's production process has two stages. In stage 1, teams are formed. In stage 2, working hours are allocated within those teams.

We describe these stages in reverse order. Section 4.1 describes the model's solution for allocating within-team working hours given the team formed in stage 1. Section 4.2 extends the model to incorporate stage 1. Section 4.3 discusses the two potential mechanisms for team productivity changes.

4.1 Labor allocation within teams

Consider a single firm (also called the employer) that operates in a production setting consisting of a set of jobs (indexed by j), each of which is completed by a team. The team's workers are indexed by i. The production technology is a Cobb-Douglas aggregator over a continuum of tasks for job j:

$$Y_j = \exp\left(\int_{s\in\Omega} \ln q_{js} ds\right), \tag{5}$$

where Y_j is team output for job j, tasks are indexed by s, q_{js} is the output of task s on job j, and Ω is the set of tasks. The measure of Ω is normalized to be 1.

The firm assigns tasks to a team of workers. Let Ω_{ij} denote the set of tasks on job j to which worker i is assigned, and let M_{ij} denote the (endogenous) measure of Ω_{ij}. For simplicity, we assume that each task can be assigned to at most one worker.[14] This subsection takes job j's team as given. Job j's team is represented by the set $\{\phi_{ij}, H_{ij} | i = 1, ..., n_j\}$, with n_j denoting job j's team size, ϕ_{ij} denoting worker i's productivity on job j (which is the output of tasks per hour), and H_{ij} denoting worker i's daily time endowment on job j. A worker with productivity ϕ_{ij} who works for h_{ijs} hours on task s of job j produces output of $q_{ijs} = \phi_{ij} h_{ijs}$. We assume that job j lasts for T_j days, which is exogenously set at the time of contracting. Although the time endowment is given on a daily basis, all analyses are conducted at the job level, and $H_{ij}T_j$ represents the maximum amount of time that worker i could devote to job j.

Both ϕ_{ij} and H_{ij} are observed by the employer. Each unit of worker i's output on task s of job j, $\phi_{ij} h_{ijs}$, is called an "effective labor hour". Let c_{ij} denote the employer's cost per effective hour of worker i's labor on job j. The total wage payment per hour, $w_{ij} \equiv c_{ij}\phi_{ij}$, is assumed to be increasing in productivity. Naturally, this implies that more productive

[14] This is relatively innocuous under the continuous task assumption, because tasks are sufficiently small so that one worker is enough.

workers earn a higher wage. Moreover, we assume that the cost per effective labor hour is decreasing in productivity, i.e., c_{ij} is lower for workers with higher ϕ_{ij}.[15] Because tasks are symmetric, in the optimal solution h_{ijs} must be equal over tasks for the same worker, so the hours spent by worker i on job j, i.e., h_{ij}, satisfy $h_{ij} = M_{ij} h_{ijs}$. Thus, given the value of h_{ijs}, a worker who is assigned to a larger measure of tasks (i.e., M_{ij} is large) will have higher working hours, h_{ij}, on job j. Each worker's total output is aggregated across tasks using the same Cobb-Douglas technology, namely $q_{ij} = \exp\left(\int_{s\in\Omega_{ij}} \ln q_{js} ds\right)$. Similarly, the optimal output levels are the same across tasks, so $q_{ij} = \exp\left(M_{ij} \ln q_{ijs}\right)$.

Taking Y_j and the team composition as given, the employer's problem for job j is:

$$\min_{h_{ijs}, M_{ij}} \left(\sum_i w_{ij} h_{ij}\right), \tag{6}$$

subject to

$$Y_j = \exp\left(\sum_i \ln q_{ij}\right),$$

$$q_{ij} = \exp\left(M_{ij} \ln q_{ijs}\right),$$

$$q_{ijs} = \phi_{ij} h_{ijs},$$

$$h_{ij} = M_{ij} h_{ijs},$$

$$h_{ij} \leq H_{ij} T_j,$$

$$\sum_i M_{ij} = 1.$$

That is, the employer assigns hours (for all workers and tasks) to minimize job j's labor costs, subject to both job j's technological constraint and a requirement that each worker's total hours (across all tasks) on job j not exceed the worker's time endowment.

[15] A justification for this assumption is that other firms do not perfectly observe worker's productivity. Therefore, the wage increase does not fully reflect workers' productivity increases.

Section A of the online appendix shows that, given M_{ij}, the solution for h_{ijs} is given by:

$$h_{ijs} = \frac{R_{ij} Y_j}{\phi_{ij}}, \tag{7}$$

where $R_{ij} \equiv \frac{c_{ij}^{-1}}{\exp\left(\sum_i M_{ij} \ln c_{ij}^{-1}\right)}$ is the reciprocal of worker i's unit cost relative to the weighted geometric mean of the reciprocals of unit costs calculated across team members. Intuitively, if the within-team relative marginal cost of allocating an effective hour to worker i is higher, then the solution assigns fewer hours to that worker. And the solution of h_{ij} is given by:

$$h_{ij} = \frac{M_{ij} R_{ij} Y_j}{\phi_{ij}}. \tag{8}$$

In general, the mass of tasks assigned to each worker, M_{ij}, does not have a closed form solution. Total working hours for job $j's$ team are the sum of the hours for each of its members, i.e., $h_j = \sum_i h_{ij}$. Job j's team productivity, A_j, is

$$A_j \equiv \frac{Y_j}{h_j} = \left(\sum_i \frac{W_{ij}}{\phi_{ij}} \right)^{-1}, \tag{9}$$

where $W_{ij} \equiv M_{ij} R_{ij}$ is the weight attributed to worker i in job j. This expression reveals how team productivity is influenced by the two channels discussed in section 3.3, i.e., the individual productivity of team members (as measured by ϕ_{ij}) and the within-team allocation of labor that the employer determines (as measured by W_{ij}).

The employer's problem is to find the assignment with the lowest labor cost that will achieve a given level of output, Y_j. Then, the intuition underlying the optimal assignment rule of M_{ij} is clear from a rearranged expression for total costs, i.e., $\sum_i w_{ij} h_{ij} =$

$Y_j \exp\left(\sum_i M_{ij} \ln c_{ij}\right)$.[16] Given the assumption that more productive workers have a lower cost per effective working hour, the employer starts by assigning the most productive worker (i.e., the one with the highest value of ϕ_{ij}, or equivalently with the lowest value of c_{ij}), exhausting that worker's hours (if necessary) before assigning the worker with the second-highest value of ϕ_{ij}, and so on, until the required output, Y_j, is achieved. At this point, all required tasks on job j are covered by the existing workers, and the team size, n_j, is determined. The implicit assumption is that the remaining employees are assigned to work on profitable activities other than job j.

Our assumption that the employer observes ϕ_{ij} is not always reasonable in a team setting. In fact, that is a reason why group-based (as opposed to individual-based) incentive contracts are often used in teams. In our context, however, it is reasonable to assume that the chief manager possesses information about workers' productivities and uses it when assigning hours to workers. This is especially so given the firm's low turnover rate; information about workers' productivities is revealed to the employer from the long job tenures and repeated observations of individual workers on a variety of projects. Our interviews with the firm's managers confirm that they are well aware of individual worker productivity.[17]

The model does not explicitly incorporate the firm's decision to outsource, even though our empirical measure of team productivity is adjusted by the outsourcing cost. The firm may be more likely to outsource when industrial demand is high, though two factors mitigate this concern. First, as shown in Figure D10 in the online appendix, the average outsourcing ratio (i.e., the ratio of total outsourcing costs to the total costs across all jobs that start in a given year) has little variation, hovering between 0.23 and 0.25. Second, if there is less outsourcing in the crisis years (2008-2010), then productivity may increase in

[16] In section A of the online appendix, the derivation of this equation (which is reproduced as Equation 4 in the online appendix) and the optimal task allocation are described.

[17] The manager's responsibilities include assigning tasks, sharing estimates of working hours, and monitoring actual working hours, and it is clear that they need to quickly grasp the productivity of their members.

those years via complementarities among the team's internal workers, given that they are more often jointly present with less variation in their working hours.[18] Similarly, in the post-crisis period (i.e., 2011-2013), as demand improves, more outsourcing would be expected. Figure D10 in the online appendix confirms that the outsourcing ratio decreased in 2008-2010 and then increased in 2011-2013. This should reduce team productivity, via complementarities among internal team members' hours, given that more of the work is being done by outsiders. But this mechanism works against our findings, so to the extent that it is relevant, our empirical result becomes harder to detect in the data.

4.2 Team formation process

We now incorporate stage 1 of the production process (i.e., team formation) into the model. Doing so is important for the forthcoming quantitative decomposition of changes in team productivity. Specifically, it allows us to generate a sample of jobs, conditional on parameter values.

In stage 1, given the value of Y_j, let $N_j\left(Y_j\right)$ denote the size of the internal candidate pool representing the firm's workers who are available for assignment to job j. We assume that this size is increasing in the level of required output, Y_j. A joint distribution of ϕ_{ij} and H_{ij} is assumed. Although exogenous, it is consistent with some key features of reality. First, most talented workers are likely to be productive in many tasks. In an extended version of the model, where the employer must allocate time across jobs for each worker, if the marginal productivity is decreasing in each job, it is likely optimal to assign such talented workers multiple jobs with limited hours per job, as if allocating time according to comparative advantage.[19] This idea suggests a negative correlation between workers' productivities and time endowments, which our model allows. Second, in the

[18] In unreported results, we find that controlling for start year, industry, and job content fixed effects, there is a negative correlation between the outsourcing ratio and team productivity.

[19] For example, the senior researcher may participate in multiple projects, contributing high-level ideas with a low time investment, whereas the junior researcher invests more time.

data, the team formation decision is fully delegated to the responsible manager. Search costs prevent the manager from considering the firm's entire workforce when staffing a job. There is also randomness in workers' availability (e.g., due to past assignment decisions or for family-related reasons). Such uncertainty is consistent with our modeling of ϕ_{ij} and H_{ij} as stochastic. Moreover, the candidate size rule embedded in $N_j\left(Y_j\right)$ assigns a limited number of draws to each job, and more draws to larger jobs, consistent with reality.

4.3 The two channels for team productivity changes

Section 3.3 suggests two potential channels through which team productivity can increase. Both channels can be analyzed using the theoretical model and are highlighted in Equation (9).

The first channel, individual productivity changes, concerns changes in A_j that arise when W_{ij} is fixed but ϕ_{ij} can change. The second channel, labor reallocation, concerns changes in A_j that arise when ϕ_{ij} is fixed but W_{ij} can change. The two mechanisms are related because changes in ϕ_{ij} influence the choice of W_{ij}. The second mechanism can either amplify or diminish the first depending on how ϕ_{ij} changes as well as how the workers' time endowments change. For example, if each worker's productivity were to improve uniformly by a certain proportion, and assuming no change in time endowments, then without the reallocation effect, the increase in team productivity would equal this proportion. But with the labor reallocation effect, the increase in team productivity exceeds this proportion.

Complementarities in production further amplify the effect of individual productivities on the second mechanism. Our theoretical model implies that, as individual skill levels improve, the marginal return of concentrating working hours on the most productive workers on team productivity also increases. The preceding mechanism also implies a smaller team size because marginal productivities amplified by complementarities reduce the need to add (less productive) team members.

Complementarities, which arise in most team settings and are one of the main reasons why employers organize production in teams, arise from interdependence among team members' labor inputs. Complementarities characterize the technology of the firm we study, based on our discussions with the firm's managers. For example, some workers must work out the space design, others must put on the electricity system, and still others must design the air conditioning system. Given that the quality of one part depends on other parts, integrating these parts can be accomplished more efficiently when team members coordinate their design policies in advance and set the same expectations. Section B of the online appendix further discusses the role of complementarities in the model.

5 Empirical analysis of theoretical model

We next use the data and theoretical model to conduct quantitative analysis. Section 5.1 calibrates the model's parameters, section 5.2 examines the model fit and provides evidence that supports the model's mechanisms, and section 5.3 quantifies the relative contributions of the two channels of influence on team productivity changes.

5.1 Calibration of the model's parameters

The theoretical model can be used to decompose the post-crisis productivity increase into parts due to increased worker-level productivity and within-team labor reallocation. To achieve this, we calibrate two instances of the model (i.e., pre and post) by allowing all model parameters to potentially change. We now describe how values are assigned to each parameter. For each job j, candidate i's productivity parameter, ϕ_{ij}, and time endowment parameter, H_{ij}, are assumed to be jointly log-normally distributed, i.e.,

$$\begin{pmatrix} \ln \phi_{ij} \\ \ln H_{ij} \end{pmatrix} \sim \mathcal{N}\left(\boldsymbol{\mu}, \boldsymbol{\Sigma}\right), \tag{10}$$

where $\boldsymbol{\mu} = \begin{pmatrix} \mu_\phi \\ \mu_H \end{pmatrix}$ is a vector of means, and the covariance matrix $\boldsymbol{\Sigma}$ contains two variance parameters (σ_ϕ and σ_H) and a correlation parameter, $\rho_{\phi H}$. The units of H_{ij} are assumed to be worker i's hours per day available for job j.

We define pre-crisis and post-crisis samples of jobs (i.e., those starting from 2005 to 2006, and those starting from 2011 to 2013). For both samples, we assign values to the following parameters:

$$\left(\mu_\phi,\ \sigma_\phi^2,\ \mu_H,\ \sigma_H^2,\ \rho_{\phi H},\ N_j\left(Y_j\right)\right),$$

where $N_j\left(Y_j\right)$ is defined in section 4.2. We calibrate $(\mu_H,\ \sigma_H^2,\ N_j\left(Y_j\right))$ directly from the data in both samples, yielding pre-crisis and post-crisis values for each parameter. For $N_j\left(Y_j\right)$, we use the idea that if a worker who participates in a particular job in one year is likely a candidate for a similar new job. Specifically, we divide the sample of labor hours into cells defined by department, year, and ten equally sized adjusted revenue bins, and count the number of workers in each cell. Then we take the average number of workers within each adjusted revenue bin across departments and years to obtain an estimate of the number of candidates for jobs whose output size is equal to the mid point of each adjusted revenue bin. Finally, we connect the ten means from the last step to obtain a piecewise-linear function as the estimate of $N_j\left(Y_j\right)$. This approach yields an estimate of $N_j\left(Y_j\right)$ that is a continuous function of Y_j between the midpoints of the first and tenth bins. The values of $N_j\left(Y_j\right)$ for the jobs with output size smaller than the mid point of the first bin and larger than the midpoint of the last bin are extrapolated using the connected lines.

The preceding steps are used to produce two estimates (i.e., pre and post) of $N_j\left(Y_j\right)$. In the steps just described, we focus on the five largest departments to reduce the noise caused by small departments which have only a few jobs in each cell. These five departments are responsible for over 97% of the jobs in our sample. Figure 6 plots the calibrated number of candidates, $N_j\left(Y_j\right)$, against $\ln Y_j$, in both the pre and post samples. For smaller jobs, the number of candidates is roughly the same between pre and post. For mid-sized jobs, the number of candidates is higher in the post-crisis period, and the reverse is true for the largest jobs.

Values for $\left(\mu_H, \sigma_H^2\right)$ are assigned using the empirical average and standard deviation of the natural logarithm of workers' hours per day in each job, computed separately for pre and post-crisis jobs for workers whose hour rank is 10 or less. The model's optimal assignment rule implies that all team members, except possibly for the least productive one, exhaust their time endowments. Therefore, the distribution of observed hours is informative about the distribution of time endowments because the two distributions nearly coincide. But including workers with trivial hours contributions likely introduces noise into the calibration. On average, workers with hour ranks of 10 or less represent over 93% of the team's total working hours.

Given the assigned parameter values for $(\mu_H, \sigma_H^2, N_j\left(Y_j\right))$, we generate simulated data sets. These are used to assign values for $(\mu_\phi, \sigma_\phi^2, \rho_{\phi H})$, in both the pre and post-crisis samples, using the method of simulated moments. Our target moments are calculated from the distributions of team productivity, within-team labor allocation, and output size. The first set of moments includes the mean and standard deviation of job-level productivity. Since team productivity is a function of worker productivity, targeting team productivity naturally helps to identify μ_ϕ and σ_ϕ^2.

The second set of moments we target is the distribution of the logarithmic value of the hour fractions for the top 10 workers in each team, namely l_{ij} for $i \leq 10$. A higher value of $\rho_{\phi H}$ shifts more hours to more productive workers, therefore generating a more concentrated labor allocation within each team. Given that we pin down the worker productivity and time endowments in the previous steps, targeting the distribution of within-team labor allocation helps to determine the value of $\rho_{\phi H}$.[20]

Finally, we include the distribution of output size to punish job failure in the model. Job failure happens if the assigned candidates, given their individual time constraints, cannot complete the required output size. As matching output size is not critical in identifying model parameters, we include in the error function only percentage deviations from the empirical moment of the output distribution.

We next describe the simulation procedure in more detail, taking the values of $(\mu_\phi, \sigma^2_\phi, \rho_{\phi H})$ as given. For each job j in the sample, output size, Y_j, and job duration, T_j, are taken from the data directly, and N_j is specified as above.[21] Next, N_j draws of individual productivity and time endowments are taken from the joint distribution of $\left(\ln \phi_{ij}, \ln H_{ij}\right)$. The draws of ϕ_{ij} and H_{ij} are independent across workers and jobs.[22]

We next describe how to specify the worker's cost per effective hour, c_{ij}. Since c_{ij} affects labor allocation only through the value of R_{ij}, and multiplying all c_{ij} by a constant does not change the value of R_{ij}, estimating c_{ij} up to a proportion (equivalently, the value of $\ln c_{ij}$ up to a constant) is sufficient for simulation. We estimate the distribution of $\ln c_{ij}$ (up to a constant) using the following steps. First, using the salary and working hours data from 2012 to 2016, we calculate the natural logarithm of the wage per hour for each worker, denoted by $\ln w_{iy}$, where the subscript y indexes years. After subtracting the

[20]The fraction of hours contributed (by rank) is targeted instead of team size because a complete profile of that fraction is more informative than team size. For example, the hours fractions in a two-person team could be split in an infinite number of ways.

[21]The contracted job duration is determined by a deadline that is stated within the contract that is signed at the start of the job. Although the observed job duration may differ from the contracted job duration due to unexpected events, such events are uncommon and should be independent across projects in the sample.

[22]Drawing from the joint distribution of $\ln \phi_{ij}$ and $\ln H_{ij}$ involves first taking draws a_{ij} and b_{ij} from the standard normal distribution and then computing:

$$\begin{pmatrix} \ln \phi_{ij} - \mu_\phi \\ \ln H_{ij} - \mu_H \end{pmatrix} = \begin{pmatrix} \sigma_\phi \sqrt{1-\rho^2_{\phi H}} & \sigma_\phi \rho_{\phi H} \\ 0 & \sigma_H \end{pmatrix} \begin{pmatrix} a_{ij} \\ b_{ij} \end{pmatrix}.$$

It is easily verified that the resulting random variables have the desired joint distribution. The draws of a_{ij} and b_{ij} are fixed throughout the simulation process.

sample median from this estimated value of $\ln w_{iy}$, we obtain a distribution of normalized logarithmic hourly wages across workers.[23] We assume the wage distribution is time invariant because we only have salary data from 2012 to 2016.[24]

Given the productivity distribution's parameters, we calculate percentiles of $\ln \phi_{ij}$, normalized by subtracting the median. Recalling that w_{ij} is monotonically increasing in ϕ_{ij}, we assign the worker at percentile q in the $\ln \phi_{ij}$ distribution the value of $\ln w_{ij}$ at percentile q in the $\ln w_{ij}$ distribution. Finally, since $\ln w_{ij} = \ln c_{ij} + \ln \phi_{ij}$, we calculate the normalized $\ln c_{ij}$ at percentile q in the $\ln c_{ij}$ distribution by subtracting the value of the normalized $\ln \phi_{ij}$ from the value of the normalized $\ln w_{ij}$.

Calculating the optimal hours for each task, given a certain worker and job, requires knowledge of the optimal task assignment M_{ij}. In general, M_{ij} must be solved for numerically using the following two-step procedure. The first step computes the realized team size. For every integer value of n_j^{temp} from 1 to N_j, we test whether a team composed of the most productive n_j^{temp} workers can complete the job. We do so by assuming that all workers exhaust their time endowments to complete a job of output size Y_j^{temp}, which permits the following closed-form solution for M_{ij}:[25]

$$M_{ij} = \frac{c_{ij}\phi_{ij}H_{ij}}{\left(\sum_{i=1}^{n_j^{temp}} c_{ij}\phi_{ij}H_{ij}\right)}. \tag{11}$$

In this case, $h_{ijs} = H_{ij}T_j / M_{ij}$, so we plug that value into the production function to compute Y_j^{temp}. If Y_j^{temp} exceeds Y_j, then the team of n_j^{temp} workers can complete the job. If n_j workers can complete the job but $n_j - 1$ cannot, the realized team size is n_j. If a team of all N_j workers cannot complete the job within their individual time constraints, the job is

[23] Normalization by subtracting the sample mean (instead of the sample median) yields a similar distribution of $\ln w_{iy}$.

[24] Japan's consumer prices were stable during our sample period. According to the World Bank, the average inflation rate during 2004 to 2016 in Japan was 0.21%.

[25] To obtain this expression, observe that when $h_{ij} = H_{ij}T_j$, Equation (8) implies $c_{ij}\phi_{ij}H_{ij}T_j = M_{ij}\prod_i (c_{ij})^{M_{ij}} Y_j^{temp}$, so M_{ij} must be proportional to $c_{ij}\phi_{ij}H_{ij}$.

regarded as failed and is dropped from the sample. The second step solves the optimal task assignment across the n_j workers. Since the most productive $n_j - 1$ workers exhaust their time endowment, we have for $i = 1, 2, ... n_j - 1$,

$$h_{ij} = \frac{M_{ij} c_{ij}^{-1}}{\exp\left[\sum_i M_{ij} \ln c_{ij}^{-1}\right]} \frac{Y_j}{\phi_{ij}} = H_{ij} T_j, \tag{12}$$

and $M_{n_j j} = 1 - \sum_{i=1}^{n_j - 1} M_{ij}$. Observe from Equation (12) that M_{ij} must be proportional to $c_{ij} \phi_{ij} H_{ij}$, except for the least productive worker. Letting $M_{ij} = D_j c_{ij} \phi_{ij} H_{ij}$ for $i = 1, 2, ..., n_j - 1$, we have

$$D_j = \frac{1 - M_{n_j j}}{\sum_{i=1}^{n_j - 1} c_{ij} \phi_{ij} H_{ij}}, \tag{13}$$

from which we can express all task shares using $M_{n_j j}$. Thus, we can use a numerical routine to solve for $M_{n_j j}$ and the task shares for all workers.

This procedure is iterated for each job in the data to obtain samples of simulated jobs (pre and post). To mitigate simulation error, we simulate three times for each job. The simulated data are used to calculate simulated moments, which are compared with the empirical data to calculated the distance function. The optimal parameter values are chosen to minimize this distance function. More specifically, we solve the following optimization problem numerically:

$$\min_{\mu_\phi, \sigma_\phi^2, \rho_{\phi H}} \frac{1}{3} \left(Err_A + Err_l + Err_Y\right),$$

where Err_A is the mean squared error between the empirical and simulated moments related to team productivity. Err_l and Err_Y are defined analogously, for the moments related to the hours fractions and output size.

To calculate Err_A, we include the mean and the standard deviation of the natural logarithm of team productivity. For example, for the mean, the error is calculated as

$\left(\ln A_{emp,mean} - \ln A_{sim,mean}\right)^2$, where $\ln A_{emp,mean}$ denotes the sample mean of the distribution of the natural logarithm of team productivity in the data, and $\ln A_{sim,mean}$ denotes its simulated counterpart. We target only the mean and standard deviation because our model cannot satisfactorily match all the quantiles. Among other things, the mean of the natural logarithm of team productivity is significantly higher than the median. For our forthcoming quantitative exercise, we must ensure that the average team productivity is matched by the model.

To calculate Err_l, we include the the 25^{th}, 50^{th}, and 75^{th} percentiles of the distribution of the natural logarithms of the hours fractions, including workers whose hours rank is 10 or less. For jobs whose team size is below 10, the observed hours fractions for all team members are included.

To calculate Err_Y, we include the 25^{th}, 50^{th}, and 75^{th} percentiles of the distribution of the natural logarithm of output size, normalized by the empirical moments. For example, the error for the 25^{th} percentile is calculated as $\left(\frac{\ln Y_{emp,25th} - \ln Y_{sim,25th}}{\ln Y_{emp,25th}}\right)^2$, where $\ln Y_{emp,25th}$ denotes the 25^{th} percentile of the distribution of the natural logarithm of output size in the data, and $\ln Y_{sim,25th}$ denotes its simulated counterpart.[26]

The preceding steps deliver pre and post-crisis values for all parameters, as shown in Table 9. The calibrated parameters reveal an increase in μ_ϕ and a decrease in σ_ϕ. These changes are identified from the fact that average team productivity increases and its standard deviation decreases. The mean of the natural logarithm of the time endowment, μ_H, increases by 0.15 after the crisis, implying that workers spend more time working per job each day. The standard deviation of the natural logarithm of the time endowment, σ_H, does not change significantly. The calibrated $\rho_{\phi H}$ is negative, consistent with the intuition that more productive workers tend to be time constrained, a pattern that we find in Table 7.[27] Given a higher value of μ_ϕ and μ_H, we expect both individual productivity and

[26]The basin-hopping algorithm (Wales and Doye, 1997) is combined with Nelder–Mead method to avoid having the optimization routine trapped at a local minimum.

[27]The salary and working hours data reveal that the correlation coefficient between the salary per hour and the working hours per day in each job is -0.263, also consistent with a negative $\rho_{\phi H}$.

labor reallocation to affect team productivity.

5.2 Model fit and validation

Concerning model fit, Figures 7 and 8 show the simulated and empirical density functions of each targeted distribution. In all figures, the dashed lines correspond to the empirical data and the solid lines to the simulated data. In each figure, the panels show the fit of the natural logarithms of team productivity, hours fractions (for the top 10 workers), and output size, respectively, from the left to the right. For the plot of hours fractions, we do not show the region smaller than the 0.1^{th} percentile of the empirical distribution (i.e., regions smaller than -7.203 for the before-crisis sample and smaller than -7.409 for the after-crisis sample) to make the model fit more apparent. The simulated data fit the mean and the standard deviation of team productivity well–the errors are below 0.0003 both before and after the crisis. But the empirical distribution of the natural logarithm of team productivity in the after-crisis sample has a spike in the middle that the simulated data cannot match. Similarly, the model is able to match the location and dispersion of the distributions of the natural logarithms of the hours fractions, but other aspects of these distributions are less well matched. Finally, the rightmost panel shows that the simulated data also fit the distribution of $\ln Y_j$ reasonably well. We also verify that our assumptions that w_{ij} is increasing in ϕ_{ij} while c_{ij} is decreasing in ϕ_{ij} are satisfied under the calibrated parameter values.

Concerning model validation, our goal is to show that the model replicates the empirical patterns documented in Table 2, Table 5 and Table 8. We first estimate the correlation between team productivity and the natural logarithm of the rank-1 hours fraction using the simulated data. Table 10 reports the results. Similar to Table 5, we find a significant positive correlation between the rank-1 hours fraction and team productivity, and a negative correlation between team size and team productivity. We then estimate regressions of the following form to examine job-level changes in several dependent variables after the crisis:

$$Outcome_j = \beta_0 + \beta_1 AfterCrisis_j + \beta_2 \ln Y_j + u_j, \tag{14}$$

using five measures of $Outcome_j$: (1) $\ln A_j$, the natural logarithm of team productivity, (2) $\ln n_j$, the team size for simulated jobs, (3) $\ln l_{1j}$, (4) $\ln l_j^{90}$, and (5) $\ln h_{1j}$, where the output size is not controlled in the first regression, as in Table 5. The latter four measures, which appear in Table 8, are for the purpose of validating the model mechanisms affecting team productivity.

Table 11 reports estimates of post-crisis changes in the job-level variables. The first row shows that in the simulated data, job-level productivity increases by 8.8%. This is close to the first column in Table 2 because we included the variable as one of the targets. The effect of labor reallocation is reflected in the next three rows of Table 11, where it is shown that after the crisis, $\ln l_{1j}$ and $\ln l_j^{90}$ increase, and $\ln n_j$ decreases, as is true in the empirical data (Table 8). These results are consistent with the firm relying on smaller teams after the crisis. Overall, the calibrated model successfully reproduces the qualitative patterns in the data.

5.3 Quantitative decomposition of changes in team productivity

We now quantify the relative importance of the two channels that affect team productivity described in section 4.3.[28] Recall, based on Equation (9), that the individual productivity change is the difference in team productivity when ϕ_{ij} changes, holding W_{ij} constant, and the labor reallocation effect is the opposite. The decomposition requires attention to three issues. First, the randomness of team members' productivities and time endowments im-

[28] As observed by a referee, this decomposition of the increase in team productivity evokes the decomposition of the increase in individual worker productivity at Safelite AutoGlass (Lazear, 2000), though with an important difference. Specifically, Lazear's decomposition results from many workers' decisions to select across firms in response to an individual employer's decision to change its compensation system to induce incentives, whereas our decomposition results from an individual employer's assignment of its workers' hours across tasks within teams in response to an exogenous change in demand for the firm's services.

plies that the pre-crisis team's hours allocation might be infeasible for the post-crisis team, even holding the job characteristics constant. Second, the (exogenous) job characteristics differ before and after the crisis, and we want to hold these constant in the decomposition. Third, the rule for assigning the number of draws (i.e., the candidate pool, $N_j\left(Y_j\right)$) changes after the crisis, which affects team productivity given that the within-team labor assignment rule prioritizes more productive workers.

In response to these issues, we only use the pre-crisis sample, thereby holding fixed the job characteristics. Then we examine the productivity changes by generating counterfactual teams using the rule for assigning the candidate pool, the productivity, and the time endownments of the labor force calibrated from the post-crisis sample. More specifically, for each job j in the pre-crisis sample, we generate five counterfactual simulations, corresponding to the five rows in Table 12. Simulation 0, the baseline, uses the parameters we calibrated using the pre-crisis sample.

Simulation 1 uses the $N_j\left(Y_j\right)$ calibrated from the after-crisis sample, with the other parameters remaining the same as in simulation 0. Comparing the *Mean* $\ln A_j$ column in the first and second rows of Table 12, reveals that average team productivity increases by 4.2% after changing $N_j\left(Y_j\right)$. This could reflect both changes in individual productivity or labor reallocation due to the changes in the number of candidates in the pool. To further decompose this change, we first calculate the average worker productivity, $\frac{1}{n_j}\sum_i^{n_j}\ln\phi_{ij}$, using the team sizes, n_j, in simulation 0. We then calculate the average worker productivity for the most productive n_j workers for the counterfactual teams in simulation 1, denoted as $\frac{1}{n_j}\sum_i^{n_j}\ln\phi'_{ij}$. Using the team size from simulation 0 is important because the team size in simulation 1, denoted as n'_j, reflects labor reallocation. For example, $n'_j < n_j$ when workers in simulation 1 are more productive than those in simulation 0. The difference, $\frac{1}{n_j}\sum_i^{n_j}\ln\phi'_{ij} - \frac{1}{n_j}\sum_i^{n_j}\ln\phi_{ij}$, thus serves as the measure of the average individual productivity change for job j. The column $\Delta\ln\phi_{ij}$ in Table 12 reports the average of this change over jobs. It measures the individual productivity change without labor reallocation, since we control for team size, n_j. As shown in the second row of columns $\Delta \ln \phi_{ij}$ and $\Delta \ln A_j - \Delta \ln \phi_{ij}$, the changes in $N_j\left(Y_j\right)$ alone imply increases of 2.6% and 1.7% for individual productivity increase and labor reallocation effect, respectively.

Table 12's other rows change different subsets of the remaining parameters to the post-crisis level, decomposing the corresponding changes in the average team productivity into the two channels. Simulation 2 uses the μ_ϕ and σ_ϕ calibrated from the post-crisis sample, while keeping other parameters the same as simulation 1. Since μ_ϕ and σ_ϕ affect worker productivity, the change in the average team productivity, as reported in the column titled $\Delta \ln A_j$, can be largely attributed to the individual productivity change. The numbers in Table 12's third row thus show that when μ_ϕ and σ_ϕ are increased to their post-crisis levels, team productivity increases by 7.3 percent, on average, of which 5.1 percentage points are attributed to the individual productivity change, and 2.2 percentage points can be attributed to labor reallocation. The fourth row shows that when μ_H and σ_H increase to their post-crisis levels, team productivity increases by 10 percent, of which 2.6 percentage points are due to an increase in individual productivity. Finally, the fifth row shows that if all parameters are at the post-crisis level, average team productivity increases by 12.4 percent, of which 5.0 percentage points (40.3% of the total change) and 7.4 percentage points (59.7% of the total change) are attributed to the individual productivity increase and labor reallocation, respectively.

If the amplification effect due to complementarity among workers' productivities also contributes to the increase in average team productivity, our estimate of the labor reallocation effect will be upward biased. Section C of the online appendix presents further simulation results showing that the amplification effect due to complementarity does not introduce such bias in our decomposition results.

6 Conclusion

This study reveals the drivers of productivity in teams of knowledge workers in a representative firm. An increase in team productivity followed the Great Recession. To analyze that variation in team productivity, we introduce a theoretical model that describes the within-team allocation of working hours and its implications for team productivity. The model permits a change in team productivity to be quantitatively decomposed into a part due to a change in individual labor productivity and a part due to within-team reallocation of working hours.

The theoretical model successfully replicates the distributions of team productivity and allocation of working hours, before and after the crisis. In the actual data, team productivity increased by 8.9% following the crisis. Our counterfactual exercise shows that team productivity would have increased by 12.4% if pre-crisis jobs were done by post-crisis teams. The difference between the actual and the simulated data may reflect compositional changes in job characteristics. Decomposing this increase in team productivity using the theoretical model reveals that 5.0 percentage points come from an increase in individual productivity, and 7.4 percentage points come from within-team reallocation of working hours. Moreover, within-team working hours are heavily concentrated, with a large fraction of the team's hours being contributed by a small number of workers, particularly the worker who invests the most hours. The fraction of time spent by that individual is positively associated with team productivity, while team size is negatively associated with team productivity.

Our quantitative analysis of the model has a clear managerial implication, revealing that team productivity is driven more by within-team labor reallocation than by the individual productivities of team members. This result points to the value of employer investments in reducing frictions in labor reallocation compared with investments in productivity-enhancing training for individual team members. Specifically, when staffing teams, managers should collect information about the availability and ability of workers.

The firm might facilitate such learning by creating opportunities for managers to interact with workers other than those they immediately supervise. Alternatively, the firm might organize its internal labor market such that departments exchange their workers for transfer prices. Then, each worker would be assigned to the job in which their marginal productivity is highest.

Our results also highlight the importance to the firm of avoiding overburdening its workers with projects by accepting too many job orders. Additionally, we could potentially examine the tradeoff between raising revenue by accepting more job orders and losing productivity by having overburdened managers and high performers. That exercise is beyond the scope of this study.

Our investigation is based on a single firm within a country that has distinctive labor market institutions, suggesting potential threats to external validity. For example, this firm might not be representative of architectural and engineering consultancy firms (even within Japan), the industry itself may be idiosyncratic even if this firm is representative of the industry, the institutional environment is specific to Japan, and the global financial crisis might be an idiosyncratic example of a major recession. Several factors mitigate these issues, leading us to expect our results to be relevant for teams of knowledge workers within the U.S. and other economies.

Japan and the U.S. respond differently to negative demand shocks. Specifically, downward adjustments in employment (as opposed to hours) are relatively more common in the U.S. than in Japan. This institutional difference does not render our analysis inapplicable to the U.S., because our primary objective is to study not productivity over the business cycle but rather the productivity effects of within-team allocation of working hours. For that purpose, Japan's distinctive emphasis on hours adjustments is more of a plus than a liability.[29] Concerns that the Great Recession might be idiosyncratic among

[29]Setting aside this point, Japan's institutional features that differentiate it from the U.S. and other industrialized economies should not be overstated. Even in Japan, adjustments in (non-standard contract) workers occur. Japan's prohibition of the "abuse of the right to dismiss" applies only to regular workers. Terminating contracts with workers hired under fixed-term contracts is not prohibited. Moreover, even in

recessions are similarly allayed, because our focus is not on the productivity effects of recessions, per se. The highly educated workers in our sample are comparable to salaried (as opposed to hourly) workers in the U.S., for whom layoffs would not be used but for whom hours would fall in recessions. Finally, team production is a widespread phenomenon not just in Japan but also internationally. It is also increasingly important in other professional service industries. Thus, the employer's problem of optimally allocating within-team working hours is relevant to other firms within and outside this industry.

After extensive conversations with the firm's management, nothing stands out to us as being unusual or idiosyncratic about this firm's characteristics, services provided, industry, business strategy, management practices, production process, position within the product and labor markets, or use of teams, that would make our findings peculiar to this firm. Thus, we anticipate that future research in other production settings should be corroborative. In particular, we expect our results from Japan to generalize to the U.S. and other industrialized economies, and specifically to large segments of the white-collar labor force, such as knowledge workers employed in R&D, consulting, law, accounting, and finance.

References

Ahmadpoor, Mohammad and Benjamin F Jones, "Decoding Team and Individual Impact in Science and Invention," *Proceedings of the National Academy of Sciences*, 2019, *116* (28), 13885–13890.

Anderson, Katharine A. and Seth Richards-Shubik, "Collaborative Production in Science: an Empirical Analysis of Coauthorships in Economics," *Review of Economics and Statistics*, 2022, *104* (6), 1241–1255.

Azoulay, Pierre, Joshua S. Graff Zivin, and Jialan Wang, "Superstar Extinction," *Quarterly Journal of Economics*, 2010, *125* (2), 549–589.

lightly regulated labor markets in which it is easier than in Japan to shed workers, downward adjustments in hours occur and are typically among the first employer responses in a recession.

Bandiera, Oriana, Iwan Barankay, and Imran Rasul, "Team Incentives: Evidence from a Firm Level Experiment," *Journal of the European Economic Association*, 2013, *11* (5), 1079–1114.

Bonhomme, Stéphane, "Teams : Heterogeneity , Sorting , and Complementarity," Technical Report, University of Chicago, Becker Friedman Institute for Economics Working Paper 2021.

Chan, Tat Y., Jia Li, and Lamar Pierce, "Learning from Peers: Knowledge Transfer and Sales Force Productivity Growth," *Marketing Science*, 2014, *33* (4), 463–484.

Coviello, Decio, Andrea Ichino, and Nicola Persico, "Time Allocation and Task Juggling," *American Economic Review*, 2014, *104* (2), 609–623.

_ , _ , and _ , "The Inefficiency of Worker Time Use," *Journal of the European Economic Association*, 2015, *13* (5), 906–947.

Hamilton, Barton H., Jack A. Nickerson, and Hideo Owan, "Team Incentives and Worker Heterogeneity: An Empirical Analysis of the Impact of Teams on Productivity and Participation," *Journal of Political Economy*, 2003, *111* (3), 465–497.

_ , _ , and _ , "Diversity and productivity in production teams," in "Advances in the Economic Analysis of Participatory and Labor-Managed Firms," Vol. 13 2012, pp. 99–138.

Hyndman, Rob J and Yanan Fan, "Sample Quantiles in Statistical Packages," *The American Statistician*, 1996, *50* (4), 361–365.

Lazear, Edward P., "Performance Pay and Productivity," *American Economic Review*, 2000, *90* (5), 1346–1361.

Prat, Andrea, "Should a Team Be Homogeneous?," *European Economic Review*, 2002, *46* (7), 1187–1207.

Shangguan, Ruo, Jed DeVaro, and Hideo Owan, "How Good Managers Steer Their Projects: Front Loading of Team Labor," 2024.

Syverson, Chad, "What Determines Productivity?," *Journal of Economic Literature*, 2011, *49* (2), 326–365.

Wales, David J. and Jonathan P.K. Doye, "Global Optimization by Basin-hopping and the Lowest Energy Structures of Lennard-Jones Clusters Containing up to 110 Atoms," *Journal of Physical Chemistry A*, 1997, *101* (28), 5111–5116.

Zacchia, Paolo, "Benefiting Colleagues But Not the City: Localized Effects from the Relocation of Superstar Inventors," *Research Policy*, 2018, *47* (5), 992–1005.

	count	mean	standard deviation	min	25%	50%	75%	max
$\frac{Rev_j}{h_j}$	6014	20,894.714	20,891.943	499.645	9615.579	14,697.006	24,157.923	314,285.714
$\frac{AdjRev_j}{h_j}$	6014	14,830.439	15,435.068	352.558	7241.110	10,423.840	16,340.193	173,109.000
Rev_j	6014	26,058,243.762	47,009,401.458	1,000,000.000	3,000,000.000	8,820,000.000	29,000,000.000	882,934,179.000
$AdjRev_j$	6014	18,146,901.451	29,794,424.731	252,449.133	2,260,745.761	6,333,059.157	21,167,966.209	354,199,866.387
h_j	6014	1949.509	3172.934	5.000	174.000	627.500	2359.375	42,079.000
$TeamSize_j$	6014	12.779	11.064	1.000	4.000	9.000	18.000	78.000
h_{1j}	6014	547.756	622.876	5.000	103.000	274.500	788.875	2725.000
l_{1j}	6014	0.485	0.243	0.051	0.293	0.426	0.636	1.000
l_j^{90}	6014	0.354	0.261	0.024	0.142	0.279	0.500	1.000
T_j	6014	405.691	333.137	5.000	182.000	321.000	515.000	3272.000
$Area_j$	6014	49,494.980	94,835.984	0.010	4000.000	13,446.000	50,000.000	1,000,000.000
$\frac{AdjArea_j}{h_j}$	6014	37,255.076	74,603.902	0.010	2847.603	9967.355	35,637.050	800,000.000
O_j	6014	0.237	0.223	0.000	0.026	0.186	0.384	0.800

Note: Summary statistics for all variables in the analysis, as defined in section 2.

Table 1: Summary statistics

	(1) $AfterCrisis_j$	(2) $AfterCrisis_j$
	0.089***	0.083***
	(0.025)	(0.025)
Industry, Job Content fixed effects	No	Yes
Sample size	3070	3070
Adj. R^2	0.004	0.078

Note: The coefficient estimates reveal the post-crisis change in team productivity. Pre-crisis definition: $2005 \leq StartYear_j \leq 2006$ Post-crisis definition: $2011 \leq StartYear_j \leq 2013$. Standard errors are reported in parentheses. Statistical significance at the 1% level on a two-tailed test is indicated by ***.

Table 2: Change of productivity

	$\ln \frac{AdjArea_j}{h_j}$	$\ln \frac{AdjArea_j}{h_j}$
$\ln l_{1j}$	0.218**	0.081
	(0.090)	(0.081)
Industry, Job Content fixed effects	No	Yes
Sample size	3070	3070
Adj. R^2	0.002	0.245

Note: The change in adjusted floor area per hour after the crisis. Standard errors are reported in parentheses. Statistical significance at the 5% level on a two-tailed test is indicated by **.

Table 3: Change of physical productivity

	% of sample	0.7	16.4	14.6	24.7	13.8	9.9	19.9
	Team Size	1	2-3	4-5	6-10	11-15	15-20	20+
Rank	1.00	1.00	0.84	0.61	0.47	0.38	0.33	0.25
	2.00		0.22	0.25	0.23	0.21	0.19	0.16
	3.00		0.07	0.10	0.13	0.13	0.13	0.12
	4.00			0.05	0.08	0.09	0.09	0.09
	5.00			0.02	0.04	0.06	0.07	0.07
	6.00				0.03	0.04	0.05	0.06
	7.00				0.02	0.03	0.04	0.05
	8.00				0.01	0.02	0.03	0.04
	9.00				0.01	0.01	0.02	0.03
	10.00				0.00	0.01	0.02	0.02
	11.00					0.01	0.01	0.02
	12.00					0.00	0.01	0.02
	13.00					0.00	0.01	0.01
	14.00					0.00	0.01	0.01
	15.00					0.00	0.00	0.01

Note: Average share of hours contributed by each worker on the team, conditional on the rank of total hours contributed and the team size group. The numbers at the top of the table are the shares of each team size group in the sample (e.g., teams with 6 to 10 people represent 24.7 percent of the sample).

Table 4: Allocation of working hours across team members

	$\ln \frac{AdjRev_j}{h_j}$	$\ln \frac{AdjRev_j}{h_j}$
$\ln l_{1j}$	0.471^{***}	0.263^{***}
	(0.024)	(0.034)
$TeamSize$		-0.015^{***}
		(0.002)
Sample size	3070	3070
Adj. R^2	0.191	0.210

Note: The correlation between team productivity and within-team labor allocation. Industry and job content fixed effects are controlled. Standard errors are reported in parentheses. Statistical significance at the 1% level on a two-tailed test is indicated by ***.

Table 5: Explaining team productivity using hours fractions

	$\ln \frac{AdjRev_j}{T_j}$	$\ln \frac{h_j}{T_j}$
$AfterCrisis_j$	0.218^{***}	0.134^{***}
	(0.040)	(0.045)
Sample size	3070	3070
Adj. R^2	0.180	0.228

Note: Decomposition of changes in adjusted revenue per hour into adjusted revenue per day and team hours per day. Industry and job content fixed effects are controlled. Standard errors are reported in parentheses. Statistical significance at the 1% level on a two-tailed test is indicated by ***.

Table 6: Decompose the change in output per hour

	$\ln NumJob_{it}$	$\ln Focus_{ijt}$
$AfterCrisis_j$	-0.169^{***}	0.042^{**}
	(0.015)	(0.019)
$\ln Age_{it}$	1.270^{***}	-1.098^{***}
	(0.037)	(0.032)
$\ln AdjRev_j$		0.335^{***}
		(0.008)
$IsTop1_{ij}$		1.118^{***}
		(0.025)
$AfterCrisis_t \times IsTop1_{ij}$		0.091^{***}
		(0.032)
Sample size	174653	174081
FE	Month	Month, Industry, Job Content
Adj. R^2	0.198	0.213

Note: Standard errors are reported in parentheses. Statistical significance at the 1%, 5% level on a two-tailed test are indicated by ***,**. For the regression of $NumJob_{it}$, standard errors are clustered at worker level. For the regression of $\ln Focus_{ijt}$, standard errors are clustered at job level.

Table 7: Change in focus for workers

Outcome	Change after crisis	Sample size	Adj. R^2
$\ln TeamSize_j$	-0.062^{***}	3070	0.608
	(0.020)		
$\ln l_{1j}$	0.031^{**}	2811	0.401
	(0.014)		
$\ln l_j^{90}$	0.070^{***}	2811	0.536
	(0.019)		
$\ln h_{1j}$	-0.076^{***}	2811	0.748
	(0.024)		

Note: Estimation results of Equation (4). Sample includes jobs with $2005 \leq StartYear \leq 2006$ or $2011 \leq StartYear \leq 2013$. Regressions control for log output size, industry and job content fixed effects. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% level on a two-tailed test is indicated by ***,**.

Table 8: Change of job-level variables after crisis

Sample	μ_ϕ	σ_ϕ	μ_H	σ_H	$\rho_{\phi H}$	Err_A	Err_l	Err_Y
Pre-crisis: $2005 \leq StartYear \leq 2006$	6.975	1.248	-1.663	1.662	-0.200	0.000	0.070	0.009
Post-crisis: $2011 \leq StartYear \leq 2013$	7.081	1.205	-1.513	1.694	-0.204	0.000	0.040	0.006

Note: Calibrated parameter values. The error is the minimized value of the objective function.

Table 9: Calibrated parameters

	$\ln A_j$	$\ln A_j$
$\ln l_{1j}$	0.774^{***}	0.441^{***}
	(0.011)	(0.015)
n_j		-0.019^{***}
		(0.001)
Sample size	8530	8530
Adj. R^2	0.370	0.433

Note: The correlation between team productivity and within-team labor allocation using simulated data. Standard errors are reported in parentheses. Statistical significance at the 1% level on a two-tailed test is indicated by ***.

Table 10: Validating the correlation between team productivity and labor concentration

Outcome	Change after crisis	Sample size	Adj. R^2
$\ln A_j$	0.088^{***}	8530	0.004
	(0.015)		
$\ln n_j$	-0.073^{***}	8530	0.244
	(0.021)		
$\ln l_{1j}$	0.028^{**}	6624	0.069
	(0.012)		
$\ln l_j^{90}$	0.060^{***}	6624	0.199
	(0.018)		
$\ln h_{1j}$	-0.080^{***}	6624	0.817
	(0.013)		

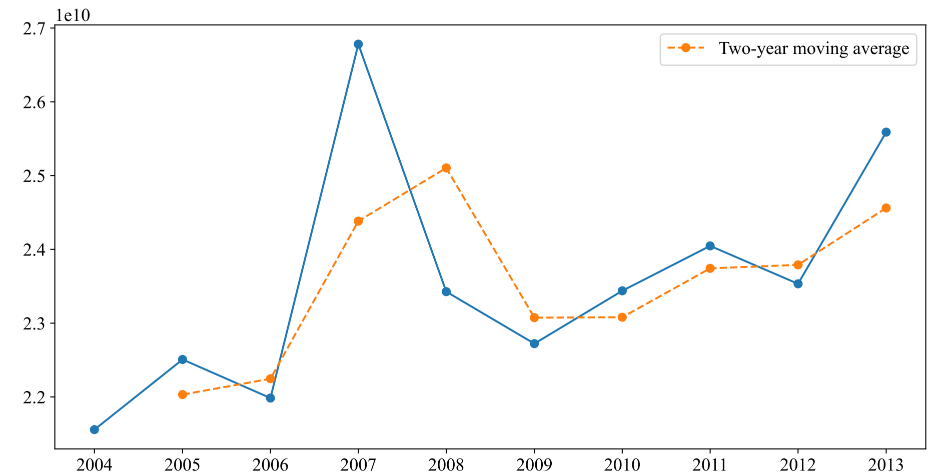
Note: Estimation results of Equation (14). Sample of real data includes jobs with $2005 \leq StartYear \leq 2006$ or $2011 \leq StartYear \leq 2013$. Regressions except for the first row control for log output size. Standard errors are reported in parentheses. Statistical significance at 1%, 5% level on two-tailed tests, are indicated by *, **.

Table 11: Model Validation

Sample	N_j	Simulation Number	μ_ϕ	σ_ϕ	μ_H	σ_H	$\rho_{\phi H}$	Mean $\ln A_j$	$\Delta \ln A_j$	$\Delta \ln \phi_{ij}$	$\Delta \ln A_j - \Delta \ln \phi_{ij}$
Pre-crisis	Before	0	6.975	1.248	-1.663	1.662	-0.200	9.306			
	After	1	6.975	1.248	-1.663	1.662	-0.200	9.348	0.042	0.026	0.017
	After	2	7.081	1.205	-1.663	1.662	-0.200	9.379	0.073	0.051	0.022
	After	3	6.975	1.248	-1.513	1.694	-0.200	9.406	0.100	0.026	0.074
	After	4	7.081	1.205	-1.513	1.694	-0.204	9.430	0.124	0.050	0.074

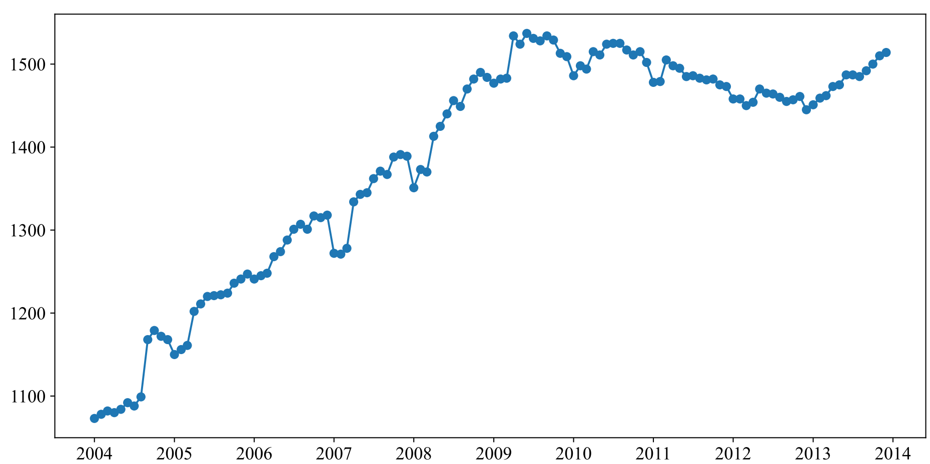
Note: Decomposition of the change in team productivity into two channels. The sample consists of pre-crisis jobs. The first row corresponds to the calibration result using the pre-crisis sample. The second to the fifth row correspond to counterfactual simulations gradually changing the model parameters. Column $\Delta \ln A_j$ reports the change in average team productivity, column $\Delta \ln \phi_{ij}$ reports the change in individual productivity, $\Delta \ln A_j - \Delta \ln \phi_{ij}$ is the difference in previous two columns, representing the labor reallocation effect.

Table 12: Decomposition based on changing parameters



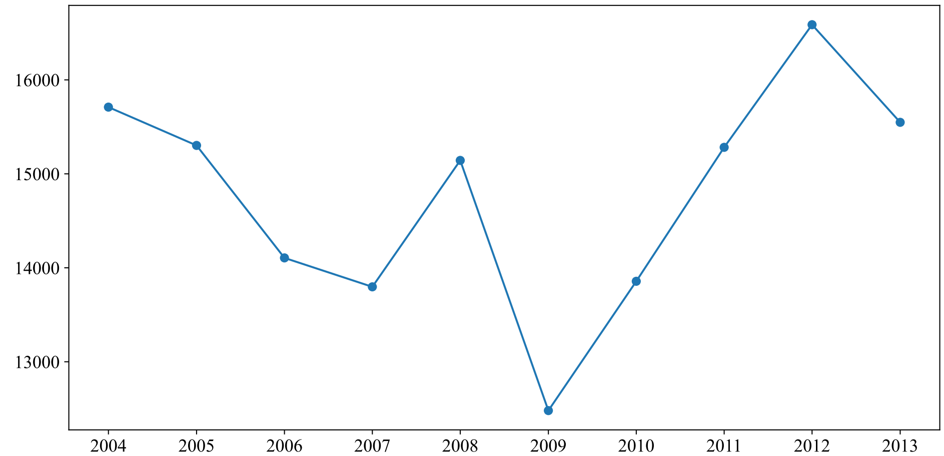
Note: Sum of the adjusted revenues from the jobs starting in each year. Year 2008 normalized to 1.

Figure 1: Total adjusted revenue by start year, 2004 to 2013



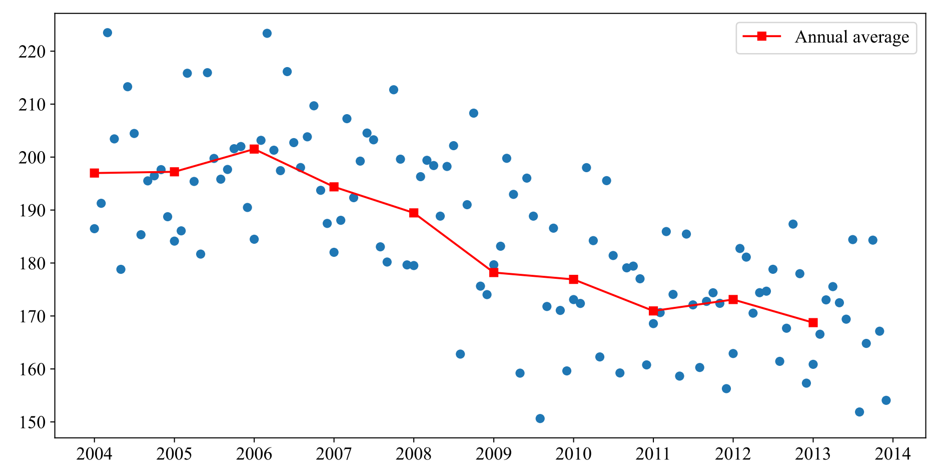
Note: Number of workers that participate in the production of revenue-generating jobs in each year.

Figure 2: Number of workers in each year, 2004 to 2013



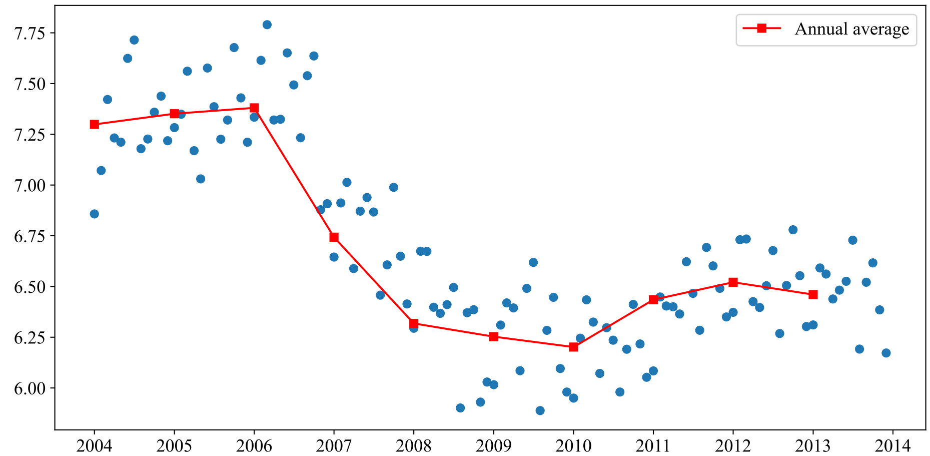
Note: For each year, the figure plots average adjusted revenue per hour, $\frac{AdjRev_j}{h_j}$, for the selected sample of jobs.

Figure 3: Revenue per hour, 2004 to 2013



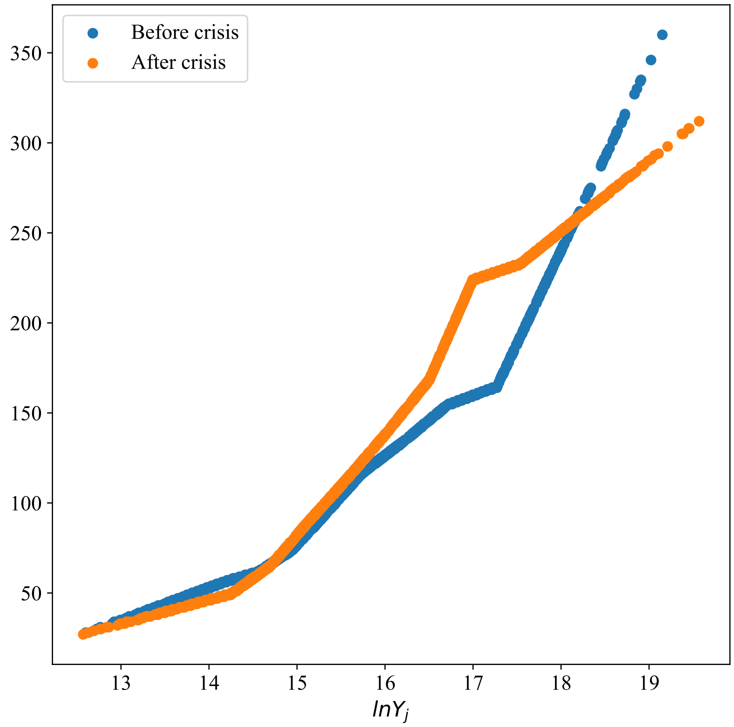
Note: Each point in the scatter represents the average monthly total working hours across workers. The solid line connects the square points, each of which is an annual average. All jobs (internal and external) are included when calculating monthly working hours.

Figure 4: Time trend of average monthly working hours, 2004 to 2013



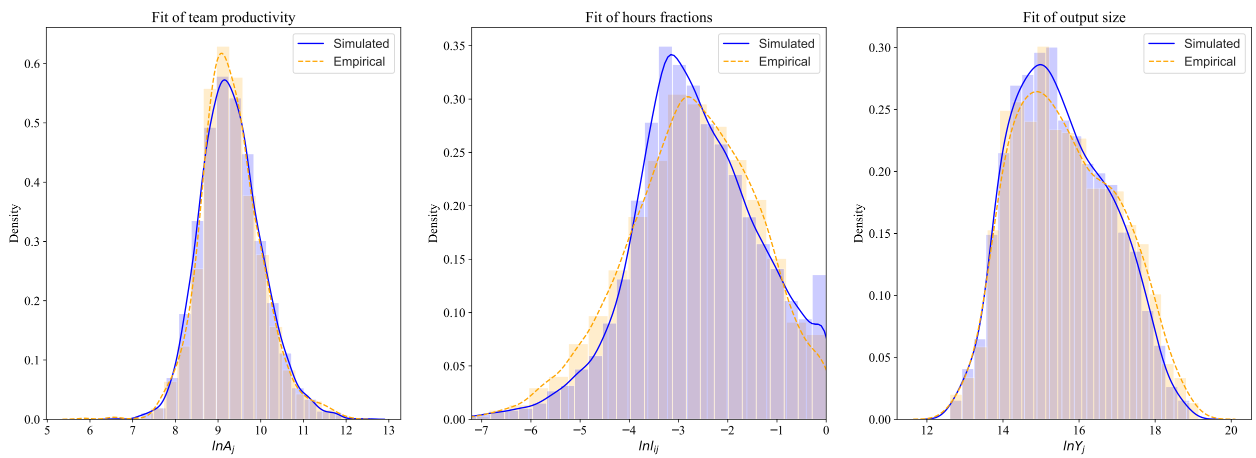
Note: Each point in the scatter represents the average number of jobs in which each worker participates. The solid line connects the square points, each of which is an annual average.

Figure 5: Average number of jobs assigned to each worker



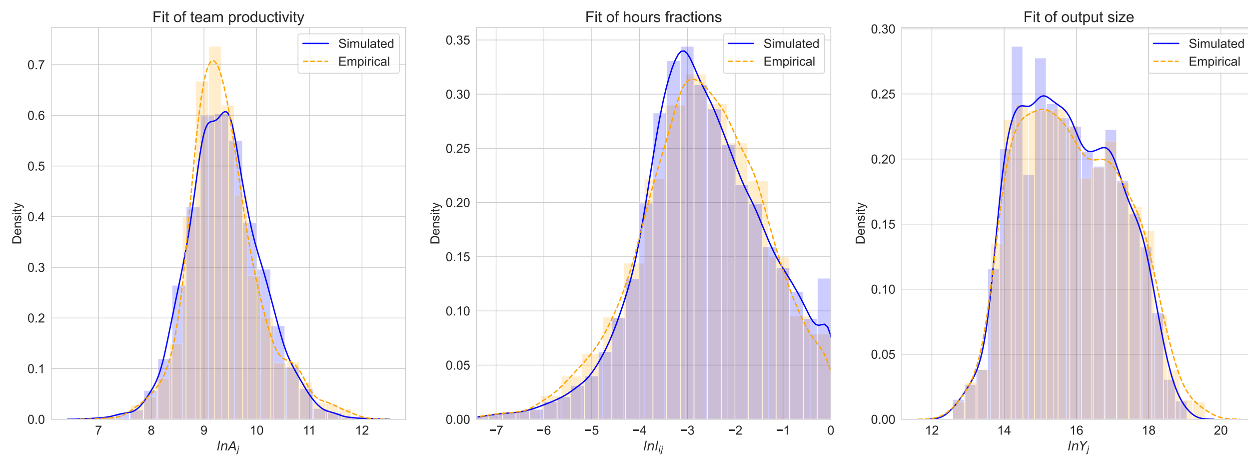
Note: Number of candidate in the simulated jobs by output size, before (left panel) and after (right panel) crisis.

Figure 6: Number of calibrated candidates



Note: From left to right, the figures show the simulated and empirical density functions for team productivity, hours fractions, and output size for the before-crisis sample.

Figure 7: Model fit, before crisis



Note: From left to right, figures show the simulated and empirical density functions for team productivity, hours fractions, and output size for the after-crisis sample.

Figure 8: Model fit, after crisis