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Multi-project Work and Project Performance: Friends or Foes?

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Abstract

Research summary: While multi-project work (MPW) is becoming an increasingly popular work arrangement, its relationship with project performance is understudied. On the one hand, MPW is deployed to increase employee worktime utilization and productivity, which should be reflected in more timely project completion. On the other hand, MPW also brings switching costs due to attention residue and cognitive setup. Based on this trade-off, we derive an inverted U-shaped relationship between MPW and project performance. We find support for this relationship in a longitudinal dataset containing 9,649 project-month-employee observations. More specialized experience, project similarity, and employee familiarity positively moderate the inverted U-shape. Furthermore, the results are robust to a host of model specifications, data structures, assumptions, and alternative explanations.

Managerial summary: How many projects can you work on simultaneously? We study this question in the context of new product development (NPD) projects in a multinational organization. We suggest that multi-project work (MPW) might be a double-edged sword. On the one hand, MPW academics or engineers can be more productive by filling the gaps in their schedules and developing time management practices. On the other hand, MPW also carries switching costs. This trade-off creates an inverted U-shaped relationship between MPW and project performance. So, how can MPW be more beneficial or less costly? We find that more specialized employees can benefit more from productivity gains while working with familiar members or similar projects can alleviate switching costs.

1. INTRODUCTION

The effective management of human resources is an important factor in organizational success (Castanias & Helfat, 2001; Gambardella, Panico, & Valentini, 2015; Starr, Ganco, & Campbell, 2018). In the light of the rapidly evolving landscape of project work, research has turned its attention to the role of flexible human resource practices. Several recent studies have linked performance outcomes to giving employees autonomy in knowledge-intensive projects (Gambardella, Khashabi, & Panico, 2020), allowing employees to engage in side hustles or smart working (Choudhury, Foroughi, & Larson, 2021; Sessions, Nahrgang, Vaulont, Williams, & Bartels, 2021), and enabling flexible contracting arrangements and projects compositions (Akşin, Deo, Jónasson, & Ramdas, 2021; Anderson & Bidwell, 2019; Jain & Mitchell, 2021). However, less is known about the consequences of another flexible human resource practice - multi-project work (MPW) –a work arrangement in which employees work on multiple projects simultaneously. Recent reports show that 80% of employees engage in MPW (Mortensen & Gardner, 2017; O'Leary, Mortensen, & Woolley, 2011; T. A. Smith, Kirkman, Chen, & Lemoine, 2018) and that 84% of project-based organizations adopt MPW as their standard work arrangement (Beşikci, Bilge, & Ulusoy, 2015). Yet, MPW might be a double-edged sword as it can present both benefits and costs. For example, MPW academics or engineers can be more productive by effectively utilizing their time across projects, increasing the chances of meeting project deadlines. However, the same individuals might also experience switching costs that can delay project completion. Whether and under which conditions MPW is positively related to project performance is an intriguing question we address in this paper.

To do so, we build a theoretical framework based on the trade-off between the benefits and costs of MPW. On the one hand, MPW is deployed to increase employee worktime utilization and productivity, which should be reflected in more timely project completion (Milgrom & Roberts, 1992; O'Leary et al., 2011). In contrast to single project workers, MPW employees can reduce or eliminate idle time by spreading their work hours (i.e., avoiding gaps in the schedule) (Kc, 2014). For instance, a mechanical engineer can maximize the activity time on a specialized machine by switching between active and idle hours across projects. MPW employees might also be more productive by developing effective work practices. For example, project engineers or academics can develop templates that can be applied across projects and serve as productivity tools (e.g., datasheet or codebook for running a statistical model). On the other hand, going back and forth between projects also carries switching costs due to "attention residue"—thoughts about a previous task that persist and intrude while performing another (Leroy & Glomb, 2018). Attention residue can create a vicious cycle by reducing the employee's effectiveness on a current project or task (Wylie & Allport, 2000) and spilling over on subsequent assignments. MPW employees might also need mental and psychical effort to re-immerse themselves in the tasks, people, roles, issues, and operations of another project context—referred to as "cognitive setup" costs (Kc & Staats, 2012; Staats & Gino, 2012). These switching costs can be detrimental to project performance.

Theoretically, the trade-off between benefits and costs gives rise to an inverted U-shape relationship between MPW and project performance (Hypothesis 1). Based on the same set of arguments, we also advance three contingencies. Hypothesis 2 suggests that employee specialized experience increases the benefits of MPW. For example, a business analyst with specialized experience in product development might be able to effectively allocate the worktime across projects and develop cutting-edge work practices (e.g., using templates to identify and help solve bottlenecks). Hypotheses 3 and 4 propose that project similarity and employee familiarity reduce switching costs. MPW employees may need to exert less physical and mental effort when transitioning between similar contexts or, namely, have lower "cognitive setup" costs. For example, a software developer can use the same code across similar projects, while a surgeon can utilize the same procedure. Employee familiarity reduces attention residue because employees can use previously established structures, relationships, and work arrangements as anchors for the current project (Reagans, Argote, & Brooks, 2005). Think of academics that write articles with familiar co-authors. They can reduce switching costs by relying on established relationships and writing routines.

To test our theoretical framework empirically, we used a longitudinal dataset that combines employee and project-level information in new product development projects in a multinational organization. These projects are subject to rigorous reporting and continuous assessments of current and prospective performance. We combined three sources of data: project reports, HR database, and work registry. The dataset is at the project-employee-month level and contains 9,649 project-month-employee observations (42 projects and 580 employees). We provided rich descriptive evidence of how MPW is related to performance which is robust to different model specifications and alternative explanations (Goldfarb & King, 2016). We first investigated the MPW allocations and found that age, location, and leadership role are related to MPW. We then tested our main model using employee and month fixed effects, control variables and clustered standard errors. We found support for the inverted U-shape relationship between MPW and project performance. In addition, when specialized experience is high (low), MPW has a more positive (negative) relationship with project performance. We also found that the switching costs of MPW are reduced when employees work on similar projects or with familiar employees.

With these findings, we aim to contribute to the literature in the following ways. First, we link a previously understudied human resource practice - MPW - to project performance. We contribute to the literature investigating the performance consequences of flexible human resource practices in knowledge-intensive and collaborative work (Fahrenkopf, Guo, & Argote, 2020; Gambardella et al., 2020; Jain & Mitchell, 2021; Sessions et al., 2021). Second, the finding that specialized experience positively moderates the inverted U-shape links to the literature that investigates the importance of specialized experience for employee productivity and organizational performance (Argote, 1999; Jain & Mitchell, 2021; Schilling, Vidal, Ployhart, & Marangoni, 2003; Toh, 2014). By showing that working with familiar members or on similar projects helps reduce switching costs, we align with research that finds that familiarity and similarity are beneficial for performance, especially in teams and projects that have temporary arrangements (Boh, Slaughter, & Espinosa, 2007; Huckman, Staats, & Upton, 2009). From a practical perspective, engineers, academics, or surgeons might consider the findings from this study to find more effective ways to utilize their MPW.

2. THEORETICAL FRAMEWORK AND DEVELOPMENT OF HYPOTHESES

2.1 The Inverted U-Shaped Relationship between MPW and Project Performance

We draw the conceptual framework in Figure 1. Based on the trade-off between benefits and costs of MPW, we derive an inverted U-shape relationship between MPW and project performance (Hypothesis 1). We then propose three moderators of this relationship: specialized experience, project similarity, and employee familiarity (Hypotheses 2-4).

[Insert Figure 1 about here]

2.1.1 Benefits of MPW

MPW is deployed to increase employee worktime utilization and productivity (Milgrom & Roberts, 1992; O'Leary et al., 2011). While timely project completion is critical for firms in competitive markets (Crama, Sting, & Wu, 2019; Eisenhardt & Tabrizi, 1995; Nobeoka & Cusumano, 1997), project work is often characterized by alternating periods of activity and idleness. In other words, once a particular job is completed, employees might not immediately have a next assignment within the same project (e.g., "beach time," see Evans, Kunda, and Barley, 2004). When employees work on one project at a time, they cannot fill such gaps in their schedules, creating inefficiencies in their time utilization (Adler, Mandelbaum, Nguyen, & Schwerer, 1996; O'Leary et al., 2011). In contrast, MPW employees can avoid costly downtime by switching to parallel projects requiring their work inputs (Mortensen & Gardner, 2017). This back and forth switching between idle and active projects can potentially increase project completion rates.

MPW can also increase employee productivity as they deploy effective work practices that satisfy multiple project demands (Kc & Terwiesch, 2009; Milgrom & Roberts, 1992; Waller, Conte, Gibson, & Carpenter, 2001). For instance, R&D engineers might deploy automated queuing processes, surgeons can develop flexible priority schemes for multiple patients (e.g., red, green codes) (Kc & Terwiesch, 2009), while recruiters rely on virtual assistants for multitasking (Aral, Brynjolfsson, & Van Alstyne, 2012). Overall, MPW allows employees to efficiently utilize their time and increase their productivity which should be reflected in more timely project completion (Kc, 2014; Milgrom & Roberts, 1992).

However, such benefits from MPW might wear out and hit a “plateau.” When MPW is high, employees might be less able to optimally allocate their time to stay productive (Milgrom & Roberts, 1992; Wheelwright & Clark, 1992). Furthermore, studies show that in the context of knowledge-intensive work, employees can drop their productivity at higher workload levels (Boh et al., 2007; Jain & Mitchell, 2021). For instance, Kc and Terwiesch (2009) show that employees' productivity in hospitals eventually becomes unsustainable and drops off when the load is too high. We thus propose that the benefits of MPW eventually level off (i.e., follow a concave shape).

2.1.2 Switching Costs of MPW

MPW employees constantly deal with severe “attention residue”—thoughts about a previous task that persist and intrude while performing another (Leroy & Glomb, 2018). Attention residue interferes with information-processing capacity and cognitive skills (Simon, 1982), thereby reducing the effectiveness of a current project or task (Wylie & Allport, 2000) and decreasing productivity levels (Groysberg, Lee, & Nanda, 2008). Similarly, MPW employees need to exert mental and psychical effort to re-immerse themselves in another project context's tasks, people, roles, issues, and operations—also referred to as "cognitive setup" costs (Kc & Staats, 2012; Staats & Gino, 2012). This involves catching up on the work done in their absence (e.g., reviewing the updated project content to get up to speed), adjusting to different roles within the project, switching tasks (Boh et al., 2007), and being exposed to team contexts with new routines, symbols, jokes, and expectations (Mortensen & Gardner, 2017). For instance, academics often shift between method and writing tasks, software programmers alternate between programming languages (Boh et al., 2007; Kc & Staats, 2012), and surgeons switch from a routine check to emergency surgery. Similarly, employees might need time to relocate between physical or virtual team settings (e.g., move from one room or Zoom call to the next) or shift between team-specific tools and technologies (e.g., from one software to another). The effort needed to transition among multiple projects can further reduce project performance.

We propose that such MPW switching costs follow a convex shape. Attention switching costs become much more salient with a rise in MPW because employees can only store a few incomplete tasks in their memory. When new tasks or projects are added, they can experience sudden drops in attention. For example, Aral *et al.* (2012) find that switching costs increase dramatically with the number of parallel tasks. Other studies find that juggling different rooms, virtual settings, colleagues, agendas, and challenges on many projects can dramatically increase the adverse "reacquainting effect" (Staats & Gino, 2012). Employees might also face too many switches at a high level of MPW, leading to mental congestion and dramatically increasing error rates (Kc, 2014). Overall, switching costs increase at an increasing rate as more tasks are juggled simultaneously.

We combine the theoretical arguments of concave benefits and convex costs to derive an inverted U-shaped relationship between MPW and project performance.

Hypothesis (H1). *The relationship between employee-level MPW and project performance is curvilinear in the shape of an inverted U.*

2.2 The Moderating Role of the Specialized Experience

We propose that specialized[1] experience moderates the inverted U-shape relationship between MPW and project performance (Cui, Rajagopalan, & Ward, 2020; Staats & Gino, 2012). In line with the NPD project context, we conceptualize the specialized experience of an employee as the total experience cumulated within the project technological area prior to working on the current project (for a similar definition, see Jain & Mitchell, 2021; Toh, 2014). We argue that such specialized experience positively alters the MPW benefit curve[2]. First, the specialized experience should help MPW employees be more productive. The tenets of the division of labor postulate that specialization increases the productivity levels of workers in different contexts (Argote, 1999; Becker & Murphy, 1992; Milgrom & Roberts, 1992). While Adam Smith's famous pin factory example was the first illustration of these productivity gains (see A. Smith, 1776), multiple studies sustain this conclusion. Empirical research in management and economics finds that specialized experience is positively related to the quality of output for workers such as

[1]Specialization can be conceptualized in different ways. We conceptualize specialization with respect to a certain task or function (Becker & Murphy, 1992; Boh et al., 2007; Cui et al., 2020). Other research has also conceptualized specialization with respect to knowledge domains (Haeussler & Sauermann, 2020; Teodoridis, 2018; Teodoridis et al., 2019). While our context is different, MPW employees who might be specialized with respect to a function may utilize this capability across different projects and application areas and fields (i.e., potentially becoming more "generalists"). We address this point in the discussion section.
[2] It is possible for specialized experience to alter the switching costs as well and thank an anonymous reviewer for this point. It can be argued that more specialized experience can reduce switching costs as employees might experience smoother transitions between projects. While this is plausible, we do not formulate such hypothesis upfront.

sewing operators (Cui et al., 2020), loan application workers (Staats & Gino, 2012), and software programmers (Boh et al., 2007). MPW can be better suited for such specialized employees who can execute their work more effectively (Milgrom & Roberts, 1992, p. 409). For instance, MPW employees with higher specialized experience might not need to "reinvent the wheel" but rather utilize specialized best practices across multiple projects. Consider, senior product-development engineers who have extensive work experience in manufacturing systems. Their specialized experience allows quickly finding similar patterns in problems and bottlenecks within projects.

Second, specialized experience allows MPW employees to allocate their time more efficiently because they are likely better equipped to estimate the workload required for each task (Clark & Huckman, 2012). Specialized experience helps better understand the project's problems and requirements, which can help anticipate the amount of time needed to execute the work on each project and prioritize accordingly. More specialized employees can also signal better what they know and can do (as the "go-to" people), reducing idle time and optimizing other employees' worktime allocation. Overall, we argue that specialized experience allows MPW employees to get more done more quickly and with fewer resources (Milgrom & Roberts, 1992). Thus;

Hypothesis (H2). *The Employee Specialized Experience moderates the inverted U-shaped relationship between MPW and project performance so that the positive association of MPW with project performance is stronger.*

2.3 The Moderating Role of Project Similarity

The switching costs of MPW can be mitigated when employees switch between more similar projects (e.g., same customer segment or core technical process). We argue that project similarity decreases attention residue because knowledge can be directly relevant, and context can be retrieved from the previous, similar project. O'Leary et al. (2011, p. 468) note, "when one switches between three relatively similar teams, the diversity of information to be managed is reduced, and switching has far less of an effect on productivity than switching between three relatively different teams." For example, a software developer can rely on the same code from the previous project; an academic can use a similar theoretical framework or analytical method; a surgeon can utilize the same procedure across different operations, and an engineer can utilize the same tool. In addition, employees may need to exert less physical and mental effort when transitioning between similar contexts or, namely, have lower "cognitive setup" costs (Kc & Staats, 2012). For instance, employees can more easily transition between situations with similar routines and technical language (Mortensen & Gardner, 2017). Also, employees may need much less time to move between buildings and virtual rooms or be able to navigate reports and updates with less effort when they are already integrated into the project's area. We formulate the following hypothesis:

Hypothesis (H3). *Project similarity moderates the inverted U-shaped relationship between MPW and project performance so that the negative association of MPW with project performance is weaker.*

2.4 The Moderating Role of Employee Familiarity

Switching costs can also be mitigated when working with familiar employees (Akşin et al., 2021; Huckman et al., 2009). This familiarity is analogous to stable work teams in which team mental models help guide social interactions. Greater familiarity reduces attention residue as employees can utilize the knowledge from shared projects to solve problems (Skilton & Dooley, 2010). Familiarity alleviates the cognitive setup costs, as employees can use existing cognitive structures, social relationships, and predictability as an "anchor" for the current project (Huckman et al., 2009; Skilton & Dooley, 2010). For example, employees can more quickly establish and communicate "who knows and does what," which may facilitate setting up roles and routines in the new project (Reagans et al., 2005). Familiarity provides a better understanding of other employees' skills (Akşin et al., 2021), allowing work to be structured to accommodate the strengths and weaknesses of all project members (Boh et al., 2007). This helps in context switching because it provides access to other project members' knowledge of different technologies, location-specific details, or task processes. Thus;

Hypothesis (H4). *Employee familiarity moderates the inverted U-shaped relationship between MPW and project performance so that the negative effects of MPW on project performance are weaker.*

3. EMPIRICAL ANALYSIS

3.1 Empirical Setting and Organizational Context: NPD Projects

We utilized a novel longitudinal dataset that combines employee- and project-level information in the context of new product development (NPD) in a multinational organization. This dataset came from a world-leading hydraulic pump manufacturer with around 20,000 employees in more than 50 countries and a net turnover of more than USD 4 billion in 2016. The company provided us full access to longitudinal data contained in monthly project reports, human-resource records, and the project work registry. We contacted the company in 2016 and obtained 20 months of data on NPD projects (January 2015 to August 2016). Table A-1 describes the data-collection process. As with any secondary data, we observed the variables as they occurred. With these data, we aim to examine the role of MPW in project performance, and although our evidence is descriptive, we strived to generate a set of robust results and explore different alternative explanations.

3.2 Data Elements

3.2.1. Monthly Project Reports and Descriptions. We obtained 840 monthly reports on 42 projects over 20 months. These reports contained the project's name, type, characteristics, and target market. In addition, they included the names and responsibilities of each project member and details on the project hierarchy (e.g., manager). In these reports, the management team provided its best estimate for project timeliness every month. We also obtained an appendix to each project report containing more detailed textual project descriptions (we used to construct the specialized experience and project similarity moderators).

3.2.2. Human Resource Records. We gathered monthly employee data from the company's HR records, including information on employees' age, gender, job role, responsibilities, and location. In addition, we obtained a detailed job catalog describing the employees' job roles.

3.2.3. Company Work Registry. We matched the above data with the company's work registration system, including records for each employee on the number of hours allocated to each project. Employees were expected to log 90 to 95 percent of their working time, including absences, illnesses, and meetings.

3.3 Dataset Construction

Our unique proprietary dataset combines the employee- and project-level variables and is constructed at the employee-project-month level. The employee-project matched dataset contains 9,649 project-month-employee observations, corresponding to 42 projects and 580 employees. We do not observe a clear multilevel hierarchy, as employees do not neatly fall into the same sets of projects over time (Rabe-Hesketh & Skrondal, 2012). We illustrate in Figure 2 how employees' project portfolios might evolve monthly. Our dependent variable is measured at the highest level (project performance). When an employee is on two different projects in the same month, we aim to capture the between-project variability in project performance for that employee. When an employee is on the same project for two different months, we aim to capture the within-project variability in project performance for that project and employee.

[Insert Figure 2 here]

3.4 Variables

We describe the variables in Table 1 (please see the Online Appendix for details).

[Insert Table 1 about here]

3.4.1. Dependent Variable: Project Timeliness. In the NPD context, judgments of project performance are primarily based on timely completion and delivery to the market (Crama et al., 2019; Krishnan & Ulrich, 2001; Nobeoka & Cusumano, 1997). This is because assessing financial measures is highly uncertain before a product's launch. The company in our study is embedded in an innovative environment in which speed to market (timeliness) is the primary performance variable. To calculate project timeliness, we used project reports, which contained three timestamps (i.e., dates) of project advancement through the stage gates. The first report was from the beginning of the project and included the expected completion time for each gate (1-7). If there were changes in those estimates after one month, they were reflected in the second monthly report. We had access to project reports for 20 months, and we used future observations for the completion date (month = 20) and compared them with the projected timeliness. The combination of expected, continuously updated, and actual timeliness enabled us to meticulously trace performance developments and deviations from both original expectations and later estimates. We operationalized project timeliness as the difference between the most recent estimated completion date of the current gate and the gate's actual completion date (obtained from future project reports). We provide examples and illustrations in Figures A-1, A-2, and A-3.

3.4.2 Independent Variable: MPW. We observed a formal allocation structure that followed a top-down process (i.e., project managers allocated employees to projects) and did not involve the self-selection of projects (e.g., Gambardella et al., 2020). We followed the extant theoretical work and measured our MPW construct as the number of projects per employee (O'Leary et al., 2011). In our dataset, 58% of employees engaged in MPW and had, on average, 2.71 projects; the maximum was 12 projects.

3.4.3 Moderator: Employee Specialized Experience. In line with the NPD project context, we conceptualized the specialized experience of an employee as the total experience cumulated within the project technological area prior to working on the current project. This aligns with previous studies in a similar context that used the "technological area in R&D" as the base for computing specialized experience (Jain & Mitchell, 2021; Toh, 2014). The case company has helped us in obtaining this measure. While we do not have information on tasks or employee knowledge (i.e., proficiency), we know which type of project employees have worked on in the past. What emerges is that we can classify the projects in major areas based on information on the Program-Category combination.

Each of the projects belongs to one of the four categories: (1) Product Integration, (2) Line Extension, (3) Platform generation, and (4) Innovation and one of the seven programs: (1) Water Circulation, (2) Monitoring, (3) Domestic water, (4) Disinfection, (5) Multiple stages, (6) Single-stage and (7) Wastewater. We observed the full 20-month history of employee experience from project reports across all the projects. According to our operationalization, two projects that belong to the same Program-Category combination (e.g., Product Integration-Circulators) proxy for the same project area. Specifically, the more time the employees spend within the same Program-Category combination, the more specialized experience is accumulated for that employee. For each employee, we calculated the cumulative number of months (across all projects) they have spent working in the same Program-Category combination previously to the current month. We provide a histogram of our measure in Figure A-6.

3.4.4 Moderator: Project Similarity. We rely on a set of detailed project descriptions to construct the similarity metric. We discovered that projects belong to one of the three market segments: Building Services, HVAC, and Water Treatment. As described in the project files, projects belonging to the same market segment share similar characteristics, such as resources, demands, and expectations. We considered two projects similar if they belonged to the same market segment. The metric ranges theoretically from a minimum of $\frac{1}{Number\ of\ Projects}$ to a maximum 1 (in situations where an employee works only on similar projects). Empirically, we observe a minimum of 0.26 to a maximum of 1 (see Figures A-7 and A-8).

*3.4.5 Moderator: Employee Familiarity***.** We operationalized familiarity for each employee as the number of familiar project members within the focal project. We classified an employee as familiar if they were currently working or had previously worked with the focal employee. We counted the number of such monthly situations for each employee. We present illustrations in Figures A-9 and A-10.

4. PRELIMINARY EMPIRICAL CONSIDERATIONS

4.1 Selection issues in MPW

This section discusses the potential selection issues that underlie the empirical analysis in Section 5. First, several studies highlight the self-selection issues in project work. For instance, Kc *et al.* (2020) highlight that employees select easier tasks when they can, and Chatain and Meyer-Doyle (2017) show that lawyers select the most incentive-compatible cases. However, such issues might not be a concern in our setting (Aghion, Dewatripont, & Stein, 2008; Gambardella et al., 2020). In our case company, the division and allocation of labor is a centralized process in which managers assign projects to employees. This limits the self-selection issues.

Second, top-down allocations might be strategic and adaptable. For example, a manager might follow a heuristic of allocating a proper employee to a vacant position based on project demand (also see Raveendran, Puranam, & Warglien, 2021). As we do not observe the managerial decision-making process, we cannot know how and why the allocations have occurred. The question is directly related to how the division of labor occurs in organizations (Becker & Murphy, 1992), an important topic that has not attracted much empirical work due to lack of access or data (Haeussler & Sauermann, 2020; Owen-Smith, 2001; Raveendran, Puranam, & Warglien, 2016). We note that an ideal approach would be to run a controlled experiment in which one could manipulate MPW and hold everything else equal. With the lack of experimental data in our study, we can only remain agnostic as to why a decision-maker (e.g., a manager) allocates employees to multiple simultaneous projects across time. This is in line with recent studies that posed similar research questions (Haeussler and Sauermann, 2020; Jain and Mitchell, 2021; Staats and Gino, 2012).

Third, while we cannot rule out endogeneity in MPW allocation[3], we attempted to alleviate some of these concerns. One argument might be that managers might assign more workers to MPW based on project performance, underlying a possible feedback loop between performance and workforce allocation. In Section 5.3, we tested the conjecture with a simple empirical test and did not find support for this, although we cannot entirely rule this out without

[3] We are grateful to an anonymous reviewer for highlighting this point.

a controlled experiment. In addition, previous research shows that allocation can depend on the size of the team, project, firm, or even industry (see, e.g., Haeussler & Sauermann, 2020). We also observed a small correlation between size variables and MPW. We thus controlled for project size and management team size in our main model, thus alleviating some of these concerns. Finally, in the next section, we explore the potential employee-level characteristics that can be related to MPW. While we strive to limit endogeneity concerns, our overall evidence should not be invested with a causal interpretation and should be considered descriptive (Bettis, Gambardella, Helfat, & Mitchell, 2014; Goldfarb & King, 2016).

4.2 Employee-level characteristics and MPW

As described in Section 3.2., we observed several employee-level descriptors. From the main HR file, we observed each employee's age and gender. We also had access to information regarding each employee's company experience (in years) and location. From the detailed job-description file, we observed whether each employee had a senior role (e.g., senior product developer), managerial responsibilities (e.g., project manager), or belonged to the project's leadership (e.g., project leader). From the project reports, we observed when each employee had formal project responsibilities in the project cycle.

We present descriptive bar charts in Figures A-11 and A-12. We also ran a regression model in which MPW acts as a dependent variable explained by the employee characteristics described above, along with employee-fixed effects and two-way clustered standard errors on project and employee-level. The results of this regression are reported in Table A-2. For descriptive charts, to ease the graphical representation, we split employee age into three categories based on three even percentile bins (bottom 33.33%, middle 33.33%, and top 33.33%) (Panel A). We kept age continuous in the regression analysis. Graphically, we observed that

MPW decreases with employee age, a pattern confirmed in the regression analysis (-.267, p = .040). Notably, MPW did not seem to vary with employee gender (Panel B). Next, to ease the graphical representation, we split company experience into three categories based on three even percentile bins (bottom 33.33%, middle 33.33%, and top 33.33%) (Panel C). We kept company experience continuous in the regression analysis. Previous research posits that company experience may be positively associated with MPW (Cummings & Haas, 2012). More company experience allows employees to develop firm-specific knowledge and skills that can be valuable for MPW. However, we did not find a meaningful association between company experience and MPW (-.149, p = .203). For employee location, we know whether the employee worked at the headquarters in Europe or in the Asian subsidiary. We inferred from previous papers that the employees who work at the headquarters might have lower switching costs, as they have more access to project information and can more easily navigate complex situations (i.e., physical proximity to decision-making) (Cummings & Haas, 2012). Thus, we expected the employees in headquarters to have a higher MPW, which we observed in Panel D and our regression analysis (.376, p = .074).

In Panels E-H, we checked for allocation patterns concerning employees' job roles. Managerial responsibilities and seniority are deduced directly from the job title if it contains the word "manager" (e.g., project manager) or "senior" (e.g., senior product developer). In addition, the company flags specific roles as "leadership" (project leader, chief project engineer, or project supervisor). Employees in senior roles might have more significant expertise and more domain-specific knowledge. Thus, they may be able to work across various projects simultaneously without necessarily experiencing the drawback of switching costs. However, seniority might also be associated with several limitations related to domain entrenchment (see Dane, 2010).

Graphically, MPW seems lower for more senior employees (Panel E). However, this pattern is not confirmed by the regression analysis (.002, p = .988). We also do not find this pattern for managers (-.507, p = .324). In turn, we observed patterns for leadership-related job roles in both Panel F and the regression analysis (1.016, p = .015). As project leaders are a valuable and scarce resource in the organization, they are asked to take on administrative duties, such as coordinating resources, guiding other employees, and regulating the work tasks (Cummings & Haas, 2012). Thus, they need to serve on more projects at once. Finally, the project reports contain information about each member being held formally responsible for different project phases. This dummy variable takes a value of 1 if the employee was formally responsible for the project phase and 0 otherwise. For instance, R&D roles were responsible for the conceptual work in the early stages of the project (gates 1-3). The manufacturing function was responsible for the production phase (gates 4-5), and marketing and sales experts were responsible for the final stages (gates 6-7). As such formal project responsibility induces greater cognitive effort (Leroy & Glomb, 2018), we expected employees formally responsible for the project phase to have a lower MPW. This is confirmed in Panel H but not in regression analysis (-.037, p = .849).

4.3 Control Variables for the main model

We included several project-level variables that control for omitted variable bias, and our results do not change with their exclusion (see Models M1- M5 in Table 2). We present the histograms of the control variables in Figure A-13. We included (1) project size, measured at the project level as the number of employees per project, and (2) management team size, measured at the project level as the number of managers on the project. Our projects vary in size (see Table 1), and it might be that project size effects explain certain projects' performance because larger projects might have more human capital deployed to them (Giustiziero, 2021). In addition, larger groups have broader areas of expertise and might be more able to solve problems (e.g., Wiersema & Bantel, 1992). Next, we included (3) project innovation level, which is a dummy variable (1 for high innovation and 0 otherwise). This controls for the fact that innovative projects might face more difficulties in product development due to unpredictability (Nobeoka & Cusumano, 1997) and, thus, might underperform. We next inserted a dummy for (4) the type of project (platform versus product) to control for heterogeneous project characteristics and resource demands (Krishnan & Ulrich, 2001). Developing a platform is much broader in scope and requires deeper integration into the business or customer infrastructure. There might also be hidden, unobserved costs that go into platform generation (versus product generation). The (5) global breadth helped mitigate the omitted variables due to the multi-location of project teams. More global projects are likely to have greater access to rich human capital (Cummings & Haas, 2012) and generally have more complex processes. Finally, the (6) number of colleagues is operationalized at the employee level as the sum of all non-overlapping employees that the focal employee works with across all projects in a given month. For instance, if an employee works on two projects in a month, with each containing twenty non-overlapping members (apart from the focal employee), the number of colleagues will be equal to 40 for that employee. This variable is different from project size, which is measured at the project level and represents the number of employees per project. Given that employees work on multiple projects simultaneously, the number of colleagues, measured at the employee level, captures the total exposure of the focal employee to all other employees in all simultaneous projects in a given month. In this way, the number of colleagues measure alleviated the omitted variables of interaction fatigue (e.g., multiple social contexts) and cognitive overload of the focal employee (e.g., adjusting to diverse forms of interaction).

5. MAIN MODEL

We tested the following model:

$$ProjectTimeliness_{ipm} = \alpha_0 + \alpha_i + \alpha_m + \alpha_1 MPW_{ipm} + \alpha_2 MPW^2_{ipm} + \alpha_3 MPW_{ipm} * Spec_{ipm} + \alpha_4 MPW_{ipm} * Sim_{ipm} + \alpha_5 MPW_{ipm} * Fam_{ipm} + \alpha_6 MPW^2_{ipm} * Spec_{ipm} + \alpha_7 MPW^2_{ipm} * Sim_{ipm} + \alpha_8 MPW^2_{ipm} * Fam_{ipm} + \tilde{\alpha}\ \mathrm{CTRL} + \varepsilon_1, \qquad (1)$$

where for each employee i, project p, and month m, $ProjectTimeliness$ is project performance, MPW is multi-project work, MPW^2 is the squared term of multi-project work, Spec is the employee specialized experience, Sim is project similarity, Fam is employee familiarity, and CTRL vector includes our control variables (described in Table 1). α_i are employee fixed effects that give each employee a different intercept and α_m are month fixed effects.

The model is estimated with the *reghdfe* Stata package that implements the computationally efficient estimator (Correia, 2017). The errors, $\epsilon 1$, are two-way clustered separately at the project and employee-level[4] (Abadie, Athey, Imbens, & Wooldridge, 2017). Employees have elements that do not change over time and across projects. Similarly, all employees on the same projects have some shared elements. Thus, controlling for clustering helped mitigate the violation of the independence of observations condition (which cannot be avoided entirely unless we use a cross-firm experiment in which contamination is not a concern).[5]

5.1 The Inverted U-shaped Relationship between MPW and Project Performance (H1)

[4] We also run a host of model specifications in which we cluster the standard errors only at the employee-level, only at the project-level and at the interaction of project and employee. We also run a model with three-way clustered errors at the project, employee and month levels separately. We find consistent results.
[5] We thank the anonymous reviewer for guidance on this issue.

Table 2 reports the main results (for the correlation matrix, see Table A-3). In our baseline model (M1), besides MPW and MPW^2, we included the three moderators and employee fixed effects. In M2, we added the two-way clustered standard errors, and then in M3, we included the month fixed effects. In M4, we added the control variables (without two-way clustered standard errors), and in M5, we further added the two-way clustered standard errors (along with the control variables). Our main model included control variables, employee fixed effects, month fixed effects, and two-way clustered standard errors (separately at the project and employee levels).

[Insert Table 2 about here]

We followed the steps outlined in Haans, Pieters, and He (2016) to test our hypotheses. We observed that the relationship is supported graphically in Figure 2 in both the model-free raw data and in the model-estimated relationships. We followed the procedure in Lind and Mehlum (2010) to formally test the evidence for the inverted U-shape. First, for all of the model specifications, we observed a positive α_1 (the coefficient for MPW) and a negative α_2 (the coefficient for MPW^2). For the main model, the estimated coefficient of MPW is 38.29 ($p = .002$) and the estimated coefficient of MPW^2 is -3.71 ($p = .000$). Second, we verified whether the slope is sufficiently steep at both ends of the data range by testing the joint significance of the direct and squared terms of MPW with the Sasabuchi (1980) test (using the *utest* command in STATA). We could reject the null hypothesis of a monotone, U-shaped relationship in favor of the alternative hypothesis of an inverse U-shaped relationship ($p = .002$) (see Table A-4). We then used the *binstest* command from the *binsreg* package (Cattaneo, Crump, Farrell, & Feng, 2021a, 2021b). The tests showed that the shape is not linear, not monotonic, and concave on the right-hand side. Third, we found that the turning point (5.16) falls within the data range for MPW [1,12] with Fieller's (1954) confidence interval [3.57; 6.19]. In a robustness test, we found that the cubic term did not improve the model fit with respect to the original specification, which rules out an S-shaped relationship. When we split the data based on the empirically determined turning point (5.16), we found that the regression on the subsample with MPW values below the turning point shows a positive coefficient for MPW. In contrast, the regression on the subsample above the turning point showed a negative coefficient, albeit with a high p-value (p=.965). Although all these tests provided further confirmation of the inverted U-shape, the latter result implies that the shape might be less pronounced above the turning point.

5.2 Moderators of the Inverted U-Shape

We computed the marginal effect plots from the effects derived in Table 2 and present them in Figures 3b, 3d, and 3e. To compute the margins, we took the high and low levels of each moderator by subtracting (adding) one standard deviation from the mean value for the low (high) value. In Figures 3a, 3c and 3e, we also present the conditional (on control variables) binned scatterplots with the *binsreg* command in STATA (Cattaneo et al., 2021a, 2021b; Starr & Goldfarb, 2020). To show these effects graphically in *binsreg*, we performed a median split on the three moderators. We also show the unconditional scatterplots in Figure A-14.

[Insert Figure 3]

To formally test Hypotheses 2, 3, and 4, we tested the slope of the coefficients $\alpha_6, \alpha_7,$ and α_8 (curvature change). First, the coefficient of the interaction term between MPW^2 and specialized experience is positive (.14, p = .026). Figures 3a and 3b illustrate this relationship. In line with our theory, we can infer that the benefits of MPW are higher for employees with more specialized experience, which provides supporting evidence for Hypothesis 2. We also observed that at high levels of MPW, high (vs. low) employee specialized experience also slightly flattens the inverted U-shape. This provides a hint that specialized experience might also reduce switching costs. We discuss this in section 6.2.

Second, the coefficient of the interaction term between MPW^2 and project similarity is positive (2.58, $p = .086$). Figures 3c and 3d suggest that high (low) project similarity corresponds to higher (lower) performance at high levels of MPW. This indicates that the switching costs of MPW are lower when project similarity is high, which provides supporting evidence for Hypothesis 3. We also observed that at high levels of MPW, high (vs. low) project similarity flattens the inverted U-shape (and even seems to switch direction, especially in the raw data in Figure 3c).

Third, the coefficient of the interaction term between MPW^2 and employee familiarity is positive (.13, $p = .005$). In Figure 3e, we can see that high (low) employee familiarity corresponds to higher (lower) performance at high levels of MPW. However, we also note that in Figure 3f, the relationship is less pronounced at lower and medium levels of MPW but is more pronounced when MPW reaches values of 11 and 12. All in all, we have mixed evidence for Hypothesis 4.

5.3 Robustness Analysis

We followed the recommendations in Goldfarb and Yan (2021) and present the roadmap of our robustness and alternative explanations in Tables A-5 and A-9. In total, we used 11 different robustness checks (Model M1-M11). Briefly, in models M1-M5, we tested the alternative model specifications presented in Table 2. Next, we tested whether some control variables could be considered alternative moderators (M6-M8), but we did not find evidence for this. We tested the alternative dependent variables of project quality and turnover (M9-M10). The estimated project turnover is the total amount (in local currency) of expected project sales after project completion in the first year of full operation. Project quality is proxied through warranty rate, which captures the expected percentage of warranty claims to total turnover. Typically, a warranty claim is a claim by a customer for a product under warranty which can entail a replacement. Both measures are mere estimates of the product's or platform's real performance. This is because we deal with "work in progress" projects that are yet unfinished. We found some evidence indicating that MPW is related to these dependent variables.

Finally, we then collapsed the data at the project-month level in model M11, which resulted in an unbalanced panel of 420 project-month observations. We found confirmation of our main results.

5.4 Alternative Explanations

We advanced several alternative explanations of our findings (e.g., Birhanu et al., 2015; Bresnahan et al., 2002). We provided the details in Table A-9 in the Online Appendix. The first conjecture is that managers might allocate employees to MPW based on project performance. We, therefore, computed the median split on project performance and then compared the levels of MPW above (2.77) and below the median (2.71), finding no statistically meaningful difference. This conclusion mitigates—to some extent—the reverse causality in our main model (Lyngsie & Foss, 2017). This was confirmed in company communication expressing a manager's reluctance to dramatically modify project composition after launch. Second, given that we found that employee age, location, and leadership role are, to some extent, related to MPW, we also investigated whether they play a role in how MPW is associated with project performance. While we do not have an *a priori* theory for why this might be the case, we speculated that employee age and leadership role might alter the benefits of MPW. We found that none of these factors seem to matter as additional moderators (see Table A-10).

Third, a part of our theoretical framework builds upon the switching costs of MPW. It is possible that including a direct metric of switching costs alters the effects of MPW on project performance. Leroy and Glomb (2018) note that many switches drain employee attention and are negatively associated with their performance. For instance, studies show that employees such as nurses or software developers face focus shifts as frequently as every 3 to 10 minutes (Leroy & Glomb, 2018; O'Leary et al., 2011). While switching costs can comprise several factors that would require survey-based data collection (e.g., the amount of attention residue, the time to transition between tasks), one possible way to capture switching costs is by counting the number of project switches. We tested two such measures (illustrated in Figure A-17). The first measure assumes that a switch occurs when an employee adds a new project with respect to the previous month. We counted the total number of such occurrences. The second measure counted the number of switches to entirely new projects (i.e., with respect to the employee's full project history). Given that switches can dampen performance, we first included them as additional control variables in our main model and found that their inclusion did not alter our main effects of MPW (see Table A-11). We also found that these measures did not moderate the effects of MPW on project performance. Finally, we tested the effect of MPW on these switches. If managers need to rebalance project composition on a regular basis, there might be a positive association between MPW and switches (especially new switches). However, we found no confirmation for these conjectures (see Table A-12). It might be that the number of switches simply does not account for the whole spectrum of switching costs. The factors considered in our main analysis (e.g., project similarity) seemed to be more relevant.

Fourth, given that the company cannot afford to have excess idle resources while still on the payroll, it might try to increase employee working hours to increase project performance.

Working hours could explain employee fatigue and stress, which dampen performance. However, we found no evidence that MPW is meaningfully related to working hours (Table A-13).

Finally, we assessed whether project time allocation altered the results (Cummings & Haas, 2012; Mortensen & Haas, 2018). We collapsed the data at the employee-month level to average the project performance and other project-level variables for each employee who worked on multiple projects in the same month. This reduced the dataset to 5,691 employee-month observations. Next, we estimated a multiple-membership model, which used project time allocation as weights in the regression estimation. As shown in Table A-14, we found that weighting by project time allocation did not alter our main findings.

6. DISCUSSION

This study advances the understanding of how employees' MPW is related to project performance in the NPD context in a multinational organization. We find that the relationship between MPW and project performance follows an inverted U-shape and is moderated by employees' specialized experience, project similarity, and employee familiarity. The model results are robust to a host of specifications, assumptions, and alternative explanations. We discuss the results in detail below.

6.1 H1: The inverted U-shape relationship between MPW and project performance

Figure 1a suggests the inverted U-shape relationship between MPW and project performance. MPW helps increase employee worktime utilization and productivity (Milgrom & Roberts, 1992; O'Leary et al., 2011). Nonetheless, MPW also carries switching costs due to attention residue and cognitive setup (Kc & Staats, 2012; Leroy & Glomb, 2018). These arguments give rise to a hypothesis on the inverted U-shaped relationship between MPW and project performance, which we tested in a dataset of 9,649 project-month-employee observations. We found support for the inverted U-shape in both model-free analysis (see Figure 2b) and regression models. This finding aligns with recent studies highlighting the importance of flexible human resource practices, such as project autonomy, side hustles, or smart working, in knowledge-intensive collaborative work (Choudhury et al., 2021; Gambardella et al., 2020; Jain & Mitchell, 2021). We also link to increasingly growing research that unveils nonlinear relationships between human resource practices and performance (Cui et al., 2020; Gambardella et al., 2020; Staats & Gino, 2012). In essence, we shed light to the idea that MPW employees such as development engineers, industrial designers, academics, or surgeons, might have a theoretical limit at which MPW can be harmful to project performance.

6.2 H2-H4: The contingent role of employee's specialized experience, project similarity, and employee familiarity

Specialized experience increases the benefits of MPW. These empirical results are presented in Figures 3a and 3b. When an employee's specialized experience is high (low), the relationship between MPW and project performance is more positive (negative). Extensive specialized experience might help employees perform their tasks better, optimize their time allocation, and develop effective work practices (Boh et al., 2007; Cui et al., 2020; Fahrenkopf et al., 2020). In addition, the specialized experience should allow MPW employees to get more done more quickly and with fewer resources, as implied three decades ago by Milgrom and Roberts (1992, p. 409). While we do not formulate a prediction regarding how specialized experience is related to switching costs, we empirically observed that at high levels of MPW, high employee specialized experience also slightly flattens the inverted U-shape. This provides a hint that specialized experience might also reduce switching costs. Indeed, research in economics seem to argue that by increasing the level of specialization, individuals can minimize switching costs (see, e.g., Edwards & Starr, 1987). For instance, employees might experience smoother transitions between projects and thus have lower attention residue and cognitive setup costs. Another possibility is that specialized experience means that employees might not need to learn all the tasks in each project but rather focus on a reduced number of tasks pertinent to their specialization. These conjectures can provide fruitful research opportunities. Overall, our findings link to the literature that investigates the importance of specialized experience for employee productivity and organizational performance (Argote, 1999; Jain & Mitchell, 2021; Schilling et al., 2003; Toh, 2014).

A relevant point is related to how specialization can be conceptualized and measured. We have conceptualized specialized experience as cumulated experience within a certain project technological area, thus aligning with the literature on task or functional specialization (Becker & Murphy, 1992; Boh et al., 2007; Cui et al., 2020). It might be worth considering whether the specialized experience of MPW employees can also be conceptualized with respect to knowledge domains (Haeussler & Sauermann, 2020; Teodoridis, 2018; Teodoridis, Bikard, & Vakili, 2019). It is possible that MPW employees can be considered specialists with respect to one aspect (e.g., task or a job role) and generalists to another (e.g., applying the task across knowledge domains). We note that, to date, the discussion on task/functional specialization and knowledge domain specialization is found in two separate literature streams. We can only speculate that MPW can potentially offer a unique setting that allows to study both specialization types. Possibly connecting and contrasting these different aspects of specialization in MPW can offer a fruitful research opportunity. For instance, studies can investigate whether engaging in MPW can lead employees to be specialists with respect to a task (e.g., using a specialized tool or applying a modeling framework) a knowledge domain (e.g., large technological area or scientific subfield) or even both (adapting the tool to each technological area, tweaking the model for the requirements of that subfield). Another potential avenue for research consists in investigating whether specialized experience can be solely dependent on the size of the project (Giustiziero, 2021; Haeussler & Sauermann, 2020) or market (Stigler, 1951) or it could be extended beyond such considerations (Becker & Murphy, 1992). In our empirical analysis, we found a positive correlation between specialized experience and MPW (.38). It is possible that MPW employees might develop specialized experience over time also in smaller projects or teams. While this conjecture seems intuitive, the issue has not been thoroughly investigated in the extant literature. We believe experimental data would help explore these suppositions (as in Fahrenkopf et al., 2020).

Turning to contingencies on the switching costs, Figures 1c and 1d suggest that project similarity and employee familiarity can help reduce switching costs. We show the model results in Figures 3d and 3f. MPW employees who work on similar projects may need much less physical time to move between buildings or rooms and can utilize the same project canvas or similar tools. Similarly, working with familiar employees might reduce the cognitive setup costs, as employees rely on already established relationships. This is reflected in a quote by one of the employees from the focal firm that describes the practical benefit of familiarity for achieving collaboration effectiveness: "As we knew each other well and were used to working together on other projects, a weekly meeting was enough to present results and make decisions about the ongoing process." A large body of research has counterposed the benefits of familiarity/ similarity and diversity (Akşin et al., 2021; Huckman & Staats, 2011; Huckman et al., 2009).

Given that MPW might also be observed in contexts in which employees have temporary work arrangements, our findings also align with research that finds familiarity to be beneficial for performance in teams and projects that have a more “fluid” composition (Boh et al., 2007; Huckman et al., 2009). However, several studies pinpoint that diversity can enable a broader exposure to knowledge and innovative ideas (Staats & Gino, 2012). Interestingly, a recent study by Akşin *et al.* (2021) finds that familiarity is good (bad) for less (more) standardized tasks. MPW is often deployed in knowledge-intensive settings in which tasks are more complex. Thus, a fruitful investigation would be to study how performing different tasks in MPW is interrelated with employee familiarity and project similarity.

6.3 Limitations and future research directions

The study has three main limitations. First, our results should not be vested with causality. The data patterns observed in our secondary data rely on assumptions and only unveil the relationships as they have occurred. One of the main endogeneity issues pertains to the managerial decision process that goes into allocating employees to projects. We make several attempts to limit such concerns by discussing the selection issues, linking employee-level characteristics to MPW, and testing alternative explanations. However, we call for a future experiment that manipulates the MPW of project workers. We anticipate that a key difficulty in such an experiment would be to hold all else equal, given that if an employee were to be “treated” with another project, it also would affect the employee’s time allocation to other projects as well as the MPW of other workers. This is known as the violation of the “stable unit treatment value assumption” (SUTVA) conditions (Rubin, 1974, 2005). A possible solution may be to observe a supply-side shock (e.g., a change in employee working hours due to new government regulation).

Second, our data come from a single large company in the context of NPD. While our findings might apply to similar settings such as creative work (e.g., academic or innovators) or software development, we cannot claim the generalizability of our findings across all industries. Therefore, we call for future firm-level studies to explore how MPW is related to performance in other settings. Finally, we note that the link between MPW and project performance can also go through employee-level performance. Previous studies have relied on questionnaires or team-leader assessments (e.g., Cummings & Haas, 2012), which are challenging to measure longitudinally. We attempted to decompose performance into individual-level measures (e.g., weighting by time allocation), and theoretically, we can speculate that our conclusions hold for employee-level performance. We look forward to future research that collects both performance levels across time within the same study.

Overall, this study was aimed at shedding light on the performance consequences of the phenomenon of MPW. We hope that illustrating the inverted U-shaped relationship between MPW and project performance can spur further research on whether and under which conditions MPW can be most effective.

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Table 1: Variable Description and Summary Statistics

Variable	Description	Role	Source	Mean	Std.	Min	Max
Project Performance	Project *timelines*: the difference between the most recent estimated completion date of the current (or updated) gate and the gate's actual completion date.	**Dependent variable**	Project reports	-125.2	146.4	-823	153
Multi-project Work	The number of simultaneous projects for the focal employee each month.	**Independent variable**	Project reports	2.714	2.000	1	12
Specialized Experience	The cumulative number of months (across all projects) that an employee has spent working in the same Program-Category combination previously to the current month.	**Moderating variable**	Project reports	10.55	12.78	1	85
Project Similarity	The ratio of similar projects to the total number of projects for each employee/month. Two projects are considered similar if they belong to the same market segment (Commercial and Domestic Building Services, HVAC OEM and Industry, and Water Treatment).	**Moderating variable**	Detailed project description and project reports	0.802	0.261	0.250	1
Employee Familiarity	The number of familiar project members with which the employee currently works or has worked in the past.	**Moderating variable**	Project reports	10.26	13.20	0	45
Project Size	The number of employees per project.	**Control variable**	Project reports and HR records	38.11	20.51	1	79
Management Team Size	The number of managers per project.	**Control variable**	Project reports and HR records	9.058	1.184	4	15
Number of Colleagues	The number of colleagues per employee.	**Control variable**	Project reports and HR records	39.42	22.36	0	122
Global Breath	Categorical variable that takes a value of 0 if the project is "low" on global breadth, a value of 1 if the project is "low-medium," 2 if "medium," 3 if "medium-high," 4 if "high," and 5 if "very high." This is based on the company's classification.	**Control variable**	Project reports	2.292	1.292	0	5
Project Categorization	Categorical variable that takes a value of 0 if the project belongs to the "platform" creation and a value of 1 if the project belongs to "product" creation. This is based on the company's classification.	**Control variable**	Project reports	0.449	0.497	0	1
Project Innovation	Categorical variable that takes a value of 0 if the project is "low" on innovation and 1 if the project is "high" on innovation. This is based on the company's classification.	**Control variable**	Project reports	0.702	0.457	0	1

Table 2: Model Results

	M1: Baseline		M2		M3		M4		M5		Main Model	
Multi-project Work (MPW)	36.37	(12.41)	36.37	(29.41)	29.54	(20.84)	42.67	(11.12)	42.67	(18.16)	38.29	(10.93)
Multi-project Work Squared (MPW^2)	-4.76	(1.29)	-4.76	(3.15)	-3.43	(2.03)	-4.68	(1.15)	-4.68	(1.75)	-3.71	(.84)
Specialized Experience	7.96	(.56)	7.96	(3.12)	6.21	(2.93)	11.24	(.52)	11.24	(2.14)	9.78	(1.74)
Project Similarity	3.23	(27.52)	3.23	(58.35)	10.35	(42.50)	11.42	(24.58)	11.42	(33.76)	21.65	(23.09)
Employee Familiarity	3.98	(.77)	3.98	(2.55)	3.92	(1.93)	1.83	(.70)	1.83	(1.55)	2.03	(1.42)
MPW * Specialized Experience	-1.62	(.27)	-1.62	(.97)	-1.13	(.98)	-2.44	(.25)	-2.44	(.66)	-2.07	(.62)
MPW * Project Similarity	-31.67	(15.25)	-31.67	(41.13)	-29.31	(29.89)	-19.54	(13.64)	-19.54	(16.82)	-19.80	(9.82)
MPW * Employee Familiarity	-1.11	(.34)	-1.11	(1.12)	-.85	(.82)	-1.62	(.30)	-1.62	(.87)	-1.48	(.59)
MPW^2 * Specialized Experience	.11	(.03)	.11	(.07)	.08	(.08)	.16	(.03)	.16	(.06)	.14	(.06)
MPW^2 * Project Similarity	4.91	(1.96)	4.91	(5.77)	3.29	(4.55)	3.73	(1.76)	3.73	(2.00)	2.58	(1.43)
MPW^2 * Employee Familiarity	.13	(.03)	.13	(.09)	.10	(.06)	.15	(.03)	.15	(.07)	.13	(.04)
Project Size							1.03	(.13)	1.03	(.90)	1.03	(.86)
Management Team Size							8.05	(1.41)	8.05	(12.89)	6.30	(12.51)
Number of Colleagues							.15	(.09)	.15	(.28)	.11	(.27)
Global Breath=1							-36.80	(18.18)	-36.80	(35.37)	-8.90	(35.11)
Global Breath=2							-165.17	(17.39)	-165.17	(44.35)	-136.47	(42.09)
Global Breath=3							-67.46	(18.57)	-67.46	(58.03)	-38.35	(52.14)
Global Breath=4							-84.57	(18.93)	-84.57	(39.86)	-49.53	(37.58)
Global Breath=5							-210.58	(18.71)	-210.58	(51.84)	-187.39	(45.91)
Project Categorization							-70.71	(4.64)	-70.71	(38.04)	-69.90	(38.09)
Project Innovation							-38.19	(5.70)	-38.19	(41.91)	-35.52	(41.13)
Constant	-211.04	(26.46)	-211.04	(67.88)	-203.87	(54.76)	-179.60	(30.86)	-179.60	(107.58)	-189.34	(107.27)
Employee Fixed Effects	YES		YES		YES		YES		YES		YES	
Month Fixed Effects	NO		NO		YES		NO		NO		YES	
Two-way Clustered Standard Errors (Project and Employee level)	NO		YES		YES		NO		YES		YES	

Note: Standard errors are in parentheses

Figure 1: Conceptual Framework

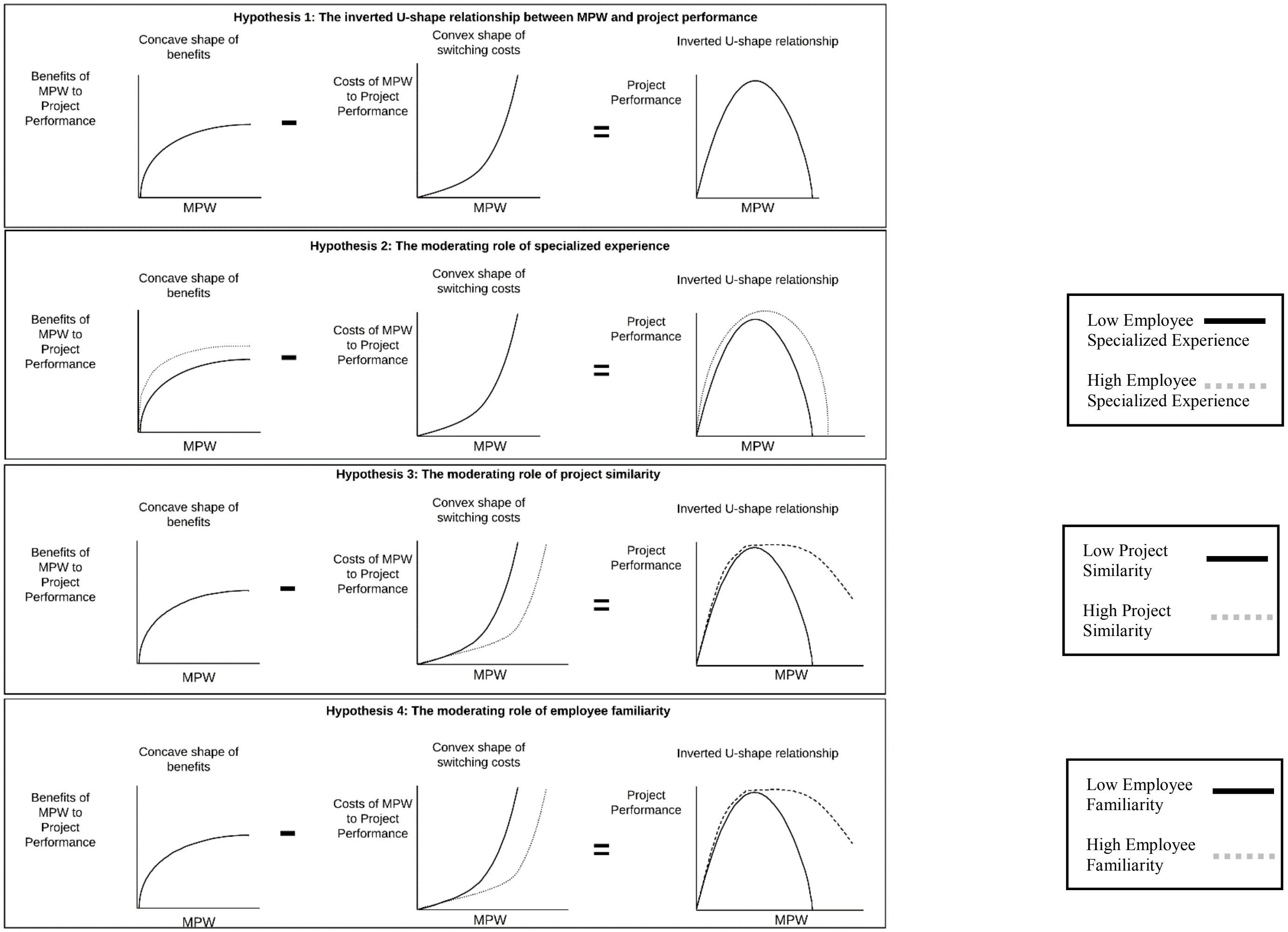
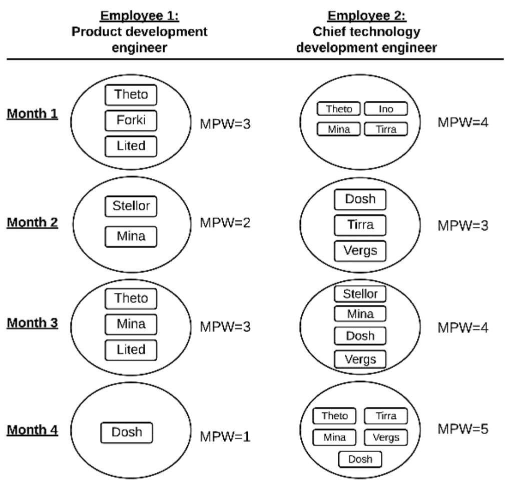


Figure 2: MPW

a. MPW Illustration



b. Data Illustration

ID	Employees	Project	Month	MPW	Project Performance
I1P1	Employee 1 (i1)	Project 1 (p1)	Month 1 (m1)	$MPW_{(i1p1m1)}$	$Perf_{(i1p1m1)}$
I1P2	Employee 1 (i1)	Project 2 (p2)	Month 1 (m1)	$MPW_{(i1p2m1)}$	$Perf_{(i1p2m1)}$
I1P1	Employee 1 (i1)	Project 1 (p1)	Month 2 (m1)	$MPW_{(i1p1m2)}$	$Perf_{(i1p1m2)}$
I1P4	Employee 1 (i1)	Project 4 (p4)	Month 2 (m2)	$MPW_{(i1p4m2)}$	$Perf_{(i1p4m2)}$
I2P1	Employee 2 (i2)	Project 1 (p1)	Month 1 (m1)	$MPW_{(i2p1m1)}$	$Perf_{(i2p1m1)}$
I2P3	Employee 2 (i2)	Project 3 (p3)	Month 1 (m1)	$MPW_{(i2p3m1)}$	$Perf_{(i2p3m1)}$
I2P1	Employee 2 (i2)	Project 1 (p1)	Month 2 (m1)	$MPW_{(i2p1m2)}$	$Perf_{(i2p1m2)}$
I2P3	Employee 2 (i2)	Project 3 (p3)	Month 2 (m1)	$MPW_{(i1p3m2)}$	$Perf_{(i2p3m2)}$

Note: When Employee 1 (i1) and Employee 2(i2) are on different sets of projects, they have different project-performance values. For instance, Employee 1 (i1) is on projects (p1) and (p2) in the month (m1), while Employee 2 (i2) is on p1 and p3 in m1. When an employee is on two different projects in the same month, we aim to capture the between-project variability in project performance for that employee. When an employee is on the same project for two different months, we aim to capture the within-project variability in project performance for that project and employee.

c. Binned Scatterplot of the Raw Data

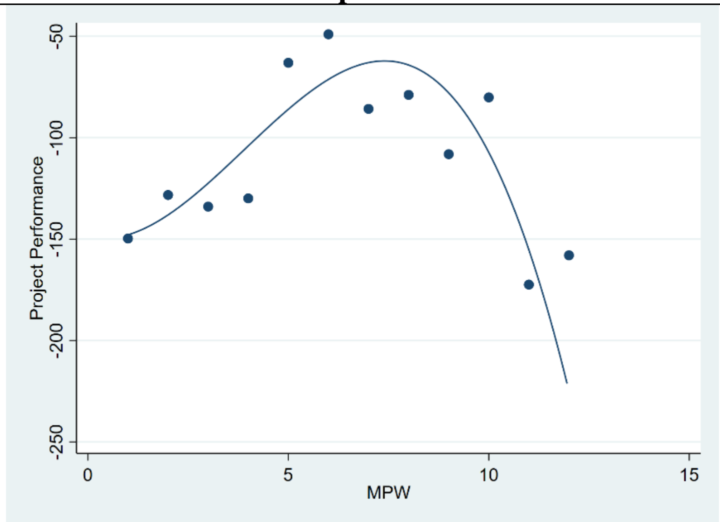
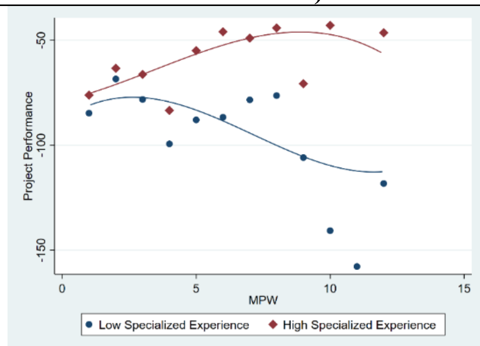
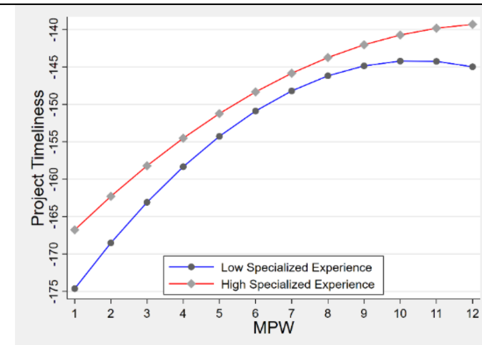


Figure 3: Moderators of the Inverted U-shaped Relationship between MPW and Project Performance

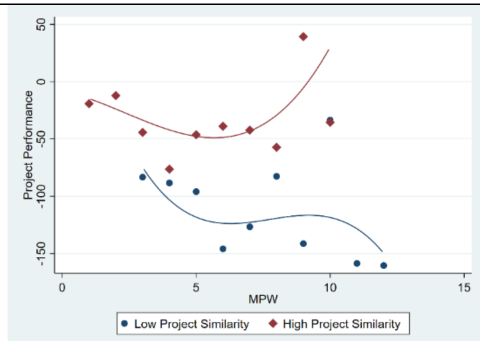
a) Specialized Experience (conditional binned scatterplot of the raw data)



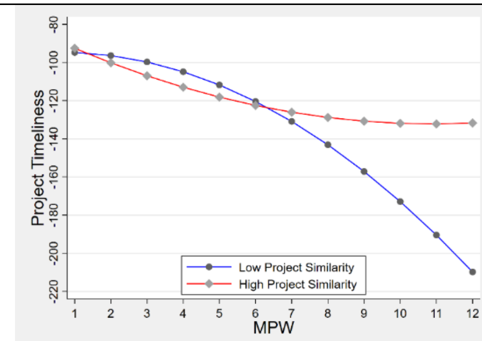
b) Specialized Experience (model estimated relationship)



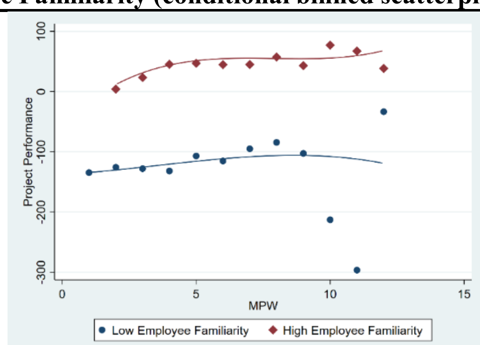
c) Project Similarity (conditional binned scatterplot of the raw data)



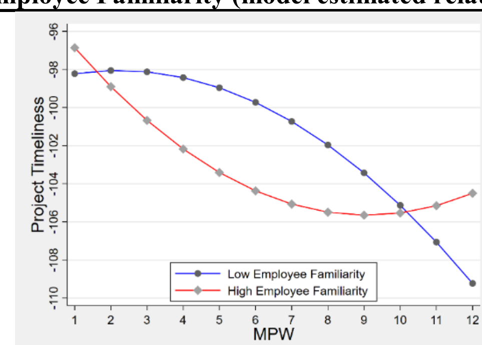
d) Project Similarity (model estimated relationship)



e) Employee Familiarity (conditional binned scatterplot of the raw data)



f) Employee Familiarity (model estimated relationship)



Online Appendix

Multi-project Work and Project Performance: Friends or Foes?

Anatoli Colicev, Tuuli Hakkarainen, Torben Pedersen

This online appendix contains all the tests and details supporting our analysis and the robustness of our results. We also provide some background about these analyses to facilitate navigation through the various tables and figures.

Table of Contents:

Part I: Data Details

Data collection process

We utilized a longitudinal dataset that combined employee- and project-level information in the context of NPD in a multinational organization. This dataset came from a world-leading hydraulic pump manufacturer with around 20,000 employees in more than 50 countries and a net turnover of more than USD 4 billion in 2016. The company provided us with full access to longitudinal data contained in monthly project reports, human resource records, and the work registry. We contacted the company in 2016 and obtained 20 months of data on NPD projects (January 2015 to August 2016). Table A-1 describes the data-collection process and outlines each step's objectives and results.

Table A-1: Data Collection Process

Phase	Date	Data Collection	Main Goals	Main Results
1. Preliminary phase to establish the collaboration	March 2016	First meeting with company representatives	To evaluate the fit between the research goal and the company's objectives	The company serves as a good empirical setting for studying MPW The company can benefit from the study's insights
	August 2016	Second meeting with the company (senior manager)	To crystallize the research objectives	Research objectives aligned between the company and the researchers
	October 2016	Third meeting with the company (senior manager and project managers)	To narrow down the specific details of data collection	Obtained a well-defined list of projects
2. Data collection	January 2017	Fourth meeting with the company (IT employee)	To download the project-level data from the company's intranet	Obtained monthly project data for a 20-month timespan
	April 2017	Virtual contact with IT employee		
	May 2017	Fifth meeting with the company (HR representative)	To download additional data from project members' HR records and worktime registry	Obtained additional data on all project members for a 20-month timespan
	October 2017	Virtual contact with the HR representative	To consolidate the three data sources	Obtained the final dataset
3. Insights	February 2018	Presentation of intermediate results to the company (senior manager and project managers)	To obtain feedback	Found support for initial results and gathered possible extensions for the analysis
	August 2018	Presentation of elaborated results (senior manager and project managers)	To obtain detailed feedback and guidance on the interpretation of the results	Found further support for results and incorporated additional revisions
	December 2018	Presentation of final results (senior manager and project managers)	To obtain feedback on the final results	Support and green light for presenting results to top managers in the company
	February 2019	Workshop in the company at which the results were presented to top management	Present results and obtain feedback	Broad confirmation of results
	May 2019	Ad hoc interviews of project managers	Collect information on specific topics	Integration of final outcomes
4. Follow-up	Mar-Aug 2021	Job Catalogue and Project Descriptions	To obtain additional information on employees' roles and project characteristics	Incorporated this information into the main analysis

Dependent Variable: Project Timeliness

In the context of NPD, judgments of project performance are primarily based on timely completion and delivery to the market (e.g., Krishnan & Ulrich, 2001; Nobeoka & Cusumano, 1997). This is because the assessment of financial measures is highly uncertain before a product's launch. Our data provider was embedded in an innovative environment in which speed to market (timeliness) was the primary performance variable.

To calculate project timeliness, we used project reports, which contained three timestamps (i.e., dates) of project advancement through the stage gates. The first report was from the beginning of the project and included the expected completion time for each gate (1-7). If there were changes in those estimates after one month, the second monthly report would reflect those changes. As we had access to project reports for 20 months, we used future observations for the completion date (month = 20) and compared them with the currently projected timeliness. This combination of expected, continuously updated, and actual timeliness enabled us to meticulously trace developments in performance as well as deviations from both original expectations and later estimates. We present an example of the raw project report data in Figure A-1.

We operationalize project timeliness as the difference between the latest estimated completion date of the current gate (fixed by management at project inception and updated at the midway point) and the gate's actual completion date (obtained from future project reports). We provide an example of these calculations in Figure A-2. We also provide a distribution of the variable in Figure A-3.

Figure A-1: Example of Project Times from a Project Report

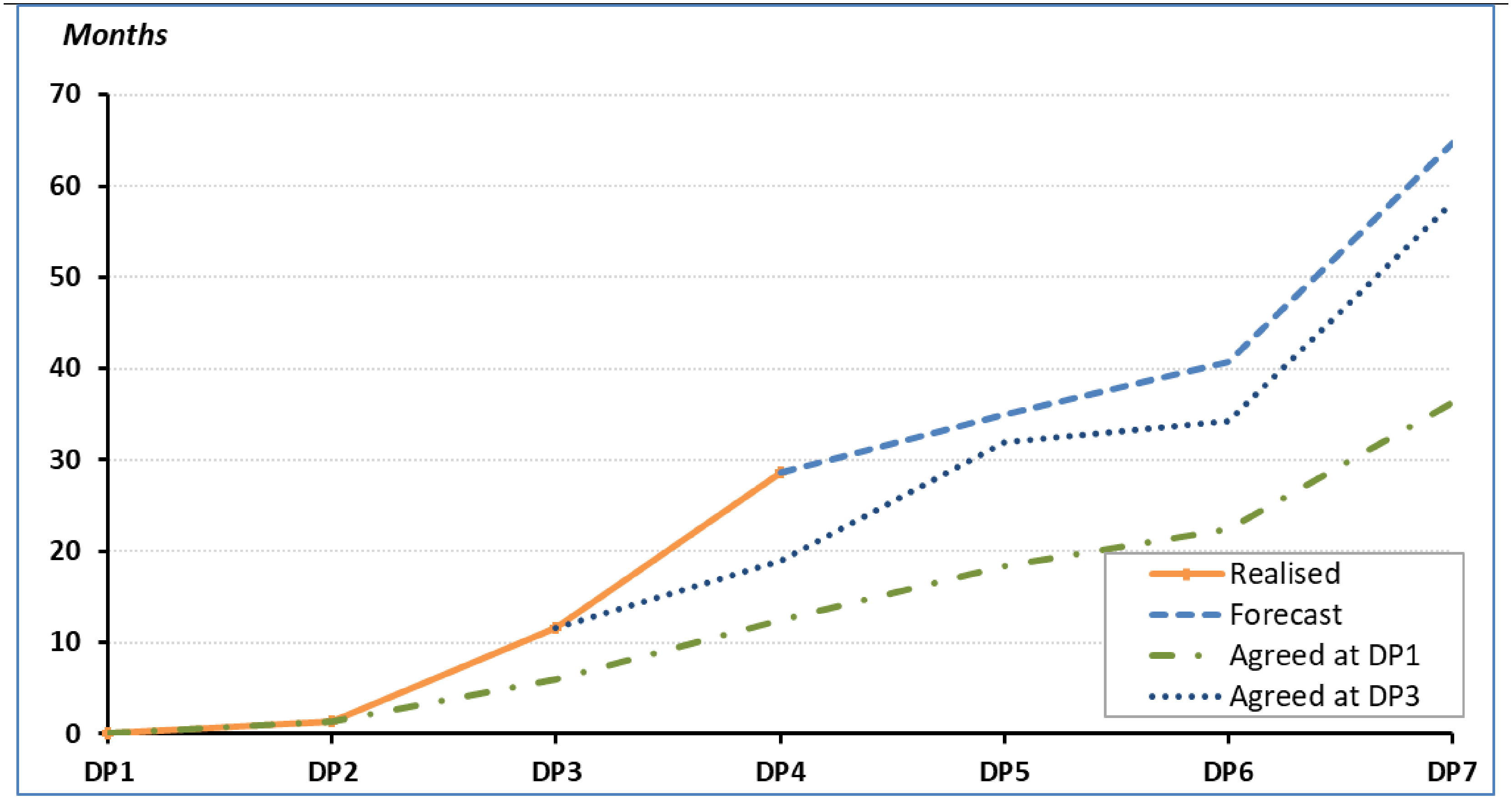
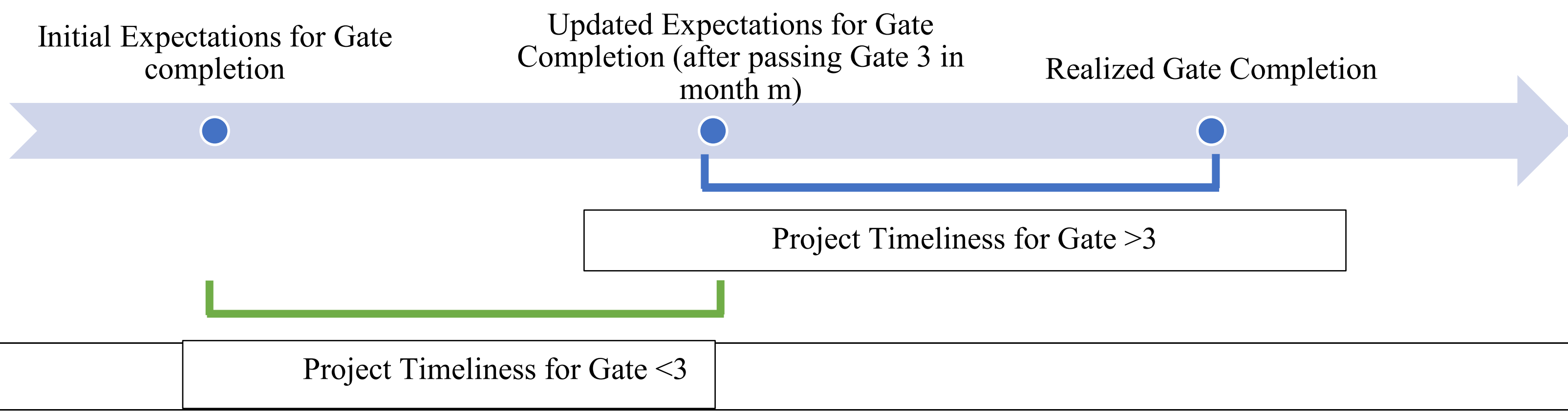


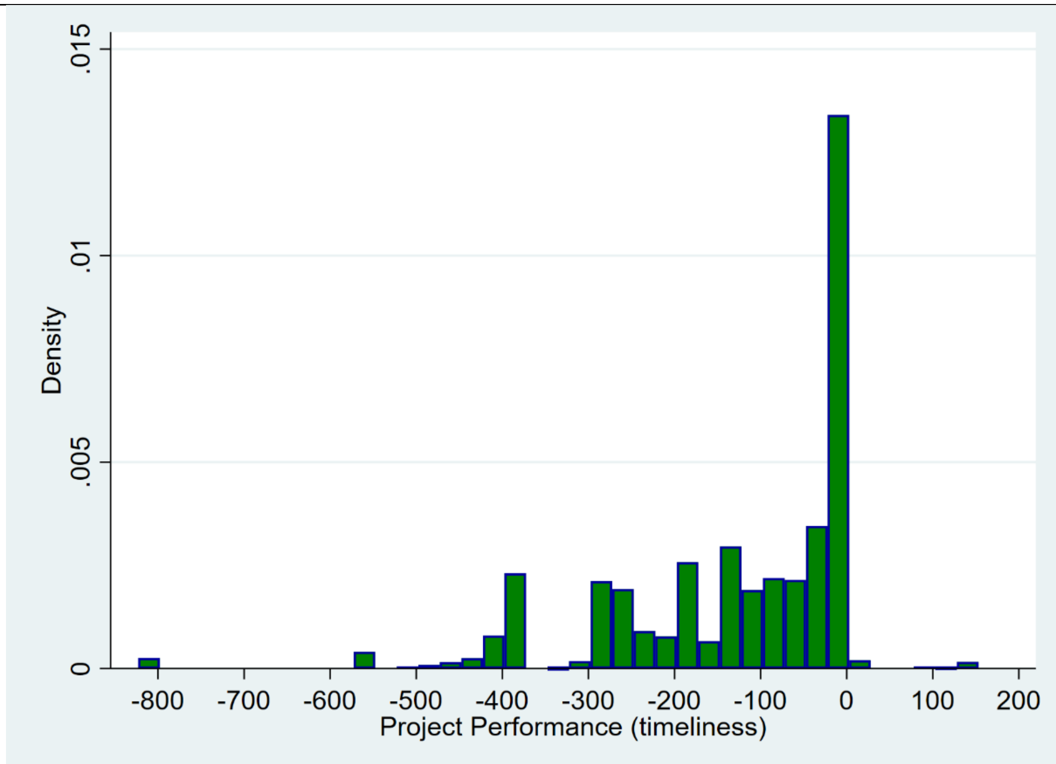
Figure A-2: Example of Project Timeliness Calculations

For Project p at month m



Next Gate	**G=3**	**G=4**	**G=5**
Month of the Project Report	1-Jan-15	1-Mar-15	1-Aug-16
Gate 3 Expectations at project start	17-Sep-14	17-Sep-14	17-Sep-14
Gate 4 Expectations at project start	2-Apr-15	2-Apr-15	2-Apr-15
Gate 5 Expectations at project start	2-Oct-15	2-Oct-15	2-Oct-15
Gate 4 Updated Expectations at Gate 3		20-Oct-15	20-Oct-15
Gate 5 Updated Expectations at Gate 3		18-Nov-16	18-Nov-16
Realized Actual Time Gate 3	10-Mar-15	10-Mar-15	10-Mar-15
Realized Actual Time Gate 4	8-Aug-16	8-Aug-16	8-Aug-16
Realized Actual Time Gate 5	1-Sep-17	1-Sep-17	1-Sep-17
Project Timeliness	(17-Sep-14) - (10 Mar-15) **= -174 days**	(20-Oct-15) - (8-Aug-16) **= -293 days**	(18-Nov-16) –(1-Sep-17) **= -287 days**

Figure A-3: Histogram of Project Performance

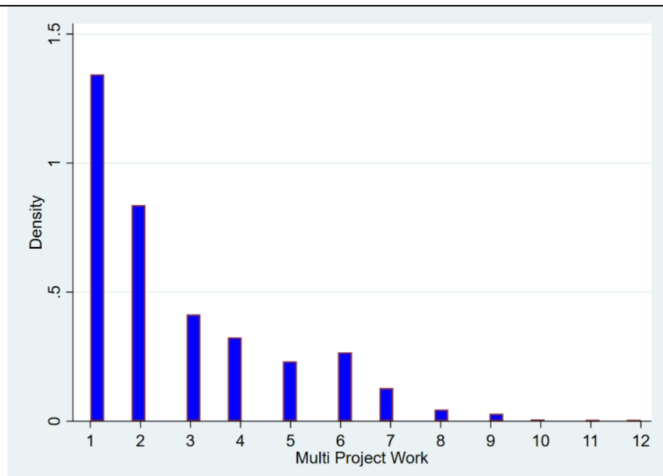


Mean	Std.	Min	Max
-125.2	146.4	-823	153

Independent Variable: MPW

We followed the theoretical work and measured our MPW construct as the number of projects per employee (O'Leary, Mortensen, and Woolley, 2011). For each employee, we consulted the project monthly reports to trace which projects the employee belongs to each month. We then counted the number of simultaneous projects each month for each employee. We found that fifty-eight percent of the employees in our sample work on multiple projects and they had 2.71 projects on average, with some employees handling up to 12 projects. We show the histogram of MPW in Figure A-4.

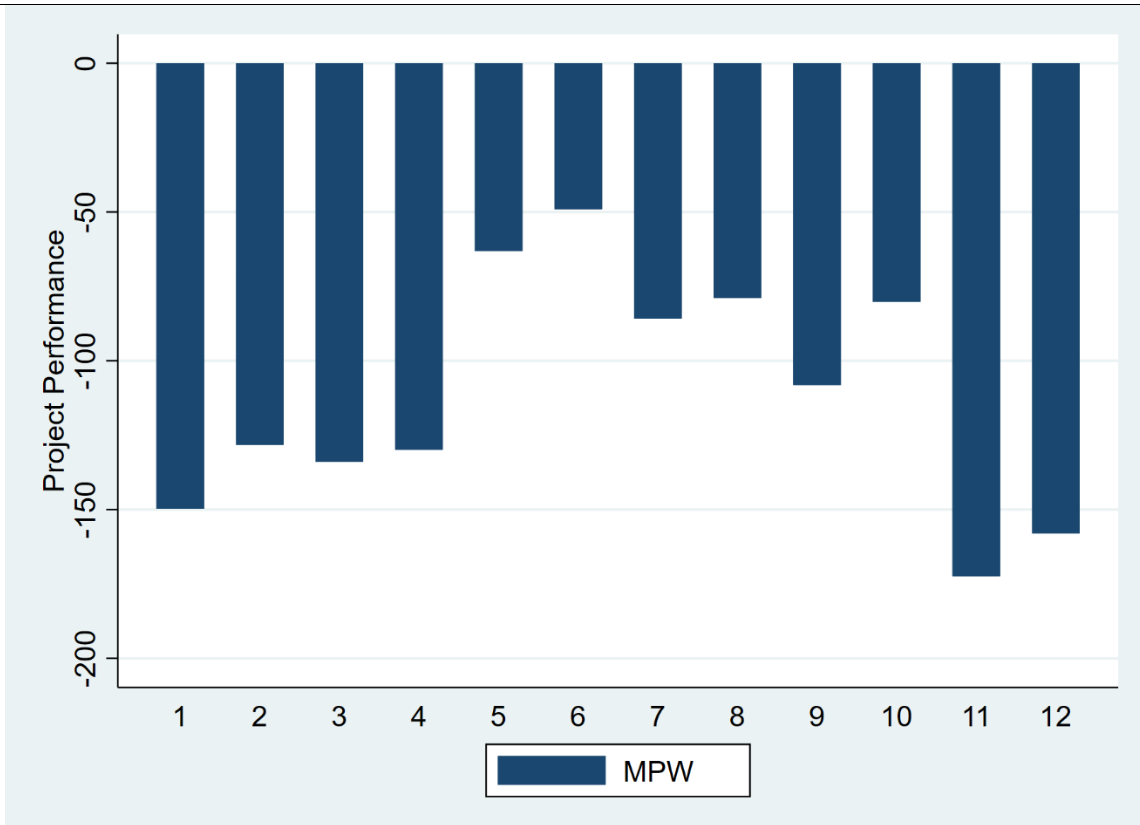
Figure A-4: Histogram of MPW



Mean	**Std.**	**Min**	**Max**
2.714	2.000	1	12

We observe that the inverted U-shaped relationship between MPW and project performance seems to be supported graphically in Figures 2 and A-5.

Figure A-5: Bar Chart of the Raw Data of MPW and Project Performance



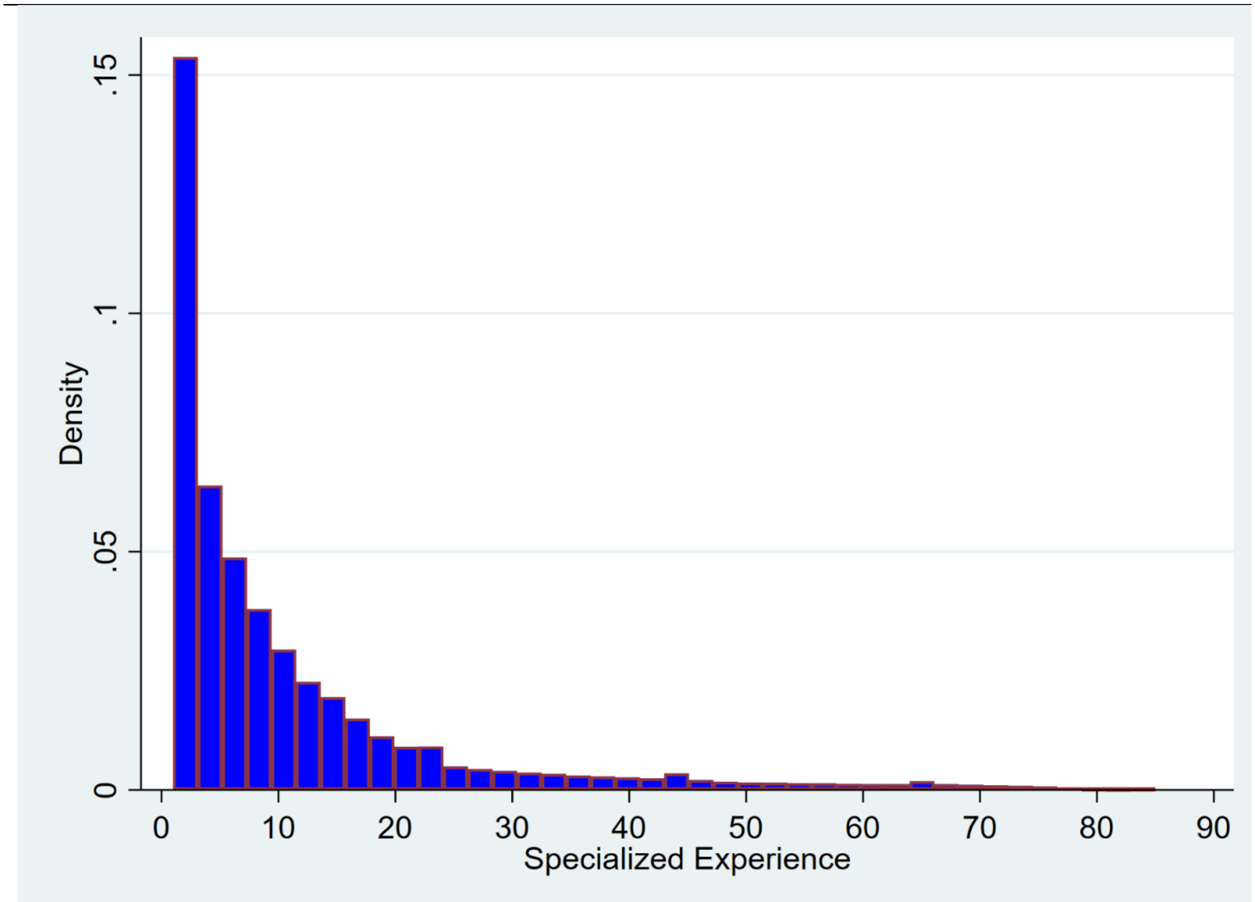
Moderator: Specialized Experience

In line with the NPD project context, we conceptualized specialized experience of an employee as the total experience cumulated within the project technological area prior to working on the current project. This aligns with previous studies in similar context that used the "technological area in R&D" as the base for computing specialized experience (Jain and Mitchell, 2021; Toh, 2014). The case company has helped us is obtaining this measure. While we did not have information on tasks or employee knowledge (i.e., proficiency), we knew on which projects employees have worked in the past. What emerged is that we could classify our projects in major areas based on information on the Program-Category combination.

We note that studies have also operationalized specialized experience based on prior task experience (Boh, Slaughter, and Espinosa, 2007; Cui *et al.*, 2020), stage-specific experience (Staats and Gino, 2012), assignment experience (Narayanan *et al.*, 2009), subfield experience (Teodoridis, Bikard, and Vakili, 2019) and proficiency in using the needed technology (Huckman and Pisano, 2006; Toh, 2014). However, we do not have empirical data on the specific tasks executed by employees in projects nor on the level of proficiency of employees in performing the tasks. Thus, we relied on the managers from our case company to assist us. The starting point for our measure was the assumption that more an employee is exposed to a certain program-category combination more specialized experience she cumulates. It might be that employees also execute overlapping tasks in such Program-Category combination.

Each of our projects belongs to one of the four categories: (1) Product Integration, (2) Line Extension, (3) Platform generation, and (4) Innovation and one of the seven programs: (1) Water Circulation, (2) Monitoring, (3) Domestic water, (4) Disinfection, (5) Multiple stages, (6) Single stage and (7) Wastewater. From project reports, we observed the full 20-month history of employee experience across all the projects. According to our operationalization, two projects that belong to the same Program-Category combination (e.g., Product Integration-Circulators) proxy for the same project area. Specifically, more time the employees spend within the same Program-Category combination, more specialized experience is accumulated for that employee. For each employee, we calculated the cumulative number of months (across all projects) that he or she has spent working in the same Program-Category combination previously to the current month. We provide a histogram of our measure in Figure A-6.

Figure A-6 Histogram of Specialized Experience



Mean	Std.	Min	Max
10.55	12.78	1	85

Moderator: Project Similarity

The company helped us derive the measure of project similarity. Based on their guidelines, we considered two projects as similar if they belonged to the same market segment. Projects belonging to the same market segment share more similar characteristics such as resources, demands, and expectations. We observe three main market segments (Commercial and Domestic Building Services, HVAC OEM and Industry, and Water Treatment). We then computed the number of similar projects for each employee in each month. The metric ranged theoretically from the minimum of (1/#projects) to a maximum of 1. In practice, we observed a minimum of 0.25 to a maximum of 1. A value of 1 means that an employee works only on similar projects each month while a low value implies that an employee works on dissimilar projects.

We illustrate project similarity in Figure A-7 and the histogram of the variable in Figure A-8. Each project fell into one of the three market segments (Water, Building, and HVAC/Industry, in brief). For example, pseudo-named projects Theto, Forki, Lited, and Stellor belong to the market segment “Water”. For employee 1, projects in month 1 have the maximum similarity (project similarity =1), because the employee works in projects Theto, Forki, and Lited that all belong to the same segment “Water”. However, in month 2, the employee now divides her work time between Stellor from the “Water” segment and Mina from the “Building” segment. Thus, the project similarity, in this case, is equal to 0.5. For employee 2, as she works on three projects from the same segment (“Building”) and one different ("Water”) in month 1, the project similarity measure is 0.75. In month 2, as she works on three projects out of which two are from the same segment and one from another, the project similarity is 0.67.

Figure A-7: Illustration of Project Similarity

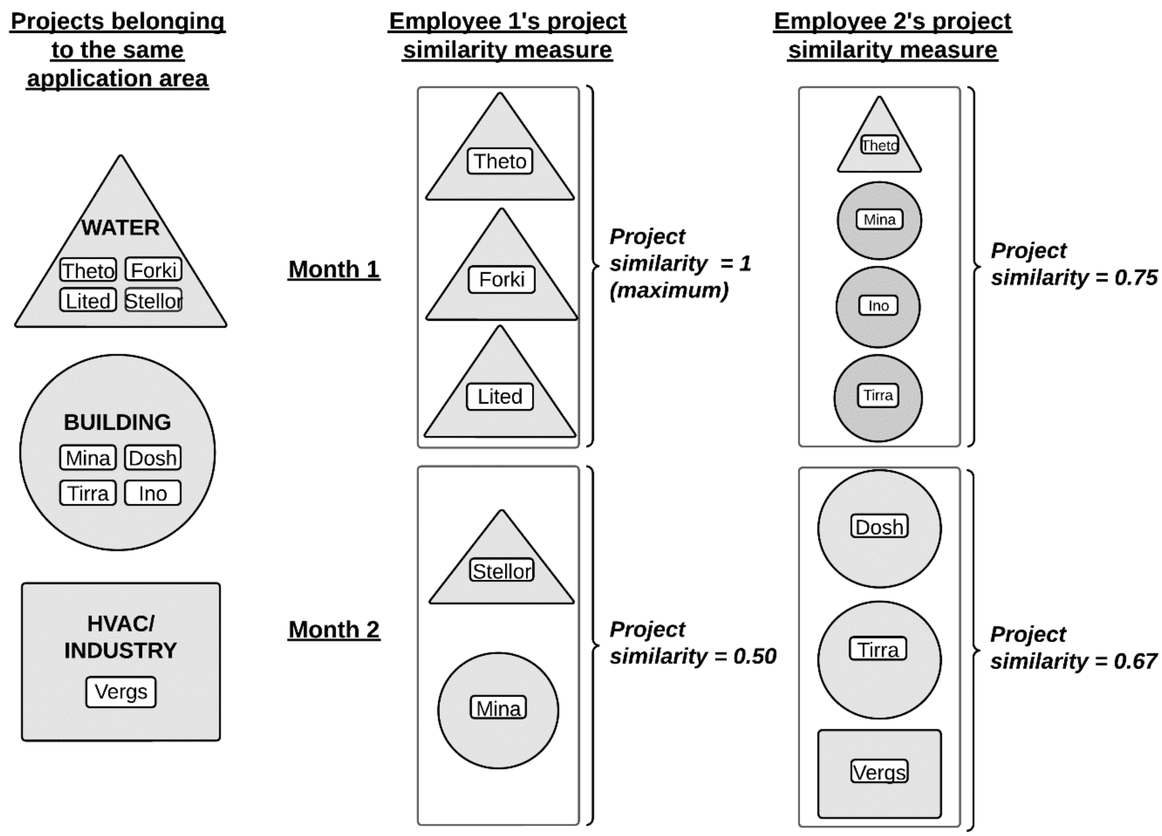
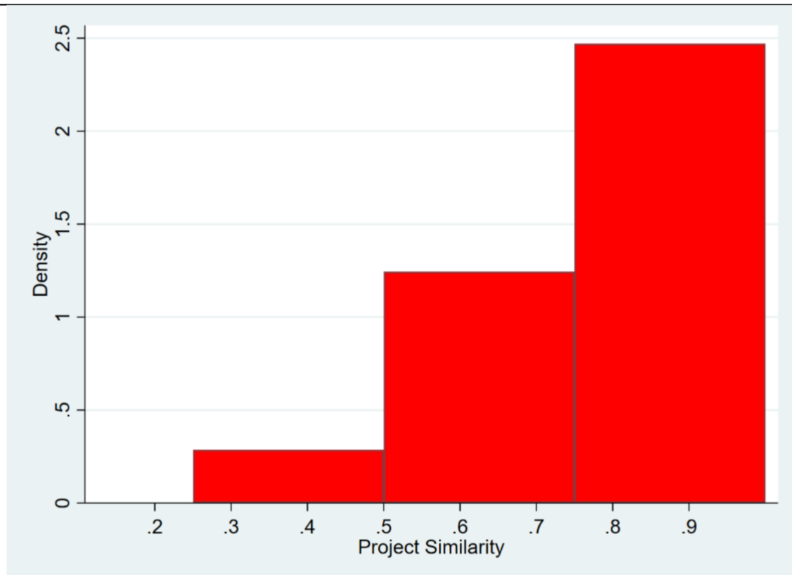


Figure A-8: Histogram of Project Similarity



Mean	Std.	Min	Max
0.802	0.261	0.250	1

Moderator: Employee Familiarity

We operationalized employee familiarity as the number of familiar project members within the focal project. Familiarity means that the employee is currently working or has worked in the past with another employee. If the focal employee is working with another employee on two projects, this means that their respective familiarity is 1 for each. We count the number of such situations for each employee each month. We illustrate employee familiarity in Figure A-9. For example, employee 1 works on three projects in month 1. She works with employees 3 and 4 on the same projects. Thus, the familiarity score for employee 1 in month 1 equals 2 (i.e., 2 familiar employees). Following the same logic, in month 2, employee 1 works with employees 3 and 11 in both projects. However, to see the overall familiarity score for month 2, we also consider that employee 1 has worked with employee 7 in month 1. Thus, the employee familiarity score is equal to 3. We present the distribution of this metric in Figure A-10.

Figure A-9: Illustration of Employee Familiarity

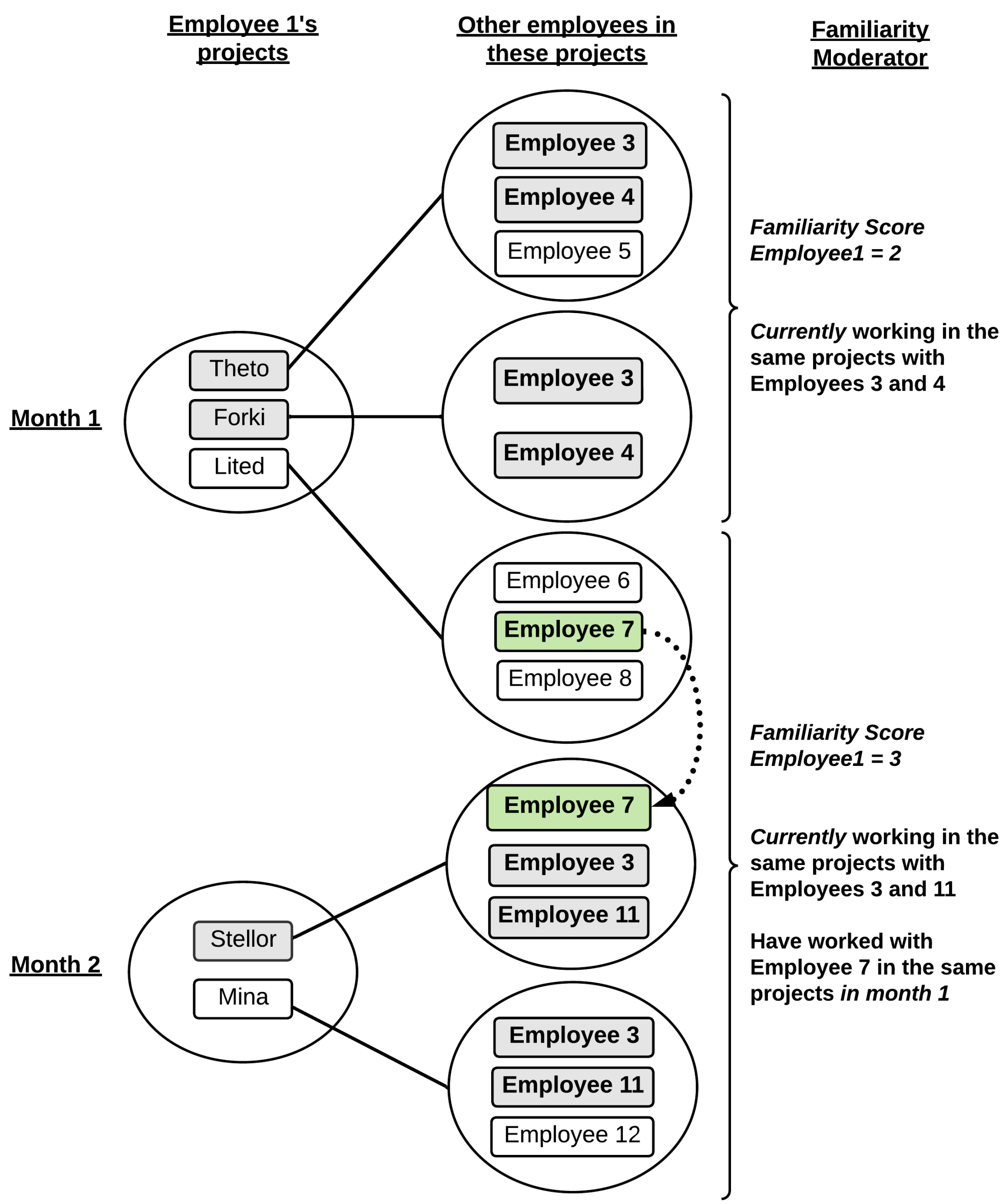
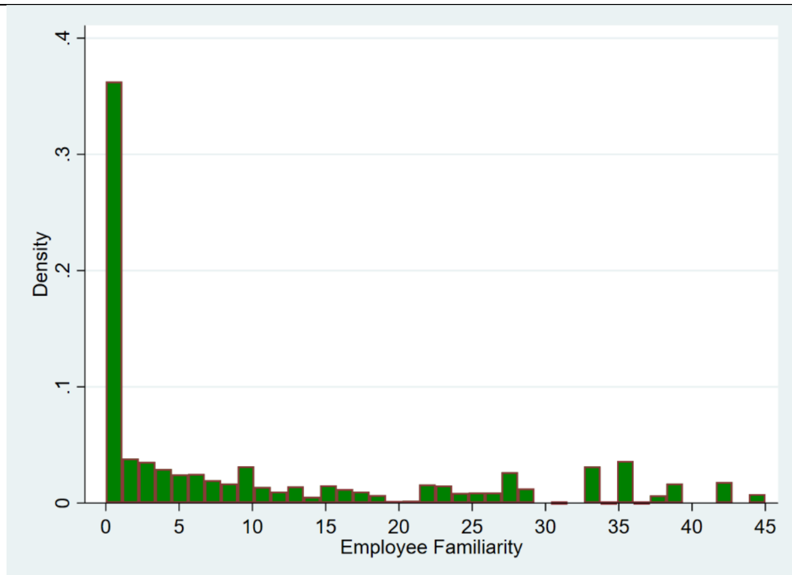


Figure A-10: Histogram of Employee Familiarity



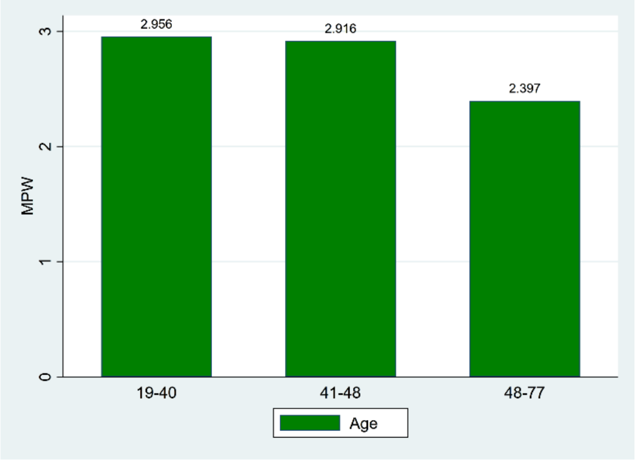
Mean	Std.	Min	Max
10.26	13.20	0	45

Part II: Employee-level Characteristics in MPW Allocations

Before testing the theoretical framework, we first discuss several employee characteristics that can explain MPW allocations. In Figures A-11 and A-12 we visually represent them.

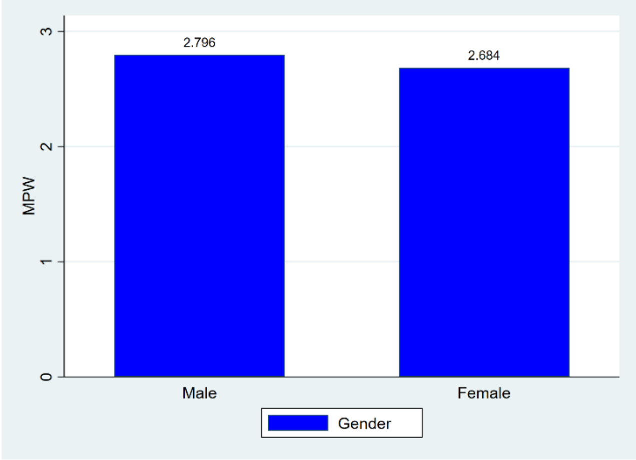
Figure A-11: Employee Characteristics and MPW

(a) Age



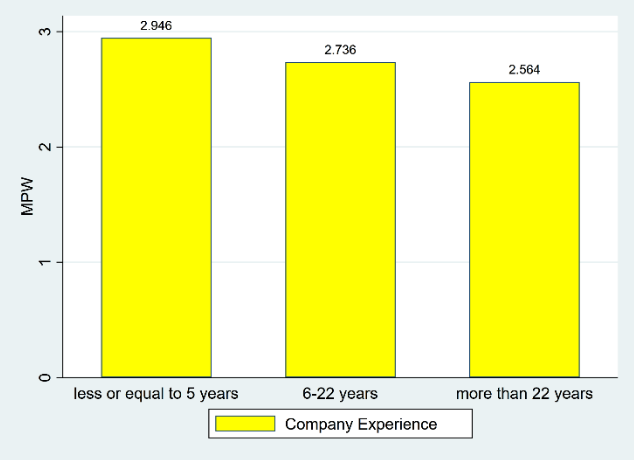
Note: In this bar plot, we represent the raw data of age, for clarity split into three categories based on three even percentile bins (bottom 33.33%, middle 33.33% and top 33.33%) with respect to MPW (y-axis). MPW is lower for older employees.

(b) Gender



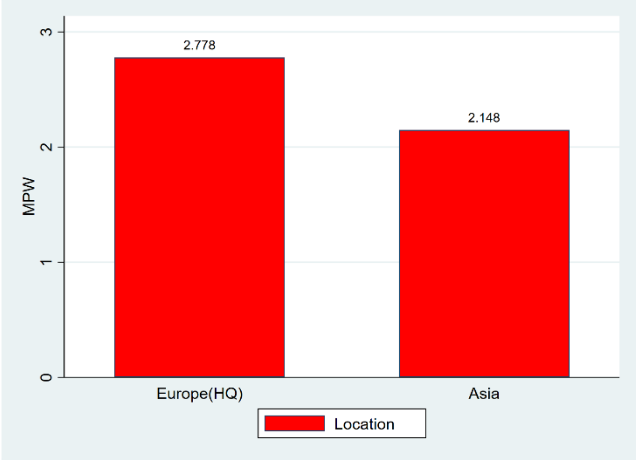
Note: In this bar plot, we represent the raw data of gender (bars) with respect to MPW (y-axis). We see that MPW does not seem to vary with gender.

(c) Company Experience



Note: In this bar plot, we represent the raw data of company experience, split into three categories based on three even percentile bins (bottom 33.33%, middle 33.33% and top 33.33%) %) with respect to MPW (y-axis). MPW is lower with experience.

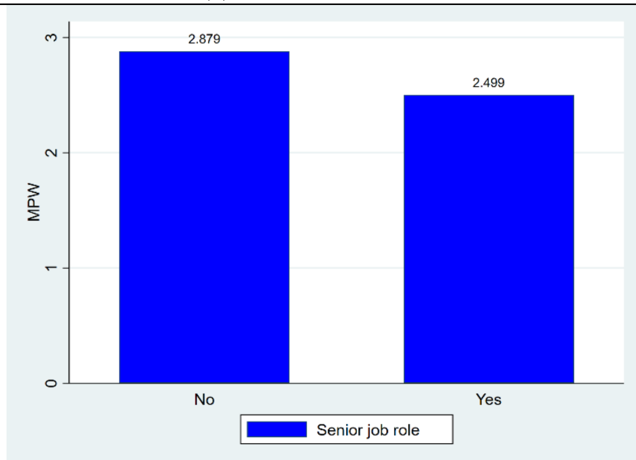
(d) Location



Note: In this bar plot, we represent the raw data of the employee's location (bars) with respect to MPW (y-axis). We see that MPW seems to be higher for employees who work in the headquarters in Europe.

Figure A-12: Employee Characteristics and MPW

(e) Senior Job Role

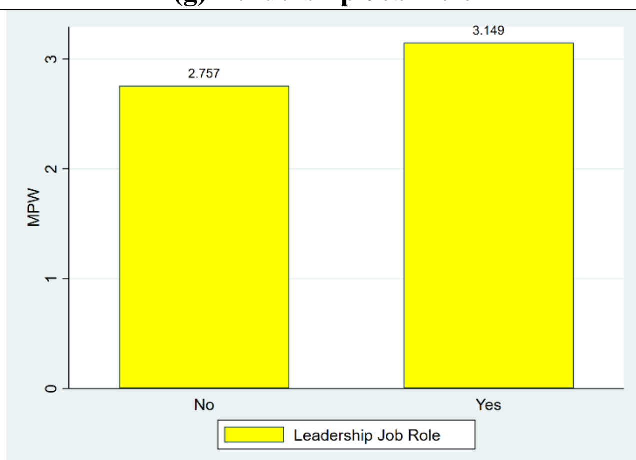


Note: In this bar plot, we represent the raw data of senior job role (bars) with respect to MPW (y-axis). We see that MPW is slightly lower for employees that have a senior job role.

(f) Managerial Responsibilities

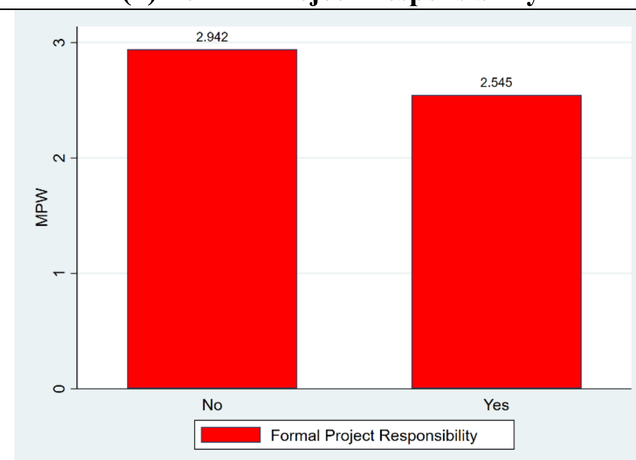
Note: In this bar plot, we represent the raw data of managerial responsibilities (bars) with respect to MPW (y-axis). We see that MPW is slightly higher for employees with managerial responsibilities.

(g) Leadership Job Role



Note: In this bar plot, we represent the raw data of leadership job role (bars) with respect to MPW (y-axis). We see that MPW is slightly higher for employees that have a leadership job role.

(h) Formal Project Responsibility



Note: In this bar plot, we represent the raw data of formal project responsibility (bars) with respect to MPW (y-axis). We see that MPW is slightly lower for employees that have a formal project responsibility.

Regression Analysis

To further investigate the relationship between employee-level characteristics and MPW, we ran the following employee-fixed effects model:

$MPW_{ipm} = \alpha_0 + \alpha_i + \alpha_1 Age_{ipm} + \alpha_2 CompExp_{ipm} + \alpha_3 Location_{ipm} + \alpha_4 Senior_{ipm} + \alpha_5 Manager_{ipm} + \alpha_6 Leader_{ipm} + \alpha_7 Formal_{ipm} + \varepsilon_1$, (A1)

where for each employee i, project p and month m, MPW is multi-project work, Age is employee's age (continuous measure), CompExp is company experience (continuous measure), Location is a dummy of employer's location (1= HQ, 0 otherwise), Senior is a dummy of seniority (1=Senior, 0 otherwise), Manager is a dummy of managerial responsibilities (1=manager, 0 otherwise), Leader is a dummy of leader role (1=leader, 0 otherwise), Formal is a dummy of formal project responsibilities (1=formal project responsibility, 0 otherwise). α_i are employee fixed effects that give each employee a different intercept. The employee's gender drops out due to employee-fixed effects.

The model is estimated with the *reghdfe* Stata package that implements the computationally efficient estimator of Guimarães and Portugal (2010), generalized in the work of Correia (2017). $\epsilon 1$ are two-way clustered on project and employee-level (Abadie *et al.*, 2017). We present the results in Table A-2.

Table A-2: The Relationship between Employee Characteristics and MPW		
	Multi-project Work (MPW)	
Employee Age	-.267	(.126)
Company Experience	-.149	(.115)
Location (1=HQ, 0 otherwise)	.376	(.205)
Managerial Responsibilities (1=manager, 0 otherwise)	-.507	(.508)
Senior Job Role (1=senior, 0 otherwise)	.002	(.104)
Leadership Job Role (1=leader, 0 otherwise)	1.016	(.401)
Formal Project Responsibility (1=responsible, 0 otherwise)	-.037	(.193)
Constant	16.899	(6.131)
Employee Fixed Effect	YES	
Two-way Clustered Standard Errors (Project and Employee-level)	YES	
Note: Standard errors are in parentheses		

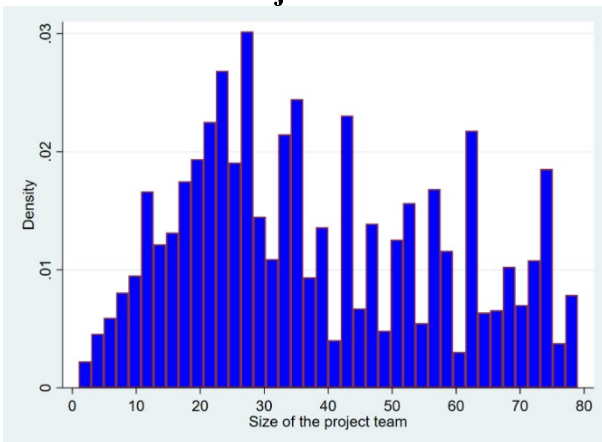
Part III: Model Details

Control Variables

In terms of control variables, we relied on a set of variables that help us mitigate omitted variable concerns. We present their distributions in Figure A-13.

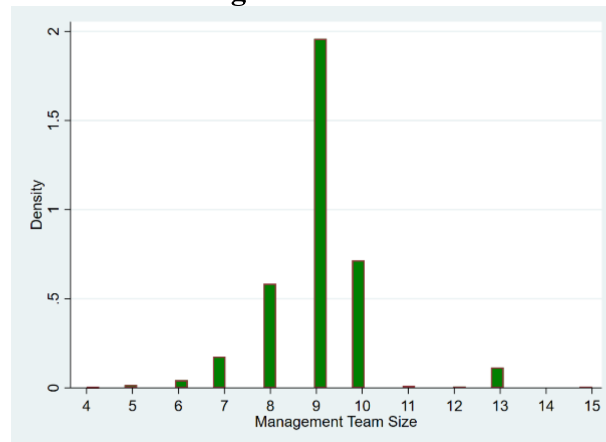
Figure A-13: Histograms of Control Variables

Project Size



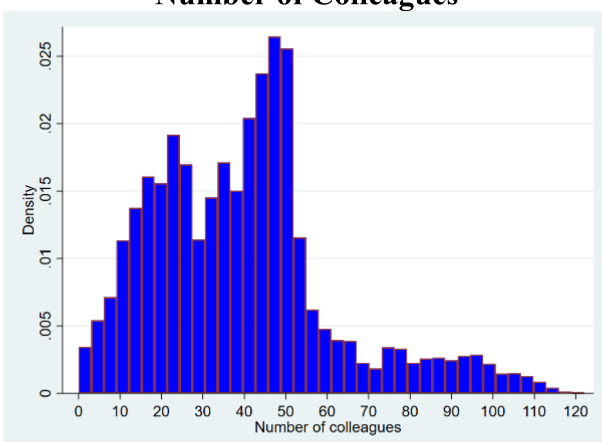
Mean	Std.	Min	Max
38.11	20.51	1	79

Management Team Size



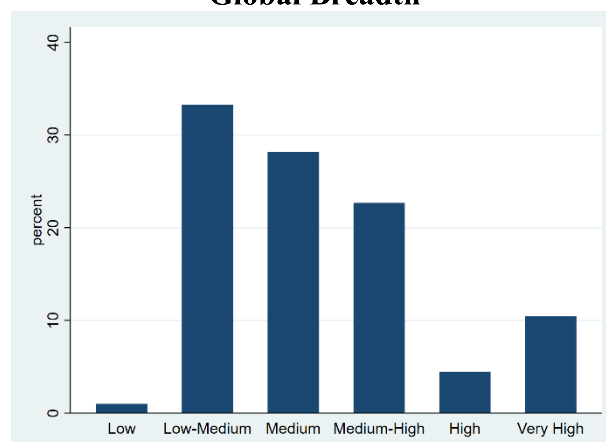
Mean	Std.	Min	Max
9.058	1.184	4	15

Number of Colleagues



Mean	Std.	Min	Max
39.42	22.36	0	122

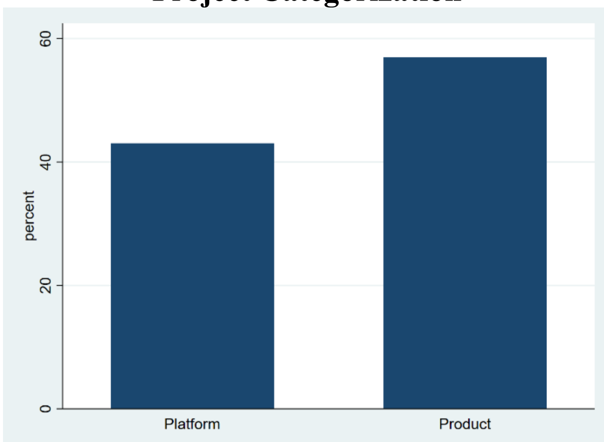
Global Breadth



Mean	Std.	Min	Max
2.292	1.292	0	5

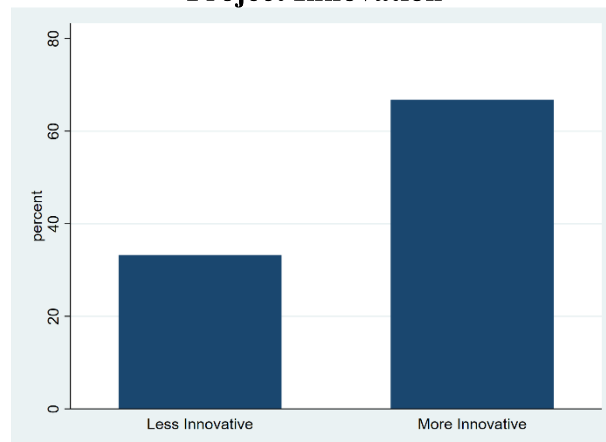
Figure A-13(cont.): Histograms of Control Variables

Project Categorization



Mean	Std.	Min	Max
0.449	0.497	0	1

Project Innovation



Mean	Std.	Min	Max
0.702	0.457	0	1

Univariate and Bivariate Analysis

Table A-3 provides the correlation matrix of the study's variables.

Table A-3: Correlation Coefficients among Key Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Project Performance (timeliness)	1.00											
Multi-project Work	0.18	1.00										
Multi-project Work (squared)	0.15	0.96	1.00									
Specialized Experience	0.26	0.38	0.33	1.00								
Project Similarity	-0.03	-0.51	-0.44	0.08	1.00							
Employee Familiarity	0.22	0.73	0.63	0.39	-0.23	1.00						
Project Size	-0.05	-0.16	-0.11	-0.13	0.04	-0.06	1.00					
Management Team Size	-0.08	-0.11	-0.11	-0.05	0.03	-0.20	0.02	1.00				
Number of Colleagues	0.13	0.49	0.49	0.16	-0.22	0.46	0.55	-0.10	1.00			
Global Breadth	-0.26	-0.38	-0.32	-0.21	0.04	-0.45	0.67	0.14	0.14	1.00		
Project Categorization	-0.35	-0.32	-0.28	-0.13	0.14	-0.42	0.31	0.31	-0.04	0.50	1.00	
Project Innovation	-0.25	-0.47	-0.42	-0.36	0.07	-0.50	0.38	0.38	-0.08	0.53	0.49	1.00

Testing for an Inverted U-shaped Relationship

We formally tested whether the slope is sufficiently steep at both ends of the data range. This is formally assessed by testing the joint significance of the direct and squared terms of MPW with the Sasabuchi (1980) test for an inverted U-shaped relationship (by using the *utest* command in STATA). The test's joint null hypotheses are that (a) the effect of MPW on project timeliness does not increase at low values of MPW and that (b) the effect of MPW on project timeliness does not decrease at high values of MPW. In Table A-4, we report the results. We rejected the null hypotheses of the monotone relationship or U-shaped relationship in favor of the alternative hypothesis of the inverted U-shape ($p=.002$).

Table A-4: Test of an Inversely U-shaped Relationship between MPW and Project Timeliness and Robustness of the Inverted U-shape

Extreme point: **5.16**
95% Fieller interval for extreme point: [**3.57; 6.19]**

Test of Joint Significance of MPW Variables [MPW and MPW^2]:
H0: Monotone or U shape
H1: Inverse U shape
p-value lower bound (.002)
p-value upper bound (.000)
Overall test of the Presence of an Inverse U shape:
t-value = 3.29
p-value= .002

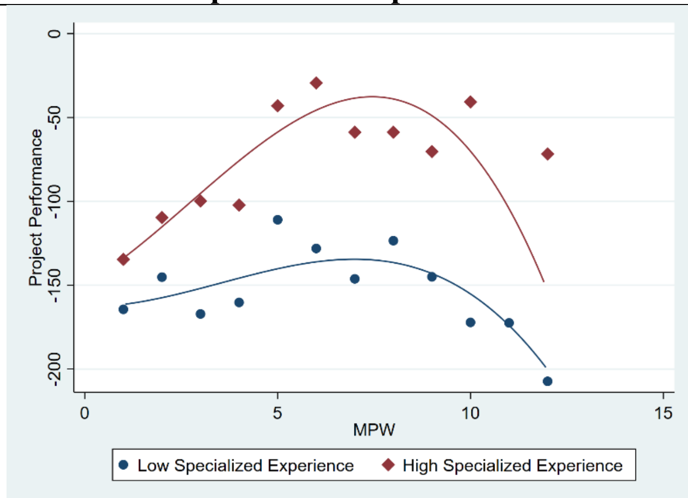
Robustness Test	Result
Cubic effect MPW^3 added to the model	The coefficient on MPW^3 is not statistically meaningful (p=.733)
Splitting the sample below/above the turning point	Below the turning point: MPW (139.20, p=.002)
	Above the turning point: MPW (-3.63, p=.965)

Unconditional Binned Scatterplots for Moderators

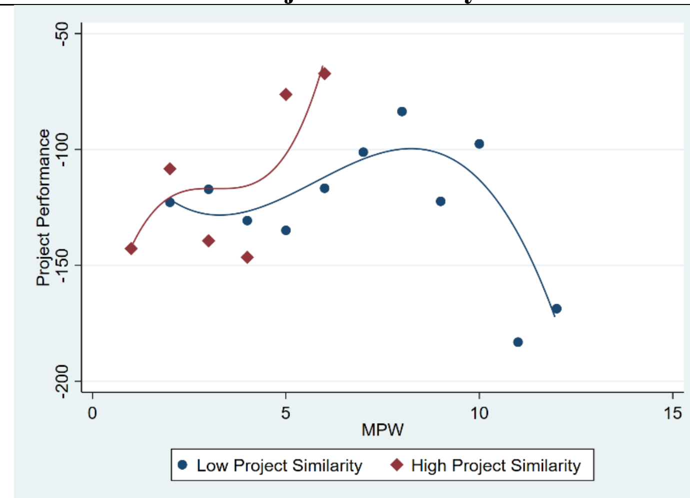
In the main analysis, we have presented in Figure 3 the conditional plots (with control variables) for the moderators on the raw data with the help of *binsreg* command in STATA (Starr and Goldfarb, 2020). In Figure A-14 we present the unconditional plots which are very similar to the conditional plots.

Figure A-14: Unconditional Binned Scatterplot (Raw Data) for the Moderators

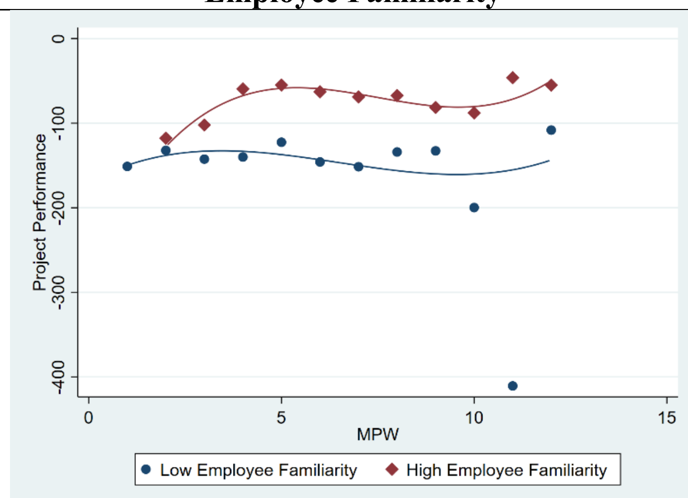
Specialized Experience



Project Similarity



Employee Familiarity



Part IV: Robustness Analysis

We checked the robustness of the results to alternative models, additional moderators, dependent variables, and data structures:

1. Models M1-M5 tested the alternative model specifications. The results are presented in Table 2.
2. Models M6-M8 tested some control variables as additional moderators
3. Models M9-M10 tested alternative dependent variables
4. Model M11 tested alternative data aggregation at the project level

We summarize this analysis in Table A-5.

Table A-5: Robustness Analysis	
Preliminary Robustness Checks	M1: No Controls, No Month Fixed Effects, No Clustered Standard Errors M2: No Controls, No Month Fixed Effects, Two-way Clustered Standard Errors M3: No Controls, Month Fixed Effects, Two-way Clustered Standard Errors M4: Controls, No Month Fixed Effects, No Clustered Standard Errors M5: Controls, No Month Fixed Effects, Two-way Clustered Standard Errors
Main Model	**Main Model**: Controls, Month Fixed Effects, and Two-way Clustered Standard Errors
Adding Additional Moderators	M6: Project Size as moderator M7: Management Team Size as moderator M8: Number of colleagues as moderator
Alternative Dependent Variables	M9: Project Quality as DV M10: Project Turnover as DV
Reshaping the Data at Project-level	M11: Project-level averages

Testing Additional Moderators

Although we do not have clear theoretical arguments for the role of some control variables as moderators, previous research seems to hint at this possibility. For instance, the project size and number of managers per project might alter the switching costs of MPW as switching to larger projects might be more problematic. On contrary, it might be that such size effects can also reduce switching costs as large groups can solve problems more effectively (e.g., Wiersema and Bantel, 1992). We did not find that such size effects serve as moderators (see models M6 and M7 in Table A-6). In addition, what happens if one employee works on 2 projects and interacts with 150 colleagues while the other employee works on 10 projects but interacts only with 100 colleagues overall? The size of the focal project might differ from the size of all the projects that the employee works on in the same month. In other words, while in theory, the number of colleagues across all projects might moderate the effects of MPW on project performance, we did not find a statistically meaningful effect of this moderator (see model M8).

Table A-6: Some Control Variables Tested as Moderators						
	M6: Project Size as an Additional Moderator		M7: Management Team Size as an Additional Moderator		M8: Number of Colleagues as an Additional Moderator	
Multi-project Work (MPW)	38.972	(15.792)	56.471	(12.052)	38.113	(14.106)
Multi-project Work Squared (MPW^2)	-3.906	(1.053)	-4.780	(.575)	-3.280	(1.030)
Specialized Experience	9.790	(1.742)	9.252	(1.859)	9.802	(1.753)
Project Similarity	19.231	(24.983)	13.741	(26.700)	19.705	(23.049)
Employee Familiarity	1.994	(1.443)	2.070	(1.389)	2.220	(1.519)
MPW * Specialized Experience	-2.076	(.638)	-1.913	(.571)	-2.061	(.626)
MPW * Project Similarity	-18.775	(10.654)	-20.608	(10.384)	-19.251	(9.551)
MPW * Employee Familiarity	-1.445	(.606)	-1.487	(.589)	-1.588	(.678)
MPW^2 * Specialized Experience	.146	(.061)	.127	(.052)	.142	(.060)
MPW^2 * Project Similarity	2.479	(1.450)	2.836	(1.528)	2.577	(1.339)
MPW^2 * Employee Familiarity	.120	(.044)	.122	(.044)	.141	(.051)
Project Size	1.091	(.560)	.963	(.899)	.758	(.933)
MPW * Project Size	-.060	(.327)				
MPW^2 * Project Size	.010	(.025)				
Management Team Size	6.361	(12.751)	.276	(21.328)	6.287	(12.472)
MPW * Management Team Size			-26.165	(17.954)		
MPW^2 * Management Team Size			1.620	(1.162)		
Number of Colleagues	.107	(.246)	.119	(.271)	.721	(.654)
MPW * Number of Colleagues					-.095	(.163)
MPW^2 * Number of Colleagues					-.002	(.012)
Global Breath=1	-7.921	(35.940)	8.063	(38.729)	-10.851	(35.314)
Global Breath=2	-135.916	(41.943)	-114.768	(58.317)	-136.923	(42.074)
Global Breath=3	-37.902	(52.263)	-24.941	(59.772)	-38.479	(51.891)
Global Breath=4	-49.423	(37.740)	-42.068	(39.526)	-47.912	(37.970)
Global Breath=5	-187.260	(45.846)	-176.940	(54.572)	-184.934	(45.988)
Project Categorization	-69.766	(37.738)	-63.312	(43.749)	-70.479	(38.145)
Project Innovation	-35.981	(42.197)	-37.037	(38.854)	-34.888	(41.018)
Constant	-189.558	(98.910)	-204.192	(126.873)	-193.914	(104.477)
Employee Fixed Effects	YES		YES		YES	
Month Fixed Effects	YES		YES		YES	
Two-way Clustered Standard Errors (Project and Employee level)	YES		YES		YES	
Note: Standard errors are in parentheses						

Alternative Dependent Variables

As alternative dependent variables, we obtained the measures of estimated project turnover and project quality from project reports.

First, the estimated project turnover is the total amount (in local currency) of expected project sales after project completion in the first year of full operation. Second, project quality is proxied through warranty rate which captures the percentage of warranty claims. Typically, a warranty claim is a claim by a customer for a product under warranty which can entail replacement.

Both measures were mere estimates of the real performance of the product or platform. This is because we deal with "work in progress" projects that are yet unfinished. The company runs multiple quality checks and turnover estimates, and these measures are reported in each project report. Project quality and turnover are not assessed at each gate but rather at the project's inception and the end. Some observations are either missing or constant in each project report. Since the real quality and turnover measures can only be assessed after the product or platform is deployed on the market (e.g. for new products, such as cars, sales peak can happen as late as after one year (Nobeoka and Cusumano, 1997), we cannot be certain whether such estimates are accurate. Given the highly uncertain outcomes of development projects, it is not helpful to plan or rely on future outcomes, but more proximate goals, such as the timeliness of reaching specific project steps are likely to be more informative about the project performance (Brown and Eisenhardt, 1995).

We did not have a theory that MPW could affect such measures of project quality or turnover (see models M9 and M10 in Table A-7). However, we found that our results hold for project quality (but not for turnover).

Table A-7: Alternative Dependent Variables

	M9: Project Quality		M10: Project Expected Turnover	
Multi-project Work (MPW)	.053	(.036)	.016	(.026)
Multi-project Work Squared (MPW^2)	-.011	(.004)	-.001	(.003)
Specialized Experience	.004	(.003)	.002	(.001)
Project Similarity	-.001	(.094)	.136	(.039)
Employee Familiarity	.007	(.003)	.014	(.002)
MPW * Specialized Experience	-.003	(.001)	-.001	(.000)
MPW * Project Similarity	-.152	(.072)	-.065	(.033)
MPW * Employee Familiarity	-.004	(.001)	-.002	(.001)
MPW^2 * Specialized Experience	.000	(.000)	.000	(.000)
MPW^2 * Project Similarity	.028	(.013)	.006	(.006)
MPW^2 * Employee Familiarity	.000	(.000)	.000	(.000)
Project Size	.000	(.001)	.000	(.001)
Management Team Size	-.013	(.018)	-.012	(.007)
Number of Colleagues	.002	(.000)	.000	(.000)
Global Breath=1	-.299	(.111)	-.097	(.049)
Global Breath=2	-.171	(.066)	-.146	(.059)
Global Breath=3	-.180	(.078)	-.152	(.069)
Global Breath=4	-.145	(.072)	-.105	(.048)
Global Breath=5	-.153	(.065)	-.106	(.046)
Project Categorization	-.098	(.038)	-.081	(.037)
Project Innovation	.119	(.071)	.091	(.057)
Constant	.234	(.287)	.076	(.114)
Employee Fixed Effects	YES		YES	
Month Fixed Effects	YES		YES	
Two-way Clustered Standard Errors (Project and Employee level)	YES		YES	

Note: Standard errors are in parentheses

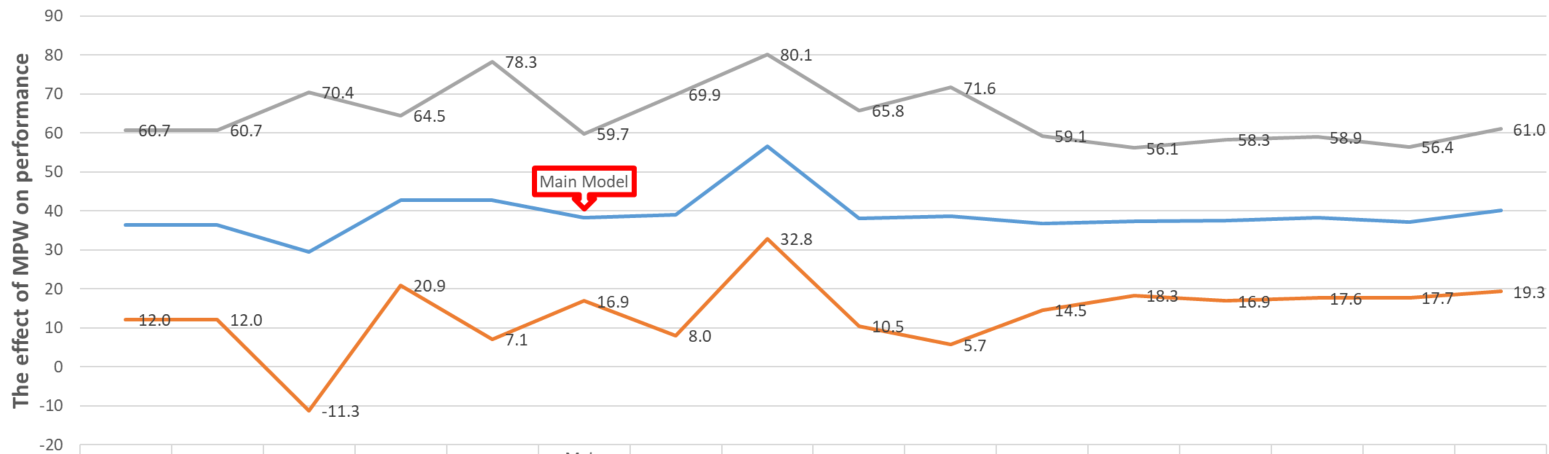
Collapsing the Data at the Project level

An alternative to our main dataset construction is collapsing the data at the project-month level. By focusing solely on the project-level analysis, we combined data on 42 projects across 20 months, resulting in an unbalanced panel of 420 project-month observations. To achieve this, we averaged the MPW and other employee-level variables for each project with multiple employees. We reran the main model at the project-month level for 420 observations. We had directional evidence for all our results, but we did not find statistically meaningful results (probably due to a low number of degrees of freedom). We present the results in Table A-8.

Table A-8: Project-level Analysis		
	M11: Project-level Analysis	
Multi-project Work (MPW)	107.743	(182.985)
Multi-project Work Squared (MPW^2)	-14.554	(23.813)
Specialized Experience	23.416	(6.458)
Project Similarity	77.277	(343.820)
Employee Familiarity	4.731	(10.146)
MPW * Specialized Experience	-9.092	(3.510)
MPW * Project Similarity	23.595	(202.496)
MPW * Employee Familiarity	-3.308	(5.496)
MPW^2 * Specialized Experience	.940	(.426)
MPW^2 * Project Similarity	-3.353	(26.228)
MPW^2 * Employee Familiarity	.379	(.578)
Project Size	-1.313	(1.613)
Management Team Size	21.597	(12.151)
Number of Colleagues	1.702	(2.150)
Global Breath=1	-143.415	(59.722)
Global Breath=2	-249.712	(65.999)
Global Breath=3	-111.268	(72.280)
Global Breath=4	-136.956	(55.242)
Global Breath=5	-226.427	(67.702)
Project Categorization	-57.318	(40.127)
Project Innovation	-43.682	(40.931)
Constant	-389.177	(350.501)
Observations	420	
Standard Errors	Standard Errors Clustered at Project-level	
Note: Standard errors are in parentheses		

We summarize the results of the previous models in Figures A-15 and A-15. We also present there the results from alternative explanations models (discussed in the next section) as they test the same dependent variable. This chart shows that MPW and MPW squared coefficients are all in the same direction in all models (90% confidence band).

Figure A-15: Plot of the Coefficients for MPW and 95% Confidence Intervals across Models

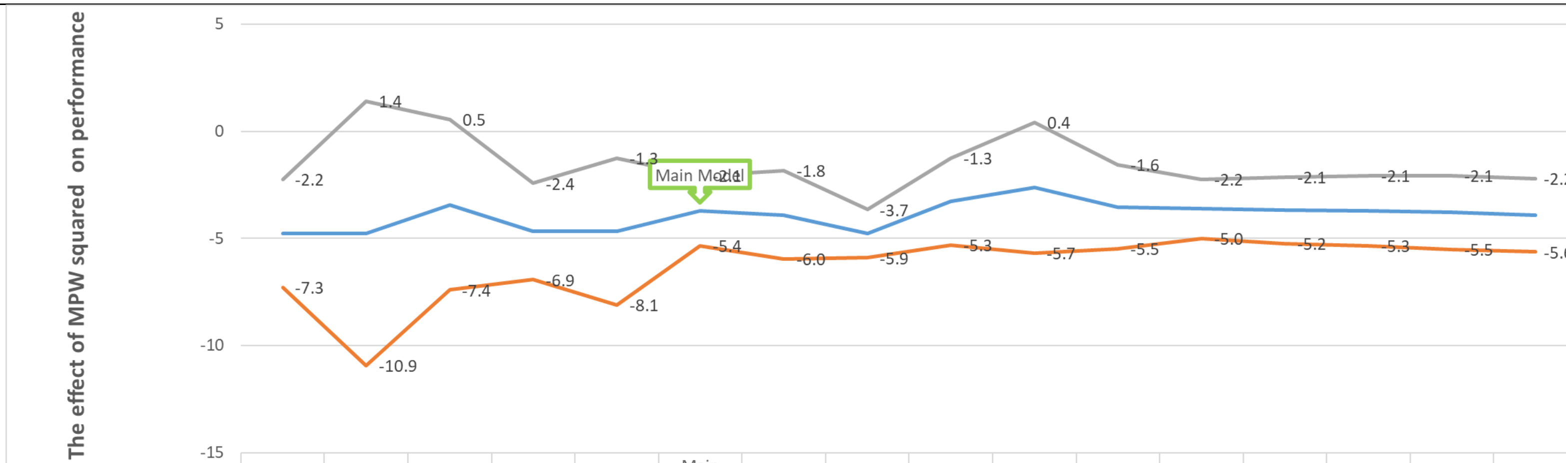


	M1	M2	M3	M4	M5	Main Model	M6	M7	M8	ALT2	ALT3	ALT4	ALT5	ALT6	ALT7	ALT8
MPW Estimate	36.37	36.37	29.54	42.67	42.67	38.29	38.972	56.471	38.113	38.648	36.827	37.22	37.563	38.268	37.044	40.134
Low 95% CI	12.0	12.0	-11.3	20.9	7.1	16.9	8.0	32.8	10.5	5.7	14.5	18.3	16.9	17.6	17.7	19.3
High 95% CI	60.7	60.7	70.4	64.5	78.3	59.7	69.9	80.1	65.8	71.6	59.1	56.1	58.3	58.9	56.4	61.0

Model Specification

MPW Estimate Low 95% CI High 95% CI

Figure A-16: Plot of the Coefficients for MPW^2 and 95% Confidence Intervals across Models



	M1	M2	M3	M4	M5	Main Model	M6	M7	M8	ALT2	ALT3	ALT4	ALT5	ALT6	ALT7	ALT8
MPW Squared Estimate	-4.76	-4.76	-3.43	-4.68	-4.68	-3.71	-3.906	-4.78	-3.28	-2.635	-3.53	-3.625	-3.687	-3.709	-3.789	-3.925
Low 95% CI	-7.3	-10.9	-7.4	-6.9	-8.1	-5.4	-6.0	-5.9	-5.3	-5.7	-5.5	-5.0	-5.2	-5.3	-5.5	-5.6
High 95% CI	-2.2	1.4	0.5	-2.4	-1.3	-2.1	-1.8	-3.7	-1.3	0.4	-1.6	-2.2	-2.1	-2.1	-2.1	-2.2

Model Specification

MPW Squared Estimate Low 95% CI High 95% CI

Part V: Alternative Explanations

We advanced several alternative explanations of our findings:

1. ALT1: Performance Feedback
2. ALT2-ALT4: Employee-level characteristics as additional moderators
3. ALT5-ALT10: Number of Switches
4. ALT11: Working Hours as an additional dependent variable
5. ALT12-ALT13: Project Time Allocations

We summarize this analysis in Table A-9.

Table A-9: Alternative Explanations

	Model	Result
Performance Feedback	ALT1: Compare MPW values for above and below the median of project performance	We do not find evidence that employees are allocated to MPW based on project performance.
Employee Age	ALT2: Employee Age as an additional moderator	Employee Age does not moderate the effects. Other results are unchanged.
Employee Location	ALT3: Employee Location as an additional moderator	Employee Location seems to have a slight moderating effect. Other results are unchanged.
Employee Leadership	ALT4: Employee Leadership Role as an additional moderator	Employee Leadership Role does not moderate the effects. Other results are unchanged.
Switches	ALT5: Number of Switches as control	The number of switches as control does not change the results.
	ALT6: Number of New Switches as control	The number of new switches as control does not change the results.
	ALT7: Number of Switches as an additional moderator	The number of switches does not moderate the effects. Other results are unchanged.
	ALT8: Number of New Switches as an additional moderator	The number of new switches does not moderate the effects. Other results are unchanged.
	ALT9: Number of Switches as Dependent variable	MPW is not related to the number of switches.
	ALT10: Number of New Switches as Dependent variable	MPW is not related to the number of new switches.
Working Hours	ALT11: Working hours as DV	MPW is not related to the number of working hours.
Project Time Allocation	ALT12: Averaged out metrics at the employee-month level	Results are largely confirmed.
	ALT13: Weighted metrics by project time allocation (MCMC)	Results are largely confirmed.

Performance Feedback

The first conjecture is that the managers might allocate employees to MPW based on project performance. We followed Lyngsie & Foss (2017) and conducted the median split on project performance and then compare the levels of MPW above and below the median. We then tested these differences with the *qreg2* command in STATA with clustered standard errors by the employee (Machado, Parente, and Santos Silva, 2011; Parente and Santos Silva, 2015) which improves the Mann–Whitney statistic for inequality of medians (Conroy, 2012). MPW is quite similar (T-value=0.01) when the project performance is below (2.71) or above the median (2.77). This conclusion also helped to some extent mitigate the reverse causality in our main model (Lyngsie and Foss, 2017). This was confirmed in a company communication that expressed the manager's reluctance to dramatically modify the project composition after the launch. This might be because managers might not be willing to mess up the other well-performing projects. Also, a short-term drop in project performance might be recovered in the long run. Thus, moving resources between projects might be suboptimal and have unpredictable consequences which the firm might want to avoid.

Relevant Employee-level Characteristics as Additional Moderators

Given that we found that employee age, location, and leadership role are to some extent related to MPW, we further investigated whether they play a role in how MPW affects project performance. We thus included them as additional moderators in our main model. We report the results in Table A-10.

Table A-10: Employee-level characteristics as additional moderators

	ALT2: Employee Age as an additional moderator		ALT3: Employee Location as an additional moderator		ALT4: Employee Leadership Role as an additional moderator	
Multi-project Work (MPW)	38.648	(16.829)	36.827	(11.386)	37.220	(9.636)
Multi-project Work Squared (MPW^2)	-2.635	(1.553)	-3.530	(1.001)	-3.625	(.710)
Specialized Experience	5.031	(1.202)	9.803	(1.784)	9.718	(1.717)
Project Similarity	54.204	(16.391)	14.659	(24.119)	17.169	(21.253)
Employee Familiarity	2.860	(1.043)	.959	(1.632)	2.065	(1.438)
MPW * Specialized Experience	-.920	(.565)	-2.067	(.649)	-2.055	(.608)
MPW * Project Similarity	-31.329	(5.616)	-13.431	(10.909)	-19.568	(9.648)
MPW * Employee Familiarity	-1.527	(.398)	-1.413	(.670)	-1.497	(.566)
MPW^2 * Specialized Experience	.059	(.055)	.144	(.062)	.143	(.058)
MPW^2 * Project Similarity	2.742	(1.320)	2.044	(1.479)	2.609	(1.516)
MPW^2 * Employee Familiarity	.120	(.026)	.124	(.046)	.126	(.038)
Employee Age	58.464	(13.146)				
MPW * Employee Age	.080	(.289)				
MPW^2 * Employee Age	-.022	(.032)				
Employee Location (2=Asia, 1=Europe HQ)			-204.752	(38.658)		
MPW * Employee Location			19.453	(15.223)		
MPW^2 * Employee Location			-1.902	(2.004)		
Employee Leadership Role					51.564	(33.622)
MPW * Employee Leadership Role					-5.786	(12.818)
MPW^2 * Employee Leadership Role					-.010	(1.225)
Project Size	.943	(.873)	.768	(.817)	1.081	(.847)
Management Team Size	8.993	(11.172)	4.821	(13.180)	7.337	(11.884)
Number of Colleagues	.048	(.244)	.089	(.258)	.113	(.266)
Global Breath=1	51.029	(36.570)	-40.997	(30.327)	-1.575	(34.978)
Global Breath=2	-85.241	(41.952)	-175.897	(40.535)	-130.723	(42.267)
Global Breath=3	20.501	(49.256)	-101.436	(46.521)	-34.499	(52.889)
Global Breath=4	16.366	(39.700)	-102.295	(29.499)	-45.643	(37.591)
Global Breath=5	-139.885	(44.987)	-237.863	(38.003)	-184.737	(46.562)
Project Categorization	-64.934	(40.579)	-96.372	(33.908)	-67.862	(39.228)
Project Innovation	-40.170	(37.702)	9.576	(42.878)	-39.180	(38.979)
Constant	-2870.510	(607.236)	-126.210	(118.265)	-199.981	(99.556)
Employee Fixed Effects	YES		YES		YES	
Two-way Clustered Standard Errors (Project and Employee level)	YES		YES		YES	

Note: Standard errors are in parentheses

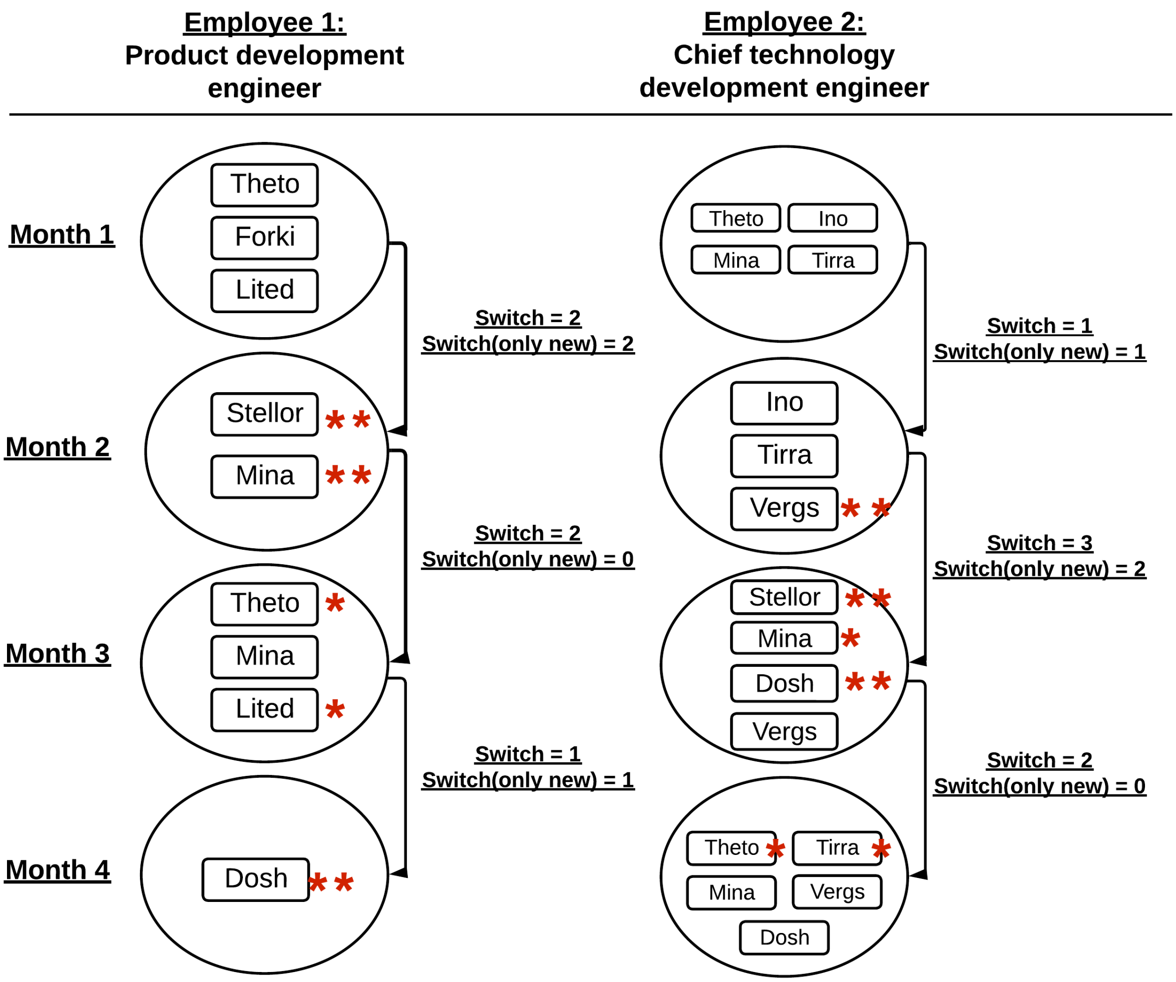
Number of Project Switches

The first measure counted the number of projects an employee has added to his portfolio with respect to the previous month. If the employee had not worked on a project in the previous month, the addition of such a new project is counted as a switch. The second measure counted the number of *completely new* projects an employee has added to his portfolio with respect to all the history we observe. If this condition is verified, the addition of such a new project is counted as a switch. In other words, the second measure is conditional on the first but added a second criterium. If an employee added a new project, has he ever worked on it before? If yes, the measure added this as a switch.

For example, employee 1, a product development engineer, works on projects Theto, Forki, and Lited in month 1. As employee 1 now works in projects Stellor and Mina and neither of these projects were the same as in month 1, we counted the switches as 2. At the same time, Stellor and Mina were completely new (as the employee did not work in them in the past), we counted them as new switches as well (=2). This is important, as it can be the case that, such as in month 3, the employee worked in Theto, Mina, and Lited, of which Theto and Lited were switches from the previous month 2 (=2). However, as employee 1 has worked in them in month 1, they were not completely new. Then again, in month 4, the employee worked solely on project Dosh, which is both a switch (=1) and a completely new (=1).

Similarly, for employee 2, chief technology development engineer, from month 1 to month 2, he worked on one new project (Vergs), which is different from month 1, so it is both a switch (=1) and new switch (=1). For month 3, there were 3 new projects (Stellor, Mina, and Dosh), but the employee worked on one of them (Mina) in month 1. We illustrate the switches in Figure A-17.

Figure A-17: Illustration of Switches



Given that switching costs should affect project performance, it is possible that including directly a metric of switching costs could alter the effects of MPW on project performance. Leroy & Glomb (2018) note that a high number of switches drain employee attention and negatively affect their performance. Another study found that software programmers who switched their attention between tasks as frequently as every 15 to 30 minutes experienced a loss of time and focus which led to a higher error rate (Parnin and Rugaber, 2011). While switching costs comprise several factors that are quite hard to measure (i.e., the amount of attention residue, the time to transition between tasks), a possible way to capture switching costs is to simply count the number of project switches (e.g. Czerwinski, Horvitz, and Wilhite, 2004). We tested two such measures which are illustrated in Figure A-17. The first measure assumed that a switch occurred when an employee added a new project with respect to the previous month and counted the total number of such occurrences. An alternative measure captured the number of switches to completely new projects (i.e., with respect to an employee's project portfolio history). Given that switches can dampen performance, we first included them as additional control variables in our main model, finding that their inclusion did not alter our main effects of MPW (see Table A-11). We also found that these measures did not moderate the effects of MPW of performance. It seems that the number of switches did not alter the switching costs of MPW as they might not account for the whole spectrum of switching costs. In turn, the factors considered in our main analysis (e.g., project similarity) seemed to matter to this extent. Finally, we also tested a possible process through which MPW affected performance by testing the effect of MPW on these switches. If managers needed to rebalance project composition regularly, employees might have had a positive association between MPW and switches (especially the new switches). However, we did not find confirmation for these results (see Table A-12).

Table A-11: Switches

	ALT5: Switches as Control		ALT6: Switches Only New Projects as Control		ALT7: Switches as a Moderator		ALT8: Switches Only New as a Moderator	
Multi-project Work (MPW)	37.563	(10.564)	38.268	(10.546)	37.044	(9.850)	40.134	(10.636)
Multi-project Work Squared (MPW^2)	-3.687	(.789)	-3.709	(.835)	-3.789	(.875)	-3.925	(.873)
Specialized Experience	9.774	(1.735)	9.778	(1.684)	9.639	(1.630)	9.933	(1.657)
Project Similarity	22.698	(22.382)	21.562	(22.045)	16.972	(20.532)	22.941	(22.581)
Employee Familiarity	1.970	(1.423)	2.034	(1.419)	1.951	(1.387)	2.009	(1.416)
MPW * Specialized Experience	-2.057	(.620)	-2.065	(.621)	-2.007	(.608)	-2.133	(.621)
MPW * Project Similarity	-19.671	(9.653)	-19.763	(9.330)	-16.289	(11.872)	-21.012	(9.947)
MPW * Employee Familiarity	-1.449	(.581)	-1.480	(.590)	-1.445	(.612)	-1.467	(.602)
MPW^2 * Specialized Experience	.144	(.060)	.144	(.060)	.141	(.060)	.149	(.062)
MPW^2 * Project Similarity	2.421	(1.416)	2.584	(1.436)	1.935	(1.916)	2.871	(1.554)
MPW^2 * Employee Familiarity	.122	(.040)	.126	(.041)	.121	(.043)	.125	(.043)
Switches	2.564	(2.020)			-5.662	(11.772)		
Switches Only New			-.491	(16.418)			18.497	(25.197)
MPW * Switches					2.148	(3.816)		
MPW2 * Switches					-.098	(.276)		
MPW * Switches Only New							-8.957	(6.575)
MPW2 * Switches Only New							.686	(.756)
Project Size	1.021	(.856)	1.026	(.856)	1.028	(.858)	1.023	(.857)
Management Team Size	6.282	(12.527)	6.313	(12.596)	6.164	(12.533)	6.331	(12.605)
Number of Colleagues	.111	(.270)	.111	(.272)	.111	(.270)	.112	(.273)
Global Breath=1	-9.166	(34.987)	-8.975	(34.536)	-9.578	(35.009)	-7.734	(34.711)
Global Breath=2	-136.670	(42.350)	-136.553	(43.907)	-136.946	(42.812)	-135.559	(44.056)
Global Breath=3	-38.464	(52.287)	-38.455	(54.118)	-39.369	(53.484)	-36.868	(54.336)
Global Breath=4	-49.396	(37.601)	-49.645	(38.678)	-50.427	(38.439)	-48.028	(39.164)
Global Breath=5	-187.246	(45.986)	-187.506	(48.060)	-187.861	(46.742)	-186.134	(48.267)
Project Categorization	-69.922	(38.097)	-69.925	(38.656)	-70.172	(38.280)	-69.601	(38.658)
Project Innovation	-35.074	(41.350)	-35.527	(41.117)	-34.142	(41.771)	-36.364	(41.266)
Constant	-189.511	(107.466)	-189.214	(106.252)	-183.541	(110.092)	-193.661	(106.505)
Employee Fixed Effects	YES		YES		YES		YES	
Two-way Clustered Standard Errors (Project and Employee level)	YES		YES		YES		YES	

Note: Standard errors are in parentheses

Table A-12: Switches as an alternative dependent variable

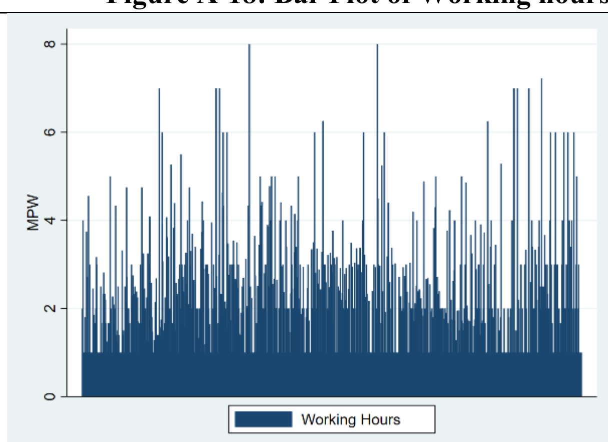
	ALT9: Switches as Dependent Variable		ALT10: Switches (Only New) as Dependent Variable	
Multi-project Work (MPW)	.296	(.269)	-.024	(.051)
Multi-project Work Squared (MPW^2)	-.010	(.028)	-.003	(.006)
Specialized Experience	.015	(.010)	-.000	(.003)
Project Similarity	-.445	(.508)	-.192	(.095)
Employee Familiarity	.025	(.014)	-.000	(.002)
MPW * Specialized Experience	-.007	(.006)	-.002	(.001)
MPW * Project Similarity	-.054	(.314)	.064	(.051)
MPW * Employee Familiarity	-.012	(.007)	-.000	(.001)
MPW^2 * Specialized Experience	.000	(.001)	.000	(.000)
MPW^2 * Project Similarity	.064	(.039)	.005	(.006)
MPW^2 * Employee Familiarity	.001	(.001)	.000	(.000)
Project Size	.002	(.002)	.000	(.001)
Management Team Size	.008	(.024)	.022	(.014)
Number of Colleagues	-.000	(.001)	.000	(.000)
Global Breath=1	-.031	(.158)	-.269	(.049)
Global Breath=2	-.028	(.135)	-.264	(.031)
Global Breath=3	-.043	(.127)	-.315	(.055)
Global Breath=4	-.120	(.107)	-.312	(.060)
Global Breath=5	-.171	(.112)	-.341	(.055)
Project Categorization	-.011	(.063)	-.064	(.030)
Project Innovation	-.183	(.123)	-.020	(.040)
Constant	.126	(.468)	.343	(.137)
Employee Fixed Effects	YES		YES	
Two-way Clustered Standard Errors (Project and Employee level)	YES		YES	

Note: Standard errors are in parentheses

Working Hours

We tested the conjecture that MPW was associated with a larger number of working hours, which captured the number of working hours in that month. On one hand, employees who work on multiple projects might clock in more working hours (Zika-Viktorsson, Sundström, and Engwall, 2006). However, the total time available for work is finite. In addition, MPW employees are likely to find more effective working methods ("work smarter"), such as prioritizing and compartmentalizing their available hours more actively, instead of working more hours (O'Leary *et al.*, 2011). We tested whether MPW is associated with working hours, as a dependent variable in place of performance. We present the bar chart of working hours in Figure A-18. We present the results of the model in Table A-13. As can be seen, MPW was not associated with working hours.

Figure A-18: Bar Plot of Working hours



Note: In this bar plot, we represent the raw data of working hours with respect to MPW (y-axis). We see that MPW does not visually relate to the number of working hours.

Table A-13: Working Hours as an alternative dependent variable

	ALT11: Working Hours	
Multi-project Work (MPW)	8.730	(5.969)
Multi-project Work Squared (MPW^2)	-.638	(.552)
Specialized Experience	.196	(.149)
Project Similarity	-.504	(11.672)
Employee Familiarity	-.546	(.443)
MPW * Specialized Experience	-.025	(.069)
MPW * Project Similarity	-1.158	(7.079)
MPW * Employee Familiarity	.186	(.223)
MPW^2 * Specialized Experience	.001	(.007)
MPW^2 * Project Similarity	-.021	(1.053)
MPW^2 * Employee Familiarity	-.015	(.016)
Project Size	-.106	(.056)
Management Team Size	-.009	(.556)
Number of Colleagues	.034	(.026)
Global Breath=1	-8.503	(6.083)
Global Breath=2	-1.506	(4.191)
Global Breath=3	-.051	(4.678)
Global Breath=4	-.314	(4.129)
Global Breath=5	2.530	(4.120)
Project Categorization	-2.416	(2.139)
Project Innovation	3.121	(4.125)
Constant	129.259	(14.085)
Employee Fixed Effects	YES	
Two-way Clustered Standard Errors (Project and Employee level)	YES	
Note: Standard errors are in parentheses		

Project Time allocation: Collapsing the Data at the Employee level

Our final conjecture is that the member time allocation in conjunction with MPW could explain our findings (Cummings and Haas, 2012; Mortensen and Haas, 2018). We combined data on 580 employees across 20 months, resulting in an unbalanced panel of 5,691 employee-month observations. We averaged the project performance and other project-level variables for each employee that works on multiple projects in the same month. As a first check, after collapsing the data at the employee level, we estimated the same model as in the main specification. These results are presented in Table A-14.

Importantly, to test the effects of employee time allocation on projects, we set up the multiple-membership model, previously used in education research (Browne, Goldstein, and Rasbash, 2001; Goldstein, Burgess, and McConnell, 2007; Leckie, 2009) and strategic management (Mollick, 2012). The assumption is that projects were nested within employees in a non-hierarchical fashion. In other words, projects can be part of multiple employees. We derived the model from (Leckie 2009) in classification notation (Browne *et al.*, 2001):

$$y_{pt} = \beta_0 + \sum_{i \in project(p)} w_{i,pt}^{(2)} u_{it}^{(2)} + e_{pt}$$

$$u_{it}^{(2)} \sim N(0, \sigma_{u(2)}^2$$

$$e_{pt} \sim N(0, \sigma_e^2$$

where y_{pt} is the average project performance for each employee, β_0 is the population mean response, $\sum_{i \in project(p)} w_{i,pt}^{(2)} u_{it}^{(2)}$ is a weighted sum of employee effects where the multiple membership weight $w_{i,pt}^{(2)}$ measures the extent to which project p belongs to employee i in month t, with an associated effect $u_{it}^{(2)}$ and e_{pt} is the residual error term. The employee effects and residual errors were assumed to follow normal distributions with zero means and constant variances. In this notation, p (p = 1, …, N) indexes projects, while the term 'employee(p)' is a 'classification function' that looks up and returns the unit number(s) of the employee(s) that project p belongs to.

$$employee(p) \subset \{1, \ldots, I(2)\}$$

where ⊂ means that a series of employees returned by employee(p) are a subset of all possible employees $\{1, \ldots, I^{(2)}\}$.

Importantly, the model required weighting by employees' time allocation to projects. For the weighting scheme $w_{i,pt}^{(2)}$ for $u_{it}^{(2)}$, we used the 1/number of projects the employee is in a given month (see Leckie *et al.*, 2013) but also found robust results in alternative weighting schemes (e.g., weighting by a percentage of time allocated to each project). The model is run using Markov chain Monte Carlo (MCMC) methods in MLwiN 3.04 for 5,000 iterations with a 500 iteration burn-in (Browne *et al.*, 2001). The MCMC algorithm, as developed by Leckie (2009) is used to estimate the multiple membership model. The results are presented in Table A-14, and the results confirmed our hypotheses.

Table A-14: Employee-level Model

	ALT12: Employee-level Analysis		ALT13: Multiple Membership Model	
Multi-project Work (MPW)	76.105	(20.228)	102.306	(25.319)
Multi-project Work Squared (MPW^2)	-11.076	(2.464)	-18.351	(3.245)
Specialized Experience	2.074	(1.091)	-1.652	(.383)
Project Similarity	138.674	(35.568)	.083	(.050)
Employee Familiarity	8.131	(1.119)	-77.838	(25.499)
MPW * Specialized Experience	-.139	(.472)	11.052	(3.475)
MPW * Project Similarity	-67.125	(19.803)	-5.786	(.748)
MPW * Employee Familiarity	-4.306	(.670)	.724	(.099)
MPW^2 * Specialized Experience	-.004	(.052)	7.889	(.570)
MPW^2 * Project Similarity	7.456	(2.492)	97.300	(41.783)
MPW^2 * Employee Familiarity	.486	(.089)	7.484	(1.264)
Project Size	.013	(.411)	-1.978	(.335)
Management Team Size	9.518	(3.687)	15.083	(1.788)
Number of Colleagues	2.817	(.521)	5.651	(.448)
Global Breath	-37.874	(4.592)	-32.371	(2.456)
Project Categorization	-91.661	(9.026)	-71.997	(4.983)
Project Innovation	-15.554	(12.170)	-32.528	(7.259)
Constant	-316.561	(46.928)	-376.087	(45.786)
Number of Observations	5,691		5,691	
Employee Fixed Effect	YES		YES	
Standard Errors	Standard Errors Clustered at Employee-level		Standard Errors obtained via Bayesian MCMC Algorithm	

Note: Standard errors are in parentheses

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