



City Research Online

City St George's, University of London

Citation: Colicev, A., Hakkarainen, T. & Pedersen, T. (2023). Multi-project work and project performance: Friends or foes?. *Strategic Management Journal*, 44(2), pp. 610-636. doi: 10.1002/smj.3443

This is the published version of the paper.

This version of the publication may differ from the final published version. To cite this item please consult the publisher's version.

Permanent repository link: <https://openaccess.city.ac.uk/id/eprint/31695/>

Link to published version: <https://doi.org/10.1002/smj.3443>

Copyright and Reuse: Copyright and Moral Rights remain with the author(s) and/or copyright holders. Copies of full items can be used for personal research or study, educational, or not-for-profit purposes without prior permission or charge, unless otherwise indicated, provided that the authors, title and full bibliographic details are credited, a hyperlink and/or URL is given for the original metadata page and the content is not changed in any way. For full details of reuse please refer to [City Research Online policy](#).

Multi-project work and project performance: Friends or foes?

Anatoli Colicev^{1,2}  | Tuuli Hakkarainen³ | Torben Pedersen^{4,5}

¹University of Liverpool Management School, University of Liverpool, Liverpool, UK

²Department of Marketing, Bocconi University, Milan, Italy

³University of Liverpool Management School, University of Liverpool, Liverpool, UK

⁴Department of Management and Technology, Bocconi University, Milan, Italy

⁵Department of Strategy and Innovation, Copenhagen Business School, Copenhagen, Denmark

Correspondence

Anatoli Colicev, University of Liverpool Management School, University of Liverpool, Chatham Street, Liverpool L69 7ZH, UK.

Email: anatoli.colicev@liverpool.ac.uk

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

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2022 The Authors. *Strategic Management Journal* published by John Wiley & Sons Ltd.

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.

KEYWORDS

multi-project work, productivity, project performance, specialized experience, 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, 2022). 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 article.

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 psychological effort to re-immers 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, 2022; 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, 2022; 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).

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, & 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, 2022). For instance, Kc and Terwiesch (2009) show that employees' productivity in hospitals eventually becomes unsustainable and drops off when the

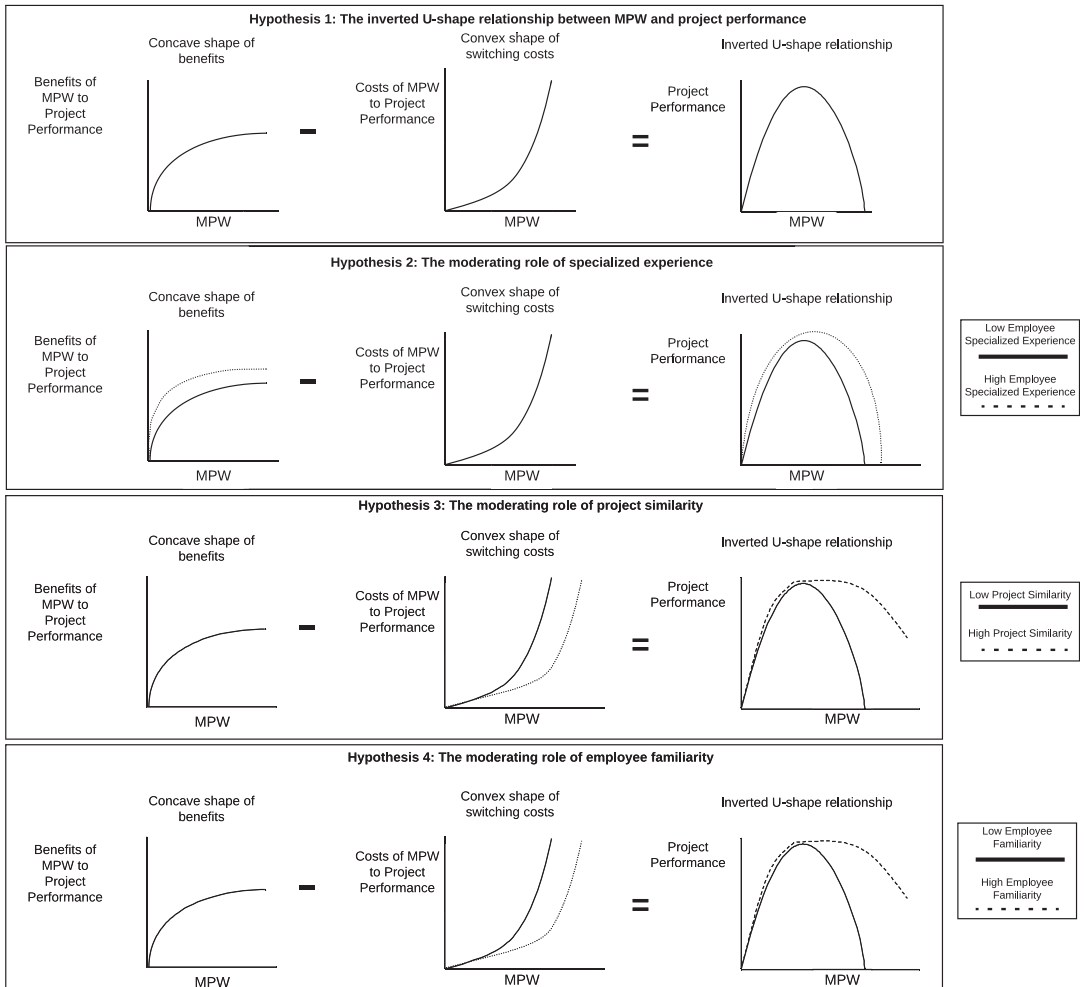


FIGURE 1 Conceptual framework

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 psychological effort to re-immerses 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 1 (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 specialized¹ experience moderates the inverted U-shape relationship between MPW and project performance (Cui et al., 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, 2022; 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

¹Specialization 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, Rajagopalan, & Ward, 2020). Other research has also conceptualized specialization with respect to knowledge domains (Haeussler & Sauermann, 2020; Teodoridis, 2018; Teodoridis, Bikard, & Vakili, 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.

²It 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.

and economics finds that specialized experience is positively related to the quality of output for workers such as 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 find 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 2 (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 3 (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 4 (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 S1 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 90–95% 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.

3.4 | Variables

We describe the variables in Table 1 (please see the Supporting Information for details).

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

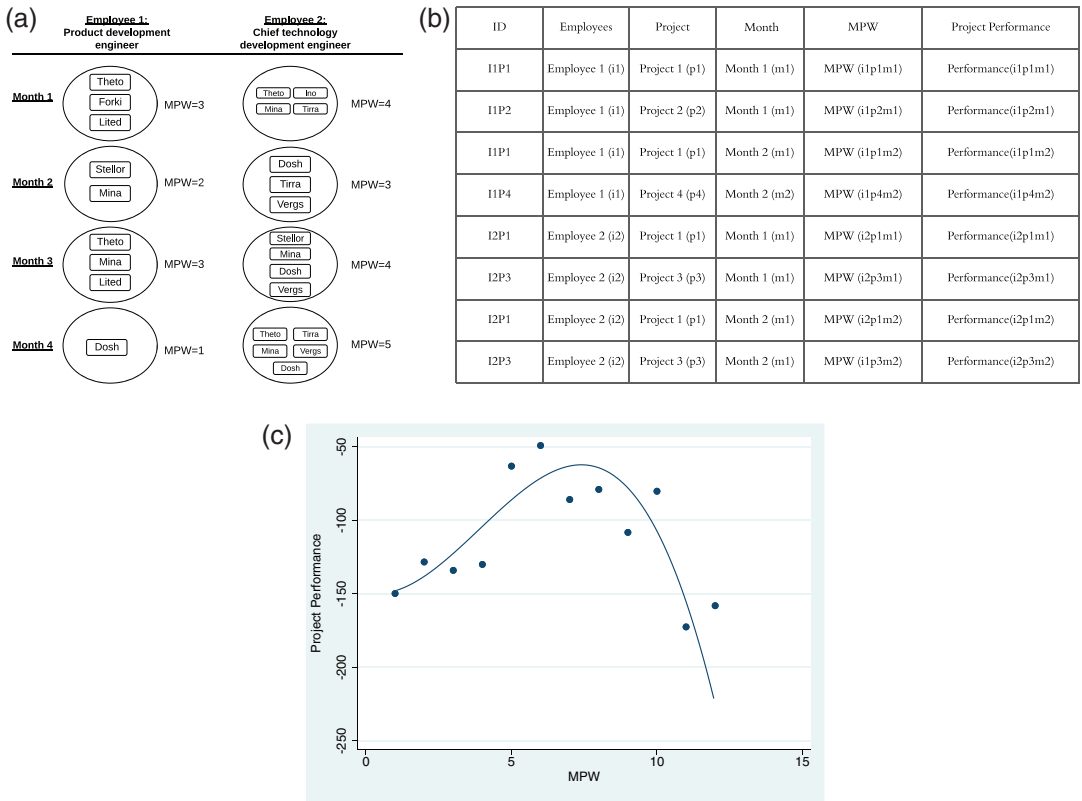


FIGURE 2 Multi-project work. (a) MPW illustration; (b) data illustration; and (c) binned scatterplot of the raw data. When Employee 1 (i1) and Employee 2 (i2) are on different sets of projects, they have different project performance values. For instance, Employee 1 (i1) is on projects (p1) and (p2) 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.

estimates after 1 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 S1–S3.

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

TABLE 1 Variable description and summary statistics

Variable	Description	Role	Source	Mean	SD	Min	Max
Project performance	Project <i>timelines</i> : 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

TABLE 1 (Continued)

Variable	Description	Role	Source	Mean	SD	Min	Max
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

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, 2022; 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 S6.

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 $\frac{1}{\text{Number of Projects}}$ to a maximum of 1 (in situations where an employee works only on similar projects). Empirically, we observe a minimum of 0.26 to a maximum of 1 (Figures S7 and S8).

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 S9 and S10.

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, Staats, Kouchaki, and Gino (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, 2022). 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 & Sauermann, 2020; Jain & Mitchell, 2022; Staats & 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 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

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

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 S11 and S12. 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 S2. 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 (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 &

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						
Management team size						
Number of colleagues						
Global breath = 1						
Global breath = 2						
Global breath = 3						
Global breath = 4						
Global breath = 5						
Project categorization						
Project Innovation						
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.

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 S13. 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 (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 vs. 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 nonoverlapping 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 20 nonoverlapping 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:

$$\begin{aligned}
 ProjectTimeliness_{ipm} = & \alpha_0 + \alpha_i + \alpha_m + \alpha_1 MPW_{ipm} + \alpha_2 MPW_{ipm}^2 + \alpha_3 MPW_{ipm} * Spec_{ipm} + \alpha_4 MPW_{ipm} \\
 & * Sim_{ipm} + \alpha_5 MPW_{ipm} * Fam_{ipm} + \alpha_6 MPW_{ipm}^2 * Spec_{ipm} + \alpha_7 MPW_{ipm}^2 * Sim_{ipm} + \alpha_8 MPW_{ipm}^2 \\
 & * Fam_{ipm} + \\
 & \alpha CTRL + \varepsilon_1,
 \end{aligned}$$

(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, ϵ_1 , are two-way clustered separately at the project and employee-level⁴ (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)

Table 2 reports the main results (for the correlation matrix, see Table S3). 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).

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 ($p = .002$; Table S4). We then used the *binstest* command from the *binsreg* package (Cattaneo, Crump, Farrell, & Feng, 2019a, 2019b). 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

⁴We 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.

⁵We thank the anonymous reviewer for guidance on this issue.

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 Figure 3b,d,e. 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 Figure 3a,c,e, we also present the conditional (on control variables) binned scatterplots with the *binsreg* command in STATA (Cattaneo et al., 2019a, 2019b; 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 S14.

To formally test Hypotheses 2, 3, and 4, we tested the slope of the coefficients α_6 , α_7 , and α_8 (curvature change). First, the coefficient of the interaction term between MPW^2 and specialized experience is positive (.14, $p = .026$). Figure 3a,b illustrates 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, $p = .086$). Figure 3c,d suggests 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 A5 and A9. 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,

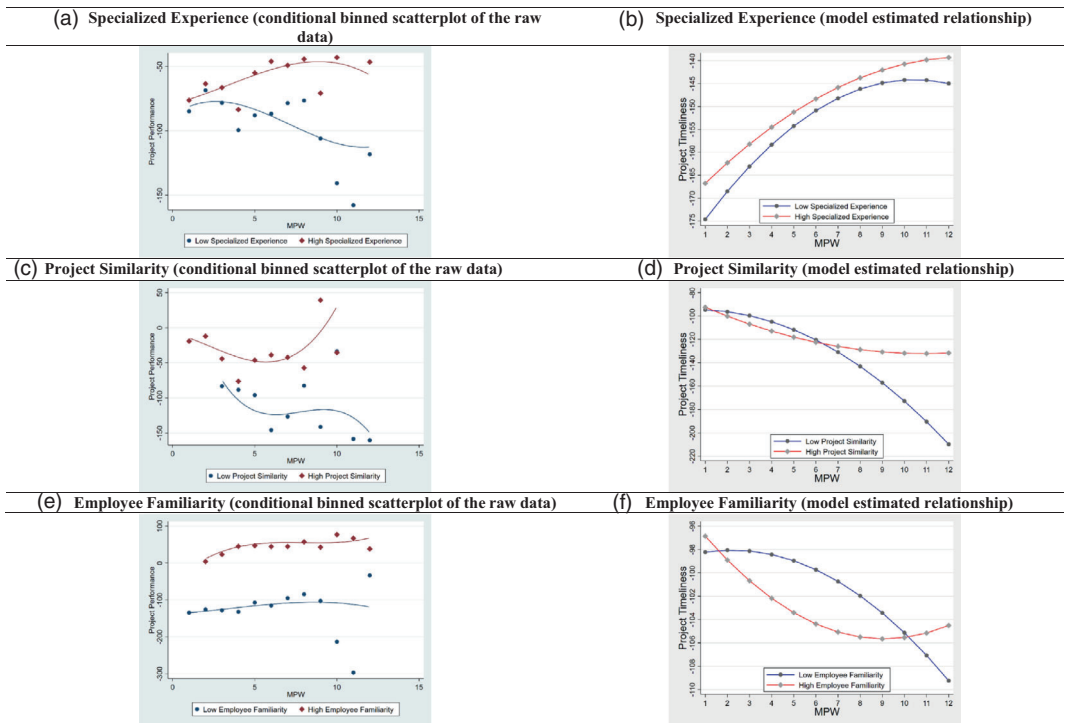


FIGURE 3 Moderators of the inverted U-shaped relationship between MPW and project performance. (a) Specialized experience (conditional binned scatterplot of the raw data); (b) Specialized experience (model estimated relationship); (c) Project similarity (conditional binned scatterplot of the raw data); (d) Project similarity (model estimated relationship); (e) Employee familiarity (conditional binned scatterplot of the raw data); and (f) Employee familiarity (model estimated relationship)

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, Gambardella, & Valentini, 2015; Bresnahan, Brynjolfsson, & Hitt, 2002). We provided the details in Table S9 in the Supporting Information. 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 (Table S10).

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 3–10 min (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 S17). 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 (Table S11). 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 (Table S12). 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 S13).

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 S14, 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 (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, 2022). 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 Figure 3a,b. 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 seems 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, 2022; 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 et al., 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, Figure 1c,d suggest that project similarity and employee familiarity can help reduce switching costs. We show the model results in Figure 3d,f. 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 (Akşın et al., 2021; Huckman et al., 2009; Huckman & Staats, 2011).

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 Akşın 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.

ACKNOWLEDGEMENTS

The authors thank Alfonso Gambardella, Thorsten Grohsjean, Mario Amore, Marco Tortoriello, Claudio Panico, Sandeep Pillai, and four anonymous reviewers from the SMS 2020 conference for their valuable comments. Finally, we are grateful for the constructive feedback from the SMJs review team and the editor for guidance on the revisions. The authors are listed alphabetically.

DATA AVAILABILITY STATEMENT

Data subject to third party restrictions and cannot be shared. The data that support the findings of this study are available from a company whose data sharing agreements are subject to confidentiality. Restrictions apply to the availability of these data, which were used under license and NDA for this study.

ORCID

Anatoli Colicev  <https://orcid.org/0000-0002-3311-8334>

REFERENCES

- Abadie, A., Athey, S., Imbens, G., & Wooldridge, J. (2017). *When should you adjust standard errors for clustering?* (No. w24003). Cambridge, MA: National Bureau of Economic Research.
- Adler, P. S., Mandelbaum, A., Nguyen, V., & Schwerer, E. (1996). Getting the most out of your product development process. *Harvard Business Review*, 74(2), 134–153.
- Aghion, P., Dewatripont, M., & Stein, J. C. (2008). Academic freedom, private-sector focus, and the process of innovation. *The Rand Journal of Economics*, 39(3), 617–635.

- Akşın, Z., Deo, S., Jónasson, J. O., & Ramdas, K. (2021). Learning from many: Partner exposure and team familiarity in fluid teams. *Management Science*, 67(2), 854–874.
- Anderson, T., & Bidwell, M. (2019). Outside insiders: Understanding the role of contracting in the careers of managerial workers. *Organization Science*, 30(5), 1000–1029.
- Aral, S., Brynjolfsson, E., & Van Alstyne, M. W. (2012). Information, technology, and information worker productivity. *Information Systems Research*, 23(3), 849–867.
- Argote, L. (1999). *Organizational learning: Creating, retaining, and transferring knowledge*. Norwell, MA: Kluwer.
- Becker, G. S., & Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, 107(4), 1137–1160.
- Beşikci, U., Bilge, Ü., & Ulusoy, G. (2015). Multi-mode resource constrained multi-project scheduling and resource portfolio problem. *European Journal of Operational Research*, 240(1), 22–31.
- Bettis, R. A., Gambardella, A., Helfat, C., & Mitchell, W. (2014). Quantitative empirical analysis in strategic management. *Strategic Management Journal*, 35(7), 949–953.
- Birhanu, A. G., Gambardella, A., & Valentini, G. (2015). Bribery and investment: Firm-level evidence from Africa and Latin America. *Strategic Management Journal*, 37(9), 1865–1877.
- Boh, W. F., Slaughter, S. A., & Espinosa, J. A. (2007). Learning from experience in software development: A multilevel analysis. *Management Science*, 53(8), 1315–1331.
- Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *Quarterly Journal of Economics*, 117(1), 339–376.
- Castanias, R. P., & Helfat, C. E. (2001). The managerial rents model: Theory and empirical analysis. *Journal of Management*, 27(6), 661–678.
- Cattaneo, M. D., Crump, R. K., Farrell, M., & Feng, Y. (2019a). On Binscatter. arXiv preprint arXiv:1902.09608
- Cattaneo, M. D., Crump, R. K., Farrell, M. H., & Feng, Y. (2019b). Binscatter Regressions. Retrieved from <https://arxiv.org/pdf/1902.09615.pdf>
- Chatain, O., & Meyer-Doyle, P. (2017). Alleviating managerial dilemmas in human-capital-intensive firms through incentives: Evidence from M&A legal advisors. *Strategic Management Journal*, 38(2), 232–254.
- Choudhury, P., Froughi, C., & Larson, B. (2021). Work-from-anywhere: The productivity effects of geographic flexibility. *Strategic Management Journal*, 42(4), 655–683.
- Clark, J., & Huckman, R. S. (2012). Broadening focus: Spillovers, complementarities and specialization in the hospital industry. *Management Science*, 28(4), 708–722.
- Correia, S. (2017). Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Working Paper.
- Crama, P., Sting, F. J., & Wu, Y. (2019). Encouraging help across projects. *Management Science*, 65(3), 1408–1429.
- Cui, H., Rajagopalan, S., & Ward, A. R. (2020). Impact of task-level worker specialization, workload, and product personalization on consumer returns. *Manufacturing & Service Operations Management*, 23(2), 346–366.
- Cummings, J. N., & Haas, M. R. (2012). So many teams, so little time: Time allocation matters in geographically dispersed teams. *Journal of Organizational Behavior*, 33(3), 316–341.
- Dane, E. (2010). Reconsidering the trade-off between expertise and flexibility: A cognitive entrenchment perspective. *Academy of Management Review*, 35(4), 579–603.
- Edwards, B. K., & Starr, R. M. (1987). A note on indivisibility, specialization and economies of scale. *American Economic Review*, 77(1), 192–194.
- Eisenhardt, K. M., & Tabrizi, B. N. (1995). Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly*, 40(1), 84.
- Evans, J. A., Kunda, G., & Barley, S. R. (2004). Beach time, bridge time, and billable hours: The temporal structure of technical contracting. *Administrative Science Quarterly*, 49(1), 1–38.
- Fahrenkopf, E., Guo, J., & Argote, L. (2020). Personnel mobility and organizational performance: The effects of specialist vs. generalist experience and organizational work structure. *Organization Science*, 31(6), 1601–1620.
- Fieller, E. C. (1954). Some problems in interval estimation. *Journal of the Royal Statistical Society: Series B: Methodological*, 16(2), 175–185.
- Gambardella, A., Khashabi, P., & Panico, C. (2020). Managing autonomy in industrial research and development: A project-level investigation. *Organization Science*, 31(1), 165–181.
- Gambardella, A., Panico, C., & Valentini, G. (2015). Strategic incentives to human capital. *Strategic Management Journal*, 36(1), 37–52.

- Giustiziero, G. (2021). Is the division of labor limited by the extent of the market? Opportunity cost theory with evidence from the real estate brokerage industry. *Strategic Management Journal*, 42(7), 1344–1378.
- Goldfarb, B., & King, A. A. (2016). Scientific apophenia in strategic management research: Significance tests & mistaken inference. *Strategic Management Journal*, 37(1), 167–176.
- Goldfarb, B., & Yan, L. (2021). Revisiting Zuckerman's (1999) categorical imperative: An application of epistemic maps for replication. *Strategic Management Journal*, 42, 1963–1992.
- Groysberg, B., Lee, L. E., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge workers' performance. *Management Science*, 54(7), 1213–1230.
- Haans, R. F. J., Pieters, C., & He, Z. L. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, 37(7), 1177–1195.
- Haeussler, C., & Sauermann, H. (2020). Division of labor in collaborative knowledge production: The role of team size and interdisciplinarity. *Research Policy*, 49(6), 103987.
- Huckman, R. S., & Staats, B. R. (2011). Fluid tasks and fluid teams: The impact of diversity in experience and team familiarity on team performance. *Manufacturing & Service Operations Management*, 13(3), 310–328.
- Huckman, R. S., Staats, B. R., & Upton, D. M. (2009). Team familiarity, role experience, and performance: Evidence from Indian software services. *Management Science*, 55(1), 85–100.
- Jain, A., & Mitchell, W. (2022). Specialization as a double-edged sword: The relationship of scientist specialization with R&D productivity and impact following collaborator change. *Strategic Management Journal*, 43(5), 986–1024.
- Kc, D. S. (2014). Does multitasking improve performance? Evidence from the emergency department. *Manufacturing & Service Operations Management*, 16(2), 168–183.
- Kc, D. S., & Staats, B. R. (2012). Accumulating a portfolio of experience: The effect of focal and related experience on surgeon performance. *Manufacturing and Service Operations Management*, 14(4), 618–633.
- Kc, D. S., Staats, B. R., Kouchaki, M., & Gino, F. (2020). Task selection and workload: A focus on completing easy tasks hurts performance. *Management Science*, 66(10), 4397–4416.
- Kc, D. S., & Terwiesch, C. (2009). Impact of workload on service time and patient safety: An econometric analysis of hospital operations. *Management Science*, 55(9), 1486–1498. <https://doi.org/10.1287/mnsc.1090.1037>
- Krishnan, V., & Ulrich, K. T. (2001). Product development decisions: A review of the literature. *Management Science*, 47(1), 1–21.
- Leroy, S., & Glomb, T. M. (2018). Tasks interrupted: How anticipating time pressure on resumption of an interrupted task causes attention residue and low performance on interrupting tasks and how a “ready-to-resume” plan mitigates the effects. *Organization Science*, 29(3), 380–397.
- Lind, J. T., & Mehlum, H. (2010). With or without u? The appropriate test for a U-shaped relationship. *Oxford Bulletin of Economics and Statistics*, 72(1), 109–118.
- Lyngsie, J., & Foss, N. J. (2017). The more, the merrier? Women in top-management teams and entrepreneurship in established firms. *Strategic Management Journal*, 38(3), 487–505.
- Milgrom, P. R., & Roberts, J. D. (1992). *Economics, organization and management*. Englewood Cliffs, NJ: Prentice Hall.
- Mortensen, M., & Gardner, H. K. (2017). The overcommitted organization. *Harvard Business Review*, 95(5), 58–65.
- Mortensen, M., & Haas, M. (2018). Perspective—Rethinking teams: From bounded membership to dynamic participation. *Organization Science*, 29(2), 341–355.
- Nobeoka, K., & Cusumano, M. A. (1997). Multiproject strategy and sales growth: The benefits of rapid design transfer in new product development. *Strategic Management Journal*, 18(3), 169–186.
- O'Leary, M., Mortensen, M., & Woolley, A. (2011). Multiple team membership: A theoretical model of its effects on productivity and learning for individuals and teams. *Academy of Management Review*, 36(3), 461–478.
- Owen-Smith, J. (2001). Managing laboratory work through skepticism: Processes of evaluation and control. *American Sociological Review*, 66(3), 427–452.
- Rabe-Hesketh, S., & Skrondal, A. (2012). *Multilevel and longitudinal modeling using Stata*. College Station, TX: Stata Press.
- Raveendran, M., Puranam, P., & Warglien, M. (2016). Object salience in the division of labor: Experimental evidence. *Management Science*, 62(7), 2110–2128.
- Raveendran, M., Puranam, P., & Warglien, M. (2022). Division of labor through self-selection. *Organization Science*, 33(2), 810–830.
- Reagans, R., Argote, L., & Brooks, D. (2005). Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management Science*, 51(6), 869–881.

- Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5), 688–701.
- Rubin, D. B. (2005). Causal inference using potential outcomes: Design, modeling, decisions. *Journal of the American Statistical Association*, 100(469), 322–331.
- Sasabuchi, S. (1980). A test of a multivariate normal mean with composite hypotheses determined by linear inequalities. *Biometrika*, 67(2), 429–439.
- Schilling, M. A., Vidal, P., Ployhart, R. E., & Marangoni, A. (2003). Learning by doing something else: Variation, relatedness, and the learning curve. *Management Science*, 49(1), 39–56.
- Sessions, H., Nahrgang, J. D., Vaulont, M. J., Williams, R., & Bartels, A. L. (2021). Do the hustle! Empowerment from side-hustles and its effects on full-time work performance. *Academy of Management Journal*, 64(1), 235–264.
- Simon, H. A. (1982). *Models of bounded rationality: Behavioral economics and business organization*. Cambridge, MA: MIT Press.
- Skilton, P. F., & Dooley, K. J. (2010). The effects of repeat collaboration on creative abrasion. *Academy of Management Review*, 35(1), 118–134.
- Smith, A. (1776). *The Wealth of Nations (Reprint 19; W. Strahan & T. Cadell, Eds.)*. Chicago, IL: University of Chicago Press.
- Smith, T. A., Kirkman, B., Chen, G., & Lemoine, G. J. (2018). Research: When employees work on multiple teams, good bosses can have ripple effects. *Harvard Business Review Digital Articles*, September, 1–5.
- Staats, B. R., & Gino, F. (2012). Specialization and variety in repetitive tasks: Evidence from a Japanese bank. *Management Science*, 58(6), 1141–1159.
- Starr, E., Ganco, M., & Campbell, B. A. (2018). Strategic human capital management in the context of cross-industry and within-industry mobility frictions. *Strategic Management Journal*, 39(8), 2226–2254.
- Starr, E., & Goldfarb, B. (2020). Binned scatterplots: A simple tool to make research easier and better. *Strategic Management Journal*, 41(12), 2261–2274.
- Stigler, G. J. (1951). The division of labor is limited by the extent of the market. *Journal of Political Economy*, 59(3), 185–193.
- Theodoridis, F. (2018). Understanding team knowledge production: The interrelated roles of technology and expertise. *Management Science*, 64(8), 3625–3648.
- Theodoridis, F., Bikard, M., & Vakili, K. (2019). Creativity at the knowledge frontier: The impact of specialization in fast- and slow-paced domains*. *Administrative Science Quarterly*, 64(4), 894–927.
- Toh, P. K. (2014). Chicken, or the egg, or both? The interrelationship between a firm's inventor specialization and scope of technologies. *Strategic Management Journal*, 35(5), 723–738.
- Waller, M. J., Conte, J. M., Gibson, C. B., & Carpenter, M. A. (2001). The effect of individual perceptions of deadlines on team performance. *The Academy of Management Review*, 26(4), 586–600.
- Wheelwright, S. C., & Clark, K. B. (1992). *Revolutionizing product development: Quantum leaps in speed, efficiency, and quality*. New York, NY: Free Press.
- Wiersema, M. F., & Bantel, K. A. (1992). Top management team demography and corporate strategic change. *Academy of Management Journal*, 35(1), 91–121.
- Wylie, G., & Allport, A. (2000). Task switching and the measurement of “switch costs”. *Psychological Research*, 63(3–4), 212–233.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Colicev, A., Hakkarainen, T., & Pedersen, T. (2022). Multi-project work and project performance: Friends or foes? *Strategic Management Journal*, 1–27. <https://doi.org/10.1002/smj.3443>