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ENSAYOS SOBRE EL DESPLIEGUE DE LOS RECURSOS HUMANOS Y EL DESEMPEÑO OPERATIVO

ESSAYS ON THE DEPLOYMENT OF HUMAN RESOURCES AND OPERATIONAL PERFORMANCE

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Doctoral Thesis Advisor: Fabrizio Salvador

RESUMEN

La mayoría de las organizaciones contemporáneas intentan atender mejor la demanda por medio de una amplia gama de practicas laborales flexibles—incluido el uso de horarios irregulares o bajo demanda, trabajadores a tiempo parcial o temporales, o el uso de equipos fluidos. Comprender el efecto de estas prácticas en el desempeño del trabajador o del equipo es de suma importancia. De hecho, a pesar de la flexibilidad operativa que brindan, estas prácticas implican costos potenciales para la empresa, debido a las limitaciones en el uso flexible del talento humano. El objetivo de esta tesis es contribuir a dicha comprensión, formulando hipótesis basadas en la investigación en los dominios de gestión de operaciones y recursos humanos y, posteriormente, estudiando rigurosamente estas hipótesis con datos secundarios de organizaciones reales. El primer ensayo presenta dos métricas de características de horarios bajo demanda: tiempo inactivo no remunerado y variabilidad en el horario, y mide su efecto sobre el absentismo del personal y la insatisfacción del paciente con el servicio prestado en un contexto de atención médica domiciliaria. El segundo ensayo explora cómo combinar trabajadores subcontratados y fijos en equipos de proyecto afecta su desempeño en una multinacional de ingeniería y manufactura de alta tecnología. El tercer ensayo investiga cómo la asignación del personal durante la ejecución del proyecto afecta su desempeño, explorando empíricamente el efecto de la práctica lean de ‘carga - anticipada’, o la asignación de más recursos humanos al comienzo del proyecto. Los hallazgos generales de la tesis establecen que, además de sus ventajas operativas, las prácticas laborales flexibles pueden tener impactos multifacéticos en el desempeño individual y del equipo, y que dichos impactos pueden ser tanto positivos como negativos, según la práctica considerada y varias contingencias.

ABSTRACT

Most contemporary organizations attempt to better serve demand by means of a wide array of flexible labor arrangements–including the use of on-demand or irregular schedules, part-time or temporary workers or the use of fluid teams. Understanding the effect of the use of these practices on worker or team performance is of primary importance. In fact, despite the operational flexibility they provide, these practices entail potential costs for the firm, due to limitations in the flexible use of human resources. The goal of this dissertation is to contribute to such understanding, building hypotheses on research in operations management and human resources domains and subsequently rigorously testing these hypotheses using secondary data from real organizations. The first essay introduces two metrics of on-demand schedule characteristics: idle unpaid time within the day and variability in the schedule across the weeks and measures their effect on employee absenteeism and patient dissatisfaction in a home healthcare setting. The second essay explores how the mix of subcontracted and permanent workers in project teams affects project performance in a high-tech engineering and manufacturing multinational. The third essay investigates how the allocation of the workforce during project execution affects its performance, by empirically exploring front-loading, or the allocation of more human resources in the beginning of the project. The overreaching finding of the dissertation is that besides their operational advantages, flexible labor arrangements can have multifaceted impacts on individual and team performance, and that such impacts can be both positive and negative, depending on the considered practice and various contingencies.

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INTRODUCCIÓN

La transición hacia una economía de ‘24 horas, 7 días a la semana’ ha obligado a muchas empresas del sector de servicios profesionales, a adoptar prácticas laborales flexibles para adaptar la oferta de sus servicios y garantizar la continuidad del negocio. La tendencia se refleja, por ejemplo, en el hallazgo de la Oficina de Estadísticas Laborales de EEUU de que más del 10 % de la fuerza laboral de EEUU en 2017 (o más de 15 millones de puestos de trabajo) han tenido empleos irregulares o no tradicionales (US BLS 2018). Las practicas laborales no tradicionales o flexibles pueden incluir estrategias tan variadas como la asignación de horarios irregulares o bajo demanda, el uso de trabajadores a tiempo parcial o temporales, así como la asignación flexible del trabajo a los recursos humanos disponibles. Las empresas, prestadoras de servicios utilizan estas prácticas para ajustar su oferta a las fluctuaciones de la demanda, manteniendo los costos bajos. Sin embargo, su uso puede tener determinados costes ocultos para la empresa, debido a las limitaciones inherentes, y a menudo ignorados, del uso flexible del talento humano.

Si bien el advenimiento de las prácticas flexibles estimuló una amplia línea de investigación, sus efectos sobre el desempeño de los trabajadores y las empresas siguen sin nítidos. Por un lado, la investigación en el dominio de la gestión de operaciones ha comenzado a explorar los efectos del uso de diferentes estrategias laborales flexibles en el coste y en el rendimiento. Aunque de alcance limitado, las investigaciones sugieren que, en un contexto minorista, el uso de trabajadores temporales permite a las empresas equiparar la capacidad con la demanda de manera más eficiente, lo que conlleva efectos positivos iniciales en los costes y los ingresos. Sin embargo, más allá de un cierto punto, las prácticas laborales flexibles comienzan a tener un efecto negativo sobre los costes y los ingresos (Kesavan et al. 2014). Además, investigaciones recientes han mostrado que al mejorar varios aspectos de los horarios del personal con el fin de hacerlos más estables, se aumenta la productividad laboral y las ventas (Kesavan et al. 2022). Por último, la literatura que estudia la forma de distribuir el trabajo a lo largo de un proyecto ha mostrado que asignar tareas intensivas en conocimiento al comienzo del proyecto está asociado con un mayor desempeño del mismo (Thomke & Fujimoto 2000). Estas investigaciones se han centrado principalmente en estudiar estrategias para identificar tareas a realizar en las diferentes etapas del proyecto, pero no han explorado el impacto de los recursos humanos (es decir, nivel de experiencia, familiaridad) y tampoco qué recursos humanos se espera que realice estas tareas.

El marco conceptual y empírico ya existente sobre el comportamiento organizacional se ha centrado principalmente en explorar cómo las diferentes estrategias laborales flexibles afectan el entorno laboral o el bienestar de los trabajadores. Por un lado, investigaciones anteriores han mostrado que combinar trabajadores temporales y permanentes en una organización puede tener un impacto negativo en el ambiente del lugar de trabajo (p. ej., George 2003, Davis-Blake et al. 2003). Sin embargo, estudios más recientes sugieren que este puede no ser el caso debido a la mayor motivación de los trabajadores temporales (p. ej., Felfe et al. 2008, Petriglieri et al. 2018). Aun así, ninguno de estos estudios midió realmente el efecto en el rendimiento de las prácticas laborales flexibles. Además, la literatura que investiga los horarios inestables se ha centrado principalmente en comprender los efectos negativos que estas prácticas tienen sobre el bienestar de los empleados, pero, no ha estudiado su efecto sobre el comportamiento de los empleados y cómo puede esto afectar a la organización. Por lo tanto, el estudio de los efectos de las prácticas laborales flexibles en el trabajador y el desempeño operativo de la empresa sigue siendo importante, pero como anteriormente se ha mencionado, muy poco estudiado.

Además de la relevancia académica de este tema, también es un tema de gran interés para los gerentes, quienes son los responsables de tomar decisiones sobre cómo y cuándo utilizar la mano de obra flexible. Para poder aprovechar al máximo las practicas laborales flexibles, los gerentes primero deben ser conscientes de sus limitaciones y luego poseer estrategias para mitigarlas. A continuación, se presenta un breve resumen de los tres ensayos de la presente tesis.

El primer ensayo de la tesis analiza la programación bajo demanda de los trabajadores por horas. Una encuesta de 2016 de residentes de EEUU encontró que el 80 % de los trabajadores por hora informaron fluctuaciones en el número de horas semanales, que están determinadas principalmente por el empleador y no por el empleado (Williams et al. 2018). Los horarios inestables e impredecibles tienen un impacto en el bienestar de los trabajadores (Henly & Lambert 2014). Este estudio permite ampliar la literatura primero centrándose en dos aspectos fundamentales de los horarios bajo demanda, que son la cantidad de tiempo de inactividad no programado durante el día laboral y la variabilidad de los horarios a lo largo de las semanas, y segundo estudiando su efecto en dos aspectos cruciales para los resultados de la empresa: absentismo e insatisfacción del paciente con el servicio prestado. El contexto en el que se realiza el análisis, es de un importante proveedor de atención médica en Canadá, que ofrece servicios de atención médica domiciliaria a pacientes con diferentes condiciones de salud. El conjunto de datos consta de más de un millón de visitas domiciliarias de los asistentes de atención médica a los pacientes durante un lapso de 5 años (de enero de 2012 a diciembre de 2016) en una de las provincias más grandes de Canadá. Los resultados muestran que la cantidad de tiempo de inactividad no remunerado, así como las variaciones en los horarios a lo largo de las semanas, se asocia con mayores niveles de absentismo de los empleados, así como con la insatisfacción de los pacientes con los servicios prestados, ya que estas prácticas impiden el uso productivo del tiempo personal de los trabajadores y afectan negativamente sus obligaciones no laborales.

El segundo ensayo se enfoca en explorar el uso de mano de obra temporal o subcontratada en un entorno de proyecto, que ha sido ampliamente ignorado en los estudios empíricos (Mayer & Nickerson 2005). El uso de trabajadores subcontratados es particularmente importante en proyectos, ya que en estos contextos los subcontratados tienen que colaborar con trabajadores fijos para realizar tareas altamente inciertas e interdependientes. La tesis amplia la literatura ya existente al estudiar el efecto de los trabajadores subcontratados en el desempeño de proyectos complejos. El contexto en el que se realiza el análisis es de una empresa europea líder de alta tecnología que realiza proyectos de ingeniería en la industria aeroespacial. El conjunto de datos consta de todos los proyectos realizados por la división aeroespacial de la empresa (un total de 413 proyectos) desde 2006 hasta 2016. El análisis del ensayo muestra que los trabajadores subcontratados tienen un efecto positivo en el desempeño del proyecto ya que tienen más incentivos para desempeñarse bien durante el compromiso actual a fin de asegurar contratos futuros. Además, este efecto beneficioso es aún mayor para los trabajadores subcontratados menos calificados. Así mismo, el efecto positivo de los trabajadores subcontratados en el desempeño del proyecto se ve moderado por diferentes factores contextuales, como el tamaño del equipo y la magnitud de los cambios en el alcance del proyecto.

El tercer ensayo explora la práctica lean de gestión de proyectos de carga anticipada. Thomke y Fujimoto (2000) definen 'carga-anticipada' (o en ingles 'front-loading') como una práctica que busca mejorar el desempeño del proyecto trasladando la identificación y resolución de problemas fundamentales en su comienzo. A pesar de la relevancia de esta práctica, hay un bajo nivel de investigación empírica sobre sus efectos en el desempeño real del proyecto. Investigar dicho efecto es importante porque las empresas no siempre pueden anticipar la carga de un proyecto, especialmente cuando la ejecución simultánea de múltiples tareas interdependientes, resultado de dicha práctica, genera una complejidad excesiva en las primeras etapas del proyecto. Utilizando como base el marco conceptual ya existente sobre cómo la carga anticipada de un proyecto facilita la reducción de errores y retrasos en las etapas posteriores, el ensayo desarrolla hipótesis para conceptualizar cómo y bajo qué condiciones dicha práctica impacta positivamente en el desempeño del proyecto. Para realizar el análisis se usan los mismos datos que en el segundo ensayo. Los resultados muestran que el efecto positivo de la asignación de más personal al comienzo del proyecto sobre su desempeño, se atenúa cuando la familiaridad con el líder del equipo, el equipo o el cliente es alta, ya que las diferentes facetas de la familiaridad permiten que los equipos colaboren mejor y se anticipen a los errores al inicio de los proyectos, en comparación con los equipos menos familiares.

En conjunto, los tres ensayos avanzan el conocimiento existente sobre el efecto de diferentes estrategias flexibles de despliegue de recursos humanos en entorno de servicios profesionales en el desempeño del proyecto o del trabajador.

Los hallazgos muestran que las practicas laborales son un impulsor fundamental del desempeño que debe tenerse en cuenta al diseñar estrategias operativas. El talento humano, a diferencia de las máquinas, tiene una motivación y limitaciones inherentes que afectan su desempeño y pueden fomentar o diferir con las estrategias operativas. Por ejemplo, las estrategias operativas que exigen demasiada flexibilidad de los trabajadores pueden llegar a sus límites de flexibilidad, causando absentismo y un peor rendimiento. De manera similar, dar responsabilidad temporal a los trabajadores, con la oportunidad de una relación laboral a más largo plazo, puede aumentar su motivación, para realizar un trabajo de alta calidad y también su desempeño y el del equipo en general.

INTRODUCTION

The move toward a 24-hour, 7-day-a week economy has forced many professional service companies to adopt flexible labor practices to adapt the service offering to ensure continuity of business. The trend is reflected, for instance, in the finding of the US Bureau of Labor Statistics that more than 10% of the US workforce in 2017 (or over 15 million jobs) engage in irregular or non-traditional employment (US BLS 2018). Non-traditional or flexible labor arrangements can cover practices as varied as assigning on-demand or irregular schedules, using part-time or temporary workers, as well as flexibly allocating work to available resources. Service firms use these practices, to adjust their service offering to the fluctuations in demand, while maintaining costs low. However, the use of flexible labor arrangements has potential hidden costs for the firm, due to inherent, and often overlooked, limitations of the flexible use of human resources.

While the advent of flexible practices spurred a rich stream of research, their effects on worker and firm performance remain unclear. Research in operations management has started to explore the effects of using different flexible workforce strategies on cost and performance. Albeit limited in scope, it suggests that the use of temporary workers indeed allows firms to more efficiently match capacity with demand, which leads to initial positive effects on costs and revenue in a retail setting. However, beyond a certain point, flexible labor practices begin to negatively affect costs and revenues (Kesavan et al. 2014). Moreover, recent research has found that improving multiple dimensions of workers schedules, by making them more stable, increases labor productivity and sales (Kesavan et al. 2022). Lastly, literature on work allocation on project performance has observed that shifting knowledge intensive work in the beginning of the project is associated with higher project performance (Thomke & Fujimoto 2000). This literature has mostly focused on strategies to identify tasks to be performed in the different stages of the project development, but has not explored the impact of the human resources (i.e., expertise level, familiarity) who are expected to perform these tasks.

Research in organizational behavior has mostly focused on exploring how different flexible labor strategies affect workplace environment or workers wellbeing. For example, past research has found that blending temporary and permanent workers in an organization can have a negative impact on work-place environment (e.g., George 2003, Davis-Blake et al. 2003). However, more recent studies suggest that this may not be the case because of higher motivation of temporal workers (e.g., Felfe et al. 2008, Petriglieri et al. 2018). Nonetheless, none of these studies actually measured the performance effect of flexible work practices. Moreover, the literature investigating unstable schedules has mostly focused on understanding the negative effects these practices have on employees' wellbeing, but has not studied the actual behavior of the employees and how it may impact the organization. Studying the effects of flexible labor practices on worker and the firm operational performance therefore remains important and vastly understudied.

Apart from the academic relevance of this topic, it is also of a major interest for managers, who are responsible for taking decisions on how and when to use the flexible workforce. To be able to take a full advantage of the flexible labor arrangements, managers need to first be aware of their limitations and then design strategies to mitigate them. Following is a brief summary of the three essays of the thesis.

The first essay of the thesis looks at on-demand scheduling of hourly workers. A 2016 survey of US residents found that 80% of hourly workers reported fluctuations in the number of their weekly hours, which are mainly determined by the employer rather than the employee (Williams et al. 2018). Unstable and unpredictable schedules have an impact on worker's well-being (Henly & Lambert 2014). This study extends the literature by focusing on two aspects of on-demand scheduling which are the amount of unscheduled idle time within the day as well as the variability of the schedules across the weeks and studying their effect on two crucial for the company outcomes: employee absenteeism and patient dissatisfaction with the service provided. The setting for the analysis is a major healthcare provider in Canada, which offers home healthcare services to patients with different health conditions. The dataset consists of over a million home visits of the health care aides to the patients of the span of 5 years (from January 2012 to December 2016) in one of the biggest provinces in Canada. The findings show that the presence of unpaid idle time within the working days as well as variations in the schedules across the weeks is associated with higher levels of employee absenteeism as well as patient dissatisfaction, as these practices impede the productive use of the workers time and negatively impacts their non-work obligations.

The second essay focuses on exploring the use of temporal or subcontracted labor in a project setting, which has been vastly overlooked in empirical studies (Mayer & Nickerson 2005). The use of subcontracted workers is particularly important in project settings as they are expected to collaborate with permanent workers for the completion of the project on highly uncertain and interdependent tasks. The thesis builds on past literature by studying the effect of subcontracted workers on complex projects performance. The setting for the analysis is a leading high-tech European company which performs engineering projects in the aerospace industry. The dataset consists of all the project the aerospace division of the company performed (a total of 413 projects) from 2006 to 2016. The essay finds that subcontracted workers have a positive effect on project performance as they have more incentives to perform well in the current engagement in order to ensure future contracts. Moreover, this beneficial effect is even stronger for lower skilled subcontracted workers. Furthermore, the positive effect of subcontracted workers on project performance is moderated by different contextual factors, such as project team size and magnitude of scope changes.

The third essay explores the lean project management practice of front-loading. Thomke and Fujimoto (2000) define front-loading as a practice that seeks to improve project development performance by shifting the identification and solving of fundamental problems to the beginning of the project. Despite the relevance of this project management practice, there is scant empirical research studying its effects on the actual project performance. Investigating such an effect is important because companies cannot always front-load a project, especially when the concurrent execution of multiple interdependent tasks, a result of front-loading, generates excessive complexity in the earlier stages. Building on previous conceptual work about how front-loading a project facilitates the reduction of errors and delays in the later stages, the essay develops hypotheses to conceptualize how and under which conditions front-loading positively impacts project performance. The setting for the analysis is the same setting as in the second essay. The findings suggest that the positive effect associated with allocating more human resources in the beginning of the project is attenuated when team leader, team or client familiarity are high as the different facets of familiarity allow teams to be better at collaborating and anticipating errors in the beginning of the projects, compared to less familiar teams.

Taken together, the three essays advance extant knowledge about the effect of different flexible strategies of human resource deployment in service settings on project or worker performance. The findings suggest that the labor arrangements in a service setting are a fundamental driver of performance which needs to be considered when designing operational strategies. Human resources, unlike machines, have inherent motivation and limitations that affect their performance and can either foster or clash with the operational strategies. For example, operational strategies that ask for too much flexibility out of the workers, may hit the workers limits of the flexibility, causing absenteeism and poor performance. In similar manner, giving temporal responsibility to workers but with the opportunity of a longer-term labor relationship, may increase their motivation and determination to signal high quality work and this can increase their and the overall team's performance.

ESSAY 1: Workers on Demand? Effects of On-Demand Schedules on Employee Absenteeism and Patient Dissatisfaction in a Home Healthcare Organization

Abstract

Many service companies today use on-demand scheduling practices to keep labor costs low and simultaneously ensure high service levels. While the benefits of such practices are apparent, much less is known about their costs. An emerging stream of research points to the fact that on-demand schedules negatively affect worker outcomes, but their impact on worker behavior and performance remains understudied. Using a proprietary dataset of more than 1.2 million home visits performed by caregivers over a 5-year period in a Canadian homecare service organization, we study how on-demand schedules impact worker absenteeism and patient dissatisfaction. We focus on two aspects of on-demand schedules that hinder workers' ability to effectively use of their non-work (i.e., personal) time: (1) variability in the schedule and (2) gaps in daily schedules. We show that these schedule features are associated with more employee absences and more patient complaints. Our results indicate that organizations should carefully evaluate the extent to which the benefits of on-demand schedules compensate their costs as relying on them intervenes with the limits of human flexibility.

***Keywords*:** on-demand schedules, split work, non-routine work, healthcare operations, worker performance, absenteeism, patient dissatisfaction

1. Introduction

A growing fraction of the working population is transitioning from the traditional nine-to-five, five-day workweek towards more flexible schedules (Kalleberg 2001, Cappelli 2008, Spreitzer et al. 2017). One reason behind this trend is employers' expectation that allowing workers to decide when and how much work to do, may improve their quality of life and productivity (Kelliher & Anderson 2010). Often, however, flexible schedules respond to employers' needs to adjust their staffing to variations in consumer demand while minimizing labor costs (Lambert 2008, Kamalahmadi et al. 2021), rather than employees' preferences for flexibility. Companies who adopt this latter kind of flexible work schedules—which we refer to as on-demand schedules—request workers to comply with schedules that not only vary in the number of hours worked, but also in how these hours are distributed across the week. By doing so, they aim to transfer to workers the burden of adapting to erratic demand patterns (Kalleberg & Vallas 2018). However, to the extent that workers incur costs when adjusting to such variability, their performance could suffer, thereby constraining the economic value of on-demand schedules for companies.

Understanding the worker-level consequences of on-demand schedules is an important question in contemporary labor markets. Close to 17% of workers in the U.S. experienced unstable schedules imposed by the employers, with the lowest income workers facing the most irregular schedules (Golden 2015). Over 45% of 1,518 workers surveyed by the International Social Survey Program in the United States informed that employers dictated their work schedules (Golden 2015). Data available from The Shift Project shows that two thirds of the 30,000 workers at 120 of the largest retail and food-service firms in the United States receive their schedules with less than two weeks advance notice with more than 70% reporting at least one change to the timings of their schedules compared to the previous month. The diffusion of on-demand schedules has attracted significant attention on business and generalist media, which report growing worker dissatisfaction with this new work arrangement. For example, Golder and Dickson (2017) discuss the urging need for regulation of irregular schedule of low wage jobs. Similarly, Collins (2020) provides anecdotal evidence of the negative effect of unpredictable schedules of truck drivers on planning personal time.

Research also has begun to investigate this societal trend to understand how on-demand schedules affect individual outcomes such as work-life balance, economic security and health (Henly & Lambert 2014, Cho 2018, Schneider & Harknett 2019). Scholars have found that these types of schedules adversely affect workers, not only because they generate economic insecurity, but also because they hinder workers' ability to use their personal time and to balance work and personal life (Henly & Lambert 2014), an aspect referred by some as temporal precarity (Schneider & Harknett 2019).

Despite the progress made by extant research, it remains unclear if and to what extent these adverse effects on workers' wellbeing impact their actual performance. Clarifying this matter is of utmost importance because poor worker performance would ultimately affect organization performance. Empirical research recently begun to uncover the existence of worker-level costs of on-demand schedules that can ultimately reduce sales and profits (Kamalamadi et al. 2021, Kesavan et al. 2022), thereby confirming the intuition that having workers adapt flexibly to demand patterns has hidden costs for the employer. However, other dimensions of worker performance remain unexplored. For instance, we do not know whether on-demand schedules affect basic compliance of the workers with their duties, as reflected in absenteeism or customer complaints. These yardsticks are of great importance in healthcare, the setting of this study as absenteeism impairs continuity of service and it can have daring consequences for patient wellbeing. Similarly, patient complaints have important consequences for the continuing of the business as patient contracts can be lost.

In this paper we explore the consequences of imposing on-demand schedules on workers' performance in the organization. Our premise is that the utility workers extract from a job is, among other things, a function of the extent to which the work schedule enables them to meet their private life goals and responsibilities. Building on work-life conflict framework (Goff et al. 1990, Henly & Lambert 2005, Henly & Lambert 2014) and boundary theory (Nipper-Eng 1996, Ashforth et al. 2000, Allen et al. 2014) we contend that there are two different fundamental characteristics of on-demand schedules that interfere with workers' ability to achieve the demands of their private life. First, the instability across time of the schedule, or variability impedes the creation of routines that workers need to effectively use their private time. Second, the presence of unpaid interruptions in work schedules, or discontinuity creates work-nonwork transition costs that interfere both with the worker private and work time. We hence argue that, by creating a conflict between personal and professional life, schedule variability and discontinuity lead to workers engaging in withdrawal behaviors, in the form of absenteeism and lower quality of service to the customer.

Our empirical inquiry is based on granular data we collected from a home healthcare service organization located in Canada. This setting is appropriate for investigating our hypotheses because on-demand schedules are prevalent in homecare (Oh 2017, Campbell 2019) and typically set by the employer subject to worker availability (Lambert et al. 2014). Studying labor practices in this industry is also important because they affect millions of workers. In the US alone, over 3.4 million caregivers were employed in 2020, and they are expected to exceed 4 million by 2026 (US Bureau of Labor Statistics). Last but not least, possible negative consequences of on-demand schedules on the quality of care provided by these workers have even larger implications for the over 15 million US homecare patients assisted in 2020 (Ankota 2020), a population that is expected to grow at a compound annual growth rate of 7.9% from 2020 to 2028 (Grand View Research 2021).

To test our hypotheses, we built a matched worker-week panel dataset that, for each worker-week between Jan-2012 and Dec-2016 (75,078 observations), captures worker schedule characteristics, worker performance outcomes, as well as a vector of covariates. Effect size estimates corrected for endogeneity using the control function approach (Papke & Wooldridge 2008, Lin & Wooldridge 2019) indicate that on-demand schedules cause nontrivial operational and service problems for the studied homecare organization. More pointedly, an increase in schedule variability from 0 (25th percentile) to 32 (75th percentile) increases the number of absences for an average employee for the focal week by 356% and the number of patients complains by 311%. Moreover, an increase in the gaps in schedule from 0 (25th percentile) to 1 (75th percentile) increases the number of absences for an average employee for the focal week by 147% and the number of patient complaints by 252%. These results are robust to alternative operationalizations of flexible schedules and are not explained by competing explanations such as the volatility in the income driven by on-demand schedules, poor labor market conditions, absenteeism due to sick leave, the presence of short or overnight gaps or any unobserved workers invariant characteristics. Our analyses also yield support for the de-motivational effects of flexible schedules for workers.

Our study contributes to both theory and practice. By identifying and empirically testing the effect of fundamental on-demand schedule characteristics on workers' behavior in the organization, we complement the extant literature that looked at the implications of on-demand schedules for workers well-being (e.g., Bohle et al. 2004, Cho 2018, Schneider & Harknett 2019, Y Zhao et al. 2019) and extent the nascent literature on the consequences such schedules have for organizations. Our examination of different characteristics of on-demand schedules, that go beyond workload or real time schedules, also contributes to the literature studying staffing and task performance (e.g., Tan & Netessine 2014, Kamalahmadi et al. 2021). By examining archival data from an actual company, we manage to quantify the effect of on-demand schedules on important operational facets such as employee absenteeism and quality of work performed. With companies across many different industries using on-demand schedules to match their labor resource with demand, our study brings to light an important aspect that can question the beneficial effects of these practices, namely the effect on the workers' likelihood of not showing up for work or performing their work poorly (i.e., resulting in patient complaints). Our findings reveal that temporal precarity, in addition to economic precarity, can also have negative consequences for organizations.

2. Background

Labor volume flexibility (shortly, labor flexibility) is a fundamental instrument firms can use to adapt to fluctuations in demand, while keeping costs in check. It is especially important in labor-intensive industries, such as healthcare—our research setting—or retail, call centers, hospitality, etc. Traditionally, labor flexibility has been pursued by extending full-time employees' hours through overtime, by recruiting part-time workers to cover systematic demand peaks within some time interval (day, week, etc.), or by relying on temporary workers to meet more irregular demand patterns (Korunka 2021). In all these cases past studies reveal that requiring flexibility from workers entails a cost for the employer that goes beyond eventual marginal salary increases. Overtime can increase employees' workload to a point where they begin to make errors due to exhaustion or shortcuts (Oliva & Sterman 2001, Kc & Terwiesch 2009), generating additional costs (Powell et al. 2012) or liabilities to the employer (Kuntz et al. 2014). Reliance on part-time workers may provide the company with less prepared workforce, in part because they lack relevant experience (Kesavan et al. 2014). In addition, blending part-time and full-time workers may impair relationships between workers and their supervisors and reduce helping behavior in the organization (Broschak & Davis-Blake 2006). Lastly, reliance on temporary workers can also generate costs for the employer. The transient nature of many temporary work relations makes it difficult to properly train these workers and integrate them within the rest of the organization (Fisher & Connelly 2017). For instance, in retail settings, temporary workers may make more frequent stocking errors or fail to properly attend customers, generating additional costs and hindering sales (Kesavan et al. 2014). Besides these adverse effects of labor flexibility practices, tightly adapting staffing levels to expected demand may send a signal to full-time employees who, anticipating a heavy workload, may opt for being absent from work, further generating costs for the employer due to capacity saturation and poor service (Green et al. 2013).

In recent years companies began to pursue a novel approach to attain labor flexibility. This approach consists of adjusting workers' schedules to the needs of demand on daily basis, eventually interrupting the schedule when there is no demand, or significantly modifying the schedule across days, while paying workers only for the hours worked (De Stefano 2015). This on-demand scheduling approach represents a sharp departure from consolidated labor relations, as it entails transferring to the workers the costs of adjusting to demand variability. Paralleling the growth of on-demand schedules, research in organizational behavior and sociology has started to investigate the consequences of on-demand schedules for workers, highlighting the negative implications of flexible schedules on work-life balance, health as well as economic stability. Using data from the year 2000 wave of the General Social Survey, Golden (2015) shows that working with on-demand schedules is strongly associated with an increase in work-life conflict. Bohle et al. (2004) studied casual workers in 5-star hotels and found that workers with irregular schedules were more likely to experience health related problems. Similarly, based on the General Social Survey US data from 2006, 2010 and 2014, Cho (2018) found that schedules involving on-call or rotating shifts were associated with lower self-rated health and more days of poor physical and mental health—this association being partially mediated by work-life conflict. Changes in the schedule (i.e., change in working hours or cancelled shift) were found to adversely affect mood and sleep quality of parents with low-wage hourly jobs (Ananat & Gassman-Pines 2020). Lastly, on-demand schedules were found to lead to economic precarity and material hardship, including hunger, residential, medical and utility deprivation (Schneider & Harknett 2021).

While there has been cumulative evidence about the negative consequences of on-demand schedules for workers' psychological, physical and economic well-being, the consequences of such schedules on worker behavior and performance are less well understood. A recent stream of papers has begun to address this question (Choper et al. 2019, Kamalahmadi et al. 2021, Kesavan et al. 2022). Using a survey of large retail and food service firms in the US, Choper et al. (2019) found that workers who experienced schedules with short advance notice and on-call shifts were more likely to leave the organization, being this effect partially mediated by work-family conflict. Kamalahmadi et al. (2021) found that waiters employed by a restaurant chain registered lower sales when experiencing a last-minute change in their schedules, but not when being notified a schedule change up to a day before the day of the service. Lastly, Kesavan et al. (2022) conducted a randomized controlled field experiment at the US retailer Gap Inc., where they introduced a multi-component intervention designed to improve multiple dimensions of work schedules (inconsistency, unpredictability, inadequacy, and lack of employee control) and explored the effects of the intervention on stores' productivity. The results showed that the stores that implemented stable scheduling increased productivity by 5%, a result of increasing sales and decreasing labor hours. Their study suggests that contrary to the expectation, reducing schedule flexibility, could positively impact store performance. The authors found that offering less flexible, but more favorable, schedule characteristics to workers can lead to benefits for the organization.

The limited empirical research available cannot provide a complete picture of how different facets of worker performance are eventually affected by on-demand schedules. Specifically, we do not know how severely on-demand schedules affect basic compliance of workers with their contractual duties. For instance, should these schedules drive absenteeism, they would represent a threat to business continuity and hence a potential risk factor for the employer. Likewise, should on-demand schedules negatively affect workers' motivation to execute satisfactorily the assigned activities, they could damage customer relations and potentially business survival or growth options. These open questions call for more research.

A second important limitation of the extant empirical research lays in the way on-demand schedules are empirically captured. So far, different papers focused on specific facets of on-demand schedules (e.g., how early a schedule change is communicated to the worker, or whether the worker has a continuous or interrupted schedule) or lumped some of these facets with other work practices meant to help workers (e.g., schedule inconsistency and lack of employee control). We see an opportunity to move beyond specific operational measures and identify essential facets of on-demand schedules that relate to the different mechanisms through which they affect worker performance.

3. Research Setting: Home Healthcare

This study is based on a collaboration with a large organization providing healthcare services in Canada, which we refer to as HealthCo. At the time of data collection (2017) the company employed over 15,000 people and operated a network of over 250 clinics and 70 home healthcare offices. The company offers a vast range of healthcare services as part of their in-clinic and home healthcare service units, such as eldercare, nursing, physiotherapy, occupational therapy, exercise, behavioral therapies and nutrition. This study focuses on the home healthcare business unit of HealthCo in one of the most populated provinces of Canada, which is organized into six departments, covering different geographical areas of the province. In particular, the study explores the work schedules of the Health Care Aides (HCA), which comprise the majority of home healthcare workforce (the rest of the home healthcare workforce are specialized personnel such as physiotherapists, nurses, etc.) and are exclusively used in home healthcare (i.e., do not work in the clinics). HCAs provide general assistance to patients, which includes a vast variety of tasks related to personal care (bathing, toileting, oral care), basic wound care, meal preparation, medication reminders, companionship as well as basic housekeeping tasks.

To be eligible to work as HCA in the focal province, applicants must be registered with the Care Aide and Community Health Worker Registry, which requires the completion of an approved HCA education program. HCAs do not need to be nurses or to have had any medical formation. They are “casual workers” (Cappelli & Keller 2013), which implies that they are paid only for the hours they actually work for the company, even though they are typically available to work for longer hours.

HCAs in this organizations work with on-demand schedules, characterized by variability and discontinuity. Multiple factors contribute to the instability of HCAs’ schedules. Patients’ physical conditions can worsen to the point that homecare is no longer needed, as they get hospitalized or on the contrary, a patient can improve to the point that there is no need for care. In fact, for the period of our study, every month an average of 62.45% patients required a change in the number homecare hours and an average of 28.25% of patients either left or entered the system. Additionally, unexpected medical examinations may interfere with a patient’s scheduled homecare, such that HCA visits need to be rescheduled. Patients are also heterogeneous relative to the nature of the treatment and their personal preferences for the timing of the homecare visit, which may also impose rigidities on when a visit needs to be scheduled (e.g., administering a particular medicine every 8 hours, not receiving visits before 9 am, etc.). All these constraints make it difficult for schedulers to create stable, filled schedules for the HCAs, as reflected, for instance, in high heterogeneity in the starting times of the visits within a day.

HealthCo aims at assigning and distributing the individual schedules on weekly or bi-weekly basis. In each department, covering a single geographic area, a Patient Coordinator schedules the home care visits, given HCAs availability, patient required services as well as other preferences (timing of the visit, specific caregiver, etc.). HCAs are committed to be available to work in the hours they have previously reported to be available. Due to the nature of the service provided, the company requires its employees to work different schedules within and across the weeks and cannot ensure continuous hours: schedule variability and split work within the day is common for these employees.

4. Theory and Hypotheses

On-demand schedules (e.g., working different hours every day) make it difficult for workers to extract utility from their personal time. The tensions workers experience between personal and work time have been explored by the literature on work-life conflict (Goff et al. 1990, Henly & Lambert 2005, Henly & Lambert 2014). Overall, this literature finds that such tensions are a source of stress for the workers (see Allen et al. 2000). In response to this stress workers engage in withdrawal behaviors (Hanisch & Hulin 1991, Hughes & Bozionelos 2007), which can be either active (e.g., do not show up for work) or passive (e.g., reduce effort in work) (Carpenter & Berry 2017). We draw from the part of work-life conflict literature that specifically deals with how the schedule is problematic for the worker, to single out the essential feature of on-demand schedules that possibly impair worker performance.

Work-life conflict literature identifies an underlying time-based source of conflict, which results from competing demands of work and personal life and shortage of resources such as time and energy (Greenhaus & Beutell 1985, Henly & Lambert 2014). More specifically, time-based conflict, occurs when the time devoted to one role (i.e., work) makes it difficult or impossible to meet the demands of the other (i.e., personal life). Irregular or variable schedules are an important driver of time-based conflict (Henly & Lambert 2014) as they make it difficult for the workers to plan and organize personal life activities in advance as their working hours vary substantially from one day to the other (Messersmith 2007). Past quantitative studies provide evidence that variability in the schedules creates time-based conflict. For example, Zeytinoglu et al. (2004), found that variable working times experienced by Canadian workers, inferred with their ability to manage personal responsibilities. Furthermore, Henly and Lambert (2014) found that day instability (i.e., if workers worked on different days of the week) experienced by hourly employees in 21 retail stores in the US is associated with higher time-based conflict. Schedule variability is a fundamental feature of on-demand schedules as the distribution of the hours worked vary substantially from one day to another or even from one week to another. This implies that workers, who experience these schedules, for example, start and finish their working day at very different times each day. It is important to note that variability is the schedule refers to variation in the work hours imposed on the employee by the employer and not to flexibility in starting and finishing times chosen by the employee.

In our setting schedule variability is particularly important as it prevents the creation of stable weekly routines. Basic health-related behaviors, such as diet, exercise, and sleep, require that the workers have a certain level of stability in their everyday life in order to be able to plan (Fenwick & Tausig 2001, Allen & Armstrong 2006). In our dataset we find that on average 30% of scheduled hours in a week do not overlap with the scheduled hours in the previous week, across all 75,078 worker-weeks represented. The difficulty to create routines therefore activates workers' withdrawal behavior, resulting into absenteeism and customer complaints, a salient manifestation of reduced effort. Therefore, we hypothesize that:

> *H1a: For a given number of hours worked, the higher schedule variability from one week to another, the higher will be worker absenteeism.*
>
> *H1b: For a given number of hours worked, the higher schedule variability from one week to another, the higher customer complaints.*

Moreover, in work-life conflict literature, boundary theory is used to understand the existence of behavioral, physical and/or cognitive boundaries between individuals' work and non-work roles and the transition across these roles (Nipper-Eng 1996, Ashforth et al. 2000, Allen et al. 2014). More specifically, when a person moves from one role (i.e., work) to another (i.e., personal life), they need to undergo a transition. On-demand schedules usually force workers to have undesirable idle, non-paid, hours between different work assignments within the same day (Golden 2015, McCrate 2018). For example, workers may be required to start by serving a patient early in the morning, and then wait for a couple of hours until their next visit is due. Therefore, schedule discontinuity or split shift is a fundamental feature of on-demand schedules. Each time a worker experiences a gap, resulting for the split shift, in their schedules, they need to transition twice from work to non-work (once in the beginning for the gap and once at the end).

These transitions can be costly for the worker as for each transition, the worker needs to cross multiple physical (i.e., location of the visit vs home or private setting), psychological (i.e., work vs nonwork) as well as social (i.e., being with the patient vs with a family or friend) boundaries to exit the work domain and enter the private domain or vice versa. This results in an important switching cost where energy and attention need to be redirected.

Transitions can also reduce the worker effectiveness in executing one activity, due to spillovers. Research on role spillover indicates that moods, stress and thoughts that are generated in one role domain often influence or spill over into other domains (Marshall et al. 1992, Williams & Alliger 1994, Hanson et al. 2006). Therefore, the psychological and physical effort needed to transition from one role to another can spill over the life domain and thus worsen the work-life balance.

In our setting these transitions can occur multiple times in a work week and, given the size of the cities in the studied province often it is not possible for the worker to return to their home, creating a problem for the worker to take advantage of this time by taking care of housekeeping or other leisure or personal activities. For example, in our dataset the median duration of these gaps is 2 hours and average distance from home of the two patients separated by idle time is 25.73 kilometers (15.98 miles). The net effect of schedule discontinuity is that it is a factor of stress, as the unpaid time between assignments cannot be fruitfully used for other activities, a factor that activates withdrawal behaviors and ultimately drives absenteeism and customer complaints. Therefore, we hypothesize that:

> *H2a: For a given number of hours worked, the higher the number of gaps in schedule the worker face during the working day, the higher will be worker absenteeism.*
>
> *H2b: For a given number of hours worked, the higher the number of gaps in schedule the worker faces during the working day, the higher will be customer complaints.*

5. Empirical Analysis

To empirically explore our questions, we use a matched worker-visit dataset comprising all the visits' records (1,252,746 visits) over the five-year period between January 2012 and December 2016 (260 weeks) of the home healthcare unit of HealthCo in one of the most populated provinces of Canada. The HCAs belong to the six different departments or locations in the focal province. We collected the data from four different sources. The first is the patient visit dataset, which consists of detailed information on each home healthcare visit, including date of the visit, start and end time of the visit, the type of service provided, an identifier of the worker who provided the service as well as an identifier of the patient. The second is the HCA schedule preference dataset, which contains information on the daily availability provided by the HCAs. Employees provide their weekly availability in the beginning of each month, including the number and distribution of the hours they are available to work for the company. Patient Coordinators build the weekly schedules based on the provided availability. Third, the human resources dataset, which includes information on the workers' demographic data, including their birth date and gender, and personnel information including their start date in the organization, their date of termination (if terminated), and title in the organization, type of training received,[1] and level of pay. Lastly, the company keeps an electronic record in the form of a note regarding whether an employee has been late for a visit or absent, as reported by the Patient Coordinator, as well as the reason for that (e.g., due to weather conditions, the employee feeling sick, problems with car, absent due to personal reasons, etc. although sometimes employee did not show up for the visit without any justification (7.96% of all absences)). The electronic notes also keep records of any communication between the firm and the patients regarding the care received from the HCAs during the particular visit (e.g., a patient that communicates the firm that she is dissatisfied with the service or that requests a change of HCA). We have access to the electronic notes for the period of study, a total of 134,273 such dated notes. We matched the information from these notes to the system records on the

[1] Training includes annual orientation programs covering different topics such as personal care training, infection control, care for children, ceiling track lift as well as universal precautions training.

visits based on the date each note was taken, as well as the employee listed in the note. Matching all the notes to the visit records allowed us to associate a note to 21.79% of the days (for the rest of the days there was no note available).

We merged the four data sources to create a panel dataset that treats employee-week as a single observation. We aggregated these data at the week level to capture the effects of gaps in schedule and variability on worker absenteeism and patient dissatisfaction and to be able to build our measure of schedule variability.[2] After merging the four data sources we obtained a dataset with 75,078 employee-week observations for 1,026 employees.

5.1. Measures

5.1.1. Dependent Variables

We measure two different outcomes: *employee absenteeism* and *patient dissatisfaction* with the employee service. Both variables are calculated at the employee-week level. We measure *employee absenteeism* as the total number of times the employee has been reported absent in the week. As mentioned before, we obtain the information on the employee absences from the company electronic notes. Note that 8.71% of the workers experience an absence in an average week, which is in accordance with the average absenteeism rate of Health Care Nurses in the studied province of 9.3% for the period 2014-2016 (Canada Labor Force Survey 2017). We measure *patient dissatisfaction* as the total number of patient complaints in the form of a ‘do not send’ requests that each HCA received from the patients they visited in the week. As with the absenteeism variable, we coded these complaints from the company electronic notes. We note that even though the company

[2] We note that as a robustness check we aggregated the data at the month level. To calculate schedule variability and gaps in schedule variables we took the average of the week level variables for the month. The results of the month level analysis are quantitatively and qualitatively the same as the week level analysis.

encourages patients to send feedback in case they are not satisfied with the service, a ‘do not send request’ is a very strong indicator of bad performance, as the patient does not want to be sent the same worker anymore. Employees received on average 2.13 ‘do not send requests’, with some receiving up to 66 such complaints in the whole studied period. Therefore, we consider our measure of patient dissatisfaction to be a very conservative measure of negative feedback.

5.1.2. Independent Variables

Regarding the independent variables, we measure *schedule variability* across two consecutive weeks. To calculate this variable, we look at the overlap of time worked and non-worked in two consecutive weeks. Specifically, we divide the day into 48 30-min slots. For each employee, we then code each time slot equal to 1 if the employee worked in that time slot and 0 if they did not work. Next, for each employee, we calculate the difference between each time slot with the same time slot the prior week; for example, we subtract the value of the Monday slot 9:00-9:30 in week t, from the value of the Monday slot 9:00-9:30 in week t-1. We take the absolute value of this difference (i.e., the difference is equal to 1 if the employee worked in one of the time slots but not in the other and is equal to 0 if the employee either worked or did work in both). To obtain the week level variable we sum all the differences for the week with respect to the prior week. Finally, due to the highly skewed nature of the variable, we take its logarithmic transformation. Higher numbers of this variable indicate high schedule variability.

We measure *gaps in schedule* as the average number of daily gaps in the schedule of the employee within the week. We consider a gap in the schedule to be an idle, unscheduled time slot of more than 30 minutes. We set the 30-min restriction, as gaps shorter than 30 mins may not impose a cost to the worker. As an additional analysis we test the effect of the shorter than 30 mins idle times on the performance of the workers and we find that they do not have a significant effect, which provides support for our identification strategy of gaps. Even though employees in our setting present heterogeneity in their preferences in terms of the number or the distribution of the hours they want to work each week, the vast majority of them (namely 91%) prefer continuous scheduling. Therefore, our variable *gaps in schedule* truly captures an undesirable characteristic of the schedules. Due to the highly skewed nature of the variable, we take its logarithmic transformation when performing the analysis. Higher numbers of this variable indicate high number of gaps in schedule.

5.1.3. Control Variables

In addition to the main variables of interest, we control for a number of variables that can affect the worker performance.

First, we control for *employee experience*, which we measure as the number of visits the HCA had conducted (with any patient) since the employee joined the company until the beginning of the focal week (Ibanez & Toffel 2020).[3] We also create an indicator variable, coded 1 if it is the *employee first week* in the company. For the workers who joined the company before the beginning of the data collection, the variable is equal to 0 in all the studied weeks.

Next, we control for employee availability, as there is heterogeneity in the amount of time employees are available to work. We calculate *employee availability* by taking the weekly availability measured in hours. The variable captures the number of hours the employee has committed to work for the company and eventually captures possible differences in the levels of family or personal

[3] For those employees who started before the studied period (23.78% of the employees), we considered the beginning of our period to calculate the experience.

responsibilities, such as childcare. Namely, higher availability of the workers, could be an indicator of lower level of nonwork responsibilities. The average daily availability of the dataset is 15.30 hours. The average daily availability is lower than 8 hours for 21.49%, indicating that the majority of the workers use the employment as a full-time commitment.

Employees need to commute to each visit. Even though, the commuting time is included in the visit duration, and workers are therefore paid for the time they are commuting, long commuting distance can still be taxing for them, affecting their performance or their decision to miss a visit. To control for such taxing condition, we include the variable *commuting distance*. To measure the variable, we first use the zip codes of the patient and employee addresses to calculate to calculate the total distance travelled by the employees for each day of the week (i.e., we sum the distance from employee's home to the first patient, from the first patient to the second,…, and from the last patient of the day to employee's home). We then take the average of the distance travelled within the week.[4] Because this variable is highly skewed to the right, we take the logarithm of it.

Next, because work variety can influence workers' attitudes and behaviors, we include two control variables that capture two sources of work variety. Namely, we calculate *task variety* and *patient variety*. Work variety is driven by the nature of the service or task provided. The services offered by the HCAs can be divided in in the following categories: companionship, home making, nursing, occupational health, overnight care and personal care. We calculate *employee task variety* as the number

[4] Note that the commuting time between the visits is included to compute working time in the total time spent on the visit. In other words, employees are paid for the time they commute during the day. The only commuting time which is not included in the paid period is the commuting from the employee's home to the address of the first visit of the day and from the last visit of the day to the employee' home. As an alternative operationalization, we calculated the *commuting distance,* considering only the distance between the employee's home and the first patient visited in a given day and the distance from the last patient in that day to the employee's home.

of different services the employee has provided over the week. Another aspect of work variety in healthcare service firms is driven by the heterogeneity in the patients and their individual needs. We capture this aspect of the work variety by *employee patient variety*. We calculate the variable as the number of different patients the employee has visited over the week.

Employees are paid per hour worked, therefore the income they generate in the week is dependent on the number of hours they work. The different level of generated income can have an effect on workers performance. Therefore, we control for *employee hours* worked, measured by the total number of hours the employee worked during the week, to capture the effect of the level of generated income. Finally, we control for employee workload by computing the *employee visits* in the week, by taking the sum of the daily visits worked during the focal week. With this control we partial away possible indirect effects of the independent variable on the outcomes such as fatigue (when *employee visits* is too high) (Ibañez & Toffel 2017).

5.2. Model Specification

We test our hypotheses by estimating conditional Poisson worker fixed-effects models, clustering the standard errors at the employee level, that predicts the number of *employee absences* and *patient complaints* in a week. Poisson panel estimators are consistent, even if data are not Poisson-distributed, provided the conditional mean is correctly specified (Cameron & Trivedi 2005, Azoulay et al. 2010). Because of the weaker distributional assumption of the Poisson estimators, they are more robust than negative binomial regression (Cameron & Trivedi 2005). Nevertheless, as negative binomial model can be preferred over Poisson when the dependent variable has excessive zeros as it could be the case of the *patient complaints* variable, as robustness tests, we estimated our analysis using negative binomial regression with conditional fixed effects and ordinary least-squares (OLS) regression, predicting log employee absences and log patient complaints and found similar results (see appendix A, Table A1). The use of worker fixed-effects enables us to control for time-invariant worker characteristics such as employee gender or race. Because employees remain in the same department, the worker fixed-effects also allows to control for any department unobserved time invariant characteristics such as the geographically spread of the department or the presence of a labor union. We also include time-fixed effects (year and month dummies) to control for potential environmental factors or seasonality that could impact the results.

5.2.1. Endogeneity Concerns and Control Function Approach

Scheduling decisions regarding *schedule variability* and *gaps in schedule* may not be random. Specifically, the presence of schedule variability and gaps in schedule may be based on factors that are also correlated with employee absenteeism and patient dissatisfaction. Therefore, the association between the undesirable schedule characteristics and employee absenteeism and patient dissatisfaction could be driven by these factors rather than by the schedule characteristics themselves. For example, schedulers may be more willing to grant favorable schedules to workers that have shown higher commitment to the work in the past by being less absent or are more experienced. Therefore, the association between unfavorable schedule characteristics and workers performance may be due to the workers' skills and past performance. Our controls on workers' fixed effects and experience should help addressing these concerns. Moreover, as a robustness check we included *employee past absenteeism* as a control variable in the employee absenteeism and patient dissatisfaction models to account for past undesirable performance of the workers. *Employee past absenteeism*, measured as the number of employee absences in the previous week, has a positive and significant at 10% coefficient in the *employee absenteeism* model and a positive but not significant coefficient in *the patient complaints* model (see appendix A, Table A2, models 1 and 3). The results for the two independent variables are robust to the inclusion of the control, indicating that this bias in not affecting our results.

Another potential source of endogeneity that could bias our results is driven by the patient characteristics. As certain characteristics, for example intrinsically problematic patients who tend to give negative feedback more easily, could be associated with both the schedule assigned to the worker as well as with workers' behavior. To address this, we first assess the extent to which some patients may be tougher (i.e., harsher in their evaluations) than others. We measured the number of past complaints each patient has issued to any employee prior to the focal week and calculated the average number of complaints across the patients visited by the employee in the focal week prior to the focal week. Second, we measured the average seniority of the patients in years, by calculating the number of years since the week the patient contract has been signed until the focal week. Patients with longer contracts are likely to be on average more satisfied with the services provided by the company than newer patients (non-satisfied patients may have self-selected out for the longer seniority patients). The results of the independent variables *schedule variability* and *gaps in schedule* are robust to the inclusion of these two client controls (see appendix A, Table A2, models 2 and 4). In the *employee absenteeism* model, the two patient controls are not significant, therefore the past complaints of the patient or their seniority do not seem to have an effect on absenteeism. However, in the *patient complaints* model the number of patients prior complaints is positive and significant, providing evidence that patients who have complained more in the past are more likely to complain in the current quarter as well. Furthermore, *patient seniority* is negative and significant, providing evidence that patients who have stayed in the company longer are less likely to complain.

Another potential source of endogeneity is that schedules could be assigned based on unobservable personal preferences of the schedulers (i.e., favoritism). To address this concern, we first explore whether the patient density of the department have an effect on the schedule assignment. When patient density is high relative to worker density, in other words, when there are more patients than available caregivers' hours, the schedulers have lower discretion to assign schedules according to their (unobserved by us) preferences. However, when the relative patient density is low, schedulers have higher discretion to assign schedules based on their preferences. We calculate patient density as the ratio of total patients in the department in the week divided by total workers available in the department in the week. We then split the sample into low patient density subsample and a high patient density subsample.[5] Our results hold (with the exception of *gaps in schedule* in the low patient density subsample) for both subsamples (see appendix A, Table A3). Nevertheless, there may still be potential unobservable time-variant factors that could bias our results related to the preferences of the schedulers or the way they assign the schedules to the workers. Therefore, to address this endogeneity concern, we use a control function approach (Papke & Wooldridge 2008, Lin & Wooldridge 2019).

Estimation with control function approach. The control function approach consists of first running a first stage model for each endogenous variable including an exogenous instrumental variable and second, adding the first-stage residuals as a

[5] We split the sample by using the median ratio of 2.67.

control in the second stage (Papke & Wooldridge 2008, Lin & Wooldridge 2019). To instrument the two endogenous variables, *schedule variability* and *gaps in schedule,* we use two "market-based" instruments, adapted for our setting. Specifically, for *schedule variability* we use the average *schedule variability* of all employees in the focal week in the department where the employee is based. The instrument satisfies the relevance condition, because in any given department, schedulers assign schedules to workers based on the demand for the week and following guidelines outlined by the department management and the labor union present in the department (if labor union is present). Therefore, we could expect that our instrument should be correlated with the schedule variability of the focal worker. Our analysis also shows that the instrument is indeed a significant predictor of the endogenous *schedule variability* variable at 1% significance level (see appendix A, Table A4, model 1). Our instrument also satisfies the exclusion restriction, as there is no reason to expect that the schedules assigned to the other workers in the department, have an impact on the employee's performance.

Next, we follow a similar logic to construct an instrument for the variable *gaps in schedule*. Specifically, we use as an instrument the average *gaps in schedule* of all employees in the department in the current week. Its validity follows the same argument as the instrument used for *schedule variability*. Our analysis shows that the instrument is a significant predictor of *gaps in schedule* at 1% significance level (see appendix A, Table A4, model 2). Similarly, to the instrument for *schedule variability*, the instrument satisfies the exclusion restriction, as there is no reason to expect that the average gaps in the schedules of the workers in the department, have an impact on the employees' performance in the current week. To check the validity of the instruments, we look at the F statistics of the first stage models presented in Table A4 of the appendix A, which are well above the common threshold of ten, confirming that our instruments are not week, as suggested by Stock and Yogo (2005).

A potential concern with our instrumental variables could be that workers are assigned to a constraint pool of patient requested hours, which could indicate a violation of the exclusion condition. For example, a worker can be left with less favorable schedule as the rest of the patient demand hours have already been filled by the other workers. To address this concern, we consider alternative instrumental variables in section 5.6.2. More specifically, we use the average *schedule variability* (*gaps in schedule*) of the workers in the same department but the prior to the focal week. The results remain the same both quantitatively and qualitatively.

To apply the control function approach, first we run a fixed-effects Ordinary Least Square (OLS) regression for *schedule variability* and *gaps in schedule* on the two instruments along with the rest of the control variables. Next, we run our main Poisson models for the two outcome variables of interest *employee absenteeism* and *patient complaints* on *schedule variability, gaps in schedule*, the rest of the control variables and the predicted residuals from the two first stages.

5.3. Results

Table 1 reports summary statistics on the full sample.[6] The logarithmic transformation of *schedule variability*, *gaps in schedule, employee experience* and

[6] Note that the conditional fixed-effects Poisson regression model automatically dropped 6,087 employee-week observations from the absenteeism model and 23,299 employee-week observations from the patient dissatisfaction model corresponding to employees that had (a) just a single week or (b) multiple weeks all citing zero absenteeism or patient dissatisfaction respectively. This results in an estimation sample containing 68,991 employee-week observation for 796 employees for the absenteeism model and 51,779 employee-week observation for 509 employees for the patient dissatisfaction model. Employees in the three samples experience similar levels of *Gaps in schedule* and *Schedule variability*. They also present similar experience and workload values, which provides confidence that no bias is created by dropping the observations in the count models.

commuting distance variables are reported. We explored potential multicollinearity and found it not to be a concern as the average variance inflation factor for all variables is 1.80 and the variance inflation factors for the two main independent variables are low (1.34 for gaps in schedule and 1.25 for schedule variability) well bellow the threshold level of 10.

Table 2 show the main results of our analysis. Positive coefficients indicate an increase in the number of employee absences or patient complaints. Similarly to other studies using Poisson models, we interpret effect sizes based on incident rate ratios (IRRs) (Ibañez & Toffel 2020).

Models 1 and 2 show the result of the Poisson models without the controls for endogeneity. Both *schedule variability* and *gaps in schedule* are positive and significant predictors of *employee absenteeism* and *patient complaints*. However, as explained in the previous section, the schedule undesirability variables may be correlated with the error term even after including all the employee and time fixed effects, controls as well as all the additional tests we performed. As such we report and base our main results on the control function approach presented in models 3 and 4 of Table 2. The significant coefficients of the residuals indicate that endogeneity may indeed be a concern. In the employee absenteeism model, a t-test shows that the *residuals_ schedule variability* (chi2 5.84, p<0.05) and that the *residuals _ gaps in schedule* (chi2=3.66, p<0.10) have a significant impact on *employee absenteeism*. In the *patient complaints* model a t-test shows that the *residuals_ schedule variability* does not have a significant impact on patient complaints, while the *residuals _ gaps in schedule* have a significant impact (ch2=5.67, p<0.05).

Although the effect of work variety variables *employee patient variety* and *employee task variety* are not the primary focus of this study, we note that patient variety has a positive and significant coefficient in the absenteeism (β=0.016, $p<0.05$) as well as in the patient complaints model (β=0.078, $p<0.01$). Moreover, task variety has a positive but not significant coefficient in the absenteeism model and positive and significant coefficient in the patient complaints model (β=0.075, $p<0.1$). These findings suggest that high variety of the patients or tasks offers a taxing condition for workers, who as a consequence are more likely to both be absent as well as to perform poorly. Furthermore, the regression results suggest that *employee visits* have negative and significant coefficients in the absenteeism and patient complaints models indicating that the more visits the workers are given, the less likely they are to be absent from work or to receive complaints. Moreover, *employee hours worked* has a negative and significant coefficient in the employee absenteeism model, while it has a negative but not significant coefficient in the patient complaints model. These findings for employee visits and hours worked provide indications that workers may be underworked in the setting and their performance may benefit from more opportunities to work and generate income.

Examining the coefficient of *schedule variability* in model 3, we find that it is positive and significant (β=0.555, $p<0.01$, IRR 1.74, IRR-1=74%), which provides support for Hypothesis 1a. A one-standard-deviation increase in *schedule variability* (that is, a 1.22 increase) increases the number of absences in the focal week by 90.3%. Applying this 90.3% to the average of 0.12 absences in a week leads to 0.11 additional absences per week per employee for a one-standard-deviation increase in schedule variability. The positive and significant coefficient (β=0.612, $p<0.05$, IRR 1.84, IRR-1=84%) of *gaps in schedule* provides support for Hypothesis 2a. A one-standard-deviation increase in *gaps in schedule* (that is, a 0.36 increase) increases the number of absences in the focal week by 30.2%. Applying this 30.2% effect to the average of 0.12 absences in a week leads to 0.04 additional absences per week per employee for a one-standard-deviation increase in gaps in the schedule.

The coefficient of *schedule variability* in model 4 is positive and significant (β=0.435, p<0.01, IRR 1.54, IRR-1=54%), which provides support for Hypothesis 1b. A one-standard-deviation increase in *schedule variability* (that is, a 1.22 increase) increases the number of patients complaints in the focal week by 65.9%. Applying this 65.9% to the average of 0.03 patient complaints in a week leads to 0.02 additional patient complaints per week per employee for a one-standard-deviation increase in schedule variability. The positive and significant coefficient (β=1.354, p<0.01, IRR 3.87, IRR-1=287%) of *gaps in schedule* provides support for Hypothesis 2b. A one-standard-deviation increase in *gaps in schedule* (that is, a 0.36 increase) increases the number of patient complaints in the focal week by 103.3%. Applying this 103.3% effect to the average of 0.03 patient complaints in a week leads to 0.03 additional patient complaints per week per employee for a one-standard-deviation increase in gaps in the schedule.

Given that there are on average 288.76 employees active on average in a week in the studied provide these findings result in 31.76 additional absences and 5.77 additional formal complaints due to one-standard-deviation increase in schedule variability and in 11.55 additional absences and 8.66 additional formal complaints due to one-standard-deviation increase in gaps in schedule of each worker.

5.4. Alternative Explanations

Next, we aim to provide evidence of the proposed mechanisms by which on-demand scheduling impacts employee absenteeism and patient dissatisfactions.

5.4.1. Variability in Income

On-demand schedules may negatively affect workers performance because of income volatility caused by the schedules. HCAs are casual workers, who are paid by the hours worked, therefore on-demand schedules often imply variability and uncertainty in income (Haley-Lock 2011, Luce et al. 2014, Ben-Ishai 2015, Golden 2015, Schneider & Harknett 2019). This is unlikely to drive our results because, if the results were driven by income volatility, then workers would reduce their absenteeism in order to secure to get paid for the hours worked. Instead, our results suggest that high *schedule variability* and *gaps in schedule* is associated with more absenteeism—consistent with the hypothesized mechanism. Nevertheless, we further investigate this alternative mechanism. Specifically, we measure *income volatility* by adapting the measure of hour volatility used by Schneider and Harknett (2021) to our setting. The authors use survey data to ask their respondents, over the prior month, the number of hours they worked in the week they worked the most and the least and take the percentage difference of the two numbers. Similarly, we measure income volatility by considering a time window of 4 weeks (i.e., the current week and the three prior weeks). We first identify the maximum and the minimum weekly hours the employee worked. Next, we take difference between the maximum and the minimum weekly hours and multiply this difference by the pay level of the employee. We test the effect of *income volatility* by adding it as a control to our main model. To correct for endogeneity concerns associated with our main independent variables, *schedule variability* and *gaps in schedule,* we used the control function approach used for the main analysis. We report the results in Table 3. The results of the independent variables *schedule variability* and *gaps in schedule* are robust to the inclusion of the income volatility control. *Income volatility* is positive and significant in the absenteeism and patient complaints model. These findings provide support of the argument that income volatility and therefore uncertainty has a negative effect on workers performance. However, the effects of the studied undesirable schedule characteristics are not only driven by economic precarity reasons but go beyond that: time-based or temporary reasons. Our results are aligned with the findings of Schneider and Harknett (2019) who show that the effect of precarious schedules on workers well-being is in part mediated through economic insecurity, however a much larger part of the association is explained by work-life conflict.

5.4.2. Labor Market

The effect of poor schedules on worker behavior can be driven by the labor market conditions. If labor market conditions are bad and HCAs perceive their on-demand schedules as a threat to their employment, they may react by exerting more effort. Moreover, in such condition, schedulers may take advantage by assigning worse schedules, knowing that the workers are less likely to react negatively to them because they have lower opportunities outside of the company. To explore the extent to which this alternative mechanism may be at place, we control for the economic conditions in the labor market. In particular, we include in our models the monthly unemployment level[7] of the studied province, correcting for endogeneity. We report the results in Table 4. The results of the independent variables *schedule variability* and *gaps in schedule* are robust to the inclusion of the unemployment control, indicating that the potential effect of a perceived threat is not driving the results. Unemployment is negative and significant in the *employee absenteeism* model, suggesting that unemployment serves as an incentive mechanism for

[7] We obtained the unemployment level for the studied period from 2012 to 2016 from Statistics of Canada.

reducing workers' absences, while it is not significant in the *patient complaints* model.

5.4.3. Absenteeism Due to Non-sick Leave

On-demand schedules may also negatively affect workers performance, absenteeism in particular, because of the negative effect schedules may have on workers' health (e.g., Fenwick & Tausig 2001, Cho 2017) rather than the proposed motivational mechanism. To rule out this potential mechanism we exclude the absences due to sick leave when calculating the dependent variable *employee absenteeism.* We then re-run our absenteeism model with the restricted dependent variable and find the results of both *schedule variability* and *gaps in schedule* maintain their significance (see Table 5).

5.5. Post-hoc Analysis

5.5.1. Short Within-day Gaps and Overnight Gaps

Next, we explore other type of gaps: *short within-day gaps* and *overnight gaps*. Recall that in our main analysis we define gaps as idle times during the day, longer than 30 mins, for which the employee was available to work but they were not scheduled. If workers have shorter gaps, of less than 30 mins, they can use the time to have lunch or make a phone call. These short gaps may not cause transition challenge to the worker as they do not need to transition from work to non-work for such a short period of time, but rather can consider them as a break between tasks. Moreover, short breaks have been found to be beneficial for workers recovery and performance (Kim et al. 2017), therefore if anything should improve workers performance.

Similarly, to our measure of *gaps in schedule*, we measure *short within-day gap* by counting the number of short gaps (i.e., shorter than 30 minutes) within the working day of the employee and we obtain the week level variable by taking the average of all the worked days in the week. We test the effect of *short within-day gaps* by adding it as a control to our main model, correcting for endogeneity. The findings, reported in Table 6, suggest that short gaps have no significant effect on either employee absenteeism or patient complaints (see Table 6, models 1 and 3) as the coefficients of *short within-day gaps* are not significant. This is consistent with our argument that *gaps in schedule* has negative impact on workers performance due to its negative effect on work-family conflict. As short-gaps are not a driver of work-family conflict, we do not observe this negative effect on performance.

Contrary to short gaps, long *overnight gaps* imply that the workers have more available time after work to recover and to meet the demands of their personal life. Therefore, if workers have long overnight gaps, they experience lower work-family conflict and may perform better their work. We measure *overnight gaps length* by calculating the time between the end of the last visit of a working day and the beginning of the first visit of the next working day. We obtain the week level variable by taking the average of all the overnight gaps in the week. A very short overnight break length captures a phenomenon commonly referred as *clopenings*: shifts that finish very late one night and start very early the following day (Ben-Ishai 2003, Spreitzer et al. 2018, Schneider & Harknett 2019). We test the effect of *overnight gaps length* by adding it as a control to our main model, correcting for endogeneity. The findings, reported in Table 6, suggest that *overnight gaps* has a positive effect on workers' performance as the variable shows a negative and significant coefficient (β=-0.153, $p<0.10$) in the patient complaint model (see Table 6, model 4). *Overnight gaps* do not have a significant effect on employee absenteeism (see Table 6, model 2). These findings are again consistent with our proposed mechanism for *gaps in* *schedule*. Our finding is also in line with the finding of Ibañez and Toffel (2019) and Danziger et al. (2011), who suggest that the length of the overnight gaps reduces bias associated with fatigue in judges and food inspection. In these settings fatigue makes decision makers put less effort in detecting violations and paying attention to details. Similarly, in our setting overnight gaps seem to reduce the effect of fatigue which impedes the person to pay attention and comply with the service offering expectations.

5.5.2. Last-minute Changes

Lastly, on-demand schedules can have a negative effect on workers behavior because of the variability induced by changes that occur in the last minute (e.g., Kamalahmadi et al. 2021). Our data does not allow us to observe last-minute changes to the schedule. Nevertheless, we empirically investigate this possibility by computing a proxy for last-minute changes. Namely, we measure the number of atypical patients the worker visited in the week. Managers at HealthCo informed that the company aims at proving continuity of care, by always trying to send the same caregiver to the patients. Therefore, atypical patient may indicate that the usual or main caregiver was not available, and the focal worker had to substitute them, presumably on a last-minute notice. We identify atypical patients as patients whom the worker has not visited in the prior or following 7-day window. We test the effect of last-minute changes by inserting it as a control in the main model. Table 7 presents the results. The results of our independent variables are robust to the inclusion of the control. To explore the effect of *last-minute changes* on the outcome variables, we run the models with outcome variables for t+1, because there is potentially a selection bias in the current week, as workers who have accepted a last-minute change are more likely to be committed to work in current week, and therefore less likely to be absent or to perform poorly. Models 3 and 4 of Table 7 present the t+1 results. The results suggest that *last-minute changes* is associated with more absenteeism. However, it does not have a significant effect on patient complaints.

5.6. Robustness Tests

5.6.1. Alternative Operationalization of Independent Variables

We provide alternative operationalizations of our main variables of interest: *schedule variability* and *gaps in schedule*, which provide further insights on their effect on the outcome variables. Namely, we measure *schedule variability* within the week instead of across the weeks and measure *gaps in schedule* with the total duration of gaps instead of the total number of gaps. Moreover, we measure the effect of another potentially important features of on-demand schedule, which is last-minute changes.

Within week schedule variability. We explore further the effect of schedule variability by calculating an alternative operationalization of the variable, within week schedule variability. Namely, we calculate schedule variability as the average standard deviation of each 30-min time slots within the week (instead of across two consecutive weeks). Similarly, to our main *schedule variability* variable, to obtain this variable we first split each day in 48 30-min slots. We then code each time slot equal to 1 if the employee worked in the time slot and 0 if the worker did not work. Next, for each employee, we calculate the standard deviation for each time slot of each day of the week, across all days of the week. For example, Monday 9:00-9:30, Tuesday 9:00-9:30, etc. To obtain the week level variable, we take the average of the 48 standard deviations. Higher numbers of this variable indicate high within week schedule variability. This operationalization captures the within week variation of the schedule, in other words, how different the days are within the week. We test the effect of *schedule variability _ within week* by inserting it in the main model and removing the *schedule variability* variable (see appendix A, Table A5, models 1 and 3). The positive and significant coefficients of *schedule variability _ within week*, imply that workers are also affected by variation in their schedules within the week.

Duration of gaps. Next, we explored further the effect of *gaps in schedule* on the two outcome variables of interest, by testing the models using an alternative operationalization of *gaps in schedule*. Namely, we calculated the variable using the total length (in hours) of the gaps within the day, instead of the number of these gaps. Although, this alternative operationalization does not account for the fact that each gap has different duration and that having multiple shorter gaps are likely to cause even more frustration because of multiple need to interrupt work and set up, it captures the overall idle not-wanted time in a given day. Because this variable is skewed to the right, we take the logarithmic transformation to calculate the *gaps in schedule _ length* variable. To test the effect of this variable we insert it in the main model after removing the main operationalization of the *gaps in schedule* variable from the model (see appendix A, Table A5, models 2 and 4). We note that *gaps in schedule* and *gaps in schedule _ length* are highly correlated (0.91) which impedes us from testing their independent effects in the same model. The positive and significant coefficients of *gaps in schedule _ length*, imply that workers are equally affected by the length of the idle time as by the number of the gaps.

5.6.2. Alternative Instrumental Variable Approach

In our main analyses, we used the average schedule variability (gaps in schedule) of the workers in the same department, the current week as an instrument to correct the endogeneity concern for the two main variables of interest *schedule variability* (*gaps in schedule*). As alternative instrumental variables, we use lagged instruments, which is a common practice in panel data settings (Kesavan et al. 2014, Tan &

Netessine 2014, Kamalahmadi et al. 2021). Specifically, we use the average *schedule variability* (*gaps in schedule*) of all employees in the department the week prior to the focal one. Our alternative instruments satisfy that relevance condition as mentioned earlier, in every department, schedulers make scheduling decisions based on common practices in the department, including their preferences, as well as on patient demand. Given that the scheduling practices are expected not to vary from one week to the next, our instrument should be correlated with schedule variability of the worker in the focal week. Moreover, even though patient demand is volatile, it does not vary substantially from a week to the next one in each department. More specifically, the average difference in the demand for each department (measured as total hours of performed weekly visits) from one week to the prior week is as low as 6.68% (st. dev. 0.14). Therefore, we argue that the average schedule variability (gaps in schedule) of the employees in the department of the previous week is a significant predictor of the *schedule variability* (*gaps in schedule*) of the focal employee in the current week. Our analysis also shows that the instruments are indeed significant predictors of the endogenous *schedule variability* and *gaps in schedule* variables at 1% significance level. Our instruments also satisfy the exclusion restriction, as there is no reason to expect that the schedules assigned to all the workers in the department the previous week, to have an impact on the employee's performance in the current week. We report the estimation results with the alternative instruments in Table A6 of appendix A. According to the results, the main findings regarding the effect of on-demand schedules on workers absenteeism as well as patient dissatisfaction are robust to the choice of instruments.

6. Conclusions and Discussion

By examining archival data from an actual company, we are able to measure and show the consequences of human behavior on important operational facets such as quality of the work performed as well as resource management. With this study, we find that when workers have high variability in the schedules or more gaps, they perform worse their jobs, as reflected by patient dissatisfaction. Likewise, these schedule characteristics are conductive to higher worker absenteeism. The size of these effects is not trivial. In fact, we find that a one-standard deviation increase in schedule variability (that is 1.22 or approximately 3 30-mins slots difference with the previous week) leads to 31.76 additional absences and 5.77 additional formal complaints for the firm in a week and a one-standard deviation increase in gaps in schedule (that is 0.36 gaps) leads to 11.55 additional absences and 8.66 additional formal complaints for the firm in a week. Nevertheless, we find that the presence of shorter than 30 mins gaps in the schedule do not harm the performance of the worker and that providing a longer overnight break, thus avoiding 'clopening' shifts, actually reduces the likelihood of receiving complaints from the patients.

6.1. Theoretical Contributions

This study is among the first to use company archival data to assess the worker performance effects of on-demand schedules. This study contributes to three literature streams. First, we extend the recent literature exploring the on-demand schedules and workers behavior and performance (Kamalahmadi et al. 2021, Kesavan el al. 2022). In particular, we identify the effect of two fundamental aspects of on-demand schedules on workers' performance. We contribute to this literature, by providing empirical evidence that schedule variability and gaps in schedule have a negative effect on two employee outcomes which have not been studied so far:

workers absenteeism and patient complains or the quality of the service they provide. Absenteeism and patient complaints, as opposed to sales, capture not only the effort the workers exert in their work, but also their compliance with the basic requirements of their work such as the one to show up for work and to provide the service at the expected level. Furthermore, we provide evidence that on-demand schedules have negative impact on workers performance in the home healthcare sector, which is not only an important sector for the economy such as retail, but also has an important societal consequences.

Second, we contribute to the work-life conflict literature (Goff et al. 1990, Henly & Lambert 2005, Henly & Lambert 2014). By examining the effects of on-demand schedules on workers performance, we contribute to the recent call to explore a more nuanced understanding of work arrangements which incorporate, flexible practices such as on-demand schedules (Kelliher et al. 2019). Moreover, we contribute to boundary theory (Nipper-Eng 1996, Ashfort et al. 2000, Allen at al. 2014). By calculating the number of gaps and how many times the worker needs to transition from work non-work in a week, we actually manage to measure the effect of transitions between work and non-worn on workers performance.

Third, by showing that workers' performance is not only affected by the workload or the hours they work but also on how these hours are distributed, our findings contribute to staffing literature (Kc & Terwiesch 2009, Green et al. 2013, Tan & Netessine 2014). More specifically, we show that for given number of hours worked, the presences of idle time within the day as well as the variability in the hours worked across the days have a negative impact on workers performance.

6.2. Practical Contributions

Our findings have important managerial implications as well. Given the instability of schedules and the causal nature of the work relation between HealthCo and HCAs, keeping HCAs committed is a nontrivial management challenge. According to HealthCo staff and management that participated in the study, poor HCA commitment immediately translates into absenteeism and patient dissatisfaction.

The clear negative effects of the use of precarious contracts shows that they need to be taken with caution and not use blindly as the benefits of using workers on demand can easily be offset by the costly consequences such patient dissatisfaction and absenteeism. Both consequences have severe direct and indirect negative effects on the operations and profitability of the firm. If a patient is dissatisfied with an employee, new employees need to be found to replace them and this requires the schedule of another employee to be changed, which will lead to more unpredictability in the schedule of this employee. Moreover, the company may lose the contract with the patient. In fact, homecare contracts are awarded by the public healthcare system or private insurance companies based on service price and quality ratings from patients. Hence on-demand schedules hold the potential for undermining the viability of a caregivers' business. Absenteeism also has very serious consequences, the first one is that last minute absences put a great stress on the scheduling as well as the rest of the employees, as a last-minute replacement must be found, otherwise the patient will be left unattended and this can put his health at risk.

The dynamic nature of the services provided and the patient needs, often time impede the establishment of highly stable and predictable schedules. Nevertheless, regulators and managers can take measures to mitigate the negative aspects of on-demand schedules to reduce absenteeism as well as patient complaints. For example, our findings indicate that one approach would be to reinforce scheduling practices that minimize as much as possible differences in the schedules across or within the weeks or ensuring workers hours are grouped in blocks. Another approach would be to ensure that workers have longer overnight breaks. Therefore, managers can use our findings to design and implement scheduling practices which reduce the negative effects of on-demand schedules on employee performance.

6.3. Limitations and Conclusions

Our study has a number of limitations that reflect the difficulties of using secondary data to study employee behavior. First, the data on workers motivational reaction to on-demand schedule was not available, making it impossible to empirically test the postulated mechanisms. We nevertheless notice that the literature supports the existence of a negative physiological reaction of workers to on-demand schedules. Moreover, we performed multiple analysis providing suggestive evidence on the mechanisms. Second, our rich data allows to control for numerous employee, geographic and occupation specific characteristics, however it limits our ability to generalize our findings to different locations with different labor practices as well as to different occupations with prevalence use of precarious contracts such as food delivery. Even though, these contracts are a global phenomenon, future research can further expand the boundaries of our findings to different settings. Moreover, even though our data contains detailed description of the daily responsibilities of the employees with the companies, it does not allow us to observe or measure the out of the job responsibilities such as a second job or family engagements such as childcare. Possible extension of our study could use such data to quantify their moderating effect of undesirable scheduling on employee performance.

Third, the available data does not allow us to calculate the overall performance consequences for the organization. Our findings suggest the on-demand practices, which induce gaps in schedule as well as schedule variability have negative effect on workers behavior such as absenteeism and poor quality of the service provided, which have important consequences for the firm. However, the actual cost of these practices to the firm remains to be explored by future research. Lastly, a natural limitation of the use of secondary data as opposed to a field experiment, is that we cannot claim causality. Nevertheless, we put great effort in ruling out alternative explanations. Moreover, the control function approach allows us to control for unobservable factors which can influence both the schedule characteristics variables as well as the outcome variables.

In closing, this study shows that the effect of variability in the schedule as well as the presence of unpaid idle hours within the working day should be taken into account when generating the schedules of hourly paid workers. Our findings provide evidence of an important limitation of flexible labor arrangements, namely that workers, in contrast to machines, are negatively affected by the flexible schedule practices and this affects their performance, which puts even further stress on the company's operations. Nevertheless, organizational practices such as ensuring fewer idle hours within the day, more stable schedules across as well as within the week and longer overnight breaks can mitigate the studied negative effects on performance and absenteeism.

TABLES

Table 1: Summary Statistics of Main Variables of Interest

Variable	Mean	S.D.	Min.	Max.
Absenteeism	0.12	0.39	0	6
Patient complaints	0.03	0.19	0	12
Schedule variability	2.63	1.22	0	5.61
Gaps in schedule	0.40	0.36	0	1.70
Employee experience	6.20	1.62	0	9.11
Employee first visit	0.01	0.11	0	1
Employee availability	15.30	7.75	1	24
Commuting distance	2.86	1.40	0	8.90
Employee patient variety	8.14	6.95	1	49
Employee task variety	1.96	1.04	0	6
Employee hours worked	22.82	15.20	0.25	168
Employee visits	14.86	12.72	1	85

Note: Descriptive statistics are given per employee-week (sample size 75,078 observations). The log transformation of Schedule variability, Gaps in schedule, Employee experience and Commuting distance are reported.

Table 2: Employee Schedule's Influence on Employee Absenteeism and Patient Complaints

	Poisson		Control function	
	Employee Absenteeism	Patient Complaints	Employee Absenteeism	Patient Complaints
Variables	(1)	(2)	(3)	(4)
Schedule variability	0.492**	0.390**	0.555**	0.435**
	(0.021)	(0.041)	(0.035)	(0.072)
Gaps in schedule	0.174**	0.379**	0.612*	1.354**
	(0.059)	(0.116)	(0.241)	(0.419)
Employee experience	0.081**	-0.130**	0.085**	-0.128**
	(0.025)	(0.040)	(0.025)	(0.040)
Employee first week	1.262**	0.505	1.448**	0.642+
	(0.180)	(0.328)	(0.196)	(0.384)
Employee availability	-0.006+	0.001	-0.006+	0.001
	(0.004)	(0.007)	(0.004)	(0.007)
Commuting distance	-0.017	0.038	-0.027+	0.023
	(0.015)	(0.029)	(0.015)	(0.030)
Employee patient variety	0.013*	0.069**	0.016*	0.078**
	(0.006)	(0.010)	(0.007)	(0.011)
Employee task variety	0.032	0.129**	0.002	0.075+
	(0.021)	(0.039)	(0.024)	(0.044)
Employee hours worked	-0.018**	-0.002	-0.019**	-0.002
	(0.003)	(0.004)	(0.003)	(0.005)
Employee visits	-0.012**	-0.011	-0.020**	-0.028**
	(0.004)	(0.007)	(0.006)	(0.010)
Residuals _ Schedule variability			-0.003*	-0.002
			(0.001)	(0.003)
Residuals _ Gaps in schedule			-0.252+	-0.528*
			(0.132)	(0.221)
Employee fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	68,991	51,779	68,991	51,779
Number of employees	796	509	796	509

Note: Models (1) and (2) are Poisson regression fixed effects regression. Models (3) and (4) are Poisson fixed effects regression with control function controls**p<0.01, *p<0.05 and +p<0.10

Table 3: Employee Schedules' Influence on Employee Absenteeism and Patient Complaints (Income Volatility)

Variables	Dependent variable: Employee Absenteeism (1)	Dependent variable: Patient Complaints (2)
Schedule variability	0.479**	0.342**
	(0.037)	(0.081)
Gaps in schedule	0.712**	1.523**
	(0.259)	(0.456)
Income volatility	0.090**	0.105**
	(0.018)	(0.038)
Employee experience	0.062*	-0.173**
	(0.028)	(0.043)
Employee first week	1.451**	0.617
	(0.219)	(0.426)
Employee availability	-0.006	-0.002
	(0.004)	(0.008)
Commuting distance	-0.024	0.036
	(0.017)	(0.035)
Employee patient variety	0.019*	0.084**
	(0.008)	(0.012)
Employee task variety	-0.026	0.080
	(0.026)	(0.050)
Employee hours worked	-0.019**	-0.002
	(0.003)	(0.005)
Employee visits	-0.022**	-0.030**
	(0.006)	(0.011)
Residuals _ Schedule variability	-0.003*	-0.000
	(0.002)	(0.003)
Residuals _ Gaps in schedule	-0.277+	-0.578*
	(0.142)	(0.239)
Employee fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	58,996	45,452
Number of employees	608	406

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

Table 4: Employee Schedules' Influence on Employee Absenteeism and Patient Complaints (Unemployment)

Variables	Dependent variable: Employee Absenteeism (1)	Dependent variable: Patient Complaints (2)
Schedule variability	0.553**	0.434**
	(0.035)	(0.072)
Gaps in schedule	0.591*	1.340**
	(0.239)	(0.420)
Unemployment	-0.079**	-0.062
	(0.028)	(0.049)
Employee experience	0.083**	-0.131**
	(0.025)	(0.040)
Employee first week	1.436**	0.632+
	(0.196)	(0.383)
Employee availability	-0.006	0.002
	(0.004)	(0.007)
Commuting distance	-0.026+	0.025
	(0.015)	(0.031)
Employee patient variety	0.016*	0.078**
	(0.007)	(0.011)
Employee task variety	0.002	0.076+
	(0.024)	(0.044)
Employee hours worked	-0.019**	-0.002
	(0.003)	(0.005)
Employee visits	-0.020**	-0.027**
	(0.006)	(0.010)
Residuals _ Schedule variability	-0.003*	-0.002
	(0.001)	(0.003)
Residuals _ Gaps in schedule	-0.244+	-0.523*
	(0.131)	(0.222)
Employee fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	68,991	51,779
Number of employees	796	509

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

Table 5: Employee Schedules' Influence on Employee Absenteeism (non-sick leave)

Variables	Dependent variable: Employee absences (non-sick)
Schedule variability	0.400**
	(0.040)
Gaps in schedule	0.874**
	(0.313)
Employee experience	-0.029
	(0.029)
Employee first week	0.828**
	(0.230)
Employee availability	-0.007
	(0.005)
Commuting distance	-0.037+
	(0.021)
Employee patient variety	0.015+
	(0.008)
Employee task variety	0.016
	(0.032)
Employee hours worked	-0.006*
	(0.003)
Employee visits	-0.013+
	(0.007)
Residuals _ Schedule variability	-0.004*
	(0.002)
Residuals _ Gaps in schedule	-0.370*
	(0.174)
Employee fixed effects	Yes
Month fixed effects	Yes
Year fixed effects	Yes
Number of observations	66,447
Number of employees	732

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

Table 6: Employee Schedule's Influence on Employee Absenteeism and Patient Complaints (Short Within-day Gaps and Overnight Gap Length)

Variables	Dependent variable: Employee Absenteeism (1)	(2)	Dependent variable: Patient Complaints (3)	(4)
Schedule variability	0.554**	0.505**	0.435**	0.401**
	(0.035)	(0.037)	(0.072)	(0.078)
Gaps in schedule	0.618*	0.633*	1.354**	1.273**
	(0.241)	(0.249)	(0.419)	(0.423)
Short within-day gaps	0.064		-0.020	
	(0.058)		(0.122)	
Overnight gap length		0.039		-0.153+
		(0.043)		(0.084)
Employee experience	0.083**	0.092**	-0.127**	-0.122**
	(0.025)	(0.026)	(0.040)	(0.040)
Employee first week	1.434**	1.490**	0.645+	0.554
	(0.197)	(0.208)	(0.384)	(0.417)
Employee availability	-0.007+	-0.004	0.001	0.001
	(0.004)	(0.004)	(0.007)	(0.007)
Commuting distance	-0.027+	-0.016	0.024	0.020
	(0.015)	(0.016)	(0.031)	(0.031)
Employee patient variety	0.016*	0.015*	0.078**	0.076**
	(0.007)	(0.007)	(0.011)	(0.011)
Employee task variety	0.001	-0.006	0.076+	0.072
	(0.024)	(0.025)	(0.044)	(0.044)
Employee hours worked	-0.018**	-0.019**	-0.002	-0.004
	(0.003)	(0.003)	(0.005)	(0.005)
Employee visits	-0.021**	-0.020**	-0.028**	-0.028**
	(0.006)	(0.006)	(0.010)	(0.010)
Residuals_ Schedule variability	-0.003*	-0.003+	-0.002	-0.001
	(0.001)	(0.001)	(0.003)	(0.003)
Residuals _ Gaps in schedule	-0.255+	-0.251+	-0.528*	-0.488*
	(0.132)	(0.136)	(0.221)	(0.222)
Employee fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	68,991	65,787	51,779	49,807
Number of employees	796	789	509	507

Note: Models are Poisson regression with robust standard errors clustered by employee. Coefficient shown are marginal effects. **p<0.01, *p<0.05 and +p<0.10

Table 7: Employee Schedule's Influence on Employee Absenteeism and Patient Complaints (Last-minute Change control)

	Week t		Week t+1	
	Employee Absenteeism	Patient Complaints	Employee Absenteeism	Patient Complaints
Variables	(1)	(2)	(3)	(4)
Schedule variability	0.565**	0.417**	0.162**	0.336**
	(0.035)	(0.072)	(0.033)	(0.075)
Gaps in schedule	0.640**	1.319**	0.477*	1.112*
	(0.240)	(0.420)	(0.225)	(0.433)
Last-minute changes	-0.091**	0.105+	0.211**	0.053
	(0.029)	(0.062)	(0.033)	(0.057)
Employee experience	0.081**	-0.124**	0.003	-0.146**
	(0.025)	(0.040)	(0.024)	(0.035)
Employee first week	1.377**	0.733+	0.628**	0.704*
	(0.196)	(0.384)	(0.173)	(0.311)
Employee availability	-0.006+	0.001	-0.014**	0.002
	(0.004)	(0.007)	(0.004)	(0.006)
Commuting distance	-0.025+	0.023	-0.028	0.003
	(0.015)	(0.030)	(0.017)	(0.035)
Employee patient variety	0.026**	0.067**	-0.014*	0.056**
	(0.008)	(0.012)	(0.007)	(0.012)
Employee task variety	0.005	0.072+	0.047+	0.085*
	(0.024)	(0.044)	(0.025)	(0.042)
Employee hours worked	-0.018**	-0.002	0.005*	-0.001
	(0.003)	(0.005)	(0.002)	(0.005)
Employee visits	-0.022**	-0.025**	-0.000	-0.023*
	(0.006)	(0.010)	(0.005)	(0.009)
Residuals _ Schedule variability	-0.003*	-0.002	-0.005**	-0.002
	(0.001)	(0.003)	(0.001)	(0.003)
Residuals _ Gaps in schedule	-0.268*	-0.509*	-0.138	-0.446+
	(0.131)	(0.222)	(0.124)	(0.232)
Employee fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	68,989	51,777	68,137	51,191
Number of employees	796	509	786	505

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

ESSAY 2: The Effect of Subcontracted Labor Mix on Financial Performance: Evidence from High-Tech Project Teams

Abstract

We investigate the effect of using subcontracted workers together with permanent workers on project financial performance. It is a widespread practice, across disparate businesses, to staff project teams with subcontracted workers—and yet, despite the prevalence of this phenomenon, there is scant research on how subcontracted workers impact project performance. Investigating such an effect is important because past findings on the effects of subcontracting in retail or assembly lines, cannot simply be extrapolated to the more qualified workers and more demanding tasks normally associated with project environments. Building on previous findings about the higher motivation level of subcontracted vs. permanent workers when the latter are protected from individual dismissal by the law, we develop hypotheses to conceptualize how and under what conditions subcontracted workers positively impact project performance. We then test our hypotheses by analyzing 413 projects of a European high-tech firm. We find that with increased use of subcontracted workers comes increased project profit margins. This positive effect is stronger for larger teams and weaker when large project scope changes occur or when higher-skilled workers are subcontracted. We also find this effect to be stronger when subcontracted workers are involved in technical rather than administrative roles and when subcontracted workers join in the later stages of the project. This study offers guidelines on how project managers can use subcontracting to increase project margins highlighting strategic and tactical factors that affect the benefits of using subcontracted labor.

Keywords: Subcontracted labor mix; project performance; team size; scope change

1. Introduction

Many firms adopt outsourcing practices (Hayes et al. 2005, Sinha & Van de Ven 2005, Anderson & Parker 2013, Mishra & Sinha 2016, Tsay et al. 2018) to better match demand while keeping costs in check (Harrison & Kelley 1993, Houseman 2001, Broschak & Davis-Blake 2006, Goyal & Netessine 2012). While outsourcing has been historically associated with transferring activities to another company, it currently often entails transferring work to subcontracted workers, including freelancers and the self-employed (Kalleberg 2000, Cappelli & Keller 2013). According to McKinsey (2016), 20% to 30% of the working-age population in the United States and Europe (up to 162 million individuals) engages in independent work. The practice of subcontracting labor is not restricted to repetitive operations, where incorporating workers to deal with demand fluctuations can be relatively straightforward. It is also becoming quite common in complex and non-repetitive project-based operations, such as new product development and professional services. In fact, a study conducted by Aberdeen Group shows that IT firms use as many as 49% of subcontracted workers and engineering firms use as many as 20% of subcontracted workers in their projects (Randstad Sourceright 2020). Most Fortune 500 companies currently rely on subcontracted, highly skilled workers for a variety of project work (Fuller et al. 2020).

Despite the prominence of subcontracting in project teams, its effect on project performance remains understudied. Past research in organizational behavior and human resource management disagrees on the consequences of subcontracting. Some studies find that subcontracting detracts from worker identification, engagement and commitment (e.g., Davis-Blake et al. 2003, von Hippel & Kalokerinos 2012), while others suggest this is not the case (e.g., Felfe et al. 2008, Petriglieri et al. 2018, Anderson & Cappelli 2021). Furthermore, these studies do not investigate the performance consequences of subcontracting. Conversely, research in operations management indicates that subcontracted labor has an inverted U-shaped relation with profits and sales in retail operations (Kesavan et al. 2014), but whether these findings apply to complex project settings remains an open question. In fact, compared to repetitive operations, project settings are characterized by more skilled workers, more complex tasks, and more fluid teams.

With this study, we investigate the effect of subcontracted workers on the financial performance of product development projects executed by the aerospace division of a high-tech firm that focuses on space, aeronautics and vehicles, defense and health care equipment. We use Bidwell and Briscoe's (2009) definition of subcontracted labor as “workers, who provide services directly to a client firm on an explicitly short-term basis”. Following Kesavan et al. (2014), we define the *subcontracted labor mix* as the ratio of subcontracted workers’ hours to permanent workers’ hours in a project. We capture project financial performance with the final project margin. We ground our theoretical framework in empirical evidence, pointing out that subcontracted workers have stronger motivation to put effort into their work compared to permanent workers, especially in countries where labor law protects permanent workers from individual dismissal (Allan & Sienko 1998, Engellandt & Riphanhn 2005, Bradley et al. 2014). Based on this premise, we expect that the heightened motivation of subcontracted workers would positively affect project margins. We further build on this motivational mechanism to argue that subcontracted workers are more beneficial to project performance when project teams are large, attenuated when project scope changes occur, and more salient for lower-skilled, easily substitutable workers than for those who are highly-skilled and difficult to substitute.

We test these hypotheses using a unique dataset of 413 projects executed over a 10-year time span. The company we study allows us to investigate the effect of a *subcontracted labor mix* on project financial performance, as over 80% of projects utilize subcontracted workers together with permanent ones. Moreover, in our sample, we observe sizeable across-project variations relative to the posited moderators, including project team size, the magnitude of scope changes, and the ratio of high- vs. low-skilled subcontracted project team members. Finally, our dataset allows us to explore whether the effects we detect are driven by different mechanisms than motivation, such as labor cost advantages, access to better talent through subcontracting or familiarity effects.

This study makes multiple contributions to theory and practice. First, we extend the limited empirical literature on the consequences of subcontracting on performance (Kesavan et al. 2014). We find that subcontracting workers can also improve profits in non-repetitive (i.e., project-based) operations. In this setting, integration diseconomies from subcontracting voiced by organizational behavior research (Davis-Blake et al. 2003, George 2003, Engellandt & Riphahn 2005, von Hippel & Kalokerinos 2012) do not appear to cancel out the benefits from outsourcing. Our approach allows us to test and quantify the effect of subcontracted workers on the project profit margins and our results indicate that a 10% increase in *subcontracted labor mix* can increase *project margins* by 5.83%.

Second, by investigating the moderating effects of *team size* and *scope changes,* we provide insights into when projects benefit most from using subcontracted labor. We find that subcontracting brings more prominent benefits when project team size is increased, thereby contributing to research on the effects of team size (Levine & Moreland 2006, Staats et al. 2012). Furthermore, the negative moderation effect of project scope changes suggests that the complexities associated with managing new goals and priorities reduce the beneficial effects of subcontracted labor, thus contributing to research on the effect of task changes (Huckman & Staats 2011). Third, past research has not examined the role of skill level on the relationship between subcontracted workers and project performance. We find that the beneficial effect of subcontracted workers is stronger for lower-skilled workers than for higher-skilled workers. Albeit in line with our theoretical predictions, this finding downplays the idea that the benefits from outsourcing are associated with reaching highly-skilled labor in projects (Vestring et al. 2005, Boh et al. 2007), especially when a sizeable percentage of the team is made up of subcontracted workers.

These findings are significant from a practical standpoint because they demonstrate how subcontracting supports project performance, and what companies can do to enhance the benefits of subcontracting project team members. Further pragmatic insights arise from our post-hoc analyses, which indicate that project margin also benefits from subcontracting workers in technical vs. administrative roles, as well as in later vs. earlier stages of projects.

2. Background

Operations management literature has explored the effect of using subcontracted workers on cost and performance from various perspectives. Modeling studies focus on defining the optimal labor pool size and *labor mix* (i.e., the ratio of subcontracted to permanent workers) that minimizes labor costs (Wild & Schneewei 1993, Berman & Larson 1994, Milner & Pinker 2001, Pinker & Larson 2003, Bhandari et al. 2008). For example, Berman and Larson (1994) develop a probabilistic model in a postal service setting that finds the optimal pool size of temporary workers, given the amount of permanent workers, absenteeism and variability. Milner and Pinker (2001) study labor contracts between external labor supply agencies and employers under the skills and supply uncertainty of subcontracted workers. They develop staffing policies by considering a mix of both types of workers and find that an optimal policy can be reached when there is uncertainty about subcontracted workers' skills but not when there is uncertainty about their supply. Pinker and Larson (2003) develop an optimization model determining the optimal pool size of permanent and subcontracted workers, which minimizes labor and backlog costs with uncertain demand. Bhandari et al. (2008) study labor configuration in call centers and demonstrate that the optimal labor mix increases with the opportunity cost of not serving a client. Their findings are based on the core assumption that subcontracted workers are hired only during peaks in demand and are let go afterward, while permanent workers are retained independent of their level of utilization.

Empirical studies have focused on the effect of subcontracted workers on firm performance and flexibility. Stratman et al. (2004) use data from an assembly line to study, via simulation, how labor mix influences line performance. They find that whereas the increasing use of subcontracted workers at the manufacturing plant achieves considerable wage cost savings, it can adversely affect quality on account of the learning and forgetting costs associated with hiring and firing subcontracted workers. Kesavan et al. (2014) use data from a large retailer and examine how the ratio of subcontracted to permanent workers (or *labor mix*) affects store performance metrics such as revenue and profit. They find a reverse U-shaped relation between labor mix and store performance and contend that this arises from the combination of nonlinear benefits and costs. The benefits of a higher labor mix accrue from lower labor costs (e.g., social benefits, insurance) and flexibility in adapting to demand peaks. Costs, however, increase with labor mix due to reduced commitment as well as training and coordination difficulties.

The organizational behavior and human resources literature focuses on studying the effects of the labor mix on workers' engagement and perceptions toward the firm. A substream of this literature suggests that including subcontracted workers in work groups can be detrimental to the workplace environment. For instance, George (2003) conducts a survey in three organizations (a research laboratory, a computer hardware manufacturer, and a consumer product retailer) and finds that the greater the use of subcontracted workers, the lower level of trust the permanent workers have in the organization. Similarly, Davis-Blake et al. (2003) use data from two 1991 U.S. surveys (General Social Survey and National Organizations Survey) and find that permanent workers have less loyalty, worse relations with their managers and higher turnover intentions when their organizations rely on subcontracted workers. Von Hippel and Kalokerinos (2012) show that if companies hire subcontracted workers for jobs of equal seniority or higher to its permanent workers, the mixing of these two types of workers could result in a perceived threat to job security and subsequently decreasing collaboration among them. All these results underscore a general concern that a "distance" or "boundary" develops between subcontracted workers and the employer (Anderson & Bidwell 2019) that limits subcontracted worker engagement in the organization's day-to-day (Ashford et al. 2007, Cappelli & Keller 2013). In contrast with these studies, a parallel stream of research downplays the difficulty of integrating subcontracted with permanent workers. Subcontracted workers can identify with the organization for which they temporarily work (George & Chattopadhyay 2005, Felfe et al. 2008). This is thanks to frontline managers, who often treat subcontracted and permanent workers similarly (Smith 2001, Barley & Kunda 2006, Bidwell 2009) and create “blended workgroups” (Ashford et al. 2007) that blur the differences between the two types of workers. When subcontracted workers lack organizational identity, they can still remain motivated and engaged by embracing alternative work identities based on work routines, workplaces, collaborators, and pursuit of purpose that is broader than the individual project assignments (Petriglieri et al. 2018).

In sum, the organizational behavior and human resources literature presents opposing views of the effects of subcontracted workers but does not explore their performance implications. The operations management literature, in particular Kesavan et al. (2014), suggests that both views may be correct in that subcontracting can have a positive impact on performance up to a certain point, beyond which it actually has a negative effect. However, it is not clear whether the findings about the effects of subcontracting in repetitive operations (e.g., assembly lines, retail outlets) can be applied to non-repetitive, project-based operations (e.g., construction, engineering, R&D).

Understanding the impact of subcontracting in project settings, where qualified workers engage in complex and nonstandard tasks, requires a reexamination of the theoretical mechanisms that have been invoked in repetitive settings. First, it is less clear that organizational identification and commitment are problems associated with subcontracting in project settings. These environments require workers qualified to perform complex and uncertain tasks, who tend to have greater employment options and salary expectations than workers who restock shelves or assemble components. Thus, employers need to provide an engaging work environment to attract this highly qualified talent, making organizational identification and commitment problems potentially less relevant. Moreover, the negative consequences of integrating subcontracted workers in repetitive environments may not be equally apparent in non-repetitive project settings. In repetitive settings, it may be costly to integrate subcontracted workers within stable teams of permanent workers because of the need to establish routines with the new external workers. Such integration costs, however, may not be salient in project settings, where permanent workers fluidly recombine into different project teams (Huckman & Staats 2011). Fluid teams inherently incur integration costs (i.e., set up and establishment of work routines) independent of whether team members are permanent or subcontracted workers. The long duration of the projects may also ease the integration of subcontracted workers compared to more volatile worker engagements in repetitive settings. Consequently, staff variability induced by subcontracted workers may be less problematic. Lastly, subcontracting can provide the project with a special type of expertise not internally available in the organization, thereby inducing learning benefits instead of costs (Vestring et al. 2005, Boh et al. 2007).

The only study that has thus far investigated project performance in the presence of subcontracting is from Mayer and Nickerson (2005). They find that the effect of contracting difficulties (i.e., monitoring or intellectual property protection) on project margins is negative for projects with subcontracted team members, while it is not significant for projects fully staffed with permanent workers. However, they neither explicitly theorize about the effect of subcontracting nor test for it; they simply report point estimates of project margins in presence and absence of subcontracting at different levels of the moderators. Additionally, their measure of subcontracting is dichotomous, a fact that makes it impossible to distinguish between situations where only a small vs. a large fraction of team members is subcontracted. Given these two limitations, our primary goal is to more thoroughly investigate the effect of a *subcontracted labor mix* on project margins, and thereby complementing research from Kesavan et al. (2014). Additionally, we seek possible moderators for the effects of a *subcontracted labor mix* in key project features such as *team size* and *scope changes*, which may interact with the ability of the firm to integrate successfully subcontracted team members. Furthermore, unlike previous research, we investigate the effect of the skill level of subcontracted team members, which is arguably an important driver of project success (Boh et al. 2007). Finally, unlike previous project research, we control for past employment of subcontracted workers with the focal company, which can confuse the effect of subcontracting with familiarity effects.

3. Hypotheses

3.1. Subcontracted Labor Mix and Project Performance

In order to study the effect of subcontracted workers on project performance, it is important to establish the differences between subcontracted and permanent workers. Permanent workers have a work contract with the employer with no formal or implied end date. That is, the work relationship between an employer and a permanent worker does not necessarily terminate with the completion of the assigned projects. Conversely, subcontracted workers have a work contract with a specific timeframe or scope of work (Bidwell & Briscoe 2009). That is, when the contractual time expires or the contracted work is completed, the work relation between the subcontracted worker and employer is terminated. Subcontracted workers are frequently recruited multiple times by the employer, as the need arises.

Beyond their nominal definitions, subcontracted and permanent workers differ in their prospects to maintain a continued employment relationship with a specific employer, especially in economic environments with strong employment protection laws. In such environments, the cost of terminating permanent worker contracts is relatively high compared to the cost of terminating subcontracted worker contracts

(Ichino & Riphahn 2005). According to individual employee dismissal regulations, to dismiss permanent workers without incurring significant severance payments, employers must provide evidence that the dismissal is based on poor performance. They typically require the employer to follow notification procedures that include multiple verbal and written warnings to the candidate (in order to allow a notice period for the permanent worker to amend their behavior) and to collect evidence of underperforming or not compliant behaviors (see OECD 2020) –all activities that can stretch for months and absorb significant time and energy (Shire et al. 2009, Ryan 2015). Employers who fail to comply with these requirements incur nontrivial costs due to severance payments to permanent workers. For instance, in the case of the major European country where the focal firm is based, a top severance compensation amounts to 33 (45 before 2012) workdays of gross salary for every year worked, up to a maximum of 24 months (48 before 2012). That is, a permanent worker dismissed in 2016 with a gross salary of 100,000 euros and 10 years of tenure has a right to a severance pay of 111,666 euros. Demonstrating that the layoff is justified is a rather difficult and uncertain endeavor that often ends up in court, one that is very protective of labor rights (Rios 2007). In the event of a lost litigation, the employer bears the legal costs for both parties, further adding to the cost of dismissal. Furthermore, even when employment protection laws are weaker, many managers find the process of firing a permanent worker emotionally stressful and unpleasant (Bidwell 2009, Gould 2018, Lotich 2018). Managers are often uncertain on how to best deal with the emotional difficulties of dismissing permanent workers, even when they feel that the employee is not meeting expectations (Knight 2019). Given the monetary and behavioral costs of dismissing a permanent worker, the employer tends not to swiftly terminate an employment relationship when the worker’s performance is unsatisfactory (Bidwell

2009). Conversely, when the contract between the employer and subcontracted worker expires, the work relation automatically terminates with no cost to the employer, unless the contract is renewed.

The difference in protection from dismissal between subcontracted and permanent workers has implications in regards to the effort subcontracted workers put into projects. If a subcontracted worker performs unsatisfactorily in a project, the employer may choose, without incurring any cost, not to hire that worker again in future. Conversely, if a subcontracted worker performs consistently well across multiple projects, the employer has an incentive to continue to hire the worker for projects, or even on a permanent basis. Future contracts are an inherent concern of subcontracted workers because they must ensure subsequent work contracts to sustain themselves economically (Connelly & Gallagher 2004, Gullhaugen 2010).

Compared to subcontracted workers, permanent workers, who are protected by labor law regulations, are aware of the costs the employer would incur in case of individual dismissal (Ichino & Riphahn 2005, García Mainar et al. 2018). Permanent workers, therefore, have the option to reduce their effort without jeopardizing their employment status (Allan & Sienko 1998) to the extent that the consequences of their reduced effort do not clearly outweigh the cost to the employer of dismissing them. Additionally, the consequences of contract termination are less troublesome for permanent workers as they can rely on a severance package and richer unemployment subsidies while looking for another job (Bonet et al. 2020). Furthermore, Smith (1997) suggests that managers may use subcontracted workers as a signal that permanent workers can be replaced if they limit their effort. Therefore, we expect that the presence of subcontracted workers in project teams will increase the overall motivation of the team to put in the extra effort.

Empirical research in OECD countries that are characterized by laws protecting workers from individual dismissals provides ample evidence of the comparatively lower motivation of permanent workers to exert effort compared to subcontracted workers. Engellandt and Riphanhn (2005) use a Swiss Labor Force longitudinal survey (1996-2001) with 15,908 respondents and find that subcontracted workers make significantly more effort, as they have a 60% higher probability of working unpaid overtime hours than permanent workers. Ichino and Riphahn (2005) study 858 workers of an Italian bank who transition from a probation period to permanent contracts and find that the number of days absent per week increases significantly after the transition. Similarly, Bradley et al. (2014) use a longitudinal Australian database of the performance of 5,380 public sector workers from 2001 to 2004 and find that when subcontracted workers transition to permanent contracts, they become more likely to be absent from work. Allan and Sienko (1998) survey 149 permanent and 48 subcontracted technical and professional workers of a large U.S. telecommunication company and find that subcontracted workers are more motivated than permanent ones. Motivation differentials between the two groups of workers are, hence, present even in countries where protection against employee dismissal is very limited.

We expect that the extra effort of subcontracted workers operating in project settings will benefit project performance. We capture the extent to which subcontracted workers are used in a project team with the variable *subcontracted labor mix*, defined as the ratio of the number of hours worked by subcontracted workers to the number of hours worked by permanent workers within a project, as in Kesavan et al. (2014). We also conceptualize project performance as the *project margin*, that is, the difference between final project revenues and direct project costs (i.e., variable costs plus fixed, project-linked costs), as in Mayer and Nickerson (2005) and Di Vincenzo and Mascia (2012).

A higher *subcontracted labor mix* can benefit project margins for multiple reasons. The heightened effort of subcontracted workers is plausibly manifested in the completion of tasks with superior speed and quality. Reducing errors and delays pertaining to a task, in turn, curtails the propagation of errors and delays in subsequent and related tasks (Anderson & Parker 2013), further reducing overall project cost and positively affecting its margin. The benefits of avoiding such chains of errors are particularly noteworthy in a high-tech setting as the one we study, where errors or delays can propagate to affect many project activities due to high task interdependency (Hamilton 2001). If the employer is part of a larger consortium of firms involved in the project, errors and delays can also imply legal penalties that would further detract from project margins. Finally, late completion of a task (e.g., a component design) can lead to unexpected system integration problems, which are often time-consuming to solve (Mishra & Sinha 2016).

These motivational benefits from subcontracted workers may, however, be offset—partially or totally—by the cost of integrating these workers into project teams. Nonetheless, in settings where project teams are fluid, like the one we study, we expect that the benefits of subcontracting outweigh the costs of integrating these workers into project teams. In fact, when project teams are fluid, each team is assembled ad hoc based on specific project requirements, and upon project completion, the team is disbanded, and its members are assigned to different projects (Huckman & Staats 2011). As these teams are not always comprised of individuals with mutually consolidated work routines, the difference between subcontracted and permanent workers tends to become less salient, and with it, the costs of integrating subcontracted workers into the teams. Hence, we expect that:

> *Hypothesis 1: The subcontracted labor mix has a positive effect on project margins*

It is worth noting that we express the above hypothesis and the forthcoming ones at the project team level but derive them from an individual-level phenomenon: higher motivation of subcontracted vs permanent workers comprising the project team. In principle, higher motivation of subcontracted workers should be reflected first, in their individual performance. However, no measures of individual worker contributions to project margin or to other project performance yardsticks were available at the studied organization. The lack of such granular information is consistent with the abovementioned interdependency of project tasks. A worker's effort affects other workers' performance, making it hard to quantify individual worker performance due to countless chains of interdependencies. It may be that in certain cases project activities are highly modular and hence the firm can collect fine-grained data on individual worker performance within a project. However, this was not the case in the studied firm, and is pretty common in project settings (Anderson & Parker 2013, Sosa 2014, Mishra & Sinha 2016).

3.2. Subcontracted Labor Mix and Team Size

Next, we expect that the positive effect of a *subcontracted labor mix* on project margins to be positively moderated by the project's team size for multiple reasons. First, large project teams are more vulnerable to performance disruptions than smaller ones (Huckman & Staats 2011) due to the propagation of errors and problems among team members (Sauer et al. 2007). This is because the number of linkages among team members increases at a nonlinear rate as there are (N(N-1))/2 possible linkages in a team with N members, as observed elsewhere (Brooks 1995, Espinosa et al. 2007, Staats et al. 2012). Errors and delays from a worker, hence, tend to potentially affect a greater number of workers, with negative consequences for project costs and, ultimately, margins. As the heightened motivation of subcontracted workers can reduce the occurrence of errors and delays, we expect that the effect of a *subcontracted labor mix* on project margins is stronger for projects with larger team sizes. Moreover, when assigning permanent workers to a project, each project manager attempts to obtain motivated and high-quality workers. However, as the project team size increases, reliance on permanent workers forces the project manager to include workers with less desirable skills. Such limitations are less stringent when recruiting subcontracted workers, as the pool of possible workers is not constrained to company employees with unfilled hours (Brewster et al. 1994). Hence, when the team size increases, a higher *subcontracted labor mix* reduces the adverse selection of internal workers, with positive effects on overall team motivation, quality and, ultimately, project margins.

Finally, large teams present challenges regarding the motivation of team members (Staats et al. 2012). Specifically, large teams can create a context of social loafing and free riding because difficulties in supervision and complexity hamper transparency and individual accountability (Latané et al. 1979, Karau & Williams 1993). Permanent workers may take advantage of such a team environment to reduce their effort without being noticed, safely maintaining their employment. This shirking possibility, which detracts from project margins, is less appealing for subcontracted workers whose interest is to signal their ability to the employer to secure future work contracts or a long-term employment relationship. Based on the abovementioned arguments, we propose the following:

Hypothesis 2: Team size increases the positive effect of the subcontracted labor mix on project margins.

3.3. Subcontracted Labor Mix and Scope Changes

While reliance on subcontracted workers can benefit project margins, such an effect can be hindered by the occurrence of project scope changes. We refer to scope changes as modifications of project activities during the execution that result in variations of the project contract value (Cheng & Carrillo 2012). Hence, larger scope changes are reflected in larger variations in project contract values. Engineering projects are frequently subject to such changes in scope, which represent a major source of uncertainty (Yeo & Ning 2002). Due to the long duration and complexity of such projects, changes in scope do not necessarily originate from poor project planning. The client may not be able to fully specify the requirements of the project in the beginning, as the knowledge generated during execution may alter the specifications (Reifer 2000) or changes in technology can trigger modifications (Kulk & Verhoef 2008, Chandrasekaran et al. 2016). Although some level of scope change is accounted for at the beginning of the project, changes in such complex systems are difficult to predict. Hence, scope changes put stress on the project, as they entail readjusting plans and reassigning tasks to team members (Sterman et al. 2015).

When there is a change in scope, it is faster to reassign tasks to permanent team members than to subcontracted ones. Permanent workers can simply be ordered to refocus their activities on new tasks. Conversely, changing the activities of subcontracted workers entails contract negotiations (Cox 1997), which can take away time and attention from project execution activities. In addition to taking more time, negotiations with subcontracted workers entail reduced bargaining capacity of the subcontracting firm since extant subcontracted workers are less easily substitutable than at the beginning of the project, as they have since acquired project-specific knowledge; substituting them would also create inefficiencies associated with the induction of new team members into an established project (van Oorschot et al. 2013).

Finally, project managers have more information on the skills and experience of permanent than subcontracted workers (Autor 2003) and hence can match new tasks to permanent workers more swiftly and aptly than to subcontracted ones in the event of a change in the scope. Being easier to reassign tasks to permanent team members, it follows that when the *subcontracted labor mix* is higher, reacting to project scope changes is more costly. We, therefore, expect that in projects with a high level of scope changes, the positive effect of *subcontracted labor mix* on the project financial performance will be attenuated. Hence, we propose that:

Hypothesis 3: Larger changes in the scope of the project decrease the positive effect of the subcontracted labor mix on project margins.

3.4. Expertise and Subcontracted Labor Mix

To obtain a more fine-grained understanding of the effect of the use of subcontracted workers on project margins, we follow past literature and investigate the effect of subcontracted workers' skill level (Barley & Kunda 2006). Comparatively "low-skilled" subcontracted workers tend to be inexperienced young professionals who use temporal work engagements as a stepping stone toward a permanent position. Because of their low level of expertise, low-skilled workers tend to perform standardized engineering tasks (Kunda et al. 2002, Barley & Kunda 2006), such as drafting blueprints or executing routine engineering calculations. The supply pool for this type of worker is relatively broader than that of highly-skilled specialists (Houseman et al. 2003, Bidwell & Briscoe 2009). For this reason, if low-skilled workers perform unsatisfactorily in a project, the employer can easily substitute them with equivalent workers for subsequent projects. Aware of their heightened substitutability, low-skilled subcontracted workers are motivated to exert greater effort in the execution of project activities. In contrast, “high-skilled” workers are experienced individuals who often choose not to be affiliated with any organization on a permanent basis (Kunda et al. 2002, Barley & Kunda 2006). High-skilled subcontracted workers are hired for a project because of their specific expertise (Broschak & Davis-Blake 2006, Bidwell 2009, Kozica et al. 2014). The supply pool for this type of workers is more constrained than that of low-skilled workers. Hence, if high-skilled subcontracted workers perform unsatisfactorily in a project, the employer cannot easily substitute them with other high-skilled workers for subsequent projects. Past research has also shown that subcontracted workers’ commitment decreases as their qualifications increase (Suβ & Kleiner 2010), as high-qualified individuals tend to feel less committed to their employers due to their high level of expertise. High-skilled subcontracted workers are, therefore, less motivated to exert greater effort in the execution of project activities than lower-skilled subcontracted workers.

In summary, in the case of poor performance in a project, low-skilled subcontracted workers face lower possibilities of being hired again by the same employer compared to high-skilled, less substitutable, subcontracted workers. Aware of the different levels of substitutability subcontracted workers face depending on their level of expertise, we expect that low-skilled subcontracted workers are more motivated than higher-skilled ones to exert greater effort. We, therefore, propose that:

Hypothesis 4: A low-skilled subcontracted labor mix has a higher positive effect on project margins than a high-skilled subcontracted labor mix.

4. Empirical Analysis

4.1. Research Setting: High-tech Company

We test our hypotheses using data we collected from a leading European high-tech firm which has an aerospace engineering, infrastructure, energy and marine divisions. In 2017, the firm generated approximately 750 million euros of revenue and employed more than 2,000 permanent and subcontracted workers. Our dataset includes all projects executed between 2006 and 2017 by the aerospace division of the firm, which performs projects in space, aeronautics and vehicles, defense and health care equipment departments. These projects entail a mix of engineering and prototyping/small series manufacturing activities. The projects are highly heterogeneous; for instance, one project may entail developing and building an alignment device for a satellite antenna, while the subsequent project may be a navigation device for a rocket or design of a work system to generate carbon fiber laminates for aircraft wings.

Due to the highly heterogeneous and complex nature of the projects, the budgeting and overall human resource requirements, such as the total number of team members (i.e., permanent and subcontracted) and the expertise required for the completion of certain tasks, are defined at the tendering stage of each project. Budgeting is performed based on the specific client requirements. Once the project has been awarded, the project manager decides which workers to involve in the project, depending on the required capabilities as well as the availability of staff members, and proceeds with the recruitment of subcontracted workers depending on the established budgeting stage requirements in terms of the number of workers and expertise level.

Even though subcontracted workers do not have a permanent contractual relationship with the company, they work full-time when hired for a specific project. To ensure their high commitment, the firm puts great care into integrating them since the beginning of the project. For instance, subcontracted workers are provided a corporate email address and are invited to participate in project kick-off meetings as well as all meetings related to the tasks they perform in the project. Moreover, subcontracted workers usually work on the company premises and collaborate closely with project managers, a practice that facilitates close control and worker engagement. Once the project is completed, the company has the practice to rehire the workers who have performed well, which provides a strong incentive for subcontracted workers to strive for high performance.

We assembled data for this study from three different archival sources. First, we accessed the records that the company's aerospace division maintained of all 413 projects initiated during the period between January 1, 2006, and November 30, 2017. For each project, the dataset includes information about the project margin, invoice variation, geographic area, project scope, project manager, etc. After removing projects with missing identifying data such as project type, department and stage, the dataset comprises 350 observations pertaining to projects that are executed in different geographic areas: the U.S. and Canada, Mexico, Brazil, China; Japan and Korea, Middle East, North Africa, South Africa, Iberia, the United Kingdom and Ireland, Poland, Eastern Europe, the rest of Europe and the rest of South America. Of the 350 projects, 258 (or 73.71%) were finalized at the time of data collection, while 92 (or 26.29%) were still ongoing. To perform the analysis, we focus exclusively on the finalized projects, therefore limiting our sample to 258 projects to ensure that the project margin is an accurate estimator of project performance. The margin data available for the ongoing projects is an estimate of the project margin up to the date of data collection and, therefore, is misleading because project performance may vary unexpectedly in the period between data collection and project termination. T test statistics confirm that the use of subcontracted labor (i.e., the *subcontracted labor mix* and the *low-* and *high-skill subcontracted labor mix*) does not significantly differ between finalized and ongoing projects. Similar to Staats (2012), we removed geographic areas that had only one project (three geographic areas), making our final sample equal to 255 projects. Each project is allocated into one of two categories by the company according to the final outcome: “Engineering” (70.20% projects), where only service is provided, and “Product” (29.80%), where physical artifacts are built as well.

Second, we augmented the dataset by including data elaborated from monthly worker timesheets for each project. These records cover 1,027 individuals in total: 665 permanent and 362 subcontracted workers. Based on these records, the average duration of a project is 1.83 years, whereas the average team size is 22.86 employees (18.63 permanent and 4.23 subcontracted workers on average). Given the nature of the work, team members usually work simultaneously on several projects (average is 6.64 projects per worker). We further used these data to calculate team composition variables for each project.

The third source of data was records from the Human Resource department, which we accessed to collect information on team members, including skill level tenure (for permanent workers) and cumulated duration of contracts with the company (for subcontracted workers). The average tenure of permanent workers in a project is 7.10 years, while the average cumulative experience in the company for subcontracted workers in a project is 1.05 years. Permanent and subcontracted workers are assigned to a specific skill level category, from 1 to 6, based on their credentials, level of seniority and expertise, where 1 indicates the highest level and 6 the lowest. In the case of the subcontracted workers, the assignment to the skill level group is based on their past experience as well as their education level (i.e., master’s degree, specialization, years of experience) to which the subcontracted worker also needs to agree. The assignment of the skill level is a highly systematic and validated procedure, as the compensation of the workers depends on the expertise category to which they are assigned. The average expertise level of permanent workers in a project is 3.54, while the one of subcontracted workers is 4.91. According to our interviews, workers assigned to category 6 are usually recent graduates and interns (40.89% of the subcontracted workers in our setting). They are therefore less experienced engineers, conducting standard drafting and technical engineering tasks. On the other hand, workers from categories 1 to 5 (59.11%) are senior experts who join the project to perform highly specialized tasks that fit their area of expertise.

Finally, we conducted numerous meetings and interviews with staff members to obtain a better understanding of the company business environment, its project management practices and procedures, and how data pertaining to the three aforementioned sources were compiled.

4.2. Measures

4.2.1. Dependent Variable

We use project margin data computed by the corporate project control office. The *project margin* is calculated at the closure of the project as the difference between the project contract value (invoiced to the client) and project costs, divided by the project contract value. Project costs include direct project costs, as well as a fraction of general overhead that is imputed based on company-defined coefficients. Among direct project costs are human resources (both permanent and subcontracted), supplies, other subcontracted services, miscellaneous R&D costs and manufacturing costs, including equipment depreciation costs. The company carefully tracked project costs to keep the project earned value under check and maintain updated predictions of the final project margin.

4.2.2. Independent Variables and Moderators

We operationalize *subcontracted labor mix* variable by dividing the number of hours worked by subcontracted workers employed in a project by the number of hours worked by the permanent workers in the project. It is defined similarly to Kesavan et al. (2014) and captures the ratio of subcontracted to permanent workers' hours for a project. We also compute an alternative measure of *subcontracted labor mix* to investigate the robustness of our results as the ratio of the number of subcontracted workers in a project and the number of permanent workers (see appendix B, Table B3).

To test Hypothesis 4, we decompose *subcontracted labor mix* into *low-skilled* and *high-skilled subcontracted labor mix*. To do that, we use the skill level category assigned to each engineer, as discussed in the previous general description of the setting. To calculate the *low-skilled subcontracted labor mix,* we divide the total number of hours worked by all subcontracted workers from category 6 (i.e., low-skilled workers) employed in a project by the total number of hours worked by permanent workers of the project. In this way, we capture the ratio of subcontracted workers with lower expertise levels to permanent workers. Similarly, to calculate *high-skilled subcontracted labor mix,* we divide the total number of hours worked by subcontracted workers from categories 1 or 5 employed in a project by the total number of hours worked by permanent workers of the project. As a robustness check, we also operationalize the ratios using the number of team members instead of the number of hours as for the *subcontracted labor mix* variable (see appendix B, Table B3). Moreover, we operationalize the ratio using an alternative categorization of the low-skilled (i.e., categories 5 and 6) and high-skilled (i.e., categories 1-4) (see appendix B, Table B4).

The *team size* variable represents the number of individuals working on a project, independent of whether they are subcontracted or permanent workers. In the final sample, the average team size was 22.86 team members, with a minimum of 1 and a maximum of 171 workers.

We measure *scope changes* during the execution of a project based on variations in the project invoicing amount. The total project invoicing amount is normally set with the client when signing the contract. As the project progresses, the invoicing amounts can be altered to address changes in the scope caused by external factors (e.g., obsolete component or software that needs to be replaced) or requested by the client (e.g., the client readjusts product specifications such as the speed or the reach of the device). Variation in total invoicing, hence, is a valid proxy for scope changes. Specifically, we compute *scope changes* as the actual minus budgeted invoicing, divided by the actual invoicing. Scope changes occurred in 79.84% of the projects.

4.2.3. Control Variables

Team familiarity. To control for the potential effect that team familiarity may have on project performance, we include team familiarity in the model. Similarly to past literature, we calculate this variable by counting the number of times each pair in the team has worked together, taking the sum for all pairs and then dividing this number by (N(N-1)/2), where N is the team size (Reagans et al. 2005, Huckman et al. 2009, Huckman & Staats 2011, Staats 2012, Avgerinos & Gokpinar 2017).

Individual average experience. We measure each project team member's prior experience in the company as the total number of months a team member has worked in the company prior to the focal project. To obtain the project-level variable, we averaged across the team members. Note that the variable captures the experience of both permanent and subcontracted workers. It is also worth noting that a low number of subcontracted workers in our sample work for some months for the company and then are rehired at a later point in time for another project. For these individuals, we count only the months that they worked for the company (i.e., excluding the months that were not working for the company).

Individual average expertise. We control for an individual's expertise level. To measure expertise, we use the skill level categories assigned to subcontracted and permanent workers, where 6 is the lowest and 1 the highest category. To obtain the project-level variable, we take the average skill level of all workers on the team.

Client familiarity. Because of the interdependent nature of engineering projects, the client and the project team interact in the creation of the project output (Larsson & Bowen 1989, Clark et al. 2013). By repeatedly interacting with the same client, the firm may learn the customer's requirements and improve their communication and coordination (Ko et al. 2005, Clark et al. 2013). We, therefore, control for client familiarity by capturing the past projects of the company with the same client. Specifically, we calculate how many projects the company has worked on with the same client up to the current project (excluding the current one).

Project manager role experience. Prior literature has argued that the project manager role experience can influence the performance of the project (Huckman et al. 2009, Staats 2012). Hence, we control for this variable by calculating the number of previous projects the project manager has managed (excluding the current one).

Multiteam membership. In our setting, employees tend to work on multiple projects at the same time, which may affect their performance in the focal project (O'Leary et al. 2011). To control for multiproject membership, we take the average number of projects each team member has worked on throughout the duration of the focal project. To obtain the project-level variable, we averaged across the team members.

Project duration. We include a variable indicating the total duration of the project in months to control for the size of the project. Projects with higher duration are spread across longer time periods, which may affect project margins. The duration of the project is estimated in the tendering stage with the client and is dependent on the unique specifications of the project and its tasks.

Project complexity. We control for project complexity with two project-level variables: *project type* and *project department*. As previously explained, the company allocates projects into two categories based on their output: engineering and product. Both project types include a certain amount of engineering work in the initial stages of the project. Nevertheless, engineering projects are considered more complex because a major part of the work is engineering. The final outcome of an engineering project is one or two prototypes of the product, such as a scanning mechanism for a satellite or a pointing mechanism for a spacecraft. In a product-type project, the project consists of a less complex initial engineering and the subsequent production of the parts. We, therefore, include the dummy variable project type, which is equal to one if the project is allocated into "Product" and zero otherwise. Moreover, the complexity of the projects also depends on the department in which the projects are executed, with the space department having more engineering-heavy projects with high complexity in the requirements than other departments, for example. We, therefore, include dummy variables indicating the department of each project, using space as our reference category (corresponding to zero values of aeronautics and vehicles, defense, health care equipment departments).

Indicator for start year. To control for potential company policy changes and technological advancements, we include a dummy variable indicating the year each project started.

4.3. Model Specifications and Results

We first use an ordinary least squares (OLS) model to examine our hypotheses. Since the projects have been performed in 11 different geographic areas, we specify geographic area random-effects regression models, with robust standard errors clustered at the geographic area level. We use a random-effects model, as the Hausman test fails to reject the null hypothesis that the random-effects model is consistent. Our approach allows us to study the differences among the areas while controlling for unobserved similarities of the projects within each area.

Table 1 shows descriptive statistics and correlations among our variables. We note that due to the highly right-skewed nature of the *team size* and *team familiarity* variables, we use their log transformation in the main model (presented in Table 1). The transformations are also consistent with Tukey's (1977) ladder of powers, which reveals the most suitable transformation. Table 2 presents the OLS model results. In model 1, we include only the control variables. In model 2, we include *subcontracted labor mix* and observe that it has a positive and significant coefficient of 1%, providing support for Hypothesis 1. Model 3 shows that the interaction term of *subcontracted labor mix* with *team size* has a positive and significant coefficient of 1%, providing support for Hypothesis 2. In model 4, we exclude the interaction term with *team size* and add the interaction term of *subcontracted labor mix* with *scope changes,* which is negative and significant at the 1% level. Finally, in model 5, we test hypothesis 4. To this end, we substitute the variable *subcontracted labor mix* with the two variables *low-skilled subcontracted labor mix* and *high-skilled subcontracted labor mix*. Both variables have positive and significant coefficients. The coefficient of *low-skilled subcontracted labor mix* is higher in magnitude than the coefficient of *high-skilled subcontracted labor mix*, providing support for Hypothesis 4.

4.3.1. Endogeneity Issue and Instrumental Variable Approach

The decision about the level of subcontracting for a project is not random. Unobservable factors may drive this decision and project performance, potentially biasing the estimated effects of *subcontracted labor mix*. One such unobservable factor is project importance for the firm. A more important project for the firm can attract better labor resources and, at the same time, be more profitable. To address this potential bias, we retest our hypotheses using instrumental variable regressions and base all robustness checks and conclusions on this approach. We use different instruments for the labor mix variables. We first describe the instruments and then argue why they satisfy both the relevance and exclusion conditions.

For Hypothesis 1, we follow Nevo and Wolfram (2002) and Kesavan et al. (2014) and identify a "market-based" instrument adjusted to our setting. For instance, Kesavan et al. (2014) examined the effect of a temporal labor mix on the performance of stores in a state. To account for endogeneity bias, the authors used the average value of the temporal labor mix of other stores in the same state. The instrument was valid since the labor cost of stores within a state would be correlated but would not affect the performance of the focal store. Similarly, we use the average values of *subcontracted labor mix* from all other projects within the same department (i.e., space, aeronautics & vehicles, defense and health care equipment) as an instrument. We name the variable *department average labor mix*. The instrument is correlated with the endogenous variable, as the requirements and supply of adequately skilled labor would be contingent on the department. For example, the space department typically features projects with highly complex and unique engineering requirements for which internal staff or highly experienced subcontracted workers are preferred compared to the more production-focused defense department, where qualified subcontracted workers could be more easily identified. The instrument also meets the exclusion restriction because there is no reason to expect that the performance of the focal project is driven by the average *subcontracted labor mix* of all other projects in the same department, as it is calculated by taking the average *subcontracted labor mix* of all projects of the department across the whole time span of the dataset (i.e., 11 years). A potential issue could be that projects performed simultaneously share resources within the same department, which could indicate a violation of the exclusion condition. Hence, we investigate this further. First, our dataset covers a period of 11 years and the average project duration is 22 months, which indicates that most projects have not been executed simultaneously and thus do not necessarily share the same resources. Second, we repeat our analysis in the online appendix using different instruments (i.e., the average subcontracted labor mix of the projects of the whole division and the average subcontracted labor mix of projects terminated the year before the start of the focal project), which are not sensitive to this potential violation of the exclusion condition. Since the health care equipment department has just one project in our sample, we dropped it from the analysis. The other departments have 120 (space), 94 (aeronautics & vehicle) and 40 (defense) projects.

When testing Hypothesis 2, we need a second instrument for the interaction terms *subcontracted labor mix* and *team size*. It is worth noting that *department average labor mix x team size* is not a valid instrument for *subcontracted labor mix x team size,* as using it would lead to biased results (i.e., forbidden regression) (Wooldridge 2002). We address this problem by applying the following procedure recommended by Wooldridge (2002). We first run the first stage of the model regressing *subcontracted labor mix* on *department average labor mix,* including all control variables and fixed effects. We then take the linear prediction from that model, multiply it with *team size* and use it as an instrument for *subcontracted labor mix x team size*. We can thus create a valid instrument to test Hypothesis 2. We test Hypothesis 3 in a separate model using the same procedure. Namely, we use the same predicted values used to instrument *subcontracted labor mix* in its interaction with *team size*. We multiply the predicted values with *scope changes* and use it as an instrument for *subcontracted labor mix x scope changes*.

Finally, Hypothesis 4 presents two endogenous variables (*low-* and *high-skilled subcontracted labor mix*), which require two different instruments. Following the approach used to instrument *subcontracted labor mix*, we calculate the two variables *department average low (high)-skilled labor mix*. They capture the average values of *low (high)-skilled subcontracted labor mix* from projects other than the focal one within the same department of the focal project. We expect them to be valid instruments for the same reasons previously discussed for *department average labor mix*.

To check the validity of all the instruments, we look at the overall R squared of the first stages, which are all above 80%, and the Wald Chi-square statistics, which are all significant at 1% and very high, indicating high values of F statistics too (well above the common threshold of ten), confirming that the instruments are not weak, as suggested by Stock and Yogo (2005). Tables B1 and B2 of the appendix B present the results of the first-stage models for the four hypotheses.

Table 3 presents the results for the second stage of the proposed instrumental variable analysis. In model 1, the coefficient of *subcontracted labor mix* is positive and significant at 1%, providing support for Hypothesis 1. An increase of one standard deviation in *subcontracted labor mix* increases *project margin* by 2.14%. In model 2, we add the interaction term with *team size*. The interaction term is positive and significant at the 1% significance level, providing full support for Hypothesis 2. In model 3, we remove the interaction term with *team size* and add one of *subcontracted labor mix* and *scope changes* and observe that it has a negative and significant 1% coefficient, providing full support for Hypothesis 3. To visualize and interpret interaction effects, we plot the predicted values for the regression models (Figures 1 and 2 examine the moderating effects of *team size* and *scope changes*). Finally, in model 4, we test Hypothesis 4. Both *low-skilled subcontracted labor mix* and *high-skilled subcontracted labor mix* have positive and significant 1% coefficients. The coefficient of *low-skilled subcontracted labor mix* is also higher in magnitude than that of *high-skilled subcontracted labor mix*, providing full support for Hypothesis 4. A chi-square test ($\chi^2 = 62.50$, $p < 0.01$) rejects the null hypothesis that the two coefficients are equal, providing further support for Hypothesis 4. An increase of one standard deviation in *low-skilled subcontracted labor mix* increases project margins by 2.06%, whereas such an increase in *high-skilled subcontracted labor mix* increases project margins by 1.15%.

4.4. Robustness Checks

4.4.1. Alternative Operationalization of Model Variables

As previously observed, an alternative way to operationalize the extent to which a project relies on subcontracted workers is to compute a ratio of the number of subcontracted workers over the number of permanent workers. Following Kesavan et al. (2014), we hence create these new measures for both *subcontracted labor mix* and for *low-skilled* and *high-skilled subcontracted labor mix*. Regression results provide ad hoc full support for all four hypotheses (see appendix B, Table B3).

We further check the robustness of our results for Hypothesis 4 by providing an alternative operationalization of *low-skilled* and *high-skilled subcontracted labor mix*. Specifically, we calculated the two ratios considering subcontracted workers from categories 5 and 6 to be low-skilled and from 1 to 4 to be high-skilled (instead of considering only category 6 as low-skilled workers). The results of the fourth hypothesis are supported again (see appendix B, Table B4).

A potential concern with our analysis could be driven by the log transformation of the *team size* variable, which corrects for team size skewness. This transformation implies an assumption in the functional form on how team size directly and interactively affects project margins, which may influence our results. We, therefore, re-ran the regression models without log-transformation of the *team size* variable and again found full support for the four hypotheses (see appendix B, Table B5).

Last, we did not log-transform experience-related variables in the model (i.e., *client familiarity*, *individual average experience*, *individual average expertise* and *project manager role experience*), while past research often used log-log models to estimate learning effects (Argote 1999, Cameron & Trivedi 2005, Cleves et al. 2010). While our choice was based on Tukey (1977), we nevertheless applied logarithmic transformations to both experience-related variables and the dependent variable and we found full support for the four hypotheses (see appendix B, Table B6).

4.4.2. Alternative Model Specifications

While we find support for a linear relationship between *subcontracted labor mix* and *project margin*, there is a chance that this relationship is non-linear (Kesavan et al. 2014). Specifically, one can expect that the marginal effect of using subcontracted workers might decrease or even turn negative beyond a specific value of *subcontracted labor mix*. We therefore repeat the analysis for Hypothesis 1 after including the square term of *subcontracted labor mix*. We do not find evidence for a significant diminishing effect. Hence, it seems that in our sample there are no projects with a subcontracted labor mix large enough to negatively affect project margin.

Second, we investigate the robustness of the geographic area random-effects specification of the model. The projects in the setting are conducted in different geographic areas but are from the same company; therefore, the random-effects specification allows us to capture the unobserved characteristics of the different geographic areas while not eliminating the common characteristics of the projects derived from being performed by the same company. Nevertheless, we repeat the analysis using geographic area fixed effects to confirm the robustness of the findings. The results provide full support for the four hypotheses (see appendix B, Table B7). Furthermore, projects of the same client, may be part of a larger project and thus be correlated. We address this concern by clustering the standard errors by Client on top of the clustering by Geographic area we have in the main model. The results of the four hypotheses are robust to this model specification (see appendix B, Table B8).

Next, we explore the effect of the total number of *billable labor hours* in the project, as one may expect that the number of billable labor hours is a significant driver of project margin. It should be noted that the variable *billable hours* and *team size* are highly correlated in our dataset with a significant pairwise correlation of 0.86, indicating that our team size variable, captures not only the number of team members who work on a project, but also the overall size of the project. Therefore, introducing the two variables in the model may bias the results. Nevertheless, we included the variable billable hours in the model and the results indicate that the four hypotheses are supported with this additional control (see appendix B, Table B9).

Finally, we check whether the results are driven by overfitting due to the limited sample size. In general, overfitting occurs when a model includes too many parameters compared to the number of observations, a fact that can lead to incorrect inferences (Freedman 2009). To mitigate this concern, we re-evaluate support for the hypotheses using simpler regression models obtained by dropping the insignificant continuous control variable (Aggarwal et al. 2015). More specifically, we drop multi-team membership from all models and client familiarity from models 2 and 4 of Table 3 and obtain full support for the four hypotheses (see appendix B, Table B10). Moreover, to further ensure that overfitting is not a concern, we re-run the models excluding all control variables (Heimeriks et al. 2014) and we obtain full support for the four hypotheses (see appendix B, Table B11).

4.4.3. Additional Specification of Instrumental Variable Approach

First, we provide an alternative specification of our instrument *department average labor mix*. Namely, we calculate the instrument by using the average labor mix of the projects of the whole firm (i.e., the aerospace division), excluding the focal project rather than the department. Therefore, we calculate firm average labor mix. We do so, as one may argue that departments share and compete for the same resources and therefore the labor mix of the other projects in the department might affect the performance of the focal project. Moreover, we calculate the same alternative instrument including only the non-overlapping projects (i.e., project which either/or finished prior to the start of the focal project or after the end of the focal project) in order to make sure that any potential bias stemming from sharing resources is eliminated. Hence, we repeat our analysis for Hypothesis 1 with the alternative instruments, and our results hold (see appendix B, Table B12, models 1 and 2).

Another potential concern is that *team size* and *scope changes* are not exogenous to our model, as the size of teams as well as the level of scope changes are not random. To address this concern, we use additional instruments to confirm the robustness of the four hypotheses. We follow the same procedure to correct for potential endogeneity concern for *team size* and *scope changes*. Namely, first, we estimate two additional instruments for *team size* (and *scope changes* respectively), one for its main effect and one for its interaction with *subcontracted labor mix*. More specifically, similarly to the instrument of *subcontracted labor mix* for Hypothesis 1, we estimate *department average team size* (*department average scope changes*) by calculating the average team size (scope changes) of projects within the same department as the focal project, excluding the focal one. For the interaction term of the second (third) hypothesis, we instrument *team size* (*scope changes*) with the linear prediction of the first stage of the later model and interact it with the linear predictions instrument used in the main model for *subcontracted labor mix* to maintain consistency with the main analysis presented in Table 3. The results provide full support for the hypotheses (see appendix B, Table B13 for the analysis for *team size* and Table B14 for the analysis for *scope change*). Note that even though the model becomes even more complicated, we conducted an additional analysis where we instrument both team size and scope changes in the same models. The results of the four hypotheses hold.

4.5. Post-hoc Analyses

4.5.1. Alternative Explanations

Subcontracted labor mix may positively affect project margins because of possible labor cost savings from the use of subcontracted workers compared to permanent ones. Hourly rates for subcontracted vs. permanent workers are similar within each worker category, but permanent workers are loaded with higher overhead. This accounting practice is unlikely to drive our results for two reasons. First, if the results were driven by fully burdened labor cost differentials, then the effect of subcontracting would be stronger for more expensive, highly-skilled workers who have higher hourly wage rates because of their higher skill category. Instead, the result of Hypothesis 4 suggests that the effect of *subcontracted labor mix* is higher for low-skill workers—consistent with the hypothesized mechanism. Second, to further investigate how project margins are affected by *subcontracted labor mix* independent of savings in hourly labor costs, we re-run the regression models using an alternative dependent variable, *margin variation* (the difference between actual and budget project margin). Budget project margins are calculated before project kick-off when the number of hours for different skill categories and for subcontracted vs. permanent team members are budgeted, considering the hourly rates loaded with the corresponding overhead rates. *Margin variation* is hence not affected by hourly cost differentials. We repeat the analysis with the alternative dependent variable and find full support for the hypotheses (see appendix B, Table B15).

Subcontracted workers may also positively affect project margins because, by means of subcontracting, the employer can select specialists that possess superior expertise (Boh et al. 2007). Likewise, it may occur that when the firm relies on more low-skilled subcontracted workers for a project, they compensate by relying on more high-skilled permanent workers. We hence calculate the variable *low (high)-skill subcontracted labor mix* as the ratio of the number of low (high)-skill subcontracted project team members hours to the number of all low (high)-skill project team members hours. Our results (see appendix B, Table B16) remain the same for the fourth hypothesis.

It may also occur that when subcontracting is used to a greater extent, the project manager staffs the permanent part of the team with employees who have a high level of familiarity among themselves because subcontracted workers tend to be less familiar with the firm's personnel. In the main model, we control for average team familiarity, but to more precisely partial away this potential confounding effect, we calculate the variables *subcontracted workers team familiarity* (i.e., the average familiarity of subcontracted with permanent team members) and *permanent workers team familiarity* (i.e., the familiarity of permanent team members among themselves). The statistical conclusions from the regression models do not change (see appendix B, Table B17).

A further confounding mechanism could be that permanent workers could have an advantage over subcontracted workers because of higher knowledgeable about the company's organization and processes (Fahrenkopf et al. 2020). To empirically investigate this possibility, we compute the control variables *subcontracted (permanent) workers average experience*. We further included in the regression model a product term of these two control variables to operationalize the "fit" hypothesis (Venkatraman & Camillus 1984). Statistical conclusions from these models support the postulated hypotheses (see appendix B, Table B18) and are comparable in size with those in the main model, reducing concerns about this potential confounding effect.

Last, subcontracted workers may also make an extra effort to perform to the best of their ability in the hope of being recruited by the company, especially if the company has a particularly good reputation as an employer. This is not the case for the focal company, which was certainly a consolidated actor in the country but did not have a remarkable reputation as an employer. The most prestigious employers ranking (www.merco.info) never ranked the company among the top 100 employers in the country where it is headquartered, with the exception of one year, when it was positioned in the bottom quartile.

4.5.2. Additional Analysis

To better characterize the contingent effects of subcontracting, we explore whether the nature of subcontracted work has a bearing on the effects of subcontracting. In product development, the nature of work tends to change across the project lifecycle (Ulrich & Eppinger 2012). In the early phases of the project, interdependent problem solving is more salient, whereas in the later phases of the project, refinement and more modular detailing and industrial engineering work are emphasized. We therefore identified the month in which the cumulated hours of each project reached 50% of the total project hours and calculated *subcontracted labor mix* for this first part of the project (*subcontracted labor mix early*), as well as for the remaining half of the project (*subcontracted labor mix late*). We then entered these two variables in the main regression model instead of the single *subcontracted labor mix* variable (see Table 4, model 1). We find that the *subcontracted labor mix*'s impact on project margin was higher in the second part of the project (t test statistics reveal that the two coefficients are different at the 5% significance level). A comparison of regression coefficients indicates that the effects of the *subcontracted labor mix* on the project margin are 56.60% greater in the late phases than in the early phases of the project.

Furthermore, we explore how the nature of work (i.e., administrative vs. technical) impacts the effects of subcontracting. Specifically, we distinguish between administrative (e.g., paperwork, administrative support tasks) and technical (e.g., engineering calculations, detailing) work executed by project team members. Accordingly, we calculate the two variables: *subcontracted labor mix administrative* (*technical*) as the ratio of administrative (technical) hours worked in the project by subcontracted team members over the administrative (technical) hours worked in the project by permanent team members. We then estimated the effect of these variables in two separate models, controlling for the average skill level of subcontracted administrative team members and subcontracted technical team members (see Table 4, models 2 and 3). We find that the effect of *subcontracted labor mix administrative* is positive, but not significant, while the effect of *subcontracted labor mix technical* is positive and significant at the 5% level. Overall, this result indicates that the benefit of subcontracting is stronger for technical than administrative tasks, in line with the idea that administrative work is more effective when executed by personnel who are more embedded in the organization (Anderson & Bidwell 2019).

5. Conclusions and Discussion

5.1. Theoretical Contributions

With this study, we extend the limited research on the financial consequences of subcontracted labor. We detect a positive and linear effect of a *subcontracted labor mix* on project margins, which increase by 62.63% as team composition moves from 0% to 34.64% of subcontracted workers (75th percentile of the *subcontracted labor mix* variable). While it is plausible that at higher levels of subcontracting—unobserved in our sample—such an effect would become marginally decreasing, our data point toward a linear association between the subcontracted labor mix and project margin, in contrast to Kesavan et al. (2014), who detect a reverse U-shaped relation. This result downplays concerns about organizational tensions associated with subcontracting suggested by research in organizational behavior (George 2003, Davis-Blake 2003, von Hippel & Kalokerinos 2012). Our post hoc analyses also suggest that cost or talent differentials between subcontracted and permanent workers do not explain this finding. In fact, both field interviews and empirical research in subcontracting (Allan & Sienko 1998, Engellandt & Riphanhn 2005, Bradley et al. 2014) point toward heightened worker motivation as the underlying performance-improving mechanism. Overall, our results challenge the view that the advantages of subcontracting are restricted to volume flexibility and access to specialized labor. Subcontracting also warrants motivational advantages that may not be offset by integration costs, at least in a project-based operational environment where permanent workers enjoy legal protections from dismissal that are not available to subcontracted workers.

A further counterintuitive contribution of this study is that the benefits of subcontracted workers are stronger for less-skilled workers than for more highly-skilled workers. This finding is in line with the proposed motivational mechanism underlying the positive effect of subcontracting (Engellandt & Riphahn 2005). That is, workers with less expertise are more likely to exert extra effort during the project, being aware that they are more easily substitutable in case of unsatisfactory performance. As one informant stated, "*The juniors are supermotivated. For those of higher categories, it is different […] because they have been working for many years and may question whether they truly want to stay in the company or not, so they may not be as motivated*." Managers at the site also agreed that subcontracting helps to tap talent not available internally (Bidwell & Briscoe 2009), but they see this benefit as limited to specific individuals and pointed out that reliance on this strategy is not necessarily reflected in the amount of subcontracting, as captured by the *subcontracted labor mix*.

The results of the study also address Mayer and Nickerson's (2005) call for research investigating when projects benefit more from using subcontracted labor. Specifically, we find that the positive effect of subcontracted workers is more prominent within larger project teams. This result complements the literature on the effect of team size on team performance, suggesting that the problems of motivation, communication and conflict associated with large teams (Levine &Moreland 1998, Hackman 2002)—reflected in our study with a negative effect of team size when the subcontracting labor mix is zero—can be mitigated by relying on subcontracted team members.

In contrast to increased team size, the occurrence of unexpected scope changes in a project tends to lessen the positive effect of the *subcontracted labor mix* on project margins. This result contributes to past research on task changes in project settings (Huckman & Staats 2011), suggesting that scope changes may induce unexpected costs of integrating subcontracted team members, which offsets the motivational benefits of subcontracted workers. If we consider project scope changes as a specific manifestation of project complexity, this result is consistent with the finding that complex projects benefit less from collaboration with external constituents (Novak & Eppinger 2001).

5.2. Practical Contributions

Our findings also provide important insights for managers. Regression results suggest that project managers can increase project margins by using subcontracted workers. Specifically, an increase of 10% in the *subcontracted labor mix* can increase the project margin in our setting by 5.83%. Managers at the research site were aware that subcontracted workers benefited project performance due to higher motivation to exert effort, given the presence of strong labor protection laws, but were not aware of the sizeable magnitude of these effects. The strategic implication of these findings is that concerns for capacity expansion investments (e.g., new R&D facilities) in areas characterized by strong labor protection laws can be mitigated by engaging in substantial subcontracting. Second, moderation effect sizes indicate that the margin impact of subcontracting further jumps to 95% when team size increases from 2.67 (average) to 3.25 (75th percentile) and decreases to 2.01% when project scope change increases from 0.27 (average) to 0.28 (75th percentile). These findings highlight the strategic interdependencies between subcontracting decisions and project portfolio management. For instance, if a company project portfolio evolves toward small projects that are prone to scope changes, our study suggests that the economic interest in subcontracting is reduced compared to project portfolios evolving toward large and more stable projects. Likewise, if a company foresees an opportunity to tap an external labor pool through subcontracting, our result suggests that pursuing large projects and discouraging scope changes is the preferred market positioning for the firm. Last, the post hoc analyses indicate that subcontracting technical vs. administrative tasks has an incremental impact on project margins of 116.46% and that subcontracting tasks in the second vs. the first half of the project has an incremental impact on project margins of 56.60%. These results provide tactical guidance for the type and timing of the subcontracted work if the goal is to foster project margins.

5.3. Limitations and Conclusions

A fundamental boundary of validity of our findings is that the company we study operates in an environment where labor laws protect permanent workers from individual dismissals. While this is common among OECD countries, it is less so elsewhere. The generalizability of the findings to countries with less protective labor laws is not warranted and should be the object of future replication studies. The data available from the studied company also determine several empirical limitations as they are non-experimental and hence conclusions about our results should be treated with caution. First, project-level data about worker motivation were not available, making it impossible to empirically investigate the postulated mechanisms through which subcontracted workers increase project profitability. We nevertheless notice that both the literature and field interviews support the existence of a motivational effect of subcontracting and that we could rule out competitive explanations by means of multiple analyses. Second, data about project schedule deviations were not available. It would certainly be of interest to study the effect of a *subcontracted labor mix* on schedule deviations. However, our model captures this effect because, as observed by multiple informants, schedule deviations automatically increase costs and, ultimately, reduce project margins. Third, multiple variables in our model capture different facets of project complexity, including project type, department, team size, project duration and scope changes. Nevertheless, other unobservable dimensions of complexity could drive both project performance and subcontracting. We downplay this concern by using an instrumental variable approach but acknowledge that future research on the effect of subcontracting project team members should capture other dimensions of project complexity. Fourth, our interviews suggest that workers with less expertise perform less complex tasks than their colleagues with greater expertise, which may have an impact on project margins. Even though our data lack detailed information on the specific tasks performed by the workers, we aim to address this concern by first controlling for the average expertise level of the team members and second utilizing the instrumental variable approach. Fifth, our setting does not allow us to control for worker, project manager or client fixed effects due to the high number of different workers (1,027), project managers (106) and clients (87) relative to the sample size. We partially address this limitation by controlling for individual average experience and skill level, project manager role experience and client familiarity.

Moreover, we have limited information about project team members' background. Specifically, we do not have information on their employment history outside of the company or how they were recruited by the company. Our interviews with project managers indicated that the company uses standard for the industry recruitment practices such as recruitment in universities or the use of specialized agencies. Future work could integrate this information to extend knowledge about how subcontracted project team members' individual characteristics and recruitment affect project performance. Finally, the cross-sectional nature of the dataset did not allow to control for unobserved projects heterogeneity. Such limitation originates because the company did not compute period-specific project margins (e.g., monthly, quarter) and only held information about the overall project margin. The reason for this practice is that revenues accrued in any period (and hence project margin) did not necessarily reflect value created in that period by the project, being typically dictated by sales negotiations and contractor's payment terms.

In conclusion, our study sheds light on the widespread yet understudied practice of involving subcontracted team members in large and complex projects, contributing to the call to advance theories at the boundary of operations and human resource management (Boudreau et al. 2003). Our results suggest that, at least in environments where labor laws protect permanent workers from individual dismissals, reliance on subcontracted workers within project teams positively affects a project's financial performance. We find this effect to be stronger for subcontracted workers with lower levels of expertise, large project teams, and for projects that do not undergo sizeable scope changes. We extend past operations management research on the effects of subcontracting to project-based operations and downplay the concern voiced by organizational behavior research about the downside of subcontracting.

TABLES

Table 1: Summary Statistics and Correlation Table of Dependent, Independent and Control Variables of Interest (n=255)

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*	*17*
1 Project Margin	1.00																
2 Subcontracted Labor Mix	0.04	1.00															
3 Low-skilled Subcontracted Labor Mi›	0.03	0.67	1.00														
4 High-skilled Subcontracted Labor Mi	0.03	0.81	0.11	1.00													
5 Team Size	-0.18	0.11	0.12	0.06	1.00												
6 Scope Changes	0.09	-0.02	-0.05	0.01	0.13	1.00											
7 Team Familiarity	0.02	0.00	0.04	-0.02	-0.03	-0.09	1.00										
8 Individual Average Experience	0.02	-0.19	-0.12	-0.16	-0.06	0.13	-0.16	1.00									
9 Individual Average Expertise	-0.02	0.45	0.47	0.24	0.31	-0.06	0.22	-0.39	1.00								
10 Client Familiarity	0.07	0.42	0.43	0.22	0.10	-0.01	0.14	-0.07	0.30	1.00							
11 Project Manager Role Experience	-0.03	0.21	0.27	0.07	0.05	-0.00	0.43	0.02	0.19	0.31	1.00						
12 Multi-team Membership	0.06	-0.12	-0.12	-0.07	-0.18	-0.01	0.51	-0.15	-0.01	-0.18	0.18	1.00					
13 Project Duration	-0.04	-0.06	-0.06	-0.03	0.69	0.24	-0.07	0.11	0.05	-0.04	-0.04	-0.02	1.00				
14 Project Type	0.06	-0.11	-0.19	-0.00	0.06	-0.02	0.03	-0.12	-0.14	-0.01	-0.08	0.11	0.14	1.00			
15 Aeronautics and Vehicles	0.06	0.40	0.33	0.28	-0.04	0.18	0.11	-0.20	0.46	0.27	0.20	-0.16	-0.18	-0.41	1.00		
16 Defense	-0.19	-0.11	-0.08	-0.08	0.13	-0.13	0.06	0.15	0.00	-0.20	-0.25	-0.16	0.16	0.17	-0.33	1.00	
17 Healthcare Equipment	0.01	-0.04	-0.02	-0.04	0.01	-0.03	0.09	-0.02	0.01	-0.04	0.00	-0.00	-0.03	-0.04	-0.05	-0.03	1.00
Mean	-13.62	0.32	0.10	0.21	2.67	0.27	0.99	73.12	3.66	6.80	2.85	6.64	22.02	0.30	0.37	0.16	0.01
Standard Deviation	271.72	0.50	0.29	0.38	0.94	0.65	0.57	55.24	0.75	8.54	2.40	3.11	18.40	0.46	0.48	0.36	0.06
Minimum	-4066.49	0	0	0	0	-0.99	0	0.67	1	1	1	1.28	2	0	0	0	0
Maximum	105.03	2.44	2.05	2.25	5.14	3.65	2.44	343.5	5.71	39	13	19.67	101	1	1	1	1

Note that the descriptive statistics of the log transformation of the Team Size and Team Familiarity variables have been shown.

Table 2: Regression of Subcontracted Labor Mix on Project Margin

	(1)	(2)	(3)	(4)	(5)
Subcontracted Labor Mix		39.442**	-158.086**	52.665**	
		(10.010)	(51.027)	(18.373)	
Low-skilled Subcontracted Labor Mix					75.685**
					(6.646)
High-skilled Subcontracted Labor Mix					24.029*
					(10.478)
Sub. Labor Mix x Team Size			74.551**		
			(20.888)		
Sub. Labor Mix x Scope Changes				-51.575**	
				(16.834)	
Team Size	-95.339**	-97.063**	-116.137**	-97.458**	-97.783**
	(18.527)	(20.460)	(24.344)	(15.423)	(17.361)
Scope Changes	25.703**	27.009**	28.431**	37.297**	27.423**
	(4.800)	(4.617)	(5.297)	(4.445)	(5.026)
Team Familiarity	29.209**	36.138**	35.825**	40.316**	37.022**
	(7.116)	(6.364)	(9.481)	(8.207)	(6.810)
Individual Average Experience	0.220**	0.239**	0.261**	0.235*	0.233**
	(0.071)	(0.066)	(0.087)	(0.098)	(0.086)
Individual Average Expertise	38.869**	32.937**	39.089**	33.724**	29.062**
	(10.324)	(8.483)	(11.487)	(7.474)	(8.659)
Client Familiarity	2.208**	1.409*	0.658	1.302**	1.113*
	(0.648)	(0.597)	(0.446)	(0.375)	(0.528)
Project Manager Role Experience	-15.525*	-16.303*	-19.017**	-16.745**	-17.071**
	(6.322)	(6.766)	(6.643)	(5.434)	(5.596)
Multi-team Membership	0.899	0.343	1.424	-0.039	0.347
	(2.169)	(1.636)	(2.170)	(2.019)	(1.779)
Project Duration	2.742**	2.816**	2.941**	2.806**	2.863**
	(0.742)	(0.791)	(0.822)	(0.669)	(0.717)
Project Type	60.887+	59.632+	66.408+	59.072+	63.517*
	(33.610)	(35.872)	(33.898)	(31.646)	(30.964)
Constant	31.725*	49.526**	67.370**	47.431**	64.299**
	(13.058)	(15.957)	(15.974)	(10.661)	(10.917)
Observations (N)	255	255	255	255	255
Start Year FE	Yes	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.130	0.133	0.144	0.135	0.135

Models are OLS random-effects regressions with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table 3: IV Regression of Subcontracted Labor Mix on Project Margin

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	58.356**	-233.911**	76.361**	
	(13.115)	(53.460)	(22.446)	
Low-skilled Subcontracted Labor Mix				96.707**
				(8.417)
High-skilled Subcontracted Labor Mix				41.268**
				(13.958)
Sub. Labor Mix x Team Size		109.062**		
		(23.133)		
Sub. Labor Mix x Scope Changes			-75.816**	
			(18.104)	
Team Size	-97.891**	-125.650**	-98.408**	-98.639**
	(14.187)	(26.062)	(16.515)	(16.514)
Scope Changes	27.636**	29.607**	42.711**	28.062**
	(5.049)	(4.610)	(3.450)	(5.007)
Team Familiarity	39.461**	38.423**	45.351**	40.314**
	(8.370)	(7.514)	(8.924)	(7.071)
Individual Average Experience	0.248**	0.279**	0.242*	0.241**
	(0.079)	(0.065)	(0.094)	(0.078)
Individual Average Expertise	30.092**	39.588**	31.464**	26.015**
	(6.426)	(11.060)	(6.392)	(7.539)
Client Familiarity	1.026+	-0.006	0.897*	0.719
	(0.536)	(0.380)	(0.359)	(0.467)
Project Manager Role Experience	-16.676**	-20.581**	-17.298**	-17.490**
	(4.944)	(6.819)	(5.795)	(5.305)
Multi-team Membership	0.076	1.704	-0.464	0.089
	(1.701)	(2.042)	(1.698)	(1.860)
Project Duration	2.852**	3.028**	2.834**	2.901**
	(0.596)	(0.760)	(0.743)	(0.678)
Project Type	59.031+	69.048*	58.253+	63.218*
	(30.340)	(33.718)	(30.265)	(30.449)
Constant	58.063**	82.676**	54.336**	73.671**
	(13.841)	(21.264)	(13.217)	(13.629)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.133	0.141	0.134	0.146
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table 4: IV Regression of Admin vs Technical Subcontracted Labor Mix and Early vs Late Subcontracted Labor Mix on Project Margin

	(1)	(2)	(3)
Subcontracted Labor Mix Early	21.991**		
	(7.495)		
Subcontracted Labor Mix Late	34.438**		
	(11.011)		
Subcontracted Administrative Labor Mix		150.387	
		(254.794)	
Subcontracted Technical Labor Mix			325.540*
			(154.440)
Team Size	-99.514**	-118.988+	-115.209*
	(14.866)	(71.033)	(53.192)
Scope Changes	28.085**	31.963	40.100**
	(6.026)	(23.572)	(13.552)
Team Familiarity	43.908**	89.277+	89.262**
	(6.330)	(51.526)	(34.183)
Individual Average Experience	0.287**	-0.102	0.655**
	(0.100)	(0.402)	(0.205)
Individual Average Expertise	31.841**		
	(5.019)		
Permanent Admin Individual Average Expertise		-4.007	
		(38.521)	
Permanent Technical Individual Average Expertise			39.046*
			(19.535)
Subcontracted Admin. Individual Average Expertise		-	
Subcontracted Technical Individual Average Expertise			28.080+
			(14.845)
Client Familiarity	0.915*	4.943	-1.193*
	(0.377)	(4.826)	(0.582)
Project Manager Role Experience	-16.791**	-49.573	-22.376
	(5.123)	(36.564)	(14.891)
Multi-team Membership	-0.460	11.677	-8.591*
	(1.420)	(21.936)	(4.329)
Project Duration	2.917**	4.938	3.689+
	(0.592)	(4.126)	(2.227)
Project Type	60.789*	22.483	110.191
	(28.907)	(109.987)	(72.714)
Constant	51.274**	157.882	-102.493
	(14.582)	(356.245)	(67.254)
Observations (N)	254	103	180
Start Year FE	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes
Overall R^2	0.133	0.203	0.159

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively

FIGURES

Figure 1: Moderating Role of Team Size

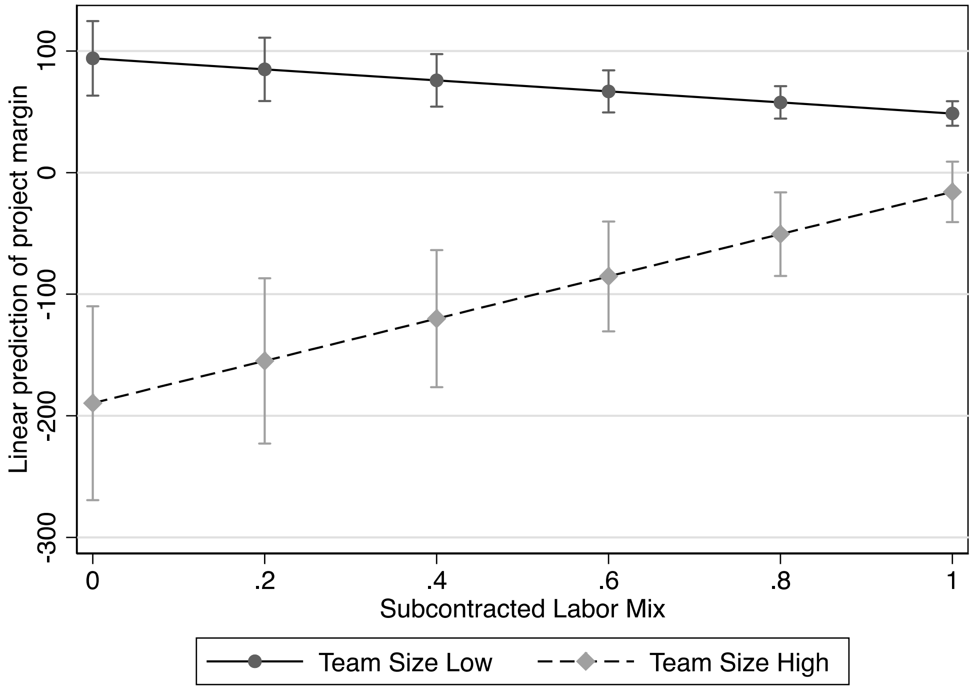
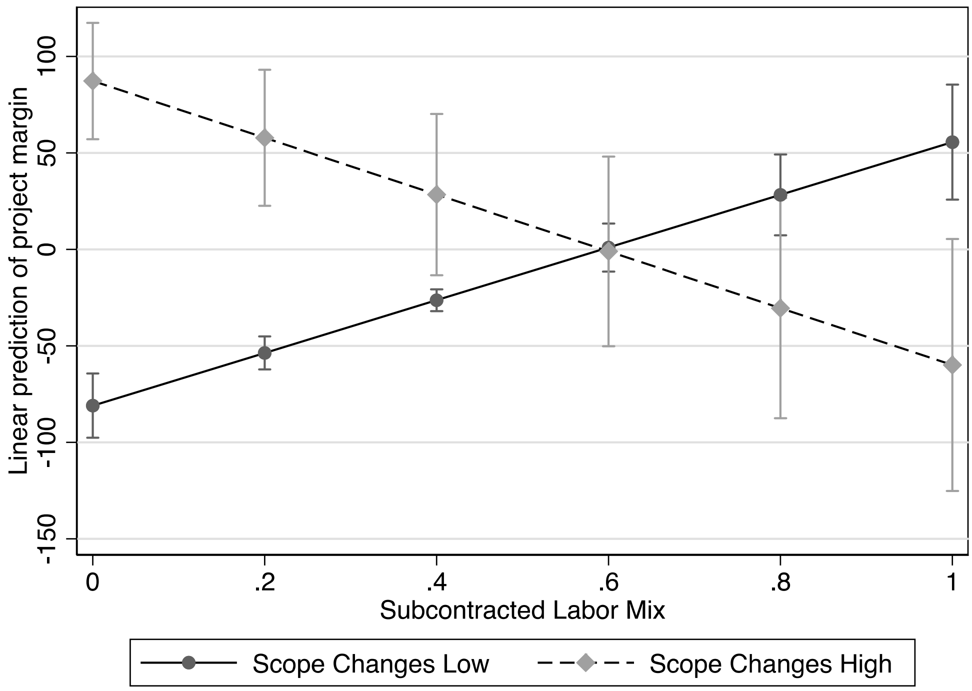


Figure 2: Moderating Role of Scope Changes



ESSAY 3: The Effect of Human Resource Allocation on Knowledge Intensive Project Performance

Abstract

We investigate the effect of front-loading on project financial performance. Front-loading refers to the practice of concentrating project members' efforts towards the beginning of the project, so that problems are solved in the earlier stages of the project, avoiding the risk of costly surprises in later stages. However, not always companies can front-load a project, especially when the concurrent execution of multiple interdependent tasks generates excessive complexity in the early stages. Companies hence face a conundrum when they cannot afford the costs of complexity associated with front-loading, but yet need to reduce the risk of discovering costly mistakes too close to project completion. Building on the literature on project teams, we develop hypotheses to conceptualize how companies can ensure high project performance when low levels of front-loading need to be applied. We test our hypotheses using a proprietary dataset of 413 project of a high-tech European firm. We find that the positive effect of front-loading is attenuated when team leader, team or client familiarity are high as the different facets of familiarity allow teams to be better at collaborating and anticipating errors in the beginning of the projects, compared to less familiar teams. The practical and theoretical implication of these moderation effects is that when project managers need to keep front-loading low, project performance can be increased by ensuring that the project team has high team leader, internal and client familiarity. More general, our findings shed light on the effect of front-loading on project performance—a question that is to date unanswered by empirical research.

***Keywords**:* Front-loading, project performance, project manager familiarity, team familiarity, client familiarity

1. Introduction

Tight competition in project-based firms, such as R&D or high-tech, forces companies to reduce project margins to remain competitive. Companies do so by improving their operational strategies. One such strategy is front-loading or the allocation of more knowledge intensive work in the beginning of the project (Thomke & Fujimoto 2000, Morgan & Liker 2006).

Front-loading is a lean product development principle, which is aimed at minimizing expensive error corrections in the later stages of the projects usually caused by inaccurate or missing knowledge generated in the beginning of the project (Morgan & Liker 2006). Past literature, mostly conceptual work, has argued that front-loading is associated with higher project performance as it facilitates the reduction in errors and delays in the later stages of the project (Thomke & Fujimoto 2000). Overall, the identified studies observe that as front-loading a project can avoid costly problems in the later stages, it makes the whole process much more efficient and effective. However, front-loading also brings challenges such as forcing more tasks to be executed simultaneously, that would have otherwise been executed consequentially. This inevitably increases the complexity of the project, especially in contexts with highly complex and interdependent tasks. Therefore, a fundamental question which remains unanswered is under which conditions front-loading would benefit project performance? More specifically what type of human resources are needed to materialize the conceptual benefits of frontloading?

Human resource allocation in projects is key to project financial performance. Human resources, in labor intensive project settings, are not only critical because of the direct labor costs they entail, which can account for 30-50% of the total project cost (Gopal & Murali 2016), but also because the level of expertise and experience of the human resources can influence how fast and how well the task is executed (Chan et al. 2008). Therefore, this study is focused on one facet of project execution that is central to a project's profitability: human resource allocation. In particular we investigate the effect of front-loading human resources, or allocating more manpower in the beginning of the project on the financial performance of product development projects executed by the aerospace division of a European high-tech firm. We capture project financial performance with the final project margin. We ground our theoretical argument in conceptual work as well as qualitative evidence obtained from interviews, pointing out that when more manpower effort is allocated in the beginning of the project, more potential problems and errors are anticipated and therefore there is lower need for re-work in the later stages. Based on this, we expect that anticipation of problems and errors, due to front-loading would positively effect project margins.

When allocating human resources to projects, it is also key to consider not only team member's individual skills and expertise, but also other key factors such as how well the team works together, the relationship with the project manager or with the client. A lack of experience of working together can complicate collaboration among team members. We build on familiarity literature to argue that high level of familiarity attenuates the positive effect of front-loading on project performance, as familiar teams are more likely to have established collaboration and work routines which facilitate the anticipation of errors and prevents integration problems in later stages. In particular, we look at three different types of familiarity. The first type we study is project manager familiarity, or the experience of the project manager working with the rest of the team members. This type of familiarity allows project managers to better allocate tasks to workers as they already know their skills and capabilities without the need to spend time in training and establishing work routines. The second type of familiarity is team familiarity, or the experience of the team members working together. It helps workers reach high performance and better communication as they have established routines of working together. The third type of familiarity is client familiarity, or the experience of the company with the client. This type of familiarity reduces the level of uncertainty in the requirements of the client and increases the trust in the client-firm relationship. We investigate the moderating effect of these types of familiarity, by further asking the question of: How do the three facets of familiarity affect the relationship between frontloading and project performance?

We develop our empirical model using a unique dataset of 413 projects executed over a 10-year time span. The research setting allows to investigate the effect of front-loading on project performance, as all projects are executed by fluid teams, assembled for the specific project with members whose participation in the project varies substantially throughout its execution. Moreover, in the sample, we observe sizeable across-project variation in the familiarity moderators.

This study makes multiple contributions to theory and practice. First, our paper is to the best of our knowledge, the first to empirically study front-loading in a complex project setting where adherence to schedule and meeting client requirements matter. Therefore, we extend front-loading literature (Thomke & Fujimoto 2000) by empirically testing the conceptual arguments. Second, our results both confirm the intuition about the effect of front-loading on project performance and highlight more nuanced elements that should be considered when allocating workers when front-loading. We find that the benefits of front-loading can be achieved by allocating more workers' hours in the beginning of the project. In particular, we find that a 10% increase in front-loading of the project is associated with a 55.06% increase in project margin. Third, by investigating the moderating effects of *project manager familiarity*, *team familiarity* or *client familiarity*, we provide additional insight into under which conditions projects performance can be increased when front-loading needs to be kept low. Specifically, the negative moderation effects of the three studied types of familiarity suggest that the benefits in coordination and collaboration associated with familiarity, compensate for the lack of front-loaded workforce, thus contributing to research on familiarity (Reagans et al. 2005, Huckman et al. 2009, Huckman & Staats 2012, Staats 2012, Avgerinos & Gokpinar 2017).

Our findings also have important implications for practice, highlighting the importance to consider how the human resources are allocated throughout the project as an important factor to the project performance. We find that when project managers need to keep front-loading low and cannot capitalize on the benefits of this practice, project performance can be increased by ensuing that the project team has high team leader, team and client familiarity.

2. Research Setting: High-tech Company

We explored front-loading at the aerospace division of a leading European high-tech firm with global presence, which we refer to as AerospaceCo. In 2017, when the data was gathered, the firm generated around 750 million euros of revenue and employed more than 2,000. The industry is a world leader of technological and science advancement with the aerospace systems being among the most complex systems, as measured by the number of components in finished products and are therefore characterized by extremely high value per unit. Aerospace industry projects have specific characteristics such as a high level of technological development, large budgets, long lead times (usually several years) as well as closely regulated control processes (Rodriguez-Segura et al. 2016).

The complexity in the project output is also reflected in the context of the human resources management. AerospaceCo as well as the rest of companies operating in the aerospace industry, face a considerable challenge organizing the work of the human resources, whose knowledge and expertise is central for the project execution. Aerospace projects involve engineering, design, production as well as piloting and testing tasks. To perform this work, it is necessary engineers to collaborate and perform highly interdependent tasks, the success of whose outcome cannot be usually assessed until later stages of the project when the integration of the individual parts happens.

In knowledge-intensive projects, such as the ones we study, one of the challenges project managers face is how to select and allocate the human resources in the teams. By using separate teams assembled for each project, the firm is able to 1) match the team expertise level to the requirement of the project, 2) leverage the experience and knowledge of the different team members, and 3) meet profit margin targets by using workers efficiently. However, human resources are a scare and costly resource, which can put a constrain on the project staffing decisions.

The managers we interviewed explained that AerospaceCo takes project staffing decisions before the projects kick-off. More specifically, once the project has been awarded, the client provides a statement of work which clearly defines the activities, deliverables as well as all the documentation that needs to be submitted throughout the project. Based on that the project manager identifies the profiles of team members the project will need from each section[8] and makes a request to the respective section heads. Next, the section heads assign the workers to the projects based on the project manager's requirements as well as their availability. Therefore, it is not solely to the project manager to select and assign the team members to form part of the project. One of the interviewed managers stated that *"You can put pressure to get the resources you want, but at the end you just go with what they give you"*.

A further challenge when staffing a project is how to allocate the assigned team members throughout the project execution. Figure 1 illustrates an example of three projects which present a different pattern of allocation of human resource hours. Figure 1a presents a project with relatively higher number of hours inserted in the first months of the project and lower number of hours in the later months (i.e., front-loading), 1b presents a project with relatively stable number of hours throughout the months, while 1c presents a project with relatively lower number of hours inserted in the first months of the projects and higher number of hours in the later months (i.e., back-loading). Therefore, AerospaceCo and the rich granular data we were granted of this company offered a great opportunity to examine in depth the conditions under which the allocation of the human resources throughout the project, front-loading in particular, affect its performance. Moreover, the staffing challenges faced by AerospaceCo are prevalent in other knowledge-intensive project settings, thereby offering opportunities to derive generalizable insights.

[8] The aerospace division in organized in a total of 39 sections some of major ones of which are Structure and Mechanisms (20.61% of the workers that work on projects are there), Precision Facilities (12.84% of the workers) and Integration and Trials (10.14%). It is important to note that 90% of the studied projects 413 projects have less than 9 sections.

3. Theory and Hypotheses

In this section, we investigate why front-loading, or the allocation of knowledge-intensive work in the beginning of the project, might have a positive effect on project performance. In particular, we theorize about under which conditions project managers can increase project performance when need to keep front-loading low.

The front-end phases of a project are usually characterized by seeking knowledge, learning and experimenting activities. It is difficult to know ex ante which design decisions will be successful or not. In such situations, team members usually have to proceed with solutions with a certain level of uncertainty in their outcome. Therefore, decisions taken in these early stages of the project can often lead to moving back and forth with more information learned from later discovered errors (i.e., trial and error approach). In projects with short problem-solving cycles, such as projects with modular and consecutive tasks, where errors can be detected promptly, and consequently solved before the overall project incurs in significant costs, the trial-and-error approach may not detrimental. However, in settings where problem solving cycles are long, such as the case of complex engineering process with high interdependent and overlapping tasks, this trial-and-error approach can be particularly costly. Therefore, minimizing errors in the initial stages of the project is a fundamental driver of project performance in such settings.

A lean project development process should be able to come up with critical design decisions in the earlier stages of the project. Thomke and Fujimoto (2000) refer to this as “front-loading”, where most critical problem solving or problem foreseeing activities take place in the beginning of the project. The fundamental idea behind front-loading is that essential project-specific knowledge should be generated in the earlier stages to reduce to the greatest extent possible engineering modifications in the later stages. Thomke and Fujimoto (2000) identify two approaches to improve project performance in terms of lead time and cost: knowledge transfer between projects, which can be obtained by preparing postmortem after the completion of each project, and rapid prototyping, which can be reached by technology and process changes. Here, it is important to note that postmortem reports are effective up to the extent that there are easily identifiable similarities between the projects. If projects are highly heterogenous, postmortem reports start to lose importance and the cost to generate and consult them may not offset the benefits. In such situation, where the knowledge becomes too costly to be encoded and transferred, the human resources act as a knowledge transfer unit (von Hippel 1994, Thomke & Fujimoto 2000).

Past literature has studied front-loading mostly conceptually. Most of the identified studies provide different front-loading strategies. For example, Kim and Wilemon (2002), identify twelve different strategies for success in fuzzy front end, a term used for high uncertain initial stages of product development. The proposed strategies involve the appointment of knowledgeable team leader, provide support as well as establish internal cooperation as well as with suppliers. However, the authors do not empirically test the proposed strategies or their effect on actual project performance. Similarly, Morgan and Liker (2006) observe how front-loading the development process was a fundamental part of how Toyota reduced project development lead time. The few empirical studies which have been identified, provide little evidence on how front-loading actually leads to higher performance. For example, Sheremata (2002) uses a survey data from 33 software development projects in 23 firms and show the positive effect of front-loading (proactive search for problem solving) on reaching product quality and schedule goals. Ohman et al. 2021 use a data from a Nordic airline to show via simulation, that frontloading in aircraft line maintenance tasks is associated with reduced maintenance cost.

Nevertheless, the role of the human resources when frontloading a project has been vastly unexplored (Kim & Wilemon 2002). Hoonsporon and Puriwat (2021) is a recent exception of an empirical study, which collects 244 survey observations from pharmaceutical and biotechnology industry and finds that directive path-goal behavior of the project manager reduces uncertainty in the fuzzy front end during innovation development.

3.1. Front-loading and Project Performance

We begin by exploring how a project can benefit from the strategy of front-loading. As mentioned earlier, front-loading a project implies that the beginning of a project should be afforded greater resources than later stages to avoid problems in downstream stages (Thomke & Fujimoto 2000). Although AerospaceCo project managers believed that the allocation of human resources throughout the whole project is important, they stressed that it is especially so in the beginning of the project, as epitomized by a project manager with over sixteen years of experience in the company: "*The projects, which since the beginning have structured the work in the correct dimensions in terms of human resources, I would think have organized better the work and are more in control of it.*".

Errors in the earlier stages of a project, can have important negative consequences in the later stages of the project, and as a consequence, for the overall project performance (Kim & Wilemon 2002). More specifically, critical problems not solved or not anticipated in the earlier stages can cause problems in the later stages, including costly errors and need for re-work or conflicts among functional departments. For example, a systems engineer of the studied company with fifteen years of experience stated that:

> "Having a lot of workers with lower categories in the beginning of the project is like tossing a coin, sometimes when things turn out badly the managers say: why did it turn so badly? Well if in the beginning, you had placed people with higher categories, that would have defined better which parameters affect the project, may be later you wouldn't have encountered the problem, because normally the lower categories do whatever the project manager tells them and do tasks such as you have to do this software with these requirements, and later when the system does not work, you have to start from the beginning and the margins go down."

Therefore, we expect that allocation more manpower in the beginning of the project execution will have a positive effect on project performance. This is so because having more workforce in the beginning of the projects, when the foundations of the project, such as the initial engineering, are set, ensures that more attention is put in performing the tasks and foreseeing potential problems. Therefore, fewer avoidable errors will be committed. This is particularly relevant for complex projects, characterized by higher interdependencies of tasks. In complex projects, errors in the early stages propagate exponentially in the later ones. The later an error is detected, the more costly and time consuming it is to correct it.

It is important to note that our argument is based on the fundamental assumption that knowledge intensive projects are characterized by overlapping tasks with mutual interdependencies. If tasks were modular and consecutive, the errors in one task would delay the project only by the time it takes to correct the mistake in the task, however consecutive tasks execution time will not be affected. Therefore, the proposed benefits of front-loading will be attenuated as the consequences of errors in the beginning of the projects will not have determinantal effect on the overall performance of the project. Therefore, we expect that:

> *Hypothesis 1: Greater allocation of human resources in the early stages of the project compared to later ones is associated with higher project margin.*

Next, we develop hypotheses on three conditions under which project performance can be increased, when the benefits of front-loading cannot be capitalized on: project manager familiarity, team familiarity and client familiarity—and argue that the effect of frontloading is decreases in projects with high level of these three types of familiarity.

3.2. Project Manager Familiarity and Front-loading

Many project-based settings, including the one we study, have a project manager who is given the right to assign tasks to the team members as well as to coordinate their activities (Munns & Bjeirmi 1996). Given their position and leadership role within the teams, project managers can influence team performance, by effectively organizing, planning and controlling the activities of the team members (Anantatmula 2010). Here, we explore how the level of familiarity of the project manager with the rest of the team members, can influence the effect of front-loading on project performance. In particular, we argue that the positive effect of front-loading on project performance is attenuated when the level of familiarity of the project manager with the rest of the team is high for the following reasons. First, when project managers work together with the rest of team members, they acquire knowledge on the capabilities and expertise of these workers (Huckman et al. 2009). Project managers can then use this knowledge when assigning tasks in the focal project, ensuring that the tasks match to the greatest extend the expertise and experience of the workers. When tasks are matched to the specific expertise, workers are more likely to be able to anticipate problems with a lower effort. For example, one project manager at AerospaceCo shared that he always aimed at assigning hardware training tasks to people he knew have done training tasks also in the software because they could approach the problems from different angles, ensuring that they consider different potential integration problems.

Second, when project managers work together with the rest of the team members, they establish work routines and learn to work together. The project can benefit from these previously established routines as the project manager does not need to implement new routines in the beginning of the project which results in a faster start of the work and therefore lower costs. One manager at AerospaceCo noted that when he is not familiar with the team members, in the beginning of the project he spends costly time training them in how things are done. More specifically he stated that "*if you go to my projects, you will see that all workers use the same philosophy, a line of continuum, but it is because I have been there, training every single team. So, in the end, you may have projects which you need to finish in 1 year and you spend 4 months training and trying to make people understand what they need to do.*"

Therefore, as project managers become more familiar with the team members, they are better at assigning workers more specific tasks matched to their expertise and ensuring that they complete those tasks following pre-established work routines and thus minimizing the opportunities for integration errors found in the later stages of the project. Hence, project manager familiarity with the team influences the relationship between front-loading and project margin, such that project manager familiarity attenuates the postulated positive effect. That is, we expect increasing project manager familiarity with the team to decrease the positive effect of front-loading on project performance. Therefore, we hypothesize the following:

Hypothesis 2: Greater familiarity of the project manager with the rest of the team decreases the positive the effect of front-loading on project margin.

3.3. Team Familiarity and Front-loading

Next, we consider how team familiarity, or the level of experience of the team members working together, influence the effect of front-loading on project performance. Team members who are familiar with each other, have had past experience working together which helps them have higher level of trust in the capabilities of each other, better information sharing as well as effective coordination (Huckman & Staats 2011, Pisano et al. 2001). We argue that the positive effect of front-loading on project performance is attenuated when team familiarity is high for the following reasons. First, when team members are familiar with each other they are more likely to have established work routines and to more effectively coordinate their activities (Gino et al 2010, Lewis et al. 2005). Therefore, for a given number of hours worked, familiar teams can be more efficient at performing their tasks.

Second, because of their established communication and coordination, familiar teams, are more likely to reach to a better understanding of the overall requirements of the tasks at hand (Balkundi & Harrison 2006, Staats 2012) which can facilitate the anticipation of errors. Moreover, team members who are actively involved in the project in the earlier stages can informally communicate with familiar members who are to join the project in later stages. For example, a project manager we interviewed explained that it was not just important for the team members to know how to do the work, but also to know their teammates and to whom they can ask question for their task at hand, for example if they need someone to build a card for them. Because as the manager explains, if people don't know the rest of the team members, they tend to start doing everything from scratch by themselves, which is not efficient as they do not re-utilize know-how that the team already possess.

Therefore, as the team becomes more familiar, they are more efficient in working together, following pre-established work routines and in communicating among themselves, seeking for common solutions, thus minimizing the opportunities for integration errors found in the later stages of the project. Hence, team familiarity influences the relationship between front-loading and project margin, such that the familiarity attenuates the postulated positive effect. That is, we expect increasing team familiarity to decrease the positive effect of front-loading on project performance. Therefore, we hypothesize the following:

Hypothesis 3: Greater team familiarity decreases the positive effect of front-loading on project margin.

3.4. Client Familiarity and Front-loading

Lastly, we consider how familiarity with the client, or the experience of the firm working with the same client, influences the effect of front-loading on project performance. In knowledge-based projects, such as the one we study, project outcomes are the result of the interaction of the specific and unique requirements of the client and the project team (Larsson & Bowen 1989, Clark et al. 2013, Langer et al. 2014). We argue that the positive effect of front-loading will be attenuated when familiarity with the client is high for the following reasons. First, by repeatedly interacting with the same client, the firm may learn their requirements and improve their communication, coordination and knowledge transfer (Ko et al. 2005, Clark et al. 2013). This, on its hand will decrease the level of uncertainty in the beginning of the project, when the fundamental design decisions are taken and will ensure that decisions with more certain outcomes are taken.

Second, the previously established relationship with the client facilitates the communication with them and increases the trust (Uzzi 1997, Clark et al. 2013), which not only ensures better knowledge transfer but also more efficient communication. A project manager of the company shared that when the client is already familiar to the company it makes the work easier and faster as there is already trust, and the company doesn't need to constantly put timely effort in showing what they have done and prepare and provide additional deliverables to show progress.

Therefore, as familiarity with the client increases, team members can reduce the uncertainty in the earlier stages in the project by having more information on the specific requirements of the client as well as be more efficient in the communication with the client, thus minimizing extra work to show progress in the beginning as well as the opportunities for integration errors found in the later stages of the project. Hence, client familiarity influences the relationship between front-loading and project margin, such that the familiarity attenuates the postulated positive effect. That is, we expect increasing client familiarity to decrease the positive effect of front-loading on project performance. Therefore, we hypothesize the following:

Hypothesis 4: Greater client familiarity decreases the positive effect of front-loading on project margin.

4. Empirical Analysis

4.1. Data

We received data from AerospaceCo on all projects executed by the division between 2006 and 2017, which belong to four different departments: space, aeronautics & vehicles, defense and healthcare equipment departments. These projects entail a mix of engineering and prototyping/small series manufacturing activities. The projects are highly heterogeneous, for instance, one project may entail developing and building an alignment device for a satellite antenna, while the subsequent project may be a navigation device for a rocket or design of a work system to generate carbon fiber laminates for aircraft wings. workers. Each project is allocated into one of two categories by the company according to the final outcome: “Engineering”, where only service is provided, and “Product”, where physical artifacts are built as well. The sample comprises 69.96% of projects in the former category and 30.04% in the latter. Figure 2 presents a detailed categorization provided by the company’s records of the final product of each project in the dataset, where it can be observed that the majority of the projects are mechanical (24.36%) and mechatronic systems (13.14%).

The studied projects present high heterogeneity in terms of how the hours are distributed throughout. Namely, on average the project we study insert 30.5% of the hours in the first quartile of the project (st.dev. 0.17, min 0.01, max 1), 23.74% in the second quartile (st.dev. 0.13, min 0, max 0.80), 24.21% of the hours in the third quartile (st.dev. 0.14, min 0, max 0.80) and 21% of the hours in the last quartile (st.dev. 0.12, min 0 and max 0.93) (see Figure 3).

We assembled data for this study from three different archival sources. First, we accessed the records that the company maintained of all 413 projects initiated during the period between January 1, 2006 and November 30, 2017. For each project, the dataset includes information about the project margin, invoice variation, geographic area, project scope, project manager, etc. After removing projects with missing identifying data such as project type, department and stage, the dataset comprises 350 observations, pertaining to projects that are executed in different geographic areas: USA and Canada, Mexico, Brazil, China; Japan and Korea, Middle East, North Africa, South Africa, Iberia, United Kingdom and Ireland, Poland, Eastern Europe, Rest of Europe and Rest of South America. From the 350 projects, 258 (or 73.71%) were finalized at the point of the data collection, while 92 (or 26.29%) were still ongoing. To perform the analysis, we focus exclusively on the finalized projects, therefore limiting our sample to 258 projects, to ensure that the project margin is an accurate estimator of project performance. Similar to Staats (2012) we remove geographic areas that had only one project (a total of three projects), making our sample equal to 255 projects.[9]

Second, we augmented the dataset by including data elaborated from monthly worker time sheets for each project. These records cover 1,027 individuals in total. Based on these records, the average duration of a project is 1.84 years whereas the average team size is 22.68 employees. Given the nature of the work, team members usually work simultaneously on several projects (average is 6.66 projects per worker). We further used this data to calculated team composition variables for each project.

The third source of data were records from the Human Resource department, which we accessed to collect information on team members, including skill level, tenure. The average tenure of all workers in a project is 6.11 years. Workers are assigned to a specific skill level category, from 1 to 6, based on their credentials, level of expertise, where 1 indicates the highest level and 6 the lowest. The assignment of the skill level is a highly systematic and validated procedure as the compensation of the workers depends on the expertise category they are assigned to. The average expertise level of all team members in a project is 3.65. According to our interviews, workers assigned to category 6 are usually recent graduates and

[9] The margin data available for the on-going projects is an estimate of the project margin up to the date of the data collection and therefore is misleading because project performance may vary unexpectedly in the time period comprised from data collection to project termination.

interns (21.57% of all workers in our setting). They are therefore less experienced engineers, conducting basic drafting and technical engineering tasks that are more structured and repetitive. On the other hand, workers from category 1 to 5 (78.43% of all workers) are senior engineers and experts that perform highly specialized and complicated tasks that fit their area of expertise.

Finally, we conducted numerous meetings and interviews with staff members to get a better understanding of the company business environment, its project management practices and procedures, as well as how data pertaining to the three aforementioned sources was compiled.

4.2. Measures

4.2.1. Dependent Variable

We use project margin data computed by the corporate project control office. *Project margin* is calculated at the closure of the project as the difference between project contract value (invoiced to the client) and project costs, divided by project contract value. Project costs include direct project costs, as well as a fraction of general overheads that is imputed based on company-defined coefficients. Among direct project costs are manpower (both permanent and subcontracted), supplies, outsourced services, as well as miscellaneous R&D costs and manufacturing costs, including equipment depreciation costs. The company carefully tracked project costs, in order to keep the project earned value under check and maintain updated predictions of final project margin.

4.2.2. Independent Variables and Moderators

Frontloading _ hours is defined as the level of front-loading of amount of work performed or the proportional fraction of work performed in the beginning of project out of the total work. To measure the variable, we first calculate the total hours worked by all team members each month of the project, we next build a cumulative curve of hours worked each month of the project. We then calculate the fraction of the area bellow the curve out of the total area for the project (i.e., calculated by total months x total hours). Higher values of the variable indicate that a higher fraction of the work was done in the earlier months of the project (i.e., presence of front-loading); whereas smaller values of the variable indicate that higher fraction of the work was performed in later months of the project (i.e., back-loading), a value equal to 0.5 indicates that the work was equally distributed among the months of the project. As an alternative operationalization we measure the variable with the total number of team members who inserted hours in each month of each project.

Project manager familiarity is defined as the level of familiarity of the project manager with the rest of the team members. To measure the variable, we first count the number of projects project manager has worked with each of the team members, resulting in a familiarity count with each team member. Next, we take the average of these individual familiarities. Due to the highly right skewed nature of the variable, we use the log transformation of team familiarity in our main model. The transformation is also consistent with Tukey's (1977) ladder of powers, which reveals the most suitable transformation.

Team familiarity measures the level of the familiarity of the team members among themselves, excluding the project manager. Similarly to past literature, we calculate this variable by counting the number of times each pair in the team (excluding pairs including the team manager) has worked together, take the sum for all pairs and then divide this number by (N(N-1)/2), where N is the team size (Reagans et al. 2005, Huckman et al 2009, Huckam & Staats 2011, Staats 2012, Avgerinos & Gokpinar 2017). Due to the highly right skewed nature of the variable, we use the log transformation of team familiarity in our main model. The transformation is also consistent with Tukey’s (1977) ladder of powers, which reveals the most suitable transformation.

We measure *client familiarity* by counting the number of past projects the division has performed for the same client up to the current project (excluding the current one). Due to the highly right skewed nature of the variable, we use the log transformation of client familiarity in our main model. The transformation is also consistent with Tukey’s (1977) ladder of powers, which reveals the most suitable transformation.

4.2.3. Control Variables

We control for several team as well as project characteristics that could affect the project margin.

Individual average experience. We measure each project team member’s prior experience in the company as the total number of months a team member has worked in the company prior to the focal project. To obtain the project level variable, we average across the team members. Due to the highly right skewed nature of the variable, we use the log transformation of team familiarity in our main model. The transformation is also consistent with Tukey’s (1977) ladder of powers, which reveals the most suitable transformation.

Individual average expertise. We control for individual’s expertise level, by using the skill level categories assigned to each worker where 6 is the lowest and 1 the highest category. To obtain the project level variable, we take the average skill level of all workers in the team.

Team size. This variable represents the number of individuals working on a project. In the final sample the average team size is 22.68 team members with minimum of 1 and maximum of 171 workers. Due to the highly right skewed nature of the variable, we use the log transformation of team size in our main model. The transformation is also consistent with Tukey's (1977) ladder of powers, which reveals the most suitable transformation.

Project manager role experience. Prior literature has argued that the project manager role experience can influence the performance of the project (Huckman et al. 2009, Easton & Rosenzweig 2012, Staats 2012). Hence, we control for this variable by calculating the number of previous projects the project manager has managed (excluding the current one). Due to the highly right skewed nature of the variable, we use the log transformation of team familiarity in our main model. The transformation is also consistent with Tukey's (1977) ladder of powers, which reveals the most suitable transformation.

Multi-team membership. In our setting, employees tend to work on multiple projects at the same time, which may affect their performance in the focal one (O'Leary et al. 2011, Chan 2014, Berolotti et al. 2015). To control for multi-project membership, we take the average number of projects each team member has worked on throughout the duration of the focal project. To obtain the project level variable, we average across the team members.

Project duration. We include a variable indicating the total duration of the project in months, to control for the size of the project. Projects with higher duration are spread across longer time periods, which may affect project margins. The duration of the project is estimated in the tendering stage with the client and is dependent on the unique specifications of the project and its tasks.

Project complexity. Next, we control for three project characteristics which can account for the project complexity: *scope changes*, *project type* and *project* *department*. We measure *scope changes* during the execution of a project based on variation in project invoicing amount. The total project invoicing amount is normally set with the client when signing the contract. As the project progresses, the invoicing amounts can be altered to address changes in the scope caused by external factors (e.g., obsolete component or software that needs to be replaced) of requested by the client (e.g., the client readjust product specifications such as the speed or the reach of the device). Variation in total invoicing hence is a proxy for changes in project scope. Specifically, we compute *scope changes* as actual invoicing minus budgeted invoicing, divided by the actual invoicing. In 79.84% of the projects in the sample there has been a change in the invoicing and a change therefore in the scope. As previously explained, the company allocates projects into two categories based on their output: Engineering and Product. Both project types include a certain amount of engineering work in the initial stages of the project. Nevertheless, the engineering projects are considered more complex because a major part of the work is engineering. The final outcome of an engineering project is one or two prototypes of the product, such as a scanning mechanism for a satellite or a pointing mechanism for a spacecraft. In a product type projects the project consists of a less complex initial engineering and the subsequent production of the parts. We therefore include the dummy variable *project type*, which is equal to one if the project is allocated into "Product" and zero otherwise. Moreover, the complexity of the projects also depends on the department in which the projects are executed, with the Space department having more engineering-heavy projects with high complexity in the requirements than other departments, for example. We therefore include dummy variables indicating the department of each project, using *space* as our reference category (corresponding to zero values of *aeronautics and vehicles*, *defense, healthcare equipment* departments).

Indicator for start year. Lastly, we control for potential company policy changes and technological advancements as well as other environmental changes by including a dummy variable indicating the year each project started.

4.3. Results

We first use an Ordinary Least Square model to test the expected relationships. Since the projects have been performed in 11 different geographical areas, we specify geographic area random-effects regression models, with robust standard errors clustered at the geographic area level to test our hypothesis. We use random-effects model as Hausman test fails to reject the null hypothesis that the random effects model is consistent. Our approach allows us to study the differences among the areas, while controlling for unobserved similarities of the projects within each area (Bollen & Brand 2010).

Table 1 shows the descriptive statistics and correlations among the variables. We note that the logarithmic transformations of *project manager familiarity*, *team familiarity*, *client familiarity*, *individual average experience*, *project manager role experience* as well as *team size* variables are reported in the table. Table 2 presents the OLS model results. In model 1, we include only the control variables. In model 2, we include *frontloading _ hours* and observe that it has a positive and significant at 1% coefficient, providing support for Hypothesis 1. In model 3 we add the interaction terms of *frontloading _ hours* with *project manager familiarity* and we see it has a negative and significant at 5% coefficient, providing support for Hypothesis 2. In model 4 we remove the interaction of *frontloading _ hours* with *project manager team familiarity* and add the interaction with *team familiarity* and we see that it has a negative and significant at 5% coefficient, providing support of Hypothesis 3. Lastly, in model 5 we test the interaction of *frontloading _ hours* with *client familiarity* and we see that it has a negative and significant at 5% coefficient, providing support for Hypothesis 4.

4.3.1. Endogeneity Concern and Instrumental Variable Approach

Project staffing decisions may not be random. Specifically, the allocation of the hours throughout the project as well the selection of the team members may be based on factors that are also correlated with project margin. Therefore, the association between the studied frontloading variables could be driven by these unobserved factors rather than the variables themselves.

For example, projects may have different importance or priority for the firm, where more important projects for the firm may be assigned better qualified or fitted team members. In addition, project managers may have the power to express their preferences in selecting the team members to work on their projects as they consider them higher skilled or a better fit for their projects. Therefore, the association between the studied frontloading variables and project margin may be due to unobserved project characteristics or project managers preferences. Our controls for project complexity as well as project manager role experience and familiarity with the team members should address part of these concerns. Moreover, the controls for workers experience and expertise should capture the observable workers capabilities.

Nevertheless, there may still be potential unobserved factors that could bias our results. Given that we cannot explicitly control for project managers preferences in selecting team members or the level of importance of the project for the firm, we use an instrumental variable approach to address the endogeneity concern driven by the mentioned omitted variables.

We use market-based instruments for the frontloading variable (Nevo & Walfram 2002, Kesavan et al 2014). More specifically, we use the average *frontloading _ hours* of all other project within the same department (i.e., space, aeronautics & vehicles, defense and healthcare equipment) as an instrument. We name the variable *department average frontloading _ hours*. The instrument should be correlated with the endogenous variable as the allocation of hours throughout the projects is dependent on the department. For example, the defense department usually has projects which include preliminary, relatively less complex, engineering and more complex and time-consuming prototyping and manufacturing in the later stages, where more manpower is needed. The instrument also meets the exclusion restriction, because there is no reason to expect that the performance of the focal project is driven by the average *frontloading _ hours* on all other projects in the same department, most of which are executed prior or after the focal project, as we take the average of all the projects executed across the whole time span of the dataset (i.e., 11 years). Since healthcare equipment department has just one project in our sample, we could not estimate the instrumental variable for this project and we therefore dropped it for the analysis. The rest of the departments have 119 (space), 94 (aeronautics & vehicle) and 40 (defense) projects.

When testing Hypotheses 2 we apply the following procedure recommended by Wooldridge (2002). We first run the first stage of the model regressing *frontloading _ hours* on *department average frontloading _ hours,* including all moderators, control variables and fixed effects. We then take the linear prediction from that model, multiply it with *project manager familiarity* and use it as an instrument for *frontloading _ hours x project manager familiarity*. We can therefore create a valid instrument for Hypotheses 2. We test Hypotheses 3 and Hypotheses 4 in separate models using the same procedure. Namely, we use the same predicted values used to instrument *frontloading _ hours* in its interaction with *project manager familiarity.* We multiple the predicted values with *team familiarity* (*client familiarity* respectively for Hypotheses 4) and use it as an instrument for *frontloading _ hours x team familiarity* (*x client familiarity*).

To check the validity of the instruments we look at the overall R squared of the first stages, which are all above 80%, and the Wald Chi square statistics, which are all significant at 1% and very high, indicating high values of F-statistics too (well above the common threshold of ten) confirming that all the instruments are indeed not weak as suggested by Stock and Yogo (2005). Tables C1 and C2 of appendix C present the results of the first stage models for four hypotheses.

Table 3 presents the results for the second stage of the proposed instrumental variable analysis. In model 1, *frontloading _ hours* is positive and significant at 1%, providing full support for Hypothesis 1. A 10% increase in *frontloading _ hours* increases *project margin* by 55.06%. In model 2, we add the interaction with *project manager familiarity*. The interaction term is negative and significant at 1%, providing support for Hypotheses 2. In model 3, we remove the interaction term with *project manager familiarity* and add the one with *team familiarity* and observe that it has a negative and significant at 5% coefficient, providing support for Hypotheses 3. Lastly, in model 4, we remove the interaction term with *team familiarity* and we add the one with *client familiarity* and observe that it has a negative and significant at 1% coefficient, providing support for Hypotheses 4. To visualize and interpret the interactions effects, we plot the margins plots of the regression models (Figures 4, 5 and 6 examine the moderating effects of *project manager familiarity*, *team familiarity* and *client familiarity*).

4.4. Robustness Checks

4.4.1. Alternative Operationalization of Independent Variables

As previously observed, an alternative way to operationalize the distribution of the work by calculating frontloading considering the number of team members rather than the hours they insert in the project. We hence create new measures for *frontloading _ hours*, namely *frontloading _ team members.* We measure the variables, using the same procedure as the main operationalization, but instead of calculating the total hours worked per month per project for the cumulative curve, we use the total number of workers who inserted hours in that project and month.

Although this operationalization does not account for the fact that some team members may insert more hours in the project than others, it captures complexities which could be derived from team size and the collaboration among number of people. To test the effect of *frontloading _ team members*, we re-run the 2SLS regressions. To calculate the instruments, we follow the same procedure as the one we did for the main analysis but with the newly calculated variables. The regression results provide full support for the four hypotheses (see Table 4) indicating that the results are robust to the number of people operationalization of the frontloading variable.

4.4.2. Alternative Model Specifications

While we find support for a linear relationship between *frontloading* and *project margin* there is a chance that this relationship is non-linear. Specifically, one can expect that the marginal effect of inserting more hours in the beginning of the project might decrease or even turn negative beyond a specific value of *frontloading _* *hours*, due to the associated complexities with performing multiple tasks simultaneously. To test for a non-linear relationship, we repeat the analysis for Hypothesis 1 after including the square term of *frontloading _ hours* corrected for endogeneity. We do not evidence for a significant diminishing effects. Therefore, it seems that in our sample there are no projects with a large enough frontloading that negatively affects *project margin*.

Second, we explore the effect of the different type of outcome the project has, as one may expect that the type of outcome or product is a significant driver of project margin. Recall that the company puts the projects in 20 categories according to their final product. In the main analysis we control for whether the project is a product or an engineering type, but due to statistical power of the analysis we do not control for the actual outcome (as controlling for the actual product results in 20 additional covariates). Nevertheless, as a robustness check we explored the effect of product by adding them as a fixed effects and we obtained full support for our hypotheses (see appendix C, Table C3).

Next, we investigate the robustness of the geographic area random-effects specification of the model. The projects in the setting are conducted in different geographic areas but are from the same company; therefore, the random-effects specification allows us to capture the unobserved characteristics of the different geographic areas while not eliminating the common characteristics of the projects derived from being performed by the same company. Nevertheless, we repeat the analysis using geographic area fixed effects to confirm the robustness of the findings (see appendix C, Table C4).

Finally, we check whether the results are driven by overfitting due to the limited sample size. In general, overfitting occurs when a model includes too many parameters compared to the number of observations, a fact that can lead to incorrect inferences (Freedman 2009). To mitigate this concern, we reevaluate support for the hypotheses using simpler regression models obtained by dropping the insignificant continuous control variable (Aggarwal et al. 2015). More specifically, we drop *individual average experience, project manager role experience, multi-team membership* and *project type* from the four models and in additional *individual average expertise* and *scope changes* from model 2. Table C5 of appendix C presents the results, which provide full support for the four hypotheses.

4.5. Post-hoc Analysis

4.5.1. Alternative Explanations

Next, we aim to provide evidence of the proposed mechanism by which front-loading impacts project margins. Our mechanism is that frontloading is beneficial for project margins because of prevention of costly errors which may occur in later stages. If the mechanism holds then front-loading will only have a positive effect on project margins if the work performed in the beginning of the project is effective at anticipating and preventing future errors. Team members with higher level of expertise are more likely to identify key potential problems in the early stages and take measures to mitigate them, than more junior team members, with lower level of expertise. Junior team members, because of their lower level of expertise, may not be able to proactively identify future problems and therefore their initial engineering may not mitigate those. It is important to note that here, we part from the underlying assumption that team members with high level of expertise, are used exclusively to perform knowledge intensive work because of the higher cost of their hour, relative to an hour of a lower skilled workers. Therefore, we can expect that the positive effect of front-loading on project margins will only be observed if workers with high level of expertise insert hours in the beginning of the project, rather than lower skilled workers who simply execute tasks which have been assigned to them.

To test this, we define two new variables: *high-skilled frontloading_hours* and *low-skilled frontloading_hours*. The variables measure the level of front-loading of amount of work performed of high (low)-skilled team members. To calculate them, we first code whether the team worker is lower or higher skilled one. We do so by relying on the skill level category assigned to each team member, as discussed previously in the general description of the setting where high-skilled workers are the ones who are assigned categories 1 to 5 and low-skilled workers are the ones who are assigned category 6. Similarly to *frontloading _ hours*, we measure *high (low)-skilled frontloading _ hours* by first calculating the total hours worked by high (low) skilled team members each month of the project. Next, we build a cumulative curve of hours worked each month of the project and calculate the fraction of the area bellow the curve out of the total area for the project. As an alternative operationalization, we also measure the variables with the total number of high (low)-skilled team members who inserted hours each month of the project.

We test the effect of the two variables by adding them to the main model, after we remove the *frontloading _ hours* variable. To correct for endogeneity, we follow the same approach used in the main analysis and calculate instruments for *high (low)-skilled frontloading _ hours*, which are *department average high (low)-skilled frontloading _ hours*. They capture the average values of the endogenous variables from all other projects within the department of the focal project. We expect them to be valid instruments for the same reasons previously discussed for *department average frontloading _ hours.* We report the results in Table 5, where it can be observed that *high-skilled frontloading _ hours* has a positive and significant coefficient at 1%, while *low-skilled frontloading _ hours* has a positive, but not significant coefficient. The results indicate that the positive effect of frontloading on project margins is only observed when higher skilled workers, who are more likely to anticipate future problems, are used in the beginning of the project. Therefore the findings are aligned with the proposed mechanism.

5. Conclusions and Discussion

5.1. Theoretical Contributions

To best of our knowledge, this is the first empirical investigation into the effect of front-loading on project performance and under which condition it is effective. Therefore, with this study we extend the limited empirical research on the performance consequences of frontloading. We find a positive and linear effect of *front-loading* on project margin, which increase by 187% as front-loading increases from 0.56 (25^{th} percentile) to 0.70 (75^{th} percentile). While it is plausible that at higher level of front-loading, the effects would become marginally decreasing our data point toward a linear association between front-loading and project margin. This result downplays a potential concern of incurring major for the project costs in case, despite a project being frontloaded, a major error to be detected in the later stages. Such a situation while arguably plausible was not observed in our sample. Our additional analysis suggests evidence for the proposed mechanism through which project margins benefit from frontloading, namely the efficient performance of knowledge intensive work in the earlier stages of the project so that problems resulting from erroneous project fundamentals are anticipated. We find that indeed, front-loading has a positive effect on project margin when high-skilled engineering hours are used in the earlier stages, as opposed to lower-skilled engineering hours.

Next, the find that when project managers need to keep front-loading low, project performance can still be increased by ensuring that the project team has high team leader, internal and client familiarity.

5.2. Practical Contributions

Our findings also have important contribution to managers. The clear positive effects of allocating more workforce with high expertise in the initial stages of the projects, provide managers with a staffing tool which can increase the performance of their projects. Moreover, our moderation analysis provides further tools that can be applied when a project manager cannot afford the costs of complexity associated with front-loading. These findings are particularly relevant for settings with highly interdependent and uncertain tasks where forcing them to be executed simultaneously can lead to substantial complexities. In such situations for instance, the firm can decide which of the projects to frontload depending on the level of familiarity of the project manager with the team, the familiarity of the team members themselves as well as familiarity with the client.

5.3. Limitations and Conclusions

The study has a number of limitations that reflect the difficulties of using secondary data to study team members behavior. First, our data allows to control measure the level of participation of each team member along each project, however it does not allow us to observe the actual tasks that each team member performs. However, we note that the conducted interviews indicated that the expertise category assigned to each worker can be used as an indicator of the complexity of the task they perform, namely engineers with high category are exclusively used for complex decision making, while lower-category engineers are used to execute less complex and more structured tasks. Second the available data also did not allow us to empirically test the postulated mechanism through which front-loading affects project margin. Nevertheless, we note that both the literature studying front-loading as well as the interviews we conducted with the company project managers support the evidence that allocating more knowledge intensive work in the earlier stages of the project reduces the errors in the latest stages. Moreover, we could provide an additional analysis providing suggestive evidence of the mechanism. Second, multiple variables in our model capture different facets of project type and complexity, including the project category, department, scope changes, team size as well as duration. Nevertheless, other unobservable dimensions of complexity could drive both project performance as well as the decision to front-load a project. We downplay this concern by providing an additional analysis where we control for a detailed categorization of projects depending on their outcomes as well as by using an instrumental variable approach but acknowledge that future research on the effect of front-loading should capture other dimensions of project complexity. Lastly, our data did not allow us to explicitly study the different stages of a project such as design, engineering, prototyping or testing. Such limitation originates because the company does not divide the project into clearly defined stages and therefore does not record performance indicators for them. This is a usual limitation of complex project settings with high interdependence between tasks where it is hard to clearly distinguish the different stages as for example testing tasks are more often than not performed in earlier design stage as well. Lastly, our outcome variable is the final project outcome which is project margin. It would be of great interest for future research to measure the project outcome on a continuous basis for each month or stage of the project. In such setting the effect of front-loading can be measured in a much more precise way and the more conclusions can be driven on the exact effect of frontloading on the later stages of the project.

In closing, this study takes human resource perspective on front-loading and provides empirical evidence of its positive effect on project performance. Furthermore, it sheds light on what human resources are needed to reach the beneficial effects of front-loading and also how projects performance can be increased when front-loading is kept low.

TABLES

Table 1: Summary Statistics and Correlation Table of Dependent, Independent and Control Variables of Interest (n=255)

Variable		*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
1	Project Margin	1.00															
2	Frontloading_hours	0.13	1.00														
3	Project Manager Familiarity	0.10	0.09	1.00													
4	Team Familiarity	0.02	0.03	0.49	1.00												
5	Client Familiarity	0.10	0.00	0.21	0.13	1.00											
6	Individual Average Experience	-0.01	-0.13	0.25	-0.14	0.01	1.00										
7	Individual Average Expertise	-0.02	0.18	0.21	0.24	0.23	-0.14	1.00									
8	Team Size	-0.18	0.21	0.01	-0.01	0.07	0.10	0.31	1.00								
9	Scope Changes	0.09	0.02	0.09	-0.11	0.01	0.15	-0.06	0.13	1.00							
10	Project Manager Role Experience	-0.03	0.07	0.40	0.41	0.23	0.03	0.18	0.08	0.01	1.00						
11	Mutli-team Membership	0.06	0.06	-0.00	0.51	-0.15	-0.41	-0.01	-0.18	-0.01	0.23	1.00					
12	Project Duration	-0.04	0.10	-0.08	-0.06	-0.01	0.16	0.05	0.69	0.24	-0.03	-0.02	1.00				
13	Project Type	0.06	-0.11	-0.14	0.03	0.05	-0.11	-0.14	0.06	-0.02	-0.08	0.11	0.14	1.00			
14	Aeronautics and Vehicles	0.06	0.19	0.42	0.09	0.23	-0.01	0.46	-0.04	0.18	0.19	-0.16	-0.18	-0.41	1.00		
15	Defense	-0.19	-0.09	-0.11	0.08	-0.21	0.21	0.00	0.13	-0.13	-0.29	-0.16	0.16	0.17	-0.33	1.00	
16	Healthcare	0.01	0.09	0.06	0.08	-0.07	0.00	0.01	0.01	-0.03	0.03	-0.00	-0.03	-0.04	-0.05	-0.03	1.00
Mean		-13.62	0.62	0.88	1.45	1.24	3.96	3.65	2.67	0.27	0.76	6.64	22.02	0.30	0.37	0.16	0.01
Standard Deviation		271.72	0.11	0.76	0.76	1.15	0.94	0.75	0.94	0.65	0.73	3.11	18.41	0.46	0.48	0.36	0.06
Minimum		-4066.49	0.24	0	0	0	-0.41	1	0	-0.99	0	1.28	2	0	0	0	0
Maximum		105.03	0.84	2.83	3.43	3.66	5.84	5.71	5.14	3.65	2.56	19.67	101	1	1	1	1

Note that the descriptive statistics of the log transformation of the Project Manger Familiarity, Team Familiarity, Client Familiarity, Project Manager Role Experience and Team Size variables have been shown.

Table 2: OLS Regression of Frontloading Hours on Project Margin

	(1)	(2)	(3)	(4)	(5)
Frontloading _ hours		513.207**	951.802*	694.873**	858.292**
		(189.192)	(374.794)	(250.563)	(287.109)
Front. _ hours x Proj. Man. Fam.			-548.940*		
			(245.136)		
Front. _ hours x Team Fam.				-126.037*	
				(49.657)	
Front. _ hours x Client Fam.					-305.223*
					(126.775)
Project Manager Fam.	42.812*	32.562**	372.181*	33.347**	35.669**
	(18.677)	(12.246)	(163.030)	(12.498)	(9.457)
Team Familiarity	0.249	14.668	12.016	90.708**	11.465
	(11.898)	(9.212)	(10.514)	(26.914)	(10.769)
Client Familiarity	19.670+	22.756*	22.125*	21.902+	213.833*
	(11.280)	(11.158)	(9.738)	(11.393)	(90.884)
Individual Avg. Experience	-6.851	-2.400	9.693	-1.292	0.316
	(5.286)	(4.108)	(7.892)	(4.888)	(5.877)
Individual Avg. Expertise	34.013*	32.175*	24.632+	27.704*	32.290*
	(16.360)	(13.272)	(13.116)	(11.008)	(13.661)
Team Size	-89.800*	-103.128**	-107.656**	-103.408**	-100.727**
	(35.304)	(36.424)	(39.972)	(36.600)	(36.450)
Scope Changes	25.319**	31.387**	20.189	29.944**	30.811**
	(7.486)	(8.738)	(16.325)	(10.689)	(11.319)
Project Man. Role Exp.	-56.997	-56.229	-50.557	-55.986	-63.416
	(38.890)	(37.923)	(36.085)	(37.961)	(41.493)
Multi-team Membership	3.524*	-0.341	1.886	-0.160	-0.121
	(1.751)	(1.966)	(2.222)	(2.123)	(2.154)
Project Duration	2.621*	2.602*	2.771*	2.585*	2.563*
	(1.269)	(1.144)	(1.254)	(1.141)	(1.217)
Project Type	49.233	51.618	52.153	49.410	49.644
	(45.452)	(49.729)	(49.379)	(49.038)	(48.249)
Constant	68.590*	-186.055*	-485.325*	-283.197*	-409.268*
	(28.037)	(93.075)	(214.293)	(127.686)	(161.668)
Observations (N)	255	255	255	255	255
Start Year FE	Yes	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.139	0.173	0.197	0.174	0.189

Models are OLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table 3: 2LS Regression of Frontloading Hours on Project Margin

	(1)	(2)	(3)	(4)
Frontloading _ hours	888.064**	1,522.527**	1,258.628**	1,498.515**
	(293.837)	(480.849)	(456.477)	(450.044)
Frontloading _ hours x Project Man. Fam.		-837.658**		
		(310.594)		
Frontloading _ hours x Team Familiarity			-243.410*	
			(110.665)	
Frontloading _ hours x Client Familiarity				-573.382**
				(202.509)
Project Manager Familiarity	25.074**	544.014**	26.198**	31.667**
	(8.846)	(200.318)	(8.964)	(8.505)
Team Familiarity	25.201**	20.175+	172.607**	18.121+
	(8.124)	(10.482)	(62.890)	(10.838)
Client Familiarity	25.009*	23.838**	23.480*	383.735**
	(10.918)	(8.688)	(11.218)	(138.991)
Individual Average Experience	0.852	19.003	3.162	5.626
	(8.591)	(12.981)	(10.791)	(11.673)
Individual Average Expertise	30.832**	19.447	22.127**	31.184**
	(11.293)	(11.997)	(6.678)	(12.071)
Team Size	-112.864**	-118.868**	-113.916**	-107.370**
	(36.277)	(40.229)	(36.857)	(37.141)
Scope Changes	35.819**	18.320	33.265*	34.290*
	(9.926)	(21.023)	(13.964)	(14.648)
Project Manager Role Experience	-55.667	-47.064	-55.170	-69.225
	(37.222)	(35.025)	(37.111)	(42.964)
Multi-team Membership	-3.164	0.497	-2.962	-2.466
	(2.265)	(2.741)	(2.625)	(2.628)
Project Duration	2.588*	2.847*	2.555*	2.517*
	(1.051)	(1.208)	(1.034)	(1.199)
Project Type	53.360	54.014	49.188	49.477
	(52.573)	(51.464)	(51.002)	(49.724)
Constant	-372.053*	-811.452**	-569.444*	-772.611**
	(161.085)	(287.574)	(249.486)	(268.263)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.162	0.187	0.162	0.176

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table 4: 2LS Regression of Frontloading Workers on Project Margin

	(1)	(2)	(3)	(4)
Frontloading _ workers	1,987.869*	3,214.801**	2,020.957**	2,976.683**
	(820.272)	(1,189.695)	(720.835)	(909.709)
Front. _ workers x Proj. Man. Fam.		-1,653.590*		
		(662.518)		
Frontloading _ workers x Team Fam.			-23.483	
			(101.859)	
Frontloading _ workers x Client Fam.				-985.646**
				(270.483)
Project Manager Familiarity	41.683*	959.615*	41.746*	55.933**
	(17.659)	(383.454)	(17.577)	(9.603)
Team Familiarity	7.908	-5.759	20.559	-10.266
	(18.458)	(29.325)	(67.332)	(23.931)
Client Familiarity	24.678+	28.324*	24.608+	580.674**
	(13.064)	(11.714)	(13.351)	(161.608)
Individual Average Experience	-6.538	-5.195+	-6.312	-10.192+
	(5.254)	(2.821)	(4.886)	(5.486)
Individual Average Expertise	30.761**	17.748**	30.533**	29.071**
	(7.641)	(6.114)	(7.891)	(6.393)
Team Size	-156.301**	-163.718*	-156.470**	-150.613*
	(60.207)	(65.330)	(59.825)	(59.185)
Scope Changes	43.936**	25.902	43.834**	39.628+
	(16.327)	(30.757)	(16.327)	(22.831)
Project Manager Role Experience	-44.191	-23.902	-44.125	-51.016
	(35.849)	(26.666)	(36.097)	(32.839)
Multi-team Membership	2.016	4.942	2.033	3.876
	(3.989)	(4.768)	(3.979)	(4.959)
Project Duration	3.213*	3.446*	3.211*	3.240+
	(1.487)	(1.704)	(1.495)	(1.733)
Project Type	35.790	24.390	35.648	32.835
	(54.237)	(47.209)	(54.714)	(53.765)
Constant	-877.650*	-1,523.146**	-895.621**	-1,430.701**
	(377.592)	(540.356)	(324.854)	(423.236)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.185	0.215	0.185	0.254

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table 5: 2LS Regression of Frontloading Workers on Project Margin

	(1)
High-skilled Frontloading _ hours	715.076**
	(101.934)
Low-skilled Frontloading _ hours	494.846
	(343.402)
Project Manager Familiarity	22.635
	(18.091)
Team Familiarity	23.712
	(19.538)
Client Familiarity	37.030**
	(13.041)
Individual Average Experience	-12.181
	(7.535)
Individual Average Expertise	47.596**
	(11.935)
Team Size	-139.739**
	(36.899)
Scope Changes	51.305**
	(13.616)
Project Manager Role Experience	-63.275
	(44.797)
Multi-team Membership	0.426
	(6.219)
Project Duration	3.264*
	(1.377)
Project Type	71.877
	(62.399)
Constant	-529.469*
	(220.243)
Observations (N)	217
Start Year FE	Yes
Project Department FE	Yes
Overall R^2	0.178

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

FIGURES

Figure 1: Project hours allocation (1a: front-loading, 1b: homogeneous load, 1c: backloading)

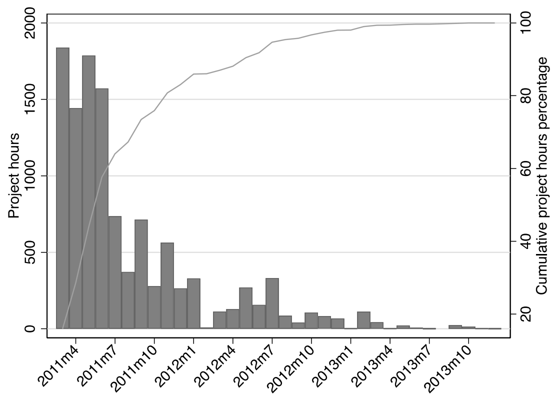


Figure 1a

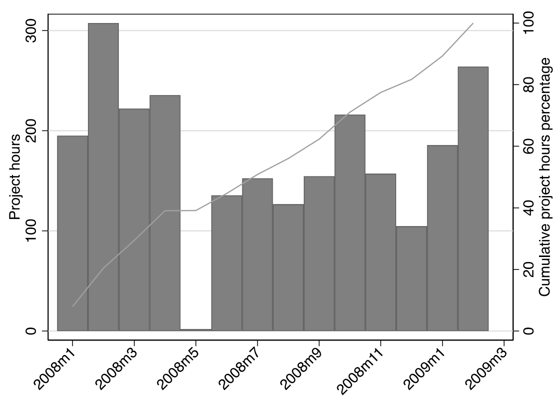


Figure 1b

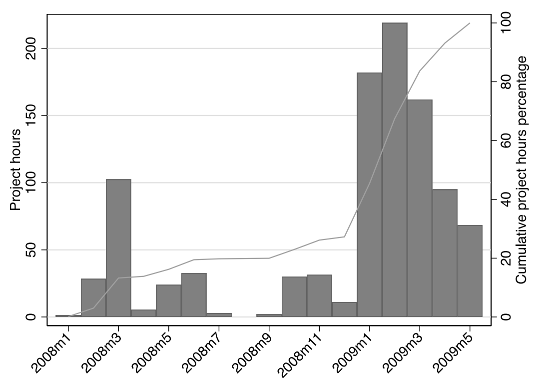


Figure 1c

Figure 2: Project product categorization

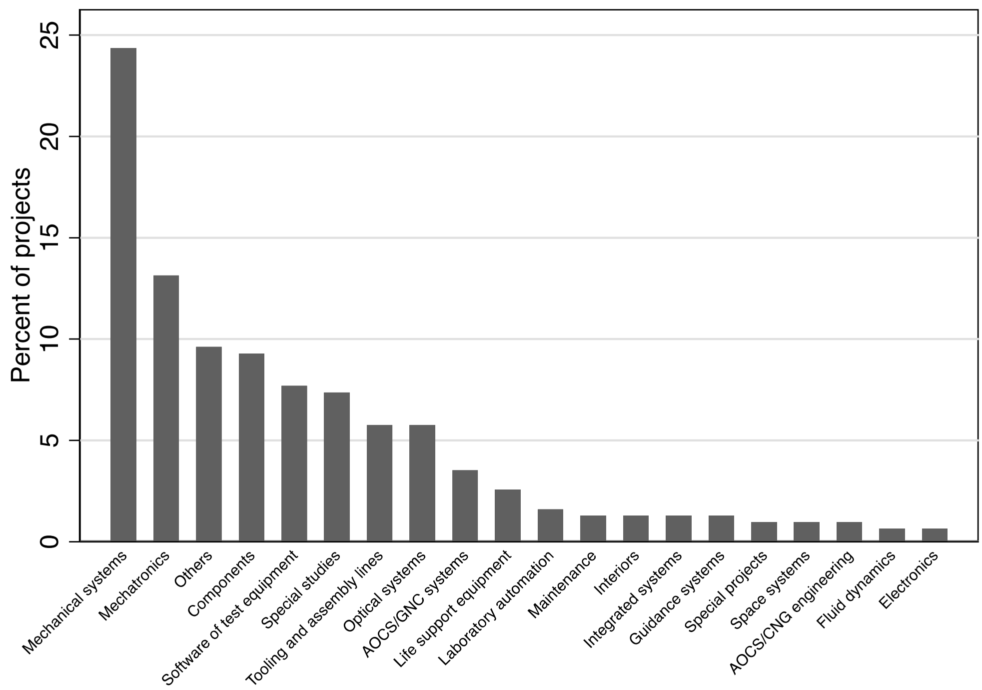
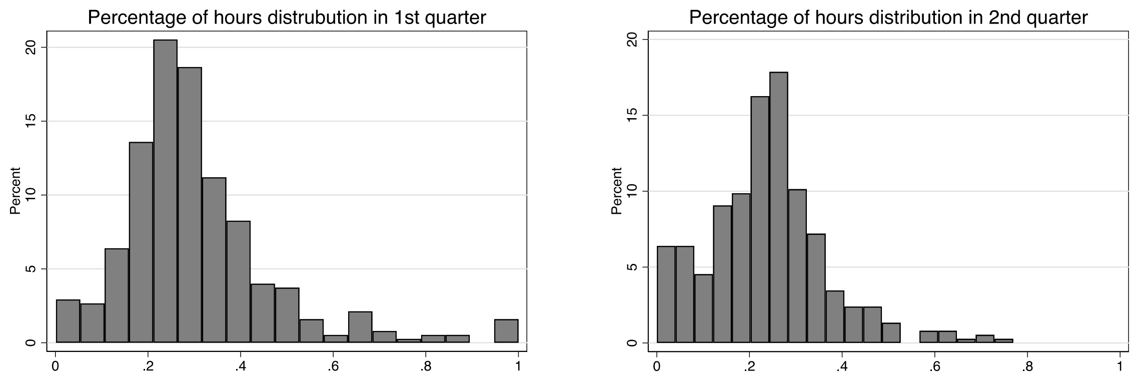


Figure 3: Percentage of hours inserted in 1st, 2nd, 3rd and 4th quarter



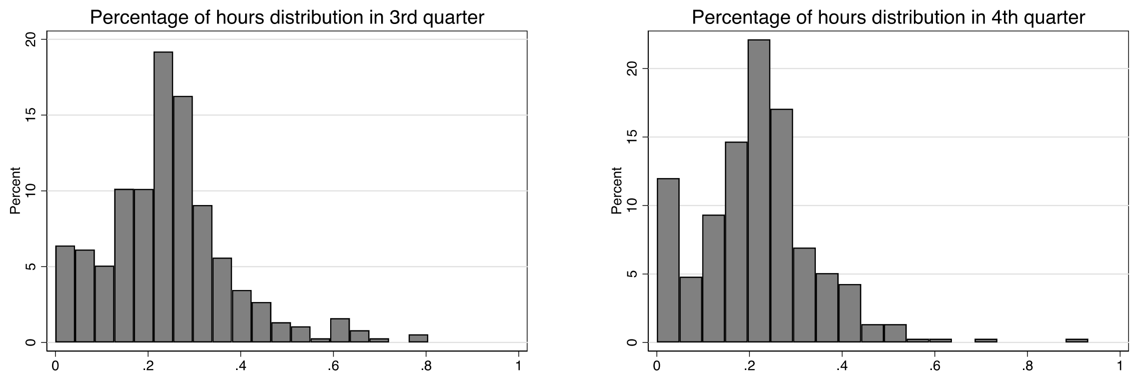


Figure 4: Moderating role of project manager familiarity of the effect of frontloading _ hours on project margin

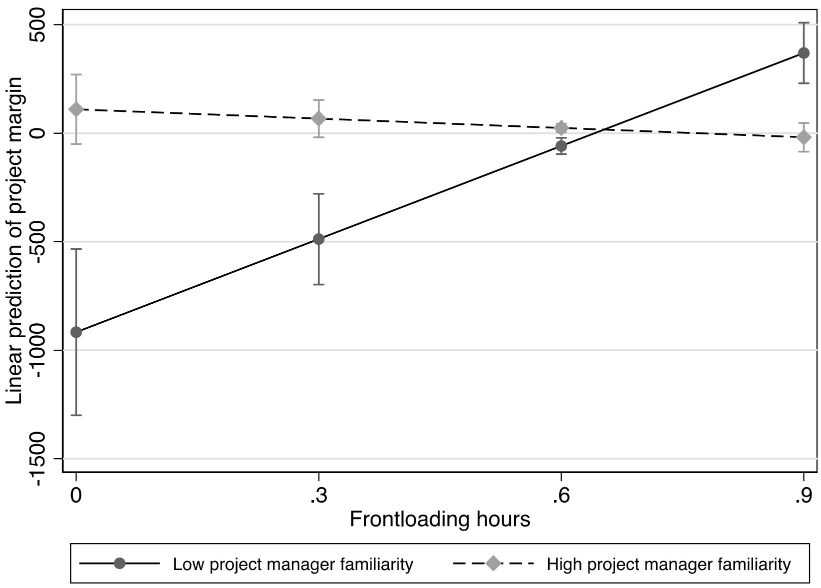


Figure 5: Moderating role of team familiarity of the effect of frontloading _ hours on project margin

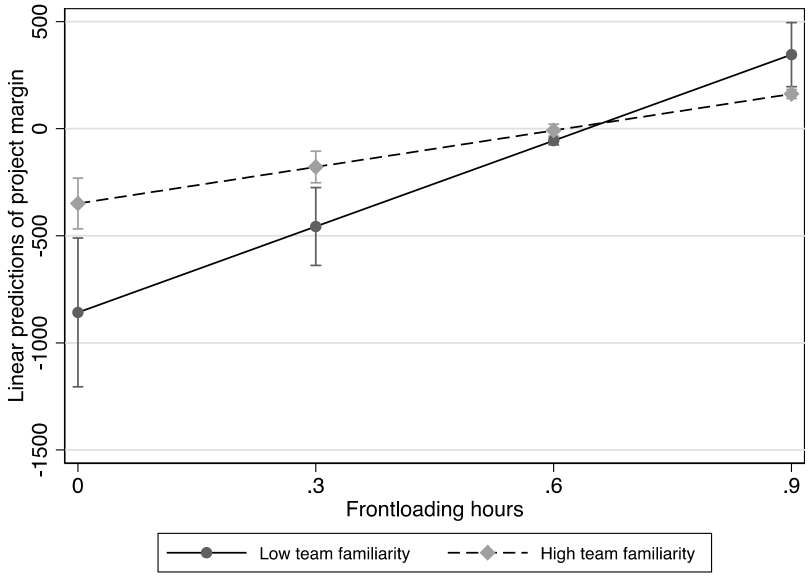
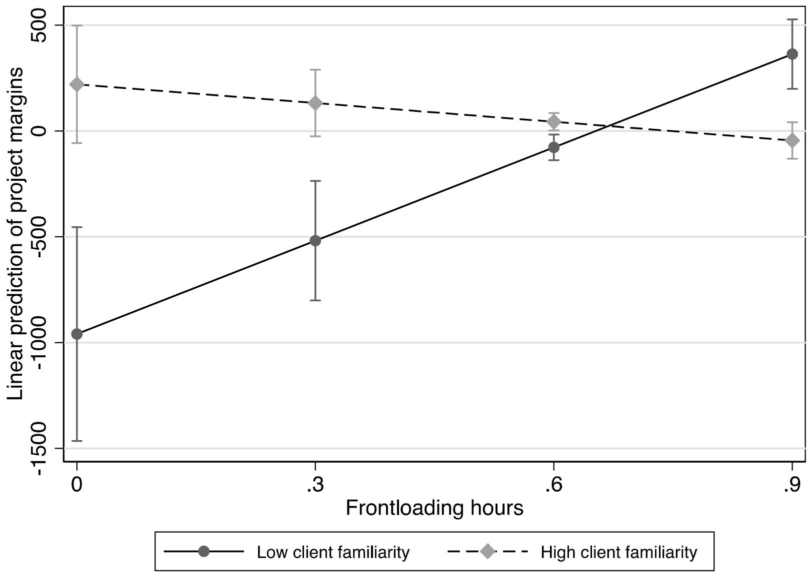


Figure 6: Moderating role of client familiarity of the effect of frontloading _ hours on project margin



CONCLUSIÓN

En conclusión, la tesis permite profundizar el conocimiento sobre las ampliamente usadas y aún poco estudiadas prácticas laborales flexibles en el entorno de prestación de servicios profesionales; lo que contribuye al llamamiento de avanzar teorías que combinan los conocimientos de operaciones y la gestión de recursos humanos (Boudreau et al. 2003). El denominador común de las conclusiones de los tres capítulos de la tesis es que el desempeño de los recursos humanos se ve afectado por la forma en la que está organizado su trabajo en términos de cómo se distribuyen sus horas de trabajo, bajo qué relación contractual trabajan y con quién se les pide que trabajen. Por lo tanto, la organización del trabajo, tiene un efecto importante en el desempeño, que va mucho más allá de un posible ahorro de costes y debe considerarse como un elemento fundamental a la hora de diseñar estrategias operativas.

Los resultados presentados son particularmente relevantes para empresas del sector servicios; ya que, a diferencia de los productos manufacturados; los servicios no solo se producen y consumen al mismo tiempo, sino que, hoy en día, en la mayoría de los casos–aún son prestados por humanos. Los recursos humanos, a diferencia de las máquinas, tienen una motivación y limitaciones inherentes que afectan su desempeño y por lo tanto como se ha verificado pueden fomentar o diferir con las estrategias operativas.

CONCLUSION

In conclusion, the thesis expands the knowledge on the widespread and yet understudied flexible labor practices in service settings, contributing to the call to advance theories at the boundary of operations and human resources management (Boudreau et al. 2003). The overall findings of the thesis suggest the performance of the human resources is affected by the way their work is organized in terms of how their working hours are distributed, under which contractual relationship they work as well as with whom they are asked to work. Therefore, the effect of the labor arrangements in a service setting, goes far beyond pure cost savings and needs to be considered as a fundamental driver of performance when designing operational strategies.

These findings are particularly relevant for service firms, because services, unlike manufactured good, are not only produced and consumed at the same time, but also in majority of the cases they are still delivered by humans. Human resources, unlike machines, have inherent motivation and limitations that affect their performance and can either foster or clash with the operational strategies.

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APPENDIX A: Essay 1

Table A1: Employee Schedules' Influence on Employee Absenteeism and Patient Complaints

	Dependent variable: Employee Absenteeism		Dependent variable: Patient Complaints	
Variables	(1)	(2)	(3)	(4)
Schedule variability	0.484**	0.025**	0.396**	0.003**
	(0.017)	(0.002)	(0.040)	(0.000)
Gaps in schedule	0.161**	0.020**	0.334**	0.008**
	(0.051)	(0.006)	(0.104)	(0.002)
Employee experience	0.077**	0.007**	-0.131**	-0.004**
	(0.018)	(0.002)	(0.031)	(0.001)
Employee first week	1.241**	0.060**	0.355	-0.015*
	(0.159)	(0.012)	(0.314)	(0.006)
Employee availability	-0.007*	-0.001+	-0.006	0.000
	(0.003)	(0.000)	(0.006)	(0.000)
Commuting distance	-0.011	-0.002	0.066*	0.000
	(0.014)	(0.001)	(0.029)	(0.001)
Employee patient variety	0.016**	0.003**	0.061**	0.003**
	(0.005)	(0.001)	(0.008)	(0.000)
Employee task variety	0.014	0.000	0.103**	0.001
	(0.019)	(0.002)	(0.034)	(0.001)
Employee hours worked	-0.019**	-0.001**	-0.004	0.000
	(0.002)	(0.000)	(0.004)	(0.000)
Employee visits	-0.011**	-0.002**	-0.002	-0.000*
	(0.003)	(0.000)	(0.005)	(0.000)
Constant	-1.570**	-0.012	-2.700**	0.006
	(0.155)	(0.011)	(0.279)	(0.005)
Employee fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	68,991	75,078	51,779	75.078
Number of employees	796	1,026	509	1,026

Note: Models 1 and 3 are Negative binomial regression. Models 2 and 4 are Ordinary least square regression with robust standard errors clustered by employee.**p<0.01, *p<0.05 and +p<0.10

Table A2: Employee Schedules' Influence on Employee Absenteeism and Patient Complaints (Past Absenteeism and Patient Controls)

	Dependent variable: Employee Absenteeism		Dependent variable: Patient Complaints	
Variables	(1)	(2)	(3)	(4)
Schedule variability	0.559**	0.538**	0.457**	0.455**
	(0.035)	(0.034)	(0.075)	(0.075)
Gaps in schedule	0.619**	0.572*	1.288**	1.349**
	(0.240)	(0.241)	(0.422)	(0.416)
Employee past absenteeism	0.036+		0.067	
	(0.020)		(0.041)	
Patient prior complaints		0.020		0.311**
		(0.026)		(0.046)
Patient seniority		0.004		-0.089**
		(0.010)		(0.024)
Employee experience	0.094**	0.089**	-0.115**	-0.141**
	(0.026)	(0.026)	(0.041)	(0.040)
Employee first week	-	1.457**	-	0.657+
		(0.198)		(0.388)
Employee availability	-0.006+	-0.005	0.002	-0.001
	(0.004)	(0.004)	(0.007)	(0.007)
Commuting distance	-0.025+	-0.023	0.024	0.027
	(0.015)	(0.015)	(0.030)	(0.030)
Employee patient variety	0.016*	0.015*	0.078**	0.079**
	(0.007)	(0.007)	(0.011)	(0.011)
Employee task variety	-0.003	-0.008	0.076+	0.071+
	(0.024)	(0.024)	(0.044)	(0.043)
Employee hours worked	-0.019**	-0.019**	-0.000	-0.001
	(0.003)	(0.003)	(0.005)	(0.005)
Employee visits	-0.020**	-0.019**	-0.029**	-0.028**
	(0.006)	(0.006)	(0.010)	(0.010)
Residuals _ Schedule var.	-0.004*	-0.003+	-0.003	-0.002
	(0.001)	(0.001)	(0.003)	(0.003)
Residuals _ Gaps in schedule	-0.258+	-0.235+	-0.500*	-0.520*
	(0.132)	(0.132)	(0.223)	(0.219)
Employee fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	68,138	66,640	51,192	50,561
Number of employees	786	784	505	507

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

Table A3: Employee Schedule's Influence on Employee Absenteeism and Patient Complaints (Patient Density Subsample)

	Low patient density		High patient density	
	Employee Absenteeism	Patient Complaints	Employee Absenteeism	Patient Complaints
Variables	(1)	(2)	(3)	(4)
Schedule variability	0.546**	0.377**	0.569**	0.384**
	(0.045)	(0.108)	(0.049)	(0.095)
Gaps in schedule	0.395	0.677	0.779**	1.713**
	(0.322)	(0.633)	(0.297)	(0.575)
Employee experience	0.061	-0.146*	0.052	-0.095+
	(0.037)	(0.060)	(0.033)	(0.057)
Employee first week	1.419**	-1.738	1.175**	1.074*
	(0.253)	(1.084)	(0.296)	(0.459)
Employee availability	-0.010+	0.016	-0.001	-0.006
	(0.006)	(0.012)	(0.005)	(0.008)
Commuting distance	-0.021	-0.006	-0.037+	0.031
	(0.023)	(0.049)	(0.022)	(0.041)
Employee patient variety	0.014	0.085**	0.027**	0.080**
	(0.010)	(0.018)	(0.009)	(0.013)
Employee task variety	0.043	0.113	-0.036	0.025
	(0.035)	(0.069)	(0.033)	(0.051)
Employee hours worked	-0.013**	0.001	-0.028**	-0.003
	(0.003)	(0.006)	(0.004)	(0.006)
Employee visits	-0.017*	-0.021	-0.023**	-0.033*
	(0.009)	(0.015)	(0.008)	(0.013)
Residuals _ Schedule variability	-0.004*	-0.000	-0.003+	-0.001
	(0.002)	(0.004)	(0.002)	(0.003)
Residuals _ Gaps in schedule	-0.250	-0.267	-0.266+	-0.655*
	(0.181)	(0.333)	(0.161)	(0.294)
Employee fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	30,380	17,972	34,686	24,216
Number of employees	613	315	598	368

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

Table A4: First stage OLS regression of Gaps in Schedule and Schedule Variability

Variables	Dependent variable: Schedule Variability (1)	Dependent variable: Gaps in Schedule (2)
Schedule variability_instrument	0.434**	-0.001*
	(0.035)	(0.001)
Gaps in schedule_instrument	-5.928**	0.198**
	(1.918)	(0.044)
Employee experience	-1.190**	0.006
	(0.217)	(0.007)
Employee first week	-25.175**	0.013
	(1.049)	(0.029)
Employee availability	0.090*	0.001
	(0.041)	(0.001)
Commuting distance	0.483**	0.027**
	(0.143)	(0.005)
Employee patient variety	0.753**	-0.026**
	(0.083)	(0.003)
Employee task variety	1.348**	0.085**
	(0.273)	(0.006)
Employee hours worked	0.324**	-0.003**
	(0.045)	(0.001)
Employee visits	-0.315**	0.038**
	(0.062)	(0.002)
Constant	10.238**	-0.025
	(1.688)	(0.047)
Employee fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	75,078	75,078
Number of employees	1,026	1,026
R squared	0.44	0.58
F test	120.36**	50.50**

Note: Models are Ordinary least square regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

Table A5: Employee Schedules' Influence on Employee Absenteeism and Patient Complaints

	Dependent variable: Employee Absenteeism		Dependent variable: Patient Complaints	
Variables	(1)	(2)	(3)	(4)
Schedule variability _ within week	4.331**		1.573+	
	(0.694)		(0.833)	
Gaps in schedule _ length		0.123*		0.220*
		(0.048)		(0.090)
Schedule variability		0.557**		0.441**
		(0.035)		(0.071)
Gaps in schedule	0.697**		1.491**	
	(0.247)		(0.389)	
Employee experience	0.051*	0.089**	-0.149**	-0.122**
	(0.025)	(0.026)	(0.031)	(0.040)
Employee first week	-0.222	1.463**	-0.699**	0.666+
	(0.166)	(0.196)	(0.254)	(0.381)
Employee availability	-0.007+	-0.007+	0.000	0.001
	(0.004)	(0.004)	(0.006)	(0.007)
Commuting distance	-0.020	-0.021	0.030	0.036
	(0.016)	(0.015)	(0.030)	(0.029)
Employee patient variety	0.026**	0.011+	0.089**	0.066**
	(0.007)	(0.006)	(0.009)	(0.010)
Employee task variety	0.026	0.024	0.095*	0.125**
	(0.025)	(0.021)	(0.038)	(0.039)
Employee hours worked	-0.027**	-0.019**	-0.002	-0.002
	(0.004)	(0.003)	(0.004)	(0.005)
Employee visits	-0.021**	-0.012**	-0.032**	-0.009
	(0.006)	(0.004)	(0.009)	(0.006)
Residuals _ Schedule variability	0.014**	-0.004*	0.010**	-0.003
	(0.001)	(0.001)	(0.001)	(0.003)
Residuals _ Gaps in schedule	-0.314*	-0.019	-0.585**	0.003
	(0.134)	(0.046)	(0.202)	(0.095)
Employee fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	68,991	68,991	51,779	51,779
Number of employees	796	796	509	509

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

Table A6: Employee Schedules' Influence on Employee Absenteeism and Patient Complaints (alternative instrumental variables)

Variables	Dependent variable: Employee Absenteeism (1)	Dependent variable: Patient Complaints (2)
Schedule variability	0.555**	0.471**
	(0.036)	(0.076)
Gaps in schedule	0.680**	1.390**
	(0.245)	(0.426)
Employee experience	0.082**	-0.131**
	(0.026)	(0.041)
Employee first week	1.377**	0.564
	(0.207)	(0.469)
Employee availability	-0.006+	0.001
	(0.004)	(0.007)
Commuting distance	-0.025	0.019
	(0.016)	(0.031)
Employee patient variety	0.017*	0.080**
	(0.007)	(0.012)
Employee task variety	0.000	0.071
	(0.025)	(0.046)
Employee hours worked	-0.018**	-0.002
	(0.003)	(0.005)
Employee visits	-0.022**	-0.030**
	(0.006)	(0.010)
Residuals _ Schedule variability	-0.003*	-0.004
	(0.001)	(0.003)
Residuals _ Gaps in schedule	-0.302*	-0.586**
	(0.134)	(0.223)
Employee fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	63,871	47,727
Number of employees	781	494

Note: Models are Poisson regression with robust standard errors clustered by employee. **p<0.01, *p<0.05 and +p<0.10

APPENDIX B: Essay 2

Table B1: First Stage of IV Approach (H1 and H4)

	Subcontracted Labor Mix (H1)	Low-skilled Subcontracted Labor Mix (H4)	High-skilled Subcontracted Labor Mix (H4)
Dep. Average Sub. Labor Mix	-74.278**		
	(3.575)		
Dep. Average Low-skilled Labor Mix		-79.153**	4.587**
		(1.153)	(0.714)
Dep. Average High-skilled Labor Mix		1.475**	-75.629**
		(0.175)	(4.237)
Team Size	0.028**	0.003	0.025**
	(0.008)	(0.002)	(0.006)
Scope Changes	-0.000	-0.003**	0.003
	(0.003)	(0.001)	(0.003)
Team Familiarity	-0.000	-0.009**	0.009
	(0.020)	(0.003)	(0.031)
Individual Average Experience	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)
Individual Average Expertise	0.008	0.001	0.007
	(0.009)	(0.004)	(0.009)
Client familiarity	0.005**	0.003**	0.003**
	(0.001)	(0.000)	(0.000)
Project Manager Role Experience	-0.001	0.003**	-0.004
	(0.002)	(0.001)	(0.003)
Multi-team Membership	0.004**	0.003*	0.002
	(0.002)	(0.001)	(0.004)
Project Duration	-0.001	-0.001	-0.000
	(0.001)	(0.000)	(0.000)
Project Type	-0.009	0.004	-0.012
	(0.012)	(0.007)	(0.014)
Constant	11.494**	1.648**	9.837**
	(0.598)	(0.036)	(0.607)
Observations (N)	254	254	254
Start Year FE	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes
Overall R^2	0.910	0.945	0.881

Models are first stage of a 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively. Note that some coefficients of the control variables are close to zero, as their values are too high compared to those of the labor mixes

Table B2: First Stage of IV Approach (H2 and H3)

	Sub. Labor Mix (H2)	Sub. Labor Mix x Team Size (H2)	Sub. Labor Mix (H3)	Sub. Labor Mix x Scope Changes (H3)
Dep. Average Sub. Labor Mix	-77.236**	-32.311**	-77.236**	-32.311**
	(7.494)	(11.040)	(7.494)	(11.040)
Predicted Values x Team Size	-0.015	0.830**		
	(0.019)	(0.018)		
Predicted Values x Scope Changes			0.185**	1.134**
			(0.027)	(0.008)
Team Size	0.033**	0.057*	0.029**	0.002**
	(0.005)	(0.024)	(0.007)	(0.001)
Scope Changes	-0.000	0.003	-0.039**	-0.037**
	(0.004)	(0.014)	(0.006)	(0.005)
Team Familiarity	-0.001	0.036	-0.011	0.013**
	(0.026)	(0.048)	(0.021)	(0.003)
Individual Average Experience	-0.000**	-0.000	-0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Individual Average Expertise	0.007	-0.021	0.005	0.001
	(0.010)	(0.016)	(0.009)	(0.001)
Client Familiarity	0.005**	0.004*	0.005**	-0.001**
	(0.000)	(0.002)	(0.001)	(0.000)
Project Manager Role Experience	-0.000	0.009*	0.000	-0.001
	(0.002)	(0.005)	(0.003)	(0.001)
Multi-team Membership	0.004*	-0.004	0.005*	-0.001
	(0.002)	(0.003)	(0.002)	(0.001)
Project Duration	-0.001	-0.001	-0.001	0.000
	(0.001)	(0.002)	(0.001)	(0.000)
Project Type	-0.011	0.003	-0.005	0.012+
	(0.007)	(0.014)	(0.008)	(0.007)
Constant	11.947**	5.002**	11.099**	0.257**
	(1.201)	(1.800)	(0.652)	(0.027)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.910	0.922	0.915	0.974

Models are first stage of a 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively. Note that some coefficients of the control variables are close to zero, as their values are too high compared to those of the labor mixes

Table B3: IV Regression of Subcontracted Labor Mix (number of employees) on Project Margin

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	154.935**	-46.708**	151.982**	
	(22.207)	(8.444)	(20.369)	
Low-skilled Subcontracted Labor Mix				186.112**
				(36.631)
High-skilled Subcontracted Labor Mix				146.016**
				(20.976)
Subcontracted Labor Mix x Team Size		95.826**		
		(6.896)		
Sub. Labor Mix x Scope Changes			-13.889+	
			(7.315)	
Team Size	-95.358**	-119.354**	-94.859**	-95.740**
	(14.935)	(16.219)	(12.812)	(16.874)
Scope Changes	28.583**	30.351**	31.094**	28.809**
	(5.498)	(4.942)	(5.546)	(5.158)
Team Familiarity	50.255**	50.825**	50.343**	50.646**
	(10.920)	(9.008)	(7.645)	(10.598)
Individual Average Experience	0.314**	0.349**	0.315**	0.315**
	(0.090)	(0.070)	(0.093)	(0.079)
Individual Average Expertise	22.260**	24.373**	22.852**	19.802**
	(5.498)	(5.765)	(4.753)	(4.347)
Client Familiarity	0.748	-0.420	0.820	0.582
	(0.499)	(0.426)	(0.513)	(0.465)
Project Manager Role Experience	-18.650**	-20.954**	-18.652**	-18.946**
	(5.338)	(4.954)	(4.852)	(5.876)
Multi-team Membership	1.033	1.362	1.082	0.918
	(1.897)	(1.879)	(1.403)	(1.463)
Project Duration	2.660**	2.674**	2.654**	2.666**
	(0.624)	(0.571)	(0.532)	(0.680)
Project Type	67.282*	74.131**	67.214*	68.432*
	(30.060)	(27.574)	(30.473)	(34.073)
Constant	54.188**	94.749**	50.858**	61.724**
	(14.059)	(15.486)	(9.208)	(14.977)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.140	0.145	0.141	0.141
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B4: IV Regression of Subcontracted Labor Mix on Project Margin

	(1)
Low-skilled Subcontracted Labor Mix	99.644**
	(8.136)
High-skilled Subcontracted Labor Mix	49.421**
	(13.963)
Team Size	-97.375**
	(16.057)
Scope Changes	28.219**
	(5.398)
Team Familiarity	40.178**
	(8.135)
Individual Average Experience	0.237**
	(0.087)
Individual Average Expertise	25.170**
	(7.101)
Client Familiarity	0.859+
	(0.453)
Project Manager Role Experience	-17.570**
	(5.125)
Multi-team Membership	0.058
	(1.679)
Project Duration	2.878**
	(0.655)
Project Type	60.874+
	(32.179)
Constant	75.145**
	(12.221)
Observations (N)	254
Start Year FE	Yes
Project Department FE	Yes
Overall R^2	0.131

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively

Table B5: IV Regression using the Linear Form of Team Size

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	58.468**	-47.087	79.685**	
	(16.916)	(36.920)	(22.473)	
Low-skilled Subcontracted Labor Mix				117.973**
				(27.509)
High-skilled Subcontracted Labor Mix				32.068**
				(11.157)
Subcontracted Labor Mix x Team Size		4.761*		
		(2.034)		
Sub. Labor Mix x Scope Changes			-89.219**	
			(16.059)	
Team Size	-3.132*	-4.395	-3.176**	-3.236*
	(1.265)	(2.734)	(1.201)	(1.520)
Scope Changes	22.863*	25.836*	40.570**	23.454*
	(10.170)	(11.660)	(7.556)	(10.534)
Team Familiarity	30.739*	27.402+	37.460**	31.539+
	(15.152)	(16.121)	(14.108)	(17.812)
Individual Average Experience	0.299**	0.321**	0.292*	0.288**
	(0.101)	(0.050)	(0.132)	(0.108)
Individual Average Expertise	13.721+	19.327	15.408*	7.676
	(7.748)	(13.413)	(7.364)	(8.275)
Client Familiarity	1.091*	0.771	0.932	0.596
	(0.436)	(1.184)	(0.593)	(0.673)
Project Manager Role Experience	-17.896**	-20.377**	-18.631**	-19.160**
	(5.197)	(5.809)	(5.136)	(5.811)
Multi-team Membership	2.928	5.066**	2.280	2.902
	(1.918)	(1.341)	(2.178)	(2.565)
Project Duration	2.802**	3.017*	2.805**	2.943**
	(0.774)	(1.184)	(0.727)	(0.926)
Project Type	32.142	37.039	30.835	37.712
	(31.335)	(31.822)	(28.112)	(33.320)
Constant	-64.404**	-72.279**	-69.897**	-42.592**
	(11.649)	(13.131)	(15.103)	(15.407)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.129	0.147	0.130	0.131
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B6: IV Regression with Learning-Curve Model

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	0.026**	-0.102**	0.034**	
	(0.008)	(0.034)	(0.011)	
Low-skilled Subcontracted Labor Mix				0.039**
				(0.006)
High-skilled Subcontracted Labor Mix				0.020*
				(0.009)
Subcontracted Labor Mix x Team Size		0.047**		
		(0.015)		
Subcontracted Labor Mix x Scope Changes			-0.032**	
			(0.008)	
Team Size	-0.039**	-0.051**	-0.039**	-0.039**
	(0.009)	(0.014)	(0.009)	(0.009)
Scope Changes	0.007**	0.008**	0.013**	0.007*
	(0.002)	(0.003)	(0.002)	(0.003)
Team Familiarity	0.017**	0.015**	0.019**	0.017**
	(0.004)	(0.003)	(0.004)	(0.004)
Individual Average Experience	0.002	0.003**	0.002*	0.002+
	(0.001)	(0.001)	(0.001)	(0.001)
Individual Average Expertise	0.031**	0.044**	0.034**	0.028**
	(0.006)	(0.011)	(0.006)	(0.005)
Client Familiarity	0.004+	0.003	0.004+	0.004+
	(0.002)	(0.002)	(0.002)	(0.002)
Project Manager Role Experience	-0.031*	-0.037*	-0.032*	-0.032**
	(0.012)	(0.016)	(0.012)	(0.012)
Multi-team Membership	0.001	0.002*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Project Duration	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Project Type	0.023+	0.027+	0.023+	0.025+
	(0.014)	(0.016)	(0.013)	(0.014)
Constant	8.463**	8.469**	8.459**	8.466**
	(0.012)	(0.013)	(0.011)	(0.012)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.112	0.120	0.113	0.113
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B7: IV Regression of Subcontracted Labor Mix on Project Margin with Geographic Area Fixed Effects

	(1)	**(2)**	**(3)**	**(4)**
Subcontracted Labor Mix	52.245**	-249.887**	69.056**	
	(12.614)	(65.493)	(19.244)	
Low-skilled Subcontracted Labor Mix				87.160**
				(8.487)
High-skilled Subcontracted Labor Mix				37.588**
				(12.776)
Subcontracted Labor Mix x Team Size		113.094**		
		(27.274)		
Sub. Labor Mix x Scope Changes			-68.953**	
			(16.879)	
Team Size	-109.592**	-138.876**	-109.856**	-109.698**
	(20.616)	(30.793)	(16.211)	(18.331)
Scope Changes	33.633**	35.879**	47.156**	33.659**
	(3.014)	(4.177)	(3.023)	(3.058)
Team Familiarity	29.468**	28.083**	34.909**	29.970**
	(3.353)	(1.798)	(2.277)	(2.850)
Individual Average Experience	0.208**	0.236**	0.202**	0.207**
	(0.039)	(0.033)	(0.050)	(0.027)
Individual Average Expertise	37.062**	46.632**	37.919**	33.169**
	(7.358)	(10.906)	(6.252)	(6.178)
Client Familiarity	1.228*	0.151	1.126*	0.961
	(0.602)	(0.559)	(0.468)	(0.616)
Project Manager Role Experience	-20.474**	-24.807**	-21.024**	-21.183**
	(7.805)	(9.019)	(6.428)	(6.796)
Multi-team Membership	-0.011	1.784**	-0.370	0.120
	(0.401)	(0.590)	(0.417)	(0.537)
Project Duration	2.783**	2.955**	2.780**	2.816**
	(0.871)	(0.908)	(0.664)	(0.747)
Project Type	63.371+	73.431+	62.745+	67.155*
	(34.029)	(38.369)	(32.056)	(32.719)
Constant	75.264**	101.477**	71.723**	87.689**
	(18.313)	(26.207)	(17.770)	(18.340)
Observations (N)	254	254	254	254
Geographic Area FE	Yes	Yes	Yes	Yes
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.131	0.140	0.132	0.132
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS fixed-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B8: IV Regression of Subcontracted Labor Mix on Project Margin (standard errors clustered by Geographic Area and Client)

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	58.356**	-233.911*	76.361*	
	(20.737)	(95.839)	(31.905)	
Low-skilled Subcontracted Labor Mix				96.707**
				(15.378)
High-skilled Subcontracted Labor Mix				41.268*
				(20.042)
Subcontracted Labor Mix x Team Size		109.062**		
		(41.549)		
Sub. Labor Mix x Scope Changes			-75.816**	
			(26.757)	
Team Size	-97.891**	-125.650**	-98.408**	-98.639**
	(33.093)	(47.632)	(33.098)	(33.240)
Scope Changes	27.636**	29.607**	42.711**	28.062**
	(3.734)	(3.556)	(1.094)	(3.400)
Team Familiarity	39.461**	38.423**	45.351**	40.314**
	(0.638)	(5.259)	(2.903)	(3.703)
Individual Average Experience	0.248**	0.279**	0.242**	0.241**
	(0.068)	(0.070)	(0.071)	(0.064)
Individual Average Expertise	30.092**	39.588*	31.464**	26.015*
	(11.196)	(17.519)	(11.567)	(11.208)
Client Familiarity	1.026	-0.006	0.897	0.719
	(1.025)	(0.763)	(0.974)	(1.064)
Project Manager Role Experience	-16.676+	-20.581+	-17.298+	-17.490*
	(9.142)	(11.380)	(9.421)	(8.791)
Multi-team Membership	0.076	1.704	-0.464	0.089
	(1.271)	(1.628)	(1.323)	(1.484)
Project Duration	2.852*	3.028*	2.834*	2.901**
	(1.132)	(1.269)	(1.116)	(1.125)
Project Type	59.031	69.048	58.253	63.218
	(45.699)	(49.653)	(44.735)	(44.488)
Constant	58.063+	82.676*	54.336	73.671*
	(34.613)	(41.557)	(34.480)	(33.361)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.133	0.141	0.134	0.134
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with clustered standard errors by Geographic Area and Client. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B9: IV Regression of Subcontracted Labor Mix on Project Margin with Controls for Billable Hours

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	70.080**	-226.334**	89.870**	
	(19.566)	(55.672)	(23.380)	
Low-skilled Subcontracted Labor Mix				108.113**
				(15.106)
High-skilled Subcontracted Labor Mix				52.818**
				(17.703)
Subcontracted Labor Mix x Team Size		110.366**		
		(25.439)		
Sub. Labor Mix x Scope Changes			-81.401**	
			(16.678)	
Team size	-59.260**	-89.494**	-58.305**	-60.725**
	(6.218)	(16.632)	(5.939)	(6.165)
Scope Changes	29.114**	31.027**	45.358**	29.512**
	(5.466)	(4.339)	(3.770)	(4.866)
Billable Hours	-26.322**	-24.862**	-27.351**	-25.831**
	(7.884)	(7.812)	(6.903)	(8.071)
Team Familiarity	55.035**	53.120**	61.968**	55.595**
	(9.995)	(13.053)	(9.252)	(10.461)
Individual Average Experience	0.312**	0.340**	0.308**	0.304**
	(0.104)	(0.094)	(0.087)	(0.098)
Individual Average Expertise	23.169**	33.162**	24.371**	19.231**
	(5.498)	(8.898)	(4.593)	(5.340)
Client Familiarity	1.421**	0.355	1.298**	1.108*
	(0.455)	(0.547)	(0.474)	(0.527)
Project Manager Role Experience	-15.962**	-19.953**	-16.601**	-16.787**
	(4.505)	(6.774)	(4.814)	(4.456)
Multi-team Membership	-3.713	-1.855	-4.441+	-3.630
	(2.677)	(2.992)	(2.378)	(2.647)
Project Duration	3.308**	3.462**	3.308**	3.349**
	(0.802)	(0.959)	(0.743)	(0.822)
Project Type	68.407+	78.024*	67.939*	72.409*
	(35.206)	(37.020)	(32.074)	(34.094)
Constant	163.590**	182.644**	163.717**	177.193**
	(45.426)	(52.771)	(41.381)	(46.027)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.138	0.147	0.140	0.140
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B10: IV Regression for Overfitting (all non-significant control variables removed)

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	58.376**	-231.294**	76.184**	
	(11.802)	(56.165)	(22.877)	
Low-skilled Subcontracted Labor Mix				102.811**
				(9.289)
High-skilled Subcontracted Labor Mix				43.400**
				(13.414)
Subcontracted Labor Mix x Team Size		107.977**		
		(23.958)		
Sub. Labor Mix x Scope Changes			-75.816**	
			(17.863)	
Team Size	-97.951**	-126.604**	-98.038**	-99.291**
	(14.934)	(25.504)	(16.865)	(14.316)
Scope Changes	27.658**	30.096**	42.533**	28.007**
	(3.166)	(4.438)	(3.189)	(3.856)
Team Familiarity	39.718**	44.352**	43.773**	39.666**
	(5.784)	(6.822)	(6.675)	(6.975)
Individual Average Experience	0.248**	0.278**	0.241**	0.251**
	(0.055)	(0.067)	(0.081)	(0.063)
Individual Average Expertise	30.142**	40.283**	31.157**	27.208**
	(5.428)	(10.543)	(5.290)	(6.361)
Client Familiarity	1.019*	-	0.940+	-
	(0.487)		(0.496)	
Project Manager Role Experience	-16.672**	-20.497**	-17.324**	-17.291**
	(5.322)	(7.120)	(5.998)	(4.560)
Project Duration	2.854**	3.068**	2.823**	2.911**
	(0.651)	(0.749)	(0.557)	(0.642)
Project Type	59.031*	68.640*	58.255+	64.906*
	(27.069)	(32.804)	(34.154)	(26.360)
Constant	58.371**	90.256**	52.473**	70.712**
	-97.951**	-126.604**	-98.038**	-99.291**
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.133	0.142	0.34	0.134
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B11: IV Regression for Overfitting (all control variables removed)

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	58.967**	-138.191**	73.863**	
	(20.602)	(20.921)	(23.040)	
Low-skilled Subcontracted Labor Mix				75.518**
				(13.060)
High-skilled Subcontracted Labor Mix				49.074**
				(18.884)
Subcontracted Labor Mix x Team Size		72.292**		
		(13.597)		
Sub. Labor Mix x Scope Changes			-66.063**	
			(19.099)	
Team Size	-56.080**	-71.882**	-56.571**	-56.581**
	(14.578)	(17.776)	(11.527)	(11.709)
Scope Changes	40.954**	42.634**	53.478**	41.628**
	(3.045)	(2.895)	(6.498)	(3.074)
Constant	171.929**	212.307**	169.621**	174.436**
	(32.025)	(37.912)	(26.602)	(27.049)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.089	0.092	0.090	0.090
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B12: IV Regression of Subcontracted Labor Mix on Project Margin (alternative instrument)

	(1)	(2)
Subcontracted Labor Mix	39.442**	114.597**
	(9.376)	(42.676)
Team Size	-97.063**	-96.175**
	(14.242)	(27.271)
Scope Changes	27.009**	32.447**
	(5.311)	(5.980)
Team Familiarity	36.138**	67.304**
	(8.942)	(10.549)
Individual Average Experience	0.239**	0.450*
	(0.092)	(0.211)
Individual Average Expertise	32.937**	24.043+
	(6.852)	(14.127)
Client Familiarity	1.409**	-0.110
	(0.457)	(0.639)
Project Manager Role Experience	-16.303**	-16.865*
	(4.841)	(6.613)
Multi-team Membership	0.343	-5.258+
	(1.996)	(3.155)
Project Duration	2.816**	2.713**
	(0.622)	(0.866)
Project Type	59.632*	59.653
	(28.549)	(53.055)
Constant	49.526**	61.345**
	(14.292)	(17.085)
Observations (N)	254	254
Start Year FE	Yes	Yes
Project Department FE	Yes	Yes
Overall R^2	0.133	0.103

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. Model 1 uses *firm average subcontracted labor mix* as an instrument *for subcontracted labor mix* and Model 2 uses *firm average subcontracted labor mix_non overlapping projects*. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B13: IV Regression with Endogenous Subcontracted Labor Mix and Team Size

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	61.199**	-350.560**	79.694**	
	(13.055)	(90.701)	(18.296)	
Low-skilled Subcontracted Labor Mix				108.531**
				(13.543)
High-skilled Subcontracted Labor Mix				40.128**
				(11.688)
Subcontracted Labor Mix x Team Size		153.682**		
		(36.377)		
Sub. Labor Mix x Scope Changes			-77.794**	
			(10.885)	
Team Size	-176.854**	-218.257**	-177.926**	-178.106**
	(23.256)	(52.607)	(28.823)	(34.012)
Scope Changes	31.012**	33.887**	46.504**	31.551**
	(7.413)	(6.142)	(5.677)	(5.581)
Team Familiarity	30.621*	28.901*	36.604**	31.636**
	(12.260)	(13.582)	(12.950)	(11.641)
Individual Average Experience	0.177**	0.219**	0.170*	0.169*
	(0.066)	(0.081)	(0.084)	(0.070)
Individual Average Expertise	61.039**	75.316**	62.658**	56.137**
	(7.046)	(15.917)	(7.173)	(8.102)
Client Familiarity	0.172	-1.306*	0.034	-0.210
	(0.366)	(0.563)	(0.379)	(0.498)
Project Manager Role Experience	-15.268**	-20.729*	-15.896**	-16.266*
	(4.822)	(8.995)	(5.610)	(6.317)
Multi-team Membership	-5.251*	-3.111	-5.842**	-5.258*
	(2.268)	(2.829)	(2.249)	(2.349)
Project Duration	5.380**	5.701**	5.379**	5.451**
	(1.027)	(1.643)	(1.118)	(1.378)
Project Type	57.932*	72.015+	57.126+	63.093+
	(27.238)	(36.890)	(29.372)	(33.488)
Constant	121.728**	158.255**	118.340**	141.252**
	(26.336)	(51.749)	(33.636)	(40.169)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.122	0.130	0.124	0.124
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B14: IV Regression with Endogenous Subcontracted Labor Mix and Scope Changes

	(1)	**(2)**	**(3)**	**(4)**
Subcontracted Labor Mix	60.452**	-235.905**	86.716**	
	(12.495)	(52.766)	(18.784)	
Low-skilled Subcontracted Labor Mix				99.546**
				(9.343)
High-skilled Subcontracted Labor Mix				43.039**
				(13.215)
Subcontracted Labor Mix x Team Size		110.560**		
		(22.815)		
Sub. Labor Mix x Scope Changes			-110.770**	
			(13.435)	
Team Size	-99.110**	-127.206**	-99.842**	-99.875**
	(13.949)	(25.182)	(12.495)	(15.651)
Scope Changes	52.290**	53.403**	73.824**	52.770**
	(8.694)	(8.866)	(8.168)	(9.458)
Team Familiarity	41.547**	40.419**	50.111**	42.420**
	(6.718)	(10.019)	(8.627)	(9.111)
Individual Average Experience	0.209**	0.242**	0.201*	0.202**
	(0.070)	(0.061)	(0.089)	(0.070)
Individual Average Expertise	33.243**	42.756**	35.185**	29.093**
	(6.376)	(8.352)	(5.904)	(7.478)
Client Familiarity	0.983*	-0.061	0.796+	0.670
	(0.417)	(0.464)	(0.445)	(0.599)
Project Manager Role Experience	-16.717**	-20.675**	-17.625**	-17.547**
	(4.941)	(6.681)	(4.859)	(5.492)
Multi-team Membership	-0.596	1.079	-1.372	-0.585
	(1.859)	(1.881)	(2.123)	(2.427)
Project Duration	2.648**	2.834**	2.627**	2.698**
	(0.561)	(0.674)	(0.604)	(0.666)
Project Type	55.274+	65.563*	54.212*	59.534+
	(29.013)	(32.579)	(26.005)	(30.810)
Constant	56.390**	81.401**	50.979**	72.296**
	(14.558)	(23.715)	(14.264)	(16.265)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.130	0.140	0.130	0.137
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B15: IV Regression of Subcontracted Labor Mix on Margin Variation

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	59.779**	-246.286**	78.358**	
	(16.080)	(49.241)	(21.980)	
Low-skilled Subcontracted Labor Mix				96.120**
				(9.610)
High-skilled Subcontracted Labor Mix				43.587**
				(14.255)
Subcontracted Labor Mix x Team Size		114.211**		
		(21.436)		
Sub. Labor Mix x Scope Changes			-78.232**	
			(16.897)	
Team Size	-93.391**	-122.461**	-93.926**	-94.100**
	(17.926)	(24.689)	(17.022)	(13.080)
Scope Changes	25.668**	27.732**	41.224**	26.072**
	(4.271)	(4.934)	(3.747)	(5.486)
Team Familiarity	42.846**	41.758**	48.923**	43.653**
	(5.978)	(5.817)	(6.262)	(6.946)
Individual Average Experience	0.298**	0.330**	0.291**	0.291**
	(0.057)	(0.063)	(0.062)	(0.084)
Individual Average Expertise	31.204**	41.148**	32.620**	27.340**
	(5.248)	(8.744)	(5.736)	(4.404)
Client Familiarity	0.869*	-0.211	0.736+	0.578
	(0.392)	(0.585)	(0.408)	(0.496)
Project Manager Role Experience	-16.910**	-20.999**	-17.551**	-17.681**
	(5.596)	(6.290)	(5.757)	(3.871)
Multi-team Membership	-0.394	1.312	-0.951	-0.381
	(1.116)	(0.996)	(1.293)	(1.382)
Project Duration	2.778**	2.963**	2.761**	2.825**
	(0.585)	(0.544)	(0.591)	(0.493)
Project Type	59.916+	70.405*	59.113+	63.883**
	(31.672)	(32.034)	(31.524)	(23.724)
Constant	29.549	55.324*	25.704	44.339**
	(18.105)	(22.523)	(16.584)	(13.399)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.126	0.136	0.127	0.127
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B16: IV Regression of Subcontracted Labor Mix on Project Margin (alternative for low (high)-skilled subcontracted workers)

	(1)
Low-skilled Subcontracted Labor Mix	227.903**
	(35.033)
High-skilled Subcontracted Labor Mix	107.384*
	(43.441)
Team Size	-122.659**
	(21.290)
Scope Changes	26.080**
	(5.567)
Team Familiarity	88.300**
	(12.861)
Individual Average Experience	-0.171
	(0.210)
Individual Average Expertise	3.072
	(7.859)
Client Familiarity	-0.236
	(0.770)
Project Manager Role Experience	-19.614**
	(7.352)
Multi-team Membership	-6.328**
	(1.977)
Project Duration	3.534**
	(1.048)
Project Type	98.037*
	(44.877)
Constant	204.247**
	(56.295)
Observations (N)	218
Start Year FE	Yes
Project Department FE	Yes
Overall R^2	0.145

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively. Note that Low (high)-skilled subcontracted labor mix variables are calculated by dividing the number of hours worked by low (high)-skilled subcontracted workers by the hours worked by all low (high)-skilled team members.

Table B17: IV Regression of Subcontracted Labor Mix on Project Margin with Control for Subcontracted Workers Team Familiarity and Permanent Workers Team Familiarity

	(1)	(2)	(3)	(4)
Subcontracted Labor Mix	51.145**	-252.580**	67.066**	
	(14.215)	(66.875)	(19.236)	
Low-skilled Subcontracted Labor Mix				88.676**
				(8.127)
High-skilled Subcontracted Labor Mix				33.493**
				(11.270)
Subcontracted Labor Mix x Team Size		112.516**		
		(27.236)		
Sub. Labor Mix x Scope Changes			-74.335**	
			(17.223)	
Team Size	-93.399**	-123.111**	-93.954**	-94.486**
	(14.556)	(24.734)	(13.537)	(13.825)
Scope Changes	28.882**	30.849**	43.752**	29.227**
	(5.020)	(6.211)	(4.169)	(4.872)
Subcontracted Workers Team Familiarity	4.759	24.149+	10.075*	9.110*
	(3.536)	(13.578)	(4.578)	(4.631)
Permanent Workers Team Familiarity	9.045**	5.651**	9.342**	8.058**
	(2.152)	(2.147)	(2.190)	(1.846)
Individual Average Experience	0.256**	0.296**	0.250**	0.249**
	(0.093)	(0.087)	(0.093)	(0.077)
Individual Average Expertise	27.566**	36.035**	28.831**	23.319**
	(6.509)	(9.060)	(5.520)	(5.608)
Client Familiarity	1.124*	-0.049	0.972*	0.807+
	(0.490)	(0.600)	(0.454)	(0.467)
Project Manager Role Experience	-17.644**	-21.171**	-18.181**	-18.239**
	(6.021)	(6.424)	(5.756)	(5.077)
Multi-team Membership	1.663	3.568+	1.387	1.914
	(1.745)	(2.091)	(1.631)	(1.464)
Project Duration	2.745**	2.914**	2.717**	2.791**
	(0.721)	(0.737)	(0.644)	(0.590)
Project Type	61.013+	71.753+	60.550+	65.332*
	(33.723)	(37.737)	(31.614)	(30.476)
Constant	61.014**	93.257**	57.911**	77.416**
	(14.455)	(24.276)	(13.997)	(13.256)
Observations (N)	252	252	252	252
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.134	0.144	0.136	0.136
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table B18: IV Regression of Subcontracted Labor Mix on Project Margin with Control for Subcontracted Workers Average Experience and Permanent Workers Average Experience

	(1)	(2)	(3)	(4)	(5)
Subcontracted Labor Mix	54.360*	-332.163+	85.483*		47.084**
	(23.610)	(194.687)	(37.940)		(16.882)
Low-skilled Subcontracted Labor Mix				102.338*	
				(49.164)	
High-skilled Subcontracted Labor Mix				33.450*	
				(13.952)	
Subcontracted Labor Mix x Team Size		140.598+			
		(76.397)			
Sub. Labor Mix x Scope Changes			-127.247+		
			(74.042)		
Team Size	-115.715*	-169.907*	-116.714*	-118.514*	-112.021*
	(54.840)	(81.180)	(48.388)	(57.502)	(54.220)
Scope Changes	38.755**	39.603**	76.030**	39.704**	36.826**
	(12.586)	(12.498)	(27.660)	(11.666)	(13.128)
Team Familiarity	66.688*	53.918*	88.512*	68.908*	72.756*
	(29.098)	(25.994)	(37.439)	(30.013)	(30.692)
Permanent Workers Avg. Experience	0.433*	0.421**	0.393*	0.414*	0.011
	(0.212)	(0.156)	(0.179)	(0.210)	(0.108)
Sub. Workers Avg. Experience	-1.478*	-1.198**	-1.640*	-1.615*	-5.283**
	(0.733)	(0.451)	(0.756)	(0.757)	(1.782)
Permanent Avg. Exp x Sub. Avg. Exp					0.043**
					(0.015)
Individual Average Expertise	47.131	45.814+	51.833+	37.014	55.484
	(30.901)	(26.765)	(28.473)	(25.410)	(38.406)
Client Familiarity	0.388	-0.687	-0.010	0.001	0.680
	(0.900)	(0.651)	(0.520)	(0.663)	(1.031)
Project Manager Role Experience	-19.785	-24.490	-21.242	-20.818	-20.745
	(14.533)	(15.705)	(13.582)	(15.125)	(14.062)
Multi-team Membership	-8.419+	-3.172	-11.602*	-8.689+	-10.169+
	(4.911)	(4.008)	(5.801)	(4.473)	(5.288)
Project Duration	3.256	3.605+	3.192+	3.334	3.233
	(2.048)	(1.966)	(1.797)	(2.093)	(2.082)
Project Type	83.028	90.628	82.368	86.960	79.385
	(63.407)	(67.746)	(55.289)	(67.215)	(59.638)
Constant	69.768*	197.821*	67.810*	119.070**	89.598**
	(27.851)	(88.258)	(28.018)	(32.295)	(26.745)
Observations (N)	197	197	197	197	197
Start Year FE	Yes	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.152	0.169	0.157	0.155	0.157
Wald ch2 (Pr>chi2)	<0.001	<0.001	<0.001	<0.001	<0.01

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

APPENDIX C: Essay 3

Table C1: First stage of 2LS Regression of Frontloading Hours on Project Margin (H1 and H2)

	H1	H2	
	Frontloading _ hours	Frontloading _ hours	Frontloading _ hours x Project Man. Fam.
Dep. Avg. Frontloading _ hours	-61.413**	-57.639**	0.025
	(5.407)	(8.233)	(3.527)
Predicted values x Project Man. Familiarity		0.091	1.118**
		(0.082)	(0.055)
Project Manager Familiarity	0.002	-0.054	-0.075+
	(0.003)	(0.055)	(0.039)
Team Familiarity	0.006	0.007	0.008
	(0.006)	(0.007)	(0.010)
Client Familiarity	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.005)
Individual Average Experience	0.000	-0.002	-0.004*
	(0.001)	(0.002)	(0.002)
Individual Average Expertise	0.003	0.004	0.001
	(0.002)	(0.003)	(0.008)
Team Size	0.012**	0.011**	-0.008**
	(0.003)	(0.003)	(0.003)
Scope Changes	0.001	0.003	-0.003+
	(0.003)	(0.004)	(0.002)
Project Manager Role Experience	0.002	0.001	0.000
	(0.002)	(0.002)	(0.003)
Multi-team Membership	0.003**	0.003	-0.003
	(0.001)	(0.002)	(0.002)
Project Duration	0.000	0.000	0.000**
	(0.000)	(0.000)	(0.000)
Project Type	0.010**	0.009**	-0.005
	(0.002)	(0.002)	(0.004)
Constant	37.642**	35.376**	0.041
	(3.269)	(4.965)	(2.128)
Observations (N)	254	254	254
Start Year FE	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes
Overall R^2	0.825	0.830	0.992

Models are OLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table C2: First stage of 2LS Regression of Frontloading Hours on Project Margin (H3 and H4)

	H3		H4	
	Frontloading _ hours	Frontloading _ hours x Team Fam.	Frontloading _ hours	Frontloading _ hours x Client Fam.
Dep. Avg. Front. _ hours	-75.189**	-11.399**	-57.731**	6.530**
	(5.452)	(3.314)	(2.481)	(1.631)
Predicted values x Team Fam.	-0.143**	0.850**		
	(0.009)	(0.057)		
Predicted values x Client Fam.			0.061	1.188**
			(0.048)	(0.161)
Project Manager Familiarity	0.003	0.001	0.001	-0.001
	(0.003)	(0.007)	(0.002)	(0.013)
Team Familiarity	0.092**	0.100*	0.006	-0.007
	(0.006)	(0.049)	(0.006)	(0.010)
Client Familiarity	-0.001	-0.003+	-0.038	-0.118
	(0.001)	(0.002)	(0.029)	(0.099)
Individual Average Experience	0.002+	0.001	-0.000	0.002
	(0.001)	(0.003)	(0.000)	(0.001)
Individual Average Expertise	-0.001	-0.009**	0.003	0.007
	(0.001)	(0.002)	(0.002)	(0.005)
Team Size	0.014**	0.002	0.010**	-0.009**
	(0.003)	(0.003)	(0.001)	(0.001)
Scope Changes	-0.000	0.001	0.002	0.004
	(0.001)	(0.003)	(0.003)	(0.003)
Project Manager Role Experience	0.003	0.001	0.003	-0.008+
	(0.002)	(0.005)	(0.002)	(0.004)
Multi-team Membership	0.004**	-0.000	0.003**	-0.002*
	(0.001)	(0.002)	(0.001)	(0.001)
Project Duration	0.000	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Project Type	0.010**	-0.003	0.010**	0.000
	(0.003)	(0.002)	(0.003)	(0.006)
Constant	45.960**	6.923**	35.425**	-3.932**
	(3.295)	(2.010)	(1.505)	(0.975)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.832	0.973	0.827	0.992

Models are OLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table C3: 2LS Regression of Frontloading Hours on Project Margin with Project Product Fixed Effects

	(1)	(2)	(3)	(4)
Frontloading _ hours	1,291.339**	2,127.415**	2,475.418**	2,061.734**
	(257.251)	(731.215)	(835.832)	(392.782)
Front. _ hours x Project Man. Fam.		-998.261+		
		(597.584)		
Frontloading _ hours x Team Fam.			-710.875*	
			(332.487)	
Frontloading _ hours x Client Fam.				-629.545**
				(141.525)
Project Manager Familiarity	5.025	629.712	5.644	14.457*
	(10.669)	(388.508)	(14.950)	(6.300)
Team Familiarity	-5.800	-11.513	438.980*	-4.885
	(6.512)	(10.492)	(203.906)	(7.542)
Client Familiarity	20.604	14.356**	14.661	411.967**
	(13.755)	(5.050)	(10.471)	(98.433)
Individual Average Experience	44.366**	73.105**	48.046**	34.304**
	(3.854)	(15.577)	(6.419)	(4.669)
Individual Average Expertise	62.678**	66.445*	59.164*	71.052*
	(21.810)	(33.835)	(23.831)	(31.611)
Team Size	-117.280**	-131.664**	-129.597**	-117.029**
	(9.451)	(10.448)	(5.600)	(3.769)
Scope Changes	39.949**	24.732*	37.359**	49.095**
	(10.277)	(9.776)	(10.515)	(12.398)
Project Manager Role Experience	-86.969+	-76.883	-86.869+	-108.098+
	(48.200)	(47.736)	(51.996)	(58.548)
Multi-team Membership	1.556	8.946	2.150	0.381
	(1.733)	(6.339)	(2.843)	(1.143)
Project Duration	-0.259*	0.440	-0.254	0.030
	(0.108)	(0.892)	(0.230)	(0.431)
Project Type	67.880	79.941	63.449	75.714
	(53.325)	(61.795)	(53.402)	(59.781)
Constant	-804.312**	-1,574.311*	-1,702.421*	-1,295.758**
	(217.744)	(731.428)	(686.565)	(331.638)
Observations (N)	198	198	198	198
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Project Product FE	Yes	Yes	Yes	Yes
Overall R^2	0.453	0.478	0.457	0.477

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area.
+, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table C4: 2LS Regression of Frontloading Hours on Project Margin with Geographic Area Fixed Effects

	(1)	(2)	(3)	(4)
Frontloading _ hours	912.082**	1,523.640**	1,229.307**	1,509.110**
	(284.444)	(486.886)	(472.889)	(451.060)
Frontloading _ hours x Project Man. Fam.		-826.937*		
		(326.141)		
Frontloading _ hours x Team Familiarity			-209.273+	
			(125.663)	
Frontloading _ hours x Client Familiarity				-568.219**
				(212.573)
Project Manager Familiarity	20.978*	533.166*	22.187*	26.520**
	(9.136)	(211.923)	(9.434)	(4.884)
Team Familiarity	19.486**	18.000+	146.460*	12.583
	(7.299)	(9.828)	(68.716)	(7.918)
Client Familiarity	26.682*	25.629**	25.397*	383.158**
	(11.701)	(9.403)	(11.919)	(146.277)
Individual Average Experience	2.964	19.183+	4.733	5.707
	(6.079)	(10.931)	(8.050)	(9.182)
Individual Average Expertise	36.808**	23.776*	29.016**	37.738**
	(10.134)	(10.510)	(5.793)	(10.415)
Team Size	-124.255**	-128.416**	-124.730**	-118.669**
	(33.915)	(38.105)	(34.405)	(34.301)
Scope Changes	41.439**	23.855	39.055**	40.416**
	(9.569)	(22.184)	(14.012)	(14.594)
Project Manager Role Experience	-66.283+	-54.420	-65.435+	-79.328+
	(39.257)	(36.544)	(39.013)	(45.175)
Multi-team Membership	-2.830+	0.480	-2.639	-2.619
	(1.635)	(2.823)	(2.318)	(2.482)
Project Duration	2.451*	2.862*	2.442*	2.548*
	(1.106)	(1.300)	(1.101)	(1.258)
Project Type	57.711	57.644	53.975	54.139
	(54.763)	(54.081)	(52.847)	(52.824)
Constant	-381.377**	-798.423**	-549.840*	-765.888**
	(137.997)	(282.031)	(238.564)	(258.104)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.161	0.188	0.162	0.177

Models are 2SLS fixed-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.

Table C5: : IV Regression for Overfitting (all non-significant control variables removed)

	(1)	(2)	(3)	(4)
Frontloading _ hours	896.121**	1,522.911**	1,298.595**	1,469.339**
	(283.253)	(471.219)	(460.888)	(430.993)
Frontloading _ hours x Project Man. Fam.		-872.196**		
		(310.112)		
Frontloading _ hours x Team Familiarity			-265.640*	
			(119.386)	
Frontloading _ hours x Client Familiarity				-545.610**
				(192.288)
Project Manager Familiarity	14.703**	563.172**	17.184**	19.226*
	(4.925)	(194.965)	(5.123)	(9.124)
Team Familiarity	-0.988	6.832*	160.030*	-10.895**
	(2.519)	(2.739)	(72.651)	(3.410)
Client Familiarity	29.712**	28.708**	27.847*	371.408**
	(11.197)	(9.513)	(11.414)	(132.616)
Individual Average Expertise	29.820**	-	19.661**	29.315**
	(2.754)		(5.208)	(3.414)
Team Size	-121.668**	-122.268**	-122.483**	-116.781**
	(31.680)	(39.093)	(33.247)	(32.717)
Scope Changes	41.014**	-	38.133**	39.853**
	(6.567)		(10.985)	(10.516)
Project Manager Role Experience	2.445*	3.261*	2.451*	2.560*
	(1.102)	(1.340)	(1.141)	(1.248)
Project Duration	-304.477**	-592.653**	-508.132**	-666.297**
	(86.861)	(178.055)	(165.820)	(176.491)
Constant	14.703**	563.172**	17.184**	19.226*
	(4.925)	(194.965)	(5.123)	(9.124)
Observations (N)	254	254	254	254
Start Year FE	Yes	Yes	Yes	Yes
Project Department FE	Yes	Yes	Yes	Yes
Overall R^2	0.141	0.168	0.142	0.152

Models are 2SLS random-effects models with robust standard errors clustered by Geographic Area. +, * and ** denote significance at 10%, 5% and 1% levels respectively.