ERC Working Papers in Economics 25/01

March / 2025

Skill-biased Wage Effects of Domestic Outsourcing

Eren Gürer

Middle East Technical University, Department of Economics, Ankara, Türkiye

E-mail: egurer@metu.edu.tr

Erol Taymaz

Middle East Technical University, Department of Economics, Ankara, Türkiye
E-mail: etaymaz@metu.edu.tr

Skill-biased Wage Effects of Domestic Outsourcing[#]

Eren Gürer[1], Erol Taymaz[2]

3 March 2025

Abstract

This study examines the impact of domestic outsourcing on the wages of workers performing outsourced tasks in Türkiye, using an administrative employee-employer linked dataset. Outsourcing events are identified by tracking worker flows across firms with specific properties. Unlike existing studies, our dataset incorporates buyer-supplier transactions, enabling us to confirm that a relationship between the predecessor and successor firm begins following the outsourcing event. This improves our ability to identify outsourcing events, which we use to explore wage effects of both high-skilled and low-skilled outsourcing. Our findings indicate that low-skilled workers experience wage losses from domestic outsourcing, while high-skilled, professional workers benefit, suggesting that domestic outsourcing may be one of the factors contributing to rising wage inequality.

JEL Codes: J31, J41, L24
Keywords: domestic outsourcing, subcontracting, wage inequality

1. Introduction

Alternative work arrangements, such as domestic outsourcing and subcontracting, have become prominent features of labor markets in recent decades. Large firms, in particular, increasingly contract out non-core tasks—previously performed in-house—to business service firms in order to focus on their core competencies (Weil, 2014; Bernhardt et al., 2016). A growing body of research examines the rise of domestic outsourcing and its wage effects, particularly in low-skilled services such as food preparation, cleaning, security, and logistics (see, e.g., Dube and Kaplan (2010), Goldschmidt and Schmieder (2017) and Dorn et al., (2018) among others, which are summarized below). A common finding in these studies is that outsourced low-skilled workers tend to experience wage losses compared to their non-outsourced counterparts.

The rise of domestic outsourcing coincides with the well-documented increase in wage inequality. Notably, a substantial portion of this increase is attributed to assortative matching—the tendency of low-wage workers to cluster in low-wage firms and high-wage workers in high-wage firms (Card et al., 2013; Song et al., 2019; Godechot et al., 2023). The wage penalty associated with low-skilled outsourcing has

[#]We would like to thank Republic of Türkiye Ministry of Industry and Technology for providing access to Entrepreneurship Information system, the participants at The Conference of Turkish Economic Association 2024, and the seminar participants at the Middle East Technical University and Goethe University Frankfurt for valuable comments and discussions.

[1] Corresponding author. Middle East Technical University, egurer@metu.edu.tr, ORCID ID: 0000-0001-8238-1967
[2] Middle East Technical University, etaymaz@metu.edu.tr, ORCID ID: 0000-0001-7525-6674

led researchers to suggest that the growth of domestic outsourcing may be a contributing factor to the recent rise in between-firm wage inequality. However, the literature has largely remained silent (with a few exceptions) on the wage effects of high-skilled domestic outsourcing, despite evidence indicating a rise in the employment share of high-skilled professional business services (Berlingieri, 2013) and outsourcing of cognitive tasks (Cortes and Salvatori, 2019).

The purpose of this study is to examine the wage effects of domestic outsourcing, with two main contributions relative to the existing literature. As in most of other studies, we face the data limitation of not being able to directly observe workers performing contracted work for other firms. Thus, we follow Goldschmidt and Schmieder (2017) and Dorn et al. (2018) by assuming that workers involved in worker flows with certain characteristics are outsourced. However, unlike previous studies, we can observe monthly transactions between domestic firms and impose an additional buyer-supplier criterion. Specifically, we verify that after a worker flow occurs, the predecessor firm makes a purchase from the successor firm—a transaction that did not happen before the flow. We show that the majority of the worker flows consistent with the set of criteria in Goldschmidt and Schmieder (2017) and Dorn et al. (2018) fail to meet our additional buyer-supplier criterion. This refinement in identifying outsourcing events constitutes our first contribution.

Our second contribution builds on this increased ability to identify outsourcing events by expanding beyond low-skilled outsourcing to explore the wage effects of outsourcing high-skilled services. The tasks performed by high-skilled workers in business service firms can be internally focused. Examples include IT specialists working on internal systems, marketing strategists focused on a firm's own campaigns, or consultants developing proprietary strategies.[3] Without the additional buyer-supplier criterion, it is challenging to classify the movements of high-skilled workers from one firm to a business service firm as domestic outsourcing. By introducing the additional criterion, we increase the likelihood that observed flows reflect true outsourcing events, ensuring a buyer-supplier relationship emerges following the worker flow. This approach allows us to more confidently study the wage effects of high-skilled outsourcing. In doing so, we provide a more comprehensive contribution to the ongoing discussion about the relationship between rising domestic outsourcing and increasing wage inequality.

We use an administrative employee-employer integrated dataset from Türkiye. First, we construct a dataset consisting of quarterly firm-to-firm worker flows during our sample period 2012 to 2022. Flows that meet the characteristics outlined in Goldschmidt and Schmieder (2017) and Dorn et al. (2018), along with the additional buyer-supplier criteria mentioned earlier, are considered outsourcing events. Workers involved in these events form our treatment group. We then apply a coarsened exact matching algorithm to create a control group with characteristics similar to those of the treatment group.

The timing of entry into treatment varies among our treated observations. To account for time and cohort heterogeneities in treatment, as recommended by the "new" differences-in-differences literature, we

[3] Low-skilled workers may also perform maintenance tasks for the business service firm itself, but the proportion of such workers engaged in internal maintenance tasks is likely to be low.

utilize the imputation-based differences-in-differences technique proposed by Borusyak et al. (2024) as our main econometric strategy for identifying wage effects.

We find contrasting effects of outsourcing on the wages of low- and high-skilled workers. Low-skilled workers experience wage losses of up to 10%, while high-skilled workers see wage increases of up to 10%. The wage decrease for low-skilled workers can result from the loss of firm-specific wage premiums. Firms may exclude low-skilled service workers from these premiums by contracting out such services. The rise in wages for high-skilled outsourced workers results from a combination of several factors. High-skilled business service firms may achieve efficiency gains by grouping specialists and enabling them to work on multiple projects simultaneously, leading to economies of scale and/or scope. As a result, these firms can perform services at a lower cost than the predecessor, amplifying profits. Additionally, the high-skilled workers transferred from the predecessor to the successor bring valuable firm-specific human capital, which increases their bargaining power, allowing them to capture part of the profits in the form of higher wages.

Next, we perform heterogeneity analyses with respect to age and gender. While the results hold for all age and gender groups, we find that the aforementioned wage effects are more pronounced for male workers and workers who are less than 40 years old, who in fact represent the majority of our treatment group. Finally, we show that our results are robust against a battery of sensitivity checks with respect to the matching procedure, pre-treatment duration length and turnover following the treatment.

Related literature. Our study is mainly related to the literature studying the implications of domestic outsourcing on the wages of outsourced workers. From a methodological point of view, the closest studies are Goldschmidt and Schmieder (2017) and Dorn et al. (2018). Goldschmidt and Schmieder (2017) is the first to develop a strategy to identify the "on-site" outsourcing events of low-skilled workers (performing food preparation, cleaning, security and logistics) based on the characteristics of worker flows between firms during the sample period. They apply their methodology to German data and find that the outsourced workers experience wage losses by 10-15% relative to non-outsourced workers. Dorn et al. (2018) implement the same methodology for the US and also find negative, but smaller, wage effects of domestic outsourcing.

As mentioned earlier, our contribution relative to Goldschmidt and Schmieder (2017) and Dorn et al. (2018) lies in refining the methodology for identifying outsourcing events and in exploring the wage effects of high-skilled outsourcing. In addition, these studies utilize a dynamic two-way fixed effects approach, which is shown to have some shortcomings (further discussed in Section 3.2) in designs with staggered entry into treatment, in order to estimate the wage effects. We employ a methodology from the new differences-in-differences literature in our estimations.

To the best of our knowledge, Spitze (2022) and Bergeaud et al. (2024) are the only studies attempting to estimate the wage effects of high-skilled domestic outsourcing. Their results align with ours in that the low-skilled workers experience wage losses due to domestic outsourcing while high-skilled workers experience wage increases (though the estimate of Spitze (2022) for high-skilled workers is insignificant). Spitze (2022) uses self-reported outsourcing status from survey data, NLSY1979, and implements fixed effects regressions to explore the wage effects of self-reported outsourcing status. Differently, we leverage an administrative dataset, identify the outsourcing events based on a pre-determined set of criteria and utilize an event-study design to study the wage effects of outsourcing.

The main purpose of Bergeaud et al. (2024) is to show that technological change is one of the drivers of outsourcing expenditures. They explore wage effects in a more suggestive manner, as they acknowledge in their study. For this purpose, they adopt a heuristic approach, assuming that a worker transitioning to a business service industry from any other industry is outsourced. Our analyses differ from Bergeaud et al. (2024) in using a set of more strict criteria for identifying the outsourced workers.

Several other studies examine the wage effects of alternative work arrangements, employing different strategies from those used by Goldschmidt and Schmieder (2017) and Dorn et al. (2018) in various contexts. These studies typically focus on either low-skilled outsourcing or, in some cases, temp agency workers altogether, without differentiating between high- and low-skilled outsourcing. The methodologies and key findings of these studies are briefly summarized below.

Dube and Kaplan (2010) utilize both cross-sectional and panel data from the Current Population Survey (CPS) of the United States, employing fixed effects regressions. Their findings reveal negative wage effects for security guards and janitors employed by business service firms. Katz and Krueger (2018) conduct their own survey as part of the Rand American Life Panel in 2015 and find that workers involved in alternative work arrangements (e.g., temporary help workers) earn lower wages compared to workers with similar characteristics in regular work arrangements.

Bilal and Lhuillier (2021) uses French data and focuses on outsourcing of food, cleaning, security and administrative workers. They employ the AKM specification (Abowd, Kramarz and Margolis, 1999) and find that contractors pay significantly lower wages to these workers than non-contractors. Drenik et al. (2023) leverages the unique information on user firm and temp agency of a worker in the Argentinian administrative data, and, using also the AKM strategy, find that regular workers are paid higher firm-specific pay premium than temp agency workers.

Felix and Wong (2024) uses Brazil's 1993 court ruling that legalized outsourcing as an exogenous shock and estimates negative wage effects of outsourcing for security guards. Guo et al. (2024), using Brazilian data, initially replicate the empirical strategy of Dube and Kaplan (2010) and subsequently apply an event study design. Their analysis reveals a wage penalty associated with domestic outsourcing for both cleaners and security guards, although this penalty appears to be rather small.

The studies of alternative work arrangements may reveal the mechanism through which low-skilled domestic outsourcing has a negative wage effect because the outsourcing (predecessor) and the outsourced (successor) firms are likely to have different work arrangements, in addition to the differences in firm wage premiums.

The rest of this study is structured as follows. Section 2 describes our dataset, provides descriptive trends on the evolution of employment shares and wages in business service industries, and introduces the methodology of identifying the outsourcing events. Section 3 presents the econometric strategy for examining the wage effects of domestic outsourcing and presents the results. Section 4 concludes.

2. Data, Descriptives and Outsourcing Identification

2.1 Data

We utilize an administrative employee-employer integrated dataset from Türkiye called the Entrepreneurship Information System (EIS). This dataset comprises various sub-datasets, each collected by different government institutions, including the Turkish Statistical Institute, the Ministry of Treasury and Finance, the Social Security Institution, the Ministry of Trade, and the Turkish Patent and Trademark Office. The Ministry of Industry and Technology combines these sub-datasets and makes them available to researchers through a single platform, EIS. The sub-datasets, which encompass firm registers, worker registers, buyer-supplier transactions, balance sheet statements, export-import data, patent data, can be linked via unique firm identifiers.

For the purposes of this study, we employ firm and worker registers along with buyer-supplier transactions data. Firm registers contain information on the firm's economic activity at the 4-digit NACE level, the establishment year, and city where the firm's headquarters is located. Worker registers belonging to each firm in each year include data on workers' age, gender, number of days worked and gross salary in a given month.[4] While EIS is available for the years 2006 to 2022, unique worker identifiers are only available as of 2012, limiting the scope of our analyses to the period 2012-22. The number of unique firms in the dataset is approximately 2.8 and 4 million respectively in 2012 and in 2022. The number of unique workers is around 10 and 17 million in the same years. Finally, buyer-supplier transactions data provide monthly records of all transactions exceeding 5000 TL. To get a sense of this figure, note that the monthly gross minimum wage was 940 TL at the end of 2012 and 6471 TL at the end of 2022.

The initial objective is to create a dataset of worker flows to identify outsourcing events during the sample period using worker registers. Our data includes worker observations at the 3rd, 6th, 9th, and 12th months up until 2018, after which workers are observed monthly. For consistency and to reduce the likelihood of observing incomplete flows, we keep worker observations from only the 3rd, 6th, 9th, and 12th months throughout the entire sample period. Some workers hold multiple jobs at different firms in a given month. We drop these observations, as it is not possible to determine which firm the worker is leaving to join another. In the next step, a dataset is created that indicates the number of workers who leave one firm (predecessor) to join another firm (successor) between the same months (e.g., 3rd and 6th month of 2015).

We supplement our worker flow dataset with predecessors' and successors' 4-digit NACE industry codes from firm registers. Firm size is determined by using worker registers themselves, as the total number of workers employed at each firm in the relevant month. Subsequently, we use buyer-supplier transaction data to compute the transactions between predecessor and successor firms over the three months before

[4] The data from the Entrepreneur Information System (EIS) cover only registered (formal) employees and do not include self-employed individuals or public sector employees.

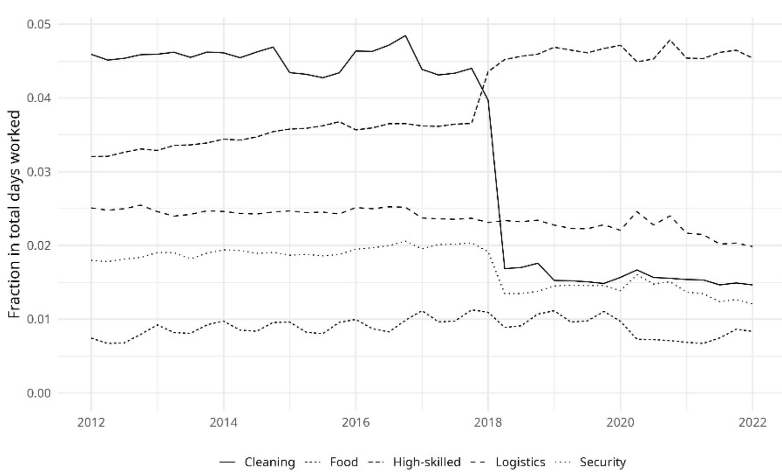
the worker flow and the nine months after it. This completes the preparation of the worker flows dataset that is utilized to determine the events of outsourcing.

2.2 Employment and Wage Trends in Business Service Industries

Before describing the methodology of identifying the outsourcing events, we present some stylized facts regarding the evolution of the employment shares and wages of the main industries of interest using worker and firm register data. As discussed further in the next section, we focus on two groups of business service firms that carry out outsourced tasks. The first industry group, which arguably employs low-skilled workers, performs food preparation, cleaning, security and logistics tasks similar to the classification used by Goldschmidt and Schmieder (2017) and Dorn et al. (2018). The second industry group, by contrast, engages in high-skilled professional business services, including activities like computer programming, engineering, architecture, IT, consultancy, R&D and market research. Appendix provides a complete list of our industry classification that perform outsourceable, business service tasks.

Figure 1 illustrates the employment share trends for the mentioned industries during our sample period. Evidently, the high-skilled business service industries steadily increase their share from slightly above 3% in 2012 to almost 5% in 2022, indicating a trend towards increased reliance on high-skilled business services in the economy.

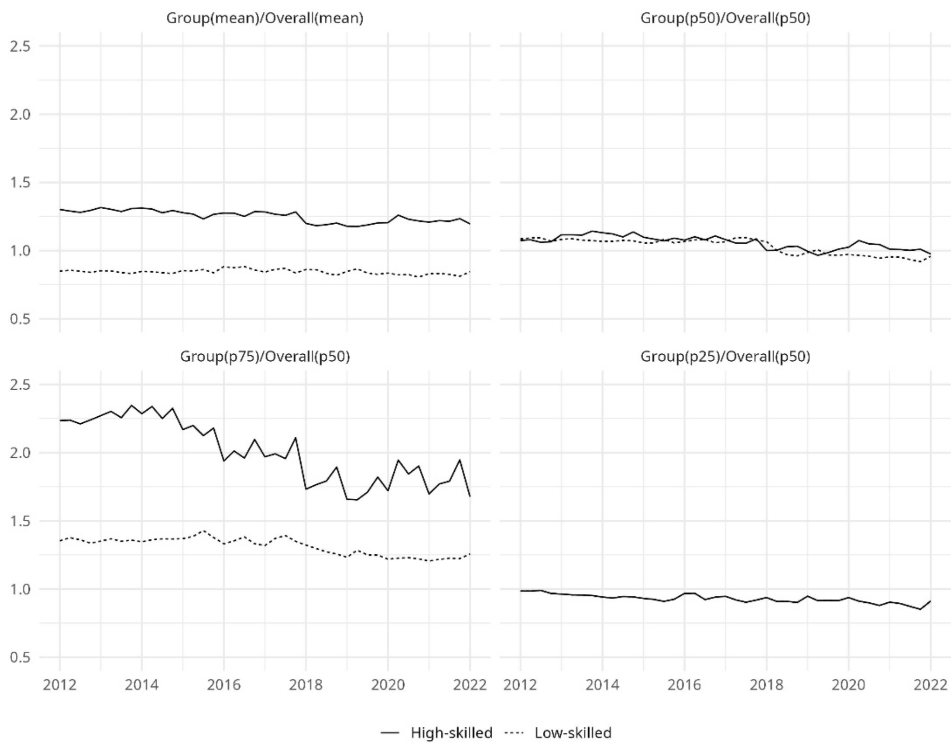
Figure 1. Employment share trends



Notes: Employment share refers to the total number of days worked in an industry, e.g., cleaning industry, relative to the total number of days worked by all the workers in Türkiye. Food, cleaning, security, and logistics industries are collectively referred to as low-skilled business service industries throughout the study.

We break down the trends within the low-skilled industry group by its individual components to highlight an interesting aspect. There is a notable decrease in the share of the cleaning industry, dropping from approximately 4.4% in Q4 2017 to 1.7% in Q2 2018. A similar but less pronounced decrease can be observed also for the security industry. These reductions in the employment shares of cleaning and security services may be attributed to a law that took effect in December 2017, which banned outsourcing for public firms.[5] Following the implementation of this law, workers previously employed by cleaning and security service firms were shifted to the payrolls of the public institutions at which they physically worked. For example, approximately 550.000 workers were employed in the cleaning services industry in Q4 2017. By Q2 2018, only 290.000 of these workers remained in our dataset. This supports our suspicion that nearly half of these workers transitioned to the payrolls of public institutions, such as ministries and universities, which are not included in our firm data. Finally, a subtle reduction in the employment share of food industry is observed right after the start of the COVID-19 crisis.

Figure 2. Wage trends



Notes: This figure illustrates the gross daily wage trends of business service industries. The NACE codes that are utilized to construct low- and high-skilled business service industries are presented in the Appendix.

Trends of the gross daily wages in the low- and high-skilled business service industries are demonstrated in Figure 2. As evident in the upper-left panel, mean wages in high-skilled business services remain relatively stable over the sample period, consistently ranging between 1.2 and 1.3 times the national average wage in Türkiye. In contrast, mean wages in low-skilled business service industries are approximately 0.85 times the national average wage. The upper-right panel, illustrating the median wages in these industries normalized by the median wage in overall Türkiye, shows a more nuanced trend. As expected, median wages in high-skilled business service industries are generally higher than those in low-

[5] Decree Law No. 696, Official Gazette, December 24, 2017, Issue: 30280, Article 127. Available in Turkish at: https://www.resmigazete.gov.tr/eskiler/2017/12/20171224-22.htm

skilled business service industries. On the other hand, this trend is less pronounced compared to the trend observed with mean wages.

An examination of wages across different wage percentiles reveals considerable heterogeneity in wage trends between industries. Wages at the 75th percentile in the high-skilled business service industry (shown in the lower-left panel) are considerably higher than those in the low-skilled business service industry. At the 25th percentile (illustrated in the lower-right panel), however, wages in both high- and low-skilled business service industries align exactly with the minimum wage. This outcome is expected in a developing economy with a high minimum wage take-up rate. Overall, wages below the median in both industries are rather similar, largely due to the influence of the minimum wage. However, wages above the median are significantly higher in high-skilled business service industries compared to low-skilled business service industries.

2.3 Identification of Outsourcing Events

Our dataset, as most datasets, does not include a variable indicating whether a worker is outsourced, i.e., serving another firm through a contractor. Furthermore, being employed by a business service firm does not necessarily mean that a worker is outsourced. While business service firms generally work for clients, workers employed by these firms, in both low-skilled and high-skilled business service industries, do not always perform work for other companies. Workers in business service firms may perform tasks that are internal to the firm, such as supporting administrative operations, marketing and sales activities, providing training or performing the maintenance tasks for the business service firm itself.

This issue is more prominent in high-skilled business service industries, where the tasks performed by workers can be more internally focused. Examples include employees in consulting firms who may develop proprietary strategies or conduct research and analysis for their own firm’s internal use, rather than working on external client projects. Similarly, in IT firms, workers might focus on maintaining and improving the firm's own software and systems, rather than providing outsourced services to other companies. Marketing agencies may employ personnel who work on internal campaigns or brand development for their own firm, rather than working on marketing tasks for external clients.

Therefore, our definition and methodology for identifying outsourcing events closely follows Goldschmidt and Schmieder (2017) and Dorn et al. (2018). Specifically, we focus on identifying domestic outsourcing events within our sample period, as these studies do. This involves a group of workers who were initially employed in-house being transferred to another firm to perform the same tasks. Workers involved in these events are considered our potential treatment group.

Definition. *A domestic outsourcing event is defined as contracting external firms to provide goods and business services that were previously produced in-house, with the contracting firm (predecessor) transferring a group of workers to the contractor firm (successor) for this purpose.*

We use the worker flow dataset, as constructed in Section 2.1, and impose that the worker flows that meet the eight criteria below can be regarded as the events of domestic outsourcing. Notably, one of these criteria (Criterion 7) extends beyond those outlined by Goldschmidt and Schmieder (2017) and Dorn et al. (2018). Using buyer-supplier transaction data, we verify that a relationship between predecessor and successor firms begins following the worker flow. Each criterion, including this additional one, is explained in detail below.

Criterion 1: *The worker flow involves at least 10 employees.*

Criterion 2: *The predecessor firm has a minimum of 50 employees prior to the flow.*

Criterion 3: *The flow constitutes no more than 30% of the predecessor's workforce prior to the flow.*

Criterion 4: *The predecessor's workforce does not decline by more than 50% after the flow.*

Criterion 5: *If the successor is a new firm, the flow accounts for at least 65% of the successor's size (in total hours worked) in the quarter following the flow.*

Criterion 6: *The predecessor and successor operate in different 2-digit NACE industries.*

Criterion 7: *There is no buyer-supplier relationship between the predecessor and successor in the three months preceding the flow, but the predecessor makes at least one purchase from the successor within nine months after the flow.*

Criterion 8: *The successor operates in either low-skilled or high-skilled business service industries.*

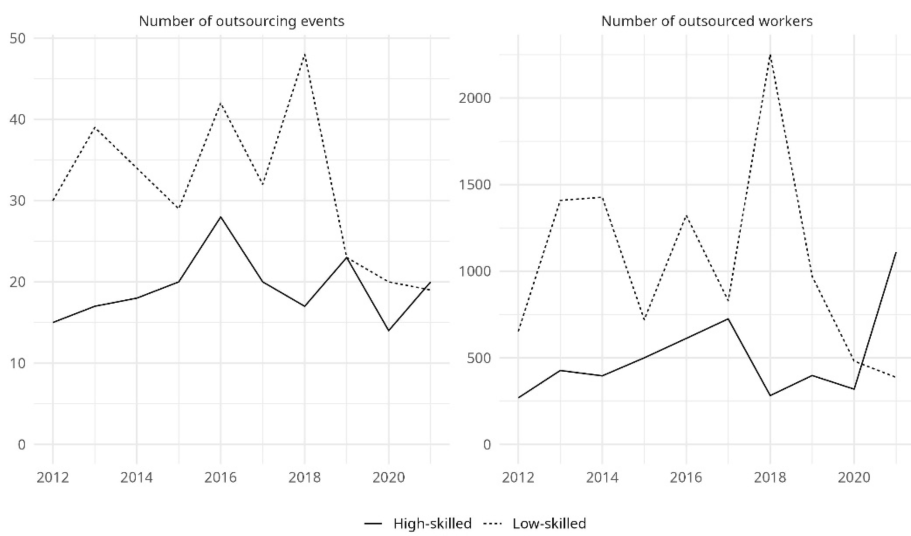
Criteria 1 to 3 ensure that the worker flow is sufficiently large and that the predecessor firm is large enough relative to the flow size to engage in an event of domestic outsourcing. Criteria 3 and 4 aim to reduce the probability that the predecessor firm is undergoing a closure or large-scale layoff. Criterion 5 aims to confirm that, if the successor is a new firm, it is established to take over tasks previously performed by the predecessor. Criterion 6 serves to decrease the probability that the worker flow results from a regular worker turnover, which is particularly common in low-skilled service industries.

Recall that we define outsourcing as transferring a group of workers to another firm to perform the same tasks, but under the payroll of the contracting firm. This arrangement requires the predecessor firm to purchase business services from the successor firm as part of the outsourcing agreement. The buyer-supplier transactions data within EIS provides us with the unique opportunity of confirming that a relationship between the predecessor and the successor firm begins following the worker flow. More specifically, Criterion 7 ensures that there is no buyer-supplier transaction between the two firms prior to the flow but the predecessor makes a purchase from the successor after the flow. Imposing this criteria, we hope to increase the likelihood that the observed flow is an outsourcing event.

Finally, we focus on two sets of outsourced workers. The first set consists of workers that are outsourced from the industry group that provides low-skilled services (such as food preparation, security, cleaning and logistics). The second set comprises workers that are outsourced from the high-skilled business services industry group (performing computer programming, engineering, architecture, IT, consultancy, R&D and market research activities). Criterion 8 ensures that the successor firm operates in one of these two outsourceable business service industry groups, meaning outsourced workers are transferred by their predecessors to either low-skilled or high-skilled industries. Lists of NACE codes that constitute low- and high-skilled business service industries are provided in the Appendix.

Figure 3 shows the evolution of outsourcing events (left panel) identified using these eight criteria, along with the number of workers involved in these events (right panel). Note that the outsourcing events of 2022 cannot be identified since the buyer-supplier transactions data for 2022 was unavailable at the time of this study. On average, we identify 20 high-skilled business service outsourcing events per year, with each year involving approximately 500 workers, except in 2021, when over 1000 workers were involved. For low-skilled services, the number of outsourcing events ranges from 30 to 40 annually until 2017, with 1,000 to 1,500 workers involved. After a small increase in 2018, a decline in the number of identified outsourcing events is observed. This decline can be attributed to a couple of factors. First, the Turkish economy entered a recession in 2019, likely contributing to an overall slowdown in business activity. Second, the COVID-19 crisis may have particularly impacted the low-skilled business service industry, where in-person work is essential.

Figure 3: Number of outsourcing events and outsourced workers

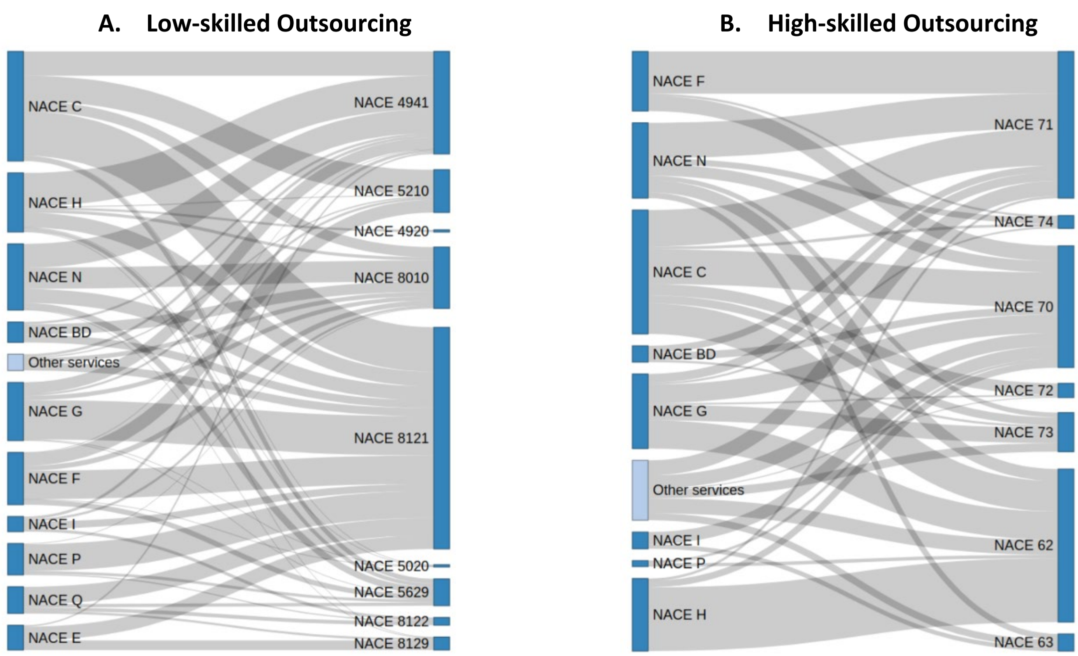


Notes: “Low-skilled” and “High-skilled” respectively refer to outsourcing events where the workers are transferred to a successor company operating in the low- and high-skilled business service industries. Definitions of high- and low-skilled business service industries are provided in the Appendix.

Figure 4 presents Sankey charts depicting low-skilled and high-skilled domestic outsourcing relationships across sectors. The left panel illustrates the number of workers involved in flows that meet criteria 1 to 8, where the successor firm operates in a low-skilled business service industry, representing low-skilled domestic outsourcing. The right panel shows the corresponding figure for cases where the successor firm belongs to a high-skilled business service industry, representing high-skilled domestic outsourcing.

As shown in the left panel, the building cleaning services industry (NACE 8121) accounts for the largest number of outsourced workers among low-skilled business service industries during the sample period, followed by freight transport by road (NACE 4941) and private security activities (NACE 8010). Nearly all industries outsource a number of workers from the building cleaning services industry. Private security activities (NACE 8010) also serve as an outsourcing destination across all industries, though with fewer workers involved compared to the building cleaning services industry. Private security activities industry primarily serves to the administrative and support service activities industry (NACE N). The manufacturing industry (NACE C) emerges as the largest outsourcer of low-skilled workers overall, outsourcing from the freight transport by road and the warehousing and storage industries (NACE 5210), in addition to the building cleaning services industry.

Figure 4: Sectoral flows of workers in low-skilled and high-skilled outsourcing



Notes: Lists of letter NACE codes (predecessors, on the left-hand-side of each panel), and NACE codes constituting low- and high-skilled business service sectors (successors, on the right-hand-side of each panel) can be found in the Appendix. The left panel displays the number of workers engaged in flows that satisfy all the domestic outsourcing criteria (criteria 1 to 8 of Section 2.3), where the successor firm operates in a low-skilled business service industry, indicating low-skilled domestic outsourcing. The right panel presents the corresponding figures for cases where the successor firm is part of a high-skilled business service industry, representing high-skilled domestic outsourcing.

As evident in the right panel, computer programming, consultancy, and related activities (NACE 62), activities of head offices and management consultancy (NACE 70), and architectural and engineering activities (NACE 71) emerge as the largest recipients of outsourced workers in high-skilled outsourcing relationships. Once again, the manufacturing industry stands out as the largest outsourcer, outsourcing a considerable number of workers from all three industries. The construction industry (NACE F) primarily outsources from architectural and engineering activities, while the transportation and storage industry (NACE H) predominantly outsources workers from computer programming, consultancy, and related activities.

2.4 Importance of Buyer-Supplier Criteria and Final Treatment Sample

In this subsection, we briefly discuss the significance of the newly added criteria, Criterion 7, and describe the construction of our final treatment sample. After applying Criteria 1-6 and Criterion 8, the resulting worker flows consist of 161,342 worker observations, as shown in the first column of Table 1. The row of "Buyer-supplier, 0-0" indicates the number of treated observations where no buyer-supplier relationship exists between the predecessor and successor either before or after the worker flow. "Buyer-supplier, 0-1" represents the number of treated observations where no relationship exists prior to the worker flow, but the predecessor makes a purchase from the successor afterward. "Buyer-supplier, 1-0" and "Buyer-supplier, 1-1" follow a similar interpretation.

Evidently, there exists no relationship between the predecessor and the successor before or after the worker flow in a vast majority of the cases ("Buyer-supplier, 0-0"). The second largest group of treated observations fall under the category of "Buyer-supplier, 1-1", i.e., the predecessor makes at least one purchase from the successor both before and after the worker flow. In this case, it is not possible to confirm the start of a relationship between predecessor and successor firms following the worker flow. Our preferred relationship type ("Buyer-supplier, 0-1"), which corresponds directly to our newly introduced Criterion 7, represents less than 10% of the potential treatment group. This highlights the significance of our contribution in refining outsourcing identification. In the rest of this paper, Criterion 7 and "Buyer-supplier, 0-1" criteria are used interchangeably.

Table 1: Treatment sample size

Observation number	**Treated, full**	**Treated, effective**
Total	*161,342*	*27,014*
Low-skilled	115,665	19,510
High-skilled	45,677	7,504
Buyer-supplier, 0-0	112,713	16,955
Buyer-supplier, 0-1 *(Criterion 7)*	15,491	3,187
Buyer-supplier, 1-0	3,689	373
Buyer-supplier, 1-1	29,449	6,499

Notes: The first column indicates the number of treated observations before imposing Criteria 7 and any other sample restrictions. The second column further restricts the sample to observations that have 16 non-missing wage observations around the period of treatment and that are treated only once. "Low-skilled" and "High-skilled" stand for treated observations that are outsourced respectively from a low-skilled and high-skilled business service industry. NACE codes that constitute these industries can be found in the Appendix. "Buyer-supplier, 0-0" indicate the number of treated observations for whom there is no relationship between the predecessor and successor prior to or after the worker flow. "Buyer-supplier, 0-0" represent the number of treated observations for whom there is no relationship between the predecessor and successor prior to the worker flow but the predecessor makes a purchase from the successor after the worker flow. "Buyer-supplier, 1-0" and "Buyer-supplier, 1-1" follow a similar interpretation.

We use a differences-in-differences design, detailed in Section 3.2, to examine the impact of domestic outsourcing on the wages of outsourced workers. First, we exclude all observations treated more than once to prevent varying treatment intensities from confounding our results. Second, we utilize 12 quarters of post-treatment periods and 4 quarters of pre-treatment periods in our differences-in-differences analysis. Consequently, we restrict our attention to treated observations that have 16 quarters of non-missing wage observations around the period of treatment. Notice that the workers that are treated before 2013 and after 2019 are automatically dropped due to the second restriction. Overall, the two restrictions yield 27,014 observations, as indicated in the first row of column 2 in Table 1. Our preferred treatment group includes workers who meet the "Buyer-supplier, 0-1" criterion, comprising 3,187 unique workers. Of these, 2,091 are outsourced from low-skilled business service industries, while 1,096 are outsourced from high-skilled business service industries.

3. Outsourcing and Wages

3.1 Control Group Selection

In order to explore the wage effect of domestic outsourcing on our treatment sample, an appropriate control group must be constructed. For this purpose, we utilize a k-to-k coarsened exact matching (CEM) algorithm. It is highlighted in Section 2.4 that our preferred treatment group consists of workers who are involved in worker flows that meet the “Buyer-Supplier, 0-1” criterion. Our main results are based on this treatment sample, which includes 3,187 workers (see Table 1). However, we are also interested in testing whether a wage effect exists when workers are involved in flows that fall under other buyer-supplier criteria, such as cases where no relationship exists between the buyer and the supplier before or after the flow (“Buyer-Supplier, 0-0”). Therefore, apply the k-to-k CEM algorithm to the entire effective treatment sample, which consists of 27,014 workers.

We apply the same matching algorithm separately to observations treated in different quarters. In particular, in order to find appropriate control observations for the workers treated, for example, in the first quarter of 2013, we begin with the full sample of potential control observations that have non-missing wage observations between the first quarter of 2012 and the last quarter of 2015 (16 quarters). Treated observations are then matched to control observations based on the following characteristics:

- The worker’s age at the quarter prior to treatment and gender,
- The size, age, headquarter city and the 2-digit NACE code of the firm employing the worker prior to treatment,
- The worker’s wage history, i.e., log wages in each of the four quarters prior to treatment.

Descriptive statistics for the matched treatment and control samples are presented in Table 2. As evident in Table 2, the characteristics of the control sample constructed using the CEM algorithm are quite similar to those of the treatment sample. Notably, majority of the treatment, and therefore, the control sample is less than 40 years old and male. The implications of this aspect on our results are going to be further investigated in the heterogeneity analyses, Section 3.4.

Table 2: Coarsened exact matching, descriptive statistics

	k-to-k CEM	
Characteristics	**Treatment**	**Control**
NACE: Manufacturing	0.12	0.12
NACE: Construction	0.07	0.07
Headquarter: Istanbul	0.60	0.60
Firm Size	2391	2060
Firm Age	13.96	13.90
Worker Age < 40	0.73	0.73
Gender: Male	0.78	0.78
Log wage, -1 quarter	5.84	5.85
Log wage, -2 quarters	5.84	5.84
Log wage, -3 quarters	5.83	5.83
Log wage, -4 quarters	5.82	5.83
N	20,897	20,897

Notes: ***"NACE: Manufacturing (Construction)"*** indicates the share of workers employed in the manufacturing (construction) industry prior to treatment. *"Headquarter: Istanbul"* refers to the share of workers employed at a firm headquartered in Istanbul. *"Log wage, -1 quarter"* represents the average log wage of workers one quarter before treatment. Other log wage rows follow a similar interpretation. The remaining rows are self-explanatory.

It should be noted that out of 27,014 treated workers, 20,897 are successfully matched to a control observation, meaning that slightly more than 20% of the effective treatment sample is dropped as a result of the matching algorithm. We additionally employ a 1-to-1 propensity score (PS) matching algorithm, in which nearly all 27,014 treated workers are matched to a control observation. The regression results using the PS-matched sample are very similar to those from the CEM-matched sample and are included as a robustness check. We select k-to-k CEM as our preferred matching algorithm because it provides stronger sample balance, particularly for workers' wage histories.

Finally, of the 3,187 workers in our preferred treatment sample (meeting Criterion 7), 2,524 are matched to a control observation. Among these 2,524 workers, 1,621 are outsourced from the industry providing low-skilled business services, and 903 are outsourced from the industry providing high-skilled business services. Since the CEM algorithm is k-to-k, the sample size in our main regression analyses are twice these values.

3.2 Econometric Methodology

Our setting involves staggered entry into treatment, meaning workers are treated at different times. As a result, treatment effects may vary across treatment cohorts (cohort heterogeneity). Additionally, treatment effects may differ depending on the duration of exposure to treatment (time heterogeneity). The recent differences-in-differences literature suggests that the traditional static and dynamic two-way fixed effects (TWFE) approaches fail to properly account for time and cohort heterogeneities in the treatment effect. In settings like ours, where cohort heterogeneity exists, even the dynamic TWFE approach makes forbidden comparisons (e.g., comparing a just treated unit to an already treated unit), leading to biased estimates of the treatment effect. As a result, a new wave of differences-in-differences techniques has been developed to address these issues (e.g., Wooldridge (2021), Callaway and Sant'Anna (2021), Borusyak et al. (2024)). For a review of the issues with traditional approaches and the newer differences-in-differences literature, see Roth et al. (2023).

We use the imputation-based differences-in-differences estimation proposed by Borusyak et al. (2024), which generates treatment effect estimates at highly granular unit-time level. In the absence of covariates, as is the case in our regressions (since our treatment and control samples are already balanced through CEM), this method produces the same treatment effect estimates as the estimator proposed by Wooldridge (2021). The treatment effect estimation procedure proposed by Borusyak et al. (2024) is outlined below.

In what follows, the constant terms of the regressions are omitted. Let $D_{i,t}$ be a binary treatment indicator that takes the value one if the observation of worker i at time t is treated. First, the following TWFE regression is implemented on untreated observations (those that are never treated or not-yet-treated), i.e., the observations with $D_{i,t} = 0$:

$$log(y_{i,t}) = \alpha_i + \varphi_t + \epsilon_{i,t}, \tag{1}$$

where $log(y_{i,t})$ denotes the log daily wages of the workers, α_i and φ_t respectively represent unit and time fixed effects, and $\epsilon_{i,t}$ is the standard error. This regression yields fixed effects estimates for all units and time periods. In a next step, the outcomes for treated observations in the absence of treatment can be imputed using the following prediction for the treated observations, i.e., those with $D_{i,t} = 1$:

$$lo\hat{g}(y_{i,t}) = \hat{\alpha}_i + \hat{\varphi}_t. \tag{2}$$

Subsequently, the treatment effect for each treated unit over time can be recovered as the difference between the observed outcome and the imputed outcome in the absence of treatment, for the sample with $D_{i,t} = 1$:

$$\beta_{i,t} = log(y_{i,t}) - lo\hat{g}(y_{i,t}). \tag{3}$$

The resulting treatment effects (on the treated) are unit- and time-specific, meaning that the aforementioned cohort and time heterogeneities are accounted for. These unit- and time-specific treatment effects can then be averaged across cohorts and by the duration of exposure to treatment to obtain the unbiased average treatment effects on the treated. In fact, this averaging is equivalent to the regression of $\beta_{i,t}$ over exposure to treatment dummies:

$$\beta_{i,t} = \sum_{r \in \{1,2,..,12\}} 1\left[R_{i,t} = r\right] \theta_r + \epsilon_{i,t}, \tag{4}$$

where $R_{i,t}$ is a variable indicating the number of quarters passed since the treatment, and θ_1, θ_2, .., θ_{12} can be interpreted as the treatment effects by the duration of exposure to treatment. The regression specification provided in (4) does not yield the correct standard error estimates. This is because the estimated unit- and time-specific treatment effects, $\beta_{i,t}$, is the difference between observed outcome and the imputed (estimated) outcome in the absence of treatment. Since the outcome in the absence of treatment is not directly observed in the data but instead predicted by the model, there is an associated prediction error. This prediction error contributes to the overall uncertainty in the treatment effect estimates and must be accounted for when calculating standard errors. Borusyak et al. (2024) describes the methodology for recovering standard errors that circumvent this problem, which they refer to as *conservative clustered standard error estimates*.

As is the case in the traditional differences-in-differences in practices, parallel trends and no anticipation assumptions must hold to generate unbiased treatment effect estimates. To test for these assumptions, we once again follow Borusyak et al. (2024) and run the following regression on the sample with $D_{i,t} = 0$:

$$log(y_{i,t}) = \alpha_i + \varphi_t + \sum_{p\in\{-1,-2,-3\}} 1[P_{i,t} = p, w_i = 1]\, \delta_p + \epsilon_{i,t}, \qquad (5)$$

where w_i is a dummy variable taking the value one if the worker belongs to the treatment groups, $P_{i,t}$ is a variable indicating the number of quarters remaining to treatment. Intuitively, coefficients δ_{-1}, δ_{-2}, δ_{-3} test for pre-trends (one out of four pretreatment quarter is omitted to be used as a benchmark) by comparing the pre-treatment wages of the workers belonging to the treatment group to those in the control group. If coefficients δ_p are insignificant, we would fail to reject the hypothesis that parallel trends and no anticipation assumptions hold.

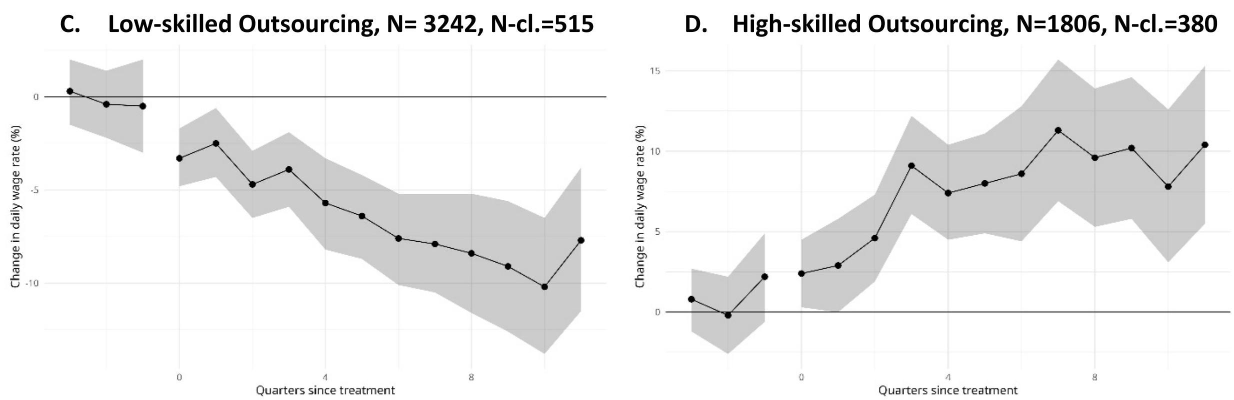
To implement all the steps mentioned above, we utilize the user-written *"did_imputation"* package available in Stata (Borusyak, 2021).

3.3 Main Results

This section presents our main results on the wage effects of domestic outsourcing. Recall that the treatment group comprises workers transferred by their predecessor (the initial firm employing the worker) to a successor (the destination company). These transfers (worker flows) meet criteria 1 through 8. The control group is constructed using a coarsened exact matching algorithm based on several characteristics. The key distinction between the two groups is that workers in the treatment group are outsourced slightly before $t = 0$, while those in the control group are not.

The left-panel of Figure 5 illustrates the evolution of wages for outsourced workers performing low-skilled business service tasks (food, cleaning, security, logistics), compared to their counterparts (selected through CEM) who are not outsourced. As shown, these workers experience considerable wage losses. Immediately after the outsourcing event, their wages decline by approximately 3–4% relative to non-outsourced workers. This negative wage effect gets stronger over time, reaching 10% by the end of the third year following the outsourcing event. The insignificant (and near-zero) coefficients for the pre-treatment periods provide no evidence to reject the hypothesis that the parallel trends and no-anticipation assumptions are valid.

Figure 5. Wage effects of domestic outsourcing



Notes: The left- and right-panels respectively show the effect of outsourcing on the wages of workers employed by successors operating in the low- and high-skilled business service industries. Definitions of high- and low-skilled business service industries are provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

The finding that workers performing low-skilled business service tasks experience wage losses after being outsourced suggests that the results of Goldschmidt and Schmieder (2017) and Dorn et al. (2018) hold with a refined, narrower definition of outsourcing (i.e., after further restricting the sample using Criterion 7). Furthermore, it supports the notion that this outcome extends to a developing economy setting. We therefore believe that the common interpretation of this finding applies in our context as well (see also Bernhardt et al. (2016)). Intuitively, outsourcing enables firms to exclude workers performing non-core tasks from the firm-specific wage premium. By pushing these workers outside the company's boundaries and sourcing these services from business service firms that compete fiercely for contracts, large firms can reduce labor costs. However, this cost reduction comes at the expense of the wages of low-skilled workers.

The majority of the literature on the wage effects of domestic outsourcing focuses on workers performing low-skilled business service tasks, since the prominence of this type of outsourcing enhances the reliability of the previously outlined outsourcing identification methodology. The newly introduced Criteria 7 increases the ability of identifying the outsourcing events during our sample period. Accordingly, we also examine the effect of domestic outsourcing on the wages of workers performing high-skilled business service tasks (engineering, consultancy, IT, programming, architecture etc.), as shown in the right-panel of Figure 5. We find that domestic outsourcing leads to wage gains for high-skilled task performers, which grow over time following the outsourcing event. The wages of outsourced high-skilled workers increase by approximately 10% by the third year after treatment, compared to workers who are not outsourced.

Pre-treatment coefficients are insignificant within the range of 95% confidence interval, providing support for the parallel trends and no anticipation assumptions.

Two factors may explain the observed increase in the wages of high-skilled outsourced workers. The first factor, explicitly captured in our analyses through Criteria 7, relates to the value of firm-specific human capital. Criteria 7 ensures that a relationship between the predecessor and successor firms begins following the outsourcing event. Consequently, it is highly likely that outsourced workers continue to provide services to their former employer (the predecessor firm) even after being transferred to the successor company. In fact, the very reason the successor firm secures a business service contract from the predecessor firm may be tied to employing certain high-skilled workers and allowing them to continue serving the predecessor firm. As a result, the workers' firm-specific (or predecessor-specific) human capital may translate into higher wages. This mechanism is less likely to result in higher wages for low-skilled outsourced workers due to their lower bargaining power, i.e., due to the fact that many people can perform tasks such as cleaning or security, unlike high-skilled roles such as engineering or programming, which require less abundant skills.

A second possible mechanism is related to specialization, as outlined by Bergeaud et al. (2024). When a high-skilled business service worker is employed by a company that does not specialize in the worker's core competencies, the worker's labor is utilized only within that single company. In contrast, high-skilled business service firms group together a specialized labor force and can offer services to multiple firms simultaneously. This broader service provision using the same workers allows business service firms to generate higher profits via economies of scale and scope. A portion of these profits may be captured by their workers, leading to higher wages, especially when the workers have high bargaining power due to the aforementioned firm-specific human capital. It is hard to make a similar argument for the outsourcing of low-skilled workers, since, for example, a cleaning worker generally performs exactly the same tasks at the same location before and after outsourcing, and thereby, not inducing efficiency gains. In any case, it is important to note that high-skilled workers typically possess greater bargaining power, enabling them to capture a larger share of the increased firm-specific rents.

Specialization may also explain why predecessor firms voluntarily engage in high-skilled outsourcing. By outsourcing, predecessor firms can reduce costs through labor reductions and eliminating non-core administrative processes, though they must pay fees to the successor firms. However, successor firms, leveraging economies of scale and/or scope, may provide these services at a lower total cost than what the predecessor firms previously incurred.

Overall, our main findings suggest a skill-bias in the wage effects of domestic outsourcing. Workers performing low-skilled business service tasks experience wage losses after being outsourced, while wages for high-skilled task performers increase. These results support the conjecture that domestic outsourcing may contribute to rising wage inequality.

3.4 Heterogeneity Analyses

In this section, we extend our regression analyses on the wage effects of domestic outsourcing by splitting the treatment group based on demographic characteristics. Table 3 provides a detailed breakdown of the effective treatment group by age, gender, and wage level relative to the minimum wage. Although slightly more than 20% of the effective treatment sample is lost during the coarsened exact matching process, this does not result in a systematic change in the sample composition. As a reminder, Section 3.5 repeats the regression analyses using a sample matched via propensity score matching, where almost all treatment observations are retained.

Table 3: Effective treatment sample by demographic characteristics

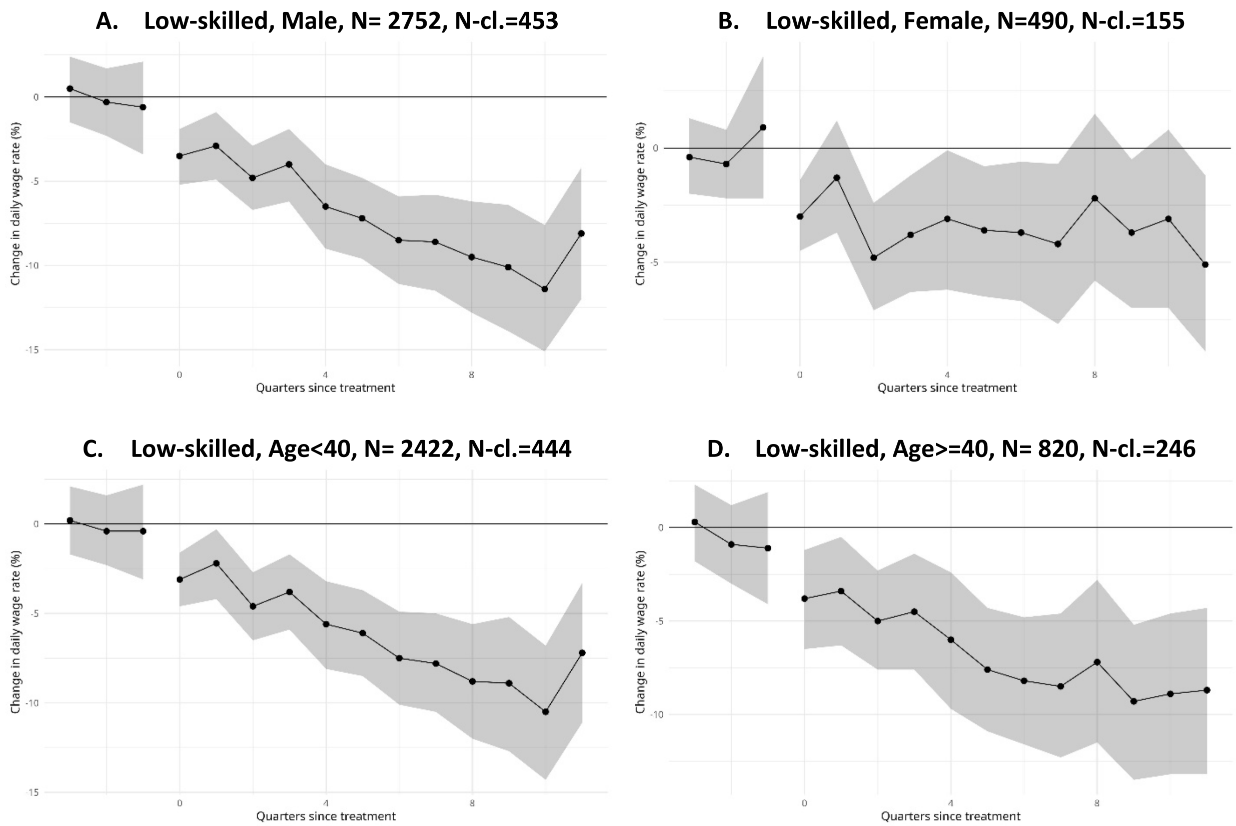
	Low-skilled, N=2,091			**High-skilled, N=1,096**		
	<=1.25*wMin	>1.25*wMin	*Total*	<=1.25*wMin	>1.25*wMin	*Total*
Male	540	1,198	*1,738*	184	605	*789*
Female	253	100	*353*	94	213	*307*
Age<40	532	918	*1,450*	195	637	*832*
Age>=40	261	380	*641*	83	181	*264*

Notes: "<=1.25*wMin" indicates the number of treatment observations whose average wage over the four quarters before treatment is smaller than 1.25 times the average minimum wage over the same quarters. ">1.25*wMin" follows a similar interpretation.

As evident in Table 3, the majority of both high- and low-skilled workers in the treatment sample are male and under 40 years old. Most low-skilled males earn more than 1.25 times the minimum wage. Interestingly, the majority of low-skilled females earn less than this threshold in contrast to the low-skilled males. Among low-skilled workers, the proportion earning above 1.25 times the minimum wage is higher across both age groups. Similarly, regardless of gender or age, most high-skilled workers earn more than 1.25 times the minimum wage.

Figure 6 presents the results of regression analyses, similar to those in the previous chapter, but applied to various subsamples of the low-skilled treatment group categorized by age and gender. Our first main result—that low-skilled workers experience a wage loss following an outsourcing event—holds across all categories. However, this effect is less pronounced among female workers. While the wage losses of male workers reach 10% by the third year of the treatment, the effect for the female workers is always less than 5% with wider confidence intervals. We interpret this outcome as follows. First, as previously explained, most low-skilled female workers in the treatment sample earn less than 1.25 times the minimum wage, leaving limited room for further wage reductions. Second, the smaller sample size of female workers compared to males likely contributes to the larger confidence intervals.

Figure 6. Heterogeneity analysis of low-skilled domestic outsourcing

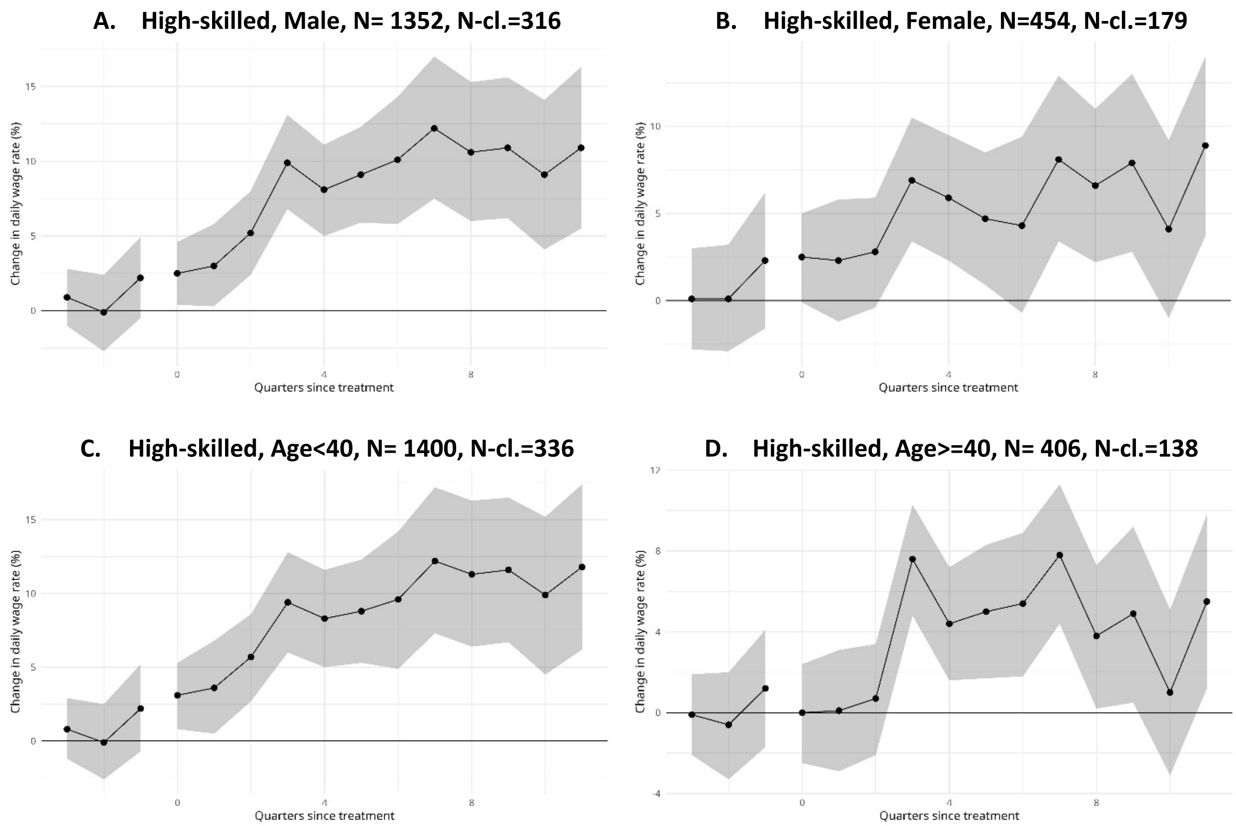


Notes: The panels illustrate the impact of outsourcing on the wages of workers with different demographics employed by successors in a low-skilled business service industry. Definition of low-skilled business service industry is provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

The same set of results are presented for the high-skilled workers in Figure 7. The wage experiences of male or under-40 high-skilled workers following outsourcing closely resemble those of the overall high-skilled sample. This similarity is unsurprising, as the high-skilled sample primarily consists of males and those under 40. For female or over-40 high-skilled workers, the point estimates are slightly lower, and the confidence intervals are wider. Nevertheless, the wage effects remain positive and significant. As before, we attribute these less pronounced effects to the smaller sample sizes of the female and over-40 groups.

Overall, we emphasize that the wage effects of domestic outsourcing are primarily driven by its impact on male or less than 40 years old workers.

Figure 7. Heterogeneity analysis of high-skilled domestic outsourcing



Notes: The panels illustrate the impact of outsourcing on the wages of workers with different demographics employed by successors in a high-skilled business service industry. Definition of high-skilled business service industry is provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

3.5 Robustness

Propensity score (PS) matching. CEM achieves a stronger balance between the control and treatment samples, not only at the mean but also at the 25th and 75th percentiles of the pre-treatment wage distribution (not reported), compared to PS-matching. However, recall that it reduces the size of the treatment sample by more than 20%. In contrast, propensity score matching retains nearly the entire treatment sample. Table A1 in Appendix illustrates the balance of the treatment and control samples under PS matching. Worker and firm characteristics utilized in the PS matching procedure are identical to those employed in CEM, presented in Section 3.1.

Appendix Figure A1 displays the wage effects of domestic outsourcing for workers performing low- and high-skilled business service tasks (as in Figure 5), but based on the PS-matched sample. The wage trends and point estimates are almost identical to those obtained using the sample matched through CEM.

Pre-treatment duration. Our sample period spans from Q1 2012 to Q4 2022. To ensure consistency in our differences-in-differences framework, we require four pre-treatment quarters and twelve post-treatment quarters for each observation. Consequently, observations treated in 2012 or during 2021–2022 are excluded from the treatment sample. For example, a worker treated in Q4 2012 would not meet the criterion of having four quarters of pre-treatment wage data. Accordingly, as the number of required pre-treatment quarters increases, the treatment sample size decreases.

To test the robustness of our results, we repeat the CEM procedure, focusing workers that have 20 non-missing wage observations around treatment and require eight pre-treatment quarters instead of four. We then rerun our regression analyses using this revised sample. Despite a considerable reduction in sample size, the results—presented in Appendix Figure A2—confirm the robustness of our main findings. Importantly, there is no statistically significant difference in wages between the treatment and control groups in any of the pre-treatment quarters.

Job-change after treatment. In our analyses, we follow the outsourced workers for three years after treatment. It is possible that some of the outsourced workers change their jobs once again within these three years. High-skilled workers, for example, may find higher paying jobs elsewhere. Alternatively, the low-skilled workers may have to move to lower paying job due to various reasons (e.g., shutdown of their business service company). If such behavior is systematically related to our definition of outsourcing, our results may (at least partly) be driven by these factors.

To address this concern, we restrict our treatment sample to workers who remain with the same firm for three years following the outsourcing event. This approach results in varying numbers of treatment and control workers within each CEM cell. Therefore, in our revised regressions, we weight each control worker by the ratio of the number of treatment workers to the number of control workers within the corresponding cell. As shown in Appendix Figure A3, the results remain robust.

3.6 Results with Other Buyer-Supplier Criteria

Our preferred treatment sample includes workers who meet Criterion 7 (or "Buyer-supplier, 0-1"): the predecessor and successor firms do not have a buyer-supplier relationship prior to the worker flow, but the predecessor firm makes a purchase from the successor firm following the flow. However, the majority of workers in the effective treatment sample are involved in worker flows that fulfill a criterion other than "Buyer-supplier, 0-1", as shown in Table 1. The primary purpose of this section is to examine the wage effects of alternative worker flows, aiming to highlight the importance of Criteria 7, i.e., the refinement we introduce to the methodology of identifying the outsourcing events.

There are 16,955 workers involved in flows that exhibit no relationship between the predecessors and the successors firms before or after the flow ("Buyer-supplier, 0-0"). For 6,499 workers, predecessor makes a purchase from the successor both before and after the flow ("Buyer-supplier, 1-1"). We implement our regression analyses on the samples of workers meeting "Buyer-supplier, 0-0" and "Buyer-supplier, 1-1" criterion, but exclude those that meet "Buyer-supplier, 1-0" (i.e., the predecessor makes a purchase from the successor before the flow but not after) due to very low sample size. As noted in Section 3.1, the CEM procedure is already applied to the entire effective treatment sample.

Appendix Figure A4 presents the results for workers involved in flows with a successor in a low-skilled business service industry, but meeting either the “Buyer-supplier, 0-0” or “Buyer-supplier, 1-1” criteria. The left panel of the figure indicates no significant wage effect associated with being involved in flows that exhibit no relationship between the predecessor and successor firms before or after the flow. We interpret this finding as evidence that workers involved in such flows are not being forced to transfer to the successor company. Instead, these flows likely reflect voluntary job changes. Even if the workers are laid off by the predecessor company, they may have some freedom in choosing their next employer and may even transition to a role different from their previous one. In other words, while these workers accept jobs in the low-skilled business service industry after leaving positions in a different industry, they are not being outsourced according to our definition of outsourcing. Consequently, the lack of significant wage effects is not surprising.

When the predecessor firm makes a purchase from the successor firm both before and after the worker flow (“Buyer-supplier, 1-1”), it is unclear whether the flow represents an outsourcing event. While the transactions between the firms may be entirely unrelated to the worker flow, it is also possible that outsourcing is occurring gradually, with workers being transferred incrementally over time. The right panel of Appendix Figure A4 shows that the wage effect coefficients for this group are generally negative and become statistically significant by the third year after the treatment. However, these effects are less pronounced compared to those observed in the "pure outsourcing" group, which meets the “Buyer-supplier, 0-1” criterion.

Appendix Figure A5 presents the corresponding results for workers involved in flows with a successor in a high-skilled business service industry. When there is no relationship between the predecessor and successor firms either before or after the worker flow (“Buyer-supplier, 0-0”), the wage effects of these transitions are consistently positive but only statistically significant in about half of the post-treatment quarters (the left-panel). In Section 3.3, we identify two key factors that may explain the positive wage effects observed in domestic outsourcing scenarios (defined by the “Buyer-supplier, 0-1” criterion): the exploitation of firm-specific human capital and specialization. A high-skilled worker transitioning from any industry to a high-skilled business service industry likely benefits from specialization, regardless of whether there is a buyer-supplier relationship between the predecessor and successor firms. However, under the “Buyer-supplier, 0-0” criterion, where no service transaction occurs between the predecessor and successor, there is no basis to expect wage gains from the exploitation of firm-specific human capital. This distinction may account for the less pronounced wage effects compared to those observed under the “Buyer-supplier, 0-1” criterion.

The right panel of Appendix Figure A5 shows positive and significant wage effects for high-skilled workers involved in flows meeting the “Buyer-supplier, 1-1” criterion. Similar to the case of low-skilled workers, it is challenging to determine whether these worker flows represent domestic outsourcing events, given that the predecessor firm makes purchases from the successor firm both before and after the flow. However, the strongly significant wage effects observed for high-skilled workers suggest that a greater portion of the events captured under the "Buyer-supplier, 1-1" case likely represent instances of domestic outsourcing.

Finally, we would like to emphasize that our results cannot be reliably interpreted as the effects of starting to work for a business service firm (which is a very broad definition of being an outsourced worker) for two key reasons. First, as outlined in Section 2.3, we exclude many workers based on factors such as the size of the worker flow and the size of the predecessor firm, which may limit the generalizability of these results. Second, while Criterion 6 ensures that the predecessor and successor firms do not operate within the same 2-digit NACE industry, it does not exclude transitions between different business service industries within separate 2-digit NACE classifications. As such, it is not surprising that the wage effects observed under, e.g., the "Buyer-supplier, 0-0" criterion differ from those observed under the "Buyer-supplier, 0-1" criterion. Our methodology is designed to capture the wage effects of a specific type of domestic outsourcing events, where the predecessor firm transfers workers from its own payroll to another firm. Flows meeting the "Buyer-supplier, 0-0" criterion may reflect transitions that do not align with this outsourcing framework. Nonetheless, the varying results observed across different buyer-supplier criteria underscore the importance of the methodological refinement introduced through Criterion 7 for identifying outsourcing events.

4. Conclusion

This study investigates the wage effects of domestic outsourcing in Türkiye from 2012 to 2022 using an administrative employer-employee linked dataset. An outsourcing event is defined as the transfer of a group of workers from one firm to another in order to produce goods or services, which were previously produced in-house, through a contractor.

We track worker flows across firms that carry specific properties in order to identify such outsourcing events. Different than the existing studies, we have access to buyer-supplier transactions dataset and are able to confirm that the predecessor firm makes a purchase from the successor firm following the worker flow. This improves the precision in identifying the outsourcing events, enabling us to explore the wage effects of both high- and low-skilled outsourcing. Low-skilled outsourcing includes activities such as food preparation, cleaning, security, and logistics, while high-skilled outsourcing encompasses computer programming, IT, engineering, architecture, management consultancy, and legal and accounting services.

Workers who are involved in outsourcing events are considered as the treatment group. We construct a control group by implementing a coarsened exact matching algorithm with a rich set of worker and firm characteristics. Subsequently, we analyze the wage effects of outsourcing using an event study design combined with the imputation-based difference-in-differences (DiD) method, which belongs to the class of new DiD estimators that can account for time and cohort heterogeneity in treatment effects.

We find that low-skilled workers experience wage losses reaching 10% relative to the workers with similar characteristics that are not outsourced. Outsourcing allows firms to exclude non-core workers from firm-specific wage premiums, reducing labor costs by sourcing services from business service firms that fiercely compete each other for contracts. We argue that the observed reduction in wages may be explained by this dynamic. In contrast, a similar analysis for the high-skilled workers indicates wage gains of around 10%. We attribute this increase primarily to their firm-specific human capital, which enables them to serve their predecessor firm more effectively. Additionally, transitioning to a firm that specializes in their core competencies may further contribute to these gains, in particular by allowing workers to take advantage of economies of scale and scope.

Our findings support the idea that domestic outsourcing can contribute to rising wage inequality, primarily through increasing assortative matching between firms and workers. Trends of increased assortative matching is documented in Germany (Card et al., 2013), in France (Godechot et al., 2023) and in the US (Song et al., 2019), among others. However, outsourcing of high-skilled workers may enhance productivity, as these workers often work at multiple (similar or slightly distinct) projects at their new firms, creating scale and scope economies. Specialization in high-skilled tasks may also help to raise productivity. Therefore, outsourcing of high-skilled workers should not necessarily be viewed as detrimental. In contrast, low-skilled workers typically continue performing the same tasks at the same physical location after being outsourced, suggesting that low-skilled outsourcing generally leads to a transfer of rents from workers to firms. Regulatory changes targeting low-skilled outsourcing or redistributive policies may be helpful to mitigate such regressive transfers.

Appendix

Lists of NACE codes constituting high- and low-skilled business service industries. The following 4-digit NACE codes are classified as low-skilled business service industries:

- Food: NACE 5629 (Other food service activities)
- Cleaning: NACE 8121 (General cleaning of buildings), NACE 8122 (Other building and industrial cleaning activities), NACE 8129 (Other cleaning activities)
- Security: NACE 8010 (Private security activities)
- Logistics: NACE 4920 (Freight rail transport), NACE 4941 (Freight transport by road), NACE 5020 (Sea and coastal freight water transport), NACE 5040 (Inland freight water transport), NACE 5121 (Freight air transport), NACE 5210 (Warehousing and storage)

The following 2-digit NACE codes are considered as high-skilled business service industries:

- Computer programming, consultancy and related activities: NACE 62
- Information service activities: NACE 63
- Legal and accounting activities: NACE 69
- Activities of head offices; management consultancy activities: NACE 70
- Architectural and engineering activities: NACE 71
- Scientific research and development: NACE 72
- Advertising and market research: NACE 73
- Other professional, scientific and technical activities: NACE 74
- Veterinary activities: NACE 75

List of NACE letter codes.

- BD: Mining and quarrying (NACE B) and Electricity, gas, steam and air conditioning supply (NACE D) combined
- C: Manufacturing
- E: Water supply; sewerage, waste management, and remediation activities
- F: Construction
- G: Wholesale and retail trade; repair of motor vehicles and motorcycles
- H: Transportation and storage
- I: Accommodation and food service activities
- N: Administrative and support activities
- P: Education
- Q: Human health and social work activities
- Other services: Agriculture, forestry and fishing (NACE A), Information and communication (NACE J), Financial and insurance activities (NACE K), Real estate activities (NACE L), Professional, scientific and technical activities (NACE M), Public administration and defense (NACE O), Arts,

entertainment, and recreation (NACE R), Other service activities (NACE S), Activities of households as employers (NACE T), Activities of extraterritorial organizations and bodies (NACE U)

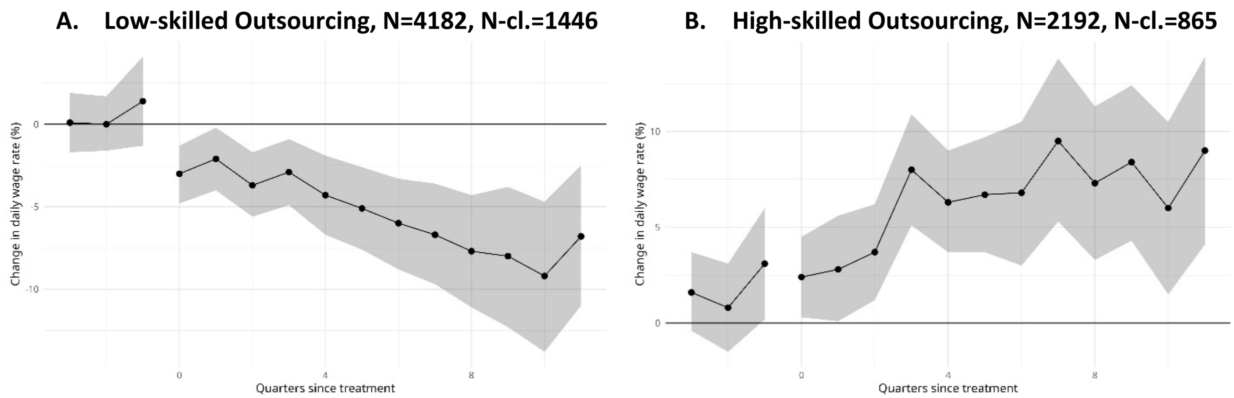
Tables and figures of the robustness tests. Table A1 presents the descriptive statistics of the treatment group and the control group constructed using PS-matching. Figure A1 shows the results using this PS-matched sample. Figure A2 illustrates the results utilizing eight pre-treatment quarters instead of four. Figure A3 displays the results over the sample of treated observations remaining at their post-treatment firm for at least three years. See Section 3.5 in the main text for interpretations of the results and further details.

Table A1: Propensity score matching, descriptive statistics

	1-to-1 PS-matching	
Characteristics	**Treatment**	**Control**
NACE: Manufacturing	0.13	0.13
NACE: Construction	0.07	0.07
Headquarter: Istanbul	0.54	0.51
Firm Size	2179	1981
Firm Age	14.07	14.69
Worker Age < 40	0.71	0.71
Gender: Male	0.76	0.76
Log wage, -1 quarter	5.82	5.85
Log wage, -2 quarters	5.82	5.84
Log wage, -3 quarters	5.81	5.83
Log wage, -4 quarters	5.80	5.83
N	27,013	27,013

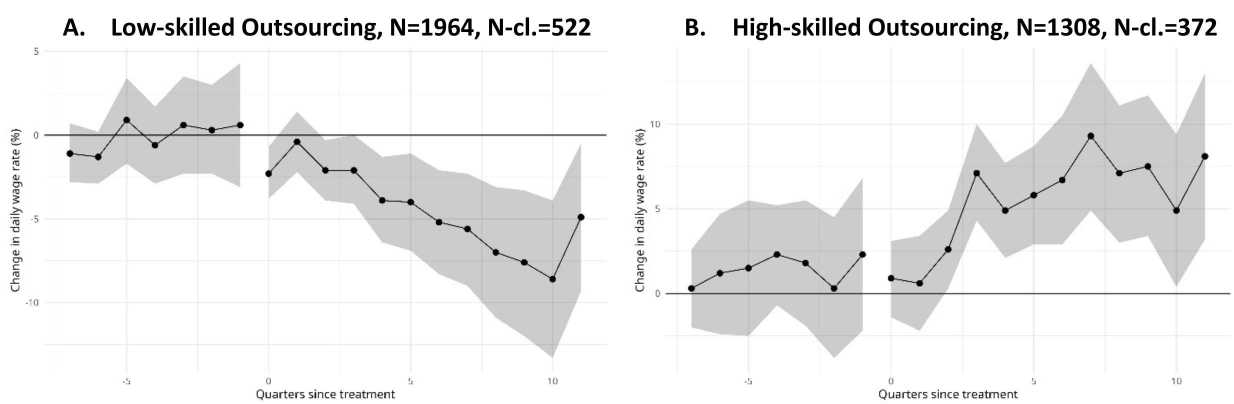
Notes: *"NACE: Manufacturing (Construction)"* indicates the share of workers employed in the manufacturing (construction) industry prior to treatment. *"Headquarter: Istanbul"* refers to the share of workers employed at a firm headquartered in Istanbul. *"Log wage, -1 quarter"* represents the average log wage of workers one quarter before treatment. Other log wage rows follow a similar interpretation. The remaining rows are self-explanatory.

Figure A1. Wage effects of domestic outsourcing, PS-matched sample



Notes: The left- and right-panels respectively show the effect of outsourcing on the wages of workers employed by successors operating in the low- and high-skilled business service industries using the PS-matched sample. Definitions of high- and low-skilled business service industries are provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

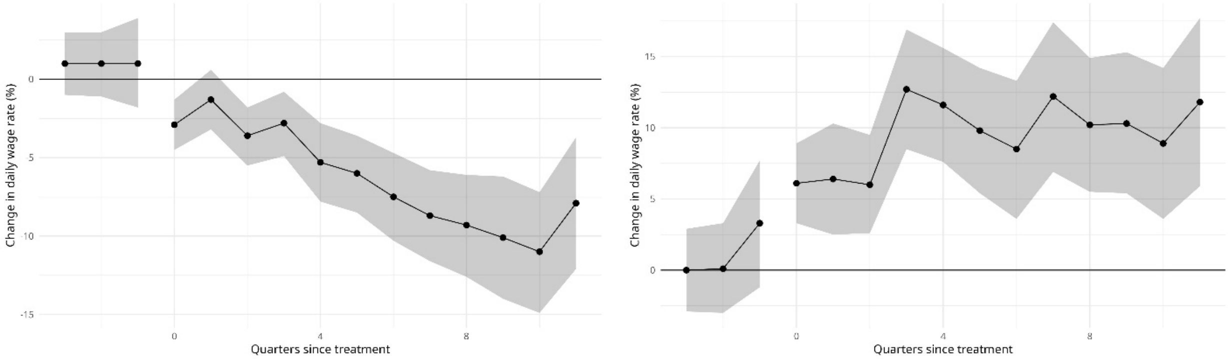
Figure A2. Wage effects of domestic outsourcing, 8 pre-treatment quarters



Notes: The left- and right-panels respectively show the effect of outsourcing on the wages of workers employed by successors operating in the low- and high-skilled business service industries using the same econometric design as the main text but with 8 pre-treatment quarters. Definitions of high- and low-skilled business service industries are provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

Figure A3. Wage effects of domestic outsourcing, no job change after treatment

A. Low-skilled Outsourcing, N=2134, N-cl.=351 **B. High-skilled Outsourcing, N=985, N-cl.=218**

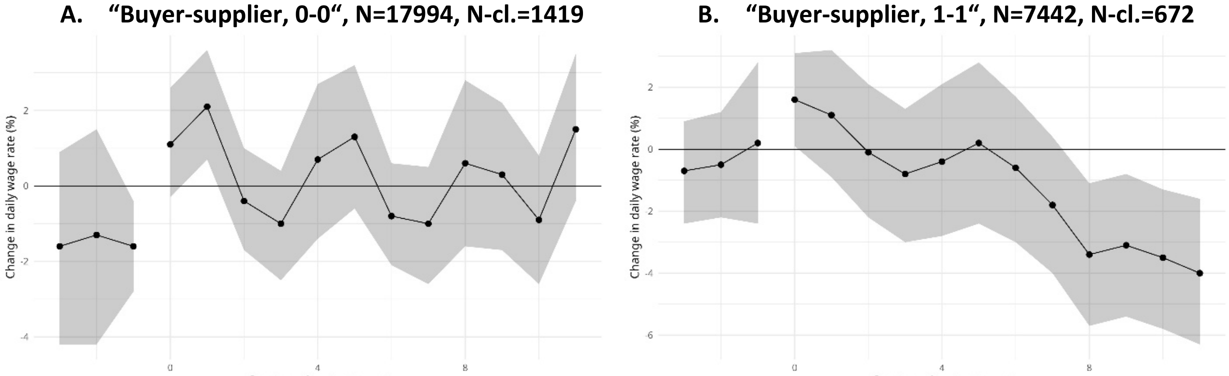


Notes: The left- and right-panels respectively show the effect of outsourcing on the wages of workers employed by successors operating in the low- and high-skilled business service industries restricting the treatment sample to workers who remain in the successor firm at least for three years after treatment. Definitions of high- and low-skilled business service industries are provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

Figures of the results with other buyer supplier criteria. Figures A4 presents the results low-skilled workers involved in flows meeting "Buyer-supplier, 0-0" (no buyer-supplier relationship between the predecessor and successor firms before or after the worker flow) and "Buyer-supplier, 1-1" (predecessor makes a purchase from the successor both before and after the worker flow) criteria. Figure A5 shows the same set of results for the high-skilled workers.

Figure A4. Wage effects of low-skilled domestic outsourcing, different buyer-supplier criteria

A. "Buyer-supplier, 0-0", N=17994, N-cl.=1419 **B. "Buyer-supplier, 1-1", N=7442, N-cl.=672**

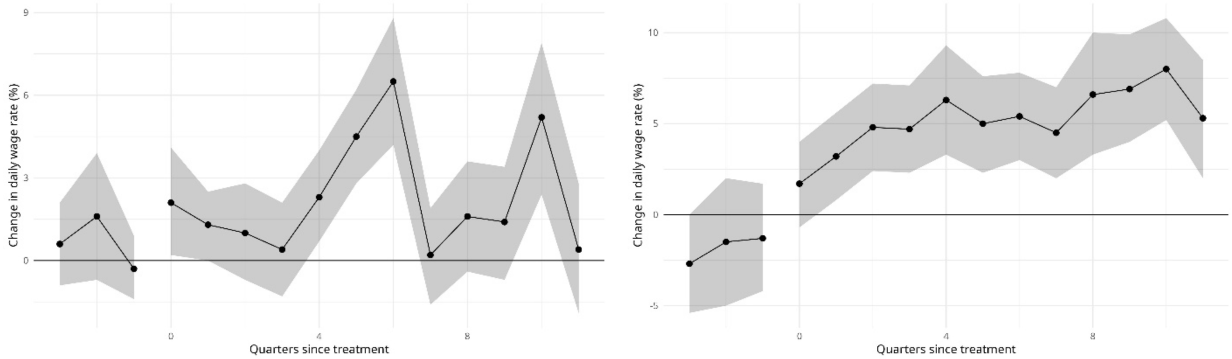


Notes: The figures show the effect of being involved in a worker flow respectively meeting criteria "Buyer-supplier, 0-0" and "Buyer-supplier, 1-1" on the wages of workers employed by successors operating in a low-skilled business service industry. Definition of low-skilled business service industry is provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

Figure A5. Wage effects of high-skilled domestic outsourcing, different buyer-supplier criteria

A. "Buyer-supplier, 0-0", N=6956, N-cl.=819

B. "Buyer-supplier, 1-1", N=3754, N-cl.=451



Notes: The figures show the effect of being involved in a worker flow respectively meeting criteria "Buyer-supplier, 0-0" and "Buyer-supplier, 1-1" on the wages of workers employed by successors operating in a high-skilled business service industry. Definition of high-skilled business service industry is provided in the Appendix. The treatment effects (coefficients for $t \geq 0$) and pre-trend coefficients ($t < 0$) are estimated separately. A detailed description of the econometric methodology is provided in Section 3.2. Standard errors are clustered at the level of firm (employing the worker just before treatment). **N**: the number of observations, **N-cl**: the number of clusters. Shaded areas represent 95% confidence intervals.

References

Abowd, John M., Francis Kramarz, and David N. Margolis (1999), "High Wage Workers and High Wage Firms", *Econometrica*, 67(2), 251–333. https://doi.org/10.1111/1468-0262.00020

Bergeaud, Antonin, Clement Malgouyres, Clement Mazet-Sonilhac and Sara Signorelli (2024), "Technological change and domestic outsourcing", *Journal of Labor Economics*, forthcoming. https://doi.org/10.1086/730166

Berlingieri, Giuseppe (2013), "Outsourcing and the rise in services", CEP Discussion Paper No. 1199. Centre for Economic Performance, London School of Economics.

Bernhardt, Anette, Rosemary Batt, Susan Houseman and Eileen Appelbaum (2016), "Domestic Outsourcing in the U.S.: A Research Agenda to Assess Trends and Effects on Job Quality", Upjohn Institute Working Paper 16-253. W. E. Upjohn Institute for Employment Research http://dx.doi.org/10.17848/wp16-253

Bilal, Adrien, and Hugo Lhullier (2021), "Outsourcing, Inequality and Aggregate Output", NBER Working Paper No: 29348.

Borusyak, Kirill (2021). "DID_IMPUTATION: Stata module to perform treatment effect estimation and pre-trend testing in event studies", Statistical Software Components S458957, Boston College Department of Economics, revised 22 Nov 2023.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess (2024), "Revisiting event-study designs: robust and efficient estimation", *The Review of Economic Studies*, 91(6), 3253-3285.

Callaway, Brantly, and Pedro H.C. Sant'Anna (2021), "Difference-in-Differences with multiple time periods", *Journal of Econometrics*, 225(2), 200-230.

Card, David, Jörg Heining, and Patrick Kline (2013), "Workplace Heterogeneity and the Rise of West German Wage Inequality", *The Quarterly Journal of Economics*, 128(3), 967-1015.

Cortes, Guido Matias, and Andrea Salvatori (2019), "Delving into the demand side: Changes in workplace specialization and job polarization", *Labour Economics*, 57, 164-176.

Dorn, David, Johannes F. Schmieder, and James R. Spletzer (2018), "Domestic outsourcing in the United States", *US Department of Labor Technical Report 14*.

Drenik, Andres, Simon Jäger, Pascuel Plotkin, and Benjamin Schoefer (2023), "Paying Outsourced Labor: Direct Evidence from Linked Temp Agency-Worker-Client Data", *The Review of Economics and Statistics*, 105(1), 206–216. https://doi.org/10.1162/rest_a_01037

Dube, Arindrajit, and Ethan Kaplan (2010), “Does outsourcing reduce wages in low-wage service occupations? Evidence from janitors and guards”, *Industrial and Labor Relations Review*, 63(2), 287–306.

Felix, Mayara, and Michael B. Wong (2024), “The Reallocation Effects of Domestic Outsourcing”, Working Paper.

Godechot, Olivier, Marco G. Palladino and Damien Babet (2023), “In the land of AKM: Explaining the dynamics of wage inequality in France”, hal-04319406. https://hal.science/hal-04319406

Goldschmidt, Deborah, and Johannes F. Schmieder (2017), “The rise of domestic outsourcing and the evolution of the German wage structure”, *The Quarterly Journal of Economics*, 132(3), 1165-1217.

Guo, Naijia, Duoxi Li and Michael B. Wong (2024), “Domestic Outsourcing and Employment Security”, Working Paper.

Katz, Lawrence F., and Alan B. Krueger (2018), “The rise and nature of alternative work arrangements in the United States, 1995–2015”, *ILR Review*, 72(2), 382–416. https://doi.org/10.1177/0019793918820008

Roth, Jonathan, Pedro H.C. Sant’Anna, Alyssa Bilinski and John Poe (2023), “What’s trending in difference-in-differences? A synthesis of the recent econometrics literature”, *Journal of Econometrics*, 235(2), 2218-2244.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter (2019), “Firming Up Inequality”, *The Quarterly Journal of Economics*, 134(1), 1-50.

Spitze, Scott (2022). “The Equilibrium Effects of Domestic Outsourcing”, Working Paper.

Weil, David (2014), *The Fissured Workplace: Why Work Became So Bad for So Many and What Can Be Done to Improve It*, Harvard University Press.

Wooldridge, Jeffrey M. (2021). “Two-way fixed effects, the two-way Mundlak regression, and difference-in-differences estimators”, SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3906345