AN INQUIRY INTO JOB SEARCH METHODS IN TURKEY

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An Inquiry into Job Search Methods in Turkey

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DECLARATION OF ORIGINALITY

I, İslam Tarlacı, certify that

- I am the sole author of this thesis and I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisor and thesis committee at Boğaziçi University, including final revisions required by them.

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ABSTRACT

An Inquiry into Job Search Methods in Turkey

This work examines the prevalence and wage effects of informal job search networks in Turkey using Household Labor Force Survey data (2005-2023). It investigates the evolution of informal job finding, its average impact on wages, after controlling for extensive characteristics, variations across occupational skills, and moderation by household members in similar occupations (a proxy for strong ties). The descriptive analysis reveals a significant rise in informal job finding, especially post-2018, becoming the dominant method after the pandemic. Employing OLS regression, results indicate a modest average wage penalty of around 2-4% for jobs found informally. However, this effect is heterogeneous: the penalty is driven by professionals, managers, and technicians, while being marginally significant for elementary and other blue-collar workers. Having a household member in the same occupation counteracts this penalty, suggesting a who you know premium. Yet, for skilled workers, finding jobs informally despite such household ties correlates with an amplified wage penalty, supporting a last resort rather than a better match explanation for this group.

ÖZET

Türkiye’de İş Arama Yöntemleri Üzerine Bir İnceleme

Bu tez, Türkiye'deki enformel iş arama ağlarının yaygınlığını ve ücretler üzerindeki etkilerini Hanehalkı İşgücü Anketi verilerini (2005-2023) kullanarak incelemektedir. Çalışma, enformel yollarla iş bulmanın zaman içindeki değişimini, kapsamlı bireysel özellikler kontrol edildiğinde ücretler üzerindeki ortalama etkisini, bu etkinin mesleki beceri gruplarına göre farklılaşmasını ve benzer mesleklerde hanehalkı üyelerinin bulunmasının (güçlü bağlar için bir vekil değişken olarak) bu ilişki üzerindeki düzenleyici rolünü araştırmaktadır. Betimleyici analiz, özellikle 2018 sonrasında enformel yollarla iş bulmada önemli bir artış olduğunu ve bu yöntemin pandemi sonrasında baskın hale geldiğini ortaya koymaktadır. Regresyon analizi sonucu bulgular, enformel yollarla bulunan işler için ortalama %2-4 civarında mütevazı bir negatif etki olduğunu göstermektedir. Ancak bu etki heterojen bir yapıdadır: negatif ücret primi temel olarak profesyoneller, yöneticiler ve teknisyenler grubunda gözlenirken, nitelik gerektirmeyen işlerde çalışanlar ve diğer mavi yakalı çalışanlar için istatistiksel olarak sınırdadır. Hanehalkında aynı meslek grubunda bir üyenin bulunması bu negatif etkiye karşı bir etki oluşturmakta, bu da tanıdık faktörünün bir prim sağladığını düşündürmektedir. Bununla birlikte, nitelikli çalışanlar için, hanehalkında benzer meslekte bir üye bulunmasına rağmen işin enformel yollarla bulunması, daha yüksek bir negatif ücret primi ile ilişkilidir; bu durum, bu grup için enformel ağların daha iyi eşleşme sağlamaktan ziyade bir son çare olduğunu desteklemektedir.

ACKNOWLEDGMENTS

My heartfelt gratitude is extended first and foremost to my advisor, Tolga Umut Kuzubaş. His unwavering support was instrumental, and without it, I might not have been able to conclude my studies. I am also eternally thankful to Burak Saltoglu and Ayşe Yeliz Kaçamak. Their consistent support, guidance, expertise, and mentorship have been invaluable both throughout my undergraduate and master’s work at Boğaziçi. Additionally, I am grateful to my external juror Ahmet Göncü for his valuable insights which enhanced quality of my work. Moreover, I would like to express my appreciation to TUBITAK for the support that they provided via the 2210A scholarship program.

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CHAPTER 1

INTRODUCTION

The mechanisms through which people seek employment are important to labor market efficiency and the matching process. Their effect on the general matching efficiency, wage, and overall productivity is a topic of inquiry in the literature, both from theoretical and empirical aspects. Especially the role of informal networks attracted many researchers from many disciplines, mostly from sociology and economics, in order to understand the effects of family, friend, or relative connections on the labor market.

Turkey presents a compelling case study due to the recent, dramatic documented increase in reliance on informal networks, overtaking formal channels. This shift raises critical questions about labor market dynamics, potential impacts on wage structures, matching efficiency, and resource allocation in a major emerging economy. This study aims to address the gap in understanding the heterogeneous wage consequences of this increased reliance on informal networks across different segments of the Turkish labor market, contributing insights relevant to both Turkish labor economics and the broader literature on network effects.

Theoretical work focuses on different aspects. Some work suggests that the effect works by signaling the productivity of a given worker and providing better match opportunities (Montgomery, 1991; Simon & Warner, 1992). Some other work suggests it is also possible that the utilization of networks can create wage penalties due to potential mismatch, or create channels for less productive matches (Bentolila et al., 2010). Moreover, sociologists, primarily, focused on the differentiation between strong and weak ties, which have different effects. In essence, the idea is that weak ties can create more avenues for information gathering, while strong ties give more support for existing jobs through existing information (M. S. Granovetter, 1973)

Empirically, the impact of informal channels for finding a job is inconclusive, as many studies are reporting positive, negative, and even mixed results utilizing different datasets in different countries or sectors (Dustmann et al., 2016; Marmaros & Sacerdote, 2002; Pellizzari, 2010; Pistaferri, 1999). The heterogeneity highlights a possibility that the effects are contingent on different characteristics for a given job, person, or market.

This work inquires into the prevalence and wage consequences of finding a job through informal networks within the context of the Turkish labor market. The context is important for several reasons. To start, there has been a significant increase in the number of people getting their jobs using informal networks, particularly after 2018 and more strikingly after the COVID pandemic. In fact, it looks like informal networks overtook market mechanisms as the primary method of job finding in the Turkish labor market. This change creates more reasons to investigate the association in more detail.

Utilizing the data from the Household Labor Force Survey's waves from 2005 to 2023, this work tries to answer several questions. First, how has the prevalence of informal job search changed over almost two decades in the Turkish context? Second, what is the average impact of finding a job through an informal network on wages after controlling for a comprehensive set of variables, including demographic, job, and firm characteristics? Third, how does this association change across different segments of Turkish society, particularly across different occupations? Lastly, does the presence of another household member in a similar occupation change the effects, as a proxy for the strong network?

This analysis utilizes ordinary least squares regression models as its baseline and includes interaction terms to differentiate the effects for different parts of the Turkish labor market, in addition to several subset analyses. Key findings of this work depict that there exists a statistically significant but minor wage penalty of around two to four percent on average for the general Turkish population. While this aggregate effect is in line with general findings of the literature, it does not tell the entire story. Verifying the criticism in the theoretical literature, this work suggests a heterogeneity of the wage penalty. The negative effect is driven mainly by professionals and managers, in addition to technicians, while the effect is either statistically insignificant or of an economically insignificant magnitude for other blue-collar workers. Furthermore, having another household member with the same occupation exerts the reverse effects, suggesting a potential who you know premium in the Turkish labor market. On the other hand, the negative effects are amplified for skilled workers, indicating a last resort argument for them instead of a better match for finding a job through informal networks.

This work aims to contribute to the empirical literature by providing an update to evidence regarding Turkey on patterns of job search in a major emerging market economy undergoing significant shifts in its labor market, while having a different lens showing considerable heterogeneity that is not discussed within the Turkish context in this detail. The findings challenge the one-size-fits-all view on the effect of finding a job through informal networks. The impacts and changing wage premiums raise important questions regarding changes in labor market efficiency and human capital allocation in the Turkish labor market context.

The remainder of this thesis is structured as follows: Chapter 2 reviews the relevant literature. Chapter 3 describes the data and presents descriptive statistics on job search trends in Turkey. Chapter 4 outlines the econometric methodology. Chapter 5 presents and discusses the regression results. Chapter 6 concludes and discusses potential avenues for future research.

CHAPTER 2

LITERATURE REVIEW

The inquiry into job-searching methods started early on in the literature. Moving from the argument comparing extensive and intensive margins for information search, it has been argued that the labor market looks more like the used cars market compared to new ones, as labor shows significant variation in quality. Hence, there is an argument to be made in favor of a strong role for intensive search, which necessitates additional sources for information in addition to standard formal procedures (Rees, 1966).

As an additional consideration, sociology literature points to the differences within the informal networks. They argued that there exists a difference between the strengths and the nature of weak and strong social networks. The argument depends on the observation that while we rely on strong ties, there exists a significant overlap between our connections and the connections of the people we are strongly connected to. Therefore, Granovetter concludes by noting that weak ties act as information bridges, which can help information to reach us from people who are seemingly irrelevant to our core group (M. Granovetter, 1983; M. S. Granovetter, 1973). In another seminal work, he directly tested that theory and found that this is also the case in job searching, and found evidence for his theory (M. S. Granovetter, 1995).

However, this argument is also contested within the sociology literature. It is also argued that after controlling for other observables, statistical significance vanishes for most groups (Bridges & Villemez, 1986). Moving on from this empirical evidence, economists theoretically showed that while having more weak ties in a network increases the reservation wage of a worker, as the distribution of wage offers from weak ties may be wider (a higher spread), even if the average offer (mean) is similar. It does not necessarily mean that jobs found using weak ties will have higher wages. As a matter of fact, it is possible that accepting a job through a strong network correlates with a higher wage, as it is more likely that a person who has a job offer through a strong network also has multiple offers from his/her weak links. Choosing an offer obtained through a strong tie, in this context, suggests it was perceived as the best available option (Montgomery, 1992)

On the other hand, economists initially investigated the issue without differentiating network types. A study investigating the reasons behind racial differences in employment outcomes reveals that a significant portion of the difference stems from differences in informal networks (Holzer, 1987b). Additionally, in later work, while Holzer found marginally significant positive effects of the referral process on employee performance initially, the effects diminished considerably after the inclusion of personal characteristics as additional controls, especially for certain demographics. Furthermore, his findings suggest that the referral process is benefiting certain demographics, namely older males. Reading both his works together, Holzer warns policymakers of the possibility that while firms try to decrease their costs to fill vacancies with more productive workers through informal channels, the process hurts certain demographics more than others (Holzer, 1987a).

While differentiation between weak and strong ties is important for information dissemination, the existence of an informal referral has another value. Another strand of the literature discusses the signaling value of informal networks. Montgomery’s seminal paper relies on the idea that the quality of an individual’s network is also a signal for his/her capabilities. Hence, firms can interpret networks as a signal for referred candidates' abilities to address information asymmetry problems in hiring (Montgomery, 1991).

In a similar manner, another model was put forward to help explain both initially higher starting wages and lower subsequent wage growth for people who found their jobs through informal networks. The starting point is quite similar to Montgomery (1991), as it also relies on reducing uncertainty in future employee traits. The difference is that Simon and Warner defined match-specific productivity as observed by all after production takes place (Simon & Warner, 1992). Since this model is a learning model, high-quality workers who were not thought to be as such will have higher wage growth compared to people who signaled their value, and the wage advantage will decrease as the initially underestimated workers prove their productive capacity. Additionally, they empirically supported their model's predictions using a survey of Natural and Social Scientists and Engineers. Likewise, similar work following the same base model but utilizing a different dataset for empirical testing, namely a matched employer-employee dataset from Germany, found similar results (Dustmann et al., 2016). They found a significant premium at the start of the work contract, which diminishes quickly, which they interpreted as fast learning of the match quality.

Contrarily, some theoretical work in the literature predicts a wage discount for workers who find their jobs through social networks, even if the unemployment spell is shorter. The underlying premise is that the benefits that we derive from the networks differ. Our more beneficial network connections do not always match where we would be most productive. Assuming we would utilize our productivity in order to find jobs in sectors where we have small endowments from network utilization and utilize our networks in sectors where we have less productivity in order to find jobs faster, networks can induce mismatch, even if they help us find jobs faster, which is also shown using European Household Panel and Multi-City Study of Urban Inequality datasets respectively for the European Union and the United States (Bentolila et al., 2010).

Furthermore, pointing out that the literature is divided, some work focused on non-monotonicity in the wage offer distribution in more detail (Tumen, 2016). The main argument of Tumen is that some informal job seekers accept lower wages than what they can generate using formal methods, and two factors determine the size of this group. These factors are unobserved heterogeneity in informal search costs and the strength of the peer effect in the group. The model suggests that as heterogeneity in the cost of informal search increases, the wage premium increases, whereas as peer effect increases, the wage premium decreases. The underlying idea is that as there are more people with low costs of informal search, they will have higher premiums out of their networks. On the other hand, if your network is connected to a tight community, e.g., mostly blue-collar factory workers, your peers will determine your prospects, even if that means you get a misplacement.

Lastly, another strand of the literature focuses on the pure effects of network structure by creating wage dispersion even within a world in which all workers are identical. The model creates an environment in which when a person hears about a job opening, he/she enters a wage bargaining process, or, if he/she is already employed, passes the offer to an unemployed contact randomly if multiple unemployed people exist in his/her network. Therefore, if your network is filled with already employed people, you are going to get more job offers, creating a better outside option for you. As a result of this, you will have more bargaining power, which increases your wage (Fontaine, 2008). Moreover, Fontaine points to another prediction. As the offer rate depends on the intensity of the search, for both employed people searching for their contacts and unemployed people, different networks may fight for spots, which can create congestion and a disadvantage for some networks. Additionally, networks with more employed people can have higher exit rates as they get more offers, while in networks with less employment, we observe persistent unemployment.

Moreover, in a different model, endogenizing the search method this time, Fontaine inquired about the effect of job search intensity on welfare, with Cahuc pointing out the potential overutilization of networks (Cahuc & Fontaine, 2009). Similar to the previous model, (Fontaine, 2008), employed people pass job offers to their contacts. In this model, an informal search is low-cost for job seekers, whereas a formal search is costly as it means checking everyone's employment situation. This model results in multiple equilibria because of a coordination problem. If workers and firms utilize formal methods, then they are going to be matched without any problem, even if it costs more. However, if one side starts to use informal networks as they are cheaper, the other side will begin to exclusively use informal networks to avoid higher search or hiring costs. They show that a potential coordination problem can arise. More importantly, they show that as a worker’s bargaining power increases, networks tend to be only a stable equilibrium, while social efficiency is independent of it. In these cases, wages and unemployment rates are also large enough to make formal methods unstable.

In addition to the above surveyed mostly theoretical work, there exists a wide range of empirical studies dealing with the effect of networks on job prospects in the literature, with varying results. As a general overview, while some empirical work in the empirical literature on the subject found a negative relationship between wage income and informal networking (Bentolila et al., 2010; Pistaferri, 1999; Yanik-İlhan et al., 2019), some found a positive relationship for the same question (Dustmann et al., 2016; Hensvik & Skans, 2016; Marmaros & Sacerdote, 2002; Simon & Warner, 1992), while some others reported more mixed results (Brown et al., 2016; Pellizzari, 2010).

Using the Italian Survey of Household Income and Wealth's 1991 and 1993 waves, it is shown that informal networking has a statistically significant negative effect on wages at around three to four percent (Pistaferri, 1999). However, it should be noted that Pistaferri's study also notes that the results might be related to specific labor market characteristics of Italy at the time. As noted, the results might be related to the regulatory environment, which exacted hiring costs of over two months of salary. That means at the bottom end, a formal recruitment might not be worth it at all, especially for smaller firms which are prevalent in the Italian context, and informal networks are mainly used to fill those positions.

In a study using a survey of Dartmouth's class of 2001 via e-mail, it is shown that people's earnings are significantly correlated with other people residing in the same hall during their studies (Marmaros & Sacerdote, 2002). Moreover, Marmaros and Sacardote show that networking differs across jobs. While eleven percent of people working in higher education got help from their professors, the number is eight percent for people working in finance. However, forty-two percent of people who found jobs in finance got help from either a relative or someone from their fraternities compared to six percent for higher education, showing that we should keep sectoral distribution in mind when we assess the effectiveness and strategies of networking even if we work with people with similar backgrounds as in this study.

Another study using a detailed dataset of 209 male employees of an Egyptian manufacturing firm tried to address the contradictory results in the literature by controlling for both job and referral characteristics (Antoninis, 2006). Limiting the analysis to people who just started their jobs, as the literature suggests premium or punishment decreases with tenure, being hired through a recommendation does not significantly affect wages. However, when reference type is disaggregated, it looks like a referral from an old colleague has a positive effect, while a friend or family reference does not have a significant effect for skilled jobs. On the contrary, for unskilled jobs, a negative and statistically significant effect was reported. Therefore, it is also important to keep job characteristics in mind even if we are working with people in the same sector.

Using the ISSP 2001 dataset in addition to the Swiss Graduate Survey, Granovetter's and Montgomery's arguments were empirically tested (Franzen & Hangartner, 2006; M. S. Granovetter, 1995; Montgomery, 1992). While datasets confirm that most of the jobs are found through social networks, it also reports that jobs found through networks pay less compared to jobs found through formal methods, and this is statistically significant for strong networks. Additionally, they report that people with more friends at work, and in general, earn more, while people with more friends in their neighborhoods earn less. Still, while they cannot find evidence for higher income due to the utilization of informal networks, they empirically showed that the jobs are both more in line with people's skills, as measured by their degrees, and take less time to find.

While most of the literature tries to understand how people are using networks to have better offers, another explanation suggests that the utilization of informal networks might be the last resort for job-seekers(Loury, 2006). Loury suggests that, while recognizing it is possible for informal networks to increase reservation wages, the story might also be related to limited choices, especially when they are in a network that can generate fewer high-wage alternatives. Utilizing 1979 National Longitudinal Survey of Youth and focusing on men aged between 17-24, Loury reported insignificantly less expected tenure in a job for men who found their jobs through female friends and relatives with significantly lower actual exit rate which can be interpreted as frustration to find better opportunities, while they significantly earn less compared to people utilized formal methods. However, reported results are different for people who utilized their older male connections with longer than expected tenure and higher wages. Also, these results are supported by the question of whether you would choose another job. While it is significantly negative for older male contacts, it is significantly positive for female contacts. Therefore, Loury suggests both the good matches and limited choices hypotheses are valid at the same time.

Another work utilized a very detailed restricted 1990 census for the Boston metropolitan area to identify people who are living in close proximity, namely at the block level, to use it as a proxy for informal networks (Bayer et al., 2008). Assuming no correlation in unobservable characteristics affecting work and residence locations due to very thin housing market, a statistically significant and positive effect of living in the same block on the probability of working at the same block were reported without considering people living at the same household and robust to reverse causality as tested by using a subset with stable residence history.

Pellizzari (2010) developed a theoretical model predicting that the wage premium for those who use informal contacts should increase with the efficiency of the formal job matching process. The rationale is that a more efficient formal process makes filling vacancies easier, rendering referrals consequently more selective. To test this hypothesis, Pellizzari utilized the European Community Household Panel (ECHP) and the National Longitudinal Survey of Youth (NLSY) data to compare outcomes across European countries and with the United States (Pellizzari, 2010). After controlling for fixed effects, Pellizzari reports significant negative effects for Italy, Portugal, the UK, and Finland, while significant positive effects for Belgium and the Netherlands. Moreover, as his model suggests premiums should vanish, he also tested the interaction of informal contact and tenure and found that after six months it becomes insignificant. Additionally, he tests his main hypothesis using the Italian labor market reform. Utilizing a difference in differences framework, Pellizzari reports a positive effect for the northern part of the country, turning from negative after the liberalization of the labor market.

Another study utilized panel data from Britain with detailed information not only on the job-seeker but also on his/her most closest friends(Cappellari & Tatsiramos, 2015). Cappellari and Tatsiramos revealed that having more employed friends increases people's job prospects, providing empirical evidence to the aforementioned theoretical work, while having mixed results for the quality of the job. They report positive effects for high-skilled workers with contacts outside of family, while their report is insignificant for low-skilled workers with the same contact type. On the other hand, while they report negative coefficients for familial contacts for both groups, they are statistically insignificant.

Another study utilized panel data for a single mid-sized US firm in financial services, trying to test different theoretical frameworks regarding the effect of referrals (Brown et al., 2016). Researchers confirmed the learning models in theoretical literature with their observation that there exists an initial wage advantage for referred applicants, which dissipates, and in fact reverses after 5 years, over time. However, unlike some other work, they report a decrease in that advantage with increasing staff level. Moreover, they report that referrals are mostly effective in filling support staff vacancies. Additionally, they report that the variance in wages also converges with tenure, further supporting theories based on learning in the literature.

Aiming to test Montgomery’s model (Montgomery, 1991) directly, another study utilized army test scores to control for cognitive abilities in addition to Swedish register data (Hensvik & Skans, 2016). They confine their analysis to occupations requiring high skill, defined by ISCO. Defining a link as a past coworker relationship, they report significantly higher cognitive scores and wages for entrants with a link, while they report less formal schooling. They also report higher wages and test scores for referring people, supporting Montgomery’s hypothesis that firms utilize their highly able workers’ networks in order to get signals in the labor market.

Additionally, the effect of referrals on productivity was studied, leveraging the same data this study uses, albeit for a shorter period until 2016 (Yanik-İlhan et al., 2019). They report an increasing share for networks in the Turkish labor market from under thirty percent to around thirty-five percent in a cyclical manner for the entire population over fifteen years old who are not at school, military, or unemployed in the previous year, with a real log wage over one in terms of 2016 prices. They used the quantile regression framework in order to control for the heterogeneous effects of referrals over different parts of the labor market. They report statistically significant and negative effects of referrals on wages at all quantile levels.

CHAPTER 3

DESCRIPTIVE ANALYSIS

This study employs data from the Turkish Household Labor Force Survey (HLFS), conducted annually by the Turkish Statistical Institute (TURKSTAT). The HLFS, which surveys thousands of households, is widely recognized as the primary dataset for labor market analysis in Turkey. The survey encompasses a broad range of variables, including occupation, industry, job finding method, public-private sector classification, NUTS regional identifiers, and demographic characteristics such as age and gender. This analysis utilizes HLFS releases spanning the years 2005 to 2023.

To precisely identify wage effects and ensure the robustness of the empirical results, the analysis relies on a carefully constructed sample. These selection criteria address specific data limitations and narrow the focus to the prime age working population, isolating the segment for whom wage income is most important. The main analysis sample is restricted to individuals aged twenty-five to sixty, and observations reporting household income below fifty percent of the minimum wage were excluded. Furthermore, due to the lack of precise interview dates and the presence of two distinct minimum wage rates in Turkey during certain years within the sample period, the annual mean minimum wage was used for calculations. Then, remaining students were dropped. Lastly, the top and bottom one percent of wages are excluded for each year as they may be influenced by implausibly low or high reported work hours. Finally, as I am mainly interested in wage effects, I restricted my sample to full-time permanent wage workers.

The primary variable of interest in this study is the method by which individuals found employment, as captured by the survey question, “How did you find your job?”. From the beginning of my analysis period to the end of 2020, the answer sheet had five options for this question. The options were, by myself, through the official Turkish Employment Organization, through private employment offices, through relatives, spouses, and friends, and others. After 2021, TURKSTAT expanded the options as follows: responding to job advertisements, through relatives, spouses, and friends, through the official Turkish Employment Organization, through private employment offices, through an educational, training or previous institution, applying directly to the employer, by the employer contacting him/her directly, and others. The pre-2021 categories of through the official Turkish Employment Organization, through private employment offices, and through relatives, spouses, and friends were considered equivalent to the post-2021 options through the official Turkish Employment Organization, through private employment offices, and through relatives, spouses, and friends, respectively, and were mapped directly. The remaining new options introduced after 2021 – responding to job advertisements, through an educational, training or previous institution, applying directly to the employer, and by the employer contacting him/her directly – were all categorized under the pre-2021 by myself option to ensure consistency. As I do not know the details of the other option, I dropped it from my analysis. Lastly, the criterion for this question changed during my analysis period, namely TURKSTAT changed the recall period. To ensure comparability, potentially affected by differing recall periods in the survey, the analysis only includes individuals who started their current job within two years prior to the survey date. This restriction was applied even though data for 2021 and 2023 allowed for reporting job starts up to seven years prior.

The general pattern of job-searching methods in Turkey is shown in Figure 1. While the presented results are broadly consistent with the literature regarding a slight upward trend at the beginning of the period (Yanik-İlhan et al., 2019), there has been a noteworthy upward break in the share of individuals finding jobs through informal networks in recent years. While the ratio of people who found their jobs using informal channels, that is, through relatives, spouses and friends, increased from twenty-three percent to twenty-nine percent in earlier period, we observe a significant spike after 2019. In 2020, the ratio reached forty-seven percent. While we do not have the same number of surveys for 2022 and 2023, the trend seems to indicate that informal channels overtook the standard way of finding a job through market interactions, reaching its new height of fifty-nine percent in 2023.

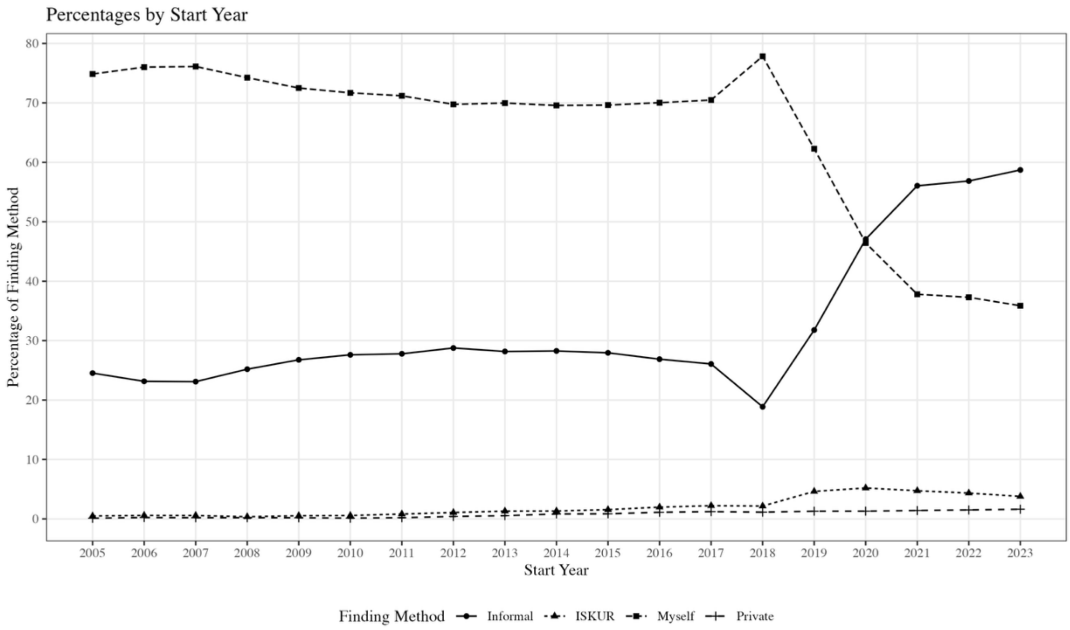

Figure 1. General trends for job searching methods

The 2018 data point seems to break the previous trend considerably. To understand this deviation, I utilized the public-private disaggregation question that was asked after 2009. A significant spike in 2018 is observable, which was the year of the first election after Turkey transitioned into a presidential system, where over 30 percent of new job seekers were employed in the public sector, with significantly fewer jobs filled through informal networks than in the private sector. However, job filling by informal networks has also increased for public sector jobs by almost fourfold from three to thirteen percent since 2018. Additionally, I document a significant share for the official employment agency, ISKUR, in public sector employment, with a seventeen percent share in 2023. These trends are shown in Figure A1 and Figure A2.

Furthermore, it is also important to investigate breakdowns for educational attainment. To investigate whether job-finding methods differ by education level, I report the breakdown by educational attainment in Figure 2. While people with at least a college degree found their jobs through standard market interactions at over

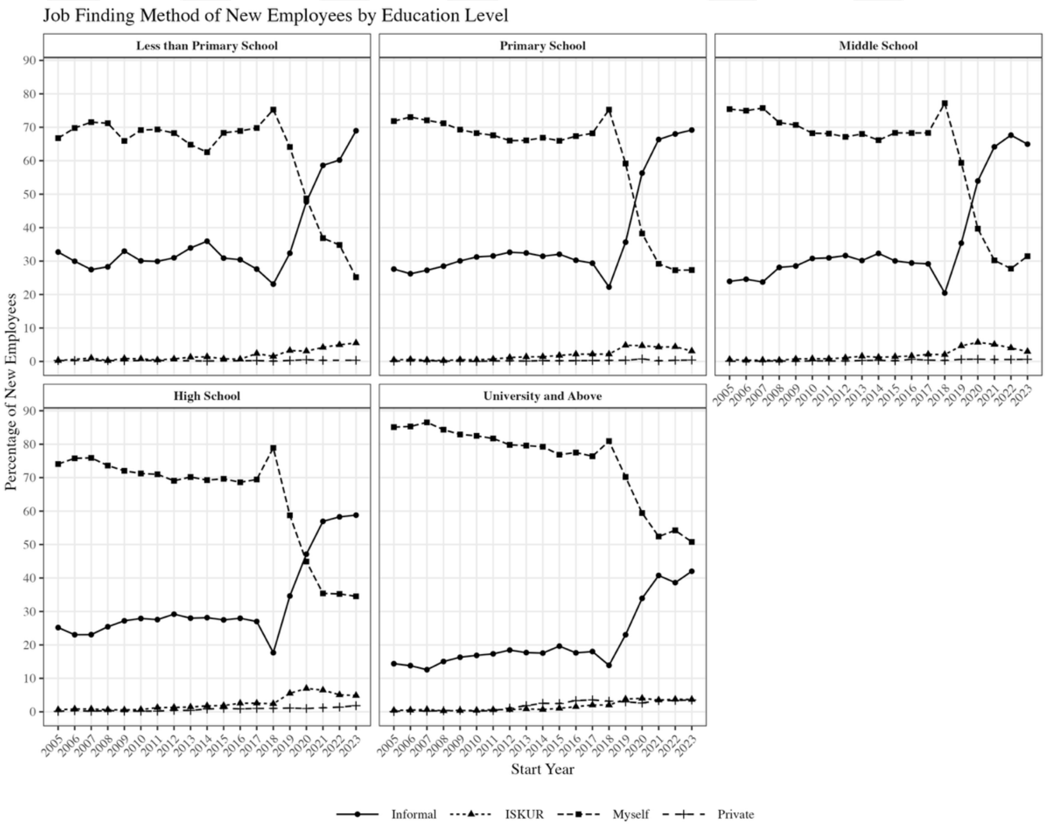

Figure 2. Educational attainment disaggregation

eighty percent in 2018, the shares fell to fifty-one percent in 2023. The same shares for people with high school degrees were seventy-nine and thirty-five percent.

Moreover, I observe a secular increase in female employment. The ratio of job fillings by females started at twenty-one percent in 2005 and reached its maximum at thirty-six percent in 2022, as shown in Figure A3. Additionally, as indicated in Figure 3, we observe similar trends for both sexes, albeit a little more pronounced for males, that they are increasingly finding their jobs through their networks of relatives, spouses, and friends. In 2017, seventy-one percent of males were finding their jobs through market interactions; that share fell to thirty-three percent in 2023. Similarly, seventy percent of females were finding their jobs through market interactions in 2017, and that share fell to forty-one percent in 2023.

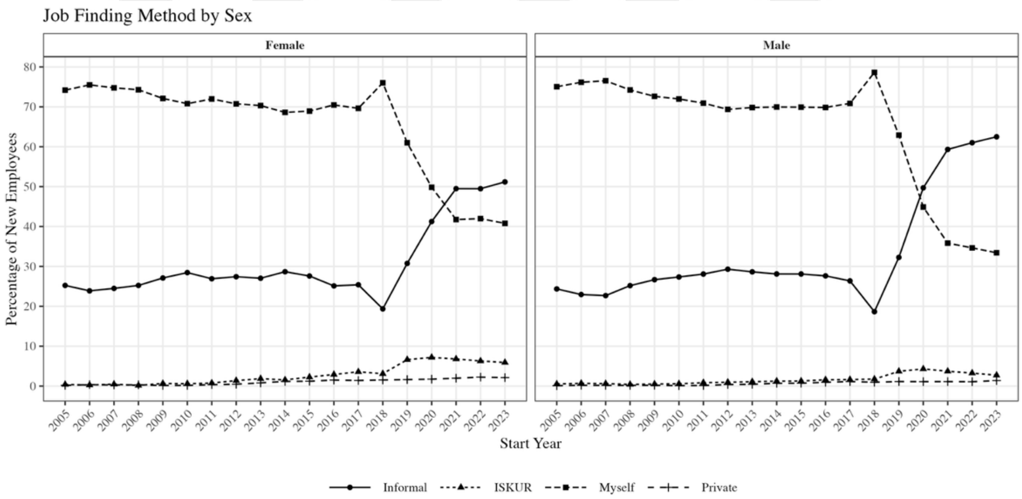

Figure 3. Sex disaggregation

Moreover, as not all sectors develop similarly, it is important to disaggregate data on the sectoral level. In Figure 4, I document how job-finding methods used by individuals changed in different sectors. Sectoral definitions are created using the International Labor Organization’s classification. Industry refers to manufacturing, mining, quarrying, and utility supplies. Market services refer to trade, transportation, accommodation, food, and business and administrative services, while nonmarket services mainly refer to public administration and social services. We observe a similar increase in reliance on informal networks for job-finding in all sectors, although the extent of these changes differs. Additionally, as Turkey has a wide

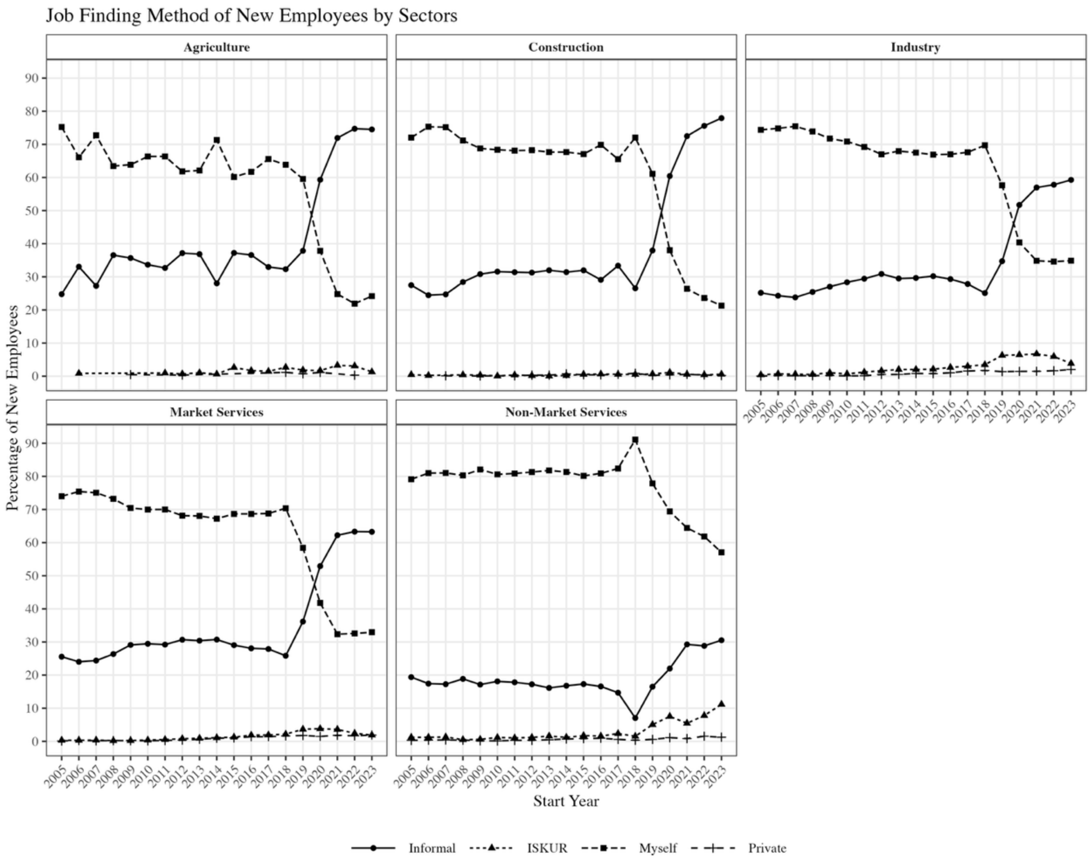

Figure 4. Sectoral disaggregation

regional developmental gap, it is vital to check regional differences. I observe a consistent decline in new job filings in Istanbul. In 2005, almost one in four jobs were filled in Istanbul at twenty-five percent, which fell to eleven percent in 2023. These trends are shown in Figure A4.

While the above descriptions suggest substantial changes, it is possible that they are caused by my mapping of recent survey answers to previous ones. In order to check their robustness, I checked the trend of the share of jobs found through informal networks using only newer waves. Instead of using only the last two years for each wave, I used all available data from newer waves. While not as stark, I documented an increase in the share of jobs found through informal networks, going from around forty percent to sixty percent. However, disaggregating by education reveals that individuals with longer job tenure, who are included when using all available data from newer waves up to seven years, tend to be more educated than recent job starters, restricted to two years, as shown in Figures A5 to A8. That observation is in line with the literature (Lazear & McCue, 2018). As shown in Figure 2, more educated people are less likely to find jobs through informal networks, and it is the only group where market mechanisms remain the primary method of job finding. Lastly, I plotted using observations who started their work in the year of the survey in Figure A9. In sum, while it may not be a more than two-fold increase, these checks support the conclusion that the share of jobs found through informal networks is on the rise since 2018, and especially after the pandemic, this study observes a jump.

Additionally, the dataset allows for several observations regarding the job search process among the unemployed. The HLFS asks people whether they searched for jobs within the last four weeks, or three months in earlier waves, if they are not employed. Then, it asks for different possible channels, including whether they asked their relatives and friends to find them a job, and how many months they searched for employment. What is interesting is that after 2019, I observe a secular decline in the share of people who asked their friends and relatives for a job from ninety percent to eighty-four percent. Moreover, the observed mean time declines from 2005 to 2016 and increases until 2021 after that point. Then it decreased and stabilized until the end of my period of analysis. Especially 2021 seems higher than the rest, which is to be expected considering it was the height of the pandemic. While the data does not allow me to make a more detailed analysis, preliminary findings indicate that the observed mean time is consistently below for people who use informal networks compared to others, which is in line with the expectation of the literature. Furthermore, a noteworthy pattern emerges. This contrasts sharply with earlier findings: during the same period that the share of individuals finding employment through informal networks increased, the share of unemployed individuals actively searching via informal networks decreased. These trends are shown in Figure A10 and Figure A11.

CHAPTER 4

METHODOLOGY

This study employs ordinary least squares regression to examine the impact of job-finding methods on wages in Turkey. The dependent variable is the real wage income of individuals' primary employment, measured in 2003 constant Turkish Lira. Nominal wages were deflated using TURKSTAT's consumer price index, with 2003 as the base year.

The ordinary least squares regression model includes several control variables to isolate the impact of job-finding methods on real wages. To account for the standard inverted U-shaped age-earnings profile, age and its squared term (age^2) are included as regressors. Additionally, the model controls individual characteristics such as gender, the highest level of educational attainment, marital status, household size and the skill level of occupation. Additionally, several job characteristics are controlled. A dummy variable indicating whether the individual worked in the week prior to the survey is included to account for potential discrepancies, as the income data refers to the previous month. Other job controls include dummy variables for moonlighting and social security status, tenure, public versus private sector employment, sector, and firm size (measured by the number of employees). Lastly, NUTS1 regional identifiers and year dummies are included as final controls.

Industry codes were aggregated into broader categories using the International Labor Organization's sector concordance table. Specifically, construction was treated as a separate industry, manufacturing was combined with mining and utilities, services were disaggregated into market and non-market services, and agriculture was kept as a distinct sector. Furthermore, occupational skill levels were aggregated using the International Labor Organization's classifications based on ISCO-08 and ISCO-88 codes, as shown in Table 1. The explicit base regression is as follows,

$$\begin{aligned} ln(RealWage) \\ &= \beta_0 + \beta_1 Finding\ Method + \Theta Demography\ Controls \\ &+ \Gamma Firm\ Controls + \Lambda Geographic\ Controls + \epsilon_i \end{aligned}$$

Table 1. Skill Levels and Occupations

SKILL LEVEL	OCCUPATIONS
4	- Legislators, Senior Officials and Managers - Professionals
3	- Technicians and Associate Professionals
2	- Clerks - Service Workers and Shop and Market Sales Workers - Skilled Agricultural and Fishery Workers - Craft and Related Trades Workers - Plant and Machine Operators and Assemblers
1	- Elementary Occupations

Although prior research has examined the heterogeneous effects of job-finding methods on wages in Turkey using quantile regression to account for wage distribution (Yanik-İlhan et al., 2019), this study employs interaction terms and subset analysis for their easier interpretability and informational content. As highlighted in the theoretical literature (Tumen, 2016), job-finding methods are not exogenous to individual characteristics, leading to differential wage impacts across different demographic groups. Specifically, informal job searches through familial networks differ significantly from referrals by former colleagues. This distinction underscores the theoretical critique of empirical studies that suffer from potential sample selection bias and omitted peer effects, which may explain negative wage outcomes associated with informal job searches (Tumen, 2016). To account for these concerns, an additional control variable is constructed. After grouping the individual data by household, a variable is generated to identify the presence of other household members currently or previously employed in the same occupation group. This variable is included as a control, along with interaction terms between relevant variables such as job-finding methods and skill level. This variable serves as a proxy for potential strong tie effects within the household. However, it should be noted that this proxy might also capture other unobserved household-level factors, such as shared economic background or localized network advantages. Still, as these other factors are mostly relevant for what the literature calls peer effect, it is used as an additional control variable. Lastly, I used the natural logarithm for the dependent variable, real wage in terms of 2003 prices, for easier interpretability, as this transformation means coefficients for independent variables will be in terms of percentages. Additionally, in order to estimate the on-the-job search, I used whether a person is searching for an additional or alternative job while employed. Using the same control variables, I used search as the dependent variable in a logistic regression and real wage.

For better interpretability, I used the average marginal effects of the variables of interest at different points to differentiate the effect of variables to account for the abovementioned critique. Moreover, while quantile regression would do a similar job, it would not help me to identify subgroups, but instead it would give me effects on different parts of the wage distribution. Therefore, I used OLS with interactions. When I add interaction terms to an OLS model, the coefficients of the independent variables are no longer sole effects on the dependent variable. Therefore, expectations and standard errors are calculated using the delta method for interpretability. Therefore, I can check the effects of informal methods, having someone with the same occupation in the same household, and skill levels at different points in my dataset.

CHAPTER 5

RESULTS

I am going to present and investigate my results on the effect of finding a job through informal networks. To understand this, I will start by baseline regressions using controls described in the methodology section. Then, I am going to introduce interaction terms to differentiate the effect on different segments of society. I followed heteroskedasticity-consistent standard errors described in (Davidson & MacKinnon, 1993), as it gives the most conservative estimates for standard errors in order to ensure that what I found is significant.

To have a baseline understanding, I started without any interaction terms and ran standard OLS regressions using different subsets. Results of these regressions can be found in Table 2. In the first three columns of the table, I did not control for the occupations within the same household. In the first and fourth columns, I used the entire dataset, including waves from 2005 to 2023. In order to be able to do this, I did not control the public-private sector distinction, which is included after the 2009 wave. In the second and fifth columns, I controlled public-private sector distinctions, as a result, the number of observations decreased. Lastly, in the third and sixth columns, I run the same regression but use only private sector employees as my main results.

In column one, it is shown that finding a job through informal networks has a negative and statistically significant effect on wages of around four percent. As expected, there exists an inverted U shape for age and increasing returns to education from seven percent for primary school to thirty-six percent for higher education. Additionally, coefficients for the characteristics of the jobs are as expected, with a four percent positive effect for jobs at skill level two compared to elementary occupations. While having a job at skill level three, technicians, have a twenty-two percent positive effect, being a professional or a manager has a forty-four percent positive effect on wage for a given person.

When I add the public-private sector distinction, the most important change happens in my variable of interest, the effect of informal job search. The additional control has an effect of forty-four percent itself, while decreasing the effect of informal finding to just under two percent, with maintained significance. Then, I ran the same regression for private sector employees only in order to focus on the main part of the labor market and found a similar effect while maintaining significance.

Then I ran the exact same regressions that I described above in the same order with the same subsets, but I used an additional control variable of whether a person has some other person working at the same occupation in the household that he/she lives, defined broadly as in the occupation column of Table 1, not a direct match between ISCO codes. Meaning if someone is a clerk, the dummy takes the value 1 if another clerk lives in the same household and 0 if not. The additional control did not change the significance or coefficients for variables of interest in a noteworthy manner, and it maintained its significance consistently.

Therefore, baseline regressions suggest around a two percent negative effect for finding a job through informal networks. While this result is important in itself, it does not fully address the criticisms and why mixed evidence is observed throughout the literature. In order to understand the effects better for different segments of society, I introduced interaction terms to these baseline regressions to address potentially differential impacts.

Table 2. Baseline Regression

Dep: Ln Real Wage	05-23 (1)	09-23 (2)	Private (3)	05-23 (4)	09-23 (5)	Private (6)
Informal	-0.038***	-0.017***	-0.016***	-0.038***	-0.017***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Occupation Check				0.015***	0.011***	0.004**
				(0.001)	(0.001)	(0.001)
Public Sector		0.441***			0.441***	
		(0.003)			(0.003)	
Age	0.019***	0.017***	0.021***	0.019***	0.018***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.003***	-0.000	-0.004***	0.003***	-0.000	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Primary School	0.066***	0.048***	0.046***	0.066***	0.048***	0.046***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
High School	0.163***	0.141***	0.139***	0.163***	0.142***	0.139***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Higher Education	0.356***	0.308***	0.279***	0.356***	0.308***	0.279***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
10-49 Workers	0.109***	0.085***	0.079***	0.109***	0.085***	0.079***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
50+ Workers	0.191***	0.148***	0.152***	0.191***	0.148***	0.152***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Household Size	-0.024***	-0.022***	-0.019***	-0.024***	-0.022***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.120***	-0.092***	-0.096***	-0.121***	-0.092***	-0.096***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Skill Level 2	0.044***	0.046***	0.043***	0.045***	0.046***	0.044***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Skill Level 3	0.217***	0.215***	0.224***	0.220***	0.217***	0.225***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Skill Level 4	0.435***	0.427***	0.436***	0.435***	0.427***	0.436***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Num.Obs.	376822	332342	301056	376822	332342	301056
R2 Adj.	0.518	0.543	0.484	0.518	0.543	0.484
• **p < 0.05, ** p < 0.01, *** p < 0.001**						

From this point onwards, I focused on private sector employees. In addition to the above controls, I introduced several interaction terms. First, I added the interaction of the job-finding method and the skill level of the job in order to check the criticism in the theoretical literature and differentiate the effect based on the job characteristics. Additionally, I introduced interactions between the job finding method and the following variables: occupation check, and tenure. Moreover, to control for year interactions with the jobs, I used skill level and year interaction. Additionally, I used skill level and occupation check interaction to address the same criticism with skill level. Lastly, I introduced a triple interaction for finding method, occupation check, and skill level.

In Figure 5, I report on the average marginal effect of my main variable of interest, finding a job through informal networks. In the base section, I reported the effect of informal networks for the general population, which is around two percent and statistically significant. However, when I fixed the characteristics of the job using skill levels of the occupation, a different picture emerges. I find a statistically marginally significant effect of informal networks for elementary occupations on earnings. However, I find a little over than negative ten percent effect for professionals and managers in finding their job through informal networks.

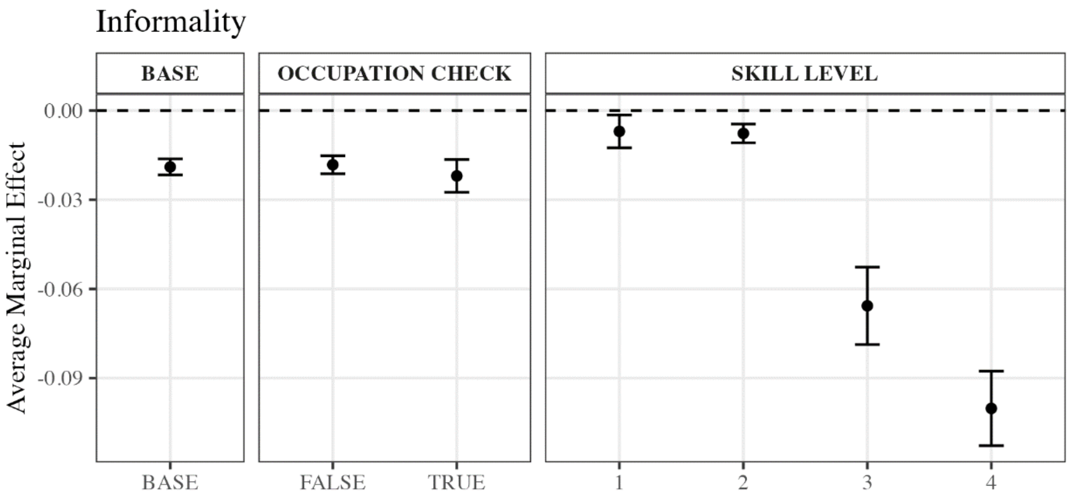

Figure 5. Average marginal effects for informal networks

Moreover, it is increasing with the skill level. While the effect is over six percent for technicians and associate professionals, it is less than one percent for other workers. Therefore, it is possible to argue that this work is more in line with the last resort hypothesis than a better match for jobs at the higher levels, as indicated by lower or statistically indifferent wages for all. As no single group has statistically significant and positive effects, I found no empirical evidence for the better match hypothesis. When compared with the base effect we observe, calculated using the same regression with interaction terms, it is obvious that the effect of informality is not the same for all people, and the two percent figure is severely underestimating the effects for white collar or sophisticated blue-collar workers.

Additionally, I rerun this regression using only waves from 2021 to 2023, with 2 years maximum tenure, as these are affected by my mapping, the effects are again statistically significant and negative for skill levels three and four, while economically insignificant for others, namely for skill levels one and two. Still, using only latter waves, albeit very close, the effect seems to be around seven percent for technicians and nine percent for managers and professionals.

Furthermore, I checked the isolated effect of having some other person in the same household and reported it in Figure 6. What I observe is almost a mirror image of what I reported in Figure 5 about informal methods. People working as professionals or managers directly benefit from having another person working in the

Figure 6. Average marginal effects for occupation check

same occupation, which is created separately for each, resulting in around nine percent increase in their wage earnings.

That is different from small yet statistically significant effects for elementary workers and blue-collar workers, other than technicians. These results are different from what we observe for the entire dataset, where we found a significant but not economically significant magnitude-wise effect with point four percent. The differentiated effects might be in support of it is not what you know but who you know hypothesis.

In order to test this, I utilized the triple interaction, as shown in Figure 7. While the effect is essentially the same in Figure 5, I document an increased effect of finding a job through informal networks, especially for professionals and managers. The effect is around negative thirteen percent for professionals and managers if they have someone working in the same occupation, amounting to over a twenty-five percent increase compared to fixing only the skill level, and around a thirty-six percent increase compared to when there is no one working at the same occupation in the same household.

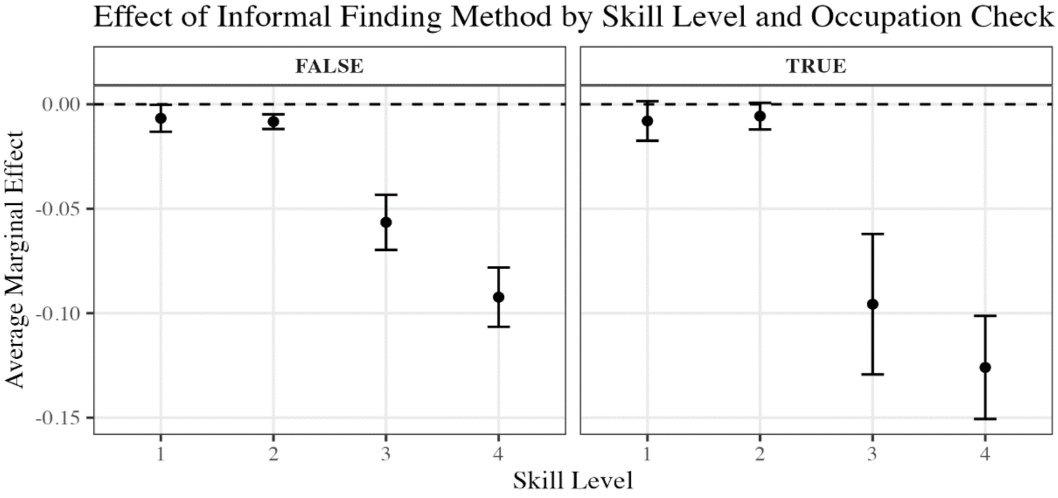

Figure 7. Average marginal effects for informal networks with triple interaction

It is important to note that this is not a perfect substitute for the more detailed questions differentiating informal networks in the literature. However, it is also noted that within informal networks, while they are not as likely to bring new information, when they do bring new information, strong ties have more reasons to help out. Therefore, it is reasonable to expect that there is a strong reason to believe that if the occupation check is true informal network is through strong links. Hence, the difference is in line with the literature suggesting the coworker link is different than strong links such as family networks.

Moreover, in order to test whether a learning process is observed after a match using informal networks, I checked the interaction between finding a job through informal networks and tenure at the job. Figure 8 shows the average marginal effects at different tenures. I find no evidence in the Turkish labor market context for learning after the employment process, as the earnings difference between people who found their jobs through market mechanisms and informal networks is growing monotonically with the tenure of the worker.

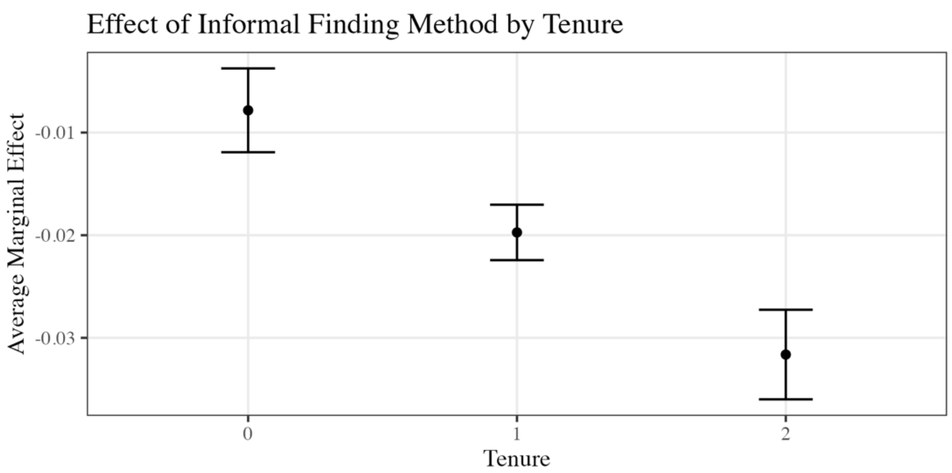

Figure 8. Average marginal effects at different tenures

Lastly, I checked the effect of skill levels over the years. I documented a decrease in the effect of the higher skill levels on income until 2021, as shown in Figure A12.

In order to check whether there exists a change in the effect of informal networks over the years, I used the subset of people who started their jobs in the year of a given survey wave. As I do not control for tenure in this regression, I did not include interaction terms with it but instead I added interaction term of year with occupation check to see whether there exists any change through years. There is no discernible difference over the years, as shown in Figure 9. The same analysis suggests a slightly increased effect for higher skill levels while completely erasing the effect for elementary occupations. The same analysis suggests similar trends for the effect of skill level over the years with the entire dataset, as shown in Figure A13.

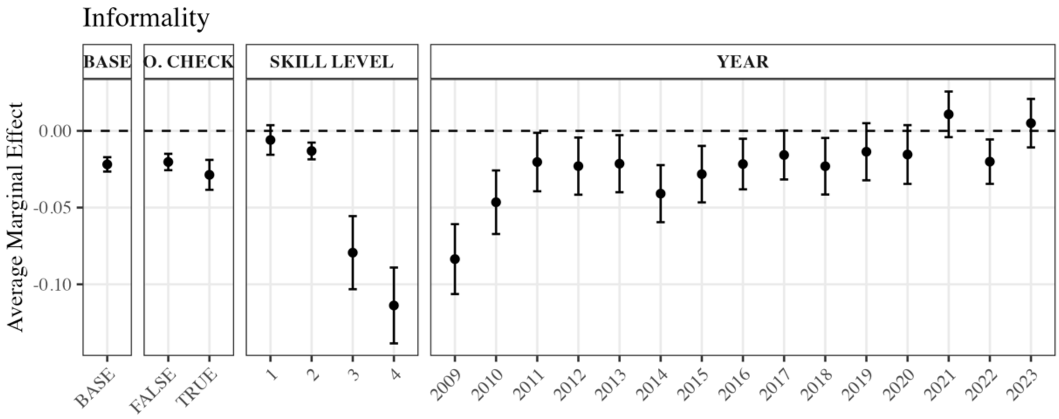

Figure 9. Average marginal effects for informal networks using starters

Lastly, all regressions up until this point used people aged between 25 and 60. I checked young people with separate regressions to be comparable with the literature, utilizing surveys of young people.

Figure 10 presents the average marginal effects of finding a job through informal networks for people below 25 years old. While the ordinality of the effects

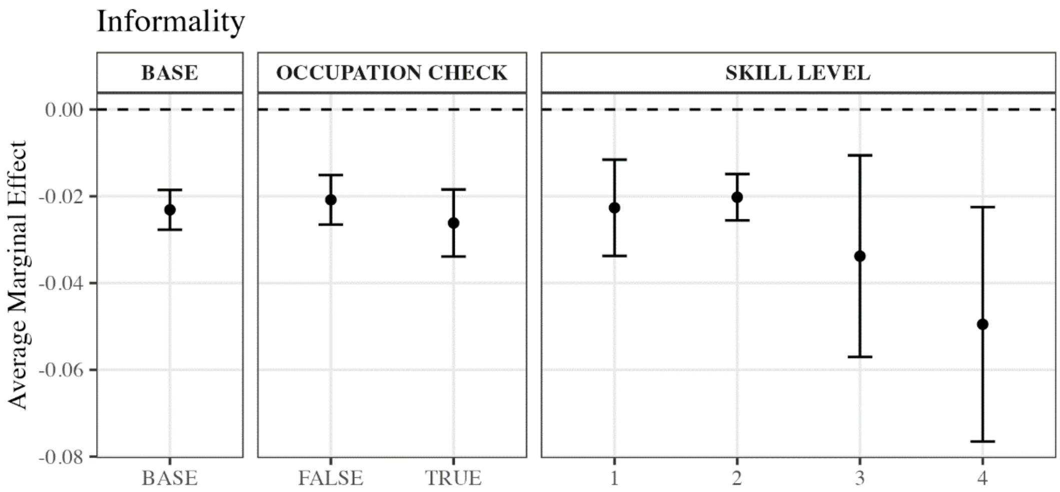

Figure 10. Average marginal effects for informal networks for people below 25

for different occupations is similar to the general population, the effects are much less pronounced.

Additionally, in Figure 11, I observe a similar picture to Figure 6 with positive and significant effects of around seven percent for managers and

Figure 11. Average marginal effects for occupation check for people below 25

professionals, and around two percent for technicians. However, I cannot make the same claim that I did for the general population.

I did not observe an increase in the effect when I checked the effect of informality on different skill levels at different values of the occupation check within the same household, as shown in Figure 12. This might be due to an insufficient number of observations, resulting in large confidence intervals. However, it might also be related to the lower likelihood for people below 25 to have previous coworkers who can recommend them. Therefore, we might not observe the expected distinction between weak ties (like former coworkers) and strong ties (like family), possibly because people under 25 often do not yet have sufficiently differentiated

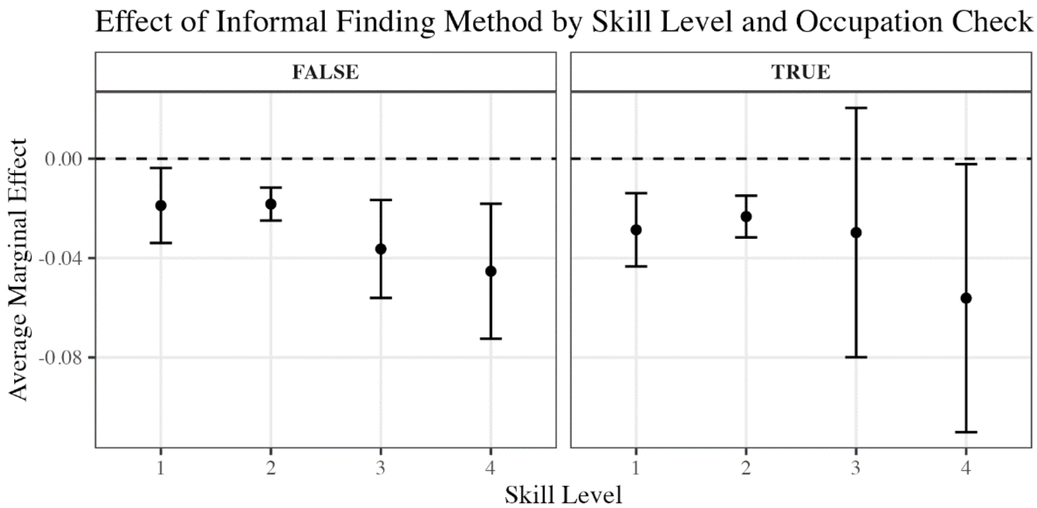

Figure 12. Average marginal effects for informal networks using triple interaction for people below 25

networks this early in their lives. This aligns with literature that highlights the differing characteristics and roles of such weak versus strong social connections.

Additionally, in order to have a sense of how informality interacts with the on-the-job search, I checked frictional unemployment. These people have jobs, in my analysis, they are full-time, permanent wage employees, but they are still searching for a job either to complement their existing jobs or to change it altogether.

To do this, I utilized the question asking whether a person tried to find a job within the last four weeks in order to change or complement his/her current job. I run a logistic regression with an answer to this question as the dependent variable. I used same control variables that I used in previous OLS models, and real wage as an additional regressor. For better interpretability than coefficients, odds ratios for variables of interest are shown in Table 3.

Table 3. Odds Ratios for Base Logistic Regression

Odds Ratios	Variable
0,578523770	Female***
1,619822902	High School***
1,335958572	Middle School***
1,198709191	Primary School**
2,437268442	Higher Education***
1,058073009	10-49 Workers*
1,148141957	50+ Workers***
0,619206187	Social Security***
1,085293800	2010
0,977084493	2011
0,901871116	2012
1,167202339	2013**
1,019412928	2014
0,983577007	2015
0,992841388	2016
1,142242956	2017*
1,151223626	2018*
1,333779542	2019***
1,354223618	2020***
2,643682443	2021***
2,887720857	2022***
4,936143294	2023***
1,008868756	Occupation Check
0,882297728	Tenure***
0,962256838	Household Size***
0,974594994	Skill Level 2
0,919190117	Skill Level 3
0,993918729	Skill Level 4
1,501763980	Informal***
0,502505906	Ln Real Wage***
*p < 0.05, ** p < 0.01, *** p < 0.001	

As shown in Table 3, in the Turkish labor market, the probability of searching for an additional or alternative job is increasing with education and firm size. On the contrary, the same probability is less for women, people who have social security, larger households, and longer tenures at their jobs. Interestingly, the odds are on a steady increase after 2017. People had fourteen percent more odds to search for an additional or alternative job in 2017 compared to 2009. Furthermore, this ratio steadily increased to thirty-five percent in 2020. However, after the COVID pandemic, I observed a break in the trend. In 2023, people had nearly five times the odds to search for an additional or alternative job. Moreover, unsurprisingly, as compensation increases, people are less likely to search for additional or alternative jobs.

More importantly, if a person found his/her job with informal networks, he/she has fifty percent more odds to search for an additional or alternative job. However, unlike what I found in preceding regressions, I do not find a monotonic relation for the job characteristics. Additionally, I do not find any relevance in someone having the same occupation within the household.

While the initial look does look like there is no difference for different jobs, I ran additional logistic regression using the same interactions as the previous OLS. In Figures A14 and A15, I find monotonic decrease for the effect of informal networks with tenure and no significant difference with respect to job characteristics using average marginal effects. In light of these results, it can be argued that even if informal networks can help people to find jobs and increase the likelihood of on-the-job search, they are not as relevant, for the on-the-job search context, when it comes to creating heterogeneous outcomes.

CHAPTER 6

CONCLUSION

I investigated the prevalence and wage effects of informal job searching within the Turkish Labor Market using the HLFS's waves from 2005 to 2023. The existing empirical literature has mixed evidence for the effect of job finding through informal networks. Keeping both the empirical and theoretical criticisms in the literature, this study aimed to understand the effect of informal networks.

The analysis revealed several key results. First, the rate of finding a job through informal networks increased significantly after 2018, and a jump is documented after the COVID pandemic. Especially after 2021, informal methods overtook market mechanisms as the primary method of job finding in the Turkish labor market. This observation is consistent for different disaggregations, such as sectoral distribution, sex distribution, and education characteristics.

Contrary to the theoretical models emphasizing efficiency gains or signaling, this study found approximately a two to four percent wage penalty for informal networks, after a wide variety of demographic controls, firm characteristic controls, year, and geographical dummies were added.

Importantly, this work documents a significant heterogeneity in wage effects by occupation characteristics. The negative association between wages and the informal job finding method is largely driven by professionals, managers, and technicians, highly-abled blue collar workers, while the effects for elementary occupation workers and other blue-collar workers are either economically or statistically insignificant.

As the HLFS dataset does not differentiate between different network types, I constructed an additional variable checking whether there exists a different worker in the same household having the same occupation. Contrary to the effect of finding a job through informal networks, having someone working in the occupation in the same household exerts a positive and significant effect of around the same degree as the negative effect of informal networks. This is in line with the hypothesis that it is not only what you know but also who you know.

Moreover, when I checked the effect of informality using triple interaction, I documented an exacerbated effect of wage penalty of around twenty-five to thirty-six percent. That is most likely due to the differences between informal networks. However, it should be noted that this approach is not a perfect proxy to differentiate between strong and weak networks. Still, as the likelihood is higher for strong networks, mostly family, for helping out, it is a reasonable proxy, giving similar results to the literature. Lastly, similar, but less pronounced, results are found for young people with no difference in occupation checks within households.

Using interaction terms and average marginal effects, the findings of this work contribute to the literature by highlighting the differences of informal networks on different segments, providing empirical evidence for heterogeneous effects, in line with the criticism of the theoretical literature. The results challenge simplistic views of network effects, suggesting that for skilled labor in Turkey, network-based job matching may lead to poorer wage outcomes, potentially indicating issues of mismatch or constrained opportunities rather than efficient signaling or information transmission. The increasing reliance on these channels, coupled with the associated wage penalties for skilled workers, raises questions about labor market efficiency and the potential for misallocation of human capital in Turkey.

While this study provides valuable insights, the limitations inherent in the available data suggest potential for future research, particularly regarding the differentiation between various types of informal ties and the use of methodologies better suited for causal inference. Nonetheless, this inquiry underscores the critical importance of understanding the nuanced role of job search methods and social networks in shaping labor market outcomes, revealing that in the Turkish case, the ties that bind workers to jobs may not always lead to the most economically advantageous positions, especially for those with higher skill levels.

APPENDIX

SUPPLEMENTARY FIGURES

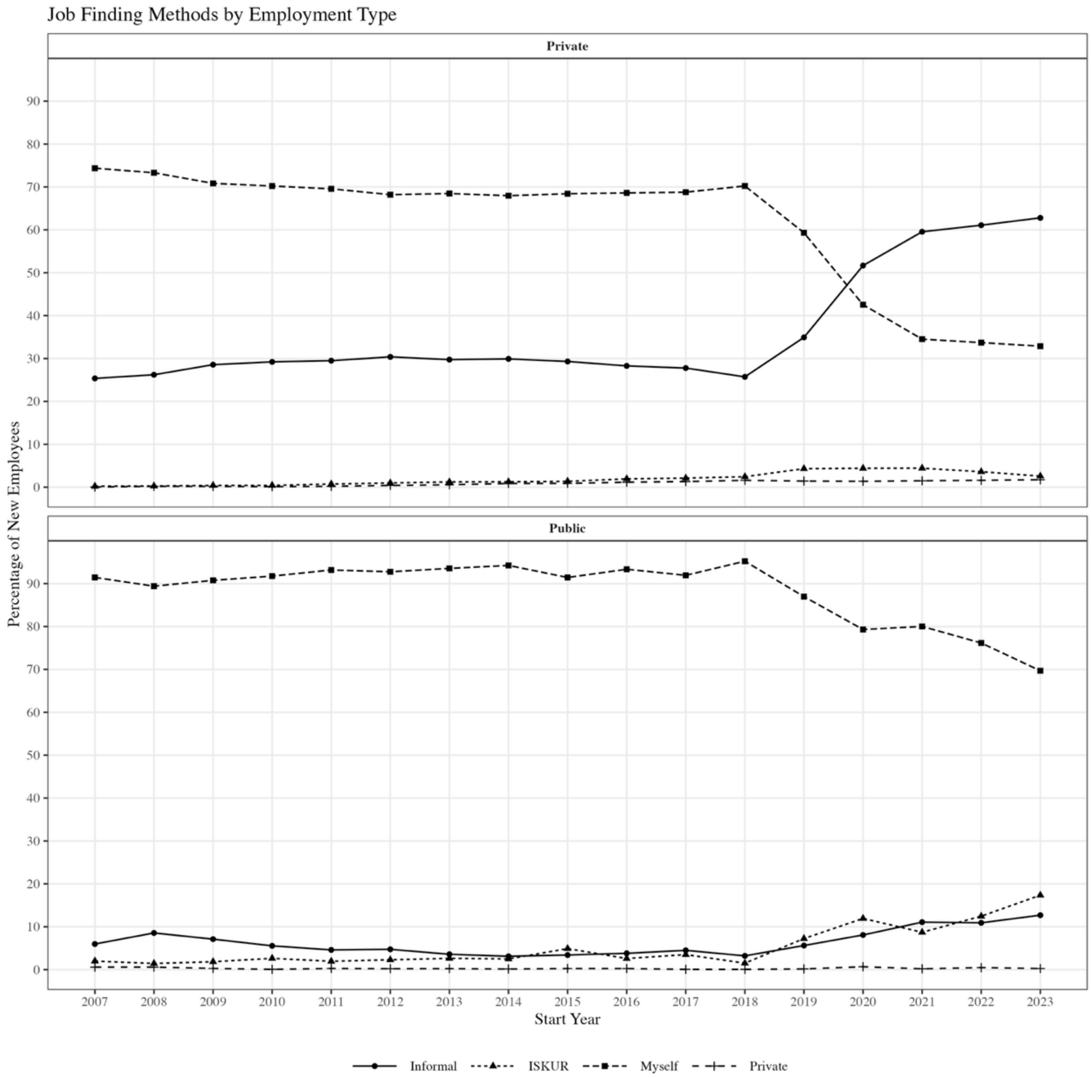

Figure A1. Job finding methods in public and private sectors

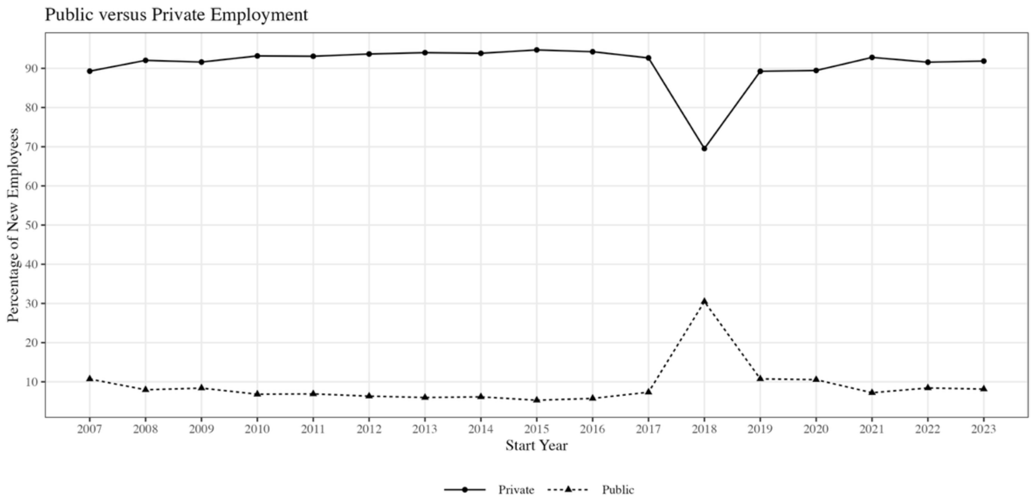

Figure A2. Public and private sector employment

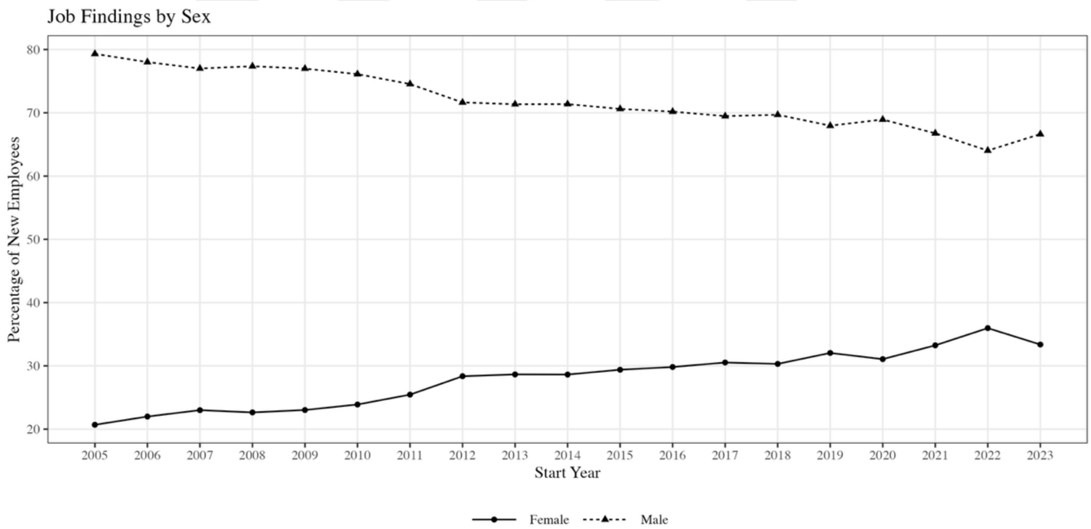

Figure A3. Employment by sex

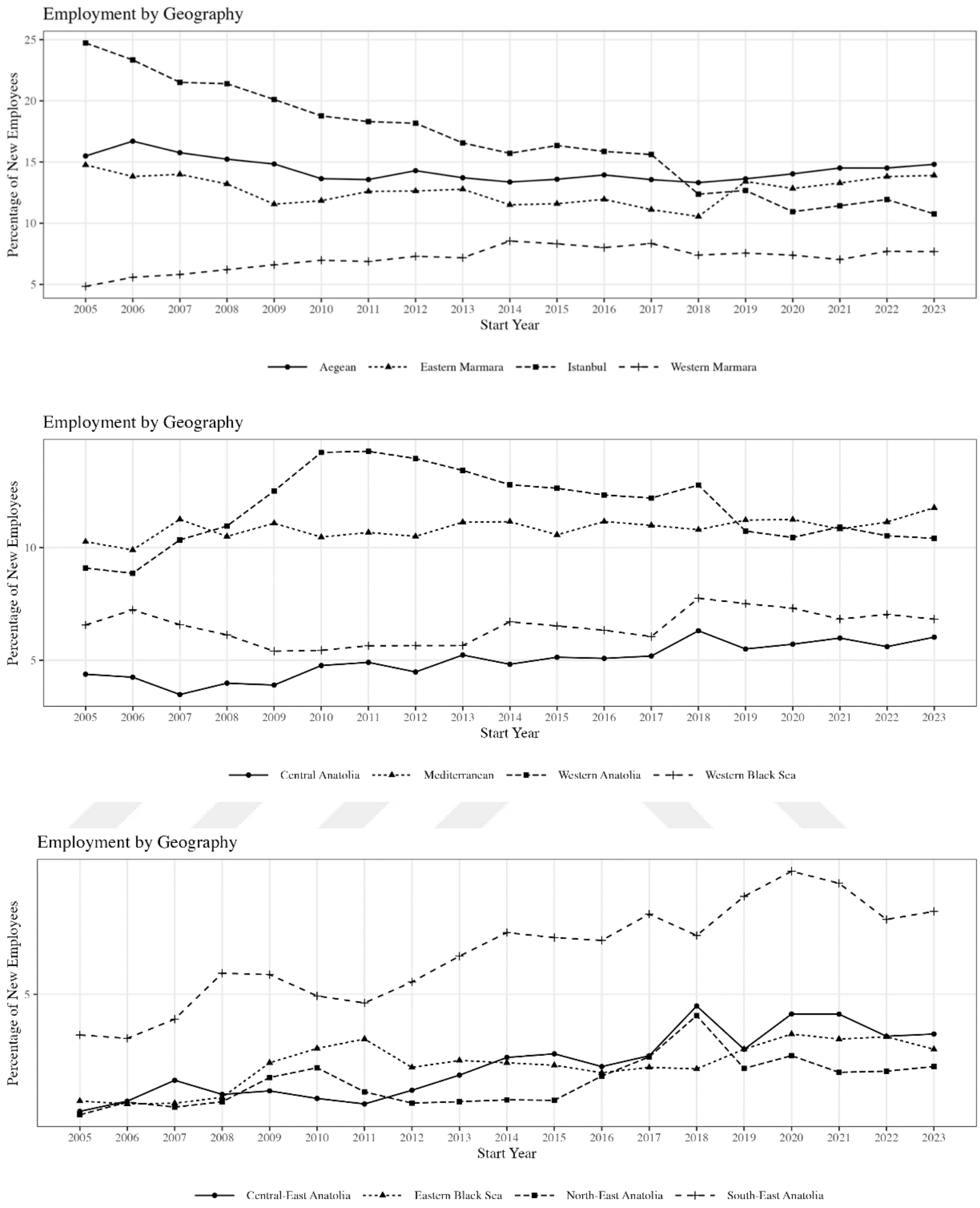

Figure A4. Employment by geography

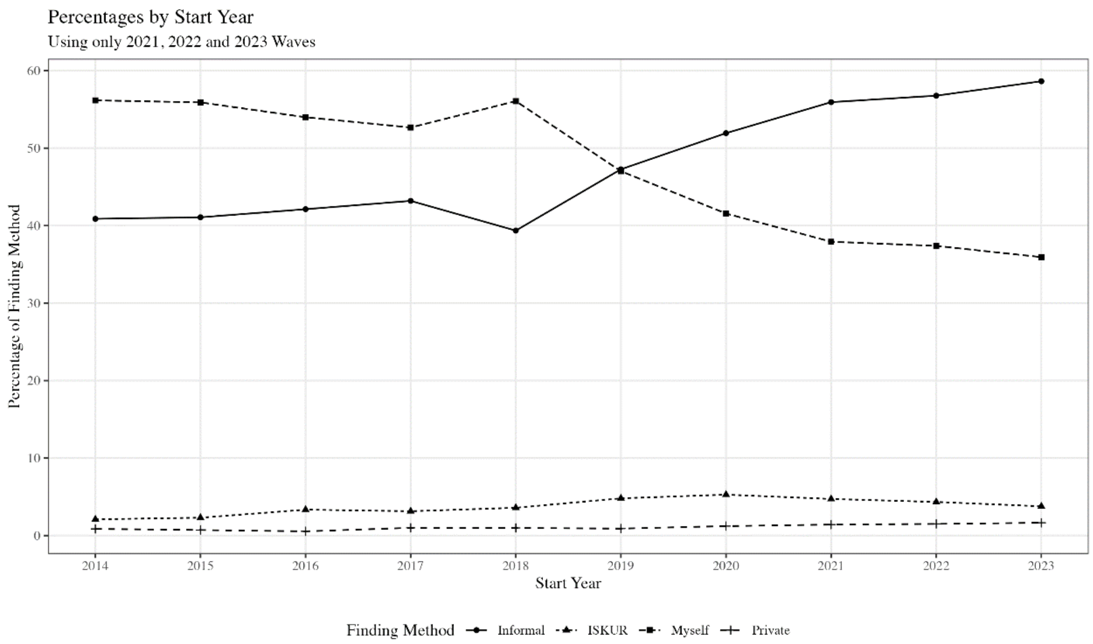

Figure A5. General trends using only waves 21-23

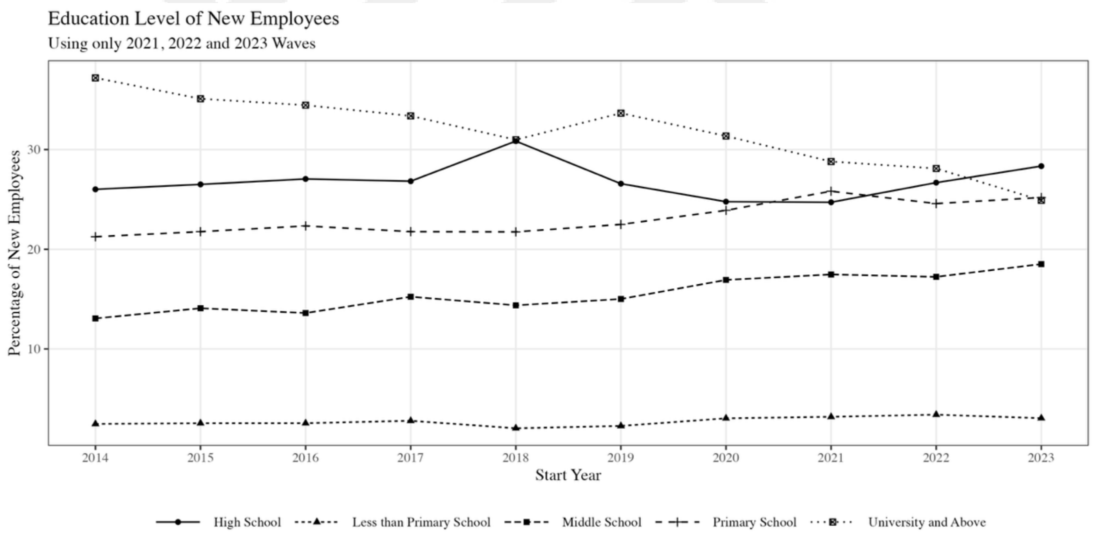

Figure A5. Educational attainments in waves 21-23

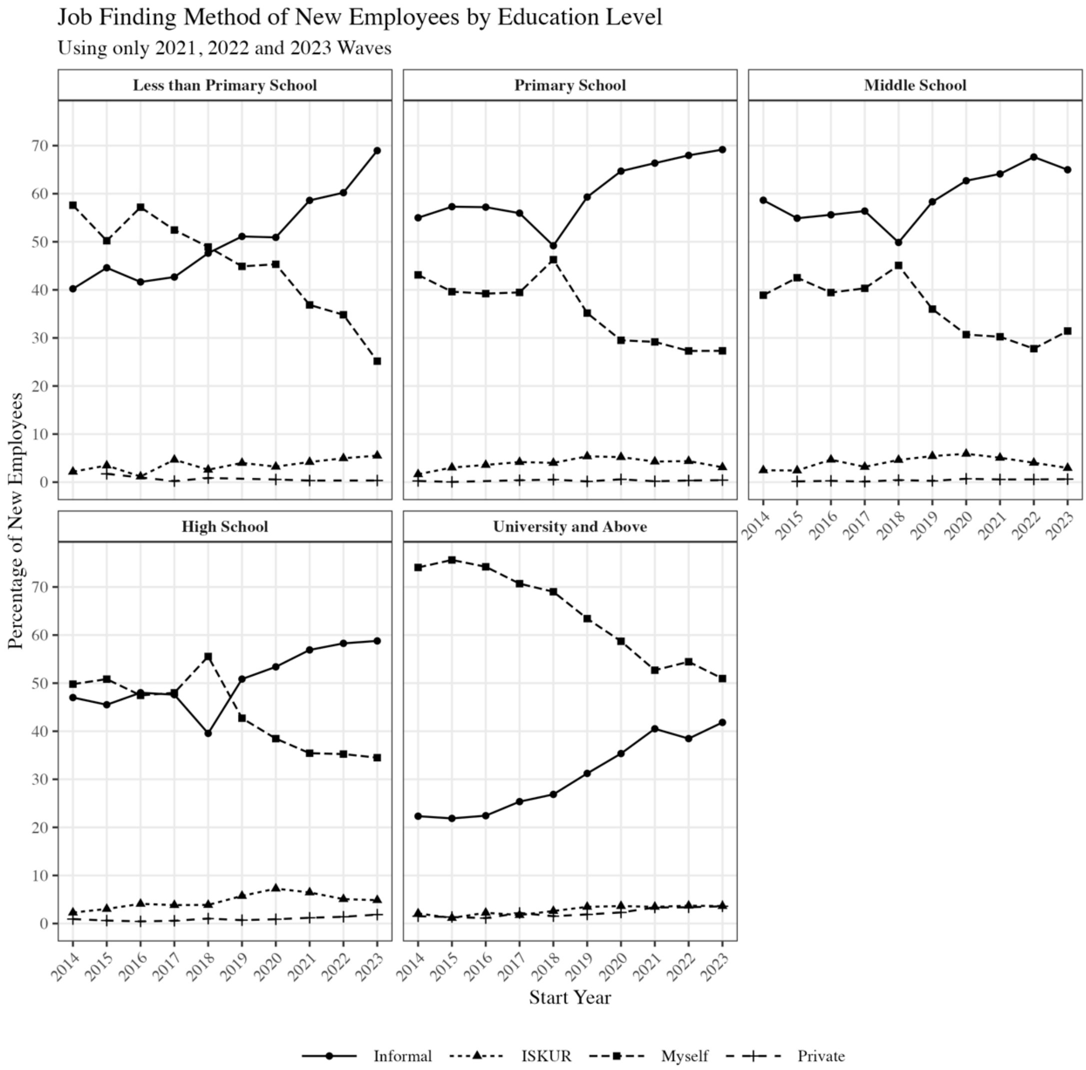

Figure A6. Educational attainment breakdowns using 21-23 waves

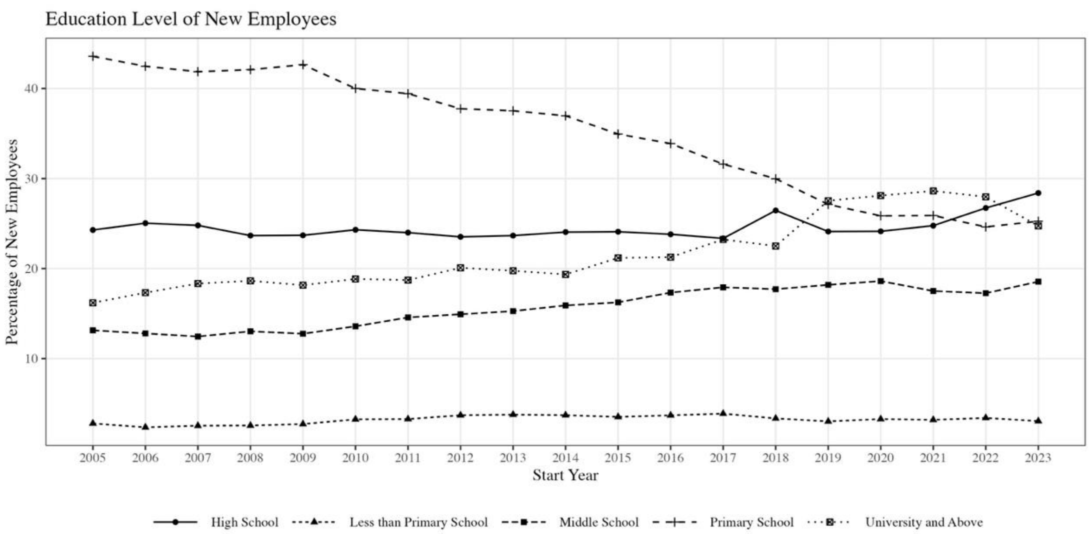

Figure A7. Education levels

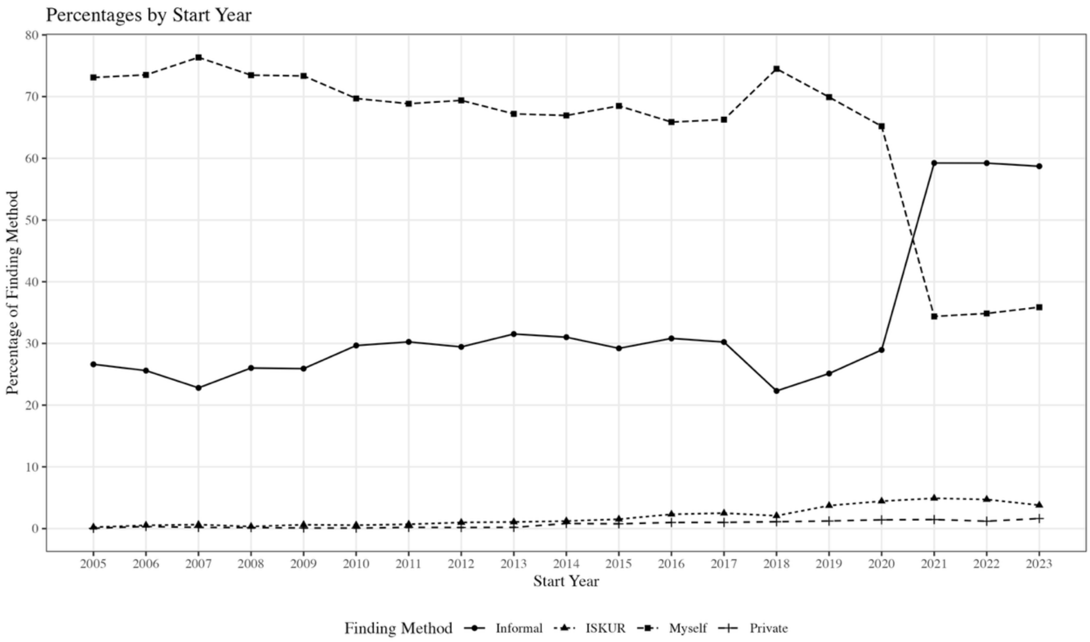

Figure A8. General trends for 0 tenure subset

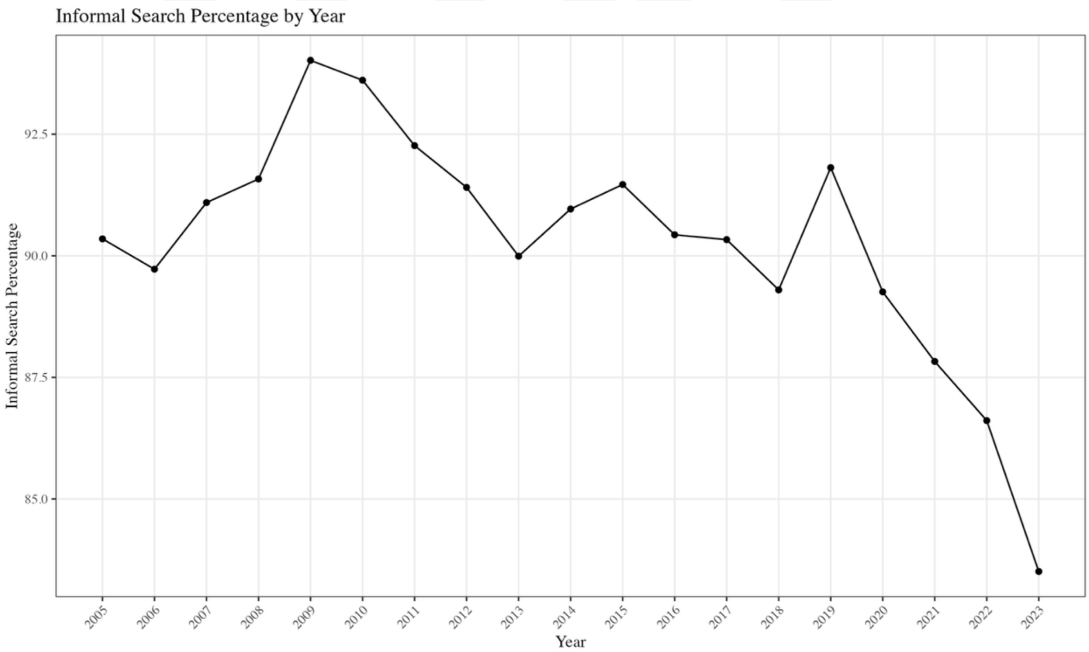

Figure A9. Prevalance of informal search

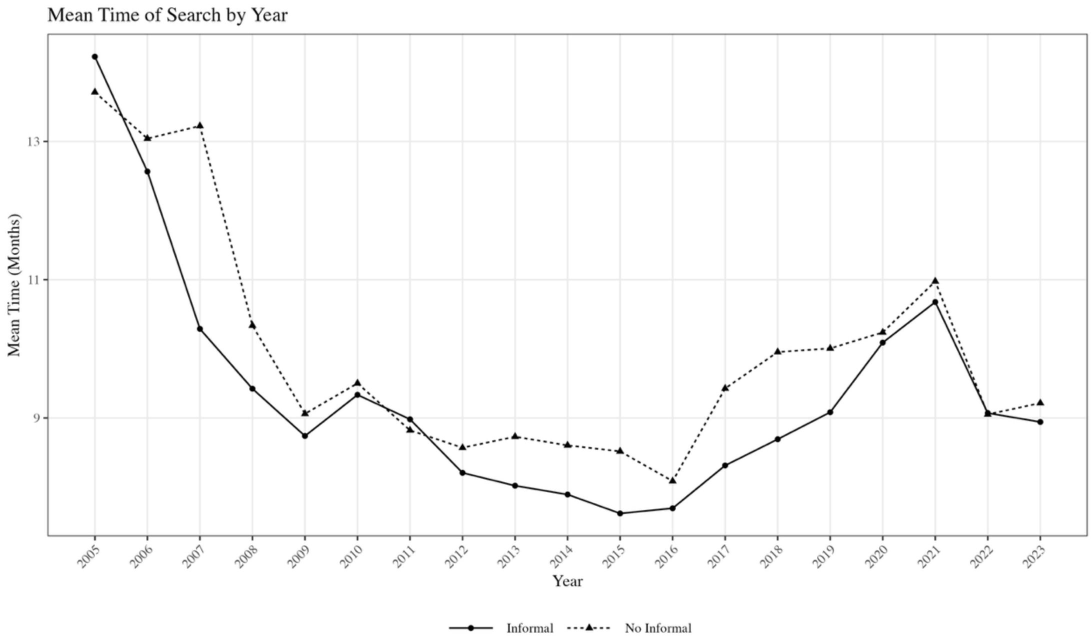

Figure A10. Mean observed time of search for unemployed people

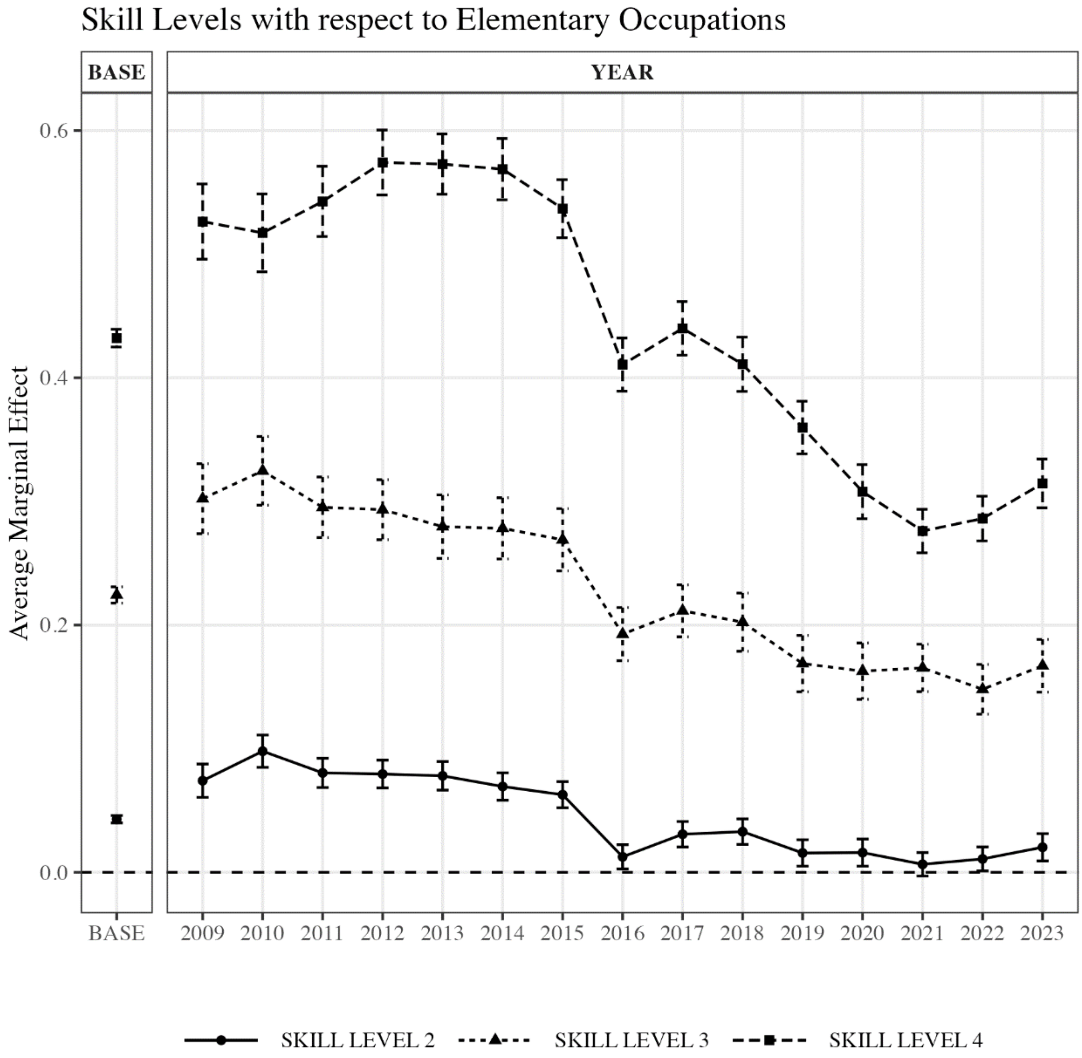

Figure A11. Average marginal effects for skill levels

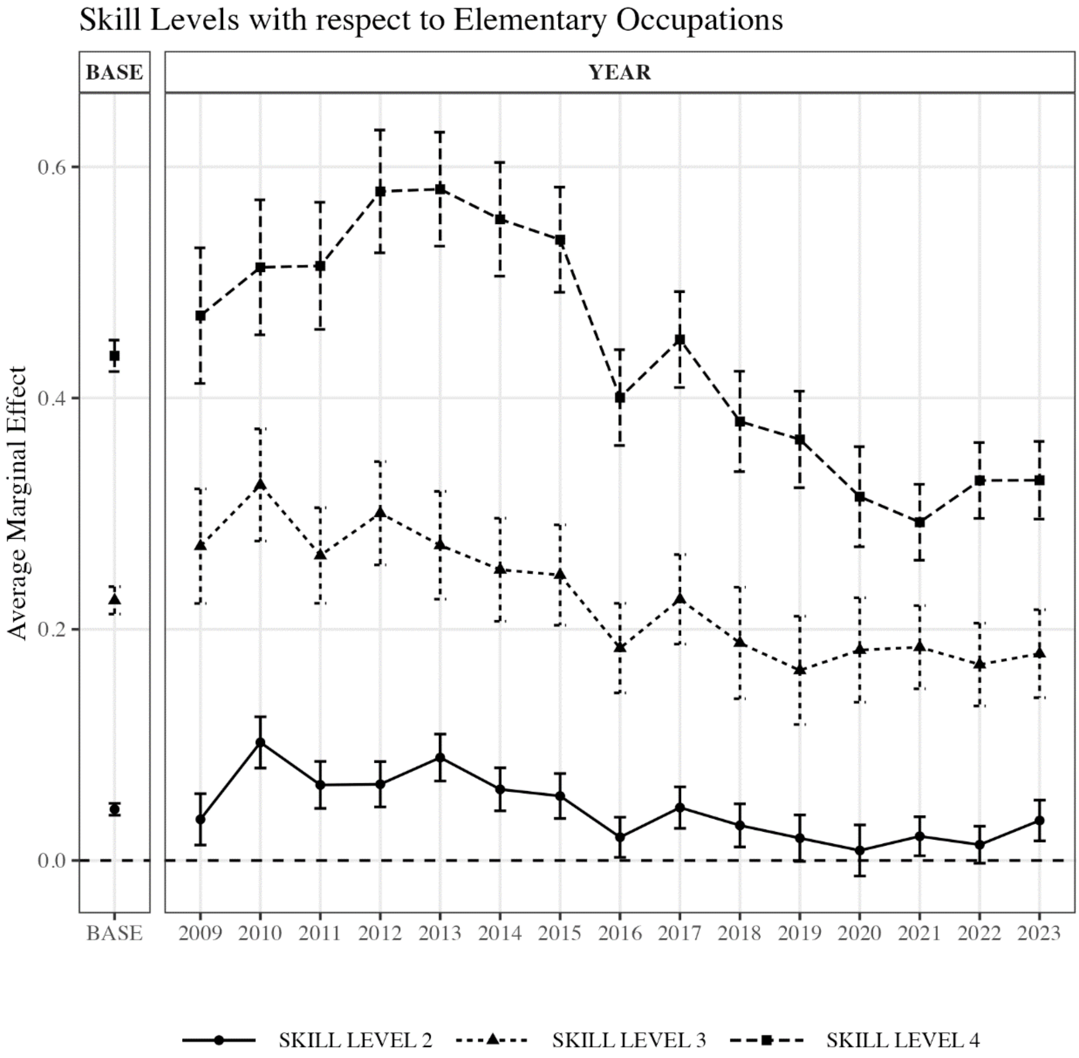

Figure A12. Average marginal effects for skill levels Using 0 tenure subset

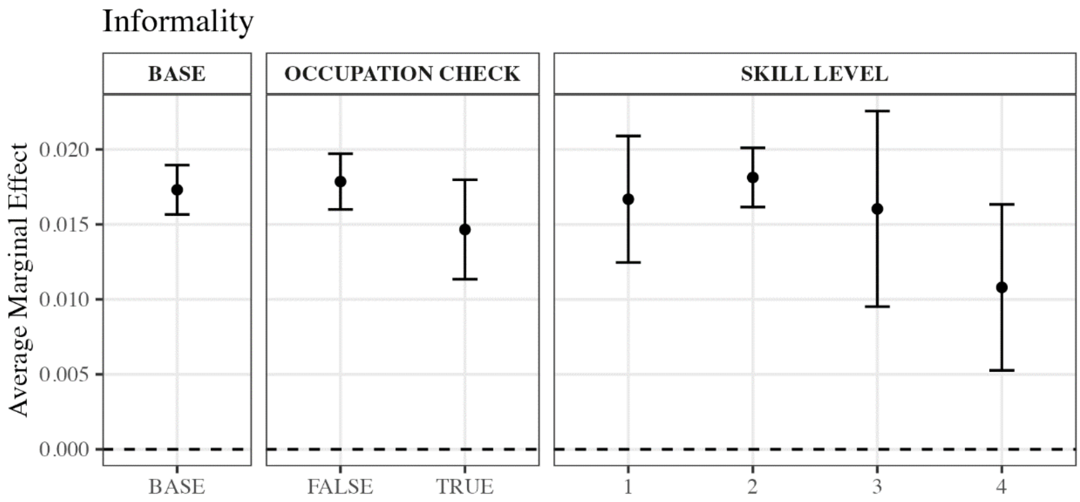

Figure A13. Average marginal effect of informality on job search for employed at different skill levels

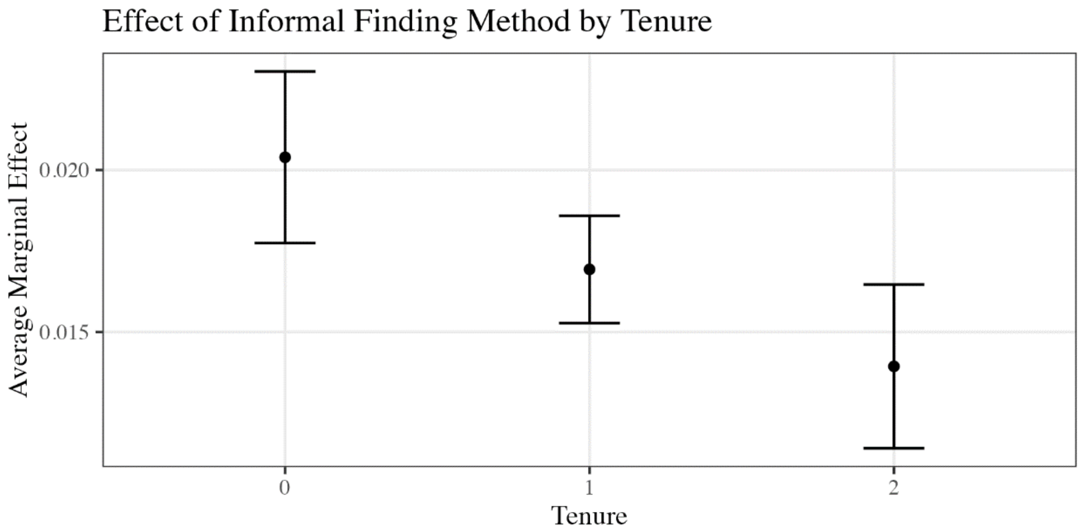

Figure A14. Average marginal effect of informality on job search for employed at different tenures

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