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How did you find your job? Effects of the job search channels on labour market outcomes in Germany

Mariya Afonina, Anna Zaharieva

How did you find your job? Effects of the job search channels on labour market outcomes in Germany*

Mariya Afonina[†], Anna Zaharieva[‡]

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Abstract

We study the effect of finding a job through one's social contact on starting wages. Using combined SOEP-INKAR data for Germany and propensity score analysis - both matching and weighting - we document that referral hiring is associated with a wage penalty of 10%. This penalty is stable over time. Separating by the type of the social contact, we find that referrals from former colleagues are associated with a 9% wage premium compared to a direct formal application. In contrast, referrals from friends are associated with a 7% wage penalty. Our results highlight persistent self-selection of workers on observable and unobservable characteristics. Using information from a short test of cognitive abilities (symbol digit test) we document that workers recommended by former colleagues perform best in the ability test, consistent with the predictions from a sorting model. The lowest performance is recorded for those relying on the help of their friends. The effects are primarily driven by the sub-sample of women. No significant differences across search channels are found for personality traits.

JEL-code: C21, J31, J62, J64

Key words: job search, social networks, referrals, cognitive abilities

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1 Introduction

There are multiple ways to find a job varying from a formal application in Internet, intermediation by the employment agency to relying on the help from one’s social network. The literature suggests that finding a job through a social contact is the most frequent channel of entering a job making up 30 – 50% of all new matches¹. Recognizing the importance of this search channel for the labour market, multiple studies tried to evaluate the relationship between the job search channel, which generated a job, and the starting wage. The empirical evidence is mixed with equally large groups of studies supporting the idea of wage premia and wage penalties from referral hiring compared to direct formal applications². This raises two questions, first, whether the selection of workers to specific search channels could explain diverse findings in the literature and, second, whether the type of the social contact matters for the starting wage.

We answer these questions by using a unique combination of variables contained in the German Socio-Economic Panel (SOEP). SOEP is a large-scale household survey which is representative on the national level. It combines information about the type of the social contact providing a referral, distinguishing between family ties, friends and former colleagues, with rich information on the socio-economic and demographic background of the respondent as well as firm and occupation-specific characteristics. Most important, it includes information about the results of a short test of cognitive abilities, called the symbol-digit test (SDT), as well as personality traits³, which allows us to shed light on the role of observed and unobserved worker heterogeneity in selecting into specific search channels. In addition, we exploit a recent linkage of SOEP with the INKAR database⁴ giving us a possibility to account for county-level regional economic indicators.

Our empirical analysis is guided by the theoretical framework developed in Stupnytska and Zaharieva (2015). This study considers a continuum of workers heterogenous in ability/productivity and searching for jobs when unemployed. Moreover, there are three search channels: formal applications and two informal channels – through family and professional networks. The model illustrates a strong selection of workers across the three search channels with high ability workers mostly entering jobs via referrals from professional contacts, low ability workers relying on their families and workers in the middle of the ability distribution entering jobs in a formal way. This selection pattern explains wage premia associated with professional recommendations borrowing from the seminal approach by Montgomery (1991) and Granovetter (1995). At the same time, it

¹Addison and Portugal (2002), Kugler (2003), Margolis and Simonnet (2003), Delattre and Sabatier (2007), Goos and Salomons (2007), Ponzo and Scoppa (2010), Gürtzgen and Pohlman (2024)

²We review and discuss both groups of studies in the next section.

³SOEP includes information about 10 personality traits which can be aggregated to the “Big Five” scale: conscientiousness, extraversion, agreeableness, openness, neuroticism. See McCrae and Costa (1999), Uysal and Pohlmeier (2011) and Caliendo et al. (2016) for further details.

⁴Indicators and Maps of Spatial and Urban Development

predicts wage penalties associated with referrals from family or close friends if worker abilities are not observable.

We test these predictions by using the approaches based on inverse-probability weighting (IPW). These are characterized by having two stages. In the first stage we model the self-selection of workers into search channels with a (multinomial) logistic regression. The multinomial specification is used to account for the four search channels (family/friends/colleagues/formal) and generates propensity scores which are used to construct the weights in the estimation of the outcome variable. In the second stage we apply three weighting methods: pure weighted mean comparison (IPW), the augmented inverse probability weighting (AIPW) and the IPW - regression adjustment (IPWRA). All the approaches make the groups of workers, finding jobs through different search channels, comparable to each other in terms of observable characteristics. However, the latter two also model the outcome, which gives rise to the “doubly-robust” estimators (Imbens and Wooldridge 2009; Glynn and Quinn 2010; Kurz 2022)⁵.

First, our descriptive results reveal that there is a strong self-selection of workers based on formal qualification and working time, contributing together about 1/3 to the raw wage penalty associated with referral hiring. Another 1/5 of the penalty stems from differences in the firm size and the likelihood of occupational mismatch. These findings support the ideas in Galenianos (2013) and Rebien et al. (2020) that referrals often lead to jobs in small firms. The observation that referred candidates are more likely to report occupational mismatch is in line with the evidence in Bentolila et al. (2010) putting forward the idea that referral hiring generates occupational mismatch between the initial qualification of the worker and the job requirements. Overall, we conclude that differences in observable characteristics contribute about 2/3 to the referral wage penalty. The IPW methods reveal a remaining wage penalty of -10% , which is persistent over time.

Second, separating by the type of the social contact, we find that referrals from friends are associated with a significant wage penalty equal to -7% . At the same time, referrals from former colleagues show a robust wage premium between 9% and 10%. In order to study the role of unobserved heterogeneity behind these findings we compared the performance of respondents in the symbol digit text (SDT)⁶. This test was already used in other studies as a proxy for cognitive abilities (e.g. Heineck and Anger (2010), Richter et al. (2017)), moreover, Lang et al. (2007) show that the SDT outcome is sufficiently

⁵Another advantage of the IPW approach, in comparison to the standard OLS, is that it does not require the linearity assumption and allows us to perform the balancing checks of covariates before and after propensity score matching. Moreover, Imbens and Wooldridge (2009) highlight that in case the normalized differences between observable characteristics are considerable, the unconfoundedness assumption of the standard OLS might not be fulfilled properly, with results being extremely sensitive to the specification. Identification relying on the estimated propensity scores allows to avoid the issue.

⁶Every participant was provided with a mapping between pairs of symbols and digits on the screen. The participants had to match as many symbols to the corresponding numbers as they could. The number of correct, total and wrong answers was recorded after 30, 60 and 90 seconds.

correlated with test scores from more comprehensive intelligence tests. We find that workers referred by their colleagues perform better in the test than any other group. The second best group in terms of cognitive scores are those who found a job in a formal way, followed by those relying on the help of their families and friends. These results indicate substantial differences in cognitive abilities between the groups and support the sorting model in Stupnytska and Zaharieva (2015). In addition, we compared the non-cognitive abilities based on the “Big Five” personality traits. We do not find systematic differences in non-cognitive abilities for workers using different search channels. One minor exception is the ability to forgive, which is highest among individuals referred by their family members.

Third, we perform the heterogeneity analysis and separate the sample by gender and region. We find that the overall wage penalty from referrals is persistent for men and women and has a similar size. However, the finding that wage penalties/premia are associated with referrals from friends/colleagues is largely driven by the subsample of women. This is inline with the observation that the spread in cognitive scores between those finding the job with a help of friends/colleagues is larger for women in comparison to men. This provides another indirect support for the important role of cognitive abilities in explaining referral wage gaps. With respect to regional heterogeneity our results demonstrate that higher unemployment is associated with a stronger use of social networks. On the contrary, there is less reliance on networks in more densely populated regions. At the same time, wage penalties from referrals by friends and premia from referrals by colleagues are more pronounced in Eastern Germany.

The rest of the paper is structured as follows. Section 2 characterizes the current state of research and briefly summarizes the underlying theoretical model. Section 3 describes the data and presents descriptive statistics. It is followed by section 4, which outlines the empirical methods. Next, section 5 presents the estimation results for the overall sample, followed by the heterogeneity analysis by gender and West/East Germany in section 6. The robustness of the results is tested in section 7, while section 8 concludes.

2 Literature Review and Theory

2.1 Related literature

The literature on the effect of referrals on wages is rich but inconclusive. Whereas some studies find a significant positive link, others report wage penalties associated with entering the job via a referral (Topa 2011). Pellizzari (2010) highlights the puzzle by showing empirically that in the European Union “... premia and penalties to finding jobs through personal contacts are equally frequent and are of about the same size” (p. 494). Thus, in the following, we review sequentially the literature on wage premiums and wage penalties

associated with referrals paying particular attention to the underlying mechanisms and formulating several testable hypotheses to guide our empirical analysis.

Wage premia: The seminal theoretical contributions date back to the work by Montgomery (1991) and Granovetter (1995). Montgomery (1991) shows that employee referrals help firms in screening the unobserved abilities of their applicants. In particular, Montgomery (1991) develops the idea of homophily by ability (or the inbreeding bias), meaning that high-ability workers are likely to have high-ability friends. Therefore, firms expect this relationship and offer higher wages to referred applicants. Hensvik and Skans (2016) confirm this result empirically and show that in Sweden entrants are more likely to be connected to high-ability employees than to low-ability ones (defined from the test scores or wages). Moreover, in their study, entering workers receive higher initial wages if they have a link to the incumbent employee.

Another explanation for wage premia associated with referrals is presented by Simon and Warner (1992) and further extended by Galenianos (2014) and Dustmann et al. (2016). Simon and Warner (1992) show that referrals from employees reduce uncertainty about applicants' productivity, which leads to higher reservation wages, higher starting wages and lower wage growth after the first period. All three studies provide empirical support for this mechanism based on the US, British and German data respectively, though the evidence in Dustmann et al. (2016) is only indirect (based on ethnic networks) and does not include detailed information about the type of social contact who provided a referral. A recent study by Gürtzgen and Pohlen (2024) extends the model of employer-learning by adding formal screening activities. The authors use data from an *employer* survey for Germany to test their model and find a 1% wage premium. The result, however, is driven solely by the male subsample.

One further study supporting the idea of wage premia is Kugler (2003). In this model, referrals reduce the cost of monitoring for firms, because workers exert peer pressure on co-workers, and make it cheaper to pay efficiency wages. Also Ioannides and Soetevent (2006) and Fontaine (2008) show theoretically that workers with a larger social network receive higher wages, whereas empirically wage premia are supported by Margolis and Simonnet (2003) for France and Goos and Salomons (2007) for the UK.

Wage penalties: Next, we consider the literature reporting wage penalties associated with referral hiring. Empirically wage penalties are documented by Pistaferri (1999) for Italy, Addison and Portugal (2002) for Portugal and Delattre and Sabatier (2007) for France. Ponzio and Scoppa (2010) argue that firms may offer low wages and hire low-ability family ties in the absence of more talented applicants. This is the idea of favouritism leading to wage penalties associated with referral hiring. Bentolila et al. (2010) develop a model showing that social contacts may generate a mismatch between the qualification of the worker and this worker's productive advantage. Bentolila et al. (2010) present empirical evidence supporting this view for the US and European Union,

though the sample is limited to young workers (below 35 years of age). Horváth (2014) and Zaharieva (2018) extend this setup by introducing a network homophily parameter, i.e., the degree to which people form social connections with others from the same occupation.

Galenianos (2013) and Rebien et al. (2020) put forward the idea that larger firms have more financial resources to advertise their vacancies compared to small firms, therefore, they receive many applications via the formal search channel making referral hiring redundant. Both studies provide empirical support for this idea.

Premia/penalties depending on the contact type: Labini (2005), Stupnytska and Zaharieva (2015) and more recently Lester et al. (2021) emphasize the point that the type of social contact may play a crucial role for the sign of the referral wage gap. In particular, they show that referrals from professional contacts and former colleagues (weak ties) lead to a wage premium, whereas referrals from relatives and close friends (strong ties) generate a wage penalty. The underlying mechanism is based on the sorting of workers with different (unobserved) abilities across search channels. According to Lester et al. (2021) the sorting framework is supported in the US data, however, their dataset does not include a direct measure of worker cognitive abilities.

Only a few other studies addressed this issue empirically, including Antoninis (2006) for Egypt, Meliciani and Radicchia (2011) for Italy and Cappellari and Tatsiramos (2015) for the UK. Even though their results are supportive of the described mechanism, the evidence in the former studies is descriptive, whereas the data in Cappellari and Tatsiramos (2015) does not include information about the type of social contact who provided a referral. Hence, in this paper we test the theoretical predictions from the sorting model by using German data (SOEP), which includes information about worker’s cognitive abilities and personality traits. We give a short overview of the sorting mechanism developed in Stupnytska and Zaharieva (2015) and summarize our hypotheses in the next section.

Heterogeneity by gender and region: Further, we acknowledge that the referral wage gap could differ between the two gender groups and across locations. For example, Huffman and Torres (2002) and Wrzus et al. (2013) show empirically for the USA that the quality of referred jobs provided to a contact differs for men and women. Marmaros and Sacerdote (2002) study the effects of the peer networks and also report differences by gender and race. Zhou (2019) emphasizes that not only the size of the network is vital for a successful job search but also the willingness of the contacts to provide a referral. Germany presents another social context as a result of previous historical events. Despite the observable convergence in many factors, West Germany and East Germany are still different on such indicators as income levels, the unemployment rate as well as work-related attitudes and gender roles (Schnabel 2016; Dirksmeier 2015). The latter can be highly-influential with regard to the quality of the job transmitted via referrals to men and women. Therefore, in the following analysis we go beyond the overall effect of referrals on wages and study separate effects by gender and region.

2.2 Theoretical considerations

In this section we briefly describe the economic mechanism leading to wage premia or wage penalties from referrals in the model by Stupnytska and Zaharieva (2015). We test it later in the main body of the paper. Consider workers with heterogeneous productivities y_i , $i = 1..p$, where p is the number of distinct worker groups. Differences in the productivity reflect differences in worker's abilities, so that higher y_i is associated with a higher wage. Workers' productivity/ability is observed by the employer upon the match (in the course of the job interview), but it is not observable to the econometrician in the data.

There are three search channels in the labour market. First, unemployed workers can find a job by sending applications to open vacancies, this is the formal channel of job search with a job-finding rate vs_i . This rate is endogenous and depends on the search effort of the worker s_i and the stock of vacancies v . The formal channel is costly for workers in terms of effort with a cost function $C(s) = s^2/c$. In addition, workers can find a job via their professional contacts at rate λ_i (weak ties) or family members λ_0 (strong ties). This setup gives rise to the following Bellman equation for unemployed workers:

$$rU_i = b + (\lambda_i + \lambda_0)R_i + v \max_s (sR_i - s^2/c)$$

where b denotes the unemployment benefit and R_i is a worker job rent increasing in the worker type y_i due to a higher wage. Maximizing the present value of unemployment U_i with respect to s leads to the result that the formal search effort of workers is increasing in the worker type y_i (via R_i) but decreasing in the job-finding rate via professional contacts λ_i . Intuitively, this shows a disincentive effect: workers with a higher probability of getting a professional referral (λ_i) reduce their formal search effort s_i .

Next, the authors derive λ_i by following the idea in Montgomery (1991) and assuming that workers form professional connections within their ability group. The idea of homophily by ability is also supported by Ioannides and Loury (2004). In general, homophily refers to the fact that people are more prone to maintain relationships with others who are similar to them. There can be homophily by race, gender, religion, skill or ability and it is generally a robust observation in social networks (see Jackson (2008) for an overview of research on network homophily). If the network size of every worker is fixed to n , the probability of finding a job via a professional referral is given by:

$$\lambda_i = va_i \frac{1 - \mu_i}{\mu_i} [1 - (1 - \mu_i)^n]$$

where a_i is the advertising effort of firms and μ_i is the unemployment rate of workers in the productivity group i . In the above equation the term $[1 - (1 - \mu_i)^n]$ stands for the probability that an incumbent type i employee addressed by the firm has at least one unemployed friend who will take the job. In addition, this equation shows that firms can

direct their informal search, i.e., choose a_i , towards specific worker groups by utilizing information about network homophily. The advertising effort is costly for firms with a cost a^2/k . This yields the following objective function for firms:

$$\max_a [a(1 - (1 - \mu_i)^n)J_i - \frac{1}{k}a^2]$$

where J_i is an expected present value of firm profits, which is increasing in the productivity and worker type y_i . Stupnytska and Zaharieva (2015) show that the advertising effort of firms a_i is increasing in the productivity of the incumbent employee y_i (via J_i), meaning that firms are more likely to ask high ability incumbent employees to refer their friends, exploiting their connections to other high ability applicants. This implies that the probability of a professional referral λ_i is increasing in the productivity and worker type y_i . The model closes with the equation for the equilibrium unemployment rate μ_i in each worker group, which is given by: $\mu_i = \delta/(\delta + \lambda_0 + s_i v + \lambda_i)$. Here δ is the job destruction rate, whereas $\lambda_0 + s_i v + \lambda_i$ is the overall job-finding rate reflecting the possibility of finding a job via three possible search channels.

In the equilibrium, professional contacts are used to match jobs with high ability workers earning high wages (see Figure 1). The formal channel is mostly used by workers with average abilities and average wages. The reason is that these workers exert high formal effort s_i to find a job on their own but they are not sufficiently productive to be frequently selected for professional referrals. Finally, family contacts λ_0 constitute an exogenous channel of last resort for workers with low abilities and low wages. These workers expect low wages, thus, their incentives to search formally are low, leading to the low search effort s_i .

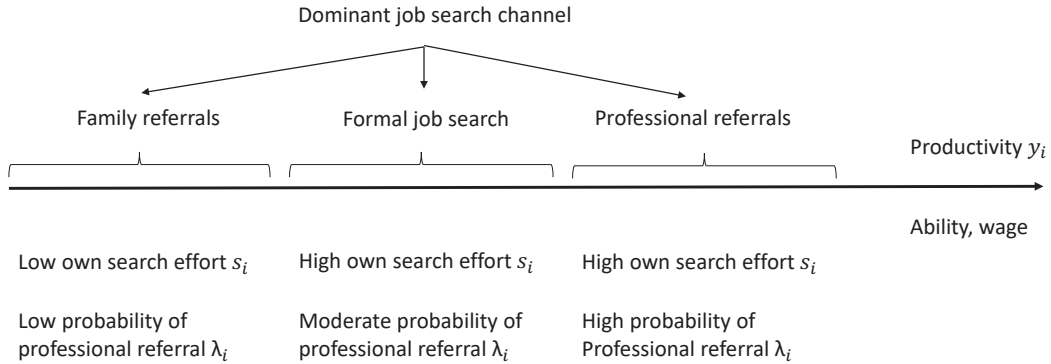


Figure 1: Distribution of own search effort and probability of referral

We use these predictions to formulate three testable hypotheses. Hypothesis H1 describes situations when worker abilities and the type of the social contact are not available, hence family and professional referrals are pooled together as social networks.

Hypothesis H1: *Finding a job via social networks is likely to be associated with a wage penalty (premium), compared to the formal search channel, if family referrals are*

more (less) frequent than professional referrals.

Similar mechanism, augmented with job-to-job transitions, is also presented in a recent study by Lester et al. (2021). Further, we borrow the original definition from Granovetter (1973) distinguishing between the *strong ties* associated with referrals from family and friends and the *weak ties* associated with referrals from colleagues and professional contacts to formulate hypotheses H2 and H3:

Hypothesis H2: *Referrals from professional contacts (weak ties) are likely to be associated with a wage premium, compared to the formal search channel, because this search channel is used by workers with high abilities.*

This hypothesis is also inline with the ideas by Montgomery (1991), Granovetter (1995), and Hensvik and Skans (2016).

Hypothesis H3: *Referrals from family contacts (strong ties) are likely to be associated with a wage penalty, compared to the formal search channel, because this channel is mostly used by workers with low abilities.*

This hypothesis is also inline with the ideas in Labini (2005) and Ponzio and Scoppa (2010) that low ability workers often rely on a network of relatives.

Finally, the model is written down for a single labour market, whereby all firms are identical and all workers have the same formal qualification/education making them suitable for all vacancies. From an empirical perspective this means that hypotheses H1-H3 should be tested after controlling for workers' education, firm size, industry and other observed socio-economic and demographic characteristics.

3 Data

To examine the hypotheses we use data from the German Socio-Economic Panel (SOEP) and augment it with selected variables from the INKAR dataset⁷. For a description see Goebel et al. (2018). The SOEP is a longitudinal household survey which covers both West and East Germany since 1984 and 1990, respectively. The sampling design is regularly updated to keep it representative on the national level. This data provides a rare overlap of rich socio-demographic characteristics of the job seekers with information about the successful job search channel, cognitive ability tests, personality traits as well as firm and occupational characteristics.

The INKAR data enriches the setup by accounting for the regional labour market characteristics. It consists of the aggregated economic indicators reported on a quarterly and/or yearly basis for different administrative levels such as federal state and county

⁷The German Socio-Economic Panel (SOEP) is managed by the German Institute for Economic Research (*germ.* Das Deutsche Institut für Wirtschaftsforschung/DIW), while the Indicators, Maps of Spatial and Urban Development (*germ.* Indikatoren und Karten zur Raum- und Stadtentwicklung, INKAR) data is provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (*germ.* Bundesinstitut für Bau-, Stadt- und Raumforschung).

(NUTS-3 classification). The analysis covers all individuals between 15 and 64 years of age who found their job in the years between 2002 and 2019⁸. Since respondents who were entering the job for the first time in life did not have former colleagues, they were excluded from the analysis.

According to the theory in Section 2.2, those who found their jobs using social networks (“treatment group”) are compared to the respondents who found their job individually using the formal procedure (“comparison group”). Table 1 summarizes the definition of treated and comparison groups in a more precise manner, featuring differences between aggregated and disaggregated network modes. In both cases, in line with the theoretical model, labour market outcomes of those who found their position through networks are compared to the ones of the respondents who obtained the job through the formal channel. This includes submitting applications to positions advertised online or in a newspaper. First, we test hypothesis **H1** by using an aggregate variable including all types of social contacts providing a referral. Second, we disaggregate the network variable to test hypotheses **H2** and **H3**. Starting from 2014 our data allows us to distinguish between the three distinct types of referrals: family, friends and colleagues. In the following we provide separate coefficients for referrals from family and friends, albeit conceptually we assign them to the same category of *strong ties* in order to test hypothesis **H2**, whereas referrals from former colleagues are assigned to the category of *weak ties*.

Table 1: Treatment alignment

		Aggregated	Disaggregated
Comparison	Formal	Formal	
Treated	Networks: overall		Networks: friends
			Networks: family
			Networks: colleagues
Years covered	2002 - 2019		2014 - 2019

Even though SOEP is a panel dataset, our variable of interest is attached to a relatively rare event when the person starts a new job. The average tenure of employees is 10 years meaning that a given person reports a new job approx. once in 10 years, thus, most individuals are observed only once in the considered period. In order to check whether the sample has cross-section or panel properties, Table 2 below provides an unweighted panel tabulation. Panel A describes the observations from the year 2002, while Panel B

⁸The beginning of the period is chosen to avoid potential effects from the German reunification shock in the 90s. Moreover, it is connected to the introduction of Euro as a currency in 2002. The spread of the COVID-19 pandemic defines the end of the time frame - it had resulted in a great shock for labour markets; thus, we omitted years 2020/2021 from the main analysis to ensure comparability of the results. However, the estimations including 2020/21 are available in Section 7.

demonstrates a subset of those from the year 2014.

In Panel A there are in total approx. 19 thousand individual-year observations, 13.5 thousand of which represent unique individuals. However, according to the between tabulation, 41% of the respondents used the formal individual approach at least once, while at least 71% of the sample found a job via the network at least once. Thus, only 12% of the respondents in the sample used two different methods. Moreover, if a person has ever found a job using one of the methods, in 89% of the cases, the same approach will be used again. On average, the person appears in the sample only 1.2 times, and this number falls to 1.1 times in the disaggregated sample between 2014 and 2019. These statistics suggest that the sample data should be classified as a stratified repetitive cross-sectional survey rather than a wide panel, which is relevant for our choice of the econometric approach in the next section.

Table 2: Panel tabulation of the job search methods

	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Panel A: from the year 2002					
Individual	6793	35.86	5566	41.04	85.14
Networking: overall	12149	64.14	9618	70.91	91.75
Total	18942	100	15184	112.0	89.32
# of unique obs			13563		
Panel B: from the year 2014					
Individual	3566	38.70	3129	41.88	90.98
Networking: friends	3704	40.20	3313	44.34	90.62
Networking: relatives	1046	11.35	997	13.34	87.63
Networking: colleagues	898	9.746	854	11.43	87.76
Total	9214	100	8293	111.0	90.10
# of unique obs			7472		

Table 3 presents descriptive statistics conditional on the successful search channel. The definitions of variables are provided in Appendix 9.2. Our final sample includes 17425 person-year observations with respondents who found a new job via the formal channel (36%) or network (64%). Note that individuals finding jobs through other channels (e.g. public employment agency) are excluded from the analysis. First, we can see that there

is a large statistically significant difference in the logarithm of gross wages, equal to 0.26 logarithmic points, in favour of the formal individual approach. The share of men in the overall sample is slightly less than 50% due to a longer job tenure, which is 11 years for men and only 9 years for women, thus, women are observed more frequently in starting a new job. Furthermore, Table 3 reveals that men are underrepresented in the comparison group with only 44% of individuals entering the job in a formal way being men.

Table 3: Demographic characteristics by the job search methods.

Variable	(1) Individually		(2) Networking		(2)-(1) Pairwise t-test	
	N/Clusters	Mean/(SE)	N/Clusters	Mean/(SE)	N/Clusters	Mean difference
Natural logarithm of gross wages	6269 288	7.298 (0.021)	11156 287	7.039 (0.023)	17425 288	-0.260***
Men	6326 288	0.441 (0.010)	11314 287	0.505 (0.007)	17640 288	0.064***
Age, years	6326 288	34.974 (0.177)	11314 287	35.378 (0.175)	17640 288	0.404
Years of educations	5988 286	12.809 (0.055)	10541 287	12.078 (0.045)	16529 287	-0.731***
Married, living together	6312 288	0.367 (0.009)	11272 287	0.385 (0.008)	17584 288	0.018
# of HH members	6326 288	2.520 (0.028)	11314 287	2.687 (0.023)	17640 288	0.167***
# of children in HH	6326 288	0.986 (0.024)	11314 287	1.081 (0.018)	17640 288	0.095***
Migration background	6326 288	0.232 (0.011)	11314 287	0.292 (0.011)	17640 288	0.060***
Transition from unempl. to empl.	5293 286	0.162 (0.009)	9462 287	0.161 (0.007)	14755 288	-0.000
Job-to-job transition	6326 288	0.716 (0.010)	11314 287	0.696 (0.009)	17640 288	-0.020*
Main job full-time	5916 288	0.774 (0.010)	10396 287	0.767 (0.007)	16312 288	-0.007
Annual work hours	6326 288	1419.259 (16.236)	11314 287	1298.996 (15.215)	17640 288	-120.264***
Occupational mismatch	6288 288	0.344 (0.009)	11229 287	0.421 (0.008)	17517 288	0.077***
Firm size: <20 employees	6071 288	0.215 (0.009)	10597 287	0.206 (0.007)	16668 288	-0.009
Firm size: [20,200) employees	6071 288	0.094 (0.005)	10597 287	0.077 (0.004)	16668 288	-0.016**
Firm size: ≥ 200 employees	6071 288	0.208 (0.008)	10597 287	0.161 (0.006)	16668 288	-0.047***

Notes: Significance: ***=.01, **=.05, *=.1. Errors are clustered at federal state-year level. Observations are weighted using sample design weighting factor (phrf) as aweight weights. Table aggregates years 2002-2019.

Regardless of the same average age of 35 years, the comparison group appears to have more education: 12.8 years vs 12.1 years, with this difference being statistically significant. Also distinctions in the annual working hours, firm size and migration background are significant. We use the following firm size categories: less than 20 employees (Small), 20-

200 employees (Middle), and more than 200 employees (Large). Further, Table 3 shows large differences in the share of respondents reporting occupational mismatch: 42% in the treatment group but only 34% in the comparison group. The information on occupational mismatch is self-reported and the corresponding mismatch variable takes value 0, if the job is in the profession for which the respondent was educated or trained. The mismatch variable takes value 1, if the respondent reports a mismatch.

Next, we address the question, how much of the observed wage penalty associated with the network channel can be explained by differences in the observable characteristics of workers and firms. The answer to this question is obtained by performing the Blinder-Oaxaca decomposition of the referral wage gap. Table 12 in Appendix 9.1 presents the results of a threefold Blinder-Oaxaca decomposition of the effects of the demographic variables on the logarithm of gross wages, covering a wide range of characteristics. The model predicts a total difference of 0.32 logarithmic points of starting wages between jobs found with the help of the formal approach and via networks. Differences in worker and firm characteristics explain 2/3 (or 0.21 l.p) of this gap. In particular, the most pronounced and statistically significant endowment effects include: the share of respondents with an occupational mismatch (3.3%), years of education (4.5%), the share of large firms (3.6%) and the annual working hours (5.6%). This evidence supports the findings from Bentolila et al. (2010), Galenianos (2013) and Rebien et al. (2020) that social networks are disproportionately used by small firms and generate more occupational mismatch between the primary qualification of the worker and job requirements than formal search. Yet, these findings do not explain the whole wage penalty from referral hiring with a remaining unexplained part being about 1/3 (or 0.11 l.p.)

Finally, Table 13 in Appendix 9.1 presents descriptive statistics for the disaggregated sample conditional on the type of social contact who was involved in the job match. This information is only available after 2014, so the sample size is smaller and includes 11479 person-year observations. Among those obtaining help from the social network, 16% were referred by a former colleague, 67% by a friend and the remaining 17% obtained help from a family member. Remarkably, Table 13 shows that wages of individuals who found a job with a help of a former colleague are 0.24 logarithmic points *higher* than wages of workers in the comparison group, so the overall wage penalty associated with the network channel is due to the particularly low wages of workers finding jobs through their family and friends supporting hypotheses **H1**, **H2** and **H3**. Moreover, in many cases those who found their current position with the help of former colleagues tend to differ from the comparison group in the opposite direction as those who found jobs through their family and friends. For example, they are more educated than the comparison group, less likely to have a migration background, less likely to come from unemployment and are more likely to move from one job to another.

Concluding this section, our descriptive analysis shows that the group of workers

referred for jobs differs significantly from the comparison group along multiple observable characteristics pointing out to the self-selection bias in the sample. Hence, further we discuss our estimation strategy building on the inverse probability weighting approach. We rely on the following family of methods, in contrast to the usual OLS estimator, as it allows not only to perform the balancing checks of selection-driving covariates and assure a common support, but it also does not require a linearity assumption in the weighting procedure (Glynn and Quinn 2010; Kurz 2022).

4 Methods

There are several challenges for performing the estimation. First, the self-selection bias is present both in the setup with aggregated and disaggregated networks. Second, the size of the treated and comparison groups is considerably different. As we can see from Table 3 there are almost two times more respondents, who found a job with the help of networks, compared to those who used a formal individual application. Last but not least, is the disaggregated network setup, which calls for a simultaneous comparison of more than two search channels.

To tackle these concerns we apply the inverse probability weighting techniques. These methods include the inverse probability weighting (IPW), the augmented inverse probability weighting (AIPW) and the inverse-probability weighting - regression adjustment (IPWRA). All of these methods have two stages. In the first stage we model the self-selection into search channels with a logistic regression. It is a binary logit in the aggregated setup with two search channels (formal/networks) and a multinomial logit in the disaggregated setup (formal/family/friends/colleagues). The corresponding propensity scores $p(x)_i$ are used as weights in the estimation of the outcome variable (starting wages) in the second stage. When estimating the average treatment effect under the IPW procedure, the weighted outcomes for both groups are calculated in the following way:

$$\ln(Y_{wti}) = \frac{\ln(Y_{ti})}{p(x)_i} \quad \ln(Y_{wci}) = \frac{\ln(Y_{ci})}{1 - p(x)_i}, \quad (1)$$

where $p(x)_i$ is a propensity score estimated for individual i using a (multinomial) logit approach. Y_{wti} is a weighted outcome for observation i assigned to the treatment group t , while Y_{cwi} is a weighted outcome for individual i in the comparison group c . Both the treatment and the comparison group weights are normalized within the respective group. The treatment effect is calculated as a simple difference of weighted means:

$$\widehat{ATE}_{IPW} = \frac{\sum_{i=1}^{N_t} \ln(Y_{wti})}{N_t + N_c} - \frac{\sum_{i=1}^{N_c} \ln(Y_{wci})}{N_t + N_c}, \quad (2)$$

where N_t and N_c correspond to the number of observations in the treatment and the

comparison groups respectively.

AIPW and IPWRA are extensions of the IPW and belong to the class of the “doubly robust” estimators: in both cases, self-selection and outcome are modeled, but for the consistency of the estimated coefficients, it is enough to specify at least one of the models correctly (Glynn and Quinn 2010; Kurz 2022). The main difference between the two methods lies in the second stage when the inverse probability weights are applied. The AIPW procedure estimates separate regression models of the outcome for each treatment group and obtains the treatment-specific predicted outcomes. It then computes the weighted means of the obtained values. In contrast, the IPWRA procedure fits weighted regression models of the outcome for each treatment group and estimates the treatment-specific predicted outcomes. It then computes the difference. The baseline model for AIPW/IPWRA in the aggregated setup can be written in the following way:

$$\ln(Y_i) = \beta_0 + \beta_1 D + \mathbf{X}_i' \boldsymbol{\beta}_2 + \mathbf{Z}_r' \boldsymbol{\beta}_3 + \tau_t + \epsilon_i, \quad (3)$$

where Y_i is a dependent variable, e.g., starting wages in the new job; D is the treatment indicator, which equals to 1 if a job was found using networks; \mathbf{X}_i is a vector of control variables on individual level; \mathbf{Z}_r is a set of regional indicators, τ_t is a time-fixed effect and ϵ_i is an error term.

In the disaggregated setup with multiple referral types (family, friends and colleagues) we adjust the regression equation to account for the three different treatment arms. The equation becomes:

$$\ln(Y_i) = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \mathbf{X}_i' \boldsymbol{\beta}_4 + \mathbf{Z}_r' \boldsymbol{\beta}_5 + \tau_t + \epsilon_i, \quad (4)$$

where Y_i is again the dependent variable, while D_1 to D_3 are dummy variables corresponding to the three referral channels: friends, family or colleagues. The interpretation of other variables remains the same.

The set of control variables \mathbf{X}_i in the AIPW and the IPWRA outcome models includes sex, age, age squared, years of education, occupational mismatch/being in studies/no training, a dummy variable for migration background; a dummy for a long distance move as well as moving to another NUTS3 region in the previous year; change in a labour market status from non-participation to employment or job-to-job transition; being in a full-time employment (compared to a part-time arrangement), logarithm of total hours worked during the year; a dummy variable for being employed in construction and if the currently employing firm is of a middle size. The set of regional characteristics \mathbf{Z}_r includes the share of migrants, the unemployment rate and the logarithm of the population density.

In order to correct for the sample selection in the first stage of the estimation, we include the following predictors: age, sex, years of education, marital status, occupational mismatch, relocation to another county, living in a rural or urban region, being

employed full-time, yearly working hours are greater than the average among the working individuals in a given year, changes in the labour market status as described in the outcome model, working in a small, middle or large firm, migration background, number of children in the household. The set of regional characteristics \mathbf{Z}_r is the same in both model stages. Moreover, we also include a dummy for a respondent living in the West or East Germany at the time of the survey.

An important condition for the validity of the IPW techniques is a balance of covariates in the adjusted sample. We test if the covariates are balanced by using the χ^2 test statistic proposed by Imai and Ratkovic (2014). This is an adaptation of GMM-overidentification test for the covariates balance. Since all the estimation methods have the same first stage, it is enough to calculate the p-values of the χ^2 -test for the IPW alone. We find that the null-hypothesis of covariates being balanced cannot be rejected (p-value=0.46)⁹.

In addition to the IPW approach, we use propensity score matching (PSM) as a robustness check in the aggregated analysis (formal/networks)¹⁰. Moreover, we report the PSM results in the second stage based on a “pure” weighted-mean comparison as well as regression-based. Note that PSM can not be applied in the disaggregated analysis with multiple treatment groups. The matching procedure was stratified between the East and the West and we used a 1:1 calliper matching algorithm with replacement¹¹. The selected calliper equals 0.15 of the SD of the propensity score. The propensity score distribution is reported in Figure 8 in Appendix 9.3. The same matching vector is used as in the treatment assignments models in the PS weighing approach. After the PSM, the median bias is reduced from 10.4% to 0.9%, the Rubin’s B parameter equals to 7.9, and the variance ratio R is 1.0¹².

We used the same set of control variables described above in the first stage of the PSM. However, since the first-stage model does not have to be saturated, the controls in the outcome stage may be extended with additional regressors (Guo and Fraser 2014).

⁹The tests were also performed for the subgroups, and the results are reported in Section 6. With the same balancing vector described above, for all of the subgroups the null-hypothesis cannot be rejected. Thus, the covariates are balanced.

¹⁰It is important to acknowledge that in the recent literature there are debates regarding the expected bias which might be introduced with the overcorrection. The paper by King and Nielsen (2019) criticized the application of PSM due to the possibility of introducing a higher bias compared to the unmatched case. The authors proposing resorting to the Mahalanobis distance or entropy matching instead. However, this paper sparked debate caused by the nature of the simulated data used. The simulation study by Vable et al. (2019) covered different types of data and highlighted that a proper common support was essential for the matching methods to be unbiased and superior to OLS in case of dissimilar estimates. Moreover, unlike OLS, PSM allows to tackle the self-selection bias (Titus 2007).

¹¹Austin (2014) compared 12 different matching approaches and found that calliper matching has performance of at least as good as other algorithms and superior in terms of bias reduction.

¹²Rubin’s B is an absolute standardized difference in means of the propensity score between treated and comparison groups. Rubin’s R is the ratio of variances in the propensity scores of the treated and comparison groups. In order to consider sample being balanced, the first parameter should be below 25%, while the second one is [0.5,2] (Rubin 2001).

Consequently, the set of additional regressors includes such variables as age squared, tenure, total years spent in unemployment and household size. In order to account for occupational differences we add a set of dummy variables for being in a particular occupation (following the NACE rev. 1.1 classification). Moreover, we extend the set of regional indicators with the federal state fixed effects and a binary indicator for the region being rural or urban. The exact construction of the main variables is discussed in detail in Appendix 9.2.

5 Results

In this section we apply the methodology discussed above. We start by considering the aggregated setup with a binary search channel indicator (formal vs. network search). Our results are summarized in Table 4 where columns (1)-(3) correspond to the IPW while columns (4)-(5) are based on the PSM approach. The overall effect of finding a position via networks on the logarithm of starting wages is negative and robust: it is statistically significant according to all estimation methods. Although the estimated wage penalty associated with referrals varies between -8% and -10% a linear hypothesis about the intra-model equality of the estimated coefficients cannot be rejected¹³. Moreover, Table 13 in Appendix 9.1 shows that referrals from friends and relatives make 84% of all referral cases with the recommendations from colleagues making up the remaining 16%. This means that referrals from strong ties are much more frequent in the data than professional recommendations. Hence, we find that hypothesis **H1** is strongly supported by the data.

In the second step we perform the disaggregated analysis by distinguishing between the three types of network ties: friends, relatives, and colleagues. Our results are summarized in columns (6)-(8) of Table 4. It shows that the coefficients for relatives and friends are negative. Referrals from friends are associated with a significant wage penalty equal to -7% . At the same time weak ties show a robust positive effect on starting wages between 9% and 10%. The observed wage differences are in line with the theoretical model and support hypotheses **H2** and **H3**. However, at this step the empirical support for these hypotheses is still incomplete since the underlying mechanism in the model is based on ability/productivity differences of worker groups using different search channels. Therefore, in the third step we use a proxy for the cognitive abilities of workers and compare them across the channels.

In the years 2006, 2012 and 2016 SOEP has introduced a short numerical test to evaluate cognitive abilities of the respondents. This test is referred to as a symbol-digit

¹³As for the sample sizes of the estimated groups, the PSM sample is smaller in terms of the number of the unique observations but the frequency weights compensate for this difference. The IPW estimates do not result in the sample shrinkage but are restricted by the collected information on control variables in the treatment assignment and/or outcome models.

Table 4: Effects of the job search channels compared to the formal approach

	Networks: overall					Networks: disaggregated		
	(1) IPW	(2) AIPW	(3) IPWRA	(4) PSM	(5) PSM	(6) IPW	(7) AIPW	(8) IPWRA
Networks	-0.074*** (0.013)	-0.106*** (0.018)	-0.104*** (0.018)	-0.131*** (0.025)	-0.082*** (0.023)			
Networks: friends						-0.071*** (0.018)	-0.071*** (0.021)	-0.072*** (0.021)
Networks: relatives						-0.023 (0.039)	-0.001 (0.035)	-0.006 (0.035)
Networks: colleagues						0.063 (0.041)	0.087** (0.040)	0.101*** (0.039)
Observations	10133	6126	6126	12677	7529	5986	5100	5100
Treatment assignment model	logit	logit	logit	logit	logit	mlogit	mlogit	mlogit
Outcome model	Weig. Avg.	linear by ML	linear	Weig. Avg.	linear	Weig. Avg.	linear by ML	linear
Control variables in outcome model	No	Yes	Yes	No	Yes	No	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level control variables. The outcome variable is logarithm of the gross monthly wages.

test (SDT) and reveals innate abilities of the individual and the speed of solving new tasks. For a detailed description see Lang et al. (2007) who show that SDT outcomes are sufficiently correlated with test scores of a more comprehensive intelligence test. During the course of the test participants are given 1.5 minutes (90 seconds) to connect the symbols with the digits, given a pre-defined conversion table. For instance, digit “1” corresponds to a symbol “*” and digit “2” to “?”. The question which the respondents are required to answer is “Which number corresponds to the symbol “*””? The number of correct, false and total answers is measured after 30, 60 and 90 seconds in the test. This test was already used as a proxy for the in-born cognitive abilities in other studies (Heineck and Anger 2010; Richter et al. 2017).

Figure 2 shows the distribution of the number of correct answers after 30, 60 and 90 seconds, aggregated over all available test years. The mean score is increasing over time from 9.4 correct answers in 30 seconds to 29.7 in 90 seconds. Moreover, the variance of the distribution increased as well, almost doubling from 5.74 to 12.52. Nevertheless, in all three cases approximately 5% of the respondents haven’t given any correct answers. Unfortunately, the available sample size is low, especially in the disaggregated network setup starting in 2014. Consequently, assuming that the test scores of adults are stable over several years, we extrapolate the results of the test performed in 2016 to the other years of interest in order to achieve a larger sample size¹⁴.

Table 5 reports the distribution of imputed test scores by search channels. First three lines of the table show a number of correct answers in 30, 60 and 90 seconds respectively.

¹⁴Raw gaps in cognitive abilities before extrapolation are provided in table 17 in appendix 9.3. However, even after the extrapolation the sample size is not sufficiently large for the cognitive scores to be included in the IPW regressions, so we are bound to the descriptive analysis of test scores.

The next three lines are dedicated to the number of wrong answers in the same time period, and the last lines demonstrate the total number of answers given. The groups have several profound statistically significant differences. Those who found a position with the help of colleagues, gave more correct answers and made fewer mistakes than any other group. The second best group in terms of cognitive scores are those who found a job individually. They make significantly more mistakes than those who located a job with the help of colleagues. At the same time, they gave more correct and total answers and made fewer mistakes than those who found a job with the help of friends or family. These discrepancies reveal that the average cognitive ability indeed differs between the groups, with relatively low-ability respondents relying on their friends or family to find a job, middle-ability ones finding a job individually and high-ability respondents acquiring a position via referrals from colleagues. We conclude that this evidence provides further support for hypotheses **H2** and **H3**.

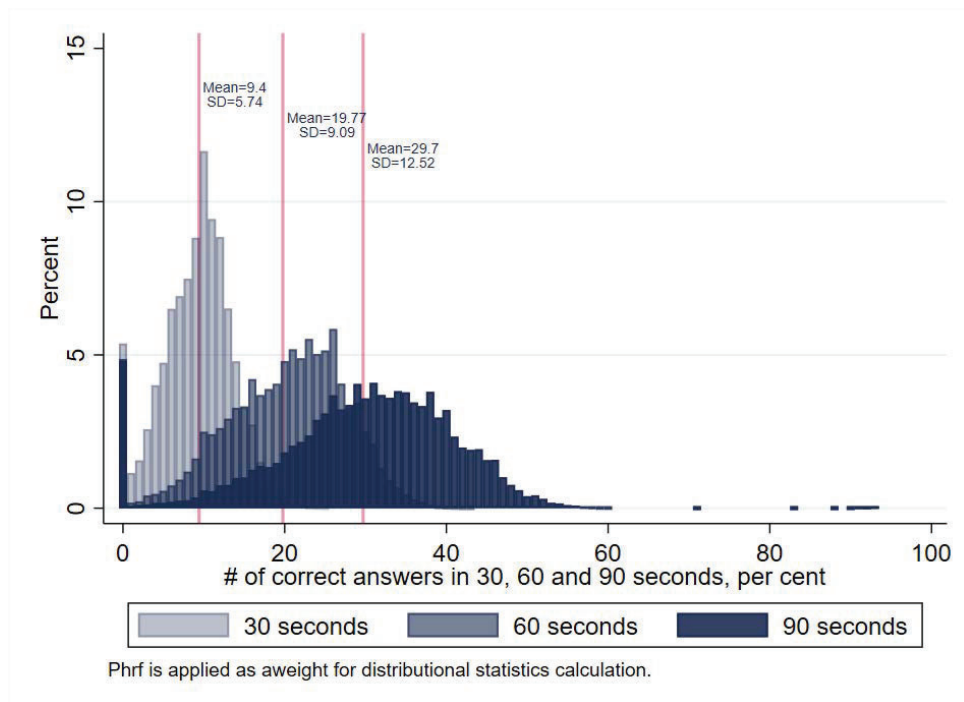


Figure 2: Distributions of scores in the Symbol digit test at different durations

Further, we find that differences in the SDT scores are robust to controlling for the years of education, mode of the interview¹⁵, and ID of an interviewer, despite a further reduction in the sample size. For instance, the number of wrong answers given in 60 seconds remains statistically significantly different between the groups. More detail is available in Table 15 in Appendix 9.3.

Another vital part of individual characteristics includes non-cognitive abilities. For example, stronger self-confidence or better negotiation skills could have an effect on the

¹⁵This is the way the questionnaire was administrated, e.g., a computer assisted personal interview (CAPI) or a paper assisted one (PAPI).

Table 5: Numeric tests (cognitive ability), disaggregated network types.

Variable	(1)	(2)	(3)	(4)	T-test					
	Individually Mean/SE	NW: friends Mean/SE	NW: family Mean/SE	NW: colleagues Mean/SE	(1)-(2)	(1)-(3)	Difference (1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)
Correct asw. (30 sec)	11.148 (0.292)	10.734 (0.176)	11.035 (0.279)	11.428 (0.246)	0.414*	0.113	-0.280	-0.301	-0.694**	-0.393
Correct asw. (60 sec)	23.499 (0.489)	22.587 (0.318)	23.015 (0.486)	23.808 (0.482)	0.911**	0.484	-0.309	-0.427	-1.220*	-0.793
Correct asw. (90 sec)	35.294 (0.614)	34.016 (0.476)	34.435 (0.677)	35.684 (0.657)	1.278**	0.859	-0.391	-0.419	-1.669*	-1.249
Wrong asw. (30 sec)	0.211 (0.018)	0.255 (0.019)	0.257 (0.038)	0.166 (0.025)	-0.044	-0.046	0.045	-0.003	0.089**	0.091**
Wrong asw. (60 sec)	0.361 (0.017)	0.490 (0.038)	0.496 (0.046)	0.260 (0.023)	-0.129***	-0.136**	0.101***	-0.007	0.230***	0.237***
Wrong asw. (90 sec)	0.574 (0.039)	0.732 (0.044)	0.803 (0.089)	0.547 (0.035)	-0.158***	-0.229**	0.028	-0.071	0.186**	0.257**
Total asw. (30 sec)	11.359 (0.283)	10.989 (0.179)	11.293 (0.274)	11.594 (0.234)	0.370*	0.066	-0.235	-0.304	-0.605*	-0.301
Total asw. (60 sec)	23.859 (0.492)	23.077 (0.309)	23.511 (0.452)	24.067 (0.478)	0.782*	0.348	-0.208	-0.434	-0.990	-0.556
Total asw. (90 sec)	35.868 (0.626)	34.748 (0.467)	35.238 (0.646)	36.231 (0.672)	1.120**	0.630	-0.363	-0.490	-1.483*	-0.993
Number of observations	1717	1945	442	484	3662	2159	2201	2387	2429	926
Number of clusters	16	16	16	16	16	16	16	16	16	16

Notes: Values are winsorised at 1 and 99 percentiles. Imputed for all years but 2016, assuming the results of the test being constant for the same respondent over 5 years. The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at federal state level. Observations are weighted using variable phrf as aweight weights.***, **, and * indicate significance at the 1, 5, and 10 percent critical level. Table 17 based on original values is available in Appendix 9.3.

starting wages. In order to test if these differences are relevant or not, we use a set of questions on the personality traits contained in SOEP (see McCrae and Costa (1999) for further details). These questions can be used to construct the “Big Five” personality traits as shown by Uysal and Pohlmeier (2011) and Caliendo et al. (2016). We use the following variables: being a thorough worker and carrying out tasks efficiently (proxies for conscientiousness), being original and valuing artistic experiences (proxies for the openness to experience), being sociable and communicative (proxies for extraversion), being able to forgive and friendly with others (proxies for agreeableness), worrying a lot and being nervous (proxies for neuroticism). However, Table 16 in Appendix 9.3 shows no systematic statistically significant differences between the groups. One minor exception is an ability to forgive, whereby more forgiving individuals are more often referred by their family members compared to those searching formally or recommended by friends.

In the final step we study the implications of regional characteristics. We find that county-specific factors have pronounced influence on the self-selection of workers into formal job search versus networks. Table 6 demonstrates the coefficients of the first-stage regressions for the regional variables, which have been included. In all cases - for the aggregated and disaggregated setup - higher regional unemployment rate is associated with a higher probability of utilizing networks. On the other hand, the logarithm of the population density in a county is negatively related to the probability of using a network tie for every group but colleagues. The contribution of the share of migrants is most

pronounced in the case of friendship ties. This is in line with the previous literature showing that immigrant workers often rely on their network of friends for obtaining jobs (see, for example, Dustmann et al. (2016)).

Table 6: Effects of regional coefficients on self-selection in job search

	PSM	IPW		
	(1) NW: All	(2) NW: Friends	(3) NW: Family	(4) NW: Colleagues
Unemployment rate	0.049*** (0.010)	0.045** (0.019)	0.055** (0.024)	0.043* (0.025)
Log of population density	-0.131*** (0.046)	-0.225*** (0.077)	-0.303*** (0.094)	-0.008 (0.097)
Share of migrants	0.006 (0.008)	0.035** (0.014)	0.005 (0.018)	0.002 (0.018)
Observations	10764	2363	564	490

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level control variables. The outcome variable is a probability of belonging to a group based on the job search method. Logit is used to model the binary choice; multinomial logit is used to predict the results disaggregated by a network type. Number of observations is weighted in the PSM. In the IPW, number of observations presents available observations by group. The total number of observations in IPW is 5986.

To sum up, when evaluating the network effect on starting wages in Germany, the coefficients are negative and robust indicating an approx. -9% lower starting wage. However, when the results are disaggregated by the network types, we can see that jobs found via friends and family are associated with a wage penalty of approximately -7% compared to the formal individual approach. Conversely, using the help of colleagues is associated with a 9% higher starting wage. In line with the theoretical model, the self-selection into job search methods is correlated with the results of the cognitive abilities tests: the group of those, who found a job with the help of colleagues shows the best outcomes.

6 Heterogeneity Analysis

6.1 Descriptive Analysis

This section is dedicated to the analysis of regional and gender differences in the job search channels and associated wages. Men and women tend to have different behavioural patterns in labour markets. However, even if the behavior is similar market forces may generate different labour market outcomes (Perez 2019), thus, we study the implications of referral hiring separately for men and women. In addition, we account for the long

historical division of Germany between the East and the West.

Figure 3 presents a spatial distribution of job search via networks (blue) and via the formal individual approach (green). Note that the sample is restricted to only these two channels. Although there is no federal state, where the formal job search method is more prevalent than networking, the spatial patterns are present for both. Finding a job formally is more common in the south (e.g. the state of Baden-Württemberg) and in the city-states Berlin and Hamburg, whereas the use of networks is most common in eastern federal states and in the west (Rheinland Pfalz). Figure 7 in Appendix 9.1 demonstrates an overlap of regional differences in the job search methods with gender. The relative importance of the formal channel in the south is mostly driven by the subsample of men. Whereas the prevalence of the network channel in the west is driven by the subsample of women. We find that up to 61% of women in the west tend to find a position with the help of networks, while in the other parts of the country the share is lower.

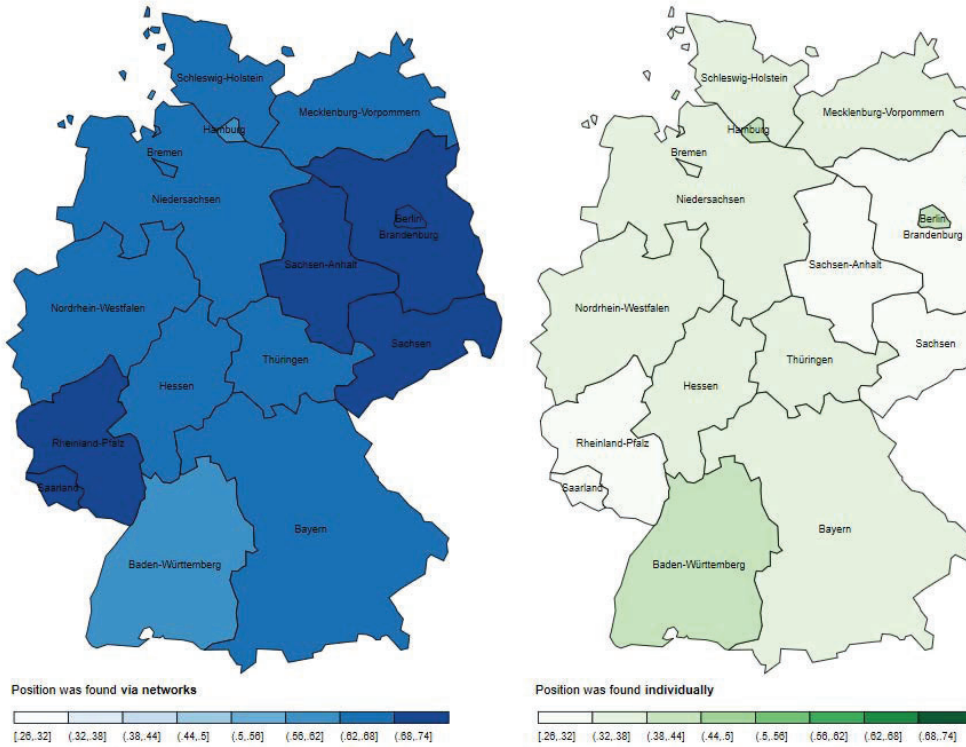


Figure 3: Job search channels in the years 2002-2019

In terms of the observable demographic characteristics of men and women, the most profound contrast is the following. Although men and women in the comparison group are statistically significantly different only in three characteristics¹⁶, the groups of men and women, who found their positions with the help of networks, are different in *all*

¹⁶The share of transitions from unemployment to employment is higher among men, while the share of respondents employed part-time and the average number of kids in a household are higher among women. The table with descriptive evidence by gender is available from the authors upon a request.

demographic characteristics but the share of mid-sized firms. This evidence supports our motivation to perform the analysis for subgroups distinguishing between the two broad regions (East vs. West) and the two gender groups.

6.2 Separating the effects by gender

Table 7 demonstrates the estimation results in the aggregated setup with a binary search channel indicator. The results for men are contained in Panel A, while the coefficients for women are reported in Panel B. Both panels indicate wage penalties associated with referral hiring, however, for men the results are not robust and vary from statistically insignificant to -9% . For women, on the other hand, all the estimators have overlapping confidence bounds and a mean close to -11% in starting wages. This suggests that the penalties from referral hiring are larger for women.

Table 7: Effects of finding a job with the help of networks compared to the formal approach, sample splitting by sex

	(1)	(2)	(3)	(4)	(5)
	IPW	AIPW	IPWRA	PSM	PSM
Panel A: Aggregated Networks, Men					
Networks	-0.036*	-0.096***	-0.088***	-0.077**	-0.039
	(0.019)	(0.029)	(0.029)	(0.037)	(0.034)
Observations	4264	2168	2168	5569	2768
Panel B: Disaggregated Networks, Women					
Networks	-0.105***	-0.107***	-0.105***	-0.161***	-0.091***
	(0.018)	(0.021)	(0.021)	(0.034)	(0.029)
Observations	5869	3958	3958	7108	4761
Treatment assignment model	logit	logit	logit	logit	logit
Outcome model	Weig. Avg	linear by ML	linear	Weig. Avg	linear
Control variables in outcome model	No	Yes	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level controls and federal state dummies. The outcome variable is logarithm of the gross monthly wages.

The disaggregated setup in Table 8 highlights an even more heterogeneous picture for the two groups. For men, none of the coefficients in any of the methods is statistically significantly different from zero. Moreover, the estimated amplitude is approaching zero as well. For women, on the other hand, the coefficients associated with referrals from friends and colleagues are robust and statistically significant in all the three estimation methods. In line with the theoretical predictions, those, who found a job with the help of

Table 8: Effects of the job search channels compared to the formal approach, sample splitting by sex

	Men: disaggregated			Women: disaggregated		
	(1) IPW	(2) AIPW	(3) IPWRA	(4) IPW	(5) AIPW	(6) IPWRA
Networks: friends	-0.034 (0.029)	-0.034 (0.031)	-0.029 (0.029)	-0.099*** (0.023)	-0.103*** (0.026)	-0.104*** (0.026)
Networks: relatives	-0.070 (0.063)	-0.019 (0.050)	-0.025 (0.050)	-0.021 (0.044)	0.002 (0.046)	-0.007 (0.046)
Networks: colleagues	-0.030 (0.063)	-0.015 (0.060)	-0.021 (0.062)	0.091 (0.061)	0.158** (0.066)	0.138** (0.055)
Observations	2457	2093	2093	3529	3007	3007
Treatment assignment model	mlogit	mlogit	mlogit	mlogit	mlogit	mlogit
Outcome model	Weig. Avg	linear by ML	linear	Weig. Avg	linear by ML	linear
Control variables in outcome model	No	Yes	Yes	No	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level controls and federal state dummies. The outcome variable is logarithm of the gross monthly wages.

a friend are likely to have a -10% reduction in starting wages. On the contrary, referrals from colleagues lead to a 13-15% increase in wages ¹⁷. Hence, the overall result is largely driven by the subsample of women rather than men.

Next, we study differences in cognitive ability scores by the job search method and gender. Figure 4 plots mean values and 95% confidence intervals for the number of correct answers in the SDT test over 90 seconds. For men the differences in cognitive abilities across the four search channels are not statistically significant. However, the group with the highest number of observations - those who found a job with the help of friends - achieved the lowest score equal to 34.8 points. The other three groups of men have on average achieved 35.5 points. This can be an explanation for the observed wage penalty associated with referral hiring for men but insignificant results in the disaggregated analysis of wages.

For women, though, the case is different. Women who found a job with the help of colleagues on average had scored 35.9 points, which is 0.8 points more compared to women who found a job in a formal way and 2.6 points more compared to those who were recommended by their family and friends. These differences are large and statistically significant indicating a considerable variation in cognitive abilities of women finding jobs in different ways. Moreover, they support the theory since a wide spread in abilities across search channels is consistent with a great dispersion in wages reported for women in table 8. More details and exact values for the SDT test results are available in Table

¹⁷Although the estimated coefficients for women seem to be widespread, the confidence intervals of all the estimates are overlapping

19 in Appendix 9.3.

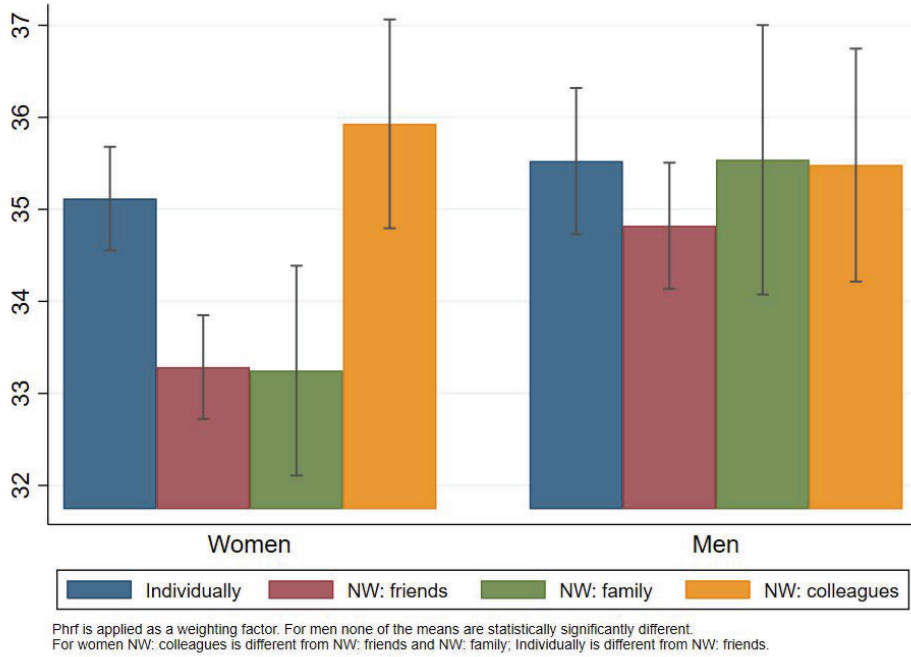


Figure 4: Mean values and confidence intervals for the number of correct answers in 90 seconds, sample splitting by sex

6.3 Separating the effects by region

Separating the effects by region provides new insights into the regional disparities. Although West and East Germany share the same labour market regulations, the consequences of the former division of the country can still be traced up to the current date. Not only there are persistent differences in the unemployment rates and labour productivity (Schnabel 2016), but also in the behavioral aspects, social norms and attitudes between the two regions (Sprengholz et al. 2022).

Table 9 shows significant wage penalties associated with finding a job via the network of contacts in both regions. For the West, the average wage penalty is approximately -7-11%. For the East, the average wage reduction is estimated between -12% and -15%, however, the confidence intervals of the estimated effects are relatively wide and overlap. Propensity score estimates without additional controls yield a result with larger amplitude, but also with a larger standard error.

Finally, in Table 10 we consider the disaggregated results with three types of social contacts transmitting job information. For West Germany the only significant coefficient is a penalty of -6-7% associated with the networks of friends as a job search method. Although the coefficient for utilizing weak ties is positive and reaches 5-8%, it is not significant. For East Germany wage penalties associated with friendship ties are large and significant but the confidence intervals are also wide. Finding a job with the help of

strong ties is associated with a $-16 - 19\%$ reduction in starting wages. On the contrary, getting help from weak ties generates a sizeable wage premium of 15% .

Table 9: Effects of the job search channels compared to the formal approach, sample splitting by West and East German federal states

	(1)	(2)	(3)	(4)	(5)
	IPW	AIPW	IPWRA	PSM	PSM
Panel A: Aggregated Networks, West					
Networks	-0.066*** (0.015)	-0.095*** (0.020)	-0.095*** (0.020)	-0.111*** (0.028)	-0.073*** (0.024)
Observations	7853	4658	4658	10299	6077
Panel B: Disaggregated Networks, East					
Networks	-0.121*** (0.028)	-0.151*** (0.036)	-0.145*** (0.035)	-0.217*** (0.061)	-0.145** (0.056)
Observations	2280	1468	1468	2378	1452
Treatment assignment model	logit	logit	logit	logit	logit
Outcome model	Weig. Avg	linear by ML	linear	Weig. Avg	linear
Control variables in outcome model	No	Yes	Yes	No	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level controls and federal state dummies. The outcome variable is logarithm of the gross monthly wages.

Table 10: Effects of the job search channels compared to the formal approach, sample splitting by West and East German federal states

	West: disaggregated			East: disaggregated		
	(1)	(2)	(3)	(4)	(5)	(6)
	IPW	AIPW	IPWRA	IPW	AIPW	IPWRA
Networks: friends	-0.074*** (0.020)	-0.060*** (0.023)	-0.062*** (0.022)	-0.161*** (0.044)	-0.193*** (0.058)	-0.166*** (0.053)
Networks: relatives	-0.016 (0.044)	-0.000 (0.041)	-0.002 (0.040)	-0.134* (0.080)	-0.069 (0.061)	-0.050 (0.052)
Networks: colleagues	0.052 (0.043)	0.065 (0.049)	0.080 (0.050)	0.077 (0.088)	0.154* (0.088)	0.155*** (0.057)
Observations	4772	4087	4087	1181	1013	1013
Treatment assignment model	mlogit	mlogit	mlogit	mlogit	mlogit	mlogit
Outcome model	Weig. Avg	linear by ML	linear	Weig. Avg	linear by ML	linear
Control variables in outcome model	No	Yes	Yes	No	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level controls and federal state dummies. The outcome variable is logarithm of the gross monthly wages.

The ability patterns are matching the model predictions. Figure 5 demonstrates that the numbers of correct answers in the SDT test performed over a period of 90 seconds vary substantially with the type of the job search method. Moreover, the differences are more pronounced in the East compared to the West, which is inline with our observation for wage gaps. However, due to the small sample size, none of the within-group differences is statistically significant.

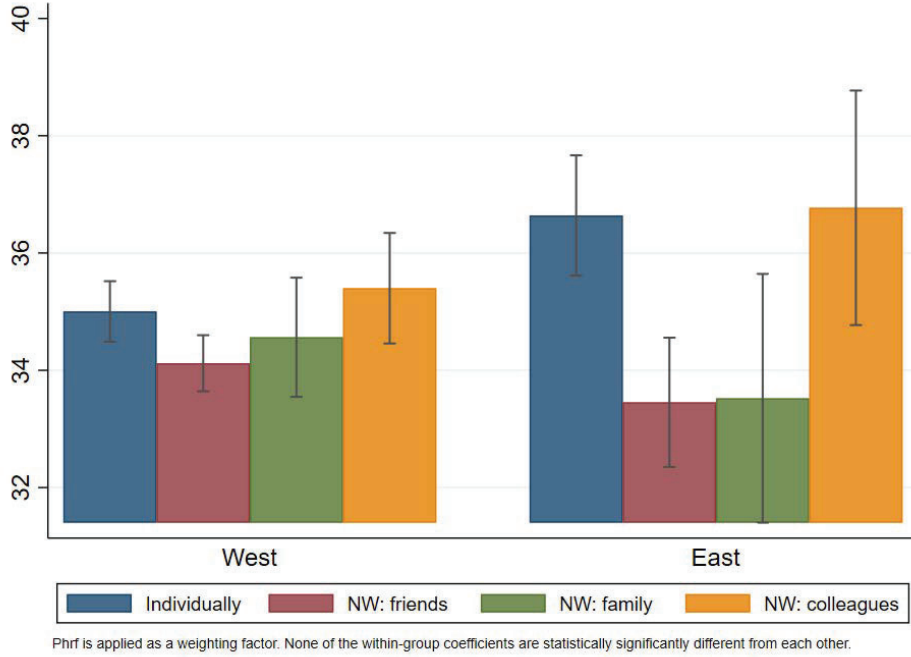


Figure 5: Mean values and confidence intervals for the number of correct answers in 90 seconds, sample splitting by West and East Germany

7 Robustness Checks

This section contains a set of robustness checks. First, we consider a narrow definition of a job change restricting the sample to those individuals, who accepted a new job in a new firm, and dropping a small subsample of those, who accepted a new job in the same firm. Second, we consider a shorter time frame between 2014 and 2019, as well as add two waves affected by the COVID-19 pandemic. Third, we study the development of wages three years after the job entry.

Narrow definition of a job change. In the main body of the article we used a broad definition of the job change including those workers who report a new job in the same firm. In Table 11 we drop this subsample and restrict our estimation to workers switching employers. We use the same matching vectors and sets of control variables as in the main analysis. The covariates remain balanced for all subsamples. Panel A of Table 11 reports results for the aggregated networks. The rows represent the job

search channels, while the subgroups of men/women as well as West/East are listed in the columns. For all subgroups the aggregate effect of social networks remains negative, moreover, the wage penalty is statistically significant for all but men. The values are comparable to those we find using a broad definition of the job change. Panel B, in turn, reports the disaggregated results for the three types of social ties. Again, the pattern repeats the main estimation results in signs and magnitudes.

Varying time periods. Another robustness check that we perform is related to the utilized time period. In particular, we repeat the estimation for a shorter period of time between 2014 and 2019. This is the time frame we used for the disaggregated analysis with detailed information about the social tie. Table 18 in appendix 9.3 reports our results for the aggregated setup with a binary network indicator over the period 2014-2019. Here again we use the main definition of the job change. The coefficients are negative and similar in magnitude to those obtained for the main sample.

Another variation of the time span that we perform is based on adding samples for 2020 and 2021 into the analysis. These are the waves which were severely affected by the COVID-19 pandemic, thus, we did not include them to the main estimation sample. Moreover, we add a dummy marking the years affected by the COVID-19 pandemic. The magnitude of the coefficients as well as their signs and significance remained the same¹⁸.

Wages in consequent years of employment. Another robustness check addresses the development of wages beyond the starting wage. Therefore, we direct attention to the respondents who stayed in the same job for three consecutive years. Unfortunately, this leads to a considerable reduction of the sample, which makes the disaggregated analysis based on the three different types of social ties impossible. Yet, the sample size is sufficient for the aggregated analysis with a binary network indicator.

Figure 6 demonstrates the estimates for the overall group based on the AIPW approach. The IPW and IPWRA show a similar picture and are omitted from the text. In all three years after the job entry, the effects of finding a position with the help of social networks are stable and negative, reaching approximately -8% . This finding indicates that lower wages associated with the network channel are persistent, and there is no wage adjustment after the first year of tenure. This suggests that the aforementioned wage gaps could be an outcome of differences in cognitive abilities or other unobserved workers characteristics, rather than uncertainty and learning on the side of the employer. The subgroups' coefficients are also negative throughout the period, however, they are primarily insignificant due to a considerable reduction in the sample size.

¹⁸Exact results are available on request.

Table 11: Effects of the job change method, narrow definition of job change

	All	Men	Women	West	East
Panel A: Aggregated Networks					
PSM - no controls	-0.048 (0.030)	-0.094** (0.045)	-0.149*** (0.033)	-0.046 (0.029)	-0.055 (0.069)
PSM - controls	-0.015 (0.030)	-0.006 (0.041)	-0.086*** (0.033)	-0.028 (0.033)	-0.055 (0.069)
IPW	-0.072*** (0.013)	-0.037* (0.019)	-0.099*** (0.018)	-0.065*** (0.015)	-0.113*** (0.029)
AIPW	-0.105*** (0.018)	-0.026 (0.019)	-0.077*** (0.018)	-0.048*** (0.015)	-0.117*** (0.028)
IPWRA	-0.104*** (0.018)	-0.023 (0.019)	-0.077*** (0.018)	-0.048*** (0.015)	-0.116*** (0.029)
Panel B: Disaggregated Networks					
IPW: Network - friends	-0.069*** (0.018)	-0.039 (0.029)	-0.093*** (0.022)	-0.070*** (0.020)	-0.100** (0.044)
IPW: Network - relatives	-0.023 (0.039)	-0.036 (0.065)	-0.018 (0.045)	-0.014 (0.045)	-0.080 (0.084)
IPW: Network - colleagues	0.061 (0.042)	-0.025 (0.065)	0.074 (0.062)	0.044 (0.045)	0.127 (0.092)
AIPW: Network - friends	-0.071*** (0.021)	-0.037 (0.031)	-0.100*** (0.026)	-0.061*** (0.023)	-0.140*** (0.053)
AIPW: Network - relatives	0.000 (0.035)	-0.005 (0.053)	0.003 (0.046)	-0.001 (0.041)	-0.064 (0.054)
AIPW: Network - colleagues	0.088** (0.040)	-0.017 (0.061)	0.152** (0.062)	0.064 (0.049)	0.137* (0.074)
IPWRA: Network - friends	-0.072*** (0.020)	-0.030 (0.029)	-0.101*** (0.026)	-0.063*** (0.022)	-0.137*** (0.053)
IPWRA: Network - relatives	-0.005 (0.035)	-0.012 (0.050)	-0.008 (0.046)	-0.003 (0.040)	-0.025 (0.051)
IPWRA: Network - colleagues	0.101*** (0.039)	-0.025 (0.063)	0.132** (0.053)	0.078 (0.050)	0.138** (0.063)

Notes: *** p<0.01, ** p<0.05, * p<0.10; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level controls and federal state dummies. The outcome variable is logarithm of the gross monthly wages. Panel A represents coefficient for the aggregated networks. The number of observations for each cell is available upon request.

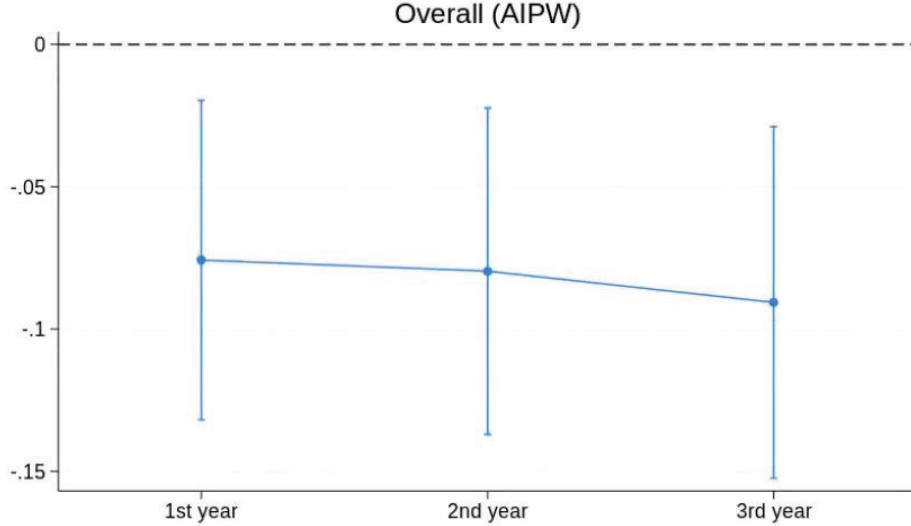


Figure 6: Effects of finding a job via networks on wages in consequent years

8 Discussion and Conclusions

In this paper we study the relationship between the job search channel and the starting wage. The analysis is focused on comparing the wages of referred with non-referred applicants by using the inverse-probability weighting approach. Our results show a stable negative effect of about -10% associated with finding a job with the help of a social contact in Germany. This wage gap is robust if estimated by different methods and using various subsamples, moreover, it remains stable several years after the start of the employment relationship. Disaggregating the effect by the type of the social contact, two opposite patterns are revealed - while jobs found via friends result in -7% lower starting wages, the positions found with the help of colleagues are associated with a wage premia of 9%.

Combining this analysis with information on the cognitive ability score from the symbol digit test (SDT) we find that applicants recommended by their colleagues perform better in the ability test than those finding jobs in the formal way. In contrast, applicants finding jobs with a help of a friend perform worse in the test than any other worker group. These findings are consistent with the sorting model of job search as developed by Stupnytska and Zaharieva (2015) and Lester et al. (2021) as well as the seminal work by Montgomery (1991) and Granovetter (1995). The heterogeneity analysis shows significant differences by gender: for men none of the coefficients is statistically significant, while for women the differences are more pronounced. It is consistent with a large variation in cognitive scores documented for women and indicating a stronger sorting of women across search channels compared to men.

Concluding the paper, we discuss the limitations of our analysis. The first limitation is in the nature of the data since SOEP has limited information about the employer, thus, unobserved employer heterogeneity is not accounted for. Further, our study does

not cover the respondents who found a job with the help of an employment agency or returned to a previous employer. Another restriction is self-selection in the labour market participation, which results in wages of non-participants not being observed. On the one hand, different methods allow controlling for this part of self-selection. On the other hand, the usual assumption is that the sign of self-selection is known. Machado (2017) argues that for women in the labour market it is not the case, with self-selection being positive for the lower deciles of the ability distribution and negative for the higher ones. Thus, one cannot claim the exact direction of the bias. However, if the usual positive self-selection is assumed, this paper estimates the lower bound of the effect.

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9 Appendix

9.1 Detailed demographic characteristics

Table 12: Blinder-Oaxaca decomposition

Panel A: overall decomposition		Estimated values	
Individual		7.149	(0.02)***
Networking: overall		6.832	(0.02)***
Total difference		0.316	(0.02)***
Endowments		0.210	(0.02)***
Coefficients		0.108	(0.02)***
Panel B: detailed disaggregation			
	Endowments	Coefficients	Interaction
Age	-0.023 (0.02)	-0.416 (0.49)	0.006 (0.01)
Age, squared	0.029 (0.02)*	0.246 (0.24)	-0.008 (0.01)
Federal State	0.001 (0.00)	0.044 (0.04)	-0.001 (0.00)
Education: less than high school	-0.005 (0.00)	-0.005 (0.03)	0.001 (0.01)
Education: more than high school	0.007 (0.01)	-0.011 (0.02)	-0.006 (0.01)
Job-to-job transition	0.000 (0.00)	0.018 (0.02)	0.001 (0.00)
Firm size by empl: No employees	0.000 (.)	0.000 (.)	0.000 (.)
Firm size by empl: Small	0.005 (0.01)	0.068 (0.06)	-0.020 (0.02)
Firm size by empl: Middle	0.001 (0.00)	0.054 (0.04)	0.001 (0.00)
Firm size by empl: Large	0.036 (0.01)***	0.049 (0.05)	0.021 (0.02)
First Job Full Time	-0.001 (0.00)	-0.049 (0.03)*	0.001 (0.00)
# of children in HH	0.003 (0.00)	0.002 (0.04)	-0.000 (0.00)
Number of Persons in HH	-0.003 (0.00)	-0.017 (0.05)	0.001 (0.00)
Annual Work Hours of Individual	0.056 (0.01)***	-0.088 (0.03)***	-0.010 (0.00)***
The youngest child is in kita age or smaller	-0.000 (0.00)	0.015 (0.01)	-0.001 (0.00)
Long-term unemployment in county (INKAR)	-0.000 (0.00)	-0.018 (0.09)	0.000 (0.00)
Married, living together	-0.000 (0.00)	-0.024 (0.02)	0.001 (0.00)
Migration background	0.000 (0.00)	0.016 (0.01)	-0.003 (0.00)
NACE code (rev 1.1)	0.001 (0.00)	0.034 (0.04)	-0.000 (0.00)
Occupation & Training: mismatch	0.033 (0.01)***	-0.013 (0.02)	0.003 (0.00)
Occupation & Training: in training	0.001 (0.01)	0.001 (0.01)	-0.000 (0.00)
Occupation & Training: no training	0.015 (0.00)***	-0.000 (0.01)	0.000 (0.00)
Tenure	-0.002 (0.00)***	0.012 (0.01)	-0.003 (0.00)
Population-workplace density in county (INKAR)	0.005 (0.00)**	-0.019 (0.01)	-0.003 (0.00)
Rural or urban region	-0.000 (0.00)	0.008 (0.03)	0.000 (0.00)
Moved to another county	0.005 (0.00)**	0.002 (0.00)	0.002 (0.00)
Sex	-0.006 (0.00)*	-0.002 (0.01)	0.000 (0.00)
Survey Year	-0.002 (0.00)	-19.524 (9.88)**	0.001 (0.00)
Total # of years a resp. spent unempl from 2001	0.004 (0.00)*	0.025 (0.03)	-0.001 (0.00)
Transition from unempl. to empl.	0.002 (0.00)	0.007 (0.01)	0.000 (0.00)
Unemployment rate in county (INKAR)	0.005 (0.00)*	0.015 (0.05)	-0.001 (0.00)
Years of education	0.045 (0.01)***	0.215 (0.18)	0.015 (0.01)
Constant		19.461	(9.86)**

Notes: Standard errors are clustered at NUTS3 level and reported in paranthesis. *, ** and *** indicate 10-, 5- and 1-percent critical level. The dependent variable is logarithm of gross monthly wages.

Table 13: Demographic characteristics conditional on the job search method, disaggregated network types.

Variable	(1) Individually			(2) Networks: friends			(3) Networks: family			(4) Networks: colleagues			(2)-(1)			(3)-(1)			(4)-(1)		
	N/Clusters	Mean/(SE)		N/Clusters	Mean/(SE)		N/Clusters	Mean/(SE)		N/Clusters	Mean/(SE)		N/Clusters	Mean difference		N/Clusters	Mean difference		N/Clusters	Mean difference	
Natural logarithm of gross wages	4269	7.442 (0.028)		4838	7.147 (0.031)		1220	7.018 (0.056)		1152	7.683 (0.040)		9107	-0.294***		5489	-0.424***		5421	0.242***	
Men	96	0.435 (0.016)		95	0.521 (0.012)		91	0.484 (0.025)		88	0.546 (0.021)		96	0.086***		96	0.049		96	0.111***	
Age, years	4305	35.272 (0.262)		4890	36.934 (0.257)		1236	34.252 (0.634)		1158	36.665 (0.420)		9195	1.661***		5541	-1.020		5463	1.393***	
Years of education	4081	12.894 (0.067)		4566	11.662 (0.092)		1145	11.539 (0.125)		1101	13.163 (0.131)		8647	-1.231***		5286	-1.354***		5182	0.270*	
Married, living together	4289	0.370 (0.012)		4859	0.420 (0.015)		1231	0.435 (0.026)		1157	0.350 (0.022)		9148	0.050***		5520	0.065**		5446	-0.020	
# of HH members	96	2.534 (0.039)		4890	2.695 (0.040)		91	3.095 (0.072)		88	2.429 (0.054)		9195	0.161***		5541	0.561***		96	-0.105*	
# of children in HH	4305	0.899 (0.030)		4890	1.091 (0.025)		1236	1.055 (0.056)		1158	0.829 (0.038)		9195	0.192***		5541	0.156**		5463	-0.070	
Migration background	96	0.326 (0.017)		4890	0.459 (0.028)		1236	0.412 (0.039)		88	0.273 (0.022)		9195	0.134***		5541	0.087**		5463	-0.053**	
Transition from unempl. to empl.	3566	0.105 (0.010)		3865	0.120 (0.012)		976	0.102 (0.016)		997	0.021 (0.006)		7431	0.015		4542	-0.003		4563	-0.084***	
Job-to-job transition	4305	0.587 (0.018)		4890	0.533 (0.022)		1236	0.474 (0.031)		1158	0.722 (0.023)		9195	-0.054***		5541	-0.112***		5463	0.135***	
Main job full-time	4008	0.728 (0.013)		4556	0.757 (0.012)		1095	0.703 (0.022)		1100	0.707 (0.023)		8564	0.029**		5103	-0.025		5108	0.039	
Annual work hours	4305	1444.608 (27.660)		4890	1262.939 (30.786)		1236	1107.793 (49.016)		1158	1732.927 (33.418)		9195	-181.669***		5541	-276.814***		5463	288.319***	
Occupational mismatch	4264	0.305 (0.012)		4807	0.441 (0.012)		1221	0.439 (0.022)		1155	0.300 (0.020)		9071	0.136***		5485	0.134***		5419	-0.005	
Firm size: <20 employees	4102	0.191 (0.010)		4499	0.213 (0.012)		1148	0.159 (0.015)		1109	0.170 (0.020)		8601	0.022		5250	-0.032*		96	-0.021	
Firm size: [20,200) employees	4102	0.087 (0.007)		4499	0.078 (0.006)		1148	0.075 (0.015)		1109	0.068 (0.012)		8601	-0.009		5250	-0.012		5211	-0.019	
Firm size: ≥ 200 employees	4102	0.228 (0.012)		4499	0.176 (0.009)		1148	0.170 (0.020)		1109	0.235 (0.021)		8601	-0.052***		5250	-0.058***		5211	0.007	

Notes: Significance: ***=.01, **=.05, *=.1. Errors are clustered at federal state-year level. Observations are weighted using variable phrf as aweight weights.

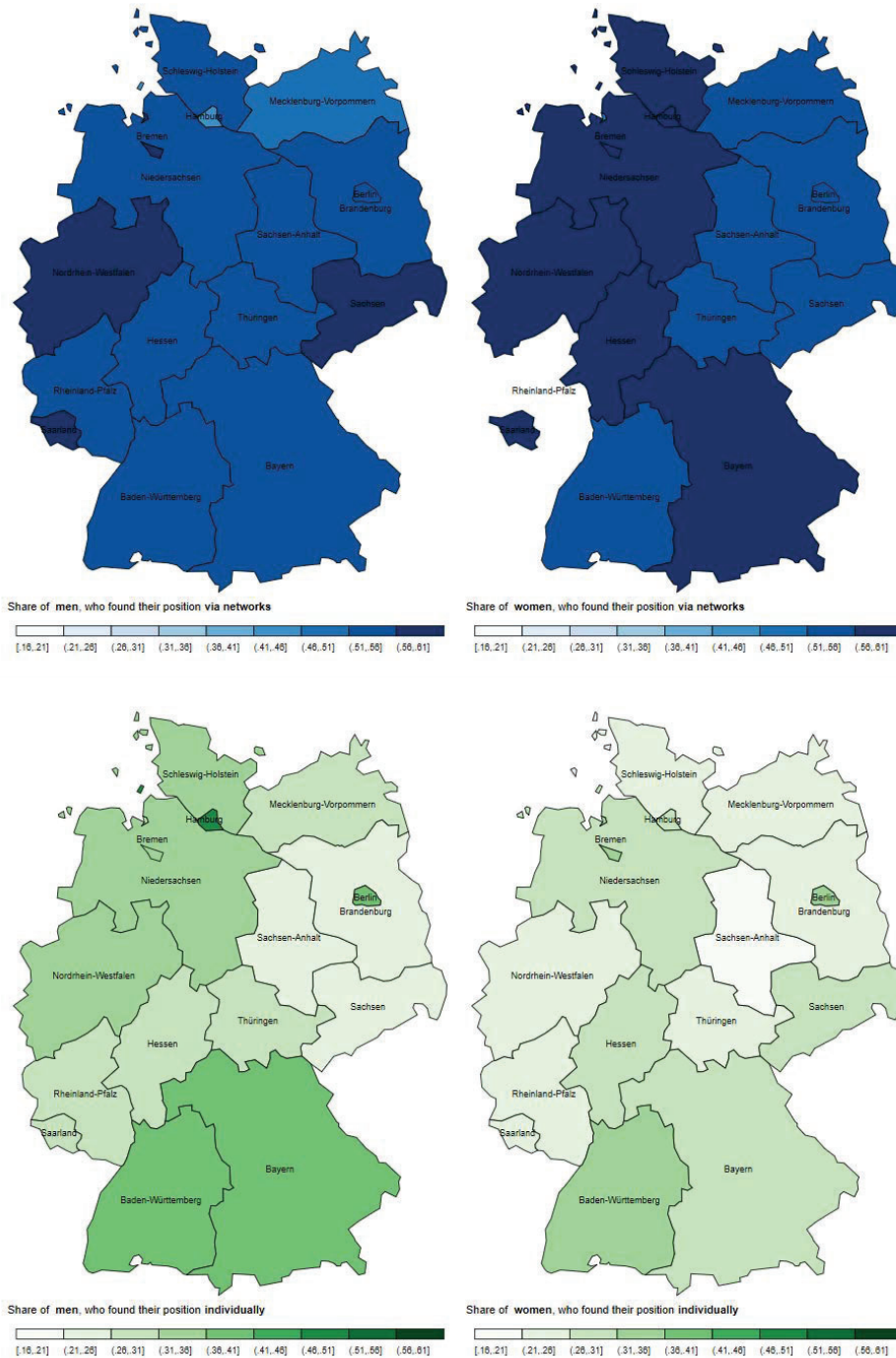


Figure 7: Regional distribution of the job search methods, sample splitting by sex.

9.2 Main variables description

This section of the appendix describes the construction of the main variables which are used in the empirical analysis.

Current job market status and transitions

We use variable *pgjobch* to define the current job market status of a respondent. It is further augmented by using information on the annual working time: if the respondent reported working more than 52+ hours, s/he is considered to be employed. Based on this information we create the following categories: job-to-job transition, unemployment-to-employment transition, non-participation-to-employment transition, first time participant. To construct a reliable measure for unemployment we additionally used variable *plb0021* variable. If in the previous year the respondent was registered unemployed (variable *plb0021*) and in the current year the status is “Employed (with/without/unclear) job change”, we counted it as a transition from unemployment to employment. First time participants are excluded from the sample.

Job search method coding

The job search method is the central variable of the analysis (“treatment”), however, it is also the one which considerably restricts the sample size. Respondents undertaking a paid activity were asked if s/he has found a new position in the period from the Jan, 1 previous year till the time of the survey. The job change includes both change of the position within one company and finding a new employer. If this question was answered affirmatively, a respondent was asked about the way which lead to the current position, i.e., the job search method. As SOEP covers a long time period, the ways to find a job have changed several times. For example, in the year 2014 networking, as a job search method, was split by the network types - friend, family or colleagues. Hence, we use a harmonized variable covering 18 possible ways to find a position. These 18 categories were aggregated to the four main job search methods:

1. Formal centralized approach (agency) includes those, who have found a position using the help from an employment office (*Arbeitsamt*), Job-Center/ARGE/social office (*Sozialamt*), personnel service agency (*Personalserviceagentur*) or private job placement.
2. Formal individual search covers the job postings in newspapers and the Internet.
3. Informal individual search includes finding a position via a social network or using social capital of friends, relatives, acquaintances or former colleagues. Thus, it is mostly referred to as networking.
4. All other types of the job search are collected into “other” category.

For the analysis in this paper only those respondents who have found their position using formal individual approach (referred to as “individually” or “comparison group”) and with the help of their social capital (“networking” or “treatment”) are included. All variables used for estimation and balance are briefly described in Table 14 below. First column shows a variable’s name in the data/regressions, while the second column provides a short description of the economic meaning. The next column indicates, if a variable was taken directly from the dataset or was constructed by the authors. The forth column indicates, if a variable is a dummy coded as 0-1. Finally, the last column provides notes on construction of the variables.

Table 14: Description of variables used

Variable Name	Short Description	Constr.	A 0-1 dummy variable	Notes
age	Age, years			
agesq	Age squared, years	Yes		
bula	Federal state			
bula_ew	Federal State According to statistic		Yes	East-West Version
educ_stage	Finished stage of education	Yes		Aggregation of the yerseduc variable. <12 - less than high school; [12,13] - high school lvl; >13 - more than high school
educ_stage_1	Less than high school	Yes	Yes	Based on <i>educ_stage</i>
educ_stage_2	High school	Yes	Yes	Based on <i>educ_stage</i>
educ_stage_3	More than high school	Yes	Yes	Based on <i>educ_stage</i>
empl_change	A job-to-job transition	Yes	Yes	See a detailed description
firm_size	A size of the firm			# of employees, based on <i>pgbetr</i> variable
firm_size_1	Very small: (0, 20) employees	Yes	Yes	Based on <i>firm_size</i>
firm_size_2	Small: [20, 100) employees	Yes	Yes	Based on <i>firm_size</i>
firm_size_3	Middle: [100, 200) employees	Yes	Yes	Based on <i>firm_size</i>
firm_size_4	Large: [200, 2000) employees	Yes	Yes	Based on <i>firm_size</i>
firm_size_5	Very large: ≥ 2000 employees	Yes	Yes	Based on <i>firm_size</i>
fulltime	Working full-time		Yes	
hh_size	# of HH members			
hours_work_year	Annual work hours			
kita_less_ch	The youngest child is in kita age or smaller	Yes	Yes	Based on <i>kidgeb01</i> - <i>kidgeb15</i> variables and <i>syear</i> variable. First, the current age of a child is defined. Then for each year the age of the youngest child is saved. Finally, a dummy variable is created, indicating if the child is below 6 years of age in a given year.

Continued on next page

Table 14: Description of variables used (Continued)

Variable Name	Short Description	Constr.	A 0-1 dummy variable	Notes
log_labgro	Logarithm of gross montly wages	Yes		Based on the labgro variable. First, it was winsorized at 1 and 99 percentiles by the type of the occupation. Secondly, a logarithm was taken.
long_unempl	Long-term unemployment, share per county			From INKAR
mar_status	Married, living together	Yes	Yes	Based on the <i>d11104</i>
nace_full_1d	NACE rev 1.1, created, 1 digit	Yes		Based on <i>pgnace</i> and <i>pgnace2</i> variables. The first variable is available from 2002 to 2017 and is coded according to the first review of NACE classification. The second variable is available from 2013 to 2019 and based on the rev. 2 of NACE classification. Both variables are aggregated to the major groups and converted to rev 1.1 according to the NACE guidelines.
nace_full_1d_1	Agriculture/fishing	Yes	Yes	As per NACE rev 1.1
nace_full_1d_10	Real estate/business cativities	Yes	Yes	As per NACE rev 1.1
nace_full_1d_11	Public administration	Yes	Yes	As per NACE rev 1.1
nace_full_1d_12	Education	Yes	Yes	As per NACE rev 1.1
nace_full_1d_13	Health and social work	Yes	Yes	As per NACE rev 1.1
nace_full_1d_14	Community and social services	Yes	Yes	As per NACE rev 1.1
nace_full_1d_15	Private HHs as employers	Yes	Yes	As per NACE rev 1.1
nace_full_1d_16	Act. of extraterr. org/bodies	Yes	Yes	As per NACE rev 1.1
nace_full_1d_2	Mining	Yes	Yes	As per NACE rev 1.1
nace_full_1d_3	Manufacturing	Yes	Yes	As per NACE rev 1.1
nace_full_1d_4	Electr/Gas/Water Supply/Management	Yes	Yes	As per NACE rev 1.1
nace_full_1d_5	Construction	Yes	Yes	As per NACE rev 1.1
nace_full_1d_6	Wholesale/retail trade	Yes	Yes	As per NACE rev 1.1
nace_full_1d_7	Hotels and restaurants	Yes	Yes	As per NACE rev 1.1
nace_full_1d_8	Transport and Communication	Yes	Yes	As per NACE rev 1.1
nace_full_1d_9	Financial Intermediation	Yes	Yes	As per NACE rev 1.1
nonpart_empl	A shift from non-participation in labour market to employment	Yes	Yes	See a detailed description
pgerljob	Occupation matches training			
pgerljob_1	Yes, matches	Yes	Yes	Based on <i>pgerljob</i>
pgerljob_2	No, occ. mismatch	Yes	Yes	Based on <i>pgerljob</i>
pgerljob_3	In training	Yes	Yes	Based on <i>pgerljob</i>
pgerljob_4	No training	Yes	Yes	Based on <i>pgerljob</i>
pgerwzeit	Tenure			At a previous employer

Continued on next page

Table 14: Description of variables used (Continued)

Variable Name	Short Description	Constr.	A 0-1 dummy variable	Notes
pop_to_job_places	Population-workplace density, county level			From INKAR
regtyp	If a region is rural or urban		Yes	
relocated_nuts3	Compared to a previous observation, a person has relocated to another county	Yes	Yes	Missing values are used, if this was a first observation for a person
sex	Sex		Yes	
syear	Survey Year			
tot_yrs_unempl	Total # of years a resp. spent unempl from 2001	Yes		# of years a person spent not in employment. The years are counted by person, if <i>pgjobch</i> equals 1.
unempl_empl	A shift from unemployment to employment	Yes	Yes	See a detailed description
unempl_rate	Unemployment rate, county level			From INKAR
yrseduc	Years of educations			

9.3 Additional Results

Table 15: Numeric Test (cognitive abilities), including control variables

Variable	(1)	(2)	(3)	(4)	T-test Difference					
	Individually Mean/(SE)	NW: friends Mean/(SE)	NW: family Mean/(SE)	NW: colleagues Mean/(SE)	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)
Correct asw. (30 sec)	11.035 (0.273)	10.616 (0.187)	10.944 (0.313)	11.152 (0.269)	0.418	0.091	-0.117	-0.328	-0.536	-0.208
Correct asw. (60 sec)	23.306 (0.472)	22.434 (0.341)	22.875 (0.549)	23.355 (0.529)	0.872	0.431	-0.049	-0.441	-0.922	-0.480
Correct asw. (90 sec)	35.059 (0.598)	33.811 (0.491)	34.244 (0.818)	35.016 (0.740)	1.248	0.815	0.042	-0.433	-1.205	-0.773
Wrong asw. (30 sec)	0.214 (0.018)	0.248 (0.021)	0.252 (0.048)	0.179 (0.028)	-0.035	-0.038	0.035	-0.003	0.070*	0.073
Wrong asw. (60 sec)	0.367 (0.018)	0.466 (0.032)	0.471 (0.058)	0.272 (0.029)	-0.099*	-0.104	0.095***	-0.005	0.195***	0.200**
Wrong asw. (90 sec)	0.582 (0.040)	0.701 (0.037)	0.753 (0.115)	0.559 (0.042)	-0.120	-0.171	0.023	-0.051	0.143**	0.194
Total asw. (30 sec)	11.248 (0.267)	10.865 (0.193)	11.195 (0.316)	11.331 (0.252)	0.384	0.053	-0.082	-0.331	-0.466	-0.135
Total asw. (60 sec)	23.673 (0.476)	22.900 (0.332)	23.346 (0.520)	23.627 (0.519)	0.773	0.327	0.046	-0.446	-0.727	-0.281
Total asw. (90 sec)	35.640 (0.609)	34.512 (0.480)	34.996 (0.792)	35.575 (0.747)	1.128	0.644	0.065	-0.484	-1.063	-0.579
Number of observations	1613	1820	410	455	3199	1854	1900	2119	2165	820
Number of clusters	16	16	16	16	16	16	16	16	16	16

Notes: The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at federal state level. Years of education, mode of interview, and interviewer IDs are included as control variables. Observations are weighted using variable *phrf* as *aweight* weights.***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table 16: Non-cognitive abilities/personality traits, self-reported

Variable	(1)	(2)	(3)	(4)	T-test					
	Individually Mean/SE	NW: friends Mean/SE	NW: family Mean/SE	NW: colleagues Mean/SE	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)
Thorough worker	6.136 (0.053)	6.167 (0.032)	6.100 (0.067)	6.176 (0.046)	-0.031	0.036	-0.040	0.067	-0.010	-0.076
Carry out tasks efficiently	5.872 (0.066)	5.807 (0.040)	5.830 (0.060)	5.764 (0.077)	0.065	0.042	0.108	-0.023	0.043	0.066
Am original	4.916 (0.036)	5.029 (0.076)	5.114 (0.095)	4.960 (0.111)	-0.112*	-0.197*	-0.043	-0.085	0.069	0.154
Value artistic experiences	4.290 (0.084)	4.218 (0.090)	4.077 (0.160)	4.180 (0.241)	0.072	0.212	0.110	0.141	0.038	-0.102
Am sociable	5.292 (0.040)	5.306 (0.051)	5.214 (0.086)	5.273 (0.086)	-0.014	0.077	0.019	0.092	0.033	-0.058
Am communicative	5.649 (0.029)	5.664 (0.036)	5.665 (0.114)	5.735 (0.061)	-0.015	-0.016	-0.086	-0.001	-0.071	-0.070
Able to forgive	5.261 (0.081)	5.381 (0.065)	5.607 (0.108)	5.418 (0.072)	-0.119	-0.346**	-0.156	-0.227**	-0.037	0.190
Friendly with others	5.951 (0.039)	5.936 (0.035)	5.973 (0.046)	5.876 (0.051)	0.015	-0.022	0.075	-0.037	0.059	0.097
Worry a lot	4.188 (0.070)	4.285 (0.067)	4.385 (0.094)	4.174 (0.186)	-0.097	-0.197	0.014	-0.100	0.111	0.211
Somewhat nervous	3.727 (0.075)	3.561 (0.084)	3.547 (0.126)	3.614 (0.087)	0.167	0.181	0.114	0.014	-0.053	-0.067
N	1142	1342	362	421						
Clusters	16	16	15	16						

Notes: The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at federal state level. Observations are weighted using variable phrf as aweight weights.***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

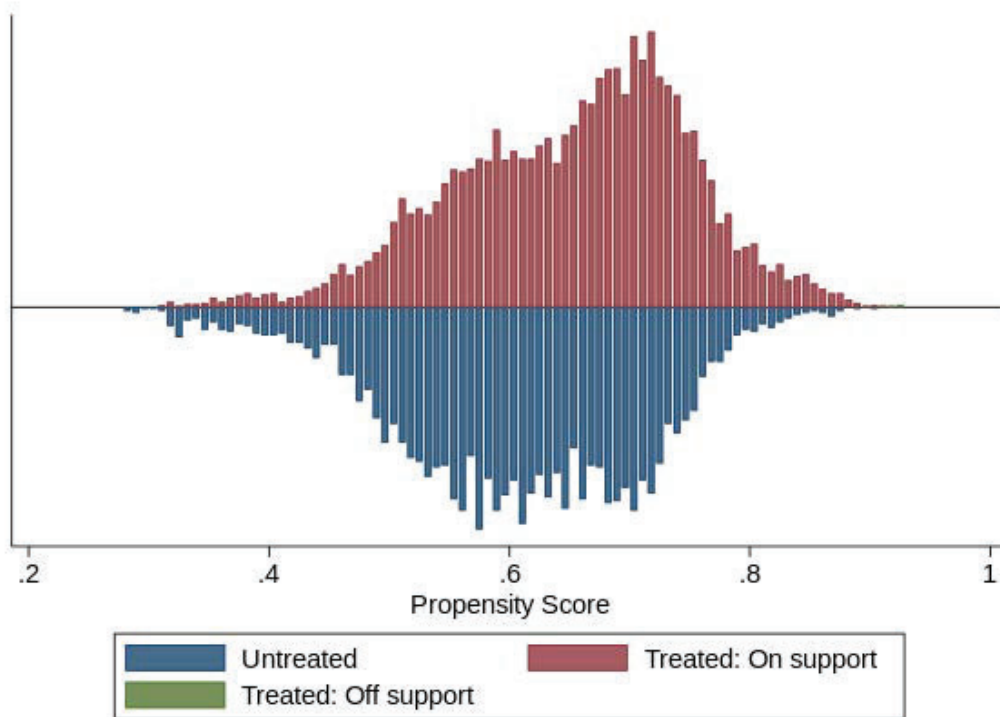
**Figure 8:** Propensity score distribution before matching

Table 17: Numeric tests (cognitive ability), disaggregated network types, initial values.

Variable	(1)	(2)	(3)	(4)	T-test					
	Individually Mean/SE	NW: friends Mean/SE	NW: family Mean/SE	NW: colleagues Mean/SE	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)
Correct asw. (30 sec)	10.865 (0.504)	10.465 (0.297)	10.524 (0.756)	11.582 (0.377)	0.399	0.341	-0.717	-0.058	-1.116**	-1.058
Correct asw. (60 sec)	23.061 (0.821)	22.197 (0.506)	21.791 (1.285)	24.201 (0.713)	0.864	1.270	-1.140	0.406	-2.004**	-2.410*
Correct asw. (90 sec)	34.681 (0.959)	33.331 (0.654)	32.885 (1.754)	36.045 (1.028)	1.349	1.796	-1.365	0.447	-2.714**	-3.161*
Wrong asw. (30 sec)	0.191 (0.049)	0.325 (0.051)	0.450 (0.137)	0.192 (0.095)	-0.134*	-0.259**	-0.001	-0.125	0.133	0.258***
Wrong asw. (60 sec)	0.342 (0.086)	0.547 (0.089)	1.291 (0.488)	0.308 (0.126)	-0.205*	-0.949**	0.034	-0.744	0.239*	0.983**
Wrong asw. (90 sec)	0.606 (0.135)	0.795 (0.134)	1.866 (0.805)	0.535 (0.171)	-0.189	-1.260*	0.071	-1.071	0.259	1.331*
Total asw. (30 sec)	11.056 (0.484)	10.790 (0.312)	10.973 (0.744)	11.773 (0.438)	0.266	0.082	-0.718	-0.183	-0.983*	-0.800
Total asw. (60 sec)	23.403 (0.800)	22.744 (0.519)	23.082 (1.157)	24.509 (0.794)	0.659	0.321	-1.106	-0.338	-1.765*	-1.427
Total asw. (90 sec)	35.286 (0.932)	34.126 (0.678)	34.750 (1.763)	36.581 (1.137)	1.160	0.536	-1.294	-0.624	-2.454*	-1.830
Number of observations	344	429	87	128	773	431	472	516	557	215
Number of clusters	16	16	13	13	16	16	16	16	16	15

Notes: Significance: ***=.01, **=.05, *=.1. Errors are clustered at the federal state level.

Table 18: Effects of the job change method from the year 2014

	All	Men	Women	West	East
PSM - no controls	-0.048 (0.030)	-0.078* (0.043)	-0.039 (0.034)	-0.046 (0.029)	-0.055 (0.069)
PSM - controls	-0.015 (0.030)	0.026 (0.053)	-0.022 (0.033)	-0.028 (0.033)	-0.055 (0.069)
IPW	-0.072*** (0.013)	-0.037* (0.019)	-0.099*** (0.018)	-0.065*** (0.015)	-0.113*** (0.029)
AIPW	-0.105*** (0.018)	-0.096*** (0.029)	-0.105*** (0.021)	-0.095*** (0.020)	-0.152*** (0.036)
IPWRA	-0.104*** (0.018)	-0.088*** (0.029)	-0.103*** (0.021)	-0.095*** (0.019)	-0.145*** (0.036)

Notes: *** p<0.01, ** p<0.05, * p<0.10; Standard errors are clustered at NUTS3 level. Control variables include demographic controls on a personal/hh level as well as regional level controls and federal state dummies. The outcome variable is logarithm of the gross monthly wages. The number of observations for each cell is available upon request.

Table 19: Numeric tests on cognitive ability, disaggregated network types and sex.

Variable	(1)	(2)	(3)	(4)	T-test					
	Individually Mean/SE	NW: friends Mean/SE	NW: family Mean/SE	NW: colleagues Mean/SE	(1)-(2)	(1)-(3)	(1)-(4)	(2)-(3)	(2)-(4)	(3)-(4)
Panel A: Men										
Correct asw. (30 sec)	11.117 (0.371)	11.040 (0.296)	11.638 (0.515)	11.393 (0.214)	0.077	-0.521	-0.276	-0.599	-0.353	0.245
Correct asw. (60 sec)	23.496 (0.680)	23.159 (0.478)	23.824 (0.785)	23.578 (0.480)	0.337	-0.328	-0.082	-0.665	-0.419	0.246
Correct asw. (90 sec)	35.524 (0.866)	34.821 (0.703)	35.538 (0.926)	35.481 (0.747)	0.703	-0.014	0.044	-0.717	-0.660	0.057
Wrong asw. (30 sec)	0.188 (0.040)	0.220 (0.029)	0.227 (0.045)	0.101 (0.029)	-0.032	-0.039	0.087**	-0.006	0.119**	0.125***
Wrong asw. (60 sec)	0.339 (0.065)	0.458 (0.064)	0.399 (0.075)	0.179 (0.034)	-0.119	-0.060	0.161**	0.059	0.279***	0.220**
Wrong asw. (90 sec)	0.533 (0.096)	0.681 (0.072)	0.798 (0.120)	0.417 (0.051)	-0.148	-0.265**	0.117	-0.116	0.265**	0.381**
Total asw. (30 sec)	11.305 (0.357)	11.260 (0.294)	11.865 (0.544)	11.494 (0.229)	0.045	-0.560	-0.190	-0.605	-0.235	0.371
Total asw. (60 sec)	23.835 (0.679)	23.617 (0.474)	24.223 (0.783)	23.757 (0.488)	0.219	-0.387	0.079	-0.606	-0.140	0.466
Total asw. (90 sec)	36.058 (0.890)	35.502 (0.712)	36.336 (0.992)	35.897 (0.755)	0.555	-0.278	0.160	-0.833	-0.395	0.439
Number of observations	634	840	191	241	1474	825	875	1031	1081	432
Number of clusters	16	16	16	16	16	16	16	16	16	16
Panel B: Women										
Correct asw. (30 sec)	11.172 (0.364)	10.457 (0.210)	10.386 (0.613)	11.470 (0.639)	0.715**	0.786	-0.299	0.071	-1.013	-1.084*
Correct asw. (60 sec)	23.500 (0.550)	22.069 (0.375)	22.143 (0.917)	24.084 (1.098)	1.432**	1.357	-0.583	-0.074	-2.015*	-1.941**
Correct asw. (90 sec)	35.116 (0.691)	33.286 (0.559)	33.247 (1.265)	35.929 (1.475)	1.831**	1.869	-0.813	0.039	-2.643*	-2.682**
Wrong asw. (30 sec)	0.229 (0.046)	0.286 (0.037)	0.291 (0.057)	0.244 (0.048)	-0.057	-0.062	-0.015	-0.005	0.042	0.047
Wrong asw. (60 sec)	0.377 (0.052)	0.519 (0.050)	0.601 (0.123)	0.357 (0.048)	-0.142	-0.224*	0.020	-0.083	0.162*	0.245
Wrong asw. (90 sec)	0.606 (0.072)	0.779 (0.063)	0.809 (0.134)	0.703 (0.052)	-0.173	-0.203	-0.097	-0.030	0.076	0.106
Total asw. (30 sec)	11.401 (0.334)	10.743 (0.229)	10.677 (0.575)	11.714 (0.609)	0.658**	0.724	-0.313	0.067	-0.971	-1.038*
Total asw. (60 sec)	23.877 (0.522)	22.588 (0.368)	22.744 (0.834)	24.440 (1.085)	1.290**	1.133	-0.563	-0.157	-1.853	-1.696**
Total asw. (90 sec)	35.723 (0.653)	34.064 (0.539)	34.056 (1.170)	36.632 (1.465)	1.658**	1.666	-0.909	0.008	-2.568*	-2.576**
Number of observations	1083	1105	251	243	2188	1334	1326	1356	1348	494
Number of clusters	16	16	15	15	16	16	16	16	16	16

Notes: Values are winsorised at 1 and 99 percentiles. Imputed for all years but 2016, assuming the results of the test being constant for the same respondent over 5 years. The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at federal state level. Observations are weighted using variable phrf as aweight weights.***, **, and * indicate significance at the 1, 5, and 10 percent critical level.