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Why do coworker networks affect job search outcomes?*

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Abstract

An extensive literature has found that former coworkers and other social connections affect the job outcomes of unemployed workers. Why does this happen? To quantify the relative importance of different possible mechanisms this paper combines: i) linked Danish administrative data on job applications made by UI recipients, ii) a theoretical job search framework that decomposes social connection effects and iii) a quasi-experimental research design that generates variation in coworker networks from the timing of past job transitions. In our setting, having a coworker connection at a firm increases the likelihood of being hired at that firm by 74 percent. About one tenth of this overall effect arises because social connections increase the likelihood that an application results in a hire by 7 percent. Virtually all of the remainder comes from application behavior because socially connected firms are more attractive to apply to. In contrast, while workers are also more likely to notice employment opportunities at firms of former coworkers, this effect is not quantitatively important in our setting.

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1 Introduction

A large literature has documented that social networks affect job search outcomes: workers looking for jobs are significantly more likely to end up hired at a firm where they have a social connection (Topa (2011)). Much less is known about why this occurs. One possibility is that social connections increase the likelihood that applications to the firm are successful, for example, because the connection at the firm passes information on the quality of the applying worker. Another possibility is that workers are more likely to seek out and apply to firms with a social connection, for example, because the connection can help them receive more favorable terms of employment, or as a response to facing a higher application success probability at these firms. Finally, having a social connection at a given firm may simply make the worker more likely to notice and consider this firm in their job search process.

In this paper, we decompose the effect of coworker connections on hiring outcomes and quantify the relative importance of the different underlying mechanisms. We do this in the context of unemployed job seekers in Denmark by combining three key ingredients: i) linked-administrative data on job applications made by the universe of Danish UI recipients, ii) a theoretical job search framework that explicitly allows social connections to affect job outcomes through different mechanisms and iii) a quasi-experimental research design that leverages variation in coworker networks stemming from the exact timing of past job transitions.

The main data we use is the so-called Joblog application data (Fluchtman et al. (2023b,a)). Since 2015, Danish UI recipients have been required to register applied-for jobs electronically to document their search activity and maintain UI eligibility. Linking these data to other administrative data on workers and firms allows us to jointly observe UI recipients, their applied-for jobs, detailed characteristics of the applied-for firms, as well as final hiring outcomes. Important for our analysis, the application data also contain information on how the UI recipient became aware of the employment opportunity they ended up applying for. We use this information to separate out the effect social connections on the likelihood of noticing and considering employment opportunities. The data for our analysis contains individuals entering UI between September 2015 and until the end of 2018 and covers the jobs they apply for during the first year of their unemployment spell.

We analyze our data through a simple theoretical job search framework, which allows for social network effects to operate via several different mechanisms. In our framework, unemployed workers periodically send a job application to a firm of their choice. When deciding where to apply, the worker takes into account the likelihood that the application is successful and results in a hire, as well as the value of becoming employed at the firm in question. Social connections are then allowed to affect job outcomes by increasing either of these. To further capture the possibility that social connections also help workers notice employment opportunities, we introduce endogenous random choice sets: at a given point in time when deciding where to apply next, a worker may not notice and consider all possible firms. The likelihood that a worker notices a given firm is allowed to depend on the firm's attractiveness but may also depend directly on whether the worker has a social connection at the firm. This allows social networks to impact hiring outcomes simply by making it more likely that the worker notices and considers the firm.

We deliberate set up the theoretical framework to have a close link with standard reduced form estimating equations and to leverage a quasi-experimental research design. Combined with an appropriate set of parametric assumptions, our framework implies that the causal effect of social connections on hiring can be estimated and decomposed via a set of standard reduced form conditional logit equations (McFadden (1974)). Intuitively, these reduced form equations compare a given worker's hiring and application outcomes across a set of socially connected and unconnected firms. The key identifying assumption is that - conditional on an appropriate set of firm and worker observables - the connected and unconnected firms in the analysis should differ only in terms of the social connections.

To help ensure the validity of the identifying assumption, we follow a string of recent papers and leverage a quasi-experimental research design that carefully selects socially connected and unconnected firms so as to make them comparable. As our measure of social connections, for each UI recipient, we identify past coworker from the last five years. Coworker ties have previously been argued to be particularly important in the job search process possibly because their relevance in the job search process may have justified their formation in the first place (see e.g. Granovetter (1983); Hensvik and Skans (2016)). For a given UI recipient, we define the set of socially connected firms as the set of firms where at least one of their past coworkers are currently working. Next, to select the comparison group of unconnected firms we identify a group of 'almost' coworkers for each UI recipient. These are workers that the UI recipient have never worked with but whom they would have been coworkers with if the timing of their past job transitions had been slightly different. As the set of unconnected firms, we use the current firms of these 'almost coworkers'. Overall, variation in whether a firm is connected or unconnected to a given UI recipient in our analysis, thus stems only from slight variation in the timing of when workers have joined or left firms in the past. Similar approaches to identifying network effects have been used recently by e.g. Hensvik and Skans (2016), Caldwell and Harmon (2020), Glitz and Vejlin (2020) and San (2022). To further bolster the identifying assumption, we further condition on a range of relevant firm characteristics in the analysis.

In our setting, having a coworker connection at a firm increases the likelihood of being hired at the firm by 74 percent. One tenth of this overall effect arises because social connections increase the likelihood that an application results in a hire by 7.4 percent. Most of the remaining effect comes from changes in application behavior because socially connected firms are more attractive to apply to. In contrast, direct information effects - in the sense of being more likely to notice a given employment opportunity - appears relatively unimportant in our setting. Having a coworker connection at a firm does significantly increases the likelihood of noticing jobs at the firm but only by 1.8 percent.

Our paper is connected to a large literature which, since at least Granovetter (1973) and Rees (1966), have documented the importance and pervasive use of social connections in the labor market. Social connections have been found to be influential in e.g. shaping location choices (Stuart and

Taylor (2021)) as well as labor market careers early on (Kramarz and Skans (2014)). More broadly social connections have been found to be important in shaping labor market matching (Dustmann et al. (2016)) and earnings inequality (Eliason et al. (2022); San (2022)).

In line with the different mechanisms we explore, different strands of the literature has argued that social connections can facilitate the job search process at different stages: First, social contacts may convey information about job openings (Calvó-Armengol and Jackson (2004); Topa (2001); Galenianos (2014), Cingano and Rosolia (2012)) or specific job characteristics such as potential amenities or simply the presence of a former coworker (Currarini et al. (2009)). Second, social contacts may convey information to employers about potential applicants which they would typically not have (Casella and Hanaki (2006), Glitz and Vejlin (2020)). This referral effect has been linked to better subsequent employment trajectories for referrals over time possible due to advantageous selection on worker unobservables (Montgomery (1991); Hensvik and Skans (2016)) and overall better job matches (Dustmann et al. (2016), Brown et al. (2016), Burks et al. (2015)).

Most recently, Barwick et al. (2023) has provided strong evidence that information flows are a central part of social network effects. Studying the information role of referrals using data on mobile phone communication from China, they provide compelling evidence of an increase in communication between referrals and referees (friends) around job changes in a sample which includes employer to employer and unemployment to employment transitions. Our paper complements this previous work by simultaneously studying a range of different mechanisms/margins and providing the first quantitative decomposition of their relative importance. Information provision may, for example, impact employment chances (by influencing hiring behavior) and/or impact the likelihood of applying (by influencing e.g. the percieved attractability of the job). Knowledge on the exact mechanisms behind social connection effects are important for understanding their implications and interactions with policy. If social connections primarily work by changing application success probabilities, for example, then their effects may tend to be zero-sum across workers; as social networks increase one workers likelihood of getting a particular job, other workers likelihood of getting this job are crowded out. Conversely, if social connections primarily work by helping workers notice more employment opportunities, then the effects of social networks can be crowded out by other policies that help workers notice more employment opportunities. Our paper therefore aims to shed light on the relative importance of these channels.

The rest of the paper is structured as follows: In Section 2 we present our theoretical job search framework and discuss the empirical implementation. In Section 3 we present our data sources and discuss our different empirical measures. In Section 4 we present the empirical results and our decomposition. Section 5 concludes.

2 Theoretical and empirical framework

In this section we introduce the theoretical job search model that frames our analysis and provides a precise decomposition of social network effects. Over the first section, we lay out the general model. We then formally introduce potential causal effects of social connections, as well as the parametric assumptions we use to arrive at reduced form estimating equations that separate out the effect of social networks on application success probabilities. Finally, we introduce the additional assumptions and reduced form equations that further separate out the effect of social connections on the likelihood of noticing a given job.

2.1 Basic setup

We consider an unemployed worker i who faces possibly employment opportunities at a number of firms indexed by j. We let $\mathcal{J}_i^{all}$ denote the set of all firms in the economy which are relevant for i. For simplicity, we will treat the job search process as if each firm only has one vacant job (at a point in time). From now on we thus use the terms job and firm interchangeably.

From the perspective of the worker, firms differ in their job search relevant characteristics. At time t, each firm j is characterized by the expected probability that the worker is hired if applying to the firm, $P_{i,j,t}$, the expected surplus that the worker gets from being hired at the firm, $S_{i,j,t}$ and the likelihood that the worker notices and considers job opportunities at the firm $R_{i,j,t}$. We expand on the nature and role of these firm characteristics in the sections below. For now, we simply note that differences in $P_{i,j,t}$, $S_{i,j,t}$ and $R_{i,j,t}$ reflect differences in the characteristics of the firm vis-a-vis the worker, including differences in whether or not the worker has a social connection at the firm. Additionally, for the purpose of setting up the empirical analysis, we let $d_{i,j}$ be an indicator for whether worker i has a social connection at firm j and let $X_{i,j}$ be a vector of worker-firm observables. In principle, $d_{i,j}$ and $X_{i,j}$ could be time-varying, however, to match our empirical analysis, we treat them as time invariant here. As a matter of notation, we let $\mathbf{P}_{i,t}$, $\mathbf{S}_{i,t}$, $\mathbf{R}_{i,t}$, $\mathbf{d}_i$ and $\mathbf{X}_i$ denote vectors/matrices stacking the characteristics of all the firms in $\mathcal{J}_i^{all}$.

While unemployed, worker i engages in job search. In particular, we assume that at some frequency (possibly stochastic, possibly endogenous), worker i has an opportunity to make a job application to one of the firms. We let t index the instances where this occur. In the data we use later, an observations it will refer to a UI recipient (i) and a particular application (t) they make at some point in time. From now on we will thus refer interchangeably to t as an application and a point in time. In the rest of our analysis, we will be completely agnostic about the process through which application opportunities arise, however, it is straightforward to expand the model framework by taking a stance on how this occurs.

2.2 Application decision

When worker i gets an opportunity to make an application, they make a choice about which firm to apply to. To allow for information frictions in the labor market we assume that a given point in time the worker may not notice and consider all possible firms. We let $\mathcal{J}_{i,t}^* \subseteq \mathcal{J}_i^{all}$ be the actual choice set of firms that the worker considers at the time of application t. In the next section, we describe how $\mathcal{J}_{i,t}^*$ is determined. In this section, we first describe the application decision that worker i makes upon seeing some choice set $\mathcal{J}$ at time t.

If worker i applies to firm j, they are hired with probability $P_{i,j,t}$ otherwise they stay unemployed. We let $U_{i,t}$ denote the continuation value of unemployment and $V_{i,j,t}$ be the value of being hired at firm j. Letting $A_{i,j,t}$ denote the value of applying to firm j at time t we have:

$$A_{i,j,t} = P_{i,j,t}V_{i,j,t} + (1 - P_{i,j,t})U_{i,t} = P_{i,j,t}(V_{i,j,t} - U_{i,t}) + U_{i,t}$$

In the latter expression, $V_{i,j,t} - U_{i,t}$ is the worker's surplus value (utility gain) from getting the job. We assume that this quantity can be decomposed into an ex ante expected surplus $S_{i,j,t}$ and an idiosyncratic multiplicative shock $\xi_{i,j,t}$:

$$V_{i,j,t} - U_{i,t} = S_{i,j,t} \left(\xi_{i,j,t}\right)^{\sigma}$$

The interpretation here is that $\xi_{i,j,t}$ reflects some combination behavioral taste shocks and unobservables of the firm or job that the worker only learns immediately when they consider applying. $\sigma > 0$ is a scale parameter governing the size of the idiosyncratic shocks. We let $\boldsymbol{\xi}_{i,t}$ denote the vector of all idiosyncratic shocks at time t. Since the shocks reflect shocks or unobservables revealed only at the time the worker considers their choice set, we will assume that these shocks are independent of the ex ante inferrable information as well as the revealed choice set :

$$\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{d}_i, \mathbf{X}_i, \mathcal{J}^*_{i,t} \perp \boldsymbol{\xi}_{i,t} \tag{1}$$

Combining all of the above the value of applying to job j will be:

$$A_{i,j,t} = P_{i,j,t}S_{i,j,t} \left(\xi_{i,j,t}\right)^{\sigma} + U_{i,t} \tag{2}$$

As usual, we assume that when faced with some choice set of firms $\mathcal{J}$, the worker chooses to apply to the one with the highest expected value of applying. Given the firm characteristics $\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}$ and shocks $\boldsymbol{\xi}_{i,t}$, we let $W_{i,t}\left(\mathcal{J}; \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \boldsymbol{\xi}_{i,t}\right)$ denote the value of making an application when faced with choice set $\mathcal{J}$. We then have:

$$W_{i,t}\left(\mathcal{J}; \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \boldsymbol{\xi}_{i,t}\right) = \max_{j \in \mathcal{J}} \left(A_{i,j,t}\right) \tag{3}$$

We let the random variable $j^*_{i,t}$ be the actual applied for job at time t. We can then characterize the probability of applying to a particular job j conditional on the actual choice set being $\mathcal{J}^*_{i,t} = \mathcal{J}$ and on the firm characteristics, $\mathbf{P}_i, \mathbf{S}_{i,t}, \mathbf{R}_i$:

$$P\left(j^*_{i,t} = j | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathcal{J}^*_{i,t} = \mathcal{J}\right) = P\left(j = \text{argmax}_{j' \in \mathcal{J}}\, A_{i,j,t} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}\right) \tag{4}$$

Finally, as we expand on in the next section, we will allow for the possibility that at time t, information frictions cause the worker to face an empty choice set $\mathcal{J}^*_{i,t} = \emptyset$, e.g. the worker fails to find or consider any relevant jobs. We simply assume that the worker in this case makes no application, that is $j^*_{i,t} = 0$. Note that since we in fact only use data on applications made, cases where no application is made does not affect our empirical analysis.[1]

2.3 Choice set and information frictions

To allow for the possibility that social connections help workers notice employment opportunities, we assume that at a point in time there is randomness in whether a worker notices and considers opportunities at the different firms. This implies that the observed choice set $\mathcal{J}^*_{i,t}$ is random and that there exists some probability measure, π_i, over the set of possible choice sets. As we expand on below, we assume that the probability of observing the different firms may depend on the key firm characteristics, $\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}$. The conditional probability of observing a particular set of firms $\mathcal{J} \subseteq \mathcal{J}^{all}_i$ at the time of application t is then:

$$P\left(\mathcal{J}^*_{i,t} = \mathcal{J} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{d}_i, \mathbf{X}_i\right) = \pi_i\left(\mathcal{J} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) \tag{5}$$

Note that the measure π_i also directly determines the likelihood of observing any single job j because this is simply the probability that the actual choice set $\mathcal{J}^*_{i,t}$ turns out to be one of the sets that include j:

$$P\left(j \in \mathcal{J}^*_{i,t} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{d}_i, \mathbf{X}_i\right) = \sum_{\mathcal{J} \subseteq \mathcal{J}^{all}_i : j \in \mathcal{J}} P\left(\mathcal{J}^*_{i,t} = \mathcal{J} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) = \sum_{\mathcal{J} \subseteq \mathcal{J}^{all}_i : j \in \mathcal{J}} \pi_i\left(\mathcal{J} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right)$$

Since our data contains no information on the actions workers take to search for jobs before making applications, we do not model this behavior explicitly. To ensure interpretability of our results, however, we discipline the behavior of π_i by reference to a particular benchmark search process. Specifically, we assume that at time t *if* workers make no strategic attempts to focus on some jobs instead of others (e.g. they discover application possibilities completely at random), then noticing a given job j is simply an independent event that occurs with probability, $0 < R_{i,j,t} < 1$. We refer to the probability $R_{i,j,t}$ as the visibility of firm j to worker i. Variation in $R_{i,j,t}$ reflects that - regardless of the attractiveness of applying $(A_{i,j,t})$ - workers may be more likely to notice and consider employment opportunities at some firms than at others. As we return to below, one reason for this may be that the worker has social connections at these firms. We let $\Gamma(\mathcal{J}|\mathbf{R}_{i,t})$, denote the likelihood of observing choice set $\mathcal{J}$ under the benchmark case where workers do not target their search effort. Simple derivations shows that this can be written as:[2]

$$\Gamma(\mathcal{J}|\mathbf{R}_{i,t}) = \left(\Pi_{j\in\mathcal{J}} R_{i,j,t}\right)\left(\Pi_{j\notin\mathcal{J}}(1 - R_{i,j,t})\right) \tag{6}$$

[1] An alternative assumptions that would leave our analysis unchanged is that if the first choice set is empty, the worker immediately draws another choice set.

[2] Observing choice set $\mathcal{J}$ means observing all the firms in this choice $j \in \mathcal{J}$ set but none of the other firms. Independence implies that this can be written

$$\left(\Pi_{j\in\mathcal{J}} P\left(j \in \mathcal{J}|\mathbf{R}_i\right)\right)\left(\Pi_{j\notin\mathcal{J}}\left(1 - P\left(j \in \mathcal{J}|\mathbf{R}_i\right)\right)\right) = \left(\Pi_{j\in\mathcal{J}} R_{i,j}\right)\left(\Pi_{j\notin\mathcal{J}}(1 - R_{i,j})\right)$$

Further we impose the restriction that this benchmark case should occur whenever workers are indifferent across jobs because in this case a rational worker would never exert effort to target some jobs over others. Formally, we impose this by assuming that the benchmark case should always occur when firms offer the same value of applying (almost surely):[3]

$$A_{i,j,t} = k \,\forall\, j \quad \text{almost surely} \quad \Longrightarrow \quad \pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right) = \Gamma(\mathcal{J}|\mathbf{R}_{i,t}) \tag{7}$$

In general, we do not expect all firms to be equally attractive and thus we will allow for the possibility that workers may be more likely to notice jobs that are attractive because they partially direct their search efforts towards such job types. In this case, it will no longer hold that $R_{i,j,t}$ equals the probability of observing job j. To ensure that $R_{i,j,t}$ still has a meaningful interpretation in this case however, we additionally impose that for any given value of the other firm characteristics, the likelihood of observing job j should still grow proportionally with $R_{i,j,t}$. This implies a restriction on the elasticity of $P\left(j \in \mathcal{J}^*_{i,t}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right)$ with respect to $R_{i,j,t}$:

$$\frac{\partial\left(\log P\left(j \in \mathcal{J}^*_{i,t}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right)\right)}{\partial\left(\log R_{i,j,t}\right)} = 1 \tag{8}$$

The restriction implies that relative changes in $R_{i,j,t}$ can always be interpreted as relative changes in the probability of seeing job j.

Finally, to reflect that workers may partially direct their search efforts towards attractive jobs, we assume that the probability of observing a given choice set is increasing in the hiring probability and surplus value of the jobs in this choice set, that is:

$$j \in \mathcal{J} \quad \Longrightarrow \quad \frac{\partial}{\partial P_{i,j,t}}\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right) \geq 0 \quad \wedge \quad \frac{\partial}{\partial S_{i,j,t}}\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right) \geq 0 \tag{9}$$

2.4 Hiring outcomes and their determinants

Assumptions 1-9 above constitute the general model framework and allow us to characterize the likelihood that a worker is hired into a particular firm at a given point in time. Let $h^*_{i,t}$ be the firm that worker i is hired into as a result of application t (and let $h^*_{i,t} = 0$ denote the case where the worker remained unemployed). The probability that the worker is hired into firm j can then be written as:

$$P\left(h^*_{i,t} = j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right) = \underbrace{\sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i : j\in\mathcal{J}} \pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right)}_{\text{(I)}} \cdot \underbrace{P\left(j = \text{argmax}_{j'\in\mathcal{J}}\, P_{i,j',t}S_{i,j',t}\left(\xi_{i,j',t}\right)^{\sigma}|\mathbf{P}_{i,t},\mathbf{S}_{i,t}\right)}_{\text{(II)}} \cdot \underbrace{P_{i,j,t}}_{\text{(III)}}$$

[3] The restriction to indifference holding almost surely reflects that in general $A_{i,j,t}$ is a random variable. Under the assumption in the previous section, indifference across jobs occurs only if $P_{i,j,t}S_{i,j,t} = k$ for all j and the distribution of $\boldsymbol{\xi}_{i,t}$ is degenerate.

As the equation shows, three things must occur in order for worker i to be hired at firm j at time t: (I) the worker actually notices and considers applying the firm, i.e. ends up with a choice set that contains the firm, (II) the worker chooses to apply to firm j because it is the most attractive option in the choice set, and (III) the worker's application is successful. The likelihood that each of these things occur in turn depend on the firm visibilities, $\mathbf{R}_{i,t}$, the surplus values of a job, $\mathbf{S}_{i,t}$, and the success probabilities that the worker faces, $\mathbf{P}_{i,t}$ as follows. In particular, we can unpack the effect of firm j's characteristics, $R_{i,j,t}, S_{i,j,t}, P_{i,j,t}$ on the likelihood of being hired at firm j as follows:

- A higher visibility, $R_{i,j,t}$, will increase the likelihood that the worker notices and considers the firm (part (I)).
- A higher surplus value of being hired at the firm, $S_{i,j,t}$, may increase the likelihood that the worker notices and considers the firm (part (I)) because of directed search. Additionally, it will also increase the likelihood that applying to the firm is the most attractive option (part (II)).
- A higher success probability from applying, $P_{i,j,t}$, may increase the likelihood that the worker notices and considers the firm (part (I)) because of directed search. Additionally, it will also increase he likelihood that applying to the firm is the most attractive option (part (II)). Finally, a higher success probability when applying will also have a direct effect on hiring (part (III)).

2.5 Potential outcomes and causal effects of social connections

In our analysis, we will allow for social connections to potentially affect hiring outcomes by changing both $R_{i,j,t}, S_{i,j,t}$ and $P_{i,j,t}$. To set this up formally, we use a potential outcomes approach and define counterfactuals. Let $d_{i,j}$ be a dummy for whether worker i has a social connection at firm j. For worker i at time t, we let $S^0_{i,j,t}$ denote the expected surplus at firm j when the worker does not have a social connection at the firm. Conversely, we let $S^1_{i,j,t}$ denote the expected surplus if the worker does have a social connection at the firm. As usual, the worker will in practice only face one of these, depending the actual value of $d_{i,j}$:

$$S_{i,j,t} = \begin{cases} S^0_{i,j,t} & \text{, if } d_{i,j} = 0 \\ S^1_{i,j,t} & \text{, if } d_{i,j} = 1 \end{cases} \tag{10}$$

Completely analogously, we define $P^0_{i,j,t}$,$P^1_{i,j,t}$,$R^0_{i,j,t}$ and $R^1_{i,j,t}$ as the success probability and visibility that worker i would face at firm j respectively with and without a social connection at the firm and assume:

$$P_{i,j,t} = \begin{cases} P^0_{i,j,t} & \text{, if } d_{i,j} = 0 \\ P^1_{i,j,t} & \text{, if } d_{i,j} = 1 \end{cases} \tag{11}$$

$$R_{i,j,t} = \begin{cases} R^0_{i,j,t} & \text{, if } d_{i,j} = 0 \\ R^1_{i,j,t} & \text{, if } d_{i,j} = 1 \end{cases} \tag{12}$$

A causal effect of social connections will be defined as the difference between two potential outcomes. We focus on the causal effect of social connections on logged quantities (e.g. relative effects). We denote them by β^S, β^P and β^R:

$$\begin{aligned} \beta^S &= \log S^1_{i,j,t} - \log S^0_{i,j,t} \\ \beta^P &= \log P^1_{i,j,t} - \log P^0_{i,j,t} \\ \beta^R &= \log R^1_{i,j,t} - \log R^0_{i,j,t} \end{aligned} \tag{13}$$

It is instructive to discuss what these three causal parameters capture and how they relate to mechanisms emphasized in previous work. β^S is the causal effect of having a social connection on the worker's expected (log) surplus of being hired at the firm. This causal effect may arise for a few different reasons. First, if social connections provides the firm with information about the unemployed worker such that the worker is more attractive (referrals), this may lead the firm to offer better employment terms to the worker or offer a better career trajectory as in e.g. Rees (1966); Montgomery (1991); Galenianos (2013); Burks et al. (2015); Hensvik and Skans (2016). Alternatively, the social connection may also pass the worker information about the firm which leads them to upwards (or downwards) revise their expectations about the firm's attractiveness as suggested by e.g. Calvó-Armengol and Jackson (2004); Galenianos (2014), Topa (2001) and Barwick et al. (2023). Finally, having a social connection at the firm could also directly increase the value of working at the firm, if the worker gets utility from worker with their connections as in Currarini et al. (2009).

β^P is the causal effect on the application success probability. As above, if social connections provide information to firms that makes the worker more valuable (in expectation), this may also make it more likely that the firm hires the worker when they apply. Alternatively, the social connection could also pass information to the unemployed worker that allows them to tailor their application better and increase the success probability. Finally, the causal effect on the success probability could stem from nepotism if the social connection explicitly meddles with the hiring decision for reasons unrelated to the productive characteristics of the unemployed worker.

β^R is the direct effect on the likelihood that the worker notices and considers the firm in their application decision. This allows for the possibility that social connections may - irrespective of the attractiveness of applying - make it more likely that a worker even considers their employment opportunities at a particular firm.

Note that since the characteristics, $R_{i,j,t}, S_{i,j,t}, P_{i,j,t}$, are the key determinants of workers application decisions and hiring outcomes, the causal effects defined above imply (reduced form) causal effects on other outcomes. We return to this below, however, it is useful already now to note that an additional causal effect of interest is the causal effect of social connections on the log surplus value of applying to firm j, $\log(A_{i,j,t} - U_i)$. From 2 it is clear that this effect will simply equal the combined effect on the log surplus and hiring probability. From now on we explicitly denote this causal effect by β^A:

$$\beta^A = \beta^P + \beta^S \tag{14}$$

2.6 Parametric assumptions

When taking the model to the data, we add additional parametric assumptions that allow us to arrive at simple estimating equations leveraging a quasi-experimental research design.

First, we impose a standard discrete choice assumption that the idiosyncratic shocks to the surplus values of jobs follow an extreme value distribution. This gives the application decision in a given choice set a standard logit structure:

$$\xi_{i,t} \sim \text{i.i.d. type II EV} \tag{15}$$

Next we impose a parametric function on the probability measure over choice sets, π_i. A convenient approach here is to assume that the probability of a given choice set depends on the expected log surplus from making an application in this choice set. We denote this by $\widetilde{w_{i,t}}$:

$$\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) = E\left(\log\left(W_i\left(\mathcal{J}; \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \boldsymbol{\xi}_{i,t}\right) - U_{i,t}\right)\right) \tag{16}$$

With this we assume the following specific functional form for π_i (for any nonempty choice set $\mathcal{J}$):

$$\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) = \left(\exp\left(\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) - \widetilde{w_{i,t}}(\mathcal{J}_i^{all}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t})\right)\right)^{\sigma^{-1}} \Gamma(\mathcal{J}|\mathbf{R}_{i,t}) \tag{17}$$

As shown in Appendix A.1, this functional forms satisfies the imposed restrictions on π_i, equations 7, 8 and 9. The functional form also has an intuitive interpretation: due to the directed nature of search, the likelihood of seeing a particular choice set $\mathcal{J}$ depend positively on the difference in the expected value of making an application in this choice set $\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t})$ relative to the expected value of making an application when seeing all firms $\widetilde{w_{i,t}}(\mathcal{J}_i^{all}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t})$.

2.7 Main identifying assumptions

As will become clear below, our analysis is based on comparing the likelihood of being hired at a particular set of socially connected firms to the likelihood of being hired at a particular set of unconnected firms. An obvious concern with this approach to identification, however, is that in general, socially connected and unconnected firms are likely to differ in a range of different dimensions that affect hiring thus confounding the effects of social connections.

In our analysis, we address this concern in two steps. First, as we expand on in Section 3.3, we restrict our analysis to only consider firms where the worker has a social connection or firms to which the worker is 'almost connected' in the sense that they *would have had* a social connection at the firm if the timing of their past job transitions had been slightly different. We refer to the subset of connected and 'almost connected' firms as the set of *potentially connected* firms. By construction, the set of potentially connected firms will differ across worker. For worker i, we denote it by $\mathcal{J}_i^{pot} \subseteq \mathcal{J}_i^{all}$.

Second, to further ensure comparability of connected and 'almost connected' firms, we condition our analysis on a vector of observable firm and worker characteristics, $X_{i,j}$. Combining this, our key identifying assumption is that for a given worker i, the connected and 'almost connected' firms with the same value of the observables, $X_{i,j}$, would have had the same surplus value, success probability and visibility in the absence of social connections, $S^0_{i,j,t}$,$P^0_{i,j,t}$,$R^0_{i,j,t}$. Combined with a standard (log) linearity assumption, we can write this key identifying assumption as imposing that the following holds in our sample of potentially connected firms:

$$\begin{aligned}
\log P^0_{i,j,t} &= \alpha^P_{i,t} + \theta^P X_{i,j} \quad \forall\, j \in \mathcal{J}_i^{pot} \\
\log S^0_{i,j,t} &= \alpha^S_{i,t} + \theta^S X_{i,j} \quad \forall\, j \in \mathcal{J}_i^{pot} \\
\log R^0_{i,j,t} &= \alpha^R_{i,t} + \theta^R X_{i,j} \quad \forall\, j \in \mathcal{J}_i^{pot}
\end{aligned} \tag{18}$$

As evidenced by the inclusion of worker-by-time fixed effects in these specifications, our analysis is based on within-worker comparisons at a point in time is reflected in that the identifying assumptions (18) allows for separate worker-by-time specific intercepts (fixed effects). The identifying assumption thus allows for a given worker to face generally higher surpluses, success probabilities or firm visibilities at a point in time.

2.8 Reduced form equations and parameters I

In the first part of our empirical analysis, we use the framework and assumptions above to estimate the effect of social connections on hiring, and to decompose out how much of this stems directly from changes in the success probability of applications. We now present the reduced form equations we use to do this.

In Appendix A.3 we show that Assumptions 1, 2, 3, 4, 5, 6, 15, 16, 17 and 18 imply that the data on hires into potentially connected firms satisfy a McFadden (1974) conditional logit model. In particular, if we let $Hired_{i,j,t}$ be an indicator for whether worker i is hired into firm j as a result of application t, we have the following reduced form equation for the log probability of being hired:

$$\log P\left(Hired_{i,j,t} = 1 | d_{i,j}, X_{i,j}, \eta_i\right) = \eta_i^{hired} + \tau^{hired} d_{i,j} + \gamma^{hired} X_{i,j} \tag{19}$$

The parameter of interest here is τ^{hired}. Under our assumptions, this captures a reduced form causal effect of social connections. In particular, under a standard logit approximation, τ^{hired} is the log point effect of having a social connection at some firm, on the likelihood of being hired at this firm at time t.[4] Moreover, since the parameters in equation 19 can be estimated as a standard conditional logit model, estimation of τ^{hired} is straightforward using off-the-shelf methods.

Given our model framework, we can also decompose the causal effect on hiring, τ^{hired}, into the primitive causal effects of social connections introduced above:

$$\tau^{hired} = \beta^R + \sigma^{-1}\beta^A + \beta^P \tag{20}$$

The causal effect on social connections on hiring reflects three things: First, irrespective of the jobs other characteristics, workers may be more likely to notice and consider socially connected firms when making application decisions (β^R). This ultimately makes them more likely to apply to these firms. Second, applying to socially connected firms may be more valuable for workers, either because social connections raise the value of working there or because it increases the likelihood that the application succeeds (β^A). Note that the scale parameter σ^{-1} appears here because it measures the elasticity of the application probability with respect to changes in the value of applying. Finally, having a social connection at a firm may raise the probability that the application results in a hire (β^P).

To start decomposing the effect empirically, we use the fact that if we let $Apply_{i,j,t}$ be an indicator for whether worker i sends their tth application to firm j, the log probability of applying satisfies the following (see Appendix A.2):

$$\log P\left(Apply_{i,j,t} = 1 | d_{i,j}, X_{i,j}, \eta_i\right) = \eta_i^{apply} + \tau^{apply} d_{i,j} + \gamma^{apply} X_{i,j} \tag{21}$$

Here τ_g^{apply} measures the causal effect of being socially connected on the likelihood of applying. Again, this parameter is straightforward to estimate via a conditional logit model. The reduced form effect on applying also decomposes into the first two primitive treatment effects as above, e.g. an effect from the firm being more attractive to apply to, and an effect from directly being more likely to notice and consider the firm irrespective of characteristics:

$$\tau^{apply} = \beta^R + \sigma^{-1}\beta^A \tag{22}$$

Comparing equation 22 and equation 31, we see that the difference in the two reduced form parameters, τ^{hired} and τ^{apply} equals the causal effect on β^P. Estimating the two reduced form equations thus allows us to decompose the causal effect of social connections into the direct effect on the hiring probability, and an effect coming from changes in application behavior.

[4]This interpretation of τ^{hired} is only exact when referring to the likelihood of being hired conditional on value of the fixed effect η_i^{hired}. For the unconditional probability, however, the interpretation holds as a very precise approximation as long as the (ex ante) likelihood of being hired into any one particular firm is low, as is the case in our data.

2.9 Additional structure on information frictions

The first part of our empirical analysis is able to decompose the overall effect of social connections into a part stemming from changes in application behavior and the direct effect of higher success probabilities when applying. In the last part of the empirical analysis, we add some additional structure for the purpose of separating out also the direct effect of social connections on the likelihood of noticing and considering firms. We present this structure below.

Rather than assuming that workers can either notice a firm or not at time t, we explicitly assume that noticing firms can happen in two distinct ways: Workers can either notice the firm through public channels (i.e. a formally posted vacancy) or through informal channels (including social connections). We let $o_{i,j,t} \in \{0, pub, inf\}$ be a variable denoting whether and how firm j was noticed at time t. $o_{i,j,t}$ takes on the value pub if the worker found the firm through public channels, the value inf if the worker found the firm through informal channels, and the value 0 if the firm was not noticed at all (so that $j \notin \mathcal{J}^*_{i,t}$). We let $\mathbf{o}_{i,t}$ denote the vector of variables denoting whether and how each of the jobs in $\mathcal{J}^{all}_i$ was noticed.

Expanding on this we also assume that instead of a single visibility $R_{i,j,t}$, firms are characterized by both a public visibility $0 < R^{pub}_{i,j,t} < 1$ and an informal visibility $0 < R^{inf}_{i,j,t} < 1$. We let $\mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}$ be the vector of public and informal visibilities. Exactly extending the interpretation of $R_{i,j,t}$, we assume that $R^{pub}_{i,j,t}$ is the probability of noticing firm j via public channels in the benchmark case where workers do not direct their search. Similarly $R^{inf}_{i,j,t}$ is the probability of noticing the firm via informal channels in this benchmark case. Formally this means:

$$\begin{aligned} A_{i,j,t} = k \,\forall\, j \quad \text{almost surely} \quad &\implies \quad P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}) = R^{pub}_{i,j,t} \\ A_{i,j,t} = k \,\forall\, j \quad \text{almost surely} \quad &\implies \quad P(o_{i,j,t} = inf | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}) = R^{inf}_{i,j,t} \end{aligned} \tag{23}$$

To relate to causal effects of social connections, we also introduce potential outcomes for the public and informal visibilities. We let $R^{pub,0}_{i,j,t}$, $R^{inf,0}_{i,j,t}$ be the public and private visibilities of firm j to worker i in the absence of a social connection, and let $R^{pub,1}_{i,j,t}$, $R^{inf,1}_{i,j,t}$ be the corresponding visibilities if the worker has a social connection at the firm. As usual we impose:

$$R^{pub}_{i,j,t} = \begin{cases} R^{pub,0}_{i,j,t} & \text{, if } d_{i,j} = 0 \\ R^{pub,1}_{i,j,t} & \text{, if } d_{i,j} = 1 \end{cases} \tag{24}$$

$$R^{inf}_{i,j,t} = \begin{cases} R^{inf,0}_{i,j,t} & \text{, if } d_{i,j} = 0 \\ R^{inf,1}_{i,j,t} & \text{, if } d_{i,j} = 1 \end{cases} \tag{25}$$

Now we impose additional assumptions: First, we trivially extend all the previous assumptions that involving the visibilites $\mathbf{R}_{i,t}$ so that they hold also for the channel-specific visibilities $\mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}$. Appendix A.4 writes out these modified assumptions 36, 37, 38, 39 and 40.

Then we make three more substantive additional assumptions: First, conditional on whether and how firm j was observed, we assume that the probability of observing any particular choice set depends only on whether firm j was observed and not on the specific channel through which this occurs:

$$P(\mathcal{J}^*_{i,t} = \mathcal{J} | o_{ijt} = pub, \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}) = P(\mathcal{J}^*_{i,t} = \mathcal{J} | o_{ijt} \neq 0, \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}) \tag{26}$$

$$P(\mathcal{J}^*_{i,t} = \mathcal{J} | o_{ijt} = inf, \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}) = P(\mathcal{J}^*_{i,t} = \mathcal{J} | o_{ijt} \neq 0, \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}) \tag{27}$$

This assumption rules out that having observed a particular job through public as opposed to informal channels makes it more likely that you observe certain other jobs. The assumption thus for example rules out the case, where randomly talking to a particular coworker is likely to yield information about employment opportunities at many different firms.

Second, we assume that the relative likelihood of observing a particular job through public vs. informal channels depends only on the visibility characteristics of this firm:

$$\frac{P(o_{i,j,t} = inf | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t})}{P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t})} = m(R^{pub}_{i,j,t}, R^{inf}_{i,j,t}) \tag{28}$$

This assumption rules out interaction effects between other firm characteristics and the likelihood of noticing the firm through a specific channel. For example, it rules out that you become relatively more likely to hear about a firm through informal channels if it offers a high surplus value or a high likelihood of being hired.

Finally, we impose that having a social connections does not have a causal effect on public visibility of firms, e.g. for a job with a given attractiveness, social connections does not affect the likelihood that you notice this job via a vacancy posting:

$$R^{pub,1}_{i,j,t}\text{-}R^{pub,0}_{i,j,t} = 0 \tag{29}$$

Note that this last assumption does not rule out that workers are more likely to notice posted vacancies at socially connected firms; our model allows for the fact that workers are more likely to notice firms that are more attractive to apply to and also allows for social connections to make it more attractive to apply.

2.10 Reduced form equations and parameters II

The added structure imposed in the previous section allows us to separate out the direct effect of social connections on the likelihood of seeing a job. In Appendix A.5, we show that adding assumptions 23, 24, 25, 26, 28 and 29 to the ones used previously, imply that the likelihood of applying to a specific firm and having noticed it via a public vacancy also obeys a conditional logit model. Letting $ApplyPosted_{i,j,t}$ be an an indicator for whether worker i sends their tth application to firm j after having noticed the job via a posted vacancy, we have the following:

$$\log P\left(ApplyPosted_{ijt}=1|d_{i,j},X_{i,j},\eta_i\right)=\eta_i^{posted}+\tau^{posted}d_{i,j}+\gamma^{posted}X_{i,j} \tag{30}$$

As above, τ^{posted} measures a log-point causal effect and is easily estimated via a conditional logit model. Importantly, under the additional structure imposed in the previous section, this parameter only reflects the effect of social connections on the value of applying to the firm:

$$\tau^{posted}=\sigma^{-1}\beta_g^A \tag{31}$$

Accordingly, estimating τ^{posted} allows us to decompose out the social connections on the value of applying to the firm. This allow us to fully decompose the effect on social connections on hiring outcomes.

2.11 Comparison to dyadic linear probability models and origin-by-destination fixed effects

We close the presentation of our empirical strategy by comparing our reduced from specifications with an alternative specification that has been used extensively in recent work on social connections and hiring. Going back to Kramarz and Thesmar (2013), a string of papers (e.g. Kramarz and Skans (2014) and Eliason et al. (2022)) have estimated the effect of social connections on hiring in a dyadic linear probability model that includes a form of 'origin-by-destination' fixed effects. In our setting and notation this would translate to having each worker belong to some group g and then using the following specification, which is estimated using OLS:

$$P\left(Hired_{i,j,t}=1|d_{i,j},X_{i,j},\rho_{g(i),j,t}\right)=\rho_{g(i),j,t}+\tau d_{i,j}+\gamma X_{i,j} \tag{32}$$

In this specification, $g(i)$ denotes the group to which worker i belongs and thus $\rho_{g(i),j}$ is a fixed effect which varies at the level of the potential hiring firm j, and the group to which the worker belongs. A common choice for the definition of worker groups is the previous employer, so that $\rho_{g(i),j}$ are fixed effects at the level of the previous (e.g. origin) and potential (e.g. destination) employer. The parameter of interest is τ and has the interpretation of the causal effect of having a social connection at a firm on the likelihood of being hired at this firm (in percentage points).

The specification in equation 32 differs from ours in two ways. First, equation 32 is a linear equation for the probability of being hired and can thus be estimated by OLS. Our reduced form equation is instead linear for the log probability. This differences stems mainly from the specific parametric assumptions we impose and which allows us to easily decompose the reduced form parameter τ^{hired} into the different primitive causal effects.

The second difference relates to the level of the fixed effect included in the specification and is more substantive. Our reduced form specification includes a fixed effect at the worker level. In comparison, the specification in equation 32, is both less flexible in the sense that it includes a fixed effect that only varies at the worker-group level (g), but also more flexible in the sense that this group-level fixed effects is allowed to differ arbitrarily across *all* the potential hiring firms (j). The fact that we opt for a worker-level fixed effect is dictated by our theoretical framework; under our framework, specifications that do not include a worker-level fixed effect will in general yield biased estimates.[5] Moreover, letting the worker fixed effect vary also across hiring firms (e.g. an i-by-j-by-t fixed effect) is not possible because it would absorb the effect of social connections.

In the analysis, we probe robustness of our results to specifications with a range of hiring firm characteristics in the vector of observables $X_{i,j}$, including specifications that interact these with worker characteristics or allow their coefficients to vary arbitrarily across worker groups.

3 Data and institutional setting

In this section, we first briefly describe the institutional setting of the Danish labor market and then turn to the data we use. At a glance our data construction starts by selecting a relevant sample of UI recipients, then constructs measures of firms to which these workers are (potentially) connected. Next, we link in data on applications made by the UI recipients from the so-called Joblog data and finally, we connect these UI recipients and applications to hiring outcomes. We describe each of these steps in detail below. Finally, we discuss the control variables we use for identification, some details regarding the implementation of estimation and present summary statistics.

3.1 Institutional setting

The Danish labor market is generally referred to as an example of the Flexicurity model (see Kreiner and Svarer (2022)). This implies relatively low degrees of employment protection and an extensive social safety net for unemployed individuals. Partly as a result of the low employment protection the labor market is very dynamic (in terms of transition rates comparable to the US, see Jolivet et al. (2006)) with a high degree of job turnover and relatively short unemployment spells on average (we return to this further below).

The Danish UI system is based on voluntary membership. Being eligible for UI when entering unemployment requires that you are a member of a UI fund and that you have been so for the last

[5]The intuition for this is that specifications without a worker fixed effect fail to control for the attractiveness and characteristics of the other firms a worker could potentially apply to and get hired into. Under our model framework, the fixed effect in our reduced form equation equals:

$$\eta_i^{hired} = \log\left(\frac{\exp\left(\alpha_i^R + \frac{1}{\sigma}\left(\alpha_i^P + \alpha_i^S\right) + \alpha_i^P\right)}{\sum_{j' \in \mathcal{J}_i^{all}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t} + \log S_{i,j',t}\right)\right)}\right)$$

If this expression varies across workers i within a given worker group g (e.g. it varies across workers from the same previous employer for example) then any correlation with $d_{i,j}$ will bias the estimated coefficient on $d_{i,j}$. Since the expression for η_i^{hired} involves the surplus value and success probability, the expressio however *has* to vary within worker groups: If workers within a group g are connected to different firms then their surplus values and success probabilities at these firms will differ (when social connection effects exist). At the same time, identification requires that workers within a group have to be connected to different firms, otherwise there is no variation in connections left to identify the causal effect of interest.

12 months. If you are not eligible for UI, or you lose eligibility because you go beyond the maximum benefit duration, you may be eligible for the lower tiered benefit scheme called social assistance. However since our analysis below focus exclusively on UI recipients we focus on this part of the system here.

As a member of a UI fund you pay quarterly membership fees and there are 23 different UI funds in Denmark. Some UI funds serve rather specific occupational groups and others are more broadly available. The system is partly financed by the government so membership fees are kept low. In general the vast majority of the workforce are members of a UI fund and eligible for UI.[6]

UI benefits have a duration of 2 years, the benefit level is determined at a replacement rate of 90 percent of previous income and a cap of 18.500 DKK per month in 2017 (2500 Euro). Since the cap is binding for the vast majority of workers the effective replacement rate is typically lower, for example in standard OECD stats it is 67 percent (see e.g. Kreiner and Svarer (2022)).

While unemployed and receiving UI, UI recipients have to satisfy different eligibility conditions. Most importantly they have to be actively searching and applying for jobs and they need to document this through an online platform called *Joblog*.[7] On the platform, UI recipients fill in forms describing the particular job they have applied for. It is mandatory to provide information on the applied-for job, including job title and information about the potential employer, including firm name and address (as explained in Fluchtman et al. (2023a) this enables identification of the firms in the administrative registers). In addition, the job seekers must also provide information on how they found and applied for the job. As we describe further below, it is the information entered on these forms that we use to measure job search behavior.

As a general rule of thumb, UI recipients are instructed that they need to register somewhere between 1.5 and 2 applications per week in the Joblog system to maintain eligibility. Failure to comply with these documentation requirements would ultimately result in sanctions in the form of lost or reduced UI payments.[8] Overall, UI recipients thus face a clear economic incentive to comply with the requirements and register submitted job applications in Joblog (see also Fluchtman et al. (2023a)).

3.2 Sample of UI Recipients

We start by constructing of a sample of UI recipients who constitute the population of interest below, i.e. the individuals for whom we define our key outcomes (employment location and application

[6] In 2015, 76 percent of Danish employees were members of a UI fund while over 70 percent of the gross unemployed were UI recipients. Among the residual group of gross unemployed, more than 20 percent receive means-tested social assistance (which amounts to around 60-80 % of the maximum UI benefits) and are therefore likely to have exhausted UI prior to this (see e.g. Danish Economic Council, 2014).

[7] Other requirements includes attending meetings with caseworkers on a regular basis as well as potential participation in training programs etc. (see e.g. Maibom et al. (2017) for more details).

[8] In the case of non-compliance (including e.g. an assessed risk of proforma search or fake applications) with the job search requirements, UI recipients will typically be given a short time period to prove eligibility and register previously unregistered (or ongoing) job search. Subsequently the UI fund makes the final assessment. In case of non-compliance, the size of the sanctions ranges from a loss of benefits for a couple of days to a permanent loss of benefits depending on the severity.

behavior). Throughout the paper we refer to these individuals as UI recipients. From the database on public income transfers (DREAM)[9] we select all individuals entering a new UI spell in the period from September 2015 to the end of 2018. Entering a new UI spell is defined as receiving 8 consecutive weeks of full time UI benefits and with no prior payment in the 8 weeks prior to entry. The 8 weeks sampling restriction ensures that we focus on a sample of truly unemployed individuals and reduce concerns about e.g. recalls and temporary unemployment between already accepted jobs. We consider the UI spell as terminated when we observe 4 consecutive weeks where the UI recipient is no longer receiving UI.

Finally, for each UI recipients, we then add detailed information on demographics, education and past labor market outcomes from standard administrative sources. These characteristics are measured at the time of entry into unemployment.

3.3 Social connections and potentially connected firms

As discussed in Section 2, our analysis will be based on analyzing UI recipients' tendency to apply and get hired into a set of 'potentially connected' firms. The set of potentially connected firms consist of actually connected firms where a former coworker is working (at the time the UI recipients unemployment spell starts) plus a set of firms that has an 'almost' former coworker employed (we return to this below).

To construct the set of actually connected firms for each UI recipient, we use the Danish employment register (BFL) to identify all establishments in which our UI recipients have worked up to 5 years prior to the onset of their defining UI spell. For establishments with at most 500 employees in a given quarter, we then select all other employees who are present (i.e. have positive earnings) in the establishment at the same time as the UI recipient. We refer to these workers as actual social (coworker) connections. Firms that employ one of these workers at the time the UI recipients spell starts will be our sample of actually connected firms; at the time the UI recipient enters unemployment, these firms are in fact employing one of the UI recipient's former coworkers.

Next, we construct the set of 'almost connected' firms for each UI recipient. To do this, we again take the data on UI recipients' employment spells in the 5 years up to the onset of the defining UI spell but now we modify it by shifting the start date at each establishment two years back in time and the end date two years forward in time - that is we extend the worker's spell at each establishment by two years in both ends. We then measure connected coworkers in this modified data in exactly the same way as above. This produces a measure of set of connections the worker *would have* had if their previous unemployment spells were slightly longer. We refer to this as the set of 'potentially connected' coworkers. Firms that employ one of these workers at the time the UI

[9] We use two core administrative data sets in our analysis: DREAM and BFL. Both of these data sets are available through servers at Statistics Denmark. DREAM is an event-history data set created by the Ministry of Employment tracing the participation of individuals in public income support programs at a weekly level. BFL, the Employment Statistics for Employees, contains data on jobs, paid hours of work and earnings for the universe of employed individuals (in the analysis we only include employment spells where recorded earnings are above 1000 DKK and 10 hours of work).

recipients spell starts will be our set of 'potentially connected' firms. Finally, removing the actually connected firms from the set of potentially connected firms leaves us with the sample of 'almost connected' firms. These are firms to which the worker is not actually connected, but who they would have been connected to if the timing of past job transitions had been slightly different.

The idea behind this definition of actual and 'almost' connected firms is as follows: Because actual and 'almost' connected coworkers differ only in the exact timing at which they join or leave the UI recipients' former establishments, we should expect these two groups of workers to be similar both in terms of their characteristics, their career stage and career trajectory. Accordingly, the firms at which these workers are employed at the start of the UI recipients' unemployment spells should also be similar. The crux of our quasi-experimental research design is thus that - after conditioning on a suitable set of observables - connected and almost connected firms would have the same surplus value, application success probability, and visibility to the worker, in the absence of social connections.

For all potentially connected firms, we are able to observe a range of firm characteristics via standard administrative firm data sets. In adding this information, we always measure the characteristics in either the quarter or year prior to the UI recipient's unemployment spell starts depending on data availability. This ensures that all firm characteristics are predetermined relative to the job applications and hiring that occur during the UI recipients unemployment spell.

Finally, in arriving at our final analysis sample we impose some additional restrictions on the set of potentially connected firms. First, to avoid confounding coworker connection effects and recalls, we drop a worker's previous employer from the last 5 years from their set of potentially connected firms. Second, to avoid our results being unduly influenced by very large or very small firms, we additionally remove firms with 5 or fewer employees and firms with more that 25,000 employees in total across all establishments. Third, since our analysis is based on within-worker comparisons between connected and almost connected firms, we restrict our final analysis only to UI recipients where the set of potentially connected firms contain at least one connected and one almost connected firm.

3.4 The job application data and its coverage

After constructing data on social connections for our sample of UI recipients, we add data on applications submitted during the UI spell from the Joblog data. As discussed previously, UI recipients in Denmark are required to regularly register applied-for jobs to remain eligible for UI. Since we require 8 weeks of unemployment in our definition of new UI entrants, we restrict attention to applications made from week 9 of the UI spell and onwards. Additionally, we restrict attention to applications made during the first year of the unemployment spell.[10] Since the application data is matched to administrative firm data, we immediately have information about the firm to which each application has been sent, including whether it is an actual or almost connected firm for the

[10] As in Fluchtman et al. (2023b,a) we do not use applications submitted in the last 1 month of the UI spell to avoid applications made after the UI recipient has already secured a job.

UI recipient. As discussed in the previous section, we restrict attention only to applications going to a potentially connected firm.

Importantly, when registering applications in the data, job seekers also directly report whether they found the job via a publicly posted vacancy or whether they heard about it through some other channel. We use this to determine whether the UI recipient noticed the employment opportunity via public channels (e.g. a vacancy posting). As discussed in Section 2.9, together with additional assumptions, this will allow us to further disentangle the effect of social connections on the likelihood of noticing and considering particular firms.

Since the applications in the Joblog data are self-reported, a natural question arises regarding the coverage. Previous work using these data have examined this extensively. Fluchtman et al. (2023b,a) find that the applications in Joblog cover about 70 percent of all job applications and that the covered subset is highly representative. In the empirical analysis, we thus take the observed applications to be a representative sample of all applications. In the context of the empirical framework from Section 2 this implies that our estimates are not affected by the fact that the data does not contain all applications.

After merging in job applications, we also impose an additional sample restriction by excluding UI recipients for whom we see no application going to any of the potentially connected firm because such individuals would mechanically drop out of our empirical analysis anyway.[11]

3.5 Hiring outcomes and final data

Finally, we link our data on UI recipients and their applications to hiring outcomes. Specifically, for each application in the data, we determine whether it resulted in the UI recipient being hired at the firm. We do this by identifying the first employment spell of the UI recipient after the end the UI spell.[12]

This completes the construction of our data. The final data (in long form) consists of observations indexed by i, t, j. Here i indexes UI recipients, while t indexes the applications that the UI recipient sends to potentially connected (or equivalently the points in time at which the UI recipient sends an application to a potentially connected firm). For each pair i, t, however, the data contains an observation j for each potentially connected firm, e.g. each firm that the application could have gone to. For each such observation, the data then contain information on whether the application did in fact go to this firm ($Apply$), whether the application went to this firm and the job was found via a posting ($ApplyPosted$) and finally, whether the application resulted in the worker being hired at this firm ($Hired$). In addition, the data contains information about whether the firm is an actually connected firm, as well as a range of worker and firm characteristics.

[11]Our analysis examines the likelihood of applying (and possibly getting hired) at potentially connected firm using specifications with individual fixed effects. Individuals who are never observed applying to any of the potentially connected firms thus contribute no information to estimation.

[12]The employment spell must start at the earliest 1 month before the UI spell ends and at the latest 3 months after the UI spell ends to be included in the analysis. We also require at least 8 weeks of consecutive employment at the firm.

3.6 Control variables

In addition to comparing only connected and 'almost connected' firms, our identification strategy is based on conditioning on key firm observables ($X_{i,j,}$). This is important to address potential remaining differences between connected and 'almost connected' firms. A key issue, for example, is mechanical size differences between the two groups of firms; because a firm is connected to a UI recipient as soon as it has just one connected coworker employed, connected firms mechanically tend to be bigger than almost connected firms. Accordingly, in our baseline specification, we include flexible controls for both the firm's size, recent hiring and wage level. Specifically we include cubic polynomials in the percentile rank of the firm in terms of total number of employees in the previous quarter, number of new hires in the previous quarter and the average wages of its employees. Second, we control flexibly for the worker's geographical distance to the firm. Specifically, we include two dummies for whether the firm has an establishment in the workers region and/or in a neighboring region, as well continuous measures of the share of the firm's wage bill in the previous year that was paid to individuals in same region as the worker and the share that was paid to individuals in neighboring region. Finally, we control for the industry and occupational makeup of the firm vis-a-vis the worker, specifically a dummy for whether the firm is in the same 1-digit industry as the workers previous firm and the share of the firm's workforce that is in the same 1-digit occupation as the workers previous job.

3.7 Summary Statistics

Column 1 of Table 1 shows summary statistics for all Danish UI recipients satisfying our individual sample selection criteria from Section 3.2. In Column 2 we report summary statistics for our final analysis sample after we additionally restrict attention to our final analysis sample, where we require that UI recipients have at least one actual and almost connected firm, and send at least one application to one of them. Comparing the initial sample of UI recipients to the final analysis sample we see only relatively small differences.

4 Results

We now present the results of the empirical analysis. Table 2 shows the reduced form estimates of the effect of coworker connections. Results are based on the conditional logit models, 19, 21 and 30, with individual-by-time fixed effects. Here and throughout, we reweigh observations so that all UI recipients are weighted equally, and use clustered standard errors at the level of the UI recipient to address potentially unmodeled time dependence within individuals.

4.1 Reduced form estimates, hiring

The first panel of the table shows estimates of the effect of having a coworker connection at a firm on the likelihood of being hired at this firm, $Hired_{i,j,t}$. Column (1) shows results from the baseline

Table 1: Summary Statistics for UI recipients and analysis sample

	All UI recipients	Analysis sample
Demographics		
Female	0.399	0.345
Age	38.36	38.69
Immigrant	0.122	0.132
North Denmark Region	0.116	0.116
Central Denmark Region	0.219	0.217
Region of Southern Denmark	0.207	0.206
Capital Region of Denmark	0.331	0.330
Region Zealand	0.127	0.131
Education		
Primary/lower secondary	0.172	0.173
Upper secondary	0.430	0.415
Short tertiary/Bachelor/Master/Doctoral	0.399	0.412
Labor history		
Previous earnings, DKK (monthly)	17,560	17,674
Previous hours (monthly)	104.6	105.2
Industry		
Agriculture, forestry, and fishing	0.005	0.002
Industry, mining, and utilities	0.083	0.082
Construction and civil engineering	0.040	0.029
Trade and transportation	0.182	0.185
Information and communication	0.029	0.030
Finance and insurance	0.012	0.014
Real estate and rental	0.009	0.008
Business services	0.130	0.134
Public administration, education, and health	0.362	0.370
Culture, leisure, and other services	0.040	0.040
Prev. Occupation		
Executive leadership	0.024	0.026
Expert work	0.260	0.263
Intermediate expertise work	0.040	0.029
General office work	0.182	0.185
Service and sales work	0.267	0.266
Agriculture, forestry, and fishing work	0.008	0.006
Craftsmanship	0.064	0.051
Operator and assembly work	0.052	0.051
Other manual work	0.134	0.135
N	159,139	93,341

Table 2: Effect of connections on job search, reduced form estimates

	Conditional Logit, individual-by-time FEs					
	(1)	(2)	(3)	(4)	(5)	(6)
			Outcome variable: $Hired_{i,j,t}$			
$Connected_{i,j}$	0.552***	0.551***	0.548***	0.552***	0.561***	0.536***
	(0.027)	(0.027)	(0.027)	(0.028)	(0.028)	(0.027)
			Outcome variable: $Apply_{i,j,t}$			
$Connected_{i,j}$	0.481***	0.481***	0.479***	0.478***	0.482***	0.476***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
			Outcome variable: $ApplyPosted_{i,j,t}$			
$Connected_{i,j}$	0.462***	0.462***	0.462***	0.460***	0.464***	0.456***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Baseline controls:	Yes	Yes	Yes	Yes	Yes	Yes
Prev. earnings. by: firm avg. wage	No	Yes	Yes	No	No	No
Prev. earnings by: firm occ. shares	No	No	Yes	No	No	No
Heterogeneity:	No	No	No	By prev. earnings	By time unemployed	By gender

The table shows conditional logit estimates with individual-by-time fixed effects, obtained via (quasi) Maximum Likelihood. Each panel corresponds to a different outcome variable. In estimation, each application is weighted by the inverse of the total number of applications sent by the individual. Standard errors in parenthesis are computed using clustering at the UI recipient level. As detailed in Section 3.6, baseline controls in Column (1) include flexible measures of firm's size, recent hiring, wage level, the worker's geographical distance to the firm, whether the firm is in same industry as the worker's previous and the share of the firms workers that are in the same occupation as the worker's previous job. Column (2) expands the controls to includes quartile dummies for the average wage at the firm, as well worker's percentile rank in terms of previous earnings. Column (3) additionally includes the share of the firm's employees within each 1-digit occupation as well as interactions between these shares and the worker's percentile rank in terms of previous earnings. Columns (4)-(6) respectively estimates the model separately by quartile of worker's pervious earnings, by unemployment duration (9-14 weeks, 15-20 weeks, 21+ weeks) and by gender, and then reports the (person-weighted) average coefficient. $***$: $p < 0.01$, $**$: $p < 0.05$, $*$: $p < 0.01$

specification, controlling flexibly for firm size and recent hiring, the firm wage-level, geographical distance and the industry and occupation makeup of the firm vis-a-vis the the UI recipients previous job. The estimated coefficient on $Connected_{i,j,t}$ in Column (1) is 0.552 and highly significant, meaning that a social connection at a firm increases the likelihood of being hired there by 55 log points (74 percent) at a point in time when actively making an application to *some* firm. While very substantial, this effect size is actually on the lower end of existing estimates of social connections.[13] [14]

Column (2) and (3) probes the robustness of this result to expanding the set of controls. To address potential concerns about sorting of high wage workers into high wage firms, Column (2) adds flexible controls for the firm's average wage level interacted with the UI recipient's previous earnings. As the table shows, the estimated effect is virtually unchanged by the additional controls. Next, Column (3) explores concerns around the exact occupational composition of the firm by adding the occupation shares at the firm as controls, as well as flexible interactions between these shares and the UI recipients' previous earnings. Again, the estimated effect is virtually unchanged.

As noted previously, the specifications in Columns (1)-(3) assumes homogeneous effects of social connections across workers. Columns (4)-(6) relaxes this assumption by estimating our specification separately for different subgroups of workers and report the average coefficient across the groups. In addition to allowing for heterogeneous effects across the different groups, this also implies that we control more flexible for covariates since it allows for heterogeneous effects of covariates across the different groups. In Column (4) we estimate the model separately across quartiles of UI recipient's previous earnings, in Column (5) we estimate the model separately by time unemployed (9-14 weeks, 15-20 weeks, 21+ weeks) and in Column (6) we estimate it separately by gender. As the Table shows, allowing for heterogeneous effects in these dimensions leads to virtually no change in the estimated average effect.

4.2 Reduced form estimates, all applications

The second panel of Table 2 shows estimates of the effect of having a coworker connection at a firm on the likelihood of sending an application to this firm, $Apply_{i,j,t}$. The estimated coefficient on $Connected_{i,j,t}$ in Column (1) is 0.481 and highly significant. Having a social connection at a firm increases the likelihood that the UI recipients' applications go to this firm by 48 log points (62

[13]If sending application at some given frequency, our estimate imply that UI recipients should be 1.74 times more likely to end up employed at a an actually connected firm as relative to an almost connected firm. Studying the effect of parents' coworkers among employeed individuals in Israel, San (2022) uses a closely related definition of 'almost connected firms' and finds workers to be 3 to 4 times more likely to work at a connected firm. Other estimates from Sweden in Eliason et al. (2022), suggest that workers may be as much as 10 times more likely to work at connected firms, although their definition of connected and unconnected firms differs somewhat more.

[14]As usual when working with worker-by-firm observations, the observed relative increase in hiring also falls on a very low baseline because each worker faces a large number of firms as potential employers. On average, when making some application, the likelihood that a UI recipient gets hired at one particular firm in our data is less than 0.001 percent, reflecting additionally that the vast majority of job application do not result in a hire. Even if restricting to successful applications that result in a hire somewhere, however, the likelihood of being hired at a particular firm remains less than 0.5 percent.

Table 3: Decomposing the effect of connections on hiring

Total effect		Direct effect on noticing firm		Higher value of applying		Direct effect on succ. prob.
τ^{hired}	$=$	β^R $(= \tau^{apply} - \tau^{posted})$	$+$	$\sigma^{-1}(\beta^P + \beta^S)$ $(= \tau^{posted})$	$+$	β^P $(= \tau^{hired} - \tau^{apply})$
0.552***		0.018***		0.462***		0.071***
(0.027)		(0.003)		(0.006)		(0.027)

The table decomposes the effect of social connections on the likelihood of being hired using equations 20, 22, 31 and the estimates from Column (1) of Table 2. Standard errors in parenthesis are computed from the cluster robust standard errors on the reduced form estimates and account for dependence across estimates. $***$: $p < 0.01$, $**$: $p < 0.05$, $*$: $p < 0.01$

percent). As will be made precise when applying the formal decomposition further below, this large effect on application behavior implies that changes in application behavior explain the bulk of why social connections matter for hiring outcomes. As for the first panel, the alternative specifications in Columns (2)-(6) shows that the estimated effect is robust.

4.3 Reduced form estimates, applications to jobs found via vacancy posting

Finally, the third panel Table 2 shows estimates the effect of having a coworker connection at a firm on the likelihood of noticing and applying to a firm via a vacancy posting, $ApplyPosted_{i,j,t}$. The estimated coefficient on $Connected_{i,j,t}$ in Column (1) is 0.462 and highly significant. Having a social connection at a firm increases the likelihood that the UI recipients' applications notices and applies to this firm via a vacancy posting by 46 log points (59 percent). We note that the similarity of this effect to the total effect on applications already suggest that past coworkers directly passing information about job opportunities accounts for a relatively small share of their overall effect on hiring. Yet again, the alternative specifications in Columns (2)-(6) suggest that the estimated effect is robust.

4.4 Decomposing the effect of coworker connections

Using the reduced form estimates from above, we now proceed to perform a quantitative decomposition of the effect of coworker connections on hiring. Under the job search framework from Section 2, there is a direct link between the reduced form effects above and the structural parameters of the model, which can be used to decompose the effect of coworker connetions on hiring. Table 3 shows the results of applying the decomposition. Standard errors in parenthesis are based on clustering at the level of the UI recipient and accounts for the dependence between the reduced form estimates.

The leftmost part in Table 3 restates the overall effect estimated above: having a past coworker at a firm increases the likelihood of being hired at the firm by 55 log points overall. Moving to the rightmost part of the table, we see that about one tenth of this effect comes from the fact that coworker connections significantly increases the success probability when applying (β^P). When applying to some firm, having a past coworker at that firm increases the success probability by 7.1 log points (7.4 percent). This confirms that - at the individual level - applying to socially connected firms can be a way to substantially speed up job finding. At the same time, the direct effect of coworker connections on hiring only accounts for a limited share of the total affect; based on the 95 percent confidence interval, we can reject that the effect on success probability exceed 13 log point and that it accounts for more than 22 percent of the overall effect. Instead the majority of the effect of coworker connections reflect that coworkers are much more likely to apply for connected firms.

As discussed previously, the increased likelihood of applying to connected firms can in turn stem from two distinct mechanisms: i) social connections may directly make it more likely that the worker notices and considers job opportunities at the firm or ii) social connections may increase the attractiveness of applying to the firm. Invoking the additional model structure and assumptions from Section 2.9, the rest of the decomposition in Table 3 separate out these effects. Results confirm that having a former coworker at a firm indeed has a statistically significant the likelihood of noticing and considering job opportunities there. The magnitude of this effect (β^R) is very small however. Based on the point estimate, having a past coworker at firm only increases the likelihood of noticing job opportunities there by 1.8 log points (1.8 percent) and the 95 percent confidence interval allows us to reject effects bigger than 5 log points. While we thus confirm that this direct information effect of connections exists, its role is extremely limited in our setting. One reason for this may be that we are looking at unemployed individuals who are likely to be full time searchers and thus may tend to notice attractive job opportunities via public channels anyway.

Finally, Table 3 shows that most of the remaining effect - about 84 percent of the total - reflects that a past coworker connection significantly raises the value of applying to a firm, either as a consequence of the higher success probability or simply by making it more attractive to work at the firm. The combined effect of this increases the likelihood of applying to this firm by 46 log points or 59 percent $\left(\sigma^{-1}\left(\beta^P+\beta^S\right)\right)$.

Summing up, we thus confirm that coworker connections affect hiring outcomes both by making workers more likely to notice job opportunities at connected firms, by directly raising the likelihood of being hired when applying, and by increasing the workers interest in applying to connected. Of these three channels, however, we find that increased interest in applying is by far the most important, although direct increases in the success probability also plays a substantial role. In contrast, the tendency for coworkers to pass information about the existence of job offers appears quantitatively unimportant in our setting.

5 Conclusion

In this paper, we examine which mechanisms cause coworker connections to affect job search outcomes (hiring) for the unemployed. To provide a quantitative decomposition of the effects of social connections, we combine linked-administrative data on job applications made by the universe of Danish UI recipients, a theoretical job search framework and a quasi-experimental research design that leverages variation in coworker connections stemming from the timing of past job transitions.

In our setting, having a social connection at a firm increases the likelihood of ending up hired at that firm by 74 percent. About one tenth of this effect is caused by the fact that having a social connection at a firm increases the success probability of job applications to this firm. The remainder of the effect stems from the fact that workers are more likely to apply to socially connected firm. These findings confirms that social connections have an economically significant effect on application success probabilities but show that this is effect is dwarfed by the effects on where workers apply.

Further decomposing the effect of social connections on application behavior, we find that virtually all of the effect reflect that having a social connection at a firm makes it more valuable to apply to this firm. This higher value of applying reflects both the higher application success probability but possibly also more attractive terms of employment (including working together with social connections).

Finally, among firms with a given level of attractiveness to the worker, we confirm that a coworker connection increases the likelihood that workers notice and consider employment opportunities at the firm. The magnitude of this effect is quantitatively unimportant however. One interpretation of this result is that in our sample of full time searchers - and in the setting of a low-friction, highly digitalized country - workers are generally able to notice and consider most of the relevant jobs simply via publicly posted vacancies.

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Part I

Appendix

A Model derivations

A.1 Properties of the probability measure over choice sets

First we verify 7. When $A_{i,j,t} = k$ almost surely, the value of choosing from any choice set is constant and we have $\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) = \log(k - U_i)$ for all $\mathcal{J}$. Then the probability measure collapses to just equal Γ :

$$\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) = \left(\exp\left(\left(\log\left(k - U_i\right)\right) - \left(\log\left(k - U_i\right)\right)\right)\right)^{\delta_g} \Gamma(\mathcal{J}|\mathbf{R}_{i,t}) = \Gamma(\mathcal{J}|\mathbf{R}_{i,t})$$

Second we verify 8 by computing the likelihood of observing a particular job j:

$$\begin{aligned}
P\left(j \in \mathcal{J}^*_{i,t}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) &= \sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i : j\in\mathcal{J}} P\left(\mathcal{J}^*_{i,t} = \mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) \\
&= \sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i : j\in\mathcal{J}} \pi_i\left(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) \\
&= \sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i : j\in\mathcal{J}} \left(\exp\left(\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) - \widetilde{w_{i,t}}(\mathcal{J}^{all}_i|\mathbf{P}_{i,t}, \mathbf{S}_{i,t})\right)\right)^{\delta_g} \Gamma(\mathcal{J}|\mathbf{R}_{i,t}) \\
&= \sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i : j\in\mathcal{J}} \left(\exp\left(\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) - \widetilde{w_{i,t}}(\mathcal{J}^{all}_i|\mathbf{P}_{i,t}, \mathbf{S}_{i,t})\right)\right)^{\delta_g} \left(\Pi_{j'\in\mathcal{J}} R_{i,j',t}\right) \big(\Pi_{j'\notin\mathcal{J}}(1 - \\
&= R_{i,j,t} \sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i : j\in\mathcal{J}} \left(\exp\left(\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) - \widetilde{w_{i,t}}(\mathcal{J}^{all}_i|\mathbf{P}_{i,t}, \mathbf{S}_{i,t})\right)\right)^{\delta_g} \cdot \\
&\quad \left(\Pi_{j'\in\mathcal{J}:j'\neq j} R_{i,j',t}\right) \left(\Pi_{j'\notin\mathcal{J}}(1 - R_{i,j',t})\right)
\end{aligned}$$

In this last expression, nothing inside the sum depends on $R_{i,j,t}$ so the elasticity with respect to $R_{i,j,t}$ is obviously 1.

Finally we verify 9. As shown in the next section, assumptions 2, 3, 16and 15 imply that we have:

$$\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) = \frac{\sum_{j\in\mathcal{J}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t} + \log S_{i,j,t}\right)\right)}{\sum_{j\in\mathcal{J}^{all}_i} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t} + \log S_{i,j,t}\right)\right)} \Gamma(\mathcal{J}|\mathbf{R}_{i,t}) = \frac{\sum_{j\in\mathcal{J}} \left(P_{i,j,t} S_{i,j,t}\right)^{1/\sigma}}{\sum_{j\in\mathcal{J}^{all}_i} \left(P_{i,j,t} S_{i,j,t}\right)^{1/\sigma}} \Gamma(\mathcal{J}|\mathbf{R}_{i,t})$$

Now for any $j \in \mathcal{J}$, we can evaluate the derivative with respect to $P_{i,j,t}$:

$$\begin{aligned}
\frac{\partial}{\partial P_{i,j,t}} \pi_i \left(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}\right) &= \frac{\frac{1}{\sigma}\left(P_{i,j,t}S_{i,j,t}\right)^{\frac{1-\sigma}{\sigma}} \sum_{j\in\mathcal{J}_i^{all}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma} - \frac{1}{\sigma}\left(P_{i,j,t}S_{i,j,t}\right)^{\frac{1-\sigma}{\sigma}} \sum_{j\in\mathcal{J}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma}}{\left(\sum_{j\in\mathcal{J}_i^{all}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma}\right)^2} \Gamma(\mathcal{J}|\mathbf{I} \\
&= \frac{\frac{1}{\sigma}\left(P_{i,j,t}S_{i,j,t}\right)^{\frac{1-\sigma}{\sigma}}}{\left(\sum_{j\in\mathcal{J}_i^{all}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma}\right)^2} \left(\sum_{j\in\mathcal{J}_i^{all}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma} - \sum_{j\in\mathcal{J}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma}\right) \Gamma(\mathcal{J}|\mathbf{R}_{i,t}) \\
&\frac{\frac{1}{\sigma}\left(P_{i,j,t}S_{i,j,t}\right)^{\frac{1-\sigma}{\sigma}}}{\left(\sum_{j\in\mathcal{J}_i^{all}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma}\right)^2} \left(\sum_{j\in\mathcal{J}_i^{all}: j\neq\mathcal{J}} \left(P_{i,j,t}S_{i,j,t}\right)^{1/\sigma}\right) \Gamma(\mathcal{J}|\mathbf{R}_{i,t}) \geq 0
\end{aligned}$$

A.2 The probability of applying to a particular firm

Combining 2 and 3 we can write the log surplus from applying in choice set $\mathcal{J}$ as:

$$\log\left(W_i\left(\mathcal{J}; \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \boldsymbol{\xi}_{i,t}\right) - U_i\right) = \max_{j\in\mathcal{J}} \left(\log P_{i,j,t} + \log S_{i,j,t} + \sigma \log \xi_{i,j,t}\right) \tag{33}$$

Similarly, we write the probability of applying to job j from this choice set as:

$$P\left(j^*_{i,t} = j|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathcal{J}^*_{i,t} = \mathcal{J}\right) = P\left(j = \text{argmax}_{j'\in\mathcal{J}} \ \log P_{i,j,t} + \log S_{i,j,t} + \sigma \log \xi_{i,j,t}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}\right)$$

Under assumption 15, $\log \xi_{i,j,t}$ is i.i.d. and follows a type I extreme value distrubution so this a standard logit discrete choice problem. Standard results therefore imply (recalling that from 16 we have $\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) = E\left(\log\left(W_i\left(\mathcal{J}; \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \boldsymbol{\xi}_{i,t}\right) - U_i\right)\right)$:

$$\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}) = \log\left(\left(\sum_{j\in\mathcal{J}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t} + \log S_{i,j,t}\right)\right)\right)^{\sigma}\right) \tag{34}$$

$$P\left(j^*_{i,t} = j|\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathcal{J}^*_{i,t} = \mathcal{J}\right) = \frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t} + \log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t} + \log S_{i,j',t}\right)\right)}$$

Combining 17 and 34we can rewrite the probability of observing a given choice set as:

$$\begin{aligned}\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right) &= \left(\frac{\exp\left(\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t})\right)}{\exp\left(\widetilde{w_{i,t}}(\mathcal{J}_i^{all}|\mathbf{P}_{i,t},\mathbf{S}_{i,t})\right)}\right)^{1/\sigma}\Gamma(\mathcal{J}|\mathbf{R}_{i,t}) \\ &= \frac{\sum_{j\in\mathcal{J}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j\in\mathcal{J}_i^{all}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}\Gamma(\mathcal{J}|\mathbf{R}_{i,t}) \end{aligned} \tag{35}$$

The overall probability of applying for firm j at time t can be broken up into the probability of observing one of the choice sets containing j and then choosing j out of this subset. Together with the results above we can evaluate this as :

$$\begin{aligned}
&P\left(j_{i,t}^*=j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t},\mathbf{X}_i,\mathbf{d}_i\right)\\
&=\sum_{\mathcal{J}\subseteq\mathcal{J}_i^{all}:j\in\mathcal{J}}\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right)\cdot P\left(j_{i,t}^*=j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathcal{J}_{i,t}^*=\mathcal{J}\right)\\
&=\sum_{\mathcal{J}\subseteq\mathcal{J}_i^{all}:j\in\mathcal{J}}\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}\right)\cdot P\left(j=\text{argmax}_{j'\in\mathcal{J}}\,P_{i,j',t}S_{i,j',t}\left(\xi_{i,j',t}\right)^{\sigma}|\mathbf{P}_{i,t},\mathbf{S}_{i,t}\right)\\
&=\sum_{\mathcal{J}\subseteq\mathcal{J}_i^{all}:j\in\mathcal{J}}\frac{\sum_{j'\in\mathcal{J}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}{\sum_{j'\in\mathcal{J}_i^{all}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\Gamma(\mathcal{J}|\mathbf{R}_{i,t})\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\\
&=\sum_{\mathcal{J}\subseteq\mathcal{J}_i^{all}:j\in\mathcal{J}}\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}_i^{all}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\Gamma(\mathcal{J}|\mathbf{R}_{i,t})\\
&=\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}_i^{all}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\sum_{\mathcal{J}\subseteq\mathcal{J}_i^{all}:j\in\mathcal{J}}\Gamma(\mathcal{J}|\mathbf{R}_{i,t})\\
&=\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}_i^{all}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}R_{i,j,t}\\
&=\frac{\exp\left(\log R_{i,j,t}+\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}_i^{all}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}
\end{aligned}$$

Next note that if j is a potentially connected firm, we can substitute in from18, 10,11,12,13 so that the numerator in this last expression becomes:

$$\exp\left(\left(\alpha_i^R + \frac{1}{\sigma}\left(\alpha_i^P + \alpha_i^S\right)\right) + \left(\beta^R + \frac{1}{\sigma}\left(\beta^P + \beta^S\right)\right) d_{i,j} + \left(\theta^R + \frac{1}{\sigma}\left(\theta^P + \theta^S\right)\right) X_{i,j}\right)$$

If we define $\tau^{apply} = \left(\beta^R + \frac{1}{\sigma}\left(\beta^P + \beta^S\right)\right)$ and $\gamma^{apply} = \left(\theta^R + \frac{1}{\sigma}\left(\theta^P + \theta^S\right)\right)$, this means that when j is a potentially connected firm we have:

$$P\left(j_{i,t}^* = j | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{X}_i, \mathbf{d}_i\right) = \frac{\exp\left(\left(\alpha_i^R + \frac{1}{\sigma}\left(\alpha_i^P + \alpha_i^S\right)\right) + \tau^{apply} d_{i,j} + \gamma^{apply} X_{i,j}\right)}{\sum_{j' \in \mathcal{J}_i^{all}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t} + \log S_{i,j',t}\right)\right)}$$

To arrive at the reduced form equation from the main text, we can take logs and get:

$$\log P\left(j_{i,t}^* = j | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{X}_i, \mathbf{d}_i\right) = \log\left(\frac{\exp\left(\alpha_i^R + \frac{1}{\sigma}\left(\alpha_i^P + \alpha_i^S\right)\right)}{\sum_{j' \in \mathcal{J}_i^{all}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t} + \log S_{i,j',t}\right)\right)}\right) + \tau_g^{apply} d_{i,j} + \gamma^{apply} X_{i,j}$$

This implies equation 19 from the main text, after defining η_i^{apply} as:

$$\eta_i^{apply} = \log\left(\frac{\exp\left(\alpha_i^R + \frac{1}{\sigma}\left(\alpha_i^P + \alpha_i^S\right)\right)}{\sum_{j' \in \mathcal{J}_i^{all}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t} + \log S_{i,j',t}\right)\right)}\right)$$

Finally, to see that this is also equivalent to a McFadden (1974) conditional logit model and can be estimated by conditional likelihood in the usual way, we can write out the probability of applying to potentially connect firm j conditional on applying to some potentially connected firm:

$$\begin{aligned}
P\left(j_{i,t}^* = j | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{X}_i, \mathbf{d}_i, j_{i,t}^* \in \mathcal{J}_i^{pot}\right) &= \frac{P\left(j_{i,t}^* = j | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{X}_i, \mathbf{d}_i\right)}{\sum_{j' \in \mathcal{J}_i^{pot}} P\left(j_{i,t}^* = j' | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}, \mathbf{X}_i, \mathbf{d}_i\right)} \\
&= \frac{\exp\left(\eta_i^{apply} + \tau^{apply} d_{i,j} + \gamma^{apply} X_{i,j}\right)}{\sum_{j' \in \mathcal{J}_i^{pot}} \exp\left(\eta_i + \tau^{apply} d_{i,j'} + \gamma^{apply} X_{i,j'}\right)} \\
&= \frac{\exp\left(\tau^{apply} d_{i,j} + \gamma^{apply} X_{i,j}\right)}{\sum_{j' \in \mathcal{J}_i^{pot}} \exp\left(\tau^{apply} d_{i,j'} + \gamma^{apply} X_{i,j'}\right)}
\end{aligned}$$

A.3 The probability of being hired at a particular firm

The probability of being hired at a particular firm at time t is simply the likelihood of applying times the probability that the application is succesful. Using results from the previous section we have:

$$
\begin{aligned}
P\left(h_{i,t}^{*}=j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t},\mathbf{X}_{i},\mathbf{d}_{i}\right) &= P\left(j_{i,t}^{*}=j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t},\mathbf{X}_{i},\mathbf{d}_{i}\right)\cdot P_{i,j,t} \\
&= \frac{\exp\left(\log R_{i,j,t}+\dfrac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}_{i}^{all}}\exp\left(\dfrac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\cdot P_{i,j,t} \\
&= \frac{\exp\left(\log R_{i,j,t}+\dfrac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)+\log P_{i,j,t}\right)}{\sum_{j'\in\mathcal{J}_{i}^{all}}\exp\left(\dfrac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}
\end{aligned}
$$

Analagous to arguments in the previous section, if j is a potentially connected firm, we can substitute in from18, 10,11,12,13 and define $\tau^{hired}=\left(\beta^{R}+\frac{1}{\sigma}\left(\beta^{P}+\beta^{S}\right)+\beta^{P}\right)$ and $\gamma^{hired}=\left(\theta^{R}+\frac{1}{\sigma}\left(\theta^{P}+\theta^{S}\right)+\theta^{P}\right)$ to get:

$$
P\left(h_{i,t}^{*}=j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t},\mathbf{X}_{i},\mathbf{d}_{i}\right)=\frac{\exp\left(\left(\alpha_{i}^{R}+\frac{1}{\sigma}\left(\alpha_{i}^{P}+\alpha_{i}^{S}\right)+\alpha_{i}^{P}\right)+\tau^{hired}d_{i,j}+\gamma^{hired}X_{i,j}\right)}{\sum_{j'\in\mathcal{J}_{i}^{all}}\exp\left(\dfrac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}
$$

Taking logs and defining η_{i}^{hired} as follows then implies equation 21 from the main text:

$$
\eta_{i}^{hired}=\log\left(\frac{\exp\left(\alpha_{i}^{R}+\frac{1}{\sigma}\left(\alpha_{i}^{P}+\alpha_{i}^{S}\right)+\alpha_{i}^{P}\right)}{\sum_{j'\in\mathcal{J}_{i}^{all}}\exp\left(\dfrac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\right)
$$

A derivation completely analagous to the one in the previous section also shows that this is equivalent to a conditional logit model.

A.4 Modifying assumptions to more detailed information structure

$$
\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,}^{pub},\mathbf{R}_{i,}^{inf},\mathbf{o}_{i,t},\mathbf{d}_{i},\mathbf{X}_{i},\mathcal{J}_{i,t}^{*}\perp\boldsymbol{\xi}_{i,t} \tag{36}
$$

$$
P\left(\mathcal{J}_{i,t}^{*}=\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}^{pub},\mathbf{R}_{i,t}^{inf},\mathbf{d}_{i},\mathbf{X}_{i}\right)=\pi_{i}\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}^{pub},\mathbf{R}_{i,t}^{inf}\right) \tag{37}
$$

$$
\Gamma(\mathcal{J}|\mathbf{R}_{i,t}^{pub},\mathbf{R}_{i,t}^{inf})=\left(\Pi_{j\in\mathcal{J}}R_{i,j,t}\right)\left(\Pi_{j\notin\mathcal{J}}(1-R_{i,j,t})\right) \tag{38}
$$

$$
\pi_{i}\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}_{i,t}^{pub},\mathbf{R}_{i,t}^{inf}\right)=\left(\exp\left(\widetilde{w_{i,t}}(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t})-\widetilde{w_{i,t}}(\mathcal{J}_{i}^{all}|\mathbf{P}_{i,t},\mathbf{S}_{i,t})\right)\right)^{\delta_{g}}\Gamma(\mathcal{J}|\mathbf{R}_{i,t}^{pub},\mathbf{R}_{i,t}^{inf}) \tag{39}
$$

$$
\begin{aligned}
\log R_{i,j,t}^{pub,0} &= \alpha_i^{R,pub} + \theta_g^{R,pub} X_{i,j} \quad \forall\, j \in \mathcal{J}_i^{pot} \\
\log R_{i,j,t}^{inf,0} &= \alpha_i^{R,inf} + \theta_g^{R,inf} X_{i,j} \quad \forall\, j \in \mathcal{J}_i^{pot}
\end{aligned} \tag{40}
$$

A.5 Additional structure on information frictions

By definition, we have:

$$
\begin{aligned}
P(o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}, \mathbf{X}_i, \mathbf{d}_i) =& P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}, \mathbf{X}_i, \mathbf{d}_i) \\
&+ P(o_{i,j,t} = inf | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}, \mathbf{X}_i, \mathbf{d}_i)
\end{aligned}
$$

From 23, the fact that this needs to hold also under the benchmark where workers are indifferent directly implies $R_{i,j,t} = R_{i,j,t}^{pub} + R_{i,j,t}^{inf}$ (because under the benchmark we have $P(o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}) = \sum_{\mathcal{J} \subseteq \mathcal{J}_i^{all} : j \in \mathcal{J}} \Gamma(J | \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}) = R_{i,j,t}$).

Next rewrite assumption 28 as:

$$
\frac{P(o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}, \mathbf{X}_i, \mathbf{d}_i)}{P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}, \mathbf{X}_i, \mathbf{d}_i)} = m(R_{i,j,t}^{pub}, R_{i,j,t}^{inf}) + 1 \tag{41}
$$

Using again 23 and evaluating this under the benchmark where workers are indifferent yields:

$$
\frac{R_{i,j,t}}{R_{i,j,t}^{pub}} = m(R_{i,j,t}^{pub}, R_{i,j,t}^{inf}) + 1 \tag{42}
$$

Combining 41 and 42 then implies that for arbitrary values of $\mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}$ we have

$$
\frac{P(o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}, \mathbf{X}_i, \mathbf{d}_i)}{P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}_{i,t}^{pub}, \mathbf{R}_{i,t}^{inf}, \mathbf{X}_i, \mathbf{d}_i)} = \frac{R_{i,j}}{R_{i,j,t}^{pub}} \tag{43}
$$

Now we evaluate the following using first Assumption 26 and then Bayes rule:

$$
\begin{aligned}
&P\left(\mathcal{J}^*_{i,t} = \mathcal{J} \wedge o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i\right) \\
&\quad = P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) \cdot P(\mathcal{J}^*_{i,t} = \mathcal{J} | o_{i,j,t} = pub, \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) \\
&\quad = P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) \cdot P(\mathcal{J}^*_{i,t} = \mathcal{J} | o_{i,j,t} \neq 0, \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) \\
&\quad = P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) \cdot \frac{P(\mathcal{J}^*_{i,t} = \mathcal{J} \wedge o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i)}{P(o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i)} \\
&\quad = P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) \cdot \frac{P(\mathcal{J}^*_{i,t} = \mathcal{J} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i)}{P(o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i)} \\
&\quad = P(o_{i,j,t} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) \cdot \frac{P(\mathcal{J}^*_{i,t} = \mathcal{J} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t})}{P(o_{i,j,t} \neq 0 | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i)}
\end{aligned}
$$

Using 43 then shows

$$
P(\mathcal{J}^*_{i,t} = \mathcal{J} \wedge o_{ijt} = pub | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t}, \mathbf{X}_i, \mathbf{d}_i) = \frac{R^{pub}_{i,j,t}}{R_{i,j}} P(\mathcal{J}^*_{i,t} = \mathcal{J} | \mathbf{P}_{i,t}, \mathbf{S}_{i,t}, \mathbf{R}^{pub}_{i,t}, \mathbf{R}^{inf}_{i,t})
$$

Now we use the results above and the independence between $\mathbf{o}_{i,t}$ and $\boldsymbol{\xi}^{inf}_{i,t}$ to evaluate the joint probability of applying to job j and noticing it via public channels. Note here that under our notation, $o_{i,j^*_{i,t},t}$, is a categorical variable indicating how the actually applied-for job ($j^*_{i,t}$) was found:

$$
\begin{aligned}
&P\left(j^*_{i,t}=j\wedge o_{i,j^*_{i,t},t}=pub|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}^{pub}_{i,t},\mathbf{R}^{inf}_{i,t},\mathbf{X}_i,\mathbf{d}_i\right)\\
&=\sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i:j\in\mathcal{J}}P(\mathcal{J}^*_{i,t}=\mathcal{J}\wedge o_{ijt}=pub|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}^{pub}_{i,t},\mathbf{R}^{inf}_{i,t},\mathbf{X}_i,\mathbf{d}_i)\cdot P\left(j^*_{i,t}=j|o_{ijt}=inf,\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathcal{J}^*_{i,t}=\mathcal{J}\right)\\
&=\sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i:j\in\mathcal{J}}\frac{R^{pub}_{i,j,t}}{R_{i,j}}P(\mathcal{J}^*_{i,t}=\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}^{pub}_{i,t},\mathbf{R}^{inf}_{i,t})\cdot P\left(j^*_{i,t}=j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathcal{J}^*_{i,t}=\mathcal{J}\right)\\
&=\frac{R^{pub}_{i,j,t}}{R_{i,j}}\sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i:j\in\mathcal{J}}\pi_i\left(\mathcal{J}|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}^{pub}_{i,t},\mathbf{R}^{inf}_{i,t}\right)\cdot P\left(j^*_{i,t}=j|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathcal{J}^*_{i,t}=\mathcal{J}\right)\\
&=\frac{R^{pub}_{i,j,t}}{R_{i,j}}\sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i:j\in\mathcal{J}}\frac{\sum_{j'\in\mathcal{J}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}{\sum_{j'\in\mathcal{J}^{all}_i}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\Gamma(\mathcal{J}|\mathbf{R}_{i,t})\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\\
&=\frac{R^{pub}_{i,j,t}}{R_{i,j}}\sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i:j\in\mathcal{J}}\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}^{all}_i}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\Gamma(\mathcal{J}|\mathbf{R}_{i,t})\\
&=\frac{R^{pub}_{i,j,t}}{R_{i,j}}\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}^{all}_i}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}\sum_{\mathcal{J}\subseteq\mathcal{J}^{all}_i:j\in\mathcal{J}}\Gamma(\mathcal{J}|\mathbf{R}_{i,t})\\
&=\frac{R^{pub}_{i,j,t}}{R_{i,j}}\frac{\exp\left(\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}^{all}_i}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}R_{i,j}\\
&=\frac{\exp\left(\log R^{pub}_{i,j,t}+\frac{1}{\sigma}\left(\log P_{i,j,t}+\log S_{i,j,t}\right)\right)}{\sum_{j'\in\mathcal{J}^{all}_i}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}
\end{aligned}
$$

Analogous to arguments further above, if j is a potentially connected firm, we can substitute in from18, 10, 11,24 and 40, and define $\tau^{posted}=\left(\frac{1}{\sigma}\left(\beta^P_g+\beta^S_g\right)\right)$ and $\gamma^{posted}=\left(\theta^{R,pub}+\frac{1}{\sigma}\left(\theta^P+\theta^S\right)\right)$ to get:

$$
P\left(j^*_{i,t}=j\wedge o_{i,j^*_{i,t},t}=pub|\mathbf{P}_{i,t},\mathbf{S}_{i,t},\mathbf{R}^{pub}_{i,t},\mathbf{R}^{inf}_{i,t},\mathbf{X}_i,\mathbf{d}_i\right)=\frac{\exp\left(\left(\alpha^{R,pub}_i+\frac{1}{\sigma}\left(\alpha^P_i+\alpha^S_i\right)\right)+\tau^{posted}d_{i,j}+\gamma^{posted}X_{i,j}\right)}{\sum_{j'\in\mathcal{J}^{all}_i}\exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t}+\log S_{i,j',t}\right)\right)}
$$

Taking logs and defining η^{posted}_i as follows then implies equation 30 from the main text:

$$\eta_i^{hired} = \log\left(\frac{\exp\left(\alpha_i^{R,pub} + \frac{1}{\sigma}\left(\alpha_i^P + \alpha_i^S\right)\right)}{\sum_{j' \in \mathcal{J}_i^{all}} \exp\left(\frac{1}{\sigma}\left(\log P_{i,j',t} + \log S_{i,j',t}\right)\right)}\right)$$

A derivation completely analogous to ones given above then also shows that this is equivalent to a conditional logit model.