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Strategic referrals and on-the-job search equilibrium

Ji-Woong Moon[1]

School of Economics, Shanghai University of Finance and Economics, 777 Guoding Rd, Yangpu District, Shanghai, China

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ABSTRACT

Referrals are prevalent in the U.S. labor market. To understand their aggregate effects, this paper studies an equilibrium model of on-the-job search and job referrals. In the model, referrals are modeled as a strategic interaction between a referrer and a firm. The equilibrium model shows that referrals benefit job searchers whose outside option is above a threshold. I support this prediction by showing that the referral wage premium exists only for employed job searchers. Quantitatively, referrals contribute to the total output by 3.93% through transmitting information and reducing search costs. The information transmission explains about 28% of the effects.

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1. Introduction

Most workers use social connections and referrals when searching for work.[2] Empirical evidence suggests that being referred for a job influences search outcomes, such as job-finding probability and wage (Brown et al., 2016; Burks et al., 2015; Dustmann et al., 2015). Many theories have been proposed to explain these patterns, and a strand of the literature focuses on referrals' role in transmitting information (Dustmann et al., 2015; Galenianos, 2013; Montgomery, 1991; Simon and Warner, 1992). However, referrers have different incentives from firms: referrers are often family and friends. They are also financially rewarded upon hiring in many cases, making referrers favor hiring more.[3] This incentive mismatch casts

E-mail address: jiwoong@mail.shufe.edu.cn

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[2] Various data sources indicate that the fraction of workers using referrals is approximately a half (Topa, 2011). I find that 42% of workers are referred to the current job, and approximately 50% of job searchers use their connections in the Survey of Consumer Expectation. Corcoran et al. (1980) documented that more than one half of male workers under 45 years old use referrals from PSID, and Galenianos (2014) found that the proportion is 20% - 40% across industries using 1994 NLSY data.

[3] Previous studies find that altruism and monetary compensation are main factors explaining referrers motivations (Bandiera et al., 2009; Beaman et al., 2018; Beaman and Magruder, 2012; Friebel et al., 2019).

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doubt on whether referral information is informative and trustworthy, but this potential source of information distortion has been largely ignored in previous literature.

This study proposes an equilibrium on-the-job search model with referrals. The innovation from the previous literature is to model referrals as an information game between a referrer and a firm (Milgrom, 1981), rather than an exogenous signal. In the game, the referrer observes the match quality of the prospective match and sends a message to the firm. Upon hiring, the referrer receives a reward but faces lying costs, and those payoffs are not perfectly aligned with the firm's profits. Given this incentive mismatch, the referrer chooses a message to maximize her payoffs. In equilibrium, information varies endogenously across jobs and referrer's incentives, affecting the firm's hiring decisions.

I then incorporate this information game into a directed on-the-job search model (Menzio and Shi, 2011), connecting information provision and labor market outcomes. When workers search for a job, they rationally anticipate the extent to which information will be transmitted in future referrals and their effects on job-finding probability. As information varies across jobs, the results of referrals depend on job searchers' labor market status. Firms post a vacancy, anticipating the extent of information transmitted, given the referrers' different motives. Workers' search and firms' recruiting decisions feed back into referrers' information strategy because search decisions affect the value of a job through the expected duration of the match.

The first contribution of this study is the complete characterization of referral information. I show that referrals are uninformative when lying costs are low, explaining why referrals' effects vary according to referrers' identities (Lang and Yang, 2019; Lester et al., 2021; Loury, 2006). When lying costs are high, the equilibrium exhibits pooling: referrers send the same "recommendation message" if the match quality exceeds a threshold, and firms hire when receiving the recommendation message. Because of this pooling, firms cannot precisely infer the match quality from the message, and referrers can induce hiring for match qualities slightly below the hiring threshold under perfect information. The recommendation threshold is higher in higher-wage jobs because referrers voluntarily respond to firms' need for better information. Consequently, better information is transmitted in higher-wage positions.

The second contribution is to integrate this information game into an equilibrium on-the-job search model, which generates testable predictions and provides a tool for quantitative analysis. When lying costs are high, referrals increase the match-creation probability and expected match quality in high-wage positions by transmitting the information. Workers understand this information effect, but not every worker directly benefits from it because workers search for different jobs. For unemployed workers, it is optimal to search for a low-wage job even though no informational advantage exists. Only workers whose outside option exceeds a certain level directly benefit from the referral information, implying that the referral wage premium exists only for these workers. Note that low-wage and unemployed workers still have an incentive to use referrals because referrals connect employers and workers, although uninformative.

The third contribution is to empirically examine the model's prediction of the referral wage premium. I use the Survey of Consumer Expectation (SCE), which has information on workers' job search behaviors including direct questions about referral status.[4] Using the SCE data, I first confirm that only referrals from business contacts are positively associated with wages. Then, I interact with the business referral dummy with workers' outside option values when receiving the current job offers. As the outside option is unobservable, I use two proxies: employment status and the previous wage. The regression results supported the prediction of the model. The business referral coefficient is positive and significant for workers with job-to-job transitions in the first specification and workers with higher residual previous wages in the second specification.

In the empirical analysis, I control for previous wages. Therefore, the results cannot be explained by effects on the offer arrival rate alone (Arbex et al., 2019; Calvo-Armengol and Jackson, 2004).[5] The results are also not easily explained by theories in which referrals fundamentally change the offer distribution because such effects exist for everyone (Dustmann et al., 2015; Galenianos, 2013; Montgomery, 1991). I argue that the employment status when receiving the current offer is not necessarily correlated with unobserved worker quality, implying that the results are less likely to suffer from the unobserved worker heterogeneity problem. The logic is that conditional on 'currently employed,' workers who have moved to the current job from unemployment are not necessarily of lower quality as good employed workers stay at a job longer.

I calibrate the model parameters and quantitatively examine the aggregate effects of referrals on the labor market. In the model, referrals connect employers and workers and transmit information about match quality. Therefore, I conduct two counterfactual exercises related to these two roles of referrals. Firstly, I compare the benchmark economy with the counterfactual economy without referrals and find that total output is 3.93% higher in the benchmark economy. The higher output comes from the higher match quality and the lower unemployment rate. Then I compare the benchmark with another counterfactual economy in which referrals exist but are uninformative. In this case, the output difference decreases to 1.07%, meaning that transmitting information accounts for about 28% of the total effects of job referrals. Regarding wage distribution, referrals increase wage dispersion because referrals disproportionately benefit the employed and boost job-to-job transitions. However, the degree of dispersion is below the empirical counterpart as in standard search models.

[4] Several recent studies on referrals also use the SCE data, such as Arbex et al. (2019), Lang and Yang (2019), and Lester et al. (2021).

[5] In Arbex et al. (2019), referred workers are highly paid in equilibrium both for better offer distribution and selection by network size.

Related literature

Many theoretical and empirical studies have been done on job referrals (see Ioannides and Datcher Loury (2004) and Topa (2011) for a comprehensive survey). Montgomery (1991) is a classic study that rationalizes the use of job referrals by transmitting information, and other studies focusing on this information channel include Simon and Warner (1992), Galenianos (2013) and Dustmann et al. (2015). Galenianos (2013) studied a model in which referrals provided information about match-specific uncertainty. Dustmann et al. (2015) built a model in which a referral wage premium exists at the beginning of a match but dissipates over tenure due to gradual information revelation. This study contributes to the literature by allowing for referrers' strategic behaviors and explaining the heterogeneous effects of referrals through incentives.[6] In addition, this study integrates the micro-founded information game and on-the-job search models, providing testable predictions regarding referral wage premia and several quantitative implications.

Lester et al. (2021) examined the effects of referrals according to the type of referrers, family or business contacts.[7] Lester et al. (2021) used a more flexible model with unobserved worker heterogeneity but assumed exogenously different match quality distribution according to the type of referrals. Lang and Yang (2019) studies the effects of referrals, separately for insider referrals and outsider referrals. They found that only insider referrals are associated with higher wages.

This study is motivated by empirical literature investigating the effects of social connections on labor market outcomes. Some of these studies directly examine the effects of referrals (Brown et al., 2016; Burks et al., 2015; Dustmann et al., 2015; Loury, 2006; Simon and Warner, 1992), while others focus on broader concepts of social capital (Cingano and Rosolia, 2012; Marmaros and Sacerdote, 2002; Schmutte, 2014). In terms of its modeling, this study integrates two strands of literature: directed search (Burdett et al., 2001; Delacroix and Shi, 2006; Menzio and Shi, 2011; Moen, 1997; Shi, 2009) and information design (Grossman, 1981; Kamenica and Gentzkow, 2011; Kartik, 2009; Lipnowski and Ravid, 2017; Milgrom, 1981). One feature of this study is that the sender optimal equilibrium exhibits pooling. This is because the sender's payoff depends on the buyer's binary decision, and the buyer has access to outside information. These features naturally arise within the labor market context.

The remainder of this paper is organized as follows. Section 2 describes the information game between a referrer and a firm. Section 3 embeds the information game into an equilibrium search model. Section 4 introduces the data and provides empirical support for the prediction of the model. Section 5 discusses the quantitative properties. Section 6 concludes the paper.

2. Model of endogenous referral information

This section proposes a static information game describing when and to what extent job referrals transmit information. Throughout the section, wages and the firm's profits from hiring are taken as given. These payoffs are endogenously determined when the information game is integrated into the search model in Section 3.

2.1. Environment

There are three agents: firm, worker, and referrer. The firm has a vacant position that guarantees wage w, which is above the worker's reservation wage, and produces output ϕ if matched. The output ϕ is match-specific, and the firm and worker observe ϕ only after forming a match. I assume that ϕ is initially drawn from a Pareto distribution $F(x) \equiv P(\phi \leq x) = 1 - \left(\frac{y}{x}\right)^{\alpha}$ for $x \geq y$. The scale parameter y determines the minimum productivity. The higher the shape parameter α is, the less disperse ϕ is. The Pareto distribution assumption does not play a role in most qualitative results.

Contrary to the firm and worker, the referrer observes ϕ before the match creation,[8] but which information to disclose is the referrer's choice. I model this information choice following Milgrom (1981). Specifically, the referrer chooses a message m from the set of closed intervals of $[y, \infty)$ and sends it to the firm after observing ϕ. Each message $m = [m_a, m_b]$ represents a statement "ϕ is in $[m_a, m_b]$." This message formulation covers various information structures. For instance, the referrer can reveal the quality by sending $[\phi, \phi]$ for all ϕ, or completely uninformative by sending $[y, \infty)$ independent of ϕ.

A particularly interesting class of strategies is 'pass-type.' A strategy $\sigma(\phi)$ is a pass-type strategy with a threshold x if

$$\forall \phi \geq x, \quad \sigma(\phi) = [x, \infty) \tag{1}$$

for some $x \in [y, \infty)$. A pass-type strategy pools match qualities above a threshold x into the same message $[x, \infty)$. By doing so, the referrer conceals any information except that the match quality "passes" the threshold. Because Eq. (1) does not specify $\sigma(\phi)$ when $\phi < x$, a continuum of pass-type strategies exists given x.

An example of the pass-type strategy is to say "Ann's skill is above average" when it is indeed the case and say "Ann's skill is below average" otherwise. Another example is to say "I do not know about her skill" instead of "Ann's skill is below average." While this below-the-threshold message can differ, the referrer must send the same $[x, \infty)$ when ϕ is above the

[6] Ekinci (2016) is one exception that considers referrers' strategic behaviors using a two-period model.

[7] Loury (2006) also studies the effects of referrals by the identity of a referrer using NLSY79 and finds that referrals from old males lead to better labor market outcomes for young workers.

[8] In the SCE data, about 70% of referrals are intermediated by firms' insiders. It means that most referrers know both firms and workers.

threshold. The crucial property is that every pass-type strategy induces the same posterior belief when the match quality realization is above the threshold.

After the referrer sends a message, the firm interviews the worker and observes a signal s of which realization is independent of the message. I assume that s equals ϕ with probability τ, and is drawn from $F(\cdot)$ independent of ϕ with probability $1-\tau$. In this sense, τ is the interview accuracy, and I focus on partially informative signal $\tau \in (0, 1)$.[9] After the interview signal is realized, the firm makes a hiring decision $h \in \{0, 1\}$, where $h = 1$ means hiring, based on the referrer's message and interview signal.

The firm's payoff upon hiring is the value of a job $J(w, \phi) = A(\phi - w)$ for some $A > 0$.[10] The referrer's payoff is independent of the firm's payoff, indicating an incentive mismatch. The referrer's payoff consists of benefits upon hiring and the cost of lying. The benefits represent either altruism or lump-sum financial rewards.[11] Regarding the cost of lying, several interpretations are possible. Reputation is one way, or a firm may punish the referrer if the referrer is an employee.

I assume that the referrer's payoffs depend on the referrer's type $j \in \{f(amily), b(usiness)\}$. I normalize the referral benefits to z for both types and set the cost of lying ν^j to satisfy $\nu^b > z > \nu^f = 0$. The referrer pays the lying cost only if the firm hires the worker. In Section 2.2, I explain how this lying cost affects the firm's off-the-path belief. $\nu^f = 0$ assumption *per se* is not critical, and most qualitative results hold under a small but positive ν^f. I discuss the role of this assumption in Section 2.5.2.

This payoff structure is motivated by empirical findings that the effectiveness of referrals differs according to the relationship between the referrer and the worker (Lang and Yang, 2019; Lester et al., 2021; Loury, 2006). I view that what varies by the relationship is the referrer's payoff. For instance, family referrers are likely to benefit from hiring more than non-family referrers. Instead, referrers through business contacts tend to care more about reputation.

To summarize, the timing of the events and payoffs are as follows:

- Timing of events
  1. $\phi \sim F$ is realized, and the referrer observes the realization of ϕ.
  2. The referrer sends a message $m \in \mathcal{M}$, where $\mathcal{M}$ is the set of closed intervals of $[y, \infty)$.
  3. An interview signal s is realized from $F_S(x|\phi) = \begin{cases} (1-\tau)F(x), & \text{if} \quad x < \phi \\ (1-\tau)F(x) + \tau, & \text{if} \quad x \geq \phi \end{cases}$ and $\tau \in (0, 1)$.
  4. The firm observes m and s, and chooses the hiring decision $h \in \{0, 1\}$.
- Payoff
  - If the firm hires the worker:
    - the referrer: z if telling the truth, and $z - \nu^j$ if lying.
    - the firm: $A(\phi - w)$ for $A > 0$
  - Otherwise 0 for the referrer and the firm

2.2. Belief formation

The firm updates the belief once after receiving m, and then after observing s. The latter belief update follows Bayes' rule with the exogenous distribution $F_S(\cdot|\phi)$. For the referral message m, Bayes' rule applies when m is one of the equilibrium messages. In this case, the posterior probability of $\phi = s$ is higher when s is consistent with more informative m. For example, given $s = 1$, the firm puts a higher probability on $\phi = 1$ when $m = [1-\epsilon, 1+\epsilon]$ than $m = [y, \infty)$.

When m is an off-the-path message, I assume that the belief is determined by skepticism. Note that a certain degree of skepticism is essential to support an equilibrium because the referrer would deviate if the firm positively interprets a deviation message. Also, it is reasonable to assume that a deviation message is evidence of low match quality because a referrer is more likely to deviate when the match quality is lower. Following this intuition, I assume that the firm puts weight one on the lowest quality y when a family referrer deviates.

The firm takes a similar skeptical stance in the business referral, but the firm understands that lying is strictly dominated. Because the message must be truthful, the firm puts weight one on the minimum match quality of the message m, which is the lowest quality conditional on the message being truthful, instead of y.

In previous papers, this skeptical belief is an equilibrium property if the equilibrium belief is uniquely determined within the model (Milgrom, 1981; Okuno-Fujiwara et al., 1990). If there is indeterminacy in the off-the-path beliefs, it is often *ex-ante* imposed (Hagenbach et al., 2014; Kartik, 2009). I adopt this off-the-path restriction *ex-ante* to make discussions clear. The belief restriction imposed here is consistent with intuitive and D1 criteria (Cho and Kreps, 1987; Cho and Sobel, 1990).

[9] Menzio and Shi (2011) use the same signal structure, but they focus on two extreme cases $\tau = 0$ (Experience good) and $\tau = 1$ (Inspection good).

[10] I endogenously derive $J(w, \phi)$ and A in Section 3.

[11] There is little academic research on how firms pay employee referral bonuses. According to 'employeereferral.com,' lump-sum payment accounts for more than 50% of the cases, and about 90% of the bonuses are paid in full within sixth months.

2.3. Equilibrium definition

Let $\sigma^j(\phi) : [y, \infty) \to \mathcal{M}$ be the j-type referrer's strategy.[12] Denote the posterior belief of the firm by $\mu^j(\phi|m, s)$, and the hiring decision by $h^j(m, s) \in \{0, 1\}$. I assume that the firm hires the worker when indifferent. In this study, I focus on a referrer-preferred PBE (Perfect Bayesian Equilibrium) with a monotone strategy. It consists of $\sigma^j(\phi)$, $\mu^j(\phi|m, s)$, and $h^j(m, s)$ such that:

i) (Optimal referral) Given $h^j(m, s)$, $\sigma^j(\phi)$ is an optimal message: for all m and ϕ, $E_s\big[h^j(\sigma^j(\phi), s)\big(z - \nu^j\mathbb{I}(\phi \notin \sigma^j(\phi))\big)|\phi\big] \geq E_s\big[h^j(m, s)\big(z - \nu^j\mathbb{I}(\phi \notin m)\big)|\phi\big]$
ii) (Optimal hiring) $h^j(m, s) = 1$ if and only if $E_\phi(J(w, \phi)|m, s) \geq 0$ under $\mu^j(\phi|m, s)$.
iii) (Consistency of belief) $\mu^j(\phi|m, s)$ is determined by Bayes' rule on the equilibrium path. For the off-the-path belief, $\mu^f(\phi|m, s)$ puts weight one on y and $\mu^b(\phi|m, s)$ puts weight one on the minimum match quality of the message m.
iv) (Monotonicity) $\sigma^j(\phi)$ is monotone in ϕ: for all $\phi \geq \phi'$, $\min \sigma^j(\phi) \geq \min \sigma^j(\phi')$ and $\max \sigma^j(\phi) \geq \max \sigma^j(\phi')$.
v) (Referrer optimality) (σ^j, μ^j, h^j) maximizes the referrer's *ex-ante* payoff: if $(\hat{\sigma}^j, \hat{\mu}^j, \hat{h}^j)$ satisfies i) - iv), then $E_\phi\Big\{E_s\big[h^j(\sigma^j(\phi), s)\big(z - \nu^j\mathbb{I}(\phi \notin \sigma^j(\phi))\big)|\phi\big]\Big\} \geq E_\phi\Big\{E_s\Big[\hat{h}^j(\hat{\sigma}^j(\phi), s)\big(z - \nu^j\mathbb{I}(\phi \notin \hat{\sigma}^j(\phi))\big)|\phi\Big]\Big\}$

Equilibrium definition iv) requires that the equilibrium strategy be monotone in ϕ. In family referral cases, only the cardinality of $\mathcal{M}$ matters without this condition. Because each message has a literal interpretation, I require that a better ϕ leads to a better (literal) message in equilibrium. For instance, in equilibrium, the referrer indicates a good match quality by saying "Match quality is good," instead of saying "Match quality is bad." It restricts the shape of the equilibrium strategy but does not impose any restrictions on deviations. This type of equilibrium is of interest in the literature when a message has an explicit interpretation (Chen, 2011; Kartik, 2009).

Definition v) is a refinement to the standard definitions of PBE i) - iv). This study focuses on an equilibrium that maximizes the referrer's *ex-ante* expected payoff among the monotone PBEs. I provide a rationale for the refinement in Section 2.5.1.

2.4. Analysis

2.4.1. Equilibrium characterization: Family referral case

In this case, a PBE exists because sending an uninformative message $\sigma^f(\phi) = [y, \infty)$ constitutes a PBE. Indeed, any PBE that satisfies i) - iv) is payoff equivalent to this uninformative equilibrium.

Proposition 1. *In any PBE that satisfies i) - iv), the firm's hiring decision is independent of the referral message. Therefore, all PBEs are payoff equivalent to the uninformative equilibrium.*

Intuitively, the referrer has an incentive to send a better but non-truthful message when ϕ is low because lying is costless. Knowing this incentive, the firm does not believe any message that leads to a strictly higher payoff to the referrer because if a message does so, other messages are not rationalizable. Thus, the referrer cannot perform better than no information. It means that all PBEs are equivalent in terms of the referrer's and firm's payoffs because the payoffs only depend on the hiring decision.

Note that there is a continuum of uninformative PBEs: for each $m \in \mathcal{M}$, sending m independent of ϕ constitutes an uninformative PBE. In addition, some PBEs are informative. If $w < y$, truth-telling is a PBE because the firm hires the worker regardless of information. While there is a continuum of informative and uninformative PBEs, all these PBEs are payoff-equivalent to the uninformative equilibrium.

2.4.2. Equilibrium characterization: Business referral case

I will omit superscript b in the strategy, belief, and hiring decision for the remainder of this section. Also, I will only consider truthful strategies: $\phi \in \sigma(\phi)$ for all ϕ. Especially, a pass-type strategy in this section refers to a truthful strategy satisfying (1). When the lying cost is higher than the referral benefit, the existence of a PBE satisfying i) - iv) is guaranteed because the full-revealing strategy $\sigma(\phi) = [\phi, \phi]$ constitutes a PBE. The question then is whether there exists another PBE which is better for the referrer. To show that this is the case, I will first prove that it is sufficient to focus on the pass-type strategy.

Proposition 2. *Let (σ, μ, h) be a PBE that satisfies i) - iv). Then,*

1. *The firm's hiring decision is independent of the interview signal.*
2. *There exists a threshold x such that the firm hires the worker if and only if ϕ is greater or equal to x.*
3. *There exists a payoff equivalent PBE in which the referrer uses a pass-type strategy.*

[12] I only consider the set of pure strategies.

In principle, the interview signal affects the hiring decision because the message is chosen before the interview. However, in equilibrium, the referrer chooses a strategy that makes the hiring decision independent of the interview signal. The interview signal realization can directly affect the hiring decision only if the firm puts strictly positive beliefs on at least two match qualities $\phi_H > w$ and $\phi_L < w$ after observing m. However, if this is the case, the referrer would reveal the match quality when the actual realization is ϕ_H. It means that the equilibrium hiring decision $h(\sigma(\phi), s)$ is a function of ϕ alone. This hiring function is a step-function of ϕ, implying that match qualities above a certain threshold are hired. A pass-type strategy can implement this hiring function.

Proposition 2 means that finding a referrer-preferred PBE is equivalent to finding the lowest hiring threshold. This threshold, say ϕ^*, makes the firm indifferent under the worst interview signal realization.[13]

$$\inf_s E(\phi|s, \phi \in [\phi^*, \infty)) \geq w, \quad \phi^* \geq y, \quad \left(\inf_s E(\phi|s, \phi \in [\phi^*, \infty)) - w\right) \cdot (\phi^* - y) = 0 \tag{2}$$

This characterization of ϕ^* establishes the referrer-preferred PBE.

Proposition 3. *In a referrer-preferred PBE that satisfies i) - v), the referrer uses a pass-type strategy with a threshold ϕ^*, and the firm hires the worker if and only if the referrer sends $[\phi^*, \infty)$. Conversely, each pass-type strategy with a threshold ϕ^* constitutes a referrer-preferred PBE.*

There is a one-to-one relationship between the set of pass-type strategies and the set of referrer-preferred PBEs. Because there is a continuum of pass-type strategies, a continuum of referrer-preferred PBEs exists. A common feature across all equilibria is that a unique message $[\phi^*, \infty)$ induces hiring when $\phi \geq \phi^*$.

The threshold quality ϕ^* is strictly lower than w if $w > y$.[14] Intuitively, the referrer can pool some qualities below w with good qualities while maintaining the firm's hiring incentive on average. In doing so, the referrer prefers pooling into a single message instead of two or more. This is because less informative messages reduce the credibility of the worst interview signal, which determines the threshold quality (Equation (2)). The referrer can lower the threshold by sending a unique message $[\phi^*, \infty)$ to induce hiring instead of sending multiple messages. Given that the referrer sends $[\phi^*, \infty)$ if $\phi \geq \phi^*$, the message choices when $\phi < \phi^*$ are irrelevant because the firm will not hire the worker unless the referrer lies. Therefore, a pass-type strategy constitutes a referrer-preferred PBE, and vice versa.

In any referrer-preferred PBE, the referrer does not differentiate how strongly she recommends once the match quality exceeds the threshold. This extensive margin choice fits the common notion of job referrals. In reality, most job referrals do not involve a formal letter with a complete description of the worker's quality. Proposition 3 shows that this norm can be an equilibrium outcome even when the referrer can freely choose the information to disclose. This equilibrium is qualitatively different from the unraveling equilibrium of Milgrom (1981) and Grossman (1981). The critical difference is that the referrer's payoff indirectly depends on μ through h, which takes only two values.[15]

Proposition 4 (Comparative Statics)**.** *If $\phi^* > y$, referrals become more informative as the wage increases: ϕ^* and ϕ^*/w are strictly increasing in w. Also, referrals become more informative as the interview signal becomes more informative: ϕ^* is increasing in τ, and $\phi^* \to w$ as $\tau \to 1$.*

The necessary and sufficient condition for $\phi^* > y$ is $w > E(\phi|s = y)$. When w is higher, a higher ϕ^* is required to make the firm indifferent. Furthermore, ϕ^*/w increases in w because the credibility of the worst interview signal increases as ϕ^* increases, which disciplines the referrer's information distortion behavior. For the same reason, ϕ^* becomes closer to w as the signal accuracy becomes more precise, $\tau \to 1$.

Let us examine how this information affects the real allocations. Denote the hiring rule without referral information by $h^n(s) \in \{0, 1\}$, and the hiring probability by $H^n(\phi) \equiv E_s(h^n(s)|\phi)$. Then, the *ex-ante* probability of hiring and expected payoff without referrals are $H^n = E_\phi(H^n(\phi))$ and $\Pi^n = E_\phi(H^n(\phi)J(w, \phi))$, respectively. Similarly, the *ex-ante* probability of hiring under business referrals is $H = E_\phi(h(\phi))$, and the *ex-ante* firm's payoff is $\Pi = E_\phi(h(\phi)J(w, \phi))$.[16]

Proposition 5 (Effects of referral information)**.** *If* $\phi^* > y$, the *ex-ante probability of hiring and firm's payoff are higher with referrals: $H > H^n$ and $\Pi > \Pi^n$. If $\tau\alpha \geq 1$, the average match quality conditional on hiring is higher with referrals: $E_\phi(\phi|h(\phi) = 1) > E_\phi(\phi|h^n(s) = 1)$*

Information *per se* may or may not increase hiring probability. For instance, precise information can reduce the probability of hiring both *ex-ante* and *ex-post*. This does not occur in the referrer-preferred equilibrium.

The firm cannot be worse off with referral information because the firm can ignore the message. However, it is not straightforward whether and why the firm is strictly better off given the referrer's information manipulation. Gains exist because the firm is indifferent under the worst s and strictly prefers hiring under any other s. If there is no interview signal

[13] Note that $\inf_s E(\phi|s, \phi \in [x, \infty))$ is increasing in x. I prove this property while proving Proposition 5 in the supplementary materials. This property is not immediate because the interview signal becomes more believable when the message becomes more precise.

[14] When w is low enough, the threshold ϕ^* coincides with y. In this case, the pass-type strategy is uninformative.

[15] See Miura (2014) for general cases in which the receiver's action set is binary.

[16] $h(\phi)$ is a short notation for $h(\sigma(\phi), s)$.

available, the firm should always be indifferent given the recommendation message. In this case, the firm's *ex-ante* payoff is zero so that the firm has no incentive to create referral vacancies.[17]

Regarding the average match quality among hires, referrals have two opposite effects. On the one hand, the hiring decision becomes more efficient as it directly depends on ϕ. On the other hand, referrals pool too many workers so that the marginal worker quality ϕ^* is lower than w. Which effects dominate depends on how close ϕ^* is to w. Because ϕ^* is closer to w when τ is higher, referrals improve the *ex-post* match quality when τ is high. The signal needs to be more precise (high τ) when the underlying distribution is more dispersed (low α), thus $\tau\alpha \geq 1$ is required. In the quantitative analysis, I calibrate τ and α and the calibrated $\tau\alpha$ is greater than 1.

2.5. Discussions

2.5.1. Equilibrium refinement

The equilibrium refinement does not play a role in a family referral case because all PBEs are payoff-equivalent. For the business referral case, one can check that a pass-type strategy constitutes a PBE satisfying i) - iv) if the threshold is in $[\phi^*, w]$. Therefore, a continuum of equilibrium payoffs exists without v). Among these PBEs, I will discuss the selection between two extreme cases: a full-revealing PBE and a referrer-preferred PBE. However, the logic can apply to comparing any PBE and the referrer-preferred PBE. For convenience, I denote the full-revealing strategy by F and the referrer-preferred strategy by R.

The first argument is based on the existence of behavioral types. Suppose there are two types of behavioral referrers, with measure ϵ each, who always play F and R respectively. Assume that the remaining $1-2\epsilon$ measure of referrers are rational, and choose a mixed strategy between F and R. Then, playing R with probability one is the only equilibrium in which all rational referrers play an identical strategy. The intuition is the following. Regardless of the probability that rational referrers play F, the posterior belief after observing $[\phi^*, \infty)$ puts measure one on the strategy R, because the probability of $[\phi^*, \infty)$ being played under F is 0. Given that firms believe $[\phi^*, \infty)$ coming from R, firms hire workers. Thus, a rational referrer prefers $[\phi^*, \infty)$ to $[\phi, \infty)$ when $\phi \in [\phi^*, w)$, meaning that there is no equilibrium in which rational referrers play F with a positive probability.

There are other justifications for the refinement. For instance, the equilibrium refinement of Matthews et al. (1991) and Farrell (1993) selects the referrer-preferred equilibrium from this model. There is also a heuristic argument favoring the referrer-preferred equilibrium. In reality, it would be reasonable to assume that referrers can be uninformative if they want to be. Referrers choose to be uninformative in the referrer-preferred equilibrium whenever it is *ex-ante* optimal. However, this is not the case in the full-revealing equilibrium.

2.5.2. General lying costs: $0 < \nu^f < z$

$\nu^f = 0$ assumption plays two roles in the $j = f$ case. First, the referral game becomes a case of cheap-talk games with $\nu^f = 0$. Second, this assumption helps to describe the off-the-path belief restriction *ex-ante*. Given $\nu^f = 0$, a PBE with the off-the-path restriction iii) always satisfies the intuitive criteria. If $\nu^f > 0$, it may not be a reasonable assumption that the firm puts weight one on y after observing a deviation message. Beyond this off-the-path restriction, zero lying cost *per se* is not critical for the model results. Once the off-the-path belief is given, Proposition 1 holds in more general cases when ν^f is positive but small. A sufficient condition is $\nu^f \leq \tau z$.

Although this study does not characterize the referrer-preferred PBE for the $\nu^f \approx z^f$ case, it can be shown that the referrer's payoff is weakly increasing in ν^f. This is because a PBE (σ^f, μ^f, h^f) under ν^f is also a PBE under $\hat{\nu}^f$ for all $\hat{\nu}^f > \nu^f$. Intuitively, as ν^f increases, the referrer becomes more credible so that the set of strategies that can be supported in equilibrium becomes larger.

3. Strategic referrals and on-the-job search equilibrium

This section embeds the referral game in Section 2 into a general equilibrium search model. Section 3.1 illustrates the model environments. I define a general equilibrium of the model in Section 3.2. Using the equilibrium labor market model, I analyze the implications of job referrals on wages and job-finding rates in Section 3.3.

3.1. Environment

3.1.1. Workers

Time is continuous. There is a unit measure of workers. Each worker belongs to an observable type $\xi \in \{1, 2, \cdots, \Xi\}$, which can represent educational attainment, occupation, industry, or a mixture of them. I use the notation x_ξ if x depends on ξ. Workers are risk-neutral and discount the future at a rate of $r > 0$. Workers are either employed ($l = 1$) or unemployed ($l = 0$), and there is a home production $b_\xi \geq 0$ when unemployed. Workers search for new jobs when employed and

[17] The equilibrium is equivalent to Kamenica and Gentzkow (2011). Note that this equilibrium occurs when $E(\phi) < w$. In this case, the firm does not have an incentive to create a non-referral vacancy whether or not there is interview signal.

unemployed. Each worker is connected to a continuum of other workers through family/friendships and business contacts. The size of the network and search efforts jointly determine the rate at which a worker receives referrals, but I normalize the network size to one. This normalization is without loss of generality because both network size and search efforts are unobserved and are not distinguishable in the calibration.

3.1.2. Production

A match between a worker and a firm produces output ϕ; an i.i.d draw from $F_\xi(x) = 1 - \left(\frac{y_\xi}{x}\right)^{\alpha_\xi}, x \in [y_\xi, \infty), \alpha_\xi > 2$. I assume that ϕ is purely match-specific, as in Jovanovic (1979) for two reasons. First, I want to isolate information transmission from learning through the employment history. If there is uncertainty in general human capital, the entire past employment history conveys information about human capital, generating complicated learning issues. Second, empirical evidence shows no significant difference in both observable and unobservable characteristics between referred and non-referred workers.[18] It suggests that job referrals are more than delivering information about a worker's permanent ability.

3.1.3. Search and matching

There are three market types $j \in \{n, f, b\}$ through which a worker meets a vacancy, where j represents non-referral, family referrals, and business referrals, respectively. There markets are not mutually exclusive. Instead, a worker searches for a job in all three markets simultaneously, where each j yields a meeting opportunity that follows an independent Poisson process. Although a meeting can occur from any of the three markets, at most one meeting occurs at each point in time because two independent Poisson shocks do not arrive simultaneously.

The meeting rate through j depends on the search target wage and the search efforts for j. As in standard directed search models, a continuum of submarkets indexed by (w, ξ) exists for each j, and market tightness θ is specific to (j, w, ξ). Taking $\theta(j, w, \xi)$ as given, a worker chooses one search target wage w_j and one effort level e_j for each j. Then, the worker meets a vacancy at a rate of $e_j p(\theta(j, w_j, \xi))$ from j market, implying that the worker's total meeting rate is $\sum_{j=n,f,b} e_j p(\theta(j, w_j, \xi))$. I assume $p(\theta) \equiv (1 + \theta^{-\gamma})^{-1/\gamma}$ for the matching function, but the specific functional form is not critical.

The meeting rate is not the rate at which a worker gets a job because not every meeting becomes a match. There is an information transmission stage after meeting, and a meeting becomes a match only if the firm decides to hire the worker based on the information realization. Once a meeting occurs in the f or b market, a corresponding referrer is randomly chosen from the worker's connections, and the chosen referrer and the firm play the referral game in Section 2. When a meeting occurs in the n market, the firm makes the hiring decision only based on the interview signal. Denote this endogenous hiring probability conditional on a meeting by $H_\xi^j(w)$. Then, a worker gets a new job from type-j market at a rate of $e_j p(\theta(j, w_j, \xi)) H_\xi^j(w_j)$, implying that the worker's job-finding rate is $\sum_{j=n,f,b} e_j p(\theta(j, w_j, \xi)) H_\xi^j(w_j)$.

There is a search effort cost $C_{l,\xi}^j(e_j)$, which is strictly increasing and convex, and $C_{l,\xi}^j(0) = 0$ for all j, l, ξ. This cost function incorporates the effects of different sizes of family and business connections. The cost function also reflects a relative difficulty between non-referral-based search methods and referrals. In reality, workers use various job search methods simultaneously.[19] They do so because the marginal return of each method is diminishing: online job postings are not infinite, nor is the number of friends. The convexity of $C_{l,\xi}^j(\cdot)$ captures this intuition.

Because the search cost is convex and additively separable, workers put a strictly positive effort into every market type. This cost structure implies that accessing several market types lowers the effective search costs. Indeed, accessing several informationally identical markets is mathematically equivalent to accessing one market with a lower search cost. Because I will calibrate the search cost functions later using macro moments instead of assuming in advance, the single non-referral market is without loss of generality. The distinction between family referrals and non-referral is for quantitative analysis.

A vacancy in a submarket (j, w, ξ) meets a worker at a rate of $q(\theta(j, w, \xi))$, and forms a match at a rate of $q(\theta(j, w, \xi)) H_\xi^j(w)$, where $q(\theta) \equiv p(\theta)/\theta$. I assume that firms pay a flow cost $k > 0$ per vacancy, which is independent of (j, w, ξ). Since few studies use a directed search approach to study referrals, it is difficult to directly compare this assumption to previous literature. Broadly, no cost difference exists in some studies (Dustmann et al., 2015; Galenianos, 2013) while others assume that referrals are less costly (Cahuc and Fontaine, 2009; Igarashi, 2016; Rebien et al., 2020). However, the rationale behind the cost difference is in informational aspects, such as lower screening costs for applicants with referrals. In this study, better information is an endogenous outcome rather than an exogenous parameter. Thus, I assume an identical cost across j.

Firms cannot adjust w after receiving information. Also, firms cannot fire workers after hiring. This contractual assumption makes information valuable in the hiring stages. The qualitative properties of the model will not change as long as hiring a bad worker is costly for firms. Relaxing this fixed-wage assumption is an interesting subject, but it requires additional structures to determine the wage path in a match.

[18] Burks et al. (2015) documented that referred and non-referred workers have a similar level of schooling, which is observable to the firm, and cognitive ability, which is unobservable to the firm. While they fail to find any significant difference in worker characteristics and preferences, they find differences in tenure and productivity between the referred and non-referred.

[19] In the SCE data, job searchers use 4.4 search methods on average.

3.1.4. Value functions

In the steady-state equilibrium, the value function of workers is follows:

$$rU_\xi = b_\xi + \sum_{j=n,f,b} R^j_{U,\xi} + \Upsilon_\xi \tag{3}$$

$$rV_\xi(w) = w + \delta_\xi(U_\xi - V_\xi(w)) + \sum_{j=n,f,b} R^j_\xi(w) + \Upsilon_\xi \tag{4}$$

where δ_ξ is the exogenous separation rate, Υ_ξ is the utility from being a referrer, which will be explained later. $R^j_{U,\xi}, R^j_\xi$ are the return to search net of search costs:

$$R^j_{U,\xi} = \max_{w'_j, e_j} \left\{ e_j p(\theta(j, w'_j, \xi)) H^j_\xi(w'_j)(V_\xi(w'_j) - U_\xi) - C^j_{0,\xi}(e_j) \right\} \tag{5}$$

$$R^j_\xi(w) = \max_{w'_j, e_j} \left\{ e_j p(\theta(j, w'_j, \xi)) H^j_\xi(w'_j)(V_\xi(w'_j) - V_\xi(w)) - C^j_{1,\xi}(e_j) \right\} \tag{6}$$

When workers choose which wages to search for, they consider the extent to which information is transmitted through referrals. The $H^j_\xi(w'_j)$ term in Eqs. (5) and (6) captures this consideration.

Denote the employed worker's search policy by $g^j_\xi(w)$ and the effort policy by $e^j_\xi(w)$ for each j. In words, an employed worker with current job w searches for a new job paying $g^j_\xi(w)$, and exerts search effort $e^j_\xi(w)$. It means that an employed worker leaves the current job through j at a rate of $S^j_\xi(w) \equiv e^j_\xi(w) \cdot p(\theta(j, g^j_\xi(w), \xi)) \cdot H^j_\xi(g^j_\xi(w))$. Thus, the value of a job $J_\xi(w, \phi)$ is the following:

$$J_\xi(w, \phi) = (\phi - w) \times \left(r + \delta + \sum_{j=n,f,b} S^j_\xi(w) \right)^{-1} \tag{7}$$

Recall that the value of a job was given by $A(\phi - w)$ in Section 2. Equation (7) shows that A is the inverse of the effective discount rate $(r + \delta + \sum_j S^j_\xi(w))$.

The free entry condition requires the expected value of a vacancy to be zero, which pins down the market tightness $\theta(j, w, \xi)$:

$$q(\theta(j, w, \xi)) \underbrace{E_\phi\left[h^j_\xi(w, \phi) J_\xi(w, \phi) \right]}_{= \Pi^j_\xi(w)} - k \le 0, \quad \theta(j, w, \xi) \ge 0, \quad \theta(j, w, \xi) \cdot (q(\theta(j, w, \xi)) \Pi^j_\xi(w) - k) = 0 \tag{8}$$

The expected value of a vacancy Π^j_ξ depends on the information through the three channels. First, the information directly affects h^j_ξ. Second, it affects the expected match quality conditional on hiring. Third, it influences J_ξ through its effects on S^j_ξ. As $\Pi^j_\xi(w)$ varies according to j, so does $\theta(j, w, \xi)$.

3.1.5. Referral payoff

The utility of being a referrer Υ_ξ is proportional to the referral benefit and the measure of referral matches created. As the latter depends on the wage distribution, U_ξ and V_ξ also depend on wage distribution. However, the dependence on distribution is not significant in this model because the value of being a referrer is not a main component of the lifetime value compared to labor income. Thus, the quantitative analysis focuses on an equilibrium in which $\Upsilon_\xi = 0$ is imposed, while taking $H^j_\xi(w)$ as given from $z, \nu^j > 0$. It is the limit equilibrium of $z, \nu^j \to 0$ keeping ν^j/z constant. Once $\Upsilon_\xi = 0$ is imposed, the value functions are independent of aggregate distributions (Menzio and Shi, 2011).

There are three justifications for this limit case. First, the referral game equilibrium depends only on the relative size between ν^j and z, and not on absolute values. Second, the payoff of a referrer is a minor component of lifetime value compared to labor income. Third, the absolute value of Υ_ξ does not affect workers' search and effort choices because it does not vary by labor market status.

3.2. Equilibrium

3.2.1. Definition of a steady-state and Block-recursive equilibrium

Definition 1. A steady-state equilibrium consists of the value functions (U_ξ, V_ξ, J_ξ), the optimal search and effort choice (g^j_ξ, e^j_ξ), the market tightness θ, the equilibrium of the referral game $(\sigma^j_\xi, \mu^j_\xi, h^j_\xi)$, the referral payoff Υ_ξ, and the aggregate distribution G over (w, ξ) such that

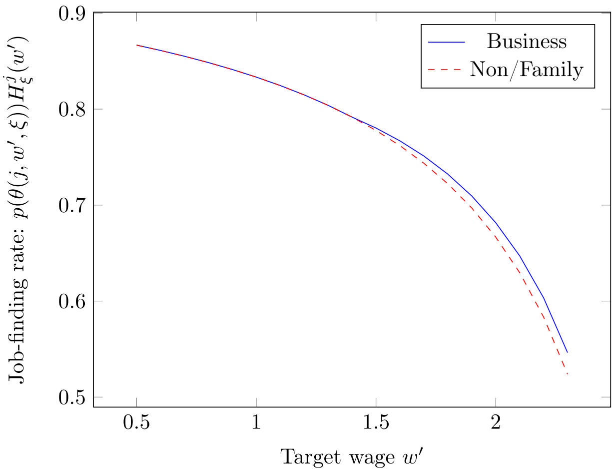

Fig. 1. Target wage and job-finding rate (given $e_j = 1$).

1. $(\sigma^j_\xi, \mu^j_\xi, h^j_\xi)$ is the referrer-preferred PBE given $J_\xi(w, \phi)$.
2. (U_ξ, V_ξ, J_ξ) is the proper value function satisfying (3) - (7), and (g^j_ξ, e^j_ξ) is the optimal policy associated with the value function given $(\sigma^j_\xi, \mu^j_\xi, h^j_\xi), \theta$, and Υ_ξ.
3. θ satisfies the free-entry condition (8) given $J_\xi(w, \phi)$ and $(\sigma^j_\xi, \mu^j_\xi, h^j_\xi)$.
4. Υ_ξ is consistent with the distribution G given $(\sigma^j_\xi, \mu^j_\xi, h^j_\xi)$ and (g^j_ξ, e^j_ξ).
5. G is the steady-state distribution over (w, ξ).

All the properties are self-explanatory. The steady-state equilibrium can be computed iteratively. Given Υ_ξ, all the other objects can be computed in a standard way. Then, the optimal search policies pin down G, which implies Υ_ξ.

Definition 2. Given $\Upsilon_\xi = 0$, a Block-recursive equilibrium consists of the value functions (U_ξ, V_ξ, J_ξ), the optimal search and effort choice (g^j_ξ, e^j_ξ), the market tightness θ, and the equilibrium of the referral game $(\sigma^j_\xi, \mu^j_\xi, h^j_\xi)$ that satisfy 1) - 3) in Definition 1.

A directed search plays a crucial role in the model tractability. If one uses the wage posting model of Burdett and Mortensen (1998), the offer distribution and the referral game equilibrium must be jointly solved. In this model, the referral game can be analyzed separately, taking the value of a vacancy as given.

3.3. Equilibrium analysis

How do referrals affect a worker's job-finding rate? In the model, the job-finding rate is a composite of the meeting rate and hiring probability. From Proposition 5, the latter probability is higher in the business-referral market when the wage of the target position exceeds a threshold. In this case, the expected value of a vacancy is also higher in the business-referral market (Proposition 5), implying a higher market tightness. As a result, the job-finding rate is higher in the business referral market.

Proposition 6. *If search target w' exceeds a threshold w_ξ, referrals from business contacts increase the job-finding rate given the search effort: $p(\theta(b, w', \xi))H^b_\xi(w') > p(\theta(n, w', \xi))H^n_\xi(w') = p(\theta(f, w', \xi))H^f_\xi(w')$*

Fig. 1 illustrates the trade-off between target wage and job-finding rate given the unit search effort $p(\theta(j, w', \xi))H^j_\xi(w')$. When the search target w' exceeds a certain level, workers face a more favorable job-finding rate through business referrals.

Whether a job searcher finds a better job from business referrals than from non-referral depends on the region where the optimal search target lies. The optimal search target is a function of the job searcher's current value, which is the outside option value when searching for a new job. From Eqs. (5) and (6), the search return $\tilde{R}^j_\xi(V)$ and optimal search target $\tilde{g}^j_\xi(V)$ satisfy Equation (9) given V, independent of the employment status and search effort choice.

$$\tilde{R}^j_\xi(V) \equiv \max_{w'_j} p(\theta(j, w'_j, \xi))H^j_\xi(w'_j)(V_\xi(w'_j) - V), \quad \tilde{g}^j_\xi(V) \equiv \arg\max_{w'_j} p(\theta(j, w'_j, \xi))H^j_\xi(w'_j)(V_\xi(w'_j) - V) \tag{9}$$

where the current value V is U_ξ for the unemployed and $V_\xi(w)$ for the employed. $\tilde{g}^j_\xi(V)$ is an increasing function of V (Shi, 2009), implying that a worker with a low outside option does not experience a higher job-finding rate nor a higher wage because the worker's optimal search lies in the low-wage region. For a worker with a high outside option, the search return is higher in the business-referral market.

Proposition 7. *The search return is higher in the business referral market for job searchers whose current value exceeds a threshold:* $\tilde{R}^b_\xi(V) > \tilde{R}^n_\xi(V)$ *for* $V > V^*_\xi$, *and* $\tilde{R}^b_\xi(V) = \tilde{R}^n_\xi(V)$ *for* $V \leq V^*_\xi$.

Given that the higher search return is associated with a higher job-finding rate and wage,[20] the referral wage premium through business contact exists only for workers with high outside options.

Proposition 8. *If a job searcher's current value exceeds a threshold* V^*_ξ, *business referrals increase the wage in the next job:* $\tilde{g}^b_\xi(V) > \tilde{g}^n_\xi(V)$ *for* $V > V^*_\xi$. *There is no wage difference otherwise:* $\tilde{g}^b_\xi(V) = \tilde{g}^n_\xi(V)$ *for* $V \leq V^*_\xi$

Several points are worth mentioning. First, if some employed workers do not experience the referral wage premium, then neither do the unemployed workers because $U_\xi < V_\xi(w)$ for any w in equilibrium. Second, the size of referral wage premium $\tilde{g}^b_\xi(V) - \tilde{g}^n_\xi(V)$ is not an increasing function of V. This is because wage gain from a job change falls as workers climb up the job ladder.[21] Motivated by these two points, in the empirical analysis, I compare the referral wage premium by employment status at the time when the current job offer was accepted. Lastly, Proposition 8 compares an identical worker's counterfactual search outcomes. Therefore, the referral wage premium in Proposition 8 is not a result of the search method selection.

The job-finding rate not only depends on the search target but also depends on the search effort, which is an increasing function of $\tilde{R}^j_\xi(V)$. Suppose the search cost of e_j is proportional to e_j^η for some $\eta > 1$. Then, high-wage workers put relatively more effort into business referrals than other methods compared to low-wage workers.[22] This relative search effort difference guarantees the relative job-finding rate difference.

Proposition 9. *If the search cost is proportional to* e_j^η, *the job-finding rate through business referrals relative to other method* $\frac{S^b_\xi(w)}{S^n_\xi(w)}$ *is higher for high-wage workers:* $\frac{S^b_\xi(w_H)}{S^n_\xi(w_H)} > \frac{S^b_\xi(w_L)}{S^n_\xi(w_L)}$ *if* $w_H > w^*_\xi > w_L$.

The previous literature finds empirical support for this pattern. Arbex et al. (2019) found that high-wage workers are more likely to find the next job through business referrals. Lester et al. (2021) find that the proportion of business-referrals increases in the occupational wage.

4. Empirical analysis

This section provides empirical support for the model prediction. The main empirical task is to estimate the referral wage premium of different types, family and business, and with high and low outside options.

4.1. Data and summary statistics

The data are from the Survey of Consumer Expectations (SCE) by the Federal Reserve Bank of New York. The SCE is a nationally representative monthly survey of approximately 1000 – 1300 individuals. This study uses the Job Search Survey 2013 – 2017. The data used in this study is a repeated cross-section.[23] For the analysis, I focus on people aged 16 to 64.

The survey asks through which channel the respondent learned about her current job. The designation "referred worker" denotes those respondents who have answered this question with one of the following: "Referred by a friend or relative;" "Referred by a former co-worker, supervisor, teacher, business associate;" "Referred by a current employee at the company." The first is denoted by "Family referral" and the second and the third are denoted by "Business referral." If a respondent answered more than one method, the respondent is classified as referred if one of the methods fell into the referral category. If a respondent answered both types of referrals, I classify the respondent as business referrals. I document the survey questions, answer options, and responses in the appendix.

According to this definition, 20.79% of workers are referred by family/friends and 20.32% are referred by business contacts, thus the total fraction is about 41%. This fraction is a bit smaller than what Topa (2011) suggests, but within a range documented in previous literature (Addison and Portugal, 2002; Galenianos, 2014; Wahba and Zenou, 2005). Another measure of job referrals is how many job searchers use their connections during the job search. The survey shows that 49.6% of

[20] It might be possible that workers increase target wages while decreasing target job-finding rates in response to the favorable shift of the choice set. Whether it happens or not depends on substitution and income effects, which depend on the functional form of F and p. I could not find analytical conditions that guarantee both $g^b_\xi(V)$ and $p(\theta(j, g^b_\xi(V), \xi))H^b_\xi(\tilde{g}^b_\xi(V))$ are increasing in information. In the calibration, workers increase both job-finding rates and wages under the calibrated parameters.

[21] Both random (Burdett and Mortensen, 1998) and directed search (Delacroix and Shi, 2006) have this feature.

[22] It cannot compare with the unemployed workers because the search cost function differs.

[23] The basic survey is a panel on which respondents stay for up to twelve months. Since I use the Job Search Surveys that are conducted once a year, the data used in this study is a repeated cross-section.

Table 1
Summary statistics.

	All	Employed	Referred	Non-referred
Observation	4522	3614	1282	2324
Age	45.171	43.855	42.535	44.557
Female	52.32%	49.07%	47.70%	49.70%
High school or less	34.15%	31.30%	33.12%	30.58%
Some Degree less than BA	31.83%	30.93%	29.44%	31.65%
Bachelor's Degree	20.66%	22.33%	22.32%	22.30%
Master's Degree	10.30%	11.88%	11.62%	11.94%
Doctoral or higher	3.05%	3.56%	3.51%	3.53%

current job searchers contacted their connections, which is higher than the fraction of workers who found the current job through referrals.

Table 1 presents the summary statistics of the individual characteristics. The group of referred workers was younger, with a higher male ratio. The educational attainment of referred and non-referred workers are similar, except for a small difference in the composition among those who hold less than a bachelor's degree.

4.2. Referral wage premium

The novel prediction of the model is that referrals from business contacts increase wages if job searchers' outside options exceed a certain level. I estimate the referral wage premium separately for worker groups with different outside options to test this prediction. Specifically, I estimate Eq. (10).

$$\log(w_i) = \alpha_{t(i)} + x_i'\beta_0 + \gamma_D \cdot D_i + \beta_{f,D} \cdot (Family_i \cdot D_i) + \beta_{b,D} \cdot (Business_i \cdot D_i) + \epsilon_i \tag{10}$$

The dependent variable w_i is the starting wage of the current job, and $\alpha_{t(i)}$ is the time-fixed effect for the year when the current job starts. x_i is individual characteristics including age, gender, schooling, part-time status, occupation, industry, region, and the last wage at the immediately preceding job. $Family_i$ and $Business_i$ are dummy variables for family and business referrals.

I use two specifications of D. The first specification is the worker's labor market status at the time of receiving the offer for the current job: $D_i \in \{\text{E–E,U–E}\}$.[24] The difference between E–E and U–E is whether the worker experienced a nonemployment spell between the immediately preceding job and the current job. The second specification is whether the worker's residual wage in the previous position exceeds the median: $D_i \in \{\text{High, Low}\}$. To calculate this residual wage, I regress the previous wage on age, gender, schooling, occupation, and time-fixed effect.[25] The parameter of interest is $\beta_{j,D}$, which represents the effects of j-type referrals dependent on D_i. The model predicts that $\beta_{b,\text{E–E}} > 0$ while all the others are insignificant in the first specification, and $\beta_{b,\text{High}} > 0$ while all the others are insignificant in the second specification.

By construction, only currently employed workers appear in the regression because the non-employed do not report the starting wage (of the current job). In addition, new labor market entrants are excluded, even though currently employed, because they do not have am immediately preceding job. The starting wage, referral status, and nonemployment spells are information at the time of hiring, which may lead to an error for workers with long tenure because those workers need to recall events that happened a long time ago. Thus, I consider workers whose current tenure is not too long, less than or equal 10 years. Lastly, I exclude the top and bottom 5% wage observations to eliminate the effects of outliers and measurement errors.

Table 2 presents the results of the estimation. In model (1), I first estimate the referral wage premium without distinguishing the types of referrals and worker groups D. The referral dummy has a positive but insignificant coefficient. In model (2), I distinguish between family/friends referrals and business referrals. Consistently with Lester et al. (2021), only business referrals have positive and significant effects on starting wages.

The main empirical result is shown in model (3). The results show that only business referrals with E–E transitions positively and significantly affect wages, while all the others are insignificant, consistent with the model's prediction. The result of model (4) is similar to that of model (3). Only business referrals for workers with previous high wages have positive and significant effects, while all the other coefficients are insignificant. While it is not the focus of this study, the U–E transition coefficient in model (3) shows a substantial earning loss (12.6%) from a job loss.

Before closing the empirical section, it is worth mentioning why the empirical results presented support the model in this study. Regarding the referral wage premium, three theories are widely cited:[26] (i) referrals reduce uncertainty in general human capital (Montgomery, 1991); (ii) referrals reduce uncertainty in match-specific productivity (Galenianos, 2013; Simon

[24] The question asks whether the respondent was employed when having received the current offer. Therefore, workers are classified as U–E if they were hired from the out of the labor force.

[25] All variables are information about the previous job or at the time when the worker left the previous job.

[26] Other theories of referrals include moral hazard (Heath, 2018), hiring costs (Igarashi, 2016), and firm heterogeneity (Rebien et al., 2020).

Table 2
Wage regression.

	(1)		(2)		(3)		(4)	
	$\log(w_i)$		$\log(w_i)$		$\log(w_i)$		$\log(w_i)$	
$\log(prewage)$	0.596***	(0.024)	0.593***	(0.024)	0.598***	(0.023)	0.532***	(0.036)
Age	0.012	(0.007)	0.013	(0.007)	0.012	(0.007)	0.018*	(0.007)
Age.Sq	−0.000*	(0.000)	−0.000*	(0.000)	−0.000*	(0.000)	−0.000**	(0.000)
Edu:Coll	0.022	(0.025)	0.024	(0.025)	0.024	(0.025)	0.026	(0.027)
Edu:BS	0.176***	(0.030)	0.176***	(0.030)	0.172***	(0.029)	0.192***	(0.032)
Edu:MS	0.261***	(0.039)	0.262***	(0.039)	0.256***	(0.038)	0.275***	(0.042)
Edu:Dr	0.362***	(0.064)	0.361***	(0.064)	0.339***	(0.063)	0.409***	(0.069)
Part-time	−0.242***	(0.029)	−0.240***	(0.029)	−0.199***	(0.029)	−0.248***	(0.030)
Female	−0.057**	(0.022)	−0.054*	(0.022)	−0.056**	(0.021)	−0.064**	(0.023)
Referral(Any)	0.024	(0.019)						
Family			−0.015	(0.026)				
Business			0.052*	(0.023)				
U-E					−0.126***	(0.026)		
Family*U-E					−0.035	(0.044)		
Family*E-E					−0.012	(0.031)		
Business*U-E					−0.017	(0.044)		
Business*E-E					0.052*	(0.026)		
Low							−0.071*	(0.033)
Family*Low							0.025	(0.036)
Family*High							−0.073	(0.040)
Business*Low							0.037	(0.034)
Business*High							0.069*	(0.032)
Constant	−0.248	(0.269)	−0.228	(0.269)	−0.170	(0.263)	−0.297	(0.274)
Observations	1006		1006		1006		960	
Adjusted R^2	0.687		0.689		0.704		0.689	

Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

and Warner, 1992); (iii) workers with better networks are more likely to be referred (Arbex et al., 2019; Calvo-Armengol and Jackson, 2004). Under the first and second theories, the referral wage premium exists for everyone because information flows regardless of the job searchers' labor market status. Under the third theory, the referral wage premium disappears once the previous wage is controlled because the frequency at which a worker receives an offer does not affect the current wage after controlling for previous wages. Thus, the empirical results are consistent with the model in this study but not with other theories.

One may be concerned that unobserved worker heterogeneity is correlated with both D and the effects of referrals. Then, the result can be due to the heterogeneous effects of referrals for different worker types instead of the outside option difference. In this regard, I prefer the first specification $D = \{\text{E–E,U–E}\}$ because this measure is not necessarily correlated with unobserved worker quality. For illustration, assume there are two unobservable qualities: high and low. Assume that high-type workers move to the next job through an on-the-job search at a rate of s_H and are separated into unemployment at a rate of δ_H. The corresponding figures for the low type are denoted by s_L and δ_L, respectively.

The unobserved qualities and D are positively (negatively) correlated if high-type workers are more likely to be in E–E (U–E) state than low-type workers. Note that the probability of being in E–E state conditional on currently employed is $s_j/(s_j + \delta_j)$ in the steady-state for $j = L, H$. Theories tell either number can be larger because high-quality workers are less likely to be separated into unemployment and stay at a job longer, meaning that $\delta_H < \delta_L$ and $s_H < s_L$ (Carrillo-Tudela and Kaas, 2015; Hom et al., 2008).

5. Quantitative analysis

In this section, I calibrate the model to quantify the aggregate effects of job referrals on the total output and distribution. Despite their widespread use, few studies have tried to quantify the effects of job referrals on the aggregate economy.[27] The model in this paper provides an appropriate tool for this exercise because the model endogenously captures both information transmission and on-the-job search.

5.1. Calibration

The model was calibrated on a monthly basis. I assume two types of workers, $\xi \in \{L, H\}$, which represent Low/High match quality dispersion. The types only differ by distribution parameter α_ξ,[28] and all the other parameters are identical

[27] The only exception is Igarashi (2016).

[28] Given y, a more dispersed distribution has a higher mean. In the data, occupations with a larger residual wage dispersion are highly paid on average.

Table 3
Parameters taken directly from data or outside.

Objects	Par	Value	Source or target
Discount rate	r	0.0069	Annual discount 5% and 30 years of lifetime
Home production	b	0.5	Shimer (2005)
Separation rate	δ	0.0123	Faberman et al. (2021)
Matching function elasticity	γ	1/3	Blanchard and Diamond (1989)
Message sending prob.	ζ	0.8	Burks et al. (2015)
Convexity of search cost	η	1.8403	Christensen et al. (2005)
Minimum productivity	y	1	Normalization
Dispersion parameter (L)	α_L	7.32	the 90/10 ratio 1.35
Dispersion parameter (H)	α_H	4.14	the 90/10 ratio 1.7

Table 4
Calibrated parameters and model fit.

Objects	Par	Value	Data Moments	Target	Model
Vacancy cost	k	0.4916	Unemployment rate	5.61%	5.53%
Search cost (non-referral)	c^n	0.2722	E-E rate	2.25%	1.41%
Search cost (family)	c^f	0.6508	Referral fraction	41.1%	41.1%
Search cost (business)	c^b	2.5817	Business/Any referrals	49.4%	49.2%
Search cost of employed	κ	0.1861	Wage premium (Business,E–E)	5.20%	4.97%
Interview accuracy	τ	0.7055	Wage premium (Business,U–E)	0%	0%

across types. When I bring the model to data, I use occupational wage dispersion to define the worker's type. The occupation classification is in the appendix. According to this classification, the proportion of L-type workers was 46%.

The discount rate r is set to 0.0069, reflecting the annual discount rate of 5% and the 1/360 hazard rate of exiting the labor market. I normalize the minimum productivity $y = 1$ and set home production b to 0.5, following Shimer (2005). The monthly separation rate δ is 1.23% according to Faberman et al. (2021). For the matching function, the CES functional form is used: $p(\theta) = (1 + \theta^{-\gamma})^{-1/\gamma}, q(\theta) = (1 + \theta^{\gamma})^{-1/\gamma}$. Different values have been used for the elasticity parameter γ, from 0.2 in Menzio and Shi (2010) to 1.6 in Schaal (2017). I use $\gamma = 1/3$ to make the elasticity of substitution between u and v 0.75, as suggested by Blanchard and Diamond (1989).

I assume that the relative cost across search methods does not differ by labor market status, implying that $C_0^j(e) = \kappa C_1^j(e)$ for some $\kappa > 0$. I impose the parametric form of $C_0^j(e) = \frac{1}{\eta} c^j e^{\eta}$, and set $\eta = 1.8403$, following Christensen et al. (2005).

There is a concern that not every referral, in reality, transmits information, so that the model may overestimate the value of referrals. To address this concern, I introduce an additional parameter ζ, the probability that referrers observe the true match quality. I assume that firms know whether referrers observe the true match quality. Therefore, the equilibrium of the game is the same when referrers observe the match quality. This modification is for quantitative purposes and does not affect the qualitative results.

There is little direct information on this parameter. In the online appendix of Burks et al. (2015), using one firm's dataset that includes both self-reporting referral status (provided by workers) and administrative data, they document that approximately 80% of job applicants who self-report having been referred are registered in the firm's administrative referral system. I interpret registration in the referral system as information transmission, which implies that $\zeta = 0.8$.

There is no direct estimate of the match quality dispersion. Thus I use information from labor productivity dispersion. Bagger et al. (2014) document that the 90/10 productivity ratio ranges from two to three, and the contribution of firm-level TFP to this dispersion is approximately 70%. I assume that half of the firm's TFP dispersion is driven by match quality, meaning that the match quality dispersion accounts for 35% of the 90/10 ratio. Consequently, I set $\alpha_L = 7.32$ and $\alpha_H = 4.14$, implying a 90/10 ratio of 1.35 for the L-type and 1.7 for the H-type. Table 3 summarizes parameter values chosen before calibration.

There are six parameters remaining: $(c^j)_{j=n,f,b}, \kappa, k, \tau$. These parameters are calibrated to match the data moments in Table 4. The heuristic argument for calibration is as follows: The unemployment rate disciplines the vacancy cost k. The fraction of referred workers in equilibrium is influenced by the cost of referrals, thus determining c^j. κ is set to match the E–E transition rate, and the referral wage premium pins down τ. All targeted moments are directly calculated from the SCE data except the E–E transition rate. I target a 2.25% E–E transition so that the fraction of employed workers without an unemployment spell between the previous and current jobs equals to 2/3.

The targeted moments and calibrated parameters are listed in Table 4. The calibrated search costs c^j show that referrals are costlier than non-referral, and business referrals are costlier than family referrals. The estimated costs are consistent with the data pattern in which contacting family and friends are more prevalent than contacting business connections.[29] It is an extensive margin in the data, but the model generates it as an intensive margin. The calibrated τ is relatively high,

[29] I documented this pattern in the supplementary materials.

Table 5
Aggregate effects.

	Benchmark	No Referrals	No information
Output	1.4773	1.4215	1.4617
$E(w)$	1.2874	1.2670	1.2791
$E(\phi)$	1.5345	1.4982	1.5176
Unemployment rate	5.53%	7.68%	5.50%
Referral fraction	41.1%	0%	35.84%
$E(w_H)/E(w_L)$	1.2590	1.2378	1.2457
Mean-min ratio	1.2440	1.2130	1.2360

Table 6
Non-targeted moments.

	L-type		H-type	
	Data	Model	Data	Model
Referral fraction	41.1%	39.3%	41.6%	42.5%
Business referrals/Any referrals	46.1%	45.4%	52.4%	52.1%
Referral premium (E–E, Business)	4.1%	2.4%	6.9%	6.5%

such that $\tau\alpha_\xi$ is much larger than 1 for both types. It means that the average match quality among employed workers is higher for the referred workers.

5.2. Aggregate effects of job referrals

To what extent do job referrals affect the aggregate labor market? In the model, referrals play two roles. First, referrals facilitate workers' search by effectively reducing search costs. Second, referrals transmit information about match quality. To quantify the effects of each role, I conduct two counterfactual exercises. In the first counterfactual exercise, I eliminated referral markets by imposing $C_l^j(e) = \infty$ for $j = f, b$. It shuts down both roles of referrals, allowing for measuring the total effects. In the second counterfactual exercise, I shut down the information transmission but do not prevent workers from searching for a job using referrals. I conduct this exercise by imposing $\nu^f = \nu^b = 0$.

Table 5 shows the results. When the benchmark economy and counterfactual economy without referrals are compared, the output is significantly higher in the benchmark economy, 3.93%. The output gap comes from 2.42% higher average productivity among the employed and 2.15%p lower unemployment rate. Intuitively, banning referrals makes it harder for workers to find jobs, raising the unemployment rate. Also, prohibiting referrals harms the average productivity through the direct information effect and slowed sorting.

The two roles of referrals, reducing search costs and transmitting information, simultaneously contribute to the higher output. The third column shows that the contribution of information transmission is about 28%, and reducing search costs explains the remaining. Considering the prevalent use of job referrals in the SCE data, it is intuitive that the quantitative effects of search costs are large.

Interestingly, the economy with only uninformative referrals has a slightly lower unemployment rate. It is not an accident but a result of heterogeneous information. In the benchmark economy, firms hiring unemployed workers do not directly benefit from referrals. By contrast, the hired worker leaves earlier because of informative referrals for employed workers. Therefore, the value of a vacancy in the low-wage region is lower in the benchmark economy, pushing down the job-finding probability of the unemployed. Nevertheless, the unemployed workers in the benchmark economy do not lower their search target because the unemployed value is not lower due to the lucrative search outcomes after being employed. As a result, the equilibrium unemployment rate is higher in the benchmark economy.

Regarding wage distribution, the wage gap between the two types is larger in the benchmark economy. Job referrals also increase the frictional wage dispersion within type, which is measured by mean-min ratio. Two mechanisms mainly work for this result. First, information disproportionately benefits high-wage workers. Second, job referrals boost the job-to-job transition rate. While referrals increase the frictional wage dispersion, the model still does not produce a realistic degree of wage dispersion, similar to other search models (Hornstein et al., 2011).[30]

In Table 6, I calculate some non-targeted moments regarding the use and effects of referrals in the benchmark economy. Recall that the only difference between L and H is the distribution parameter α_ξ, and the search costs are common across types. The model reproduces data features qualitatively: a larger fraction of referred workers, a larger fraction of business referrals among the referred, and a larger referral premium for H-type workers.

[30] In the benchmark economy, the mean-min ratio is in the middle of the mean-min ratio within each type.

6. Conclusion

In the U.S. labor market, nearly a half of workers use referrals when searching for a job. This study examines an equilibrium labor market model with referrals to understand how job referrals affect individuals' search outcomes and the aggregate labor market. In the model, the extent of information transmission through referrals is determined endogenously by a strategic game. In equilibrium, referrals are more informative when referrers face higher costs of lying, and the prospect match's wage is higher. I embed this information game into an equilibrium labor market framework where search decisions and information interact. The model predicts that referrals from business connections increase wages for workers with higher option values. Using the Survey of Consumer Expectations, I confirm the model prediction by showing that referral status is positively associated with wages only for employed job searchers. Quantitatively, referrals increase the total output by 3.93%, and transmitting information about match quality explains about 28% of this effect. Regarding wage distribution, referrals increase wage dispersion both within and between groups.

Data Availability

Data will be made available on request.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2022.12.003

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