The Cyclical Behavior of a Firm's Optimal Market and Referral Hiring

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Abstract

A stochastic matching model is proposed to study the cyclical behavior of a firm's market and referral hiring. Market hiring is frictional while referral hiring is congestional. Both market and (employee) referrals yield good and bad matches. At the steady state, relative to the market, the referral channel is more likely to yield a good match, less costly to hire but it is less likely to yield a match. This quantity-quality-cost tradeoff produce an interior solution to a firm's hiring choice. Three types of shocks are considered - match productivity shocks, market and referral match quality shocks. Negative shocks to match productivity encourage market hiring and discourage referral hiring. This is consistent with the empirical evidence of firms' hiring in the U.S. between 2013 and 2021. Shocks to market match quality are the least efficient in explaining the data patterns of hiring and standard labor market variables. Shocks to referral match quality are the most efficient in explaining the observed variation of hiring, while shocks to match productivity are the most efficient in explaining the observed variation of labor market tightness. Shocks to both market and referral match quality generate an upward sloping Beveridge Curve, but the one from referral match quality shocks is more volatile around the trend.

Keywords: Market Hiring, Referral Hiring, Network, Labor Productivity, Business Cycle, Unemployment
JEL classification: J240, E320, J640, J0

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1 Introduction

Empirical evidence from the Survey of Consumer Expectations (SCE) show that firms in U.S. hire more through the market hiring channel and less through the employee referral hiring channel during the recession year (2020) relative to other non-recessionary years.[1] But, the question is why it is so? Apart from these empirical facts, there is a large body of empirical literature (Bradshaw (1973), Granovetter (1974), Montgomery (1991), Bortnick and Ports (1992), Ports (1993), Burks et al. (2015), Topa (2011), Bentolila et al. (2010)), which finds that referral hiring accounts for a substantial part, about 15-75%, of the total hiring. Also, some articles like Shimer (2005), Hagedorn and Manovskii (2008), Mortensen and Nagypal (2007), Shimer and Borovickova (2024)) etc. present stochastic matching models, studying only market hiring and unemployed workers, attempting to understand the driving forces behind the cyclical behavior of equilibrium unemployment and vacancies rate, while Zaharieva (2018) study only referral hiring. Additionally, there is also a burgeoning theoretical and empirical literature which tries to understand referral hiring - Burks et al. (2015), Calvo-Armengol (2003), Fontaine (2007), Igarshi (2016), Galenianos (2020), (Montgomery (1991), Calvo-Armengol and Jackson (2004), Boucher and Gousse (2018)) etc.

Works like Pissarides (2000), Nagypal (2006), Krause and Lubik (2010), Elsby and Gottfries (2022) propose theoretical frameworks to match the business cycle mechanics of on-the-job search intensity, worker and job flows, quits, layoffs, hires, job-to-job transitions and other labor market variables using idiosyncratic productivity shocks. Gertler et al. (2020), explains that controlling for composition effects like procyclical upgrading of job match quality make the observed wages of new hires acyclical. They also develop a theoretical model incorporating staggered wage contracting, variable match quality and on-the-job search with endogenous search intensity to illustrate various observed moments in their data.

The corresponding empirical literature on job search is vast and growing. Sahin et al. (2018) examines the cyclicality of job search effort of nonemployed individuals using time-series, cross-state and individual variation and finds that it is counter-cyclical. Faberman and Kudlyak (2016) studies the search intensity and search duration of non-employed job seekers. They argue that job seekers with the lowest returns to job search exert the highest effort, and that the standard matching

[1] Due to data availability from 2013 onwards only, I only have the COVID year as the so called "recession" year.

models fail to capture this phenomenon. Barnichon and Zylberberg (2019) demonstrate that in the U.S., unemployed workers with lower job-finding rates tend to search more than others. Moreover, Ahn and Shao (2021) provides empirical evidence that on-the-job search is counter-cyclical while Fallick and Fleischman (2004) finds it to be pro-cyclical in U.S.. Ann and Shao (2021) suggests that the fear of job loss, employment uncertainty and workers' liquidity or credit situations are crucial in determining the on-the-job search intensity over the business cycle apart from other factors like risk aversion and absence of income insurance.

But no article has theoretically modelled a firm's decision to hire through both the channels simultaneously and studied the cyclical behavior of optimal market and referral hiring rate over the business cycle. To study that, this paper presents a stochastic infinite horizon discrete time Mortensen-Pissarides (MP) search and matching model, which endogenizes the firm's hiring decisions through the market and referral channel, and where firm-worker matches happening through both the hiring channels can be both good and bad. [2] In the model, the likelihood of a match is endogenous but the likelihood of a good match and the cost of hiring are distinct and exogenous across the two hiring channels. A good match is highly productive and lowly separable while a bad match is lowly productive and highly separable. Both match productivity and match separation rates are exogenous in the model. [3] This framework allows me to analyze how much a firm's market and referral hiring is responsive to shocks to match productivity, shocks to market and referral match quality. The results help conclude which types of shocks propagate the most in the MP model and how much it helps in explaining the cyclicality of market, referral hiring and other labor market variables in the data.

Market matching is frictional and is proxied by a standard Cobb-Douglas matching function in equilibrium vacancies and unemployment rate. The market job-finding and job-filling rates are given by the ratio of the market matching rate over the unemployment rate and vacancies rate respectively.

[2] Besides, there are a plethora of articles (Burks et al. (2015), Zaharieva and Alaverdyan (2022), Galenianos (2020), Galenianos (2016), Horvath (2014), Bentolila et al. (2010), Pellizzari (2010), Montgomery (1991) , Granovetter (1974), Holzer (1988) etc.) talking about which hiring channel is more likely to yield a match and which one is more likelier to produce a good match and the debate is still ongoing.
Galenianos (2020) finds that referrals improve welfare if workers are productively heterogeneous. Referrals worsen welfare if workers face discrimination despite being equally productive.

[3] It is assumed that the firms don't know the worker's type when hiring the worker. Also, there is no employer learning in this model.

Referral matching is congestional. The network is assumed to be homogeneous and identical in the sense that each employee or unemployed worker has identical number of social contacts. Both well matched and badly matched employees can provide a good or a bad referral depending on how hompohilous (fraction of similar type employee-worker links) their network is. The referral job-filling rate is given by the ratio of chance of finding at least one unemployed contact in the employee's network to the expected number of unemployed contacts in the network. The referral job-finding rate is given by the expected number of unemployed workers in the network of each employee.

Firms incur a vacancy posting cost to advertise market vacancies while they don't advertise vacancies filled through the employee referral channel. Besides, they also incur market and referral hiring costs. Given this, each firm maximize expected profits from referral and market hiring net of hiring costs by choosing the fraction to hire through each channel such that the market and referral hiring rates are normalized to 1.

Labor market is competitive, and thus the free entry-exit of firms guarantee that an unfilled vacancy earns zero profits in equilibrium. The equilibrium market tightness is determined by the equality of vacancy posting costs and discounted expected profits from market hiring. Inflow and outflow of well and badly matched workers determines the fraction of good and bad matches in the aggregate labor market. Wages are bargained between the firm and the unemployed worker using the generalized Nash bargaining rule.

The calibrated model at the steady state shows that referred matches are less likely to be formed but they are more likely to be good compared to the market matches. Additionally, referral hiring is cheaper than market hiring. This quantity-quality-cost trade-off is integral to producing an interior solution to the firm's choice. The referral channel is less profitable to the firm than the market channel and also the average expected profits per referred worker is less than the average expected profits per market hired worker (contradictory to Burks et al. (2015)).

Negative match productivity shocks (recessions) increase the unemployment rate and decrease the vacancies rate, resulting in a decrease in market tightness. Lower market tightness increases the chance of each advertised market vacancy to get filled up. This leads to increase in the market hiring rate. Higher unemployment rate also decreases the probability that a vacancy is filled through the employee referral channel. This is because higher unemployment rate increases the expected

number of unemployed contacts in the employee's network. In other words, network becomes more congested with more unemployed workers, so the chance of each worker hearing of a job opening reduces. In the calibrated model, productivity shocks of observed magnitude generates about one-third of the observed variation in market hiring rate and one-fourth of the observed variation in referral hiring rate in U.S. between 2013 and 2021. Moreover, shocks of this magnitude generates about 22% of the observed variation in market tightness.

Positive shocks to market good match rate increase market hiring rate and decrease referral hiring rate. Higher values of market good match rate increase both vacancies and unemployment rates. This is because, relative to the referral channel, as the market becomes more efficient in providing a good match, the firms want to hire more through the market and to do that they advertise more. But market matching being frictional, equilibrium unemployment rate rises. Quantitatively, the increase in unemployment rate dominates the increase in vacancies rate and therefore the market tightness decreases. This results in higher market job-filling rates and hence more market hiring. The referral matching, on the other hand, suffers the negative externalities of frictional market matching in terms of more unemployed workers in the employee's network, which results in lower referral job-filling rates and hence lower referral hiring. In the calibrated model, the market good match rate shocks has about one-third of the observed variation in the data. Shocks of this magnitude generate about 13% of the observed variation in market and referral hiring rate. Shocks of this magnitude generates less than 1% of the observed variation in the tightness.

Positive shocks to referral good match rate increase referral hiring rate and decrease market hiring rate. Higher values of referral good match rate decrease both vacancies and unemployment rates. This is because, as the network becomes more efficient in providing a good match, the firms want to hire less through the market and as a result they advertise less. The referral channel being not congestional at the steady state, unemployment rate decreases. Quantitatively, the decrease in unemployment rate dominates the decrease in vacancies rate and therefore the market tightness increases. This results in lower market job-filling rates and hence less market hiring. The lower market hiring is the negative externality of higher referral good match rates and higher referral hiring. But, lower unemployment rates and a tighter market imply that it is easier for the unemployed workers to find a job through both the market and referral channel. So, higher referral good match rates reduce the network congestion and make market hiring more frictional for the

firms. Therefore, the referral hiring increases. The model incorporates referral good match rate shocks near to observed magnitude. The model produced variation in market hiring rate is about 37% of its observed variation and that of referral hiring rate is about 40% of its observed variation.

Shocks to match productivity and market good match rate make expected referred wage exceed expected market wage in steady state, with referred employees enjoying approximately 50% wage premium relative to market hired employees in each case. With productivity shocks, expected market wage is counter-cyclical while expected referred wage is pro-cyclical. Therefore, the cyclicality of market and referral hiring rates determine the cyclicality of expected market and referral hiring rates. With shocks to market good match rate, expected market wage is pro-cyclical while expected referred wage is counter-cyclical. The intuition being the same - higher market good match rates imply more market hiring and hence the market wage goes up. But interestingly, shocks to referral good match rate makes expected market wage exceed expected referred wage, with market hired employees enjoying a wage premium of 80% relative to the referred employees. This is because at steady state, although market hiring and market job-filling rate decreases, the steady state market good match rate is big enough relative to referral good match rate to favor the market hired workers earn higher wages. With shocks to referral good match rate, expected market wage is counter-cyclical while expected referred wage is pro-cyclical. So, in all three types of shocks, the uniform conclusion is that the cyclicality of market and referral hiring rate plays a determining role in the cyclicality of market and referred wages.

I also find some interesting predictions on the shape of Beveridge Curves (BC) with match quality shocks [4]. With shocks to market good match rate, the non-detrended and the cyclical BCs are both upward sloping, contrary to the conventional BC. As market good match rate increases, firms post more vacancies, thus decreasing the chance of each vacancy getting filled. In other words, the frictions for the firms to form a match through the market increases and hence unemployment rate also increases. With shocks to referral good match rate, the non-detrended BC is U-shaped with no trend, which is again contrary to the conventional BC. But, the deviations from trend of vacancies rate increase with deviations from trend of unemployment rate. For the non-detrended curve, there exists a critical level of referral good match rate. For any value less than that, market matching rate reduces because firms reduce vacancy posting and therefore unemployment rate

[4]Match productivity shocks generate a conventional downward sloping BC.

increases. For any value above that, firms increase vacancy posting because referral matching is congestive at higher unemployment rates. More vacancy posting means more market matching, but market matching is also frictional, so unemployment rate rises due to both network congestion and market frictions.

So, the contributions of this paper are two-fold: (i) propose a theoretical model with endogenous firm's market and referral hiring, where the former is frictional while the later is congestional. (ii) quantify the cyclical behavior of optimal market, referral hiring rates and other equilibrium variables in response to three types of shocks. The effect of shocks on market aggregates help identify which channel is suffering the negative externality of the shocks, which depends on whether matching becomes more frictional or more congestional or both. (iii) non-standard predcitions on the shape of BC with respect to match quality shocks.

The rest of the paper is organized as follows: Section 2 talks about the Data, Section 3 details the model and defines the competitive equilibrium, Section 4 presents the quantitative results from productivity shocks in the model, Section 5 discusses the cyclical behavior of the endogenous variables from productivity shocks in the model, Section 6 and 7 detail the quantitative results from market match quality and referral match quality shocks respectively, and Section 8 concludes.

2 Data

2.1 Market and Referral Hiring Rate

The data on the fraction of workers who were referred and non-referred (market hired) has been taken from SCE (Survey of Consumer Expectations, FED NY) Job Search Supplement. The sample period is from 2013-2021. The annual supplement is a series of repeated cross section of survey respondents with roughly around 1300 respondents each survey year. Moreover, the survey is a nationally representative sample of household heads aged 18 and older.

To precisely know how the respondent learnt about their best job offer (who had at least one job offer in the last 4 weeks or 6 months), I look for the answer to the survey question: "For this (your best) offer, how did you learn about this job?". The respondent can choose from among these choices: found through the employer's website, inquired with the employer directly through other means, including in-person, found through an employment agency or career center, found through

an online job search engine, found job opening through other means, including help-wanted ads, found through union/professional registers, referred by a friend or relative, referred by a former co-worker, supervisor, business associate, referred by a current employee at the company, a temporary job was converted to a permanent job, had worked for this employer previously.

To find whether they eventually accepted or wished to accept their best job offer, I look for the answer to the survey question: "Have you accepted, or do you plan to accept, this (your best) job offer?". The choices available to them to choose from are: accepted or will accept, rejected or will reject, don't know yet.

The respondents who self reported to have learnt about their best job offer from a referral by a friend or relative or from a referral by a former co-worker, supervisor, business associate or from a referral by a current employee at the company or from an unsolicitated contact by potential/employer, recruiter or headhunter and has accepted/will accept the job offer has been counted as being referred in the constructed/cleaned sample. The respondents who self reported to have found their best job offer through the employer's website or inquired with the employer directly through other means, including in-person or found through an employment agency or career center or found through an online job search engine or found through other means, including help wanted ads or found through union/professional registers and has accepted/will accept the job offer has been counted as being market hired in the constructed/cleaned sample.

Finally, the constructed/cleaned sample consists of a total of 773 (with an average year containing approximately 86) survey respondents and information on how they were hired. On average, in the sample, about 50% of workers learnt about their jobs through referral and market channel. Figure 2.1 shows the market/referral hiring rates over the business cycle between 2013 and 2021. We can see that market hiring rate is counter-cyclical with real GDP while the referral hiring rate is pro-cyclical with real GDP. Moreover, the cyclical component of the annual series on market and referral hiring rate has a standard deviation of 0.053. The cyclical component of market and referral hiring rate has a yearly auto-correlation coefficient -0.37. The cyclical component of log real GDP is positively and negatively correlated with the cyclical component of referral and market hiring rate respectively, the magnitude being 0.724. More on the data source for the calibrated parameters can be found out in Section 4.1 (Calibration).

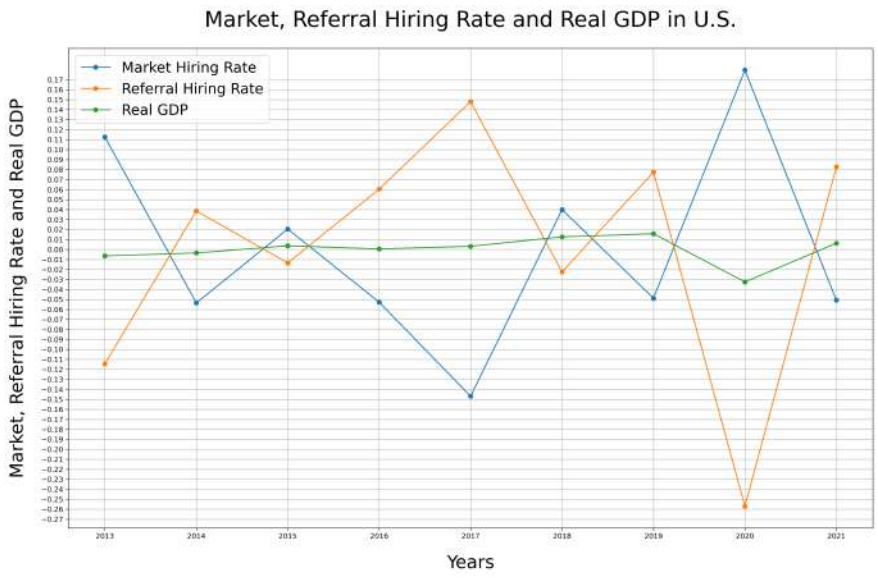


Figure 2.1: Annual Market, Referral Hiring Rate and Real GDP in U.S., 2013-2021.

Notes: The above figure shows the variation of annual time series data on market, referral hiring rates and real GDP. The annual time series on hiring rate comes from the Survey of Consumer Expectations (SCE), conducted by Federal Reserve Bank of New York. The quarterly time series data on real GDP comes from the U.S. Bureau of Economic Analysis. It has been averaged at the annual level. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600

2.2 Vacancies Rate

I use seasonally adjusted monthly data on job openings rate for all non-farm sectors constructed by BLS (U.S. Bureau of Labor Statistics) from JOLTS (Job Openings and Labor Turnover Survey) between 2013 and 2021 and then average at the quarterly level. The log cyclical component of job openings rate is moderately pro-cyclical with real GDP, with a correlation coefficient of 0.64. Moreover, it has a weak negative auto-correlation coefficient of -0.34. Figure 2.2 plots the deviations from the trend and the trend superimposed on the actual series. Comparing figure 2.2 with 2.1, we can see that both vacancies rate and referral hiring rate are pro-cyclical with real GDP.

In the data, job openings include all positions that are open on the last business day of the reference month. A job is open only if it meets all three of these conditions:

(i) A specific position exists and there is work available for that position. The position can be full-time or part-time, and it can be permanent, short-term or seasonal.

(ii) The job could start within 30 days, whether or not the employer can find a suitable candidate during that time.

(iii) The employer is actively recruiting workers from outside the establishment to fill the posi-

tion. Active recruiting means that the establishment is taking steps to fill a position. It may include advertising in newspapers, on television, or on the radio; posting "help-wanted signs", networking or making word-of-mouth announcements; accepting applications; interviewing candidates; contacting employment agencies; or soliciting employees at job fairs, state or local employment offices, or similar sources.

Excluded are positions open only to internal transfers, promotions or demotions, or recall from layoffs. Also excluded are positions with start dates more than 30 days in the future, positions for which employees have been hired but not yer reported for work, and positions to be filled by employees of temporary help agencies; employee leasing companies, outside contractors, or consultants.

2.3 Unemployment Rate

The monthly time series data on seasonally adjusted unemployment rate is taken from Current Population Survey (CPS) and is constructed by BLS. Unemployment Rate is defined as the number

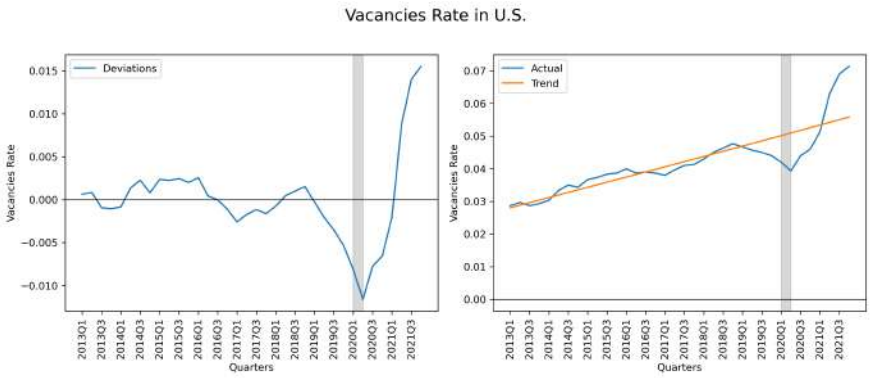


Figure 2.2: Quarterly Job Openings Rate in U.S., 2013Q1-2021Q4.

Notes: The left hand side figure shows the deviations from trend of a seasonally adjusted and an HP filtered time series data on job openings rate with smoothing parameter 1600. The right hand side figure shows the trend and the actual time series of job openings rate. The grey shaded bars denote U.S. recessionary periods.

of unemployed people as a percentage of the labor force in the reference month (where the labor force constitutes of the employed and the unemployed. The quarterly unemployment series is generated by a quarterly average of the monthly series. The cyclical component of the log quarterly unemployment series is strongly counter-cyclical with real GDP, with a correlation coefficient of -0.91 . Also, it has a weak negative auto-correlation coefficient -0.18 and a standard deviation of

0.23. Figure 2.3 shows the deviations from the trend, the trend and the actual quarterly time series of unemployment rate.. Comparing figure 2.3 with 2.1, we can see that while the unemployment rate is counter-cyclical, but the referral hiring rate is pro-cyclical with real GDP.

Unemployed people are all people who meet all of the following criteria:

(i) were not employed during the survey response week.

(ii) were available for work (except for temporary illness)

(iii) had made a specific, active effort to find employment sometime during the 4-week period ending with the survey reference week.

An exception to the active job search requirement is that people waiting to be recalled to work while temporarily laid off do not need to look for a job in order to be classified as unemployed. Also, for the people waiting to start a new job must have actively looked for a job within the last 4 weeks in order to be classified as unemployed. Otherwise, they are classified as not in the labor force.

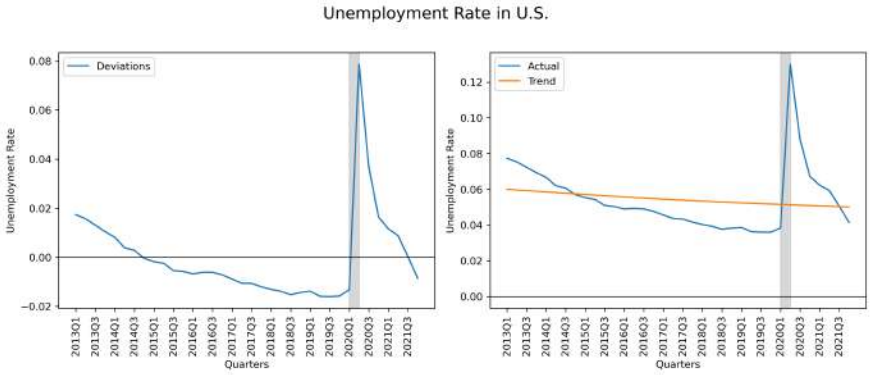


Figure 2.3: Quarterly Unemployment Rate in U.S., 2013Q1-2021Q4.

Notes: The left hand side figure shows the deviations from trend of a seasonally adjusted and an HP filtered quarterly time series data on unemployment rate with smoothing parameter 1600. The right hand side figure shows the trend and the actual time series of unemployment rate. The grey shaded bars denote U.S. recessionary periods.

2.4 Labor Market Tightness

Labor market tightness is defined as the vacancies rate to unemployment rate ratio. It is strongly pro-cyclical with real GDP, with a correlation coefficient of 0.91. The quarterly time series is computed by taking the ratio of the quarterly series of job openings rate to unemployment rate. The cyclical component of the log time series exhibits weak negative quarterly auto-correlation coefficient of -0.29. The negative auto-correlation implies the mean-reverting nature of the labor

market tightness over the business cycle. The standard deviation of the cyclical component is about 0.28. Figure 2.4 shows the deviations from trend, the trend and the actual seasonally adjusted times series of labor market tightness. Comparing figure 2.4 with 2.1, as expected, we can see that both labor market tightness and referral hiring rate are pro-cyclical with real GDP.

2.5 Market Job Finding Rate

Following Shimer (2005), I calculate the monthly market job-finding rate of an unemployed worker in a given month t between January 2013 and December 2021 using the expression:

$$f_t = 1 - \frac{u_{t+1} - u^s_{t+1}}{u_t}$$

where, u_{t+1} and u^s_{t+1} denotes the unemployment level and number of workers unemployed

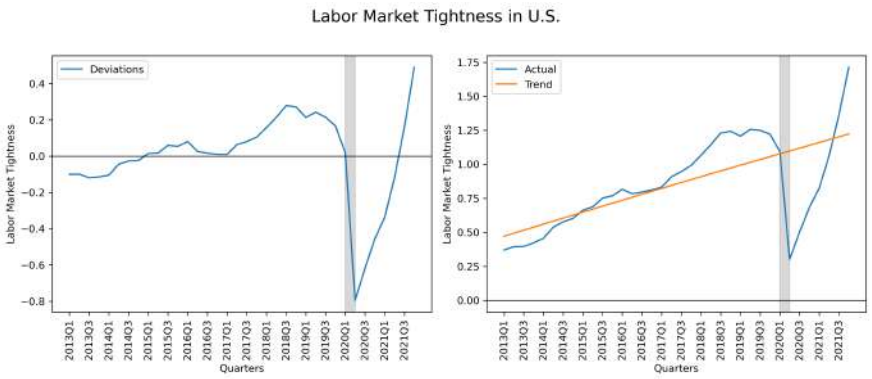


Figure 2.4: Quarterly Labor Market Tightness in U.S., 2013Q1-2021Q4.

Notes: The left hand side figure shows the deviations from trend of a seasonally adjusted and an HP filtered quarterly time series data on labor market tightness with smoothing parameter 1600. The right hand side figure shows the trend and the actual time series of labor market tightness. The grey shaded bars denote the U.S. recessionary periods.

between 0-4 weeks is collected from BLS (Bureau of Labor Statistics) which is constructed by BLS from CPS (Current Population Survey). The monthly times series is then averaged at the quarterly level. The log cyclical component of the time series is weakly pro-cyclical with real GDP, with a correlation coefficient of 0.32. The quarterly auto-correlation coefficient of the log cyclical component is about 0.07 with a standard deviation of 0.13. Figure 2.5 shows the deviations from the trend, the trend and the actual time series. Similarly, comparing figure 2.5 with 2.1, we can see that both job-finding rate and referral hiring rate are pro-cyclical.

2.6 Real GDP

The seasonally adjusted quarterly time series data on real GDP between 2013Q1 and 2021Q4 comes from the U.S. Bureau of Economic Analysis. The log cyclical component of the time series has a weak negative quarterly auto-correlation coefficient of -0.24 and has a standard deviation of 0.017. Figure 3.6 shows the deviations from trend, the trend and the actual time series.

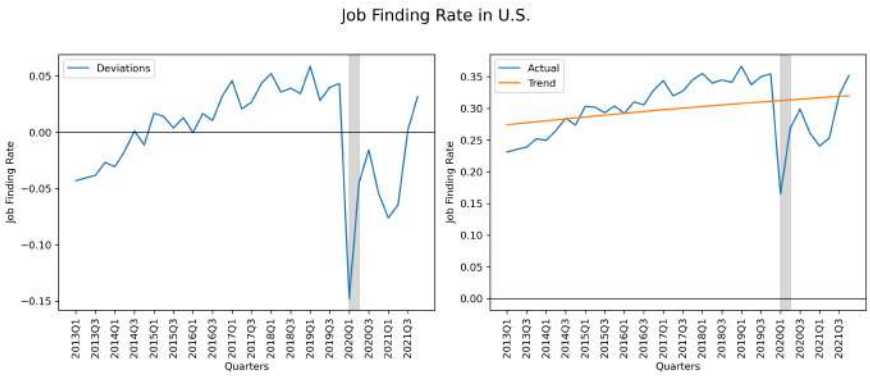


Figure 2.5: Quarterly Market Job Finding Rate in U.S., 2013Q1-2021Q4.

Notes: The left hand side figure shows the deviations from trend of a seasonally adjusted and an HP filtered quarterly time series data on market job finding rate with smoothing parameter 1600. The right hand side figure shows the trend and the actual time series of market job finding rate. The grey shaded bars denote the U.S. recessionary periods.

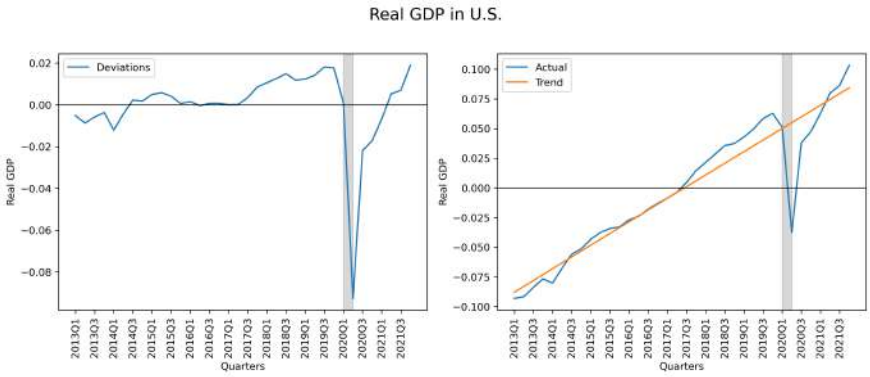


Figure 2.6: Quarterly Real GDP in U.S., 2013Q1-2021Q4.

Notes: The left hand side figure shows the deviations from trend of a seasonally adjusted and an HP filtered quarterly time series data on normalized real GDP with smoothing parameter 1600. The right hand side figure shows the trend and the actual time series of market job finding rate. The grey shaded bars denote the U.S. recessionary periods.

Table 2.1: Summary Statistics - Quarterly US Data, 2013Q1 to 2021Q4

	u	v	v/u	f	y
Standard Deviation	0.227	0.088	0.286	0.135	0.017
Quarterly Autocorrelation	-0.163	-0.35	-0.29	0.072	-0.24
Correlation Matrix					
u	1	-0.549	-0.966	-0.26	-0.918
v	—	1	0.746	0.475	0.646
v/u	—	—	1	0.354	0.931
f	—	—	—	1	0.328
y	—	—	—	—	1

Notes: Seasonally adjusted unemployment rate, u, is constructed by the BLS from the Current Population Survey (CPS). The seasonally adjusted job openings rate, v, is constructed by the BLS from JOLTS. Both u and v are quarterly averages of monthly series. Real GDP y is seasonally adjusted real GDP normalized to 1, constructed by the U.S. Bureau of Economic Analysis. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

Table 2.2: Summary Statistics - Annual Hiring and Match Quality Rates (SCE), 2013-2021

	Ω^M	$1-\Omega^M$	γ_M	γ_R	y
Standard Deviation	0.099	0.122	0.138	0.11	0.014
Autocorrelation	-0.361	-0.385	-0.567	-0.336	-0.298
Correlation Matrix					
Ω^M	1	-0.97	0.006	0.65	-0.66
$1-\Omega^M$	-	1	0.035	-0.514	0.79
γ_M	-	-	1	0.151	0.291
γ_R	-	-	-	1	0.057
y	-	-	-	-	1

Notes: Annual Market and Referral Hiring Rates have been constructed from SCE (2013-2021). Annual Good and Bad Match Rates by Hiring Strategy is also constructed from SCE (2013-2021). Annual Real GDP is the annual average of quarterly real GDP, constructed by the U.S. Bureau of Economic Analysis. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

3 Model

3.1 Model Environment

Time is discrete and infinite. The labor market is in steady state. Aggregate state of the economy is uncertain. Firms post job openings and try to fill advertised vacancies and they also contact the incumbent employees to provide a referral from their social network. There is no on-the-job search. Unemployed workers are simultaneously hired through the two channels, namely, market and referral channel. Firms and workers are treated as the only entities in the aggregate labor market.

Each unemployed worker possesses certain type of skills/experiences and each job vacancy demands certain type of skills/experiences. If the job fits well to the unemployed worker's skills/experiences, then a higher productivity (good) match is formed while if the job does not fit well to the unemployed workers skills/experiences then a lower productivity (bad) match is formed. In other words, the employer does not know worker's type when recruiting the worker and hence the match formed can either be good or bad. Good and bad matches can happen in both market and referral hiring. I discuss in detail about match quality by hiring strategy in **Match Quality**. The match quality is revealed to the employer only when the productivity is realized. The state-specific average productivity in a good and a bad match is denoted by y_s and y_s^0 respectively, where $0 < y_s^0 < y_s \leq 1$. Stochastic processes for productivity y_s, y_s^0 follows a first order Markov chain according to a normal distribution with mean μ, μ^0 and standard deviation σ, σ^0. I also assume that bad matches are not too bad so that they get dissolved instantaneously, while good matches are not too good so that they last forever. The first assumption implies that the productivity in a bad match exceeds a threshold productivity level $\underline{y_s}$ below which production is not feasible. Given both the assumptions, it is realistic to assume that a good match is separated with a lower probability (δ) relative to a bad match (δ_0), where $0 < \delta < \delta_0 < 1$. In the model, δ and δ_0 are exogenous.

The state-specific payoffs to a well-matched employee, a badly-matched employee are given by endogenous Nash bargained wage rates w_s, w_s^0 respectively. The unemployed worker collects benefits b. Similarly, the state-specific payoffs to the firm from a good and a bad match are given by $y_s - w_s$ and $y_s^0 - w_s^0$ respectively.

Market Matching: Market matching process between a vacancy and an unemployed worker is assumed to **frictional**. Firms advertise vacancies on their websites, online job search platforms, use help wanted ads etc. to search for interested workers to fill a vacancy. Posting vacancies is costly and incurs a flow cost $k > 0$. Workers use market job search methods like visiting the employer's website, meeting the employer in-person, using online job search engine, employment agencies/career centers, union/professional centers etc. to get matched to an employer. In the model, matches produced in the market are represented by a standard matching function which is Cobb-Douglas in the state-specific endogenous vacancies rate (v_s) and unemployment rate (u_s) and denoted as: $m(v_s, u_s) = A v_s^{\eta} u_s^{(1-\eta)}$, where parameter $A > 0$ is a scale parameter and parameter

$\eta \in (0,1)$ denotes the matching function elasticity. More specifically, η denotes the percentage change in aggregate market matching rate when vacancies rate change by 1%.

Given this market matching function, the state-specific job-finding probability of each unemployed worker per unit market hire is given by: $f(\theta_s) = \frac{Am(v_s,u_s)}{u_s} = A\theta_s^{\eta}$, and the job-filling probability of each vacancy per unit market hire is given by: $q(\theta_s) = \frac{Am(v_s,u_s)}{v_s} = A\theta_s^{\eta-1}$, where $\theta_s = \frac{v_s}{u_s}$ denotes the labor market tightness. $f(.)$ is strictly increasing and strictly concave in θ_s while $q(.)$ is strictly decreasing and strictly convex in θ_s. [5]

Referral Matching: Referral matching process is assumed to be **congestional**. I assume each employee in a firm is connected to other employees and workers in her social network. Let's denote, in each state, the fraction of employees in each firm by $1-u_s$ and each of them has n contacts in their network, where $n > 0$ denotes the network size of each employee. Therefore, the expected number of unemployed and employed workers in the network are denoted by $u_s n$ and $(1-u_s)n$ respectively. Upon availability of a vacant position in the firm, the employer randomly contacts one of her employees. Referral vacancies are not advertised and hence the firm saves on the advertisement cost. On hearing about a job vacancy from the employer, each employee randomly chooses to pass the job information to any one of her $u_s n$ unemployed contacts in her network. In other words, network agents share favorable relationships [6].

It is assumed that the job information flows between direct employee-unemployed links and not between indirect employee-unemployed links. In other words, job information flows from employee to unemployed worker and not between two unemployed workers. Allowing for this second order job information transmission will make the model more intractable without adding additional insights in this context. Also, the firm might fill the vacancy through the market channel or decide not to reopen while information exchange continues between unemployed workers. Additionally, employment is a better outcome than unemployment for any unemployed worker. Hence, the assumption

[5] It is possible that given the values of A, both $f(\theta_s)$ and $q(\theta_s)$ exceed 1. Then, a more general way to define f and q will be $f(\theta_s) = min[1, A\theta_s^{\eta}]$ and $q(\theta_s) = min[1, A\theta_s^{\eta-1}]$. But the quantitative solutions show that corner solutions doesn't exist. Mathematically, the general form of the job-finding and job-filling rates will make the function non-differentiable at 1. Hence, $f(\theta_s) = A\theta_s^{\eta}$ and $q(\theta_s) = A\theta_s^{\eta-1}$.

[6] Network relationships/connections are maintained for reasons apart from job information transmission, for example risk sharing. Also recommending a contact who can potentially be a bad fit to the employer comes with a threat of reputation loss of the incumbent employee. Overall, it might happen that the benefits of risk sharing outweighs the loss from reputation (Beaman and Magruder (2012)). Moreover, it might also be the case that, passing along the job offers might help in maintaining the links as such behaviors can be reciprocated in future, thus reducing the unemployment spell of the incumbent (Bramoulle and Goyal (2016)).

is well supported by some intuitive and analytical reasons.

From the unemployed worker's perspective, an unemployed worker has n contacts, each of them is employed with a probability $1-u_s$ and unemployed with a probability u_s. This assumption implies network structure is homogeneous and network type is identical for each employee/unemployed worker, which simplifies the analysis to a great extent.

I will now define the referral job-filling and job-finding probabilities through the social network. The probability with which job information flows to at least one unemployed worker (referral job-filling rate) is given by:

$$q_R(n,u_s) = \sum_{m=0}^{n-1} \binom{n-1}{m} u_s^m (1-u_s)^{n-1-m} \frac{1}{m+1} = \frac{1-(1-u_s)^n}{nu_s}$$

A random draw of n social contacts from the network contains $0 \leq m \leq n-1$ other contacts, besides the contacted unemployed worker, with probability $\sum_{m=0}^{n-1} \binom{n-1}{m} u_s^m (1-u_s)^{n-1-m}$. Then, the job information is assigned to any one of the $m+1$ unemployed contacts with a uniform probability, and thus the contacted unemployed worker receives the information with a conditional probability $\frac{1}{m+1}$. $1-(1-u_s)^n$ denotes the probability that at least one worker is unemployed in the network, and nu_s denotes the expected number of unemployed workers in the network. The ratio of these two quantities constitutes the job-filling rate $q_R(n,u_s)$. This expression directly follow from Calvo-Armengol and Zenou (2005).

The intuition is that as the network size n increases, on one hand, the probability of finding at least one unemployed worker in the network given by $1-(1-u_s)^n$ increases, but on the other hand, the expected number of unemployed workers also increases. Combining the two opposite effects, it seems that the second effect dominates the first effect.

The referral job-finding rate of each unemployed worker per unit market hire is given by: $f_R(u_s,n) = (1-u_s)^{nu_s}$. Each employee has nu number of expected unemployed workers in her network.

Match Quality: Good and bad match can happen both in market and referral hiring. Market hiring provides good matches at the rate $\gamma_M = \frac{\lambda_M}{1+\lambda_M}$, where $\lambda_M > 0$ denotes market efficiency parameter, that is how efficient the market is in providing a good match. Higher is λ_M, higher is γ_M. An interpretation of $\lambda_M > 0$ can be how state employment agencies, school placement officers, private employment services and social network sites facilitate formation of good matches between firms and workers. Referral hiring provides good matches at the rate $\gamma_R > 0$. The parameter γ_R refers to

the degree of homophily level in the society, in other words, what fraction of unemployed workers are of similar type to the employee, where the type can vary by race, gender, age, skills, risk averseness etc. [7].

Hiring: A firm chooses to hire Ω^M fraction of workers through the market hiring channel and the rest $1-\Omega^M$ fraction of workers through the referral hiring channel, where $\Omega^M \in [0,1]$. Unit costs of market and referral hiring are denoted by c_M and c_R, where $0 < c_R \neq c_M \leq 1$. The reason is market hiring might involve a series of screening processes, interviewing, adhering to administrative / organizational rules, contacting a search firm etc. while referral hiring being more informal might not entail all of them but can require formal employee referral hiring programs to be in place, paying a referral bonus to the referee or even more accurate screening techniques.

3.2 Worker's Problem

Suppose unemployed workers are risk neutral and for analytical simplicity assume job search is not costly [8]. There are no taxes in this economy. The unemployed worker takes the firm's hiring choices $(\Omega_s^M, 1-\Omega_s^M)$, the labor market aggregates u_s, θ_s (and hence the vacancies rate v_s) and the network size n as given, collects unemployment benefits $b > 0$ today and searches for work. With probability $p_s^e(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s)$ the worker finds a good match, with probability $p_s^{e0}(\Omega_s^M, 1-\Omega_s^M, , \theta_s, n, u_s)$ the worker finds a bad match and with probability $p_s^u(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s)$ the worker do not find a match and remains unemployed in each state s, where,

$$
\begin{aligned}
p_s^e &\equiv p_s^e(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s) = \Omega_s^M f(\theta_s)\gamma_M + (1-\Omega_s^M) f_s^R(n, u_s)\gamma_R \\
p_s^{e0} &\equiv p_s^{e0}(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s) = \Omega_s^M f(\theta_s)(1-\gamma_M) + (1-\Omega_s^M) f_s^R(n, u_s)(1-\gamma_R) \\
p_s^u &\equiv p_s^u(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s) = 1 - \Omega_s^M f(\theta_s) - (1-\Omega_s^M) f_s^R(n, u_s)
\end{aligned}
$$

An employee in a good and a bad match receives wages w_s, w_s^0 respectively at the beginning of each period, with probability δ, δ_0 respectively faces a threat of getting separated by the end of each period due to exogenous reasons and discounts expected utility at the end of each period at the rate β. Given this, I denote the continuation utilities of an unemployed worker, an employee in a good match and an employee in a bad match as of the beginning of each period by V_u, V_e and

[7] If $\gamma_R = 0.5$, then 50% of an employee's contacts are of same type and 50% are of different type. If $\gamma_R = 1$, then all of employee's contacts are of same type and if $\gamma_R = 0$, then none of employee's contacts are of her type.

[8] In this paper, the objective is to model firm's hiring decisions and not worker's search incentives, hence it is not modelled. But, one is always free to include that.

$V_s^{e_0}$, and define them as:

$$V_s^e \equiv V_s^e(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s) = w_s + \beta\big[(1-\delta)\mathbb{E}_s V_{s'}^e + \delta \mathbb{E}_s V_{s'}^u\big] \tag{1}$$

$$V_s^{e_0} \equiv V_s^{e_0}(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s) = w_s^0 + \beta\big[(1-\delta_0)\mathbb{E}_s V_{s'}^{e_0} + \delta_0 \mathbb{E}_s V_{s'}^u\big] \tag{2}$$

$$V_s^u \equiv V_s^u(\Omega_s^M, 1-\Omega_s^M, \theta_s, n, u_s) = b + \beta\big[\mathbb{E}_s(p_{s'}^e V_{s'}^e) + \mathbb{E}_s(p_{s'}^{e_0} V_{s'}^{e_0}) + \mathbb{E}_s(p_{s'}^u V_{s'}^u)\big] \tag{3}$$

such that $0 < b < w_s^0 < w_s < 1$.

3.3 Firm's Problem

From the firm's perspective, each well matched, badly matched employee produces y_s, y_s^0 units of output, is paid a Nash bargained wage w_s, w_s^0 respectively and at the rates δ, δ_0 respectively get separated by the end of each period and a vacancy is created. Like workers, firms discount future expected profits at the rate β. Profits of an unfilled vacancy equals vacancy posting (advertisement) cost $k\Omega_s^M$ plus the expected discounted profits from hiring through market channel denoted by Π_M[9]. Denote by J_s^e, $J_s^{e_0}$ and J_s^v the continuation profits of a well matched, badly matched and an unfilled vacancy as of the beginning of each period and define them as:

$$J_s^e \equiv J_s^e(\Omega_s^M, \theta_s, n, u_s) = y_s - w_s + \beta\big[(1-\delta)\mathbb{E}_s J_{s'}^e + \delta \mathbb{E}_s J_{s'}^v\big] \tag{4}$$

$$J_s^{e_0} \equiv J_s^{e_0}(\Omega_s^M, \theta_s, n, u_s) = y_s^0 - w_s^0 + \beta\big[(1-\delta_0)\mathbb{E}_s J_{s'}^{e_0} + \delta_0 \mathbb{E}_s J_{s'}^v\big] \tag{5}$$

$$J_s^v \equiv J_s^v(\Omega_s^M, \theta_s) = -k\Omega_s^M + \beta \mathbb{E}_s\, \Pi(\Omega_s^M, \theta_s) \tag{6}$$

The continuation profits functions J_s^e, $J_s^{e_0}$ and J_s^v are all functions of the firm's choices, aggregates and the employee's network size in each state s.

3.4 Firm's Optimization problem

In each realized state, a firm maximizes the sum of expected profits net of costs from market and referral hiring by choosing to hire $\overline{\Omega}_s^M$ fraction of workers through the market channel and the rest $1-\Omega_s^M$ fraction of workers through the referral channel, taking as given the aggregates v_s, u_s, θ_s and the network size n [10]. The firm's net expected profits from market and referral hiring are given as:

[9] A firm's expected profits from market hiring is a function of it's own choice Ω_s^M and tightness θ_s

[10] $\Omega_s^{M'}$ denotes any other Ω_s^M apart from the optimal $\overline{\Omega}_s^M$.

$$\Pi(\overline{\Omega}_s^M, \theta_s) = \overline{\Omega}_s^M \Big[q(\theta_s) \left\{ \gamma_M J_s^e + (1-\gamma_M) J_s^{e_0} \right\} + \big(1 - q(\theta_s)\big) J_s^v \Big] - \frac{1}{2} c_M \overline{\Omega}_s^{M\,2} \tag{7}$$

$$\Pi(1-\overline{\Omega}_s^M, n, u_s, v_s) = (1-\overline{\Omega}_s^M) \Big[q^R(n, u_s) \left\{ \gamma_R J_s^e + (1-\gamma_R) J_s^{e_0} \right\} + \big(1 - q^R(n,u)\big) J_s^v \Big] - \frac{1}{2} c_R (1-\overline{\Omega}_s^M)^2 \tag{8}$$

where, $C_M(\Omega_s^M) = \frac{1}{2} c_M \Omega_s^{M\,2}$ and $C_R(1-\Omega_s^M) = \frac{1}{2} c_R (1-\Omega_s^M)^2$ are the market and referral hiring cost functions respectively. $C_M(.)$ and $C_R(.)$ are strictly increasing and strictly convex in Ω_s^M and $(1-\Omega_s^M)$ respectively, with $C_M(0) = C_R(0) = 0, C_M(1) = \frac{1}{2} c_M, C_R(1) = \frac{1}{2} c_R$. Given this, the firm's optimal choice $(\overline{\Omega}_s^M, 1-\overline{\Omega}_s^M)$ is the solution to,

$$\underset{\Omega^{M\prime}, 1-\Omega^{M\prime}}{\text{argmax}} \quad \Pi(\Omega^{M\prime}, \theta_s) + \Pi(1-\Omega^{M\prime}, n, u_s, v_s) \tag{9}$$

3.5 Labor Market Clearing Conditions

In each state, the labor market is characterized by inflow and outflow of good and bad matches and is normalized to a size of 1. This gives us:

$$\delta e_s = p_s^e u_s \tag{10}$$

$$\delta_0 e_s^0 = p_s^{e_0} u_s \tag{11}$$

$$e_s + e_s^0 + u_s = 1 \tag{12}$$

3.6 Wage Bargaining

Wages w and w_0 are bargained between the firm and the unemployed worker using the generalized Nash bargaining rule, where the unemployed worker keeps fraction ϕ and the firm gets fraction $(1-\phi)$ of the surplus from a good and a bad match. The surplus from a good and a bad match respectively is given by:

$$Z_s = V_s^e + J_s^e - V_s^u - J_s^v \tag{13}$$

$$Z_s^0 = V_s^{e_0} + J_s^{e_0} - V_s^u - J_s^v \tag{14}$$

Wages w_s and w_s^0 are solutions to the following problems respectively:

$$\underset{\overline{w}_s}{\text{argmax}} \ (V_s^e - V_s^u)^{\phi} (J_s^e - J_s^v)^{1-\phi} \tag{15}$$

$$\underset{\overline{w}_s^0}{\text{argmax}} \ (V_s^{e_0} - V_s^u)^{\phi}(J_s^{e_0} - J_s^v)^{1-\phi} \tag{16}$$

3.7 Equilibrium

A stochastic competitive equilibrium, given the match separation rates (δ, δ_0), market good match level (λ_M), network homophily rate (γ_R), network size (n), and aggregate states of the economy (y_s, y_s^0), is a measure of vacancies rate (v_s), labor market tightness (θ_s), employment rate in good and bad matches, unemployment rate (e_s, e_s^0, u_s) and firm's hiring choices (Ω_s^M, 1- Ω_s^M) such that:

(i) The labor market is in steady state as described by (10) -(12).

(ii) The surplus is split between firm and worker according to (15) and (16).

(iii) Firm's optimal hiring choice is given by solution to (9).

(iv) There is free entry of firms given by $J_s^v = 0$.

4 Model Quantification

4.1 Calibration

In this section, I talk about how I calibrate the model to uncover the values of the model parameters in order to match the targeted data moments.

Separation rates: I use monthly data on separation rates for all non-farm sectors from JOLTS (Job Openings and Labor Turnover Survey) between 2013 and 2021 and then average at the annual level. The annual average separation rate in the data is 0.037 and the calibrated values also exactly match data values. Moreover, Horvath (2014) reports that the ratio of separation rates of a bad/good match lies between $[1, 5]$. Additionally, as I don't have data on match specific separation rates, I calibrate the ratio of bad/good match separation rates within this interval.

Average labor productivity and Real GDP: For each realized state, I use normalized good and bad match productivity values ($y_s = 1, y_s^0 = 0.95$) from Horvath (2014). To compare the correlation between hiring and productivity in the model and the data over the business cycle, I use quarterly data on real GDP from U.S. Bureau of Economic Analysis during the sample period (2013-2021), average at the annual level, log the data series, and find out the correlation between firm's hiring

(market and referral) rate and log real GDP.

Unit hiring costs and vacancy posting costs: I refer to the ratio of recruitment cost per hire for referred to non-referred workers reported in Burks et al. (2015) to calibrate the unit market and referral hiring costs in the model. For the vacancy posting cost, I again refer to range of values reported in the scholarly literature (namely Shimer (2005), Caitlin (2023)).

Unemployment benefits: I calibrate it in the range [0.44, 0.47] widely reported in many articles in the literature (Horvath (2014), Shimer (2005), Pei and Xie (2020).

Market and Referral Match Quality: SCE asks the survey respondents who found a job (either referred or market hired), that "What characteristics of this job made it worth accepting?". The respondent who was referred and answered that the "job fits well with my experience or skills" was counted as a good referred match. The respondent who was referred and had other reasons for accepting the job was counted as a bad referred match [11]. The respondent who was market hired and answered that the "job fits well with my experience or skills" was counted as a good market match. The respondent who was market hired and had other reasons for accepting the job was counted as a bad market match. Given this, the fraction of good and bad market matches are normalized to 1. Similarly, the fraction of good and bad referred matches are also normalized to 1. More precisely, $\textit{fraction of good market matches} = \frac{\textit{no. of good market matches}}{\textit{no. of good market matches} + \textit{no. of bad market matches}}$ and $\textit{fraction of good referred matches} = \frac{\textit{no. of good referred matches}}{\textit{no. of good referred matches} + \textit{no. of bad referred matches}}$. Figure 4.1 shows how the good and bad match rates vary across the years and their deviations from trend by hiring strategy.

Bargaining power, matching function elasticity and Network size: As far as the bargaining power is concerned, it varies between 0.5 to 0.72 in most of the peer-reviewed articles. I calibrate it in this range. Similarly, for the matching function elasticity and network size, they have been calibrated within the reported range in the literature.

Table 4.1 presents the calibrated parameters in the steady state CE:

[11] In this paper, I focus on skill mis-match to define match quality. There can be several other reasons like pay, benefits, flexible work hours, commute time to work etc. which might broaden the definition of match quality.

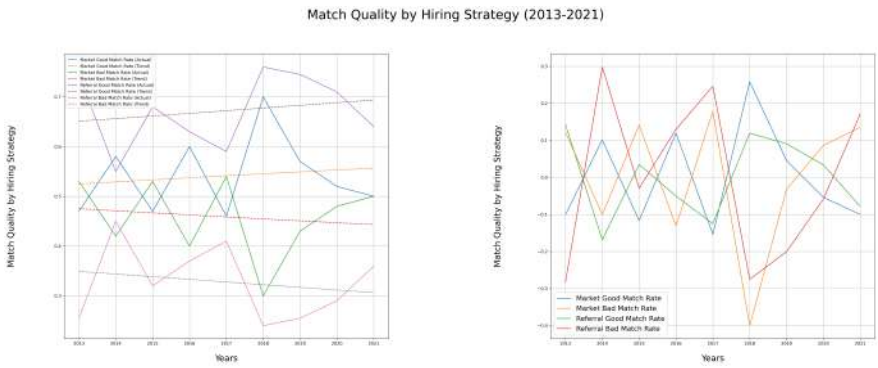


Figure 4.1: Match Quality by Hiring Strategy in U.S., 2013-2021.

Notes: The left hand side figure shows the variation of annual time series data on good and bad match rates in market and referral hiring. The annual time series on match quality comes from the Survey of Consumer Expectations (SCE), conducted by Federal Reserve Bank of New York. The right hand side figure shows the deviations from trend of match quality by hiring strategy. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600. We can also clearly see from the LHS figure that non de-trended series of referral good match rate lies above that of the market good match rate series. However, the pattern does not hold for the deviations from trend in the RHS figure. Moreover, the differences in means are not statistically significant due to insufficient sample size.

Table 4.1: Calibration - Productivity Shocks in the model

Description	Parameter	Value	Source	Value
Discount factor, match productivity	β, y, y_0	$0.98, 1, 0.95$	Horvath(2014)	$0.98, 1, 0.95$
separation rates	δ, δ_0	$0.037, 0.037$	Data	$0.037, 0.037$
market good match (level and rate), homophily rate	$\lambda_M, \gamma_M, \gamma_R$	$2, 0.66, 0.7$	Horvath (2014), Data	$[2, 8]$, 0.541, 0.672
unemp. benefits	b	0.45	Horvath (2014)	0.45
matching function elasticity	η	0.35	Galenianos (2014)	0.565
bargaining power	ϕ	0.55	Shimer (2005)	0.72
unit market and referral hiring cost	c_M, c_R	$0.3, 0.2$	Hoffman (2015)	$\frac{c_R}{c_M} \in \{0.66, 0.75\}$
vacancy posting cost	k	0.21	Shimer (2005)	0.213
network size	n	20	Horvath (2014)	$[10, 45]$
matching function scale parameter	A	0.6	Shimer (2005)	1.355

4.2 Quantitative Results

This section summarizes the steady state CE with table 4.2 presenting the targetted endogenous variables and their moments in the data and in the model and the non-targetted moments of other endogenous variables in the model. From table 4.2, I find that the steady state Markov competitive equilibrium is characterized by slightly more market hiring than referral hiring and it matches the data closely. The model is producing reasonably close results for the other targetted moments too. The market job-filling rate is higher than the referral job-filling rate, the market channel is less likely to produce a good match ($\gamma_M < \gamma_R$ in Table 4.1) and is more costlier hiring through the the market

channel ($c_R < c_M$ in Table 4.1). So, the steady state market and referral hiring rates are characterized by quantity-quality and cost trade-offs. More precisely, $\frac{\sum_{s=1}^{9} \frac{q_s^R(n,u_s)}{q(\theta_s)}}{9} = 0.95$, $\frac{\gamma_M}{\gamma_R} = 0.942$ and $\frac{c_R}{c_M} = 0.67$. Moreover, the market channel is too frictional for the unemployed workers compared to the referral channel to get employed, where $\frac{\sum_{s=1}^{9} \frac{f(\theta_s)}{f^R(n,u_s)}}{9} = 0.42$. Finally, the expected market and referred wages are calculated to be $0.011, 0.025$ using the formula $\frac{\sum_{s=1}^{9} \Omega_s^M m(v_s,u_s)(\gamma_M w_s + (1-\gamma_M) w_s^0)}{9}$ and $\frac{\sum_{s=1}^{9} (1-\Omega_s^M) f_R(n,u_s) u_s (\gamma_R w_s + (1-\gamma_R) w_s^0)}{9}$ respectively. This shows the existence of wage inequality in equilibrium as referred workers earn more than the market hired workers, with the wage premium being 56%.

Furthermore, market hiring is more profitable than referral hiring. The bad matches are associated with a wage discount of about 10% relative to the good matches and the fraction of good matches exceeds the fraction of bad matches by about 26%. Moreover, the expected number of unemployed workers in the network equals 1.16 (> 1), which implies that there exists at least one unemployed worker in each employee's network.

All these results showcase the fact that the firm's choice of market and referral hiring plays a significant role in determining the network and wage inequality.

Table 4.2: Markov Competitive Equilibrium - Productivity Shocks in the model

Endogenous Variables	Model	Data	Targetted
Market and Referral Hiring Rate $(\Omega^M, 1-\Omega^M)$	$0.51, 0.49,$	$0.507, 0.493$	Y
Vacancies Rate (v)	0.036	0.041	Y
Unemployment Rate (u)	0.058	0.054	Y
Labor Market Tightness (θ)	0.63	0.851	Y
Market Job Finding Rate $(f(\theta))$	0.394	0.298	Y
Market Job Filling Rate $(q(\theta))$	0.63	-	N
Referral Job Filling Rate $(q_R(n,u))$	0.6	-	N
Referral Job Finding Rate $(f_R(n,u))$	0.932	-	N
Fraction of Good and Bad Matches (e, e^0)	$0.6, 0.342$	-	N
Good Match Wage (w)	0.994	-	N
Bad Match Wage (w^0)	0.894	-	N
Expected Market Hiring Profits (Π^M)	0.087	-	N
Expected Referral Hiring Profits (Π^R)	0.078	-	N

5 Markov Policy Functions

5.1 Hiring Rate

In this section, I discuss the numerical solutions on market and referral hiring rates produced by the stochastic model. The left hand side panel of Figure 5.1 shows the negative correlation between market hiring rate and productivity across 9 state values of productivity y. The right hand side panel shows the log deviations from trend of market and referral hiring rates. We can conclude from the figure that market hiring rate is counter-cyclical, and vice-versa for the referral hiring rate. These patterns match the data findings shown earlier in figure 2.1. The intuition is that during recessions, lower market tightness increases the market job-filling rate. Moreover, higher unemployment rate reduces the referral job-filling rate. Besides, market hiring also provides more good matches than referral hiring. All these make market hiring more attractive during the recessions.

The correlation coefficient between the cyclical component of log market hiring rate and log productivity series is -0.996, and -0.998 for the referral hiring rate series. The standard deviation of the cyclical component of log market hiring rate is 0.031 and that of log referral hiring rate is

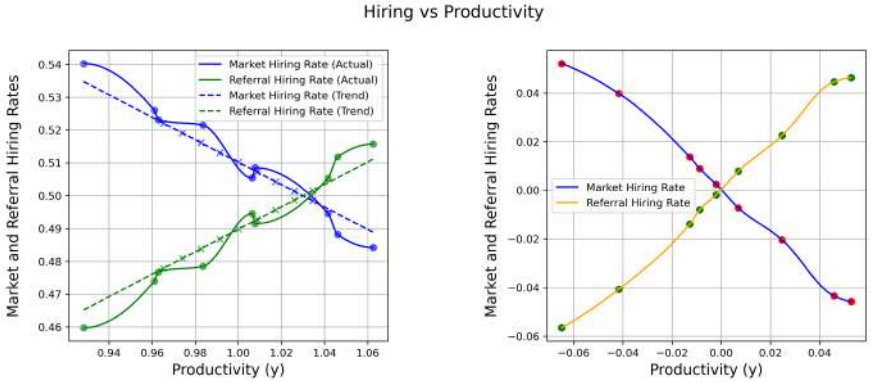


Figure 5.1: Market and Referral Hiring Rates across productivity states and their deviations from trend.

Notes: The left hand side figure shows how market and referral hiring rates vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure the log deviations from trend of an HP filtered quarterly data on market and referral hiring rates versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

0.033, compared to 0.099 in the data. The standard deviation of the cyclical component of log productivity series is 0.036, compared to 0.017 in the data. In other words, the variation in market

and referral hiring rate series is completely explained by the variation in the productivity series in the model, but the numbers are a little larger compared to the data evidence.

I find that the quarterly auto-correlation coefficient for the market hiring rate series is 0.29, for the referral hiring rate series is 0.32 and that of the productivity series is 0.32.

5.2 Vacancies Rate

This section discusses the numerical solutions on vacancies rate produced by the stochastic model. The left hand side panel of Figure 5.2 shows the positive correlation of vacancies rate with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of vacancies rate. We can conclude from the figure that vacancies rate is pro-cyclical and is positively correlated with referral hiring rate, although for referral hiring vacancy posting is not required. These patterns match the data findings shown earlier in figure 2.2. The intuition is that during recessions, lower vacancies rate increases the market job filling rate and hence decreases the referral hiring rate and increases the market hiring rate.

The correlation coefficient between the cyclical component of log vacancies rate and log productivity series is 0.997. The standard deviation of the cyclical component of log vacancies rate

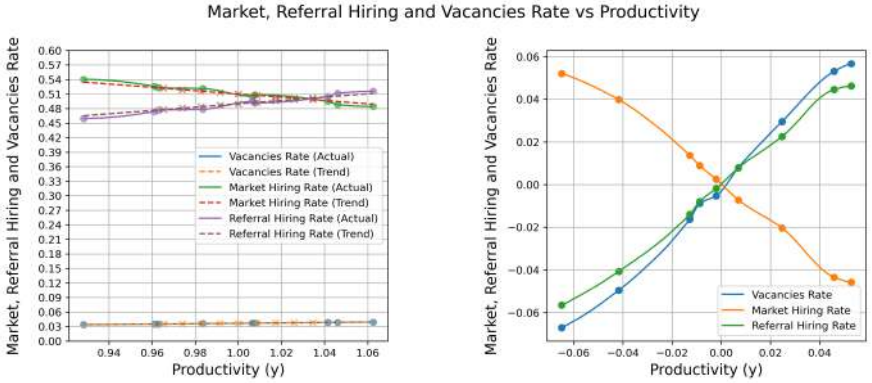


Figure 5.2: Market, Referral Hiring and Vacancies Rate across productivity states and their deviations from trend.

Notes: The left hand side figure shows how vacancies rate vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and vacancies rate versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

is 0.039 compared to 0.088 in the data. In other words, the model produced deviations from trend of log vacancies rate is about 50% of the data counterpart. The quarterly auto-correlation coefficient of log vacancies rate series is 0.287.

5.3 Unemployment Rate

This section discusses the numerical solutions on unemployment rate produced by the stochastic model. The left hand side panel of Figure 5.3 shows the positive correlation of unemployment rate with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of unemployment rate. We can conclude from the figure that unemployment rate is counter-cyclical and is positively correlated with market hiring rate. In other words, recessions inducing higher unemployment rate and more market hiring reduces referral job filling and finding rates. This is because higher unemployment rate increases the expected number of unemployed workers in the network, thus decreasing referral and increasing market hiring rate. These patterns match the data findings shown earlier in figure 2.3.

The correlation coefficient between the cyclical component of log unemployment rate and log productivity series is -0.998. The standard deviation of the cyclical component of log unemployment rate is 0.023 compared to 0.227 in the data. In other words, the model produced deviations from trend of log unemployment rate is about 10% of its data counterpart. The quarterly auto-correlation coefficient of log unemployment rate series is 0.323.

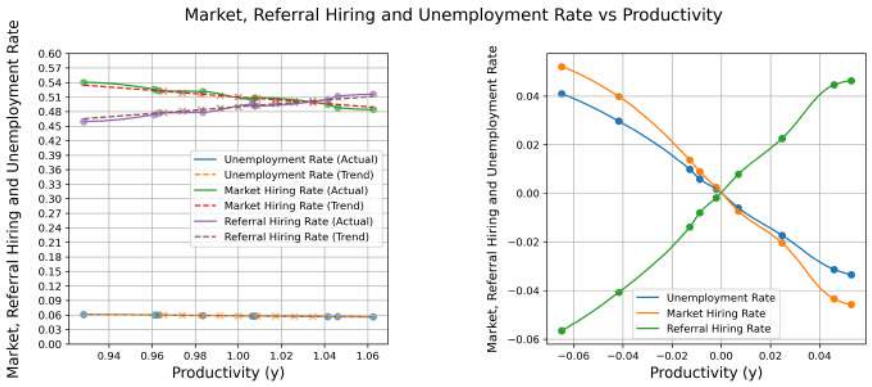


Figure 5.3: Market, Referral Hiring and Unemployment Rate across productivity states and their deviations from trend.

Notes: The left hand side figure shows how unemployment rate vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and unemployment rate versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

5.4 Labor Market Tightness

In this section, I discuss the numerical solutions on labor market tightness produced by the stochastic model. The left hand side panel of Figure 5.4 shows the positive correlation with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of tightness. We can conclude from the figure that tightness is pro-cyclical and positively correlated with referral hiring rate. The intuition is that during recessions, lower vacancies rate and higher unemployment rate decreases the market tightness, hence promoting more market hiring and less referral hiring. The correlation coefficient between the cyclical component of log tightness and log productivity series is 0.996. The standard deviation of the cyclical component of log tightness is 0.063 compared to 0.286 in the data. In other words, the model produced deviations from the trend of log market tightness is about 22% of the data counterpart. The quarterly auto-correlation coefficient of log labor market tightness is 0.294.

5.5 Market Job Finding and Job Filling Rates

In this section, I discuss the numerical solutions on market job-finding and job-filling rates produced by the stochastic model. The left hand side panel of Figure 5.5.1 shows the positive

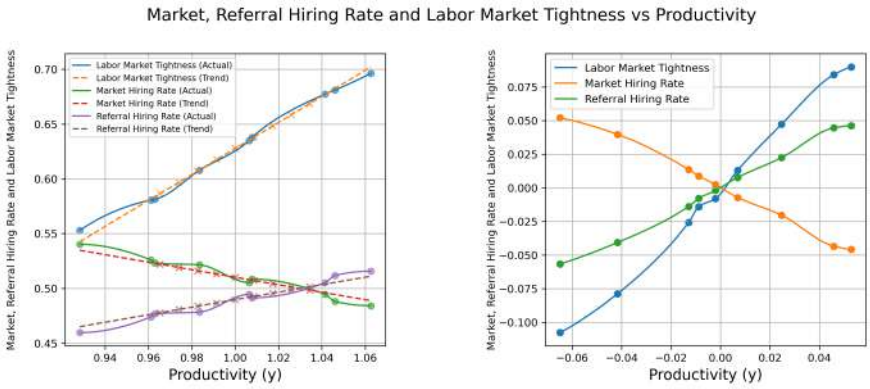


Figure 5.4: Market, Referral Hiring and Labor Market Tightness across productivity states and their deviations from trend.

Notes: The left hand side figure shows how labor market tightness vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and labor market tightness versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

correlation of market job-finding rate with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of market job-finding rates. We can conclude from

the figure that market job-finding rate is pro-cyclical and positively correlated with referral hiring rate. The intuition is that when match productivity is high, market tightness is high which implies higher market job-finding rate but lower market job-filling rate. This means less market hiring and more referral hiring. The correlation coefficient between the cyclical component of log market job-finding rate and log productivity series is 0.998. The standard deviation of the cyclical component of log market job-finding is 0.032 compared to 0.135 in the data. In other words, the model produced deviations from the trend of log market job-finding rate is about 24% of the data counterpart. The quarterly auto-correlation coefficient of log market job-finding rate is 0.294.

The left hand side panel of Figure 5.5.2 shows the negative correlation of market job-filling rates with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of market job-filling rates. We can conclude from the figure that market-job filling rate is counter-cyclical and negatively correlated with referral hiring rate. The intuition is that when match productivity is high, market tightness is high which implies lower market job-filling rate. This means less market hiring and more referral hiring. The correlation coefficient between the cyclical component of log market job-filling rate and log productivity series is -0.998. The standard deviation of the cyclical component of log market job-filling rate is 0.031 and the quarterly auto-correlation coefficient of log market job-filling rate is 0.294.

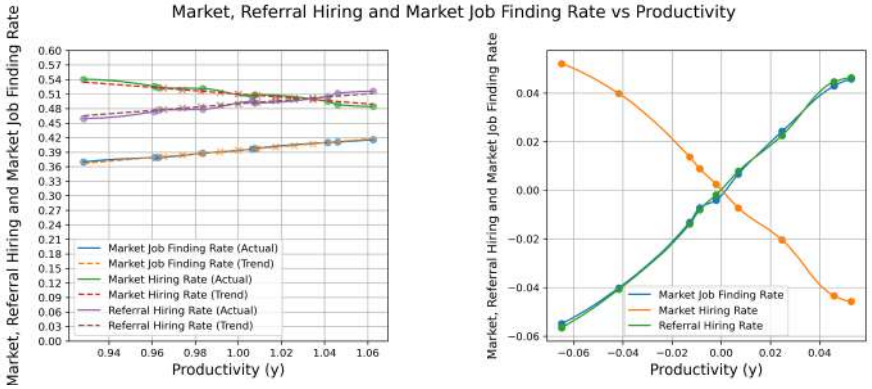


Figure 5.5.1: Market, Referral Hiring and Market Job-Finding Rate across productivity states and their deviations from trend.

Notes: The left hand side figure shows how market job-finding rate vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and market job-finding rate versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

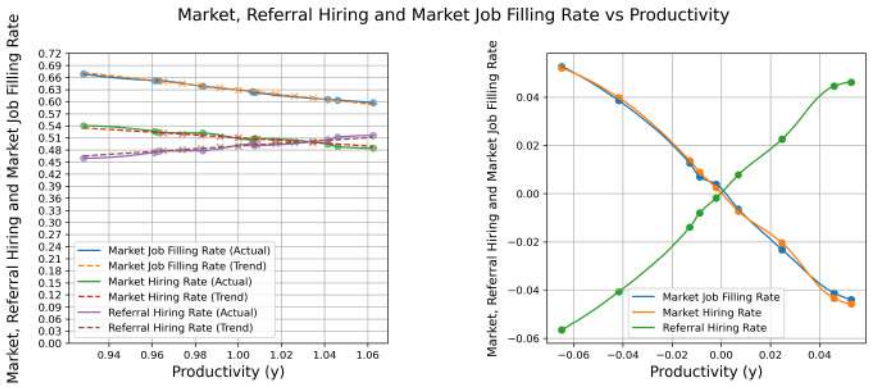


Figure 5.5.2: Market, Referral Hiring and Market Job-Filling Rate across productivity states and their deviations from trend.

Notes: The left hand side figure shows how market job-filling rate vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and market job-filling rate versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

5.6 Referral Job Finding and Job Filling Rates

In this section, I discuss the numerical solutions on referral job-finding and job-filling rates produced by the stochastic model. The left hand side panel of Figure 5.6.1 shows that referral job-finding rates does not vary with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of market job-finding rates. We can conclude from the figure that referral job-finding rate is pro-cyclical and positively correlated with referral hiring rate. The intuition is that when match productivity is high, market tightness is high which implies higher market-job finding rate but lower market job-filling rate. This means less market hiring and more referral hiring. The correlation coefficient between the cyclical component of log market job-finding rate and log productivity series is 0.998. The standard deviation of the cyclical component of log referral job-finding rate is 0.003. The quarterly auto-correlation coefficient of log referral job-finding rate is 0.313.

The left hand side panel of Figure 5.6.2 shows the positive correlation of referral job-filling rates with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of referral job-filling rates. We can conclude from the figure that referral job-filling rate is pro-cyclical and positively correlated with referral hiring rate. The intuition is that when match productivity is high, unemployment rate is low which implies, more people are employed and each of them have lower expected number of unemployed workers in their network. This increases the

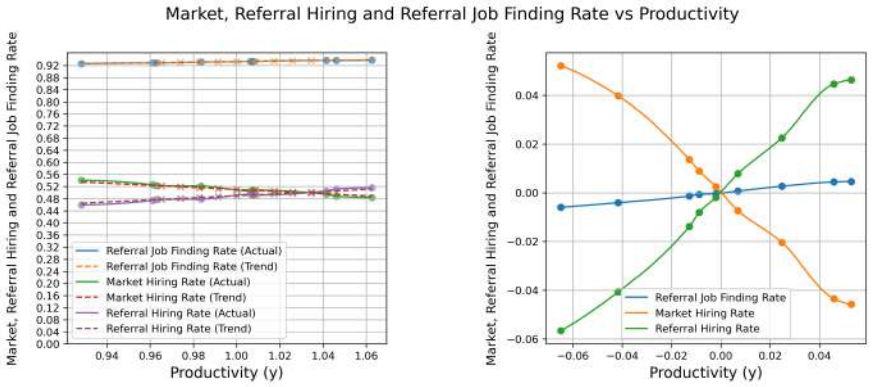


Figure 5.6.1: Market, Referral Hiring and Referral Job-Finding Rate across productivity states and their deviations from trend.

Notes: The left hand side figure shows how referral job-finding rate vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and referral job-finding rate versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

chance of each worker in the network to get employed through the referral channel, thus the higher referral job-filling rate. This means less market hiring and more referral hiring. The correlation coefficient between the cyclical component of log referral job-filling rate and log productivity series is -0.99. The standard deviation of the cyclical component of log referral job-filling rate is 0.01 and the quarterly auto-correlation coefficient of log referral job-filling rate is 0.31.

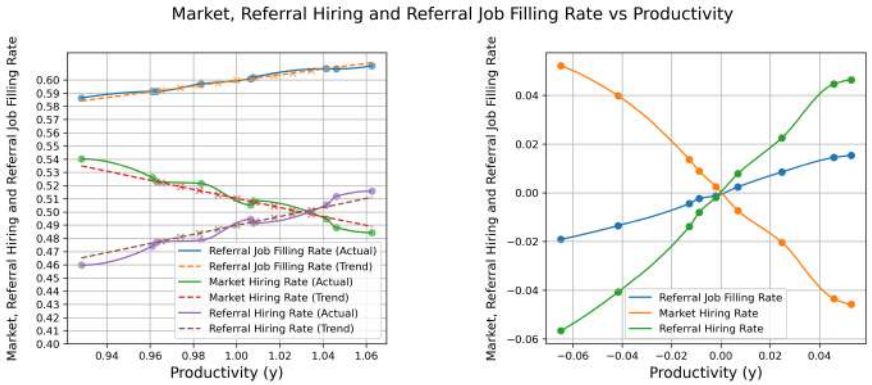


Figure 5.6.2: Market, Referral Hiring and Referral Job-Filling Rate across productivity states and their deviations from trend.

Notes: The left hand side figure shows how referral job-filling rate vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and referral job-filling rate versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

5.7 Good and Bad Match Wage Rates

In this section, I discuss the numerical solutions on expected market and referred wage rates produced by the stochastic model. The left hand side panel of Figure 5.7 shows the positive correlation of good and bad match wage rates with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of good and bad match wage rates. We can conclude from the figure that the wage rates are pro-cyclical. The intuition is that when match productivity is high, total surplus from a match is also high. Higher surplus implies higher wages. The correlation coefficient between the cyclical component of log good and bad match wage rates with log productivity series is 0.995 and 0.986 respectively. The standard deviations of the cyclical component of log good and bad match wage rates are 0.03 and their quarterly auto-correlation coefficient are 0.215 and 0.496 respectively.

5.8 Expected Market and Referred Wage Rates

In this section, I discuss the numerical solutions on expected market and referred wage rates produced by the stochastic model. The left hand side panel of Figure 5.8 shows that the expected market and referred wages do not vary with productivity across 9 state values of y. The right hand side panel shows the log deviations from trend of expected market and referred wage rates. We can conclude from the figure that both expected market and referred wage rates

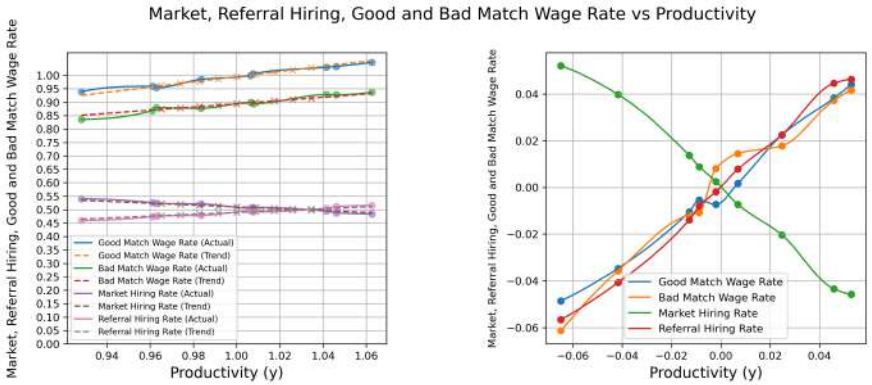


Figure 5.7: Market, Referral Hiring, Good and Bad Match Wage Rates across productivity states and their deviations from trend.

Notes: The left hand side figure shows how good and bad match wage rates vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring, good and bad match wage rates versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

are pro-cyclical. But expected referred wage rates are more fluctuating about its trend than the expected market wage rates. The intuition is that market matching rate is less variable due to the less variable market matching function. But, referral matching rate equal to the product of referral job-finding rate and unemployment rate, is more variable. Referral job-finding rate is pro-cyclical and unemployment rate is counter-cyclical, but their product is pro-cyclical. This means the variability of referral job-finding rate outweighs the variability of unemployment rate over the business cycle. The correlation coefficient between the cyclical component of log expected market wage rate and log expected referred wage rate with log productivity series is 0.961 and 0.99 respectively. The standard deviation of the cyclical component of log expected market and referred wage rates are 0.007 and 0.042 respectively. Their quarterly auto-correlation coefficients are 0.343 and 0.326 respectively.

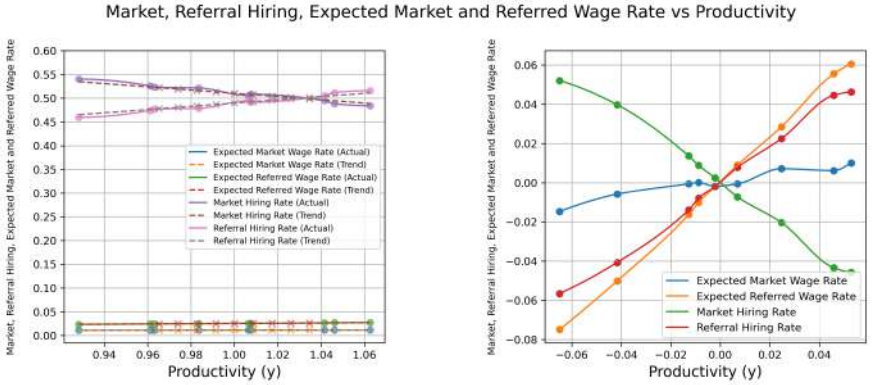


Figure 5.8: Market, Referral Hiring, Expected Market and Referred Wage Rates across productivity states and their deviations from trend.

Notes: The left hand side figure shows how expected market and referred wage rates vary across a 9 state Markov Chain of order 1 in the model. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring, expected market and referred wage rates versus productivity with smoothing parameter 1600. The dots denote the realized states in the model.

5.9 Beveridge Curve

The non-detrended and the cyclical Beveridge Curves (BC) are both downward sloping, similar to the conventional BC. As productivity y increases, vacancies rate increase and unemployment rate decreases, thus the inverse relationship between vacancies and unemployment rate.

Table 5.1: Summary Statistics from Productivity Shocks in the model

	Ω^M	$1-\Omega^M$	u	v	v/u	f	y
Standard Deviation	0.031	0.033	0.023	0.039	0.063	0.032	0.036
Quarterly Autocorrelation	0.29	0.32	0.323	0.287	0.294	0.294	0.32
Correlation Matrix							
Ω^M	1	-0.99	0.998	-0.998	-0.998	-0.998	-0.996
$1-\Omega^M$	-	1	-0.999	0.999	0.999	0.999	0.998
u	-	-	1	-0.999	-0.999	-0.999	-0.998
v	-	-	-	1	0.999	0.999	0.997
v/u	-	-	-	-	1	1	0.998
f	-	-	-	-	-	1	0.998
y	-	-	-	-	-	-	1

Notes: All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

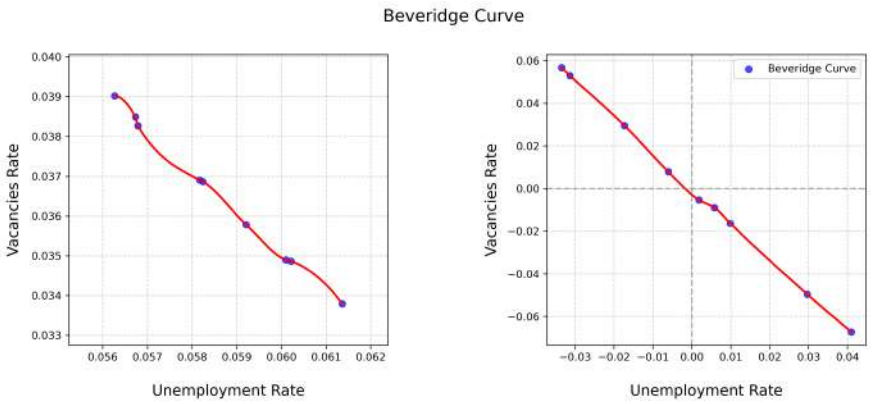


Figure 5.9: Beveridge Curve from Productivity Shocks

Notes: The left hand side figure shows the non-detrended Beveridge Curve across 9 state values of y. The right hand side figure shows the cyclical Beveridge Curve with smoothing parameter 1600.

6 Market Match Quality Shocks

In this section, I introduce shocks to the market good match level λ_M. I assume that λ_M follows a Gamma Distribution with the shape parameter being equal to the average value of λ_M at 5 and the scale parameter being set at 1. Each state is characterized by a random draw of λ_M from the corresponding gamma distribution. A realistic example for assuming the distribution of λ_M can be the waiting time required to find a good match while searching in the market. Positive shocks to market match quality might imply that market matching becomes more efficient in providing a good match (may be more good matches or lower wait times to find a good match). In other words,

it might be the case that market matching technology has become more efficient, for example, advent of LinkedIn job advertisements, opening of more job advertisement platforms in the form of websites, etc. The calibrated model has 15 states. Table 6.1 presents the calibrated parameters in the steady state CE and Table 6.2 presents the steady state CE.

Table 6.1: Calibration - Market Good Match Level Shocks

Description	Parameter	Value	Source	Value
discount factor, match productivity	β, y, y_0	$0.98, 1, 0.95$	Horvath(2014)	$0.98, 1, 0.95$
separation rates	δ, δ_0	$0.037, 0.037$	Data	$0.037, 0.037$
market good match (level and rate), homophily rate	$\lambda_M, \gamma_M, \gamma_R$	$5, 0.68, 0.7$	Horvath (2014), Data	[2, 8], 0.541, 0.672
unemp. benefits	b	0.45	Horvath (2014)	0.45
matching function elasticity	η	0.35	Galenianos (2014)	0.565
bargaining power	ϕ	0.55	Shimer (2005)	0.72
unit market and referral hiring cost	c_M, c_R	$0.3, 0.2$	Hoffman (2015)	$\frac{c_R}{c_M} \in \{0.66, 0.75\}$
vacancy posting cost	k	0.21	Shimer (2005)	0.213
network size	n	20	Horvath (2014)	$[10, 45]$
matching function scale parameter	A	0.6	Shimer (2005)	1.355

Table 6.2: Competitive Equilibrium - Market Good Match Level Shocks

Endogenous Variables	Model	Data	Targetted
Market and Referral Hiring Rate $(\Omega^M, 1-\Omega^M)$	$0.53, 0.47,$	$0.507, 0.493$	Y
Vacancies Rate (v)	0.037	0.041	Y
Unemployment Rate (u)	0.059	0.054	Y
Labor Market Tightness (θ)	0.63	0.851	Y
Market Job Finding Rate $(f(\theta))$	0.39	0.298	Y
Market Job Filling Rate $(q(\theta))$	0.62	-	N
Referral Job Filling Rate $(q^R(n,u))$	0.59	-	N
Referral Job Finding Rate $(f^R(n,u))$	0.93	-	N
Fraction of Good and Bad Matches (e, e^0)	$0.6, 0.341$	-	N
Good Match Wage (w)	0.97	-	N
Bad Match Wage (w^0)	0.94	-	N
Expected Market Hiring Profits (Π^M)	0.094	-	N
Expected Referral Hiring Profits (Π^R)	0.078	-	N

From table 6.2, I find that the steady state CE is characterized by more market hiring than referral hiring. The market job-filling rate is higher than the referral job-filling rate, the market channel is less likely to produce a good match ($\gamma_M < \gamma_R$ in Table 6.1) and is more costlier

hiring through the the market channel ($c_R < c_M$ in Table 6.1). So, the steady state market and referral hiring rates are characterized by quantity-quality and cost trade-offs. More precisely, $\frac{\sum_{s=1}^{15} \frac{q_s^R(n,u_s)}{q(\theta_s)}}{15} = 0.95$, $\frac{\gamma_M}{\gamma_R} = 0.97$ and $\frac{c_R}{c_M} = 0.67$. Moreover, the market channel is too frictional for the unemployed workers compared to the referral channel to get employed, where $\frac{\sum_{s=1}^{15} \frac{f(\theta_s)}{f^R(n,u_s)}}{15} = 0.42$. Finally, the expected market and referred wages are calculated to be $0.012, 0.025$ using the formula $\frac{\sum_{s=1}^{15} \Omega_s^M m(v_s,u_s)(\gamma_M w_s + (1-\gamma_M) w_s^0)}{15}$ and $\frac{\sum_{s=1}^{15} (1-\Omega_s^M) f_R(n,u_s) u_s (\gamma_R w_s + (1-\gamma_R) w_s^0)}{15}$ respectively. This shows the existence of wage inequality in equilibrium as referred workers earn more than the market hired workers, with the wage premium being 56%.

Furthermore, market hiring is more profitable than referral hiring. The bad matches are associated with a wage discount of about 3% relative to the good matches and the fraction of good matches exceeds the fraction of bad matches by about 26%. Moreover, the expected number of unemployed workers in the network equals 1.16 (> 1), which implies that there exists at least one unemployed worker in each employee's network.

All these results showcase the fact that the firm's choice of market and referral hiring plays a significant role in determining the network and wage inequality with shocks to market match quality.

Policy Functions

6.1 Hiring Rate

In this section, I discuss about the numerical solutions on market and referral hiring rates when market good match rate γ_M is stochastic. The left hand side panel of Figure 6.1 shows the positive correlation between market hiring rate and market good match rate γ_M. The right hand side panel shows the log deviations from trend of market and referral hiring rates. The correlation coefficient between the cyclical component of log market hiring rate and log γ_M series is 0.977, and -0.963 for the referral hiring rate series. The standard deviations of the cyclical components of log market hiring rate and log referral hiring rate series are each 0.013, compared to 0.053 in the data. The standard deviation of the cyclical component of log γ_M series is 0.047.I also find that the quarterly auto-correlation coefficient for the log market hiring rate series is -0.22, for the referral hiring rate series is -0.24 and that of log γ_M series is -0.25.



Figure 6.1: Market and Referral Hiring Rates across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how market and referral hiring rates vary across 15 state values of γ_M. The right hand side figure the log deviations from trend of an HP filtered quarterly data on market and referral hiring rates versus market good match rate γ_M with smoothing parameter 1600.

6.2 Vacancies Rate

This section discusses the numerical solutions on vacancies rate when referral good match rate γ_M is stochastic. The left hand side panel of Figure 6.2 shows the variation of vacancies rate with γ_M. The variation in vacancies rate being of the order 2×10^{-3}, the figure apparently fails to capture the variation. The right hand side panel shows the log deviations from trend of vacancies rate. Higher chance of a good match through the market channel induces more entry of firms and hence more vacancy posting.

The correlation coefficient between the cyclical component of log vacancies rate and log γ_M series is 0.908. The standard deviation of the cyclical component of log vacancies rate is 0.006 compared to 0.088 in the data. The quarterly auto-correlation coefficient of log vacancies rate series is -0.507.

6.3 Unemployment Rate

This section discusses the numerical solutions on unemployment rate when market good match rate γ_M is stochastic. The left hand side panel of Figure 6.3 shows almost no variation of unemployment rate with γ_M as the variation is of the order of 10^{-3}. The right hand side panel shows the log deviations from trend of unemployment rate. Unemployment rate increases with better market match quality rate due to more hiring happening through the market channel which is frictional

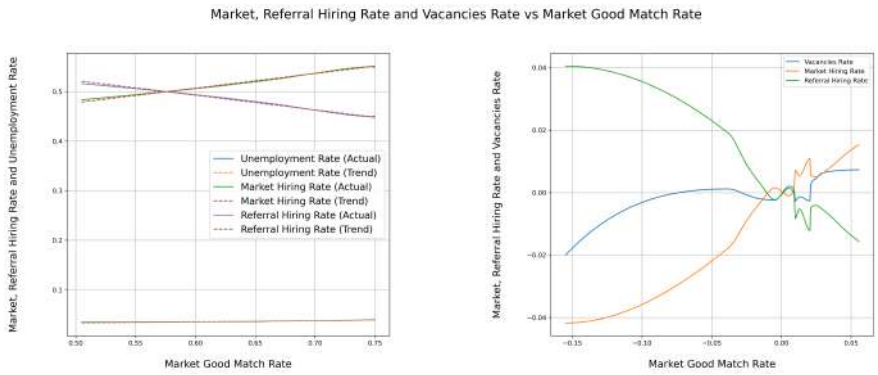


Figure 6.2: Market, Referral Hiring and Vacancies Rate across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how vacancies rate vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and vacancies rate versus market good match rate γ_M with smoothing parameter 1600.

than the referral channel which is not at all congested.

The correlation coefficient between the cyclical component of log unemployment rate and log γ_M series is 0.82. The standard deviation of the cyclical component of log unemployment rate is 0.002. The quarterly auto-correlation coefficient of log unemployment rate series is -0.56.

6.4 Labor Market Tightness

This section discusses the numerical solutions on labor market tightness when market good match rate γ_M is stochastic. The left hand side panel of Figure 6.4 shows that labor market tightness increases with γ_M. The right hand side panel shows the log deviations from trend of the tightness. Both log deviations from trend of vacancies rate and unemployment rate increase, but overall the log deviations from trend of unemployment rate increase more than the log deviations from trend of vacancies rate, hence the log deviations from trend of market tightness decrease with log deviations from trend of γ_M. This shows that market matching being frictional make the market less tighter even when the market is more efficient in producing good matches.

The correlation coefficient between the cyclical component of log tightness and log γ_M series is -0.377. The standard deviation of the cyclical component of log tightness is 0.002. The quarterly auto-correlation coefficient of log tightness series is -0.43.

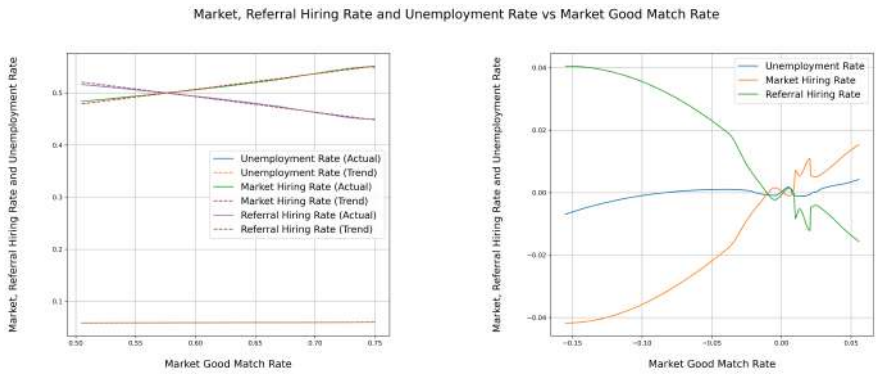


Figure 6.3: Market, Referral Hiring and Unemployment Rate across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how unemployment rate vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and unemployment rate versus market good match rate γ_M with smoothing parameter 1600.

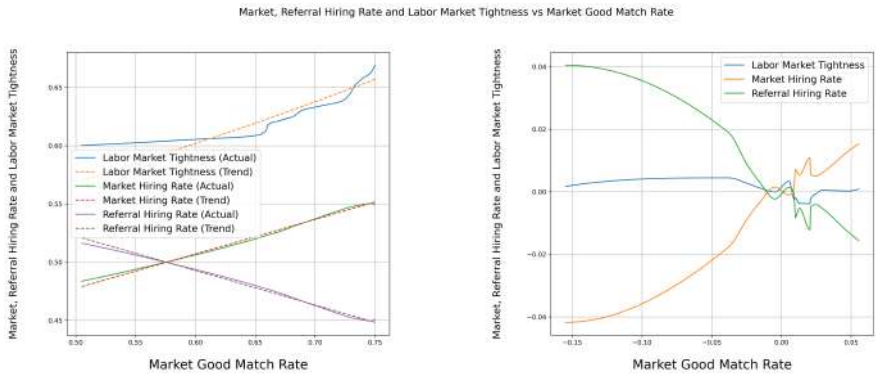


Figure 6.4: Market, Referral Hiring and Labor Market Tightness across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how tightness vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and tightness versus market good match rate γ_M with smoothing parameter 1600.

6.5 Market Job Finding and Job Filling Rates

This section discusses the numerical solutions on market job-finding rates when market good match rate γ_M is stochastic. The left hand side panel of Figure 6.5.1 shows that market job-finding rate increases with γ_M. The right hand side panel shows the log deviations from trend of market job-finding rate. Log deviations from trend of market job-finding rate f is decreasing in γ_M, since f is increasing in θ which is decreasing in γ_M (fig 6.4).

The correlation coefficient between the cyclical component of log market job-finding rate and log γ_M series is -0.377. The standard deviation of the cyclical component of log market job-finding rate is 0.001. The quarterly auto-correlation coefficient of log market job-finding rate series is -0.43.

The left hand side panel of Figure 6.5.2 shows that market job-filling rate decreases with γ_M. The right hand side panel shows the log deviations from trend of market job-filling rate. Log deviations from trend of market job-filling rate are weakly increasing in log deviations from trend of γ_M, since q is decreasing in θ, and log deviations from trend of θ which are decreasing in log deviations from trend of γ_M (fig 6.4).

The correlation coefficient between the cyclical component of log market job-filling rate and log γ_M series is 0.37. The standard deviation of the cyclical component of log market job-filling rate is 0.001. The quarterly auto-correlation coefficient of log market job-filling rate series is -0.43.

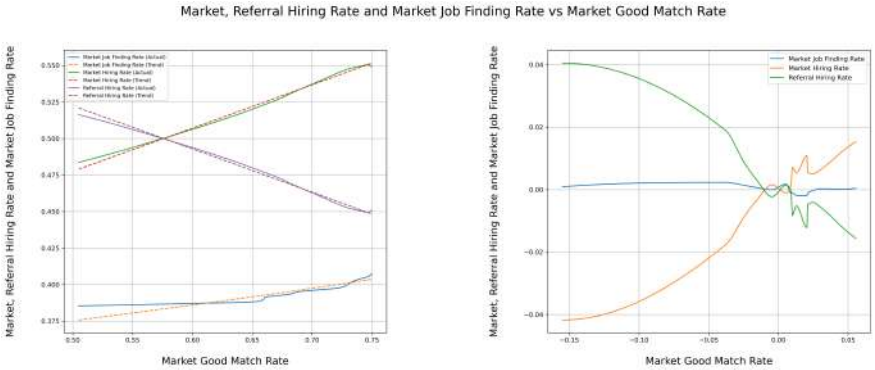


Figure 6.5.1: Market, Referral Hiring and Market Job-Finding Rate across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how market job-finding rate vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and market job-finding rate versus market good match rate γ_M with smoothing parameter 1600.

6.6 Referral Job Finding and Job Filling Rates

This section discusses the numerical solutions on referral job-finding rates when market good match rate is stochastic. The left hand side panel of Figure 6.6.1 shows that referral job-finding rate does not vary with γ_M because the variation is of the order of 10^{-3}. The right hand side panel shows the log deviations from trend of referral job-finding rate. Log deviations from trend of referral job-finding rate are decreasing in log deviations from trend of γ_M, since log deviations from f_R are decreasing in log deviations from trend of u which is increasing in log deviations from trend of γ_M (fig 6.3).

The correlation coefficient between the cyclical component of log referral job-finding rate and log γ_M series is -0.97. The quarterly auto-correlation coefficient of log referral job-finding rate series

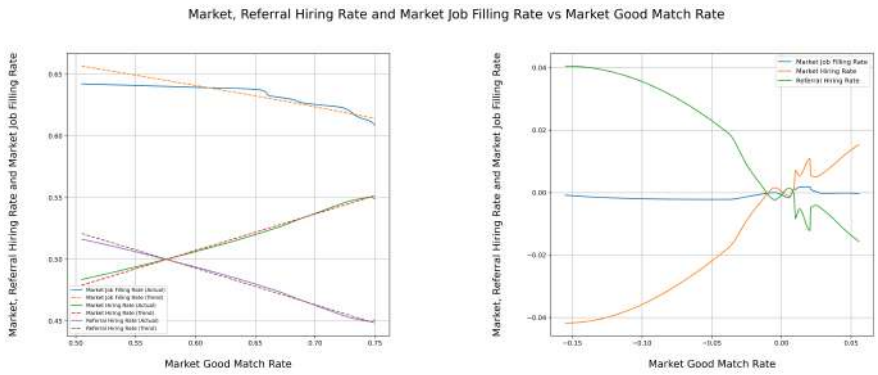


Figure 6.5.2: Market, Referral Hiring and Market Job-Filling Rate across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how market job-filling rate vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and market job-filling rate versus market good match rate γ_M with smoothing parameter 1600.

is -0.3.

The left hand side panel of Figure 6.6.2 shows that referral job-filling rate decreases with γ_M. The right hand side panel shows the percentage deviations from trend of referral job-filling rate. Log deviations from trend of referral job-filling rate are decreasing in log deviations from trend of γ_M, since log deviations from trend of q_R is decreasing in log deviations from trend of u which is increasing in log deviations from trend of γ_M (fig 6.3).

The correlation coefficient between the cyclical component of log referral job-filling rate and log γ_M series is -0.97. The standard deviation of the cyclical component of log referral job-filling rate is 0.003. The quarterly auto-correlation coefficient of log referral job-filling rate series is -0.3.

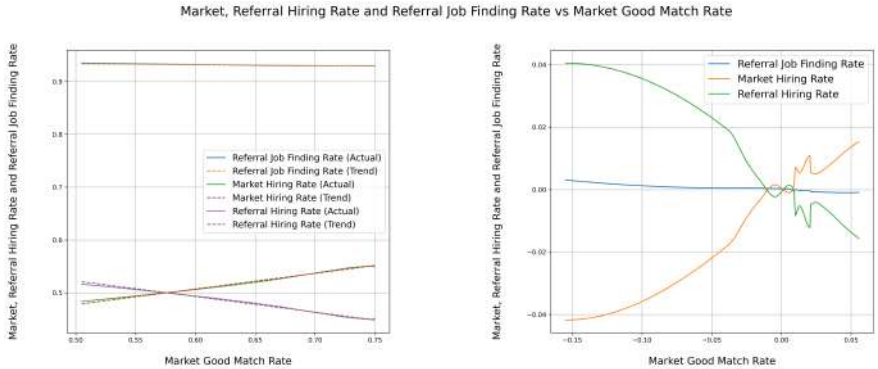


Figure 6.6.1: Market, Referral Hiring and Referral Job-Finding Rate across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how referral job-finding rate vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and referral job-finding rate versus market good match rate γ_M with smoothing parameter 1600.

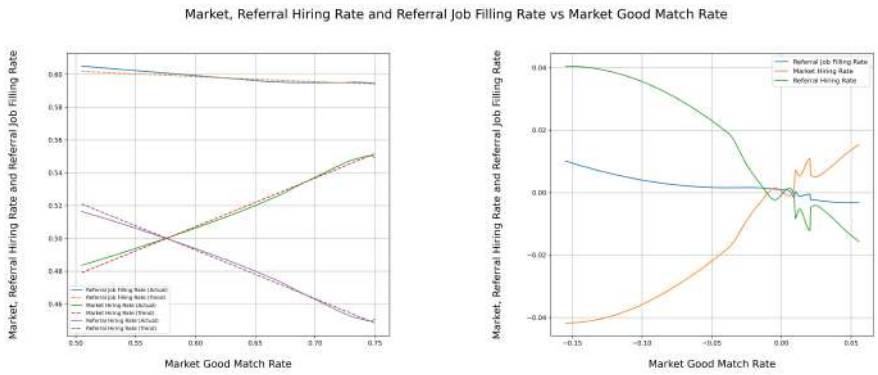


Figure 6.6.2: Market, Referral Hiring and Referral Job-Filling Rate across 15 state values of γ_M and their log deviations from trend.

Notes: The left hand side figure shows how referral job-filling rate vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and referral job-filling rate versus market good match rate γ_M with smoothing parameter 1600.

6.7 Good and Bad Match Wage Rates

This section discusses the numerical solutions on good and bad match wage rates when market good match rate γ_M is stochastic. The left hand side panel of Figure 6.7 shows that good match wage increases and bad match wage decreases with γ_M. The right hand side panel shows the log deviations from trend of good and bad match wage rates. Log deviations from trend of good match wage rates are weakly decreasing and that for bad match wage rates are increasing in log deviations from trend of γ_M. These results are due to stochastic general equilibrium effects.

The correlation coefficients between the cyclical component of log good and bad match wage rates and log γ_M series are -0.3 and 0.93 respectively. The quarterly auto-correlation coefficient of log good match wage and log bad match wage rate series are -0.4 and -0.32 respectively.

6.8 Expected Market and Referred Wage Rates

This section discusses the numerical solutions on expected market and referred wage rates when market good match rate is stochastic. The left hand side panel of Figure 6.8 shows no variation in expected market and referred wage rates with γ_M respectively. The right hand side panel shows the log deviations from trend of expected market and referred wage rates. Log deviations from trend of expected market and referred wage rates are increasing and decreasing in log deviations from trend of γ_M. It seems that the cyclical variation of expected market and referred wage rates



Figure 6.7: Market, Referral Hiring, Good and Bad Match Wage Rates across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how good and bad match wage rate vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring, good and bad match wage rate versus market good match rate γ_M with smoothing parameter 1600.

seem to be driven by the cyclical variation of log market and referral hiring rates.



Figure 6.8: Market, Referral Hiring, Expected Market and Referred Wage Rates across 15 state values of γ_M and their deviations from trend.

Notes: The left hand side figure shows how expected market and referred wage rates vary across 15 state values of γ_M. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring, expected market and referred wage rates versus market good match rate γ_M with smoothing parameter 1600.

The correlation coefficient between the cyclical component of log expected market wage rate and log γ_M series is 0.99 and that for the log expected referred wage rate series is -0.94. The standard deviation of the cyclical component of log expected market wage rate series is 0.015 and that for the log expected referred wage rate series is 0.012. The quarterly auto-correlation coefficients of log expected market and referred wag rate series are -0.28 and -0.24 respectively.

Table 6.3: Summary Statistics from Market Good Match Level Shocks in the model

	Ω^M	$1-\Omega^M$	u	v	v/u	f	γ_M
Standard Deviation	0.013	0.013	0.002	0.006	0.002	0.001	0.047
Quarterly Autocorrelation	-0.22	-0.24	-0.56	-0.51	-0.43	-0.43	-0.25
Correlation Matrix							
Ω^M	1	-0.998	0.716	-0.801	-0.51	-0.51	-0.977
$1-\Omega^M$	-	1	-0.694	-0.77	0.53	0.53	-0.963
u	-	-	1	0.93	0.187	0.187	0.82
v	-	-	-	1	-0.03	-0.03	0.908
v/u	-	-	-	-	1	0.99	-0.377
f	-	-	-	-	-	1	-0.377
γ_M	-	-	-	-	-	-	1

Notes: All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

6.9 Beveridge Curve

The non-detrended and the cyclical Beveridge Curves (BC) are both upward sloping, contrary to the conventional downward sloping BC. As γ_M increases, firms post more vacancies, thus decreasing the chance of each vacancy getting filled. In other words, the frictions for the firms to form a match through the market increases and hence unemployment rate also increases.

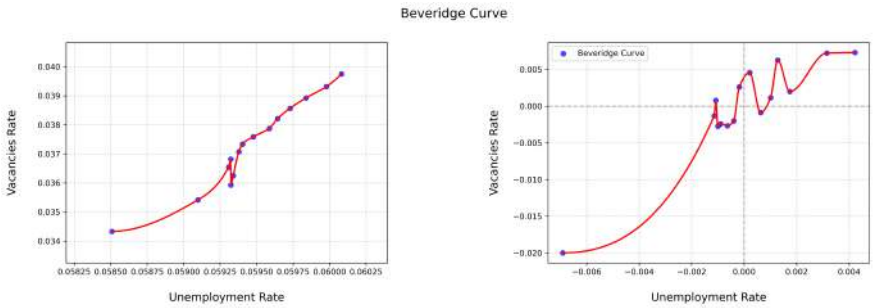


Figure 6.9: Beveridge Curve from Market Good Match Level Shocks

Notes: The left hand side figure shows the non-detrended Beveridge Curve across 15 state values of γ_M. The right hand side figure shows the cyclical Beveridge Curve with smoothing parameter 1600.

7 Referral Match Quality Shocks

In this section, I introduce shocks to the referral match quality rate (or the network homophily rate) γ_R. I assume that γ_R follows a Beta Distribution with the shape parameters α and β equal to 10 and 40 respectively. The average value of γ_R is set at 0.85. Each state is characterized by

a random draw of γ_R from the corresponding Beta distribution. A realistic example for assuming the distribution of γ_R can be the waiting time required to find a good match through the network contacts. Positive shocks to referral match quality might imply that more similar type contacts are formed in the network which might help form better matches. In other words, more similar type contacts might be able to alleviate the asymmetric information problem about the worker's background and skills, to a certain degree, for the employer. The calibrated model has 11 states. Table 7.1 presents the calibrated parameters in the steady state CE and Table 7.2 presents the steady state CE.

From table 7.2, I find that the steady state CE is characterized by more market hiring than referral hiring. The market job-filling rate is higher than the referral job-filling rate, the market channel is less likely to produce a good match ($\gamma_M < \gamma_R$ in Table 7.1) and is more costlier hiring through the the market channel ($c_R < c_M$ in Table 7.1). So, the steady state market and referral hiring rates are characterized by quantity-quality and cost trade-offs. More precisely, $\frac{\sum_{s=1}^{11} \frac{q_s^R(n,u_s)}{q(\theta_s)}}{11} = 0.84$, $\frac{\gamma_M}{\gamma_R} = 0.78$ and $\frac{c_R}{c_M} = 0.67$. Moreover, the market channel is too frictional for the unemployed workers compared to the referral channel to get employed, where $\frac{\sum_{s=1}^{11} \frac{f(\theta_s)}{f^R(n,u_s)}}{11} = 0.38$. Finally, the expected market and referred wages are calculated to be $0.14, 0.03$ using the formula $\frac{\sum_{s=1}^{11} \Omega_s^M m(v_s,u_s)(\gamma_M w_s + (1-\gamma_M) w_s^0)}{11}$ and $\frac{\sum_{s=1}^{11} (1-\Omega_s^M) f_R(n,u_s) u_s (\gamma_R w_s + (1-\gamma_R) w_s^0)}{11}$ respectively. This shows that the market hired workers earn substantially more than the referred workers.

Furthermore, market hiring is more profitable than referral hiring. The bad matches are associated with a wage discount of about 1.5% relative to the good matches and the fraction of

Table 7.1: Calibration - Referral Good Match Rate Shocks

Description	Parameter	Value	Source	Value
discount factor, match productivity	β, y, y_0	$0.98, 1, 0.95$	Horvath(2014)	$0.98, 1, 0.95$
separation rates	δ, δ_0	$0.037, 0.037$	Data	$0.037, 0.037$
market good match (level and rate), homophily rate	$\lambda_M, \gamma_M, \gamma_R$	$2, 0.66, 0.85$	Horvath (2014), Data	$[2, 8]$, 0.541, 0.672
unemp. benefits	b	0.45	Horvath (2014)	0.45
matching function elasticity	η	0.35	Galenianos (2014)	0.565
bargaining power	ϕ	0.55	Shimer (2005)	0.72
unit market and referral hiring cost	c_M, c_R	$0.3, 0.2$	Hoffman (2015)	$\frac{c_R}{c_M} \in \{0.66, 0.75\}$
vacancy posting cost	k	0.21	Shimer (2005)	0.213
network size	n	20	Horvath (2014)	$[10, 45]$
matching function scale parameter	A	0.6	Shimer (2005)	1.355

good matches exceeds the fraction of bad matches by about 58%. Moreover, the expected number of unemployed workers in the network equals 1.16 (> 1), which implies that there exists at least one unemployed worker in each employee's network.

All these results showcase the fact that the firm's choice of market and referral hiring plays a significant role in determining the network and wage inequality with shocks to referral match quality.

Policy Functions

7.1 Hiring Rate

In this section, I discuss the numerical solutions on market and referral hiring rates when referral good match rate γ_R is stochastic. The left hand side panel of Figure 7.1 shows the positive correlation between market hiring rate and referral good match rate γ_R. The right hand side panel shows the log deviations from trend of market and referral hiring rates. Higher referral good match rate leads to more referral hiring. The correlation coefficient between the cyclical component of

Table 7.2: Competitive Equilibrium - Referral Good Match Rate Shocks

Endogenous Variables	Model	Data	Targetted
Market and Referral Hiring Rate $(\Omega^M, 1-\Omega^M)$	$0.45, 0.55,$	$0.507, 0.493$	Y
Vacancies Rate (v)	0.037	0.041	Y
Unemployment Rate (u)	0.06	0.054	Y
Labor Market Tightness (θ)	0.5	0.851	Y
Market Job Finding Rate $(f(\theta))$	0.35	0.298	Y
Market Job Filling Rate $(q(\theta))$	0.7	-	N
Referral Job Filling Rate $(q^R(n,u))$	0.58	-	N
Referral Job Finding Rate $(f^R(n,u))$	0.93	-	N
Fraction of Good and Bad Matches (e, e^0)	$0.76, 0.18$	-	N
Good Match Wage (w)	0.951	-	N
Bad Match Wage (w^0)	0.936	-	N
Expected Market Hiring Profits (Π^M)	0.076	-	N
Expected Referral Hiring Profits (Π^R)	0.091	-	N

log market hiring rate and log γ_R series is -0.989, and 0.991 for the referral hiring rate series. The standard deviations of the cyclical components of log market hiring rate series log referral hiring

rate series are 0.058 and 0.11 respectively, compared to 0.053 in the data. The standard deviation of the cyclical component of log γ_R series is 0.22. I also find that the quarterly auto-correlation coefficient for the log market hiring rate series is -0.399, for the referral hiring rate series is -0.392 and that of log γ_R series is -0.44.



Figure 7.1: Market and Referral Hiring Rates across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how market and referral hiring rates vary across 11 state values of γ_R. The right hand side figure the log deviations from trend of an HP filtered quarterly data on market and referral hiring rates versus referral good match rate γ_R with smoothing parameter 1600.

7.2 Vacancies Rate

This section discusses the numerical solutions on vacancies rate when market good match rate γ_M is stochastic. The left hand side panel of Figure 7.2 shows the variation of vacancies rate with γ_R. The variation in vacancies rate being in the range of 2×10^{-3} and 9×10^{-3}, the figure apparently fails to capture the variation. The right hand side panel shows the log deviations from trend of vacancies rate. When referral matching provides more good matches than the market hiring, then vacancy posting declines, as firms hire more through employee referrals and referral hiring do not need vacancy posting. The correlation coefficient between the cyclical component of log vacancies rate and log γ_R series is -0.912. The standard deviation of the cyclical component of log vacancies rate is 0.014 compared to 0.088 in the data. The quarterly auto-correlation coefficient of log vacancies rate series is -0.415.

7.3 Unemployment Rate

This section discusses the numerical solutions on unemployment rate when referral good match rate γ_R is stochastic. The left hand side panel of Figure 7.3 shows almost no variation of unem-

ployment rate with γ_R as the range of variation is of the order of 10^{-2}. The right hand side

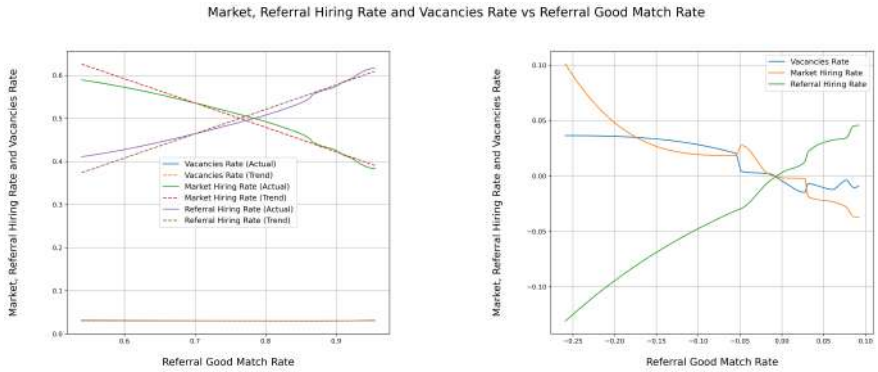


Figure 7.2: Market, Referral Hiring and Vacancies Rate across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how vacancies rate vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and vacancies rate versus referral good match rate γ_R with smoothing parameter 1600.

panel shows the log deviations from trend of unemployment rate. The log deviations unemployment rate decrease with higher values of log deviations of γ_R. This is because referral matching is not at all congestional whereas market matching is frictional and more referral hiring takes place with higher values of γ_R.

The correlation coefficient between the cyclical component of log unemployment rate and log γ_R series is -0.99. The standard deviation of the cyclical component of log unemployment rate is 0.02. The quarterly auto-correlation coefficient of log unemployment rate series is -0.492.

7.4 Labor Market Tightness

This section discusses the numerical solutions on labor market tightness when referral good match rate γ_R is stochastic. The left hand side panel of Figure 7.4 shows that labor market tightness increases with γ_R. The right hand side panel shows the log deviations from trend of the tightness. Both log deviations from trend of vacancies rate and unemployment rate are decreasing in log deviations from trend of γ_R, but overall, the log deviations from trend of unemployment rate decrease more than the log deviations from trend of vacancies rate, hence the log deviations from trend of market tightness decrease with log deviations from trend of γ_R. This shows that referral matching being not congestional, make the market tighter when the referrals generate more good matches than the market.

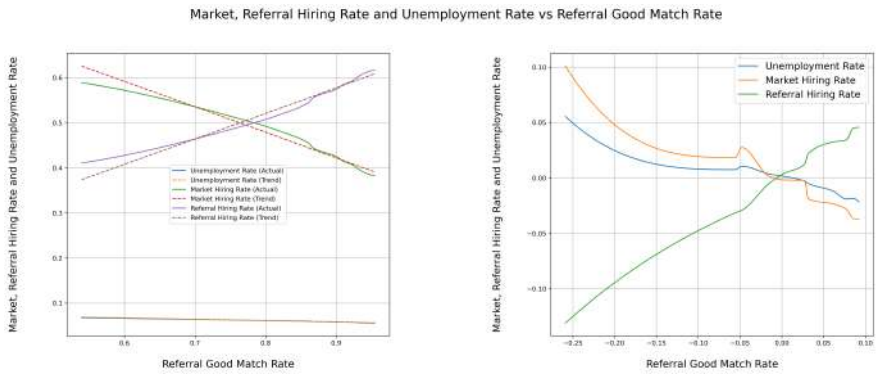


Figure 7.3: Market, Referral Hiring and Unemployment Rate across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how unemployment rate vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and unemployment rate versus referral good match rate γ_R with smoothing parameter 1600.

The correlation coefficient between the cyclical component of log tightness and log γ_R series is 0.95. The standard deviation of the cyclical component of log tightness is 0.023. The quarterly auto-correlation coefficient of log tightness series is -0.51.

7.5 Market Job Finding and Job Filling Rates

This section discusses the numerical solutions on market job-finding rates when referral good match rate γ_R is stochastic. The left hand side panel of Figure 7.5.1 shows that market job-finding rate increases with γ_R. The right hand side panel shows the log deviations from trend of market job-finding rate. Log deviations from trend of market job-finding rate f are increasing in log deviations from trend of γ_R, since f is increasing in θ, which is increasing in γ_R (fig 7.4).

The correlation coefficient between the cyclical component of log market job-finding rate and log γ_R series is 0.955. The standard deviation of the cyclical component of log market job-finding rate is 0.011. The quarterly auto-correlation coefficient of log market job-finding rate series is -0.51.

The left hand side panel of Figure 7.5.2 shows that market job-filling rate decreases with γ_R. The right hand side panel shows the log deviations from trend of market job-filling rate. Log deviations from trend of market job-filling rate are decreasing in log deviations from trend of γ_R, since q is decreasing in θ, which is increasing in γ_R (fig 7.4).

The correlation coefficient between the cyclical component of log market job-filling rate and log γ_R series is -0.955. The standard deviation of the cyclical component of log market job-filling rate is 0.011. The quarterly auto-correlation coefficient of log market job-filling rate series is -0.51.

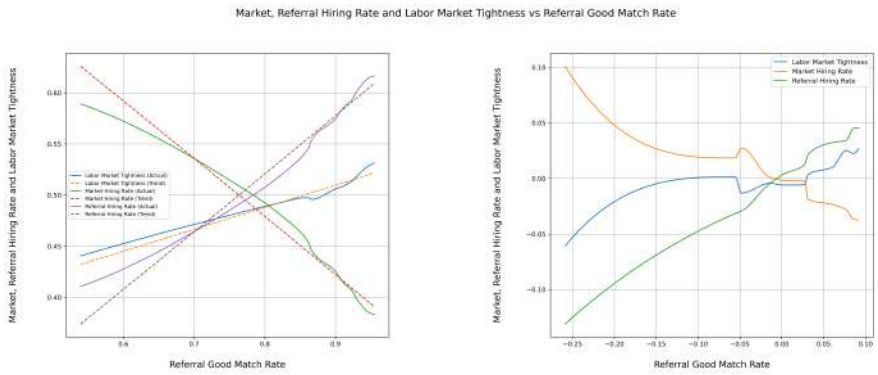


Figure 7.4: Market, Referral Hiring and Labor Market Tightness across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how tightness vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and tightness versus referral good match rate γ_R with smoothing parameter 1600.

7.6 Referral Job Finding and Job Filling Rates

This section discusses the numerical solutions on referral job-finding rates when referral good match rate γ_R is stochastic. The left hand side panel of Figure 7.6.1 shows that referral job-finding rate increases with γ_R. The right hand side panel shows the log deviations from trend of referral job-finding rate. Log deviations from trend of referral job-finding rate are also increasing in log deviations from trend of γ_R, since log deviations from f_R are decreasing in log deviations from trend of u which are decreasing in log deviations from trend of γ_R (fig 7.3). Lower the unemployment

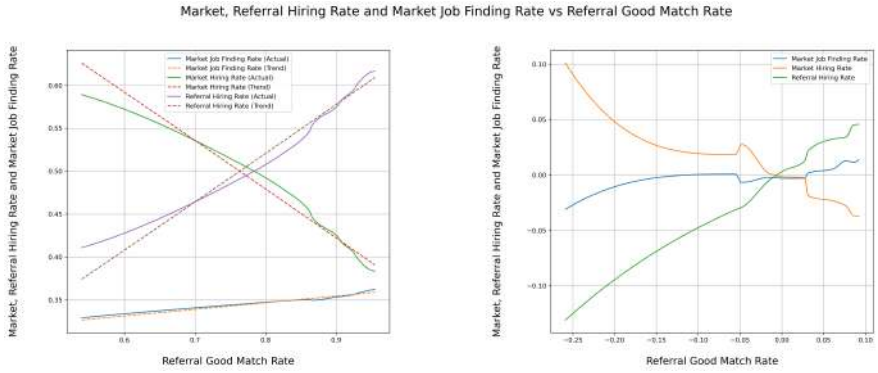


Figure 7.5.1: Market, Referral Hiring and Market Job-Finding Rate across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how market job-finding rate vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and market job-finding rate versus referral good match rate γ_R with smoothing parameter 1600.

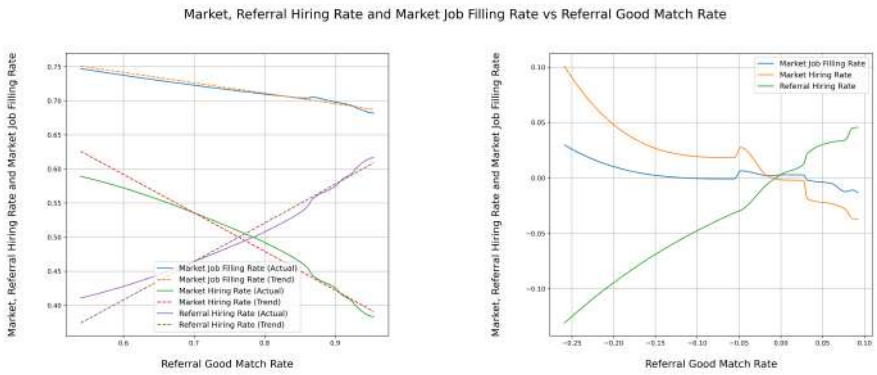


Figure 7.5.2: Market, Referral Hiring and Market Job-Filling Rate across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how market job-filling rate vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and market job-filling rate versus referral good match rate γ_R with smoothing parameter 1600.

rate, higher is the chance of finding a job through the employee's network.

The correlation coefficient between the cyclical component of log referral job-finding rate and log γ_R series is 0.99. The standard deviation of the cyclical component of log referral job-finding rate series is 0.006. The quarterly auto-correlation coefficient of log referral job-finding rate series is -0.47.

The left hand side panel of Figure 7.6.2 shows that referral job-filling rate increases with γ_R. The right hand side panel shows the log deviations from trend of referral job-filling rate. Log deviations from trend of referral job-filling rate are also increasing in log deviations from trend of γ_R, since log deviations from trend of q_R are decreasing in log deviations from trend of u, which are decreasing in log deviations from trend of γ_R (fig 8.3). Lower unemployment rate reduces the expected number of unemployed workers in the employee's network and also increases the chance of passing on the job information to an unemployed worker.

The correlation coefficient between the cyclical component of log referral job-filling rate and log γ_R series is 0.99. The standard deviation of the cyclical component of log referral job-filling rate is 0.018. The quarterly auto-correlation coefficient of log referral job-filling rate series is -0.473.

7.7 Good and Bad Match Wage Rates

This section discusses the numerical solutions on good and bad match wage rates when referral good match rate γ_R is stochastic. The left hand side panel of Figure 7.7 shows that good match

wage increases and bad match wage decreases with γ_R. The right hand side panel shows the log deviations from trend of good and bad match wage rates. Log deviations from trend of good match wage rates are weakly decreasing and that for bad match wage rates are increasing in log deviations from trend of γ_R, with standard deviations being of the order 10^{-3} and 4×10^{-3} respectively for log good and bad match wage rates. The correlation coefficients between the cyclical component of log good and bad match wage rates and log γ_M series are -0.4 and 0.96 respectively. The quarterly auto-correlation coefficients of log good match wage and log bad match wage rate series are -0.795 and -0.693 respectively.

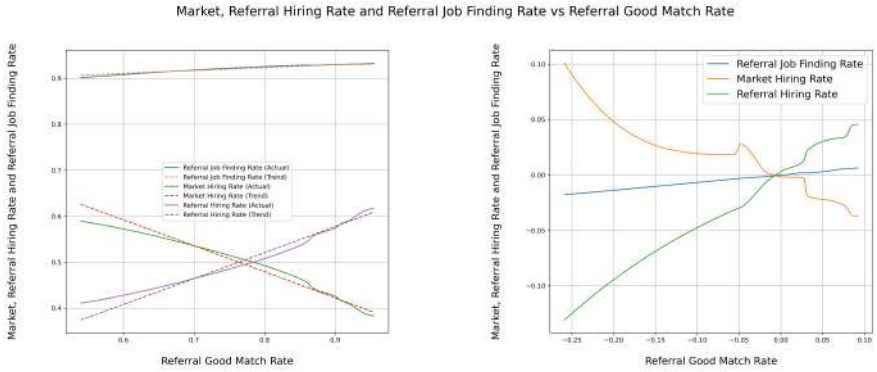


Figure 7.6.1: Market, Referral Hiring and Referral Job-Finding Rate across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how referral job-finding rate vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and referral job-finding rate versus referral good match rate γ_R with smoothing parameter 1600.

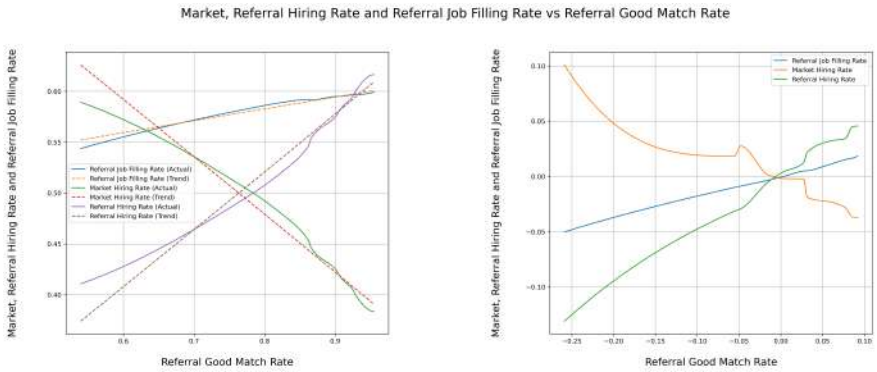


Figure 7.6.2: Market, Referral Hiring and Referral Job-Filling Rate across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how referral job-filling rate vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring and referral job-filling rate versus referral good match rate γ_R with smoothing parameter 1600.

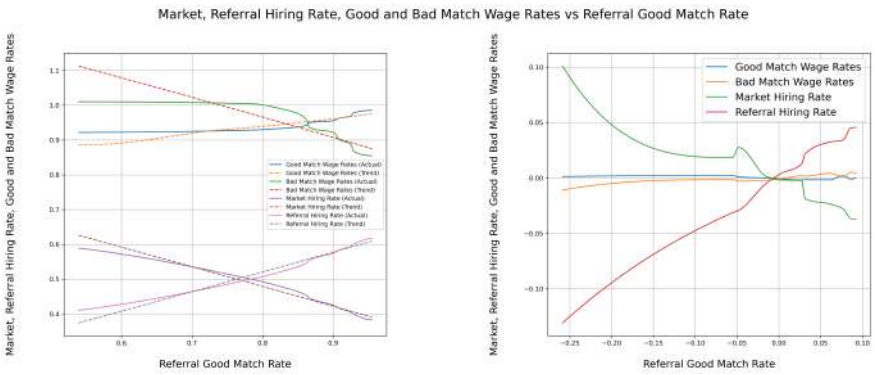


Figure 7.7: Market, Referral Hiring, Good and Bad Match Wage Rates across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how good and bad match wage rate vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring, good and bad match wage rate versus referral good match rate γ_R with smoothing parameter 1600.

7.8 Expected Market and Referred Wage Rates

This section discusses the numerical solutions on expected market and referred wage rates when referral good match rate is stochastic. The left hand side panel of Figure 7.8 shows downward trend in expected market wage rates and no substantial variation in referred wage rates with γ_R. The right hand side panel shows the log deviations from trend of expected market and referred wage rates. Log deviations from trend of expected market and referred wage rates are increasing and decreasing in log deviations from trend of γ_R. It seems that the cyclical variation of expected market and referred wage rates seem to follow the cyclical variation of log market and referral

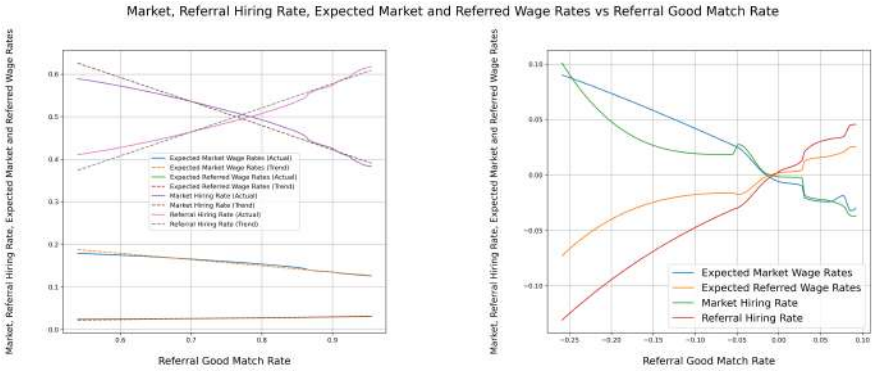


Figure 7.8: Market, Referral Hiring, Expected Market and Referred Wage Rates across 11 state values of γ_R and their deviations from trend.

Notes: The left hand side figure shows how expected market and referred wage rates vary across 11 state values of γ_R. The right hand side figure shows log deviations from trend of an HP filtered market, referral hiring, expected market and referred wage rates versus referral good match rate γ_R with smoothing parameter 1600.

Table 7.3: Summary Statistics from Referral Good Match Rate Shocks in the model

	Ω^M	$1-\Omega^M$	u	v	v/u	f	γ_R
Standard Deviation	0.037	0.048	0.02	0.015	0.023	0.011	0.095
Quarterly Autocorrelation	-0.366	-0.423	-0.492	-0.415	-0.517	-0.517	-0.454
Correlation Matrix							
Ω^M	1	-0.995	0.99	0.883	-0.961	-0.961	-0.992
$1-\Omega^M$	-	1	-0.989	-0.921	0.944	0.944	0.997
u	-	-	1	0.868	-0.98	-0.98	-0.994
v	-	-	-	1	-0.03	-0.03	0.908
v/u	-	-	-	-	1	1	0.955
f	-	-	-	-	-	1	0.955
γ_R	-	-	-	-	-	-	1

Notes: All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

hiring rates.

The correlation coefficient between the cyclical component of log expected market wage rate and log γ_R series is -0.985 and that for the log expected referred wage rate series is 0.996. The standard deviation of the cyclical component of log expected market wage rate series is 0.034 and that for the log expected referred wage rate series is 0.027. The quarterly auto-correlation coefficients of log expected market and referred wag rate series are -0.383 and -0.386 respectively.

7.9 Beveridge Curve

The non-detrended Beveridge Curve (BC) is U-shaped with no trend, contrary to the conventional downward sloping BC. But, the log deviations from trend of vacancies rate increase with log deviations from trend of unemployment rate, thus making the BC positively sloped. For the non-detrended curve, there exists a critical level of γ_R. For any γ_R less than that, market matching rate reduces because firms reduce vacancy posting and therefore unemployment rate increases. For any γ_R above the critical level, firms increase vacancy posting because referral matching is congestive at higher unemployment rates. More vacancy posting means more market matching, but market matching is also frictional, so unemployment rate rises due to both network congestion and market frictions.

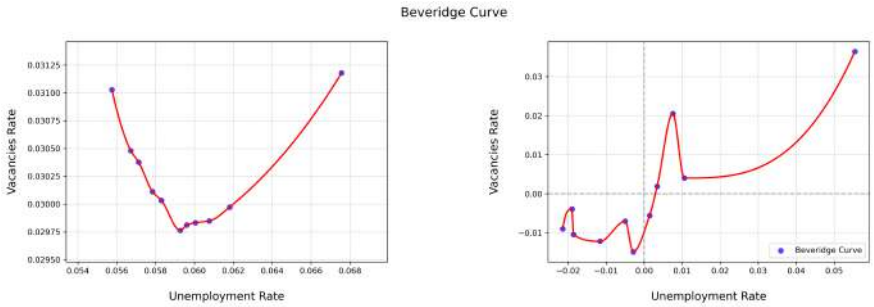


Figure 7.9: Beveridge Curve from Referral Good Match Rate Shocks

Notes: The left hand side figure shows the non-detrended Beveridge Curve across 11 state values of γ_R. The right hand side figure shows the cyclical Beveridge Curve with smoothing parameter 1600.

8 Conclusion

This is the first paper to optimize a firm's decision to hire through market and referral channel and to study their variation over the business cycle. At the steady state CE, the referral channel is more likely to yield a good match and is less costly to hire relative to the market channel. But, the referral channel is less likely to yield a firm-worker match. These quantity-quality trade-offs makes a firm always hire through both the channels, regardless of the type of shock.

Three types of shocks are considered - match productivity shocks, match quality shocks through both market and referral hiring channel. Shocks to match productivity produce one-third and one-fourth of the observed variation of market and referral hiring rate respectively. Also, the model produced labor market tightness exhibits about half of the observed variation. This finding adds to the debate that standard textbook matching models do not produce the observed volatility of labor market tightness. But, this result is an improvement on Shimer (2005). Shocks to match quality are less propagative for market tightness than shocks to match productivity. Shocks to referral match quality are the most propagative for market and referral hiring rates among the three types of shocks. Shocks to market match quality are least propagative for all the endogenous variables. Shocks to match productivity make expected referred wage most volatile while shocks to referral match quality make expected market wage most volatile.

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