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

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Abstract

Empirical evidence from the United States (U.S.) and the European Union (EU) shows that referral hiring is pro-cyclical, while market hiring is counter-cyclical, with labor productivity. I build and calibrate a stochastic search-and-matching model in which firms choose how to allocate recruiting resources between market and referral hiring. Expected match quality is endogenous, and conditional on successful matching, workers hired through referrals earn expected wages about 13% higher. The firm's optimal allocation is governed by a quantity–quality–cost trade-off. In particular, the referral channel is less scalable in converting vacancy-side network connections into filled jobs, but it is more likely to generate a good-fit applicant and has a lower per-hire cost. I also allow referral effectiveness to differ from the network-implied contact rate through a reduced-form referral wedge that governs how referral links convert into hiring-relevant opportunities, and I allow referral job filling to be further limited by employee-side transmission congestion when many referral vacancies are processed through the same stock of employed workers. I study three aggregate environments: productivity shocks only; a linked separation-risk specification in which separations are counter-cyclical with productivity; and a joint-shock specification in which separation risk fluctuates independently. I show that turnover risk strengthens cyclical reallocation across channels by shifting expected match duration and vacancy creation. Quantitatively, the joint specification generates the largest hiring fluctuations among the three environments. It accounts for about 81% of cyclical variation in market hiring and 66% in referral hiring in the targeted U.S. economy. By contrast, the other regimes generate about 23–53% of cyclical hiring variation in the U.S.

Keywords: Market Hiring, Referral Hiring, Labor Productivity, Business Cycle
JEL classification: J24, E32, J64, J08

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1 Introduction

Combined empirical evidence from the U.S. Survey of Consumer Expectations (SCE) and Greece's Labor Force Surveys shows that during recessions—including the COVID-19 downturn in 2020[1] and the years of the "Greek Depression"[2]—firms systematically shift toward market hiring and away from referral hiring relative to non-recessionary periods. I develop a stochastic search-and-matching model that rationalizes this pattern through a cyclical *quantity–quality–cost* trade-off across hiring channels and quantifies how aggregate shocks map into the market–referral hiring mix.

The key force is that the two channels differ along three dimensions. First, from the employer's perspective, the referral channel is less likely to produce a filled vacancy because it operates through incumbent employees' networks, is subject to congestion, and does not convert every referral contact into a hiring-relevant opportunity. Conditional on connection, however, referrals are more likely to be *potentially* good matches. Second, the referral channel has a lower per-hire cost than market hiring. Third, match quality responds differently across channels: market match quality is reasonably inelastic and declines when hiring becomes more intensive (i.e., when vacancy-filling conditions tighten screening capacity), whereas referral match quality is highly responsive to the expected flow of good referrals generated by employed referees. Productivity fluctuations change vacancy creation and unemployment, altering tightness and network congestion and therefore shifting the relative return to recruiting through each channel over the business cycle.

The baseline economy is driven by aggregate labor productivity shocks. I then consider extensions in which separation risk also varies over the cycle. In a *linked* specification, separation rates move systematically with the aggregate state, shifting expected match duration in a way that strengthens firms' incentives to reallocate hiring across channels. In a *joint* specification, separation risk fluctuates independently, introducing an additional source of aggregate uncertainty that can magnify movements in vacancy creation, tightness, and the market–referral mix. Finally, the model includes a reduced-form wedge in the effectiveness of referrals—capturing non-network factors that shift how referral contacts translate into callbacks/offers and hires. Together, these ingredients deliver a transparent mapping from aggregate shocks to the cyclicality of hiring composition and help rationalize the recessionary shift toward market hiring in the data.

The existing literature largely studies either market matching of unemployed workers (e.g., Shimer (2005), Hagedorn and Manovskii (2008), Mortensen and Nagypal (2007), Sahin et al. (2018),

[1] U.S. data are available from 2013 onward.

[2] The multi-year government-debt crisis within the broader European sovereign-debt crisis.

Krueger and Mueller (2011), Shimer and Borovičková (2024)) or referral matching and network mechanisms (e.g., Zaharieva (2018), Burks et al. (2015)), and a smaller set considers both channels jointly (e.g., Galenianos (2014), Horvath (2014)). However, to the best of my knowledge, no existing paper endogenizes an employer's simultaneous market and referral hiring choices in a stochastic DMP environment *and* quantifies their business-cycle implications and policy relevance. This paper fills that gap.

I model a firm's and a job seeker's stochastic matching process in the labor market using a stochastic Diamond–Mortensen–Pissarides (DMP) framework, with the firm's endogenous hiring decision and two hiring channels as the primary extensions to the standard model. Time is discrete and the horizon is infinite. In each period, the aggregate state (productivity and, in extensions, separation risk) is realized; firms choose vacancy creation and allocate hiring resources across two channels. Market meeting of a vacancy and a job seeker is governed by a constant-returns-to-scale matching function in vacancies and unemployment. A job seeker's market job-arrival rate is the meeting rate per job seeker, while an employer's market applicant-arrival rate is the meeting rate per vacancy.

Referral hiring operates through incumbent employees' networks. Upon opening a vacancy (or becoming available), the employer contacts an incumbent employee and asks them to refer a job-seeking contact; the referee then selects one job-seeking contact from their network. The probability that a vacancy becomes connected to a job seeker therefore depends on whether a contacted employee has actively searching contacts and on how many job seekers compete for attention from the same referee (congestion). This firm-side *applicant contact rate* is the raw vacancy-level referral connectivity term: it summarizes how the network structure and congestion determine whether a vacancy becomes connected to a job-seeking contact before any additional wedge or transmission-capacity adjustment is applied.

To capture how firms may *treat* referred candidates differently, I allow the referral channel to be perceived as more or less effective than what the network alone would mechanically imply. This does not change the network's role in transmitting job information; instead, it changes how likely a firm is to translate a referred contact into an interview, an offer, and ultimately a hire relative to an otherwise comparable applicant coming through the market. Economically, this captures situations in which managers place extra weight on referrals from trusted colleagues, close professional ties, or strong endorsements—or, conversely, where they apply additional scrutiny to referrals because of concerns about fit, workplace dynamics, or fairness. For example, in academic hiring, a strong

letter from a well-known researcher who is connected to members of the hiring committee can make a candidate more likely to be shortlisted and interviewed, increasing the chance of receiving an offer.[3] As a result, the referral channel becomes more or less effective at transforming raw vacancy–applicant contacts into hiring-relevant referral opportunities and, ultimately, into realized hires.

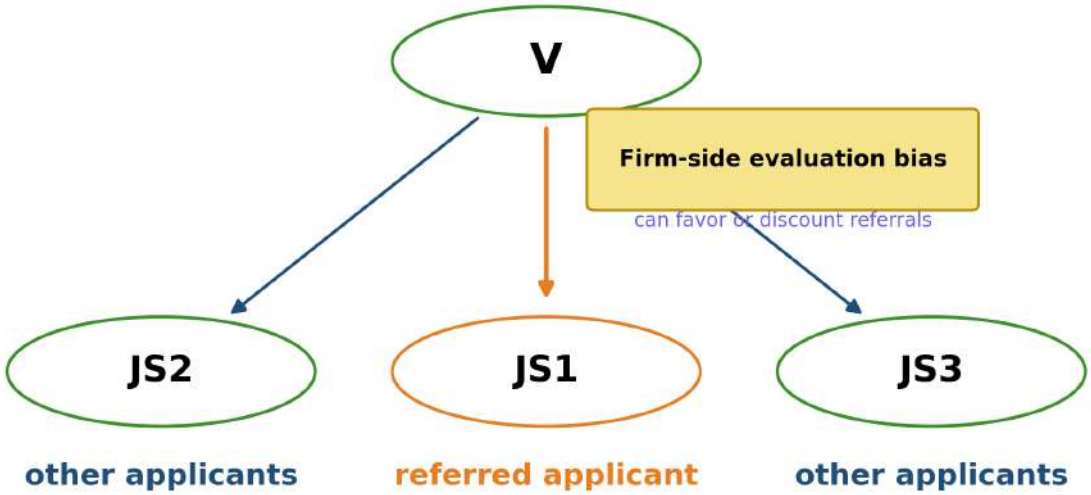
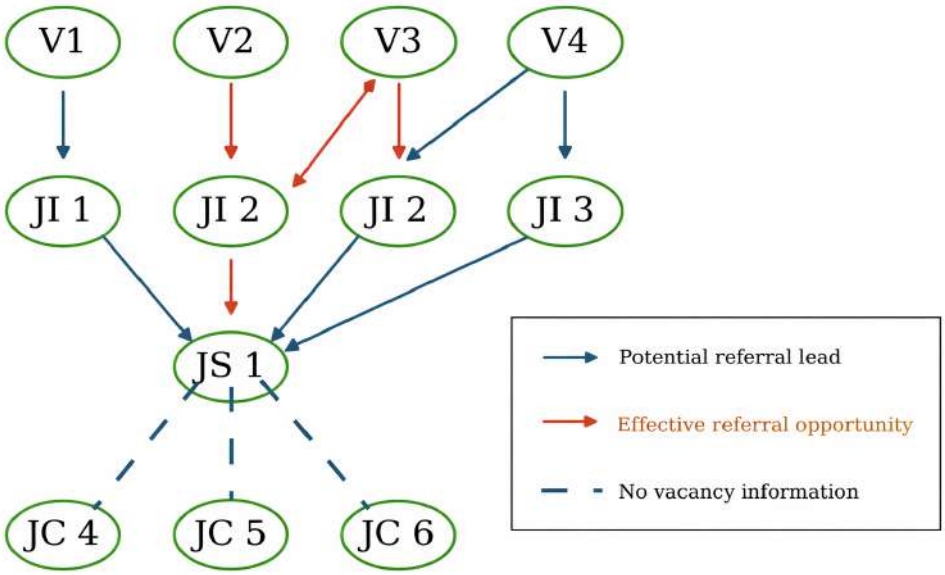


Figure 1: *Firm-side evaluation bias in referral hiring.* In a given period, multiple job seekers compete for attention from a vacancy V. The network determines the baseline chance that a referred applicant is connected to the vacancy. Firms may then apply an evaluation bias to referrals—either favoring them (e.g., stronger endorsement or lower screening costs) or discounting them (e.g., additional scrutiny or stricter screening). This bias changes the effective potency of referrals in hiring outcomes without altering the underlying network contact opportunities.

From the job seeker's perspective, I focus on the *referral job-finding rate*, that is, the probability that an unemployed worker finds a job through referrals in a given period. This worker-side probability increases with firm-side referral effectiveness and with the share of employed contacts in the worker's network, but it falls when congestion within the network becomes more severe. Intuitively, a worker's referral prospects are strongest when she has enough employed contacts to receive job information, but not so many competing job seekers per contact that referral transmission becomes diluted. As networks become "thicker"—either because more job seekers rely on the same contacts or because each contact faces more competing referral demands—the likelihood that any given worker is the one who ultimately receives and converts referral information into a job declines.

[3] Consider an academic job requiring a reference letter: a well-known researcher who knows someone on the hiring committee writes a strong letter on behalf of their student. As a result, the student gets shortlisted for an interview, receives a flyout and finally a job offer.

The worker-side referral job-finding rate differs from the firm-side referral filling rate because the two objects are defined on opposite sides of the market and condition on different units. The worker-side object asks: "for a given unemployed worker, what is the probability of finding a job through referrals this period?" The firm-side object asks: "for a given referral vacancy, how likely is it to be converted into a realized hire?" The two typically move together over the cycle, but they need not coincide in level or volatility, since network congestion and referral transmission frictions affect workers and vacancies through different margins.



Applicant's referral opportunity and employee-side transmission congestion. The figure illustrates four vacancies (V1–V4), employed job informers (JI1–JI3), and a job seeker (JS1). Vacancies generate potential referral leads through incumbent employees' networks, but not all such leads become hiring-relevant referral opportunities. The figure also highlights employee-side transmission congestion: when multiple vacancies are routed through the same stock of employed informers within a period, the capacity of those workers to process and relay referral information becomes limited, so only some potential leads are converted into effective referral opportunities. Blue arrows denote potential referral leads, red arrows denote referral leads that become effective referral opportunities, and dashed links denote connections along which no vacancy information is transmitted.

In addition, the model allows the firm-side referral job-filling rate to be lower than the effective referral contact rate when a larger volume of referral vacancies must be processed through the same stock of incumbent employees, introducing an employee-side transmission-capacity constraint on referral hires.

Firm–worker matches can be of two types: good or bad. They occur in both market and referral hiring. Good matches are more productive and less separable than bad matches; consequently, good matches generate higher wages and higher profits.

Market hiring consists of an intensive screening process. The market arrival rate of good matches is governed by aggregate screening technology, augmented by a state-dependent vacancy-filling rate that captures congestion in the market screening margin: when vacancies fill quickly, the probability that an applicant is a good match is lower.[4] As a result, the market good-match arrival rate is procyclical: expansions reduce vacancy-filling frictions in a way that improves market match quality. The referral arrival rate of good matches is given by the expected composition of employed referees' networks—including the homophily rate, i.e., the fraction of same-type links within a network.[5] In booms, higher employment raises the pool of potential referees and, given homophily, improves conditional referral good-match rates.

A firm's optimal hiring strategy maximizes the continuation value of a vacant position by trading off the present discounted expected profits from market and referral hires against vacancy opening costs and channel-specific hiring costs. Wages depend on match type and are determined by Nash bargaining. Competitive equilibrium is characterized by standard market frictions together with network congestion and channel-specific match-quality dynamics. In this environment, the quantity–quality–cost trade-off emerges endogenously: referrals are cheaper and (conditionally) higher quality, but the firm-side referral filling rate is shaped in stages—first by raw network connectivity, then by the effective conversion of referral contacts into hiring-relevant opportunities, and finally by the limited capacity of incumbent employees to transmit referrals—whereas market hiring is more scalable but can yield lower expected quality when hiring expands to more marginal applicants.

In the calibrated economy, expected profits net of costs from referral hiring are about 16% lower than those from market hiring. Although referrals are cheaper and yield more good matches conditional on connection, their lower likelihood of progressing from network contact to effective referral opportunity and ultimately to a filled vacancy makes them less profitable on the margin in equilibrium.

Negative shocks to labor productivity reduce referral hiring and increase market hiring. When productivity is below trend, surplus falls and firms post fewer vacancies. Vacancy opening declines and tightness falls, so the market "cools" in downturns, while unemployment rises because inflows exceed outflows. These forces reduce both the vacancy's applicant contact rate (firm-side referral connectivity) and the applicant's vacancy contact rate (worker-side referral offer arrival). Although

[4] Landais, Michaillat, and Saez (2018) show that the recruiter–producer ratio rises with market tightness, but remain silent about how it might determine match quality.

[5] Here, "type" refers to skills and experiences (match quality potential), not employment status.

good-match arrival declines in both channels, the market good-match arrival rate falls faster than the referral good-match arrival rate because market job-filling conditions respond directly to tightness, which is more volatile than the underlying employment and unemployment stocks. In my calibration, market matching is close to inelastic with respect to vacancies, so movements in vacancy posting translate primarily into movements in tightness and vacancy-filling rather than large changes in the job-finding rate driving the employment and unemployment rates. As a result, market job-filling rises in recessions, even as job-finding and employment adjust more slowly, shift the composition of hires toward the market channel when productivity is low.

In the calibrated model, the values of both good and bad matches from the firm's perspective are strongly procyclical. For good matches, Nash bargaining allocates part of cyclical gains to wages: in expansions, the worker's outside option strengthens and wages absorb a substantial share of the productivity increase; in downturns, the outside option deteriorates and wages adjust downward, but less than one-for-one with productivity. This cushions profit movements. Bad-match values are also procyclical, but profits in bad matches exhibit greater cyclical variation because wages are more tightly anchored to the value of unemployment, creating a comparatively flatter wage floor in recessions and sluggish wage adjustment in booms.

Quantitatively, unemployed workers expect to earn about 50–56% lower wages than existing employees, and wages from bad matches are about 3% lower than wages from good matches. Productivity shocks of the observed magnitude generate about 31%, 24%, and 22% of the observed cyclical variation in market hiring, referral hiring, and market tightness in the U.S. economy. In a non-targeted economy (Greece), the model accounts for about 1.5 times and 20% of the observed cyclical variation in market and referral hiring, respectively. The model explains a larger share of market-hiring volatility in Greece because observed market-hiring volatility in Greece is only about 20% of that in the U.S., whereas referral hiring is similarly volatile in both countries.

To assess whether additional margins of cyclical adjustment materially change firms' hiring choices, I extend the baseline productivity-shock economy by allowing separation rates to vary with the aggregate state. In the *linked* specification, separations are deterministic functions of the productivity regime. The economy is still driven by a single Markov process for productivity, but the aggregate state now embeds expected match duration as an additional margin that co-moves with productivity by construction. This strengthens reallocation because the payoff to creating a match through the market versus referrals depends on both (i) job-filling and match-quality conditions and (ii) expected durability. Quantitatively, this extension generates larger fluctuations

in market versus referral hiring shares (roughly 45–61% of observed U.S. volatility), while remaining parsimonious.

I also consider a *joint* specification in which separations evolve as an independent aggregate process. Conditioning on productivity no longer pins down match duration; the economy mixes over multiple turnover realizations for a given productivity state. This richer uncertainty strengthens replacement-demand forces and increases dispersion in objects that load directly on turnover—vacancy creation, market tightness, job-finding and job-filling rates, and the market–referral allocation. In practice, this specification generates even larger fluctuations because hiring composition responds to both surplus variation and independent movements in separation risk, even holding productivity fixed. This joint specification accounts for about 63–83% of observed U.S. volatility in market and referral hiring.

To the best of my knowledge, this is the first paper to embed an endogenous hiring-channel choice in a stochastic DMP environment and to quantify its business-cycle implications. The key innovation is a tractable framework in which firms allocate hires between market hiring and referral hiring while simultaneously accounting for channel-specific match quality. Market match quality depends on labor-market conditions through vacancy-filling and screening intensity, whereas referral match quality depends on homophily and the employment composition of the network. The model also introduces a disciplined form of evaluation bias in firms' treatment of referrals, capturing systematic differences in how referrals are translated into hires and thereby shifting the perceived attractiveness of the referral channel over the cycle.

The framework speaks directly to the Shimer (2005) debate: endogenizing expected match quality and allowing reallocation across hiring channels adds a propagation margin that can amplify cyclical movements in hiring outcomes relative to a market-only benchmark, without departing from standard wage-setting mechanisms. Beyond positive implications, the model provides a foundation for policy counterfactuals—for example, changes in referral incentives, network size, screening technology, or referral transmission capacity—that quantify how hiring costs, network composition, and the *conversion of referral contacts into effective fills* transmit into aggregate volatility through the channel-allocation margin.

The rest of the paper is organized as follows: Section 2 reviews the literature, Section 3 describes the data and measures, Section 4 details the model and defines the competitive equilibrium, Section 5 presents the calibration, Section 6 discusses results for productivity shocks, Section 7 considers productivity and separation-rate shocks, and Section 8 concludes.

2 Literature Review

This paper connects with several strands of empirical and theoretical literature in search theory. Firstly, a large, multidisciplinary literature shows that employee referrals are both prevalent and consequential in hiring. Classic sociological and labor-survey evidence documents the high share of jobs obtained via personal contacts (often on the order of 30-50%), from early fieldwork (Granovetter (1974)) and labor statistics (Bradshaw (1973); Bortnick and Ports (1992); Ports (1993)) to more recent reviews that assemble comparable magnitudes across settings. In theory, referrals reshape who applies and who is selected, because information and screening flow through networks (Montgomery (1991)), a mechanism consistent with later evidence on industry/occupation heterogeneity in referral payoffs and usage (Pellizari (2010); Holzer (1998)). Firm-level studies then show that referred candidates are more likely to be hired, accept offers, and remain with the firm, with similar productivity on many margins but lower quit and accident rates - yielding higher per-worker profits in several industries (Burks et al. (2015)). Taken together, these findings imply systematic differences in applicant volume (quantity), match quality, and hiring costs across channels - the exact quantity-quality-cost trade-off my model formalizes. Unlike them, I find that expected profits from referral hiring are lower than those from market hiring. This is because differences in the arrival rates of good matches, in favor of the referral channel, fail to outweigh differences in the arrival rates of job seekers, in favor of the market channel – leading to higher profits from market hiring.

Secondly, turning to the strand of *business-cycle search and job-ladder dynamics*, the baseline DMP framework in Pissarides (2000) provides the organizing logic: aggregate labor productivity shocks move vacancies and tightness, generating cyclical patterns in unemployment, hires, separations, and wages. Building on this, a large theoretical literature studies how on-the-job search and match heterogeneity determine the depth, duration, and co-movement of labor-market variables over the business cycle. Models with job-ladder dynamics and endogenous search intensity, e.g., Nagypál (2006) and related extensions with idiosyncratic productivity/match shocks (Krause and Lubik (2010); Elsby and Gottfries (2022)) generate realistic co-movement in job search behavior, quits, layoffs, hires, and JJ transitions, as well as the composition of matches over the business cycle. A common message across these papers is that who matches with whom (quality/composition) is itself cyclical and helps explain observed movements in worker and job flows. Pei and Xie (2021), Pei and Xie (2022) provide a wealth of evidence and arguments on the cyclical dynamics of the

unemployed's job search behavior and unemployment rate, when the government commits versus when it does not commit to unemployment benefit extensions. My setup establishes a connection between the government policy – the unemployment benefits level – and a firm's hiring, laying the foundation for future research on the optimal level of benefits in a similar setting.

Thirdly, the strand on *composition and new-hire wages* debates whether new-hire wages are highly procyclical or mostly acyclical once match composition is held constant. Using U.S. micro data, Gertler et al. (2020) show that after controlling for procyclical upgrading in match quality, new-hire wages are roughly as acyclical as incumbents', rationalized by a model with staggered wage contracts, variable match quality, and endogenous on-the-job search. By contrast, classic evidence finds strong procyclicality in individual wages – especially for job movers relative to stayers (Devereux and Hart (2006); Bils (1985)) – highlighting selection into better matches in booms. Reinforcing this tension, Haefke et al. (2013) report that new-hire wages move almost one-for-one with labor-market conditions. A complementary perspective reframes the firms' relevant price as the user cost of labor—the discounted path of wages for a hire – which is more procyclical than either average or new-hire wages (Kudlyak (2014)). Taken together, these papers imply that measured wage cyclicality is driven by *who* is hired – especially the mix of job movers versus job seekers – and by match-quality selection, not wage-setting alone. My contribution extends this selection logic to a new margin: the *hiring channel*. Embedding market versus referral hiring in a DMP framework, I show that productivity shocks reallocate hiring toward market openings in downturns, shifting match composition and thus the apparent cyclicality of new-hire wages, even when within-channel wage-setting is stable.

Finally, in the strand of *empirical job-search behavior over the cycle*, an extensive worker-side literature shows that search effort among the non-employed is countercyclical. Using time-series, cross-state, and individual variation, Sahin et al. (2018) document that unemployed search effort rises in downturns. Time-use evidence also shows how effort evolves within spells and with institutions: Krueger and Mueller ((2011)) find that search time declines with duration and responds to unemployment insurance incentives. Besides the search effort level, search intensity and duration are also tightly linked: leveraging online applications, Faberman and Kudlyak (2019) show that intensity falls over an unemployment spell but longer-duration seekers apply more each week–patterns that standard matching models struggle to capture. On on-the-job search (OJS), recent work using American Time Use Survey (ATUS) and other sources find that employed workers are more likely to engage in OJS during recessions (Ahn and Shao (2021)), while classic evidence on

employer-to-employer (E2E) flows show they are procyclical, implying more successful OJS in booms (Fallick and Fleischman (2004). Finally, heterogeneity matters: workers with lower job-finding rates search more (Faberman and Kudlyak (2019)), and under-employment rises in recessions, consistent with search reallocations down the job ladder (Barnichon and Zylberberg (2019)). This evidence establishes that who searches, how intensively, and with what outcomes varies over the cycle, but the focus is primarily on workers and aggregate matching. By contrast, my paper endogenizes firms' joint choice of market and referral hiring within a stochastic DMP framework, allowing the composition and profitability of channels–and thus the optimal hiring mix–to move with the cycle. This fills a gap between worker-side search behavior and employer-channel decisions that drive observed hiring dynamics.

An interior hiring mix arises because the firm equalizes marginal net returns across channels. Even if referrals deliver higher match probabilities and higher expected match values on average, increasing returns to referrals are limited by (i) convex channel-share costs and (ii) equilibrium feedback from unemployment and match composition that governs referral availability and quality. Meanwhile, market hiring is scalable through vacancy opening and, via endogenous screening, can improve match quality when market filling becomes difficult. These forces prevent full specialization and support of interior solution in steady state.

3 Data and Measures

3.1 Market and Referral Hiring Rate

3.1.1 United States

The data on the fraction of workers who were referred and those who were not market-hired comes from the SCE Job Search Supplement. The sample period spans from 2013 to 2021. The annual supplement is a series of repeated cross-sections of survey respondents, with approximately 1,300 respondents per survey year. Moreover, the survey is a nationally representative sample of household heads aged 18 and older.

To precisely know how the respondent learned about their best job offer (who had at least one job offer in the last 4 weeks to 6 months), I looked 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, or business associate," "referred by a current employee at the company," "a temporary job was converted to a permanent job," or "had worked for this employer previously."

To determine 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," or "don't know yet." The respondents who self-reported to have learned about their best job offer from a referral by a friend or relative, from a referral by a former co-worker, supervisor, or business associate, or a referral by a current employee at the company, or from an unsolicited contact by a potential/employer, recruiter, or headhunter and has accepted/will accept the job offer have 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, found their offer through an employment agency or career center, through an online job search engine, 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 and cleaned sample consists of a total of 773 respondents (with an average year containing approximately 86 respondents) and information on how they were hired. On average, about 50% of workers learned about their jobs through referral and market channels. Figure 3.1.1 illustrates the market and referral hiring rates over the business cycle from 2013 to 2021. We can see that the market hiring rate is counter-cyclical to real GDP, whereas the referral hiring rate is pro-cyclical, with a correlation of 0.724. Moreover, the cyclical components of the annual series on market and referral hiring rates have standard deviations of 0.097 and 0.11, respectively. The cyclical component of the market and referral hiring rate has an annual autocorrelation coefficient of -0.37.

3.1.2 Greece

Besides US, Greece, an European Union (EU) member country, experienced a long standing recession for almost 6 years starting from late 2008 and continuing beyond 2013. I use quarterly data on referred versus market-hired workers from the EU Labor Force Survey (EULFS) between

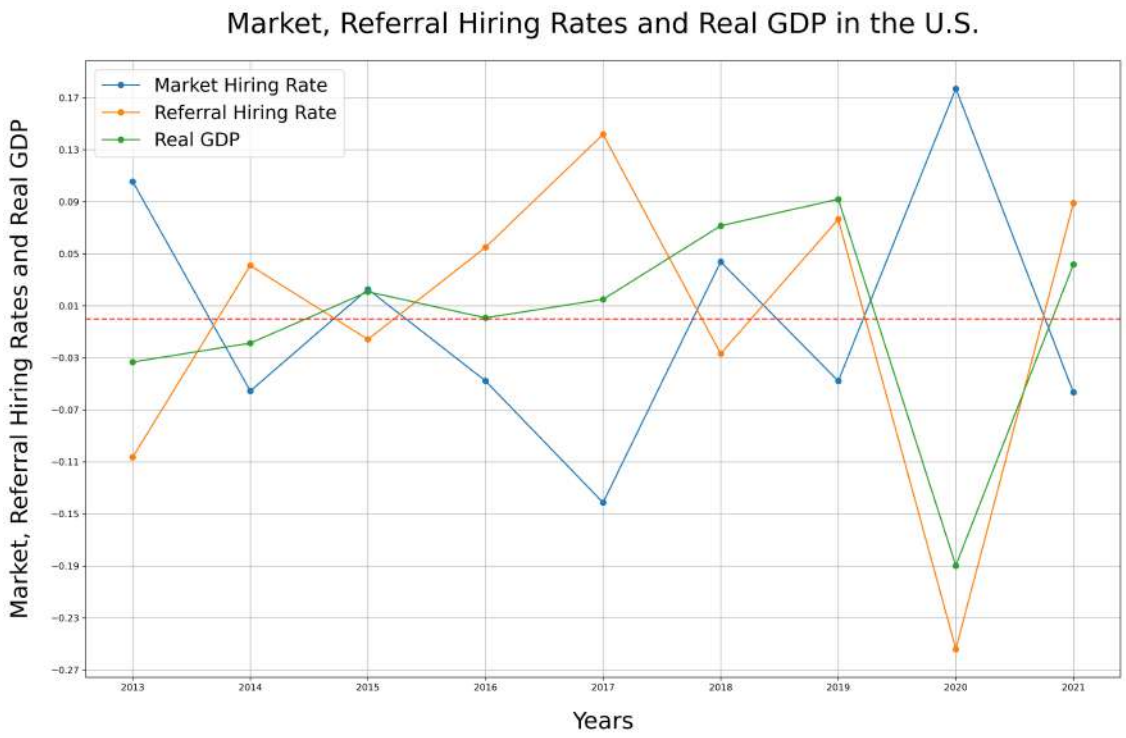


Figure 3.1.1: Annual Market, Referral Hiring Rate and Real GDP in U.S., 2013-2021.

Notes: The above figure illustrates the variation in annual time series data for the market, referral hiring rates, and real GDP. The annual time series on hiring rate comes from the Survey of Consumer Expectations (SCE), conducted by the 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 100.

2004 and 2013, which covers the Great Recession period. The survey is a harmonised household sample survey run by National Statistical Institutes and coordinated by Eurostat ((Statistical office of the European Union)). It continuously interviews people aged 15-89 living in private households, producing quarterly and annual labor-market statistics.

The survey contains information on the "Most effective method used to find the current main job (for persons in employment)", for which the respondents can answer either job advertisements, or friends, relatives or acquaintances, or public employment service, or private employment agency, or education or training institution, or internship or previous work experience, or contacted employer directly, or employer contacted person directly, or applying for a public competition, or other method. The respondents who answered "friends, relatives or acquaintances", were counted as referred. Remaining respondents who answered any of the other answer choices were counted as market-hired. Figure 3.1.2 plots the deviations from the trend in logs for the quarterly market hiring rate, referral hiring rate, and real GDP in logs between 2004 and 2013. The correlation

coefficient between the log cyclical components of market and referral hiring rate series with real GDP series are -0.02, and 0.12, respectively. This further supports the cyclical nature of market and referral hiring rates found in the U.S. – the former is countercyclical and the latter is procyclical. The standard deviations of the cyclical components of market and referral hiring rate series (in logs) are 0.02 and 0.138, respectively.

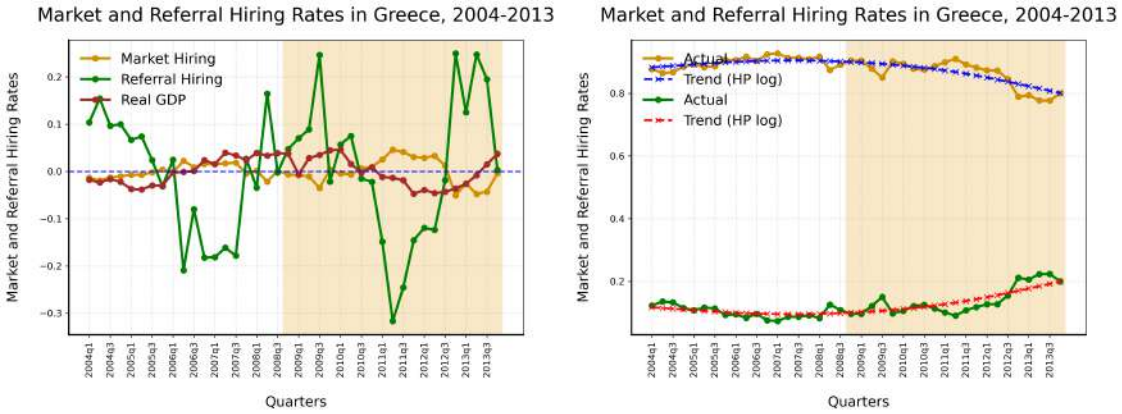


Figure 3.1.2: Quarterly Market, Referral Hiring Rates and Real GDP in Greece, 2004-2013.

Notes: The above figure illustrates the variation in the seasonally-adjusted quarterly time series data for the market, referral hiring rates, and real GDP. The quarterly time series on hiring rate comes from European Union Labor Force Survey, conducted by Eurostat. The quarterly time series data on real GDP comes from the Eurostat's Quarterly National Accounts. All variables are reported in logs as deviations from an HP trend with smoothing parameter 1600.

3.2 Vacancy Rate

I use seasonally adjusted monthly data on job opening rates for all non-farm sectors, constructed by the U.S. Bureau of Labor Statistics (BLS) from the Job Openings and Labor Turnover Survey (JOLTS), for 2013-2021, and then average them at the quarterly level. The log cyclical component of the job openings rate is moderately pro-cyclical with real GDP, with a correlation coefficient of 0.6. Moreover, it has a weak negative autocorrelation coefficient of -0.3 and a standard deviation of 0.096. Figure 3.3 plots the deviations from the trend and the trend superimposed on the actual series. Comparing Figure 3.2 with Figures 3.1.1 and 3.1.2, we can see that both the vacancy rate and the 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.

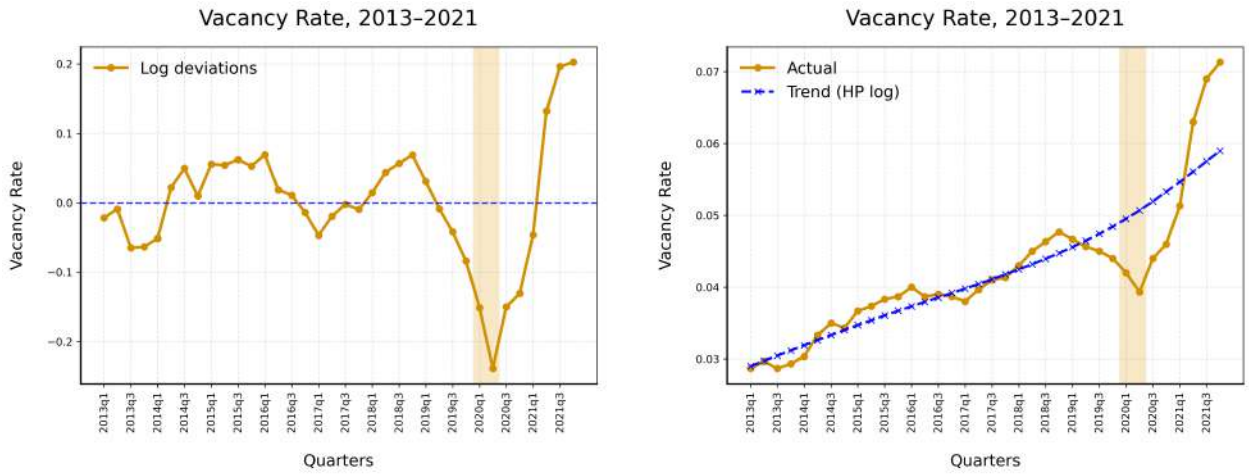


Figure 3.2: Quarterly Job Openings Rate in U.S., 2013Q1-2021Q4.

Notes: The left-hand side figure shows the log 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 the job openings rate. The shaded bars denote U.S. recessionary periods.

(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 position. Active recruiting refers to the process by which an establishment takes 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. Other activities may involve accepting applications, interviewing candidates, contacting employment agencies, and soliciting employees at job fairs, state or local employment offices, or similar sources.

Excluded are positions open only to internal transfers, promotions, demotions, or recalls 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 yet reported for work, and positions to be filled by employees of temporary help agencies, employee leasing companies, outside contractors, or consultants.

3.3 Unemployment Rate

The monthly time series of seasonally adjusted unemployment rate is from the Current Population Survey (CPS) and is constructed by the BLS. Unemployment Rate is defined as the number of unemployed people as a percentage of the labor force in the reference month (where the labor force consists of the employed and the unemployed. A quarterly average of the monthly series generates

the quarterly unemployment series. The cyclical component of the log quarterly unemployment series exhibits a strong counter-cyclical relationship with real GDP, with a correlation coefficient of -0.91. Also, it has a weak negative autocorrelation coefficient of -0.18 and a standard deviation of 0.23. Figure 3.3 illustrates the deviations from the trend, the trend itself, and the actual quarterly time series of the unemployment rate. Comparing Figure 3.3 with Figures 3.1.1 and 3.1.2, we see that while the unemployment rate is counter-cyclical, the referral hiring rate is pro-cyclical with real GDP.

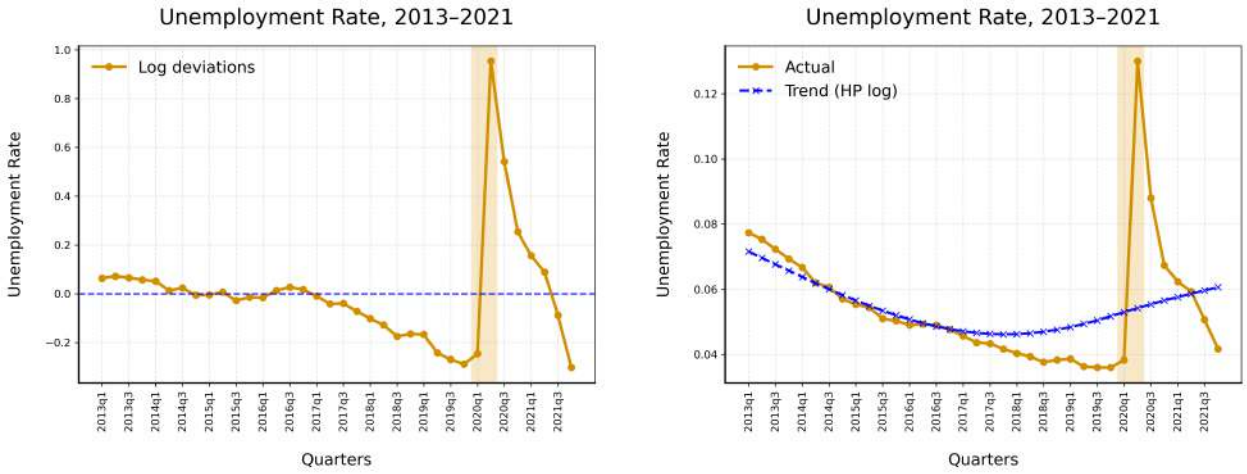


Figure 3.3: Quarterly Unemployment Rate in U.S., 2013Q1-2021Q4.

Notes: The left-hand side figure shows the log 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 the unemployment rate. The shaded bars denote U.S. recessionary periods.

Unemployed people are all people who meet all 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 individuals waiting to be recalled to work after being temporarily laid off do not need to actively search for a job to be classified as unemployed. Additionally, individuals waiting to start a new job must have actively sought employment within the last four weeks to be classified as unemployed. Otherwise, they are classified as not in the labor force.

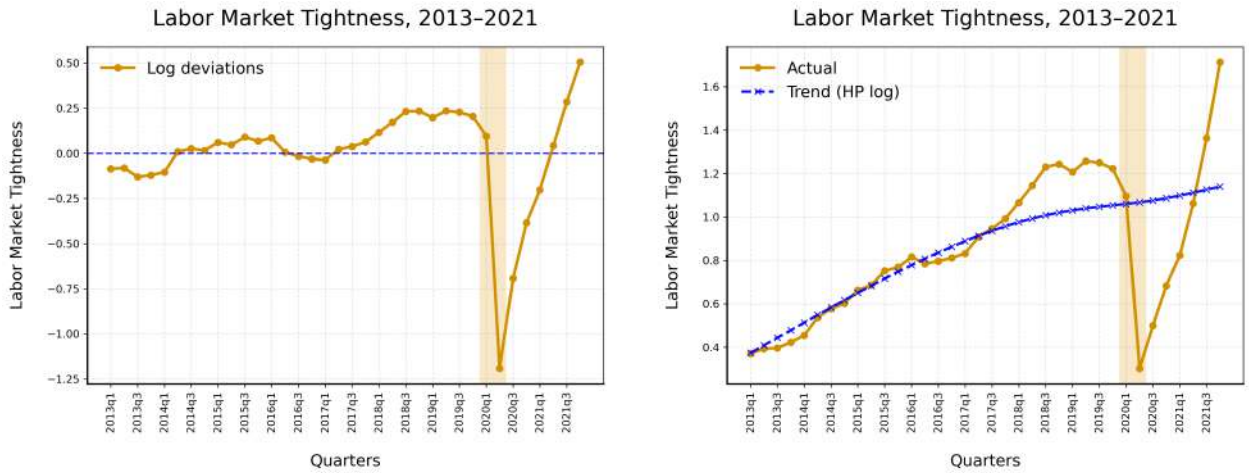


Figure 3.4: Quarterly Labor Market Tightness in U.S., 2013Q1-2021Q4.

Notes: The left-hand side figure shows the log 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 shaded bars denote the U.S. recessionary periods.

3.4 Labor Market Tightness

Labor market tightness is defined as the ratio of the vacancy rate to the unemployment rate. It is strongly pro-cyclical with real GDP, with a correlation coefficient of 0.93. The quarterly time series is computed by dividing the quarterly job openings rate by the unemployment rate. The cyclical component of the log tightness series exhibits a weak negative quarterly autocorrelation coefficient of -0.29. The negative autocorrelation 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 3.4 shows the deviations from trend, the trend, and the actual seasonally adjusted time series of labor market tightness. Comparing Figure 3.4 with Figures 3.1.1 and 3.1.2, as expected, we can see that both labor market tightness and the referral hiring rate are pro-cyclical with real GDP.

3.5 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} denote the unemployment level and the number of workers unemployed between

0-4 weeks at month $t+1$ (with the 4 week period ending with the survey reference week).[6] The monthly series comes from the BLS, which constructs it from the Current Population Survey (CPS). The monthly series is then averaged at the quarterly level. The log cyclical component of the time series exhibits a weak pro-cyclical relationship with real GDP, with a correlation coefficient of 0.31. The quarterly autocorrelation coefficient of the log cyclical component is 0.26 with a standard deviation of 0.16. Figure 3.5 illustrates the deviations from the trend, the trend itself, and the actual time series. Similarly, comparing Figure 3.5 with Figure 3.1.1 and 3.1.2, we can see that both the market job-finding rate and the referral hiring rate exhibit pro-cyclical behavior.

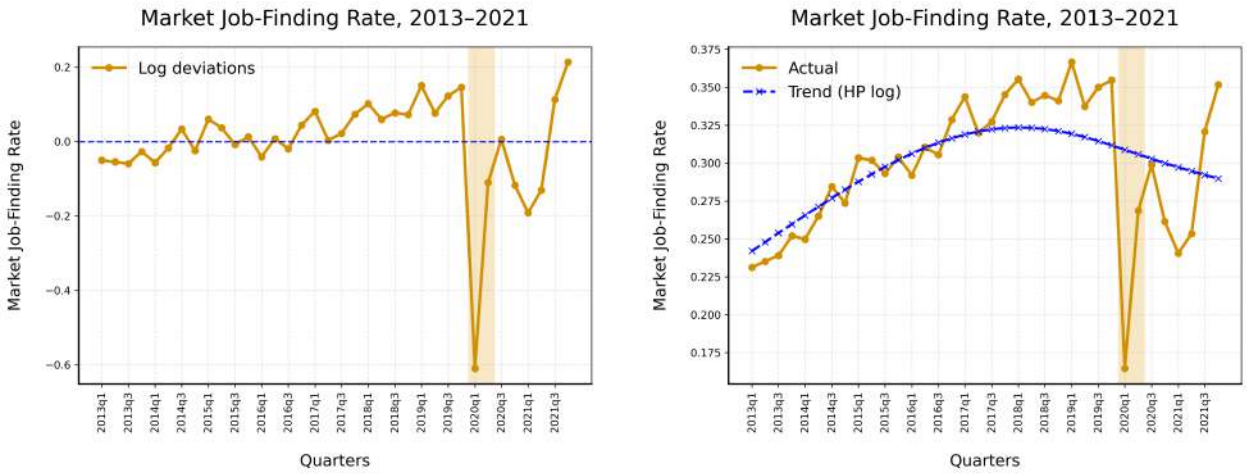


Figure 3.5: Quarterly Market Job Finding Rate in U.S., 2013Q1-2021Q4.

Notes: The left-hand side figure shows the log 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 the market job finding rate. The shaded bars denote the U.S. recessionary periods.

3.6 Market Job Filling Rate

Following Davis et al. (2013), I calculate the quarterly market job-filling rates. I use the monthly series of total nonfarm job openings and hires, and average at the quarterly level. These measures are produced by JOLTS and published by the BLS.

I use a stock-flow approximation to generate the monthly job-filling rate series. As in Davis et al. (2013), I assume that each vacancy is filled at a constant instantaneous filling rate Q_t (filling

[6] An individual with 0 weeks of unemployment is not necessarily unemployed. It typically means the person has recently become unemployed - i.e., they lost their job during the survey reference week and have already started looking for a new one. The "weeks employed" variable is often calculated as the number of full weeks the person has been looking for work. So, if someone became unemployed 3 days ago, they would show up as 0 weeks unemployed, but they are still considered unemployed under BLS definitions.

hazard rate) per workday, has an instantaneous lapse rate l_t per workday (lapse hazard - the rate at which the vacancy exits without a hire), and its stock increases by the posting inflow ζ_t per workday. Assuming that within a month t, Q_t and l_t remains constant, we write the change in vacancy stock T workdays after the month starts as:

$$\frac{dV}{dT} = \zeta_t - (Q_t + l_t)V(T)$$

Solving the above equation, we can write an equation for the vacancy stock at the end of the month t, $V(t)$ as,

$$V_t = V_{t-1}e^{-(Q_t+l_t)\tau} + \frac{\zeta_t}{Q_t + l_t}(1 - e^{-(Q_t+l_t)\tau})$$

where τ denotes the total number of workdays in a given month.

Similarly, the monthly hires H_t are the time integral of the fill flow $Q_t V_t(T)$ given by:

$$H_t = \int_0^\tau Q_t V(T) dT$$

Plugging the solved equation for $V_t(T)$, we get,

$$H_t = Q_t \left[\frac{V_{t-1}}{Q_t + l_t}(1 - e^{-(Q_t+l_t)\tau}) + \frac{\zeta_t}{(Q_t + l_t)^2} \left((Q_t + l_t)\tau - \left(1 - e^{-(Q_t+l_t)\tau}\right) \right) \right]$$

For estimating a simpler version of the above equation for H_t I use a tractable approximation that collapses the above equation to:

$$H_t \approx Q_t \int_0^\tau V_t(T) dT \approx Q_t \tau \overline{V}_t$$

where $\overline{V}_t$ approximates the integral of the vacancy stock by the trapezoid average $\overline{V}_t \approx \frac{1}{2}(V_{t-1} + V_t)$

For simplicity, I further assume that the lapse rate l_t is 0 [7]. Therefore, the survival function with a constant hazard $Q_t\tau$ is given by $e^{-Q_t\tau}$., and the probability that at least one vacancy fills within the month is $P_t = 1 - e^{-Q_t\tau}$. The monthly series is then averaged at the quarterly level. Figure 3.6 shows the deviations from trend, the trend fit, and the actual seasonally adjusted quarterly time series of market job-filling rates.

[7] Davis et al. (2013) argue that the daily lapse rate is an order of magnitude smaller than the job-filling rates Q_t and its dynamics minimally affect the dynamics of Q_t.

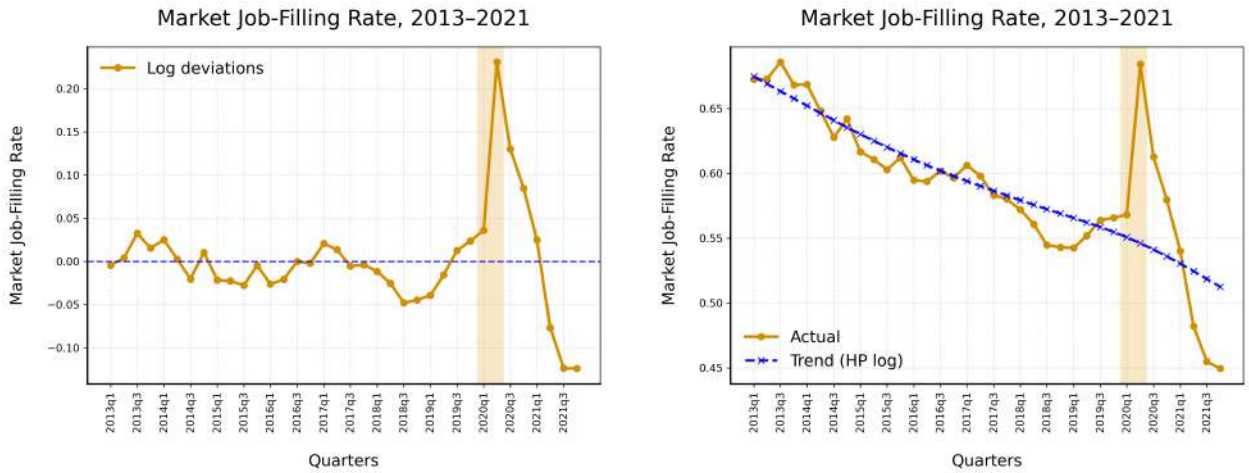


Figure 3.6: Quarterly Market Job Filling Rate in U.S., 2013Q1-2021Q4.

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

3.7 Real GDP

3.7.1 United States

The seasonally adjusted quarterly time series of real GDP, spanning 2013Q1 to 2021Q4, is sourced from the U.S. Bureau of Economic Analysis. The log cyclical component of the time series has a negative quarterly autocorrelation coefficient of -0.24 and has a standard deviation of 0.017. Figure 3.7.1 shows the deviations from the trend, the trend, and the actual time series.

3.7.2 Greece

For Greece's quarterly real GDP data, I use the series published by FRED from Eurostat. I use seasonally and calendar-adjusted real GDP (chain-linked volumes) at market prices (European System of Accounts 2010, indicator B1GQ) from Eurostat's Quarterly National Accounts. The underlying national accounts are compiled by ELSTAT (Hellenic Statistical Authority - Greece's National Statistics Office) in line with European System of Accounts (ESA) 2010 using survey and administrative sources; Eurostat validates and disseminates the harmonized series for EU member states.

Greece does not have an official NBER-style national dating committee. Centre for Economic Policy Research's (CEPR's), London, Euro Area Business Cycle Dating Committee dates only the euro area aggregate (e.g., 2008Q2-2009Q2 and 2011Q3-2013Q1) and explicitly does not date

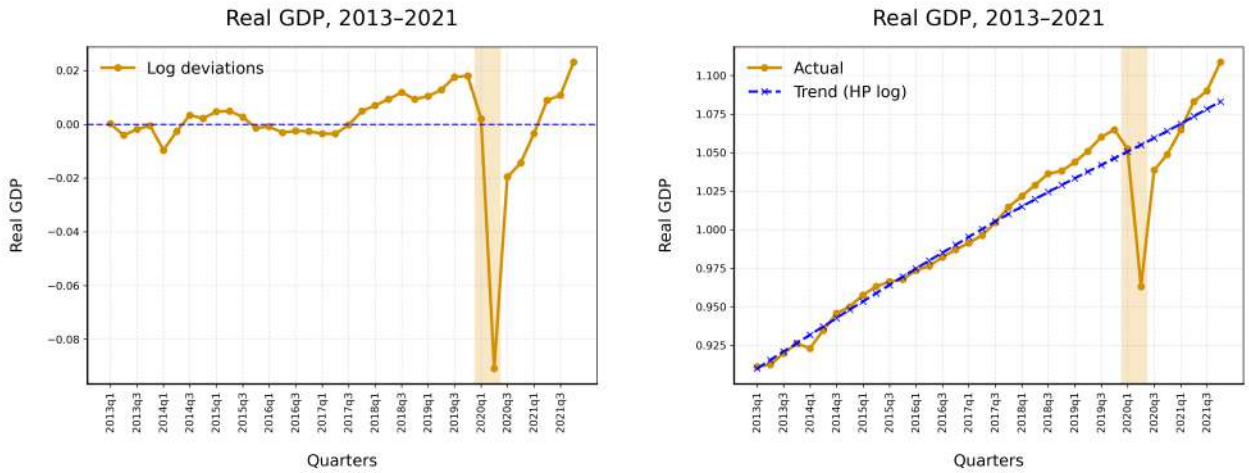


Figure 3.7.1: Quarterly Log Real GDP in U.S., 2013Q1-2021Q4.

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

individual countries. Accordingly, I adopt a transparent rule: a recession quarter is any quarter in which seasonally adjusted real GDP falls relative to the previous quarter, and contiguous declines are grouped into a recession spell. Under this rule, Greece experienced a prolonged contraction that I label 2008Q4-2013Q4, consistent with widely documented output losses of roughly 25-26% over 2008-2013. The standard deviation of cyclical component of log real GDP is 0.029. Figure 3.7.2 shows the deviations from the trend, the trend, and the actual quarterly time series.

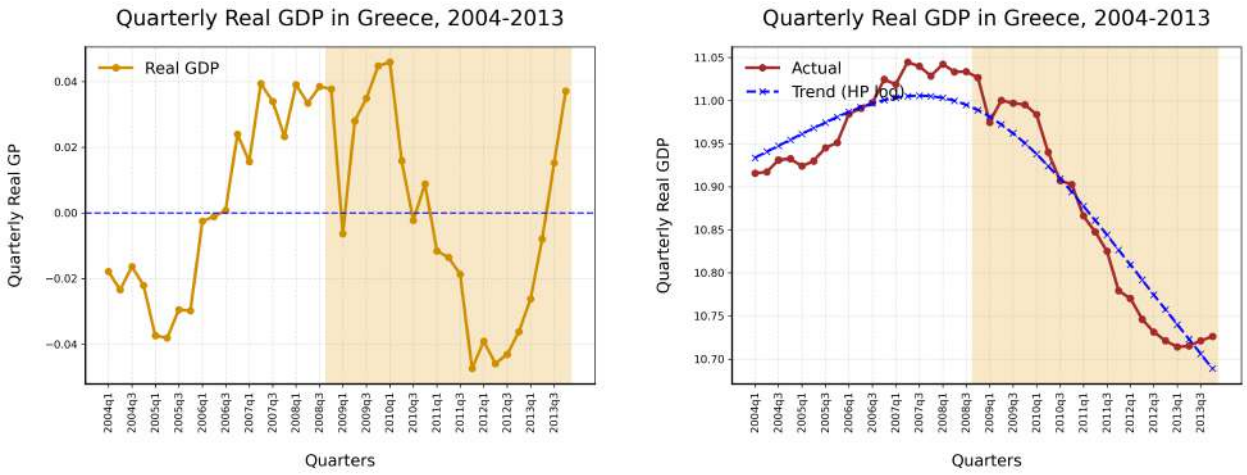


Figure 3.7.2: Quarterly Real GDP in Greece, 2004Q1-2013Q4.

Notes: The left-hand side figure shows the log deviations from trend of a seasonally adjusted and an HP filtered quarterly time series data on normalized log real GDP with smoothing parameter 1600. The right-hand side figure shows the trend and the actual time series of the normalized log real GDP. The shaded bars denote the Greece's recessionary periods.

4 Model

4.1 Model Environment

Time is discrete and infinite. The aggregate state of the economy today is certain, but that of tomorrow is uncertain. Firms advertise job openings and try to fill them. Simultaneously, they contact incumbent employees to request referrals from their social networks. There is no on-the-job search. Firms and unemployed workers (job seekers) are the only entities in the aggregate labor market. The size of the labor market is normalized to $\mathcal{N} \gg 1$.

Each job seeker possesses a specific skill or experience, and each job vacancy demands a particular skill or expertise. If a job aligns well with an job seeker's skills/experiences, a good match is formed. In contrast, if the job does not align well with the job seeker's skills and experience, a bad match results. In other words, the employer does not know exactly a job seeker's type when she is recruiting, and hence, the match can be either good or bad. Good and bad matches can happen in both market and referral hiring. I discuss match composition by hiring strategy in detail under **Match Composition**. The match type 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 follow a log-linear AR (1) process, a first-order stationary Markov chain governs the transition matrix, and the error term follows a normal distribution, has a zero mean and a standard deviation of σ. Both y_s, y_s^0

Table 3.1: Summary Statistics - Quarterly US Data, 2013Q1 to 2021Q4

	u	v	v/u	f	Q	y
Standard Deviation	0.227	0.096	0.286	0.13	0.059	0.017
Quarterly Autocorrelation	-0.18	-0.3	-0.29	0.26	-0.42	-0.24
Correlation Matrix						
u	1	-0.5	-0.966	-0.31	0.46	-0.918
v	—	1	0.7	0.37	-0.59	0.6
v/u	—	—	1	0.37	-0.55	0.931
f	—	—	—	1	-0.2	0.31
Q	—	—	—	—	1	0.31
y	—	—	—	—	-0.5	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 the JOLTS data. 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 the logs as deviations from an HP trend with a smoothing parameter of 1600.

Table 3.2: Summary Statistics - Annual Hiring and Match Composition (SCE), 2013-2021

	Ω^M	$1-\Omega^M$	γ^M	γ^R	y
Standard Deviation	0.097	0.11	0.136	0.11	0.014
Autocorrelation	-0.4	-0.43	-0.59	-0.34	-0.33
Correlation Matrix					
Ω^M	1	-0.97	0.037	0.65	-0.65
$1-\Omega^M$	—	1	0.007	-0.51	0.78
γ^M	—	—	1	0.151	0.27
γ^R	—	—	—	1	0.06
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 are 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 a smoothing parameter 100.

share the same standard deviation σ^y. More precisely, the stochastic process of labor productivity is described as:

$$\log y_{s+1} = \rho^y \log y_s + \epsilon_{s+1}, \quad \text{where} \quad \epsilon_s \sim \mathcal{N}(0, \sigma^{y2}), \rho^y = 0.9895, y_s^0 = r y_s, 0 < r < 1. \tag{1}$$

I also assume that bad matches are not so bad that they get dissolved instantaneously, while good matches are not so good that they last forever. The first assumption implies that productivity in a bad match exceeds a threshold productivity level $\underline{y_s}$ below which production is not feasible. The second assumption implies that matches are separated due to exogenous reasons that are independent of match quality. Given both assumptions, it is realistic to assume that a good match is separated with a lower probability (δ_s) relative to a bad match (δ_s^0), where $0 < \delta_s < \delta_s^0 < 1$. In the model, δ_s and δ_s^0 are exogenous. In the baseline framework with only labor productivity shocks, I drop the subscript s from δ_s, δ_s^0. The state-specific payoffs to a well-matched employee and a badly matched employee are given by the endogenously Nash-bargained wage rates w_s and 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 between a vacancy and a job seeker is assumed to be **frictional**. Firms advertise vacancies on their websites, online job search platforms, and use help-wanted ads, etc., to search for interested workers to fill a vacancy. Opening vacancies is costly and incurs a flow cost of $k > 0$. Job seekers employ various job search methods, including visiting an employer's website, meeting the employer in person, utilizing online job search engines, and consulting employment agencies, career centers, and union or professional organizations, to find a suitable match with an employer. In the model, matches produced in the market are represented by a standard Constant Returns to Scale (CRS) matching function, which is Cobb-Douglas in the state-specific endogenous vacancy rate (v_s) and unemployment rate (u_s), and denoted as:

$$m(v_s, u_s) = A v_s^{\eta} u_s^{1-\eta} \tag{2}$$

where parameter $A > 0$ is a scale parameter, $\eta \in (0, 1)$ denotes the matching function elasticity. More specifically, η denotes the percentage change in aggregate market matching rate when the vacancy rate changes by 1%. Given this market matching function, the state-specific job-finding and the job-filling rates of an unemployed worker and a vacancy per unit market hire are defined respectively as:

$$f_s^M(\theta_s) = \frac{m(v_s, u_s)}{u_s} = A\theta_s^{\eta} \tag{2.1}$$

$$q_s^M(\theta_s) = \frac{m(v_s, u_s)}{v_s} = A\theta_s^{\eta-1} \tag{2.2}$$

where $\theta_s = \frac{v_s}{u_s}$ denotes the labor market tightness. $f_s^M(.)$ is strictly increasing and strictly concave in θ_s while $q_s^M(.)$ is strictly decreasing and strictly convex in θ_s.

Referral Matching: Referral matching is assumed to be **congestive**. I assume each employee is connected to other employees and unemployed workers in their social network. Let the fraction of employees in a firm be $1 - u_s$, and assume each of them has n contacts in her network, where $0 < n < N$ denotes the network size of each unemployed or employed link. Therefore, the expected number of unemployed workers and employees in the network are denoted by $u_s n$ and $(1 - u_s)n$, respectively. Upon a vacant position becoming available at the firm, the employer contacts an incumbent employee. Upon learning of a job vacancy from the employer, the employee randomly selects one of her $u_s n$ job-seeking contacts in her network to share the job information with. In other words, it is assumed that network agents share favorable relationships.[8]

It is assumed that job information flows only between direct employee–unemployed links. In other words, job information flows directly from an employee to an unemployed worker, and not indirectly through some shared employed link. From an unemployed worker's perspective, the network structure is identical to that of an employee. This assumption of a symmetric network structure vastly simplifies the analysis.

I now define a vacancy's applicant-contact rate (q_s^R) and an applicant's vacancy-contact rate (f_s^R) through the social network. The rate at which job information reaches an unemployed worker from a randomly contacted employed employee, referred to as the vacancy's applicant-contact rate, is given by:

$$q_s^R(u_s) = \sum_{\tilde{n}=0}^{n-1} \binom{n-1}{\tilde{n}} u_s^{\tilde{n}} (1-u_s)^{n-1-\tilde{n}} \frac{1}{\tilde{n}+1} = \frac{1-(1-u_s)^n}{nu_s} \tag{3}$$

A random draw of n social contacts from the network contains $0 \leq \tilde{n} \leq n-1$ other contacts

[8] Network relationships/connections are maintained for reasons apart from job information transmission, for example, risk sharing. Additionally, recommending a contact who may not be a good fit for the employer carries a risk of reputational damage to the incumbent employee. Overall, the benefits of risk sharing might outweigh the loss from reputation (Beaman and Magruder (2012)). Moreover, it might also be the case that passing along job offers helps maintain links, as such behaviors can be reciprocated in the future, thus reducing the unemployment spell of the incumbent (Bramoulle and Goyal (2016)).

besides the contacted job-seeker, with probability

$$\sum_{\tilde{n}=0}^{n-1} \binom{n-1}{\tilde{n}} u_s^{\tilde{n}} (1-u_s)^{n-1-\tilde{n}}.$$

Then, the job information is assigned to any one of the $\tilde{n}+1$ job-seeking contacts with uniform probability. Thus, the contacted unemployed worker receives the information with conditional probability $\frac{1}{\tilde{n}+1}$. The term $1-(1-u_s)^n$ denotes the probability that at least one unemployed worker exists in the network, and nu_s denotes the expected number of unemployed workers in the network. Therefore, the ratio of these two quantities constitutes the rate at which job information reaches an unemployed worker from one of her n employed contacts. This expression directly follows from Calvo-Armengol and Zenou (2005).

As the network size n increases, on the one hand, the probability of finding at least one job seeker in the network increases; on the other hand, the expected number of job seekers also increases. Combining the two opposing effects, I find that the second effect dominates the first. Therefore, a congestive network implies that each unemployed worker hears of a job opening from her contact list with a lower probability.

Referral effectiveness wedge (non-network conversion of contacts into opportunities): I allow the *effective* referral contact rate relevant for hiring to differ systematically from the network-implied vacancy's applicant-contact probability. Let

$$q_s^{R,\text{true}}(u_s) \equiv q_s^R(u_s)$$

denote the *network-implied* vacancy's applicant-contact rate in state s, as given by equation (3). I introduce a parsimonious wedge that captures *non-network* factors—such as endorsement strength, screening intensity, referral program design, or other institutional frictions—that affect how referral links convert into actionable callbacks or offers. I model the effective referral contact probability, $q_s^{R,\text{eff}}(u_s)$, as a log-odds shift of the network-implied object. Define the logit transform

$$\ell(p) \equiv \log\left(\frac{p}{1-p}\right), \qquad p \in (0,1),$$

and its inverse (the logistic map) as

$$\ell^{-1}(z) \equiv \frac{1}{1+e^{-z}}.$$

Assume that the effective referral contact rate satisfies

$$\ell\Big(q_s^{R,\text{eff}}(u_s)\Big) = \ell\big(q_s^{R,\text{true}}(u_s)\big) + \zeta,$$

where $\zeta \in \mathbb{R}$ is a *referral-effectiveness (conversion) wedge*. Solving yields

$$q_s^{R,\text{eff}}(u_s) = \ell^{-1}\Big(\ell\big(q_s^{R,\text{true}}(u_s)\big) + \zeta\Big) = \frac{q_s^{R,\text{true}}(u_s)e^{\zeta}}{1 - q_s^{R,\text{true}}(u_s) + q_s^{R,\text{true}}(u_s)e^{\zeta}}.$$

By construction, $q_s^{R,\text{eff}}(u_s) \in (0,1)$ for all states and all finite ζ, and it is strictly increasing in $q_s^{R,\text{true}}(u_s)$. The log-odds specification makes ζ a smooth, monotone wedge that preserves the state dependence generated by u_s and the network parameter n. Importantly, ζ does *not* alter the network primitives that determine $q_s^{R,\text{true}}(u_s)$; instead it shifts the mapping from network-implied contacts to hiring-relevant opportunities. For convenience, I denote the effective referral contact rate prior to vacancy-capacity congestion as

$$\tilde{q}_s^R(u_s;\zeta) \equiv q_s^{R,\text{eff}}(u_s).$$

The benchmark $\zeta = 0$ implies $\tilde{q}_s^R(u_s;0) = q_s^{R,\text{true}}(u_s)$ for all s. When $\zeta > 0$, the odds that a network-implied referral contact becomes an actionable opportunity are scaled up (for example, stronger endorsements, lower screening frictions, or more effective referral processing), raising $\tilde{q}_s^R$ and shifting equilibrium channel choices toward referrals. When $\zeta < 0$, referral links still occur under the network structure, but they translate into callbacks or offers less efficiently (for example, tighter formal screening, weaker endorsements, or compliance constraints), so $\tilde{q}_s^R(u_s;\zeta) < q_s^{R,\text{true}}(u_s)$ and the referral channel becomes less potent in equilibrium.

Employee-capacity congestion in referral transmission: In addition to congestion on the unemployed side of the network, I allow for congestion on the employed side of referral transmission. The idea is that incumbent employees have limited capacity to process referral requests within a period. As more vacancies are routed through the referral channel, each employed worker is solicited more intensively, which lowers the probability that any given referral vacancy is converted into a usable

referral opportunity.

Let the mass of referral vacancies in state s be given by,

$$(1 - \Omega_s^M)v_s.$$

Normalizing by the mass of employed workers, $1 - u_s$, I define the referral-vacancy per employed worker as,

$$a_s \equiv \frac{(1 - \Omega_s^M)v_s}{1 - u_s}.$$

I then model employee-side referral-capacity congestion through the attenuation factor,

$$\mathcal{C}(a_s) \equiv \frac{1 - e^{-a_s}}{a_s},$$

with the continuous extension $\mathcal{C}(0) = 1$. This term is strictly decreasing in a_s: when referral-vacancy pressure is low, $\mathcal{C}(a_s)$ is close to one and employee-side congestion is negligible; when referral-vacancy pressure is high, $\mathcal{C}(a_s)$ falls and referral transmission becomes less effective. This approach scales referral effectiveness by the endogenous intensity of referral vacancies relative to the stock of employed workers available to pass information along.

Accordingly, I define the referral job-filling rate in equilibrium as

$$\tilde{q}_s^{R,*} \equiv \tilde{q}_s^R(u_s; \zeta)\, \mathcal{C}(a_s) = \tilde{q}_s^R(u_s; \zeta)\, \frac{1 - e^{-a_s}}{a_s}.$$

Thus, referral matching is congestive along two margins. First, network congestion on the unemployed side reduces the probability that any particular job-seeking contact receives vacancy information. Second, when more vacancies are routed through referrals, those vacancies must be processed through the same stock of employed workers, so referral-vacancy pressure per employed worker rises and the referral job-filling rate falls.

The unemployed applicant's referral job-finding rate is then given by

$$f_s^R(u_s, \Omega_s^M, v_s; \zeta) = (1 - u_s)\tilde{q}_s^{R,*} \tag{4}$$

Each unemployed worker has an employed contact with probability $(1 - u_s)$, and conditional on having such a contact, receives a referral opportunity at rate $\tilde{q}_s^{R,*}$. Equation (4) can therefore be interpreted as a reduced-form *referral opportunity-arrival* rate from the worker's perspective,

where $\tilde{q}_s^{R,*}$ summarizes three components: the network-implied contact structure, the non-network conversion wedge governed by ζ, and employee-side congestion arising from referral-vacancy pressure per employed worker.

Match Composition: Good and bad matches can happen in both market and referral hiring. Market hiring provides good matches at the rate,

$$\gamma_s^M(q_s^M;\lambda) = \lambda(q_s^M)^{-\psi} > 0 \tag{5}$$

where $\lambda > 0$ denotes the (state-independent) market screening technology. Higher λ raises the probability that a market hire is a good match. The conditional probability γ_s^M is decreasing in the market job-filling rate q_s^M with elasticity $\psi \in (0,1)$. Since q_s^M is typically higher in slack labor markets and lower in tight ones, equation (5) implies that market match quality is pro-cyclical: good matches are more likely in booms and less likely in recessions. Intuitively, when vacancies are harder to fill (low q_s^M), firms screen more intensively and are less likely to settle for marginal fits; when vacancies fill quickly (high q_s^M), a thicker but noisier applicant pool and limited screening capacity can reduce the likelihood that the eventual hire is a good match.

Referral hiring provides good matches at a rate,

$$\gamma_s^R(e_s, e_s^0, u_s; h^R) = \frac{h^R e_s + (1-h^R)e_s^0}{1-u_s} > 0 \tag{6}$$

where h^R denotes the fraction of similar-type job seeker-informer links in the network — the network homophily rate. For example, an employee can be in a bad match but h^R fraction of her links are of her type (and similarly for an unemployed worker), where type can vary by race, gender, age, skills, risk aversion, job-preferences etc[9]. Conditional on the match happening at the q_s^R, a good match happens at the rate $h^R e_s$ from existing good matches and $(1-h^R)e_s^0$ from existing bad matches, normalized by the fraction of referees $1-u_s$. The complement of γ_s^R denotes the referral bad match rate. More specifically, the bad match happens at the rate $h^R e_s^0$ from existing bad matches and $(1-h^R)e_s$ from existing good matches, normalized by the fraction of referees $1-u_s$.

Hiring: In each realized state, a firm chooses to hire Ω_s^M fraction of workers through the market channel and the rest $1-\Omega_s^M$ fraction of workers through the referral channel, where $\Omega_s^M \in [0,1]$. The cost of market and referral hiring is convex in the fraction of market hired and referred, given by:

$$C_s^M(\Omega_s^M) = \frac{1}{2}c^M {\Omega_s^M}^2, C_s^R(1-\Omega_s^M) = \frac{1}{2}c^M(1-\Omega_s^M)^2$$

[9]If $h^R = 0.5$, then 50% of links are of same type and 50% are of the different kind. If $h^R = 1$, then all the links are of the same type, and if $h^R = 0$, then none of the network links are of the same type.

where, c^M and c^R denote the unit costs of market and referral hire, such that $c^R \neq c^M > 0$.

4.2 Employees/Unemployed Worker's Problem

Suppose unemployed workers are risk neutral and, for analytical simplicity, assume job search is not costly [10]. 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, e_s^0, θ_s (and hence the vacancy 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 the worker finds a good match, with probability $p_s^{e^0}$ the worker finds a bad match and with probability p_s^u the worker does not find a match and remains unemployed in each state s, where,

$$p_s^e = \Omega_s^M f_s^M \gamma_s^M + (1-\Omega_s^M) f_s^R \gamma_s^R \tag{7.1}$$

$$p_s^{e^0} = \Omega_s^M f_s^M (1-\gamma_s^M) + (1-\Omega_s^M) f_s^R (1-\gamma_s^R) \tag{7.2}$$

$$p_s^u = 1 - \Omega_s^M f_s^M - (1-\Omega_s^M) f_s^R \tag{7.3}$$

An employee in a good match receives a wage w_s at the beginning of each period, pays lump-sum tax T, with probability δ 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. An employee in a bad match receives wage w_s^0, pays lump-sum tax T, at the beginning of each period, with probability 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_s^u, V_s^e, and $V_s^{e^0}$, and define them as:

$$V_s^e = w_s - T_s + \beta\big[(1-\delta)\mathbb{E}_s V_{s'}^e + \delta \mathbb{E}_s V_{s'}^u\big] \tag{8.1}$$

$$V_s^{e^0} = w_s^0 - T_s + \beta\big[(1-\delta^0)\mathbb{E}_s V_{s'}^{e^0} + \delta^0 \mathbb{E}_s V_{s'}^u\big] \tag{8.2}$$

$$V_s^u = b + \beta\big[p_s^e \mathbb{E}_s V_{s'}^e + p_s^{e_0} \mathbb{E}_s V_{s'}^{e^0} + p_s^u \mathbb{E}_s V_{s'}^u\big] \tag{8.3}$$

such that $\quad 0 < b < w_s^0 < y_s^0 < w_s < y_s$.

[10] In this paper, the objective is to model a firm's hiring decisions and not workers' search incentives, hence it is not modeled. But one is always free to include.

4.3 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 gets separated by the end of each period, and a vacancy is created. Like workers, firms are risk-neutral and discount future expected profits at the rate β. The continuation profits of an unfilled vacancy equal the discounted expected profits from filling the vacancy through the market channel, plus the expected profits from filling through the referral channel, net of the unit vacancy opening cost k, the market hiring costs $\frac{1}{2}c^M{\Omega_s^M}^2$, and the referral hiring costs $\frac{1}{2}c^R(1-\Omega_s^M)^2$, plus the expected profits from an unfilled vacancy [11]. The implicit assumption is that a vacancy enters the market and can get filled through the market channel at the rate q_s^M. At the same time, the vacancy can be filled through the referral channel at the rate $\tilde{q}_s^{R,*}$, and with the remainder probability remains unfilled by the end of the period. 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:

$$J_s^e = y_s - w_s + \beta\big[(1-\delta)\mathbb{E}_s J_{s'}^e + \delta\mathbb{E}_s J_{s'}^v\big] \tag{9.1}$$

$$J_s^{e^0} = y_s^0 - w_s^0 + \beta\big[(1-\delta^0)\mathbb{E}_s J_{s'}^{e^0} + \delta^0\mathbb{E}_s J_{s'}^v\big] \tag{9.2}$$

$$J_s^v = -k - \frac{1}{2}c^M{\Omega_s^M}^2 - \frac{1}{2}c^R(1-\Omega_s^M)^2 + \beta\Bigg(\Omega_s^M q_s^M\big[\gamma_s^M\mathbb{E}_s J_{s'}^e + (1-\gamma_s^M)\mathbb{E}_s J_{s'}^{e^0}\big] + (1-\Omega_s^M)\tilde{q}_s^{R,*}\Big[\gamma_s^R\mathbb{E}_s J_{s'}^e + (1-\gamma_s^R)\mathbb{E}_s J_{s'}^{e^0}\Big] + \big(1-\Omega_s^M q_s^M - (1-\Omega_s^M)\tilde{q}_s^{R,*}\big)\mathbb{E}_s J_{s'}^v\Bigg) \tag{9.3}$$

The continuation profit functions J_s^e, $J_s^{e^0}$, and J_s^v are all functions of the firm's choices, aggregates, given the set of model parameters in each state s. In each state of the economy, each unfilled vacancy continuation profit J_s^v takes a zero value because the labor market is assumed to be competitive, which implies that there exists free entry-exit of the firms. The aggregate market variable that drives the profit to zero is the vacancy rate v_s. In other words, the implicit assumption is that each vacancy is equivalent to a firm.

[11] A firm's expected profits from market hiring are a function of its own choice Ω_s^M and tightness θ_s

4.4 Firm's Optimization problem

In each realized state, a firm maximizes the sum of expected profits net of costs from market, referral hiring and vacancy opening by choosing to allocate Ω_s^M of its resources (can be labor, financial resources, etc.) to hire through the market channel and the rest $1-\Omega_s^M$ of its resources to hire through the referral channel, taking as given the aggregates, u_s, e_s^0, v_s, θ_s[12]. Without loss of generality, I normalize the total available resources to 1. In other words, a firm optimally chooses Ω_s^M to maximize (9.3). Thus the optimal hiring rates are given by the solution to,

$$\underset{\Omega_s^{M\prime},1-\Omega_s^{M\prime}}{\operatorname{argmax}} \quad J_s^v(\Omega_s^{M\prime}, 1-\Omega_s^{M\prime}) \tag{10}$$

4.5 Labor Market Clearing Conditions

In each state, the labor market is characterized by the inflow and outflow of good and bad matches, and the sizes of job seekers and employees are normalized to 1. This gives us:

$$\delta e_s = p_s^e u_s \tag{11.1}$$

$$\delta^0 e_s^0 = p_s^{e^0} u_s \tag{11.2}$$

$$e_s + e_s^0 + u_s = 1 \tag{11.3}$$

4.6 Wage Bargaining

Wages w_s and w_s^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:

$$Z_s = V_s^e + J_s^e - V_s^u - J_s^v \tag{12.1}$$

$$Z_s^0 = V_s^{e^0} + J_s^{e^0} - V_s^u - J_s^v \tag{12.2}$$

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

$$\underset{\overline{w}_s}{\operatorname{argmax}} \ (V_s^e - V_s^u)^\phi (J_s^e - J_s^v)^{1-\phi} \tag{12.3}$$

$$\underset{\overline{w}_s^0}{\operatorname{argmax}} \ (V_s^{e^0} - V_s^u)^\phi (J_s^{e^0} - J_s^v)^{1-\phi} \tag{12.4}$$

[12] $\Omega_s^{M'}$ denotes any other Ω_s^M apart from the optimal Ω_s^M.

4.7 Equilibrium

Given primitives $\{\delta_s, \delta_s^0, \lambda, h^R, n, y_s, y_s^0\}_{s=1}^N$ and a time-invariant Markov transition matrix $\chi \in \mathbb{R}^{N\times N}$ over aggregate states $s \in \{1, \ldots, N\}$, a *stationary (recursive) competitive equilibrium* is a collection of state-contingent objects

$$\{v_s, \theta_s, e_s, e_s^0, u_s, \Omega_s^M,\ w_s,\ f_s^M, q_s^M,\ f_s^R, q_s^{R,*},\ J_s^v, J_s^e, J_s^{e^0},\ V_s^u, V_s^e, V_s^{e^0},\ T_s\}_{s=1}^N$$

such that for each state s, we have:

(i) **Flow-balance (state-contingent stationarity):** Employment and unemployment stocks satisfy the steady-flow conditions in (11.1)–(11.3), given the state-s job-finding and separation hazards.

(ii) **Worker–firm surplus splitting:** Wages satisfy Nash bargaining and/or surplus-sharing conditions (12.3)–(12.4), given continuation values.

(iii) **Firms' optimal hiring mix:** The firm's hiring choice Ω_s^M solves the firm problem in (10), taking as given equilibrium wages and hiring technologies.

(iv) **Free entry / vacancy creation:** Vacancy creation satisfies free entry, $J_s^v = 0$, as in (9.3), which pins down equilibrium tightness (and hence v_s given θ_s and u_s).

(v) **Matching and contact-rate consistency:** Market and referral job-finding/job-filling objects are consistent with the matching/contact technologies (e.g., $q_s^M = q^M(\theta_s)$, $f_s^M = \theta_s q_s^M$, and the referral contact-rate equations implied by network congestion and wedge).

(vi) **Firm's Continuation Profits and Worker's Continuation Utilities:** A firm's continuation profits and a worker's continuation utilities are given by equations (9.1-9.3) and (8.1-8.3), respectively.

(vii) **Government budget balance:** The government finances unemployment benefits via lump-sum taxes:

$$T_s = \frac{u_s\, b}{1 - u_s} \qquad \text{for all } s.$$

5 Model Quantification

Calibration

(a) **Parameter estimation**: We discipline the model by choosing the parameter vector

$$\Theta \equiv (c^M\, n, A, \psi)$$

to match a set of four empirical targets. For any trial Θ, we solve for a stationary Markov equilibrium across all productivity states $s \in \{1, \ldots, N\}$ (holding Θ *common across states*). Let $\pi(\Theta)$ denote the stationary distribution implied by the equilibrium transition matrix.[13] Given the equilibrium state vectors $\{m_j(s;\Theta)\}_s$, we compare their stationary (ergodic) averages to the corresponding data moments $\overline{m}_j^{\text{data}}$,

$$\overline{m}_j^{\text{model}}(\Theta) \;=\; \sum_{s=1}^{N} \pi_s\, m_j(s;\Theta).$$

(b) **Identification**: The mapping from moments to parameters is economically disciplined as follows: (i) c^M is tied to the firms' first-order conditions for market hiring Ω^M; (ii) A is pinned by the market matching technology and hence the market job-finding and filling rates f^M, q^M; (iii) ψ governs the elasticity in market good-match shares γ_s^M; (iv) n is jointly calibrated.

Therefore, relations (i)-(iii) guide identification and provide reasonable starting values, but the *final* parameter vector is chosen by optimizing the objective below.

(c) **Objective**: Because I target four moments with four parameters, the system is exactly-identified and I estimate Θ by weighted least squares,

$$\min_{\Theta} \;\sum_{j=1}^{4} \left(\frac{\overline{m}_j^{\text{model}}(\Theta) - \overline{m}_j^{\text{data}}}{\sigma_j} \right)^2,$$

where σ_j is the empirical standard deviation for target j used as a weight.[14] The four targets are the stationary averages of u, v, Ω^M, and γ^M.

Next, I describe how I preset the remaining externally calibrated parameters and their sources, as well as the parameters derived from the data and the literature findings of all the internally calibrated parameters. I set the model period as a month, and suppose each period corresponds to each state.

[13] In robustness checks, I also report simple cross–state averages.

[14] This is equivalent to minimum distance with a diagonal weighting matrix $W = \text{diag}(1/\sigma_j^2)$.

Separation rates: Bagga et al. (2025) provides the literature reference for the long-run average monthly separation rate (employment to unemployment) from CPS data at $\delta^{monthly} = 0.015$. The corresponding steady state quarterly rates are computed using the formula,

$$\delta^{quarterly} = 1 - (1 - \delta^{monthly})^3 = 0.045$$

Moreover, Shimer (2005) reports the monthly separation rate, due to exogenous reasons, to be 0.03. Furthermore, Horvath (2014) reports that the ratio of separation rates of a bad to good match lies between $[1, 5]$. The model tolerates preset separation rates of good and bad matches at $0.025, 0.03$, respectively.

Average labor productivity and Real GDP: For the long-run steady state, I normalized the ratio of $\frac{y^0}{y}$ to be 0.95 as in 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 real GDP. Similarly, I refer to data on real GDP for Greece during the sample period (2004-2013), log the data series, and find out the correlation between firm's hiring rate and real GDP.

Unit hiring costs and vacancy opening costs: I preset the ratio of recruitment costs per hire for referred versus non-referred workers to 0.7, which is consistent with Burks et al. (2015) and calibrate the unit market hiring cost in the model. Then, the unit referral hiring cost is calculated back from the calibrated unit market hiring cost, given the cost ratio. For the vacancy opening cost, I again refer to the range of values reported in the scholarly literature (namely, Shimer (2005), Treanor (2023)) and set it at 0.14.

Unemployment benefits: I preset b to 0.42, the U.S. average as in Griffy and Rabinovich (2025). Besides, the consensus in many scholarly articles in the literature, like Horvath (2014), Shimer (2005), Pei and Xie (2021), is that it is in the range [0.4, 0.47].

Market screening technology level and network homophily rate: The market screening technology level, denoted by λ, is exogenously set at 0.45, and the homophily rate h^R is set at 0.7. The network size n has been calibrated; Horvath (2014) reports that n can take any value between 10 and 45.

Bargaining power: The worker's bargaining power ϕ has been set at 0.7, which lies in the range well documented in the literature.

Market and Referral match composition: SCE asks the survey respondents who found a job (either referred or market hired), "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 [15]. 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.[16] Given this, the fraction of good and bad market matches is normalized to 1. Similarly, the fraction of good and bad referred matches is 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 $\textit{fraction of good referred matches} = \frac{\textit{no. of good referred matches}}{\textit{no. of good referred matches} + \textit{no. of bad referred matches}}$. The average fraction of referred and market hired good matches equal 0.672 and 0.54 respectively and they have been been targeted while solving the model.

6 Labor Productivity Shocks

6.1 Quantitative Results

This section summarizes the steady-state competitive equilibrium (CE) under labor-productivity shocks. Table 6.1.2 reports the targeted endogenous variables—along with their empirical counterparts—and a set of additional, non-targeted equilibrium objects. The model is solved on a discrete productivity grid with 21 states generated from the Markov process in (1). After computing the state-contingent equilibrium, I simulate a long Markov path using the transition matrix χ and map the state solutions into a synthetic time series to compute moments.

Table 6.1.2 indicates that the equilibrium features moderate slack: the mean unemployment rate is $u = 0.055$, market tightness is $\theta = 0.883$, and the vacancy rate is $v = 0.049$. Firms actively recruit through both channels, with a slight tilt toward referrals. The average market-hiring share is $\Omega^M = 0.49$, implying a referral-hiring share of $1 - \Omega^M = 0.51$. This is consistent with the empirical evidence that referrals account for a substantial fraction of hires, while still leaving an important role for market recruiting.

[15] In this paper, I focus on skill mismatch 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.

[16] I have also checked that the workers who were counted as well-matched earned substantially higher wages than badly matched workers. Insufficient sample size prevented the wage difference from being statistically significant.

The channel split is best understood through a *quantity–quality–cost tradeoff*, together with the role of non-network wedge in shaping effective contacts. On the quantity margin, the market channel delivers a higher effective contact rate: $q^M = 0.621$, whereas the effective referral offer-arrival and the referral job-filling probabilities are $\tilde{q}^R = 0.47$ and $\tilde{q}^{R,*} = 0.46$, respectively. Referrals compensate partly on the quality margin: expected match quality is higher for referrals, with $\gamma_g^M = 0.55$ and $\gamma_g^R = 0.59$. Taken together, the market's quantity advantage is strong enough that market recruiting dominates in quality-adjusted arrivals,

$$\frac{q^M \gamma_g^M}{\tilde{q}^{R,*} \gamma_g^R} \approx 1.26.$$

A key driver of referral effectiveness is the wedge parameter ζ. In the calibration, $\zeta < 0$ implies that referral leads are *discounted* relative to the network-implied contact rate, so even when firms allocate vacancies toward the referral channel, only a smaller fraction of referral contacts becomes hiring-relevant opportunities. Economically, a negative ζ summarizes lower referral throughput on the firm side—for example, weaker endorsement content, reduced follow-through, compliance or procedural frictions, or stricter screening thresholds for referred candidates. This is why the model distinguishes the raw network contact rate q^R from the wedge-adjusted referral rate $\tilde{q}^R$: referral links do not map one-for-one into economically relevant hiring opportunities.

In addition to this wedge, the referral channel is further constrained by the limited transmission capacity of incumbent employees. When a larger share of vacancies is routed through referrals, the same stock of employed workers must process and relay more opportunities, which weakens the conversion of referral leads into realized hires. As a result, the equilibrium referral job-filling rate $\tilde{q}^{R,*}$ lies below $\tilde{q}^R$. In the baseline equilibrium, this employee-side congestion is quantitatively mild relative to the wedge effect, but it still plays an important structural role: it makes referral hiring less than perfectly scalable and thereby reinforces the interior channel allocation observed in equilibrium. More broadly, this mechanism implies that expanding referral recruiting raises pressure on the employed network itself, so the effectiveness of the referral channel cannot increase one-for-one with the number of vacancies routed through it.

Costs then push in the opposite direction and prevent full specialization in the market channel. Referral hiring is substantially cheaper in the calibrated equilibrium: the per-hire cost ratio satisfies $\frac{c^R}{c^M} \simeq 0.7$. This cost advantage keeps referral recruiting attractive even when market applicants are more plentiful. At the same time, the referral channel is not perfectly scalable—routing additional

vacancies through referrals raises marginal referral recruiting costs (e.g., via congestion/diminishing returns embedded in the technology). As a result, the firm optimally chooses an *interior* allocation: it uses the market channel to generate contacts at scale, while relying on referrals for their quality edge and lower per-hire cost.

From the worker side, job finding chance is slightly higher through market: $f^M = 0.517$ and $f^R = 0.434$, so $\frac{f^M}{f^R} \approx 1.2$. Finally, the implied flow value of unemployment (the expected unemployed wage rate in the model) is $w^u = 0.44$. Equation (13) clarifies why w^u is an equilibrium object: it is a probability-weighted average of employment wages and unemployment benefits, where the weights are pinned down by equilibrium tightness and the endogenous channel allocation. Intuitively, w^u is higher when unemployment transitions into employment are more likely (through either channel), because more probability mass is placed on w and w^0 rather than on b.

$$w^u = \Bigg\{ \Bigg[\Omega^M m(.)\gamma^M(.) + (1-\Omega^M) f^R(.) u \gamma^R(.) \Bigg] w + \Bigg[\Omega^M m(.) \Big(1 - \gamma^M(.) \Big) + (1-\Omega_s^M) f^R(.) u \Big(1 - \gamma^R(.) \Big) \Bigg] w^0 + \Bigg[1 - \Omega^M m(.) - (1-\Omega^M) f^R(.) u \Bigg] \Bigg\} b \tag{13}$$

The equilibrium also implies meaningful wage dispersion *within* employees. Bad matches earn about a 3.6% wage discount relative to good matches ($w^0/w \simeq 0.964$). Moreover, bad-match employment is quantitatively important in steady state: $e^0 = 0.367$, far exceeding unemployment $u = 0.055$. Thus, an important portion of earnings differences arises not only from employment versus unemployment, but also from the match-quality composition of employment induced by firms' hiring and screening decisions.

6.2 Cyclical behavior of the endogenous variables

This section describes how aggregate labor-productivity shocks propagate through firms' surplus, vacancy creation, and the two hiring channels, shaping the cyclical behavior of equilibrium outcomes. Throughout, productivity moves exogenously, while tightness, hiring rates, match composition, and wages respond endogenously through firms' recruiting incentives and workers' job-finding prospects.

Vacancy rate: Vacancies are pro-cyclical. The core mechanism is surplus-driven vacancy creation: when productivity y_s falls, the match surplus from both match types, Z_s and Z_s^0, declines, which lowers continuation profits of matched firms, J_s^e and $J_s^{e^0}$. With weaker expected profits, free-entry incentives weaken and vacancy opening falls. Although referral hiring does not require

Table 6.1.1: Parameters — labor productivity shocks

Description	Parameter	Value
Internally Calibrated parameters		
market matching scale	A	0.811
market match quality elasticity	ψ	0.39
per-hire costs	c^M, c^R	0.427, 0.299
network size	n	22
Shock Parameters		
productivity AR(1) for $\log y$	ρ^y, σ^y	0.970, 0.002
grid size	N	21
target/achieved σ(HP cycle of $\log y$)	$\sigma^{y,\text{target}}, \sigma^{y,\text{actual}}$	0.013, 0.013
Externally Calibrated and Preset Parameters		
discount factor	β	0.980
unemployment benefit	b	0.420
separation rates	δ, δ^0	0.025, 0.030
vacancy posting cost	k	0.140
bargaining power	ϕ	0.700
market screening tech	λ^M	0.450
homophily	h^R	0.9
ref. wedge	ζ	-0.500
matching elasticity	η	0.400

Table 6.1.2: Competitive Equilibrium — labor productivity shocks

Endogenous Variables	**Model**	**Data**	**Targeted**
Market and Referral Hiring rates ($\Omega^M, 1-\Omega^M$)	0.490, 0.510	0.507, 0.493	**Y**
Vacancy rate (v)	0.049	0.041	**Y**
Unemployment rate (u)	0.055	0.054	**Y**
Market Good-match prob. (γ_g^M)	0.551	0.54	**Y**
Labor market tightness ($\theta = v/u$)	0.883	0.74	**N**
Market job-finding rate (f^M)	0.517	0.298	**N**
Market job-filling rate (q^M)	0.621	0.591	**N**
Good and Bad match shares (e, e^0)	0.578, 0.367	–	**N**
Ref. good-match prob. (γ_g^R)	0.589	0.672	**N**
Vacancy's applicant contact rates ($q^R, \tilde{q}^R$)	0.59, 0.47	–	**N**
Ref. job-filling rate ($\tilde{q}^{R,\star}$)	0.46	–	**N**
Ref. job-finding rate (f^R)	0.434	–	**N**
Wages (w, w^0)	0.979, 0.944	–	**N**
Per-hire profits (Π^M, Π^R)	0.207, 0.163	–	**N**

Table 6.1.3: Summary statistics — labor productivity shocks

Quarterly series (HP $\lambda = 1600$)						
	u	v	v/u	f^M	q^M	y
Standard Deviation	0.014	0.065	0.079	0.022	0.028	0.013
Quarterly Autocorrelation	0.717	0.718	0.718	0.718	0.718	0.718
Correlation Matrix						
u	1.000	-0.988	-0.992	-0.996	0.978	-0.996
v	—	1.000	1.000	0.998	-0.998	0.998
v/u	—	—	1.000	0.999	-0.997	0.999
f^M	—	—	—	1.000	-0.992	1.000
q^M	—	—	—	—	1.000	-0.993
y	—	—	—	—	—	1.000

Annual series (annualized; HP $\lambda = 100$)					
	Ω^M	$1 - \Omega^M$	γ^M	γ^R	y
Standard Deviation	0.027	0.026	0.014	0.009	0.016
Annual Autocorrelation	0.584	0.584	0.584	0.584	0.584
Correlation Matrix					
Ω^M	1.000	-0.993	-1.000	-1.000	-0.993
$1 - \Omega^M$	—	1.000	0.993	0.996	1.000
γ^M	—	—	1.000	1.000	0.993
γ^R	—	—	—	1.000	0.996
y	—	—	—	—	1.000

Notes: Quarterly variables are HP-filtered in log space with $\lambda = 1600$. Annual variables are constructed by averaging four consecutive quarters and then HP-filtered with $\lambda = 100$. Correlations are computed on the corresponding HP cycles.

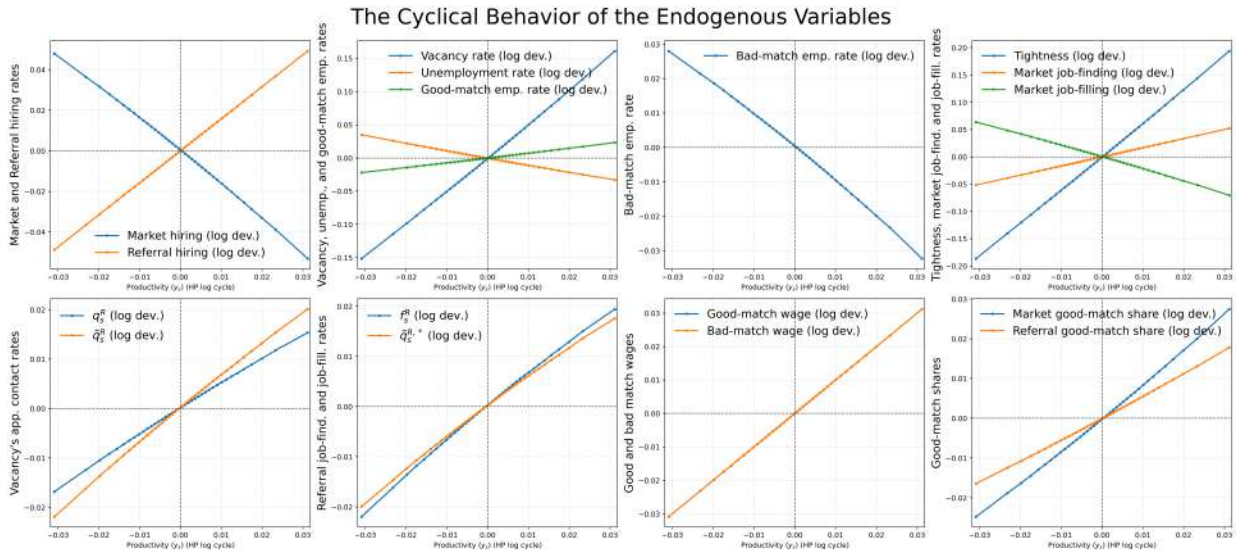


Figure 6.3.1: Log deviations from trend of the endogenous variables.

Notes: The figure plots the cyclical behavior of the endogenous variables against the labor-productivity cycle. For each series, I compute HP-filtered log deviations from trend ($\lambda = 1600$) along a long simulated path. I then form date-level pairs (x_t, z_t), where x_t is the productivity cycle and z_t is the corresponding variable cycle, sort the observations by x_t, and partition them into equal-frequency (quantile) bins. For each bin b, the plotted point is $(\bar{x}_b, \bar{z}_b)$, the mean productivity cycle and mean variable cycle within that bin; lines connect these bin means rather than individual simulated observations. The underlying labor-productivity process is discretized as a 21-state first-order Markov chain. Figure 6.3.2 in Appendix A.1 plots the actual and trend fits.

posting an open vacancy in the same way as market hiring, the vacancy rate still co-moves with referral activity because both channels are ultimately disciplined by the same surplus and profitability conditions that determine firms' recruiting intensity.

Quantitatively, the model matches the volatility of labor productivity by construction: the standard deviation of the HP-filtered log productivity cycle is 0.017, consistent with the data. Vacancies fluctuate more than productivity, with $\sigma^y(\log v) = 0.065$ relative to $\sigma^y(\log y) = 0.013$, reflecting the familiar amplification from small surplus changes to recruiting incentives. However, vacancy volatility remains below the data counterpart (0.096), so productivity shocks alone explain about 67% of observed vacancy volatility.

Unemployment and bad-match employment rates: Unemployment is counter-cyclical because low productivity depresses vacancy creation and market tightness, which reduces job-finding and slows the exit rate from unemployment. This can be seen directly from the steady-state market-clearing condition (for intuition, take $\delta = \delta^0$). Given Ω_s^M, a decline in tightness lowers market

job-finding, so the left-hand side falls:

$$\Omega_s^M \underbrace{f_s^M(\theta_s)}_{\downarrow} = \delta\Big(\frac{1}{u_s} - 1\Big) - (1 - \Omega_s^M) f_s^R(u_s, \tilde{q}_s^R) \quad \Rightarrow \quad u_s \text{ must rise.}$$

That is, when recruiting becomes less attractive, the job-finding margin weakens and the unemployment stock adjusts upward to restore flow balance.

Bad-match employment is also counter-cyclical. In downturns, hiring slows and separations destroy matches, increasing the relative weight of low-quality matches among those remaining employed, and preventing rapid upgrading into good matches.

Quantitatively, unemployment volatility is small: $\sigma^y(\log u) = 0.014$ versus 0.227 in the data (about 6% of the observed volatility). The bad-match employment rate fluctuates even less, with $\sigma^y(\log e^0) = 0.013$. In this regime, productivity shocks mainly move profits and vacancies, while employment and match composition adjust more sluggishly.

Labor market tightness: Tightness is pro-cyclical, reflecting the joint movement of vacancies and unemployment. When productivity falls, vacancies contract and unemployment rises, so $\theta_s = v_s/u_s$ declines. Quantitatively, $\sigma^y(\log \theta) = 0.079$ compared to 0.286 in the data (about 28%). Since unemployment is relatively smooth in this regime, most of the variation in tightness is driven by vacancy movements.

Market job-finding and job-filling rates: The market job-finding rate f_s^M is pro-cyclical because it rises with tightness: expansions increase vacancy opening, making it easier for unemployed workers to locate jobs through the market channel. Still, the response is muted: $\sigma^y(\log f^M) = 0.022$ versus 0.13 in the data (about 17%), consistent with a low elasticity of the matching function in the calibrated economy.

The market job-filling rate q_s^M is counter-cyclical. In booms, a tighter labor market means each vacancy attracts fewer available job seekers, lowering the probability that a given vacancy is filled quickly. The cyclical volatility of market job-filling is $\sigma^y(\log q^M) = 0.028$.

Referral contact and job-filling rates: The vacancy-side referral contact rates, q_s^R and $\tilde{q}_s^R$, are pro-cyclical. In stronger labor-market conditions, a larger employed workforce and a more favorable composition of matches strengthen the referral network and improve the transmission of vacancy information to relevant contacts. The wedge-adjusted rate $\tilde{q}_s^R$ follows the same qualitative pattern as q_s^R, but at a lower level, since not every network contact translates into a hiring-relevant referral opportunity. The equilibrium referral job-filling rate, $\tilde{q}_s^{R,*}$, is lower still because it also reflects

employee-side transmission limits: when more vacancies are directed toward referrals, incumbent workers must process and relay more opportunities, which reduces the efficiency with which referral leads are converted into realized hires. Even so, because expansions are associated with a larger stock of employed workers, this congestion is partly mitigated, so $\tilde{q}_s^{R,*}$ remains pro-cyclical as well. Quantitatively, the cyclical variation in these vacancy-side referral objects is modest, with $\sigma^y(\log q^R) = 0.007$, $\sigma^y(\log \tilde{q}^R) = 0.008$, and $\sigma^y(\log \tilde{q}^{R,*}) = 0.008$.

Referral job-finding rate: The referral job-finding rate, f_s^R, is also pro-cyclical. When unemployment is lower, fewer job seekers compete for referral-transmitted opportunities within the network, so any given unemployed worker is more likely to learn about and obtain a job through referrals. Thus, the worker-side probability of finding a job through referrals moves positively with the cycle, consistent with the stronger vacancy-side referral pipeline in expansions. At the same time, its cyclical volatility remains limited because unemployment itself evolves relatively smoothly over the business cycle: $\sigma^y(\log f^R) = 0.009$.

Market and referral good-match shares: Both good-match arrival shares, $\gamma_s^M(q_s^M)$ and $\gamma_s^R(u_s, e_s, e_s^0)$, rise with productivity. The market channel improves because high tightness reduces congestion per vacancy and increases the likelihood that the realized hire is a good fit. The referral channel improves because expansions tilt the network toward employed and good-match workers, which increases the probability that referrals connect firms to higher-quality applicants. The standard deviations of the cyclical components of the log good-match shares are 0.011 (market) and 0.007 (referral).

Market and referral hiring rates: The model generates cyclical reallocation across recruiting channels. The optimal market-hiring share Ω_s^M is counter-cyclical, while referral hiring is pro-cyclical. In downturns, unemployment rises and market search becomes relatively more effective because the pool of job seekers expands; at the same time, higher unemployment increases network congestion and weakens referral-based diffusion. These forces shift recruiting effort toward market hiring in recessions and toward referrals in expansions, consistent with the patterns shown in Figures 3.1.1–3.1.2.

Quantitatively, the volatilities of market and referral hiring are $\sigma(\log \Omega^M) = 0.027$ and $\sigma(\log(1 - \Omega^M)) = 0.026$, compared to 0.097 and 0.110 in the data. Thus, productivity shocks alone generate meaningful variation in channel allocation, but they do not fully match the large fluctuations observed empirically.

Good- and bad-match wage rates: Both wage rates are pro-cyclical. Wages rise in expansions

because higher productivity increases match output and, through continuation values, raises the surplus available to be shared in Nash bargaining:

$$w_s = \phi\left[y_s + \beta(1-\delta)\mathbb{E}_s J^e_{s'}\right] + (1-\phi)\left[V^u_s - \beta\Big((1-\delta)\mathbb{E}_s V^e_{s'} + \delta\mathbb{E}_s V^u_{s'}\Big)\right] \tag{12.3.1}$$

and

$$w^0_s = \phi\left[y^0_s + \beta(1-\delta^0)\mathbb{E}_s J^{e_0}_{s'}\right] + (1-\phi)\left[V^u_s - \beta\Big((1-\delta^0)\mathbb{E}_s V^{e^0}_{s'} + \delta^0\mathbb{E}_s V^u_{s'}\Big)\right] \tag{12.3.2}$$

Higher productivity increases wages both directly (through y_s and y^0_s) and indirectly (through continuation values), and the quantitative equilibrium confirms that both w_s and w^0_s increase with y_s. The cyclical volatilities are $\sigma^y(\log w) = \sigma^y(\log w^0) = 0.013$.

Expected unemployed wage rate: The expected unemployed wage w^u_s in equation (13) is pro-cyclical. The reason is that unemployment earnings are a probability-weighted average of employed wages (w_s, w^0_s) and benefits b, where the weights depend on the equilibrium job-finding probabilities in both channels. In expansions, employed wages are higher and the probability mass shifts toward employment rather than remaining unemployed, increasing the weight on (w_s, w^0_s) relative to b. While some transition components (e.g., channel-specific match probabilities) move in opposite directions over the cycle, the net effect in the quantitative equilibrium is that the pro-cyclical forces dominate, making w^u_s rise with productivity.

7 Separation-Rate Shocks

Shock Process: To introduce cyclical variation in job separations while keeping the state space tractable, I model separation rates as state-dependent probabilities that remain strictly admissible. The implementation is multiplicative: in every state, each separation rate equals its calibrated mean times a positive multiplier. Concretely, the code constructs a state vector of multipliers (`sep_mult`) and then forms the state-dependent separation inputs used in the equilibrium iteration as

$$\delta_s = \bar{\delta}\,\tilde{\mu}_s, \qquad \delta^0_s = \bar{\delta}^0\,\tilde{\mu}_s,$$

(or the analogous objects in the joint state space). Because the multiplier is strictly positive by construction and its support is modest in the calibrated exercises, implied separations stay

comfortably inside $(0, 1)$ in every state, which helps keep the fixed-point iteration stable.

Two specifications used in the paper: I consider two separation-rate specifications. The first links separations countercyclically to the productivity regime. The second allows separations to evolve independently of productivity and combines the two processes into a joint Markov chain.

Productivity linked separations

Regime-dependent separations: Let s index the aggregate productivity regime with productivity y_s generated by a finite-state Markov chain with stationary distribution π. In the linked specification, separation rates move systematically with productivity through a mean-preserving multiplier $\tilde{\mu}_s > 0$:

$$\delta_s^0 = \bar{\delta}^0 \, \tilde{\mu}_s, \qquad \delta_s = \bar{\delta} \, \tilde{\mu}_s.$$

Since both match types share the same multiplier, the relative separation rate is constant across states,

$$\frac{\delta_s}{\delta_s^0} = \frac{\bar{\delta}}{\bar{\delta}^0} \equiv \delta_{ratio},$$

so good- and bad-match separations move proportionally over the cycle.

Multiplier construction and mean preservation: The multiplier is chosen to be counter-cyclical by construction: it increases when productivity is low and decreases when productivity is high. In the implementation, it is an exponential function of demeaned log productivity with a single link-strength parameter $\alpha > 0$ and is normalized to preserve the unconditional mean:

$$\tilde{\mu}_s = \frac{\exp\big(-\alpha \, (\log y_s - \mathbb{E}_\pi[\log y])\big)}{\mathbb{E}_\pi\big[\exp\big(-\alpha \, (\log y_s - \mathbb{E}_\pi[\log y])\big)\big]}, \qquad \mathbb{E}_\pi[\tilde{\mu}_s] = 1.$$

This normalization implies $\mathbb{E}_\pi[\delta_s^0] = \bar{\delta}^0$ and $\mathbb{E}_\pi[\delta_s] = \bar{\delta}$, while allowing separations to co-move systematically with productivity. Importantly, this specification introduces *no additional state dimension*: separations vary deterministically with y_s, so the state space remains $S = N^y$.

Admissibility and numerical stability: Because $\tilde{\mu}_s > 0$ and the calibrated mean separations are small, the linked construction keeps δ_s and δ_s^0 well inside $(0, 1)$ across all productivity states in the exercises reported in the paper. This delivers the intended cyclical movements in separations

without requiring an enlarged regime space, and provides stable state-by-state separation inputs to the equilibrium iteration.

Joint productivity and separation regimes

Independent separation component and joint state space. To allow separations to vary independently of productivity, I introduce a separate Markov component for a separation multiplier and combine it with the productivity chain through a product state space. Let d index the separation regime and define a log-multiplier z_d that follows an AR(1) process,

$$z_{d+1} = \rho_d \, z_d + \varepsilon_{d+1}, \qquad \varepsilon_{d+1} \sim \mathcal{N}(0, \sigma_d^2),$$

which is discretized to a finite-state Markov chain (via Rouwenhorst). The separation multiplier is then $\tilde{\mu}_d = \exp(z_d)$, normalized so that $\mathbb{E}[\tilde{\mu}_d] = 1$ under the stationary distribution of the separation chain. The joint state is (s, d), with transition matrix given by the Kronecker product of the productivity and separation transition matrices. Separation rates depend on the separation component only:

$$\delta^0_{s,d} = \bar{\delta}^0 \, \tilde{\mu}_d, \qquad \delta_{s,d} = \bar{\delta} \, \tilde{\mu}_d, \qquad \frac{\delta_{s,d}}{\delta^0_{s,d}} = \frac{\bar{\delta}}{\bar{\delta}^0} = \delta_{ratio} \;\text{ in all states.}$$

This specification preserves unconditional mean separation rates by construction (up to the discretization and normalization step) while permitting separation risk to move independently from productivity fluctuations. In the code, the resulting state vectors $\{\delta_{s,d}\}$ and $\{\delta^0_{s,d}\}$ enter the equilibrium iteration as state-by-state inputs exactly as in the linked case.

Equilibrium implications and interpretation

Linked versus joint shocks: Separation-rate shocks affect equilibrium outcomes primarily through a *duration margin*: vacancy creation and the market–referral hiring mix depend not only on contemporaneous flow surplus, but also on the expected continuation values that are directly shaped by separation risk. The key distinction is informational. Under linked separations, δ_s and δ^0_s are pinned down by y_s, so conditioning on productivity effectively collapses aggregate uncertainty to a one-dimensional regime. This produces a tight mapping from the productivity cycle into tightness, job-finding, and the channel allocation: most conditional relationships are close to one-to-one

because separation risk does not add dispersion conditional on y_s.

Under joint separations, the aggregate state is two-dimensional, so conditioning on productivity does not uniquely determine separation risk. As a result, productivity-conditioning plots average over multiple separation regimes within a given productivity bin, and the relevant objects (tightness, vacancy opening, and the market–referral split) reflect both current productivity and the state-contingent replacement motive induced by separations. Put differently, variation in separation risk shifts continuation values and replacement demand independently of productivity, weakening the one-to-one mapping from y to equilibrium outcomes and generating systematic within-y dispersion in variables that are most sensitive to expected match duration.

Hiring reallocation and tightness: Across specifications, the model reallocates hiring across channels over the business cycle. The proximate drivers are (i) state-dependent job-finding and job-filling conditions in the market channel and the corresponding contact conditions in the referral channel; and (ii) the continuation value of a hire formed today, which depends on expected match survival $(1 - \delta)$ and on how future states affect the surplus from continuing the match.

In the linked (countercyclical) specification, separation risk moves in the opposite direction of productivity. A rise in y_s raises flow surplus and strengthens vacancy profitability, but it also lowers separation risk and therefore lengthens expected match duration while reducing replacement needs. Conversely, in low-productivity states, separations are higher: lower flow surplus discourages vacancy creation, but higher turnover strengthens replacement demand and shortens expected duration. Because these forces pull in opposite directions, linked separations need not uniformly amplify all moments. In particular, the countercyclical replacement motive tends to raise unemployment fluctuations (by moving job destruction more over the cycle), while it can dampen vacancy volatility when lower separations in booms meaningfully reduce replacement-driven vacancy creation.

In the joint specification, separations vary independently of productivity, so replacement needs become a separate driver of vacancy opening and tightness. Holding productivity fixed, higher-turnover states raise replacement demand and alter continuation values, shifting vacancy creation and hiring allocations even without changes in y. Conversely, conditioning only on productivity, averages over multiple turnover regimes, weakening the one-to-one mapping between y and equilibrium outcomes and increasing within-y dispersion in variables that are especially sensitive to match duration and replacement demand.

Volatility across specifications: Table 7.4 summarizes the shock specifications considered and the implied business-cycle volatility of key labor-market moments. Two patterns stand out. First, allowing separations to vary as an independent Markov component delivers the *largest unconditional fluctuations*. Relative to productivity-only and linked regimes, the joint specification generates substantially more volatility in unemployment and vacancies (e.g., $\sigma^y(u)$ rises from 0.004 under productivity-only and 0.045 under linked separations to 0.116 under the joint regime, and $\sigma^y(v)$ rises to 0.095, explaining nearly all of the data volatility). The same mechanism also produces the strongest fluctuations in the hiring mix: the annual volatility of Ω^M increases monotonically across regimes and is largest in the joint specification (0.080 versus 0.059 under linked and 0.030 under productivity-only).

Second, it is useful to distinguish unconditional volatility from the appearance of productivity-conditioning plots. In the linked case, separation risk is pinned down by productivity, so movements in y simultaneously shift flow surplus and expected duration/replacement incentives. This concentrates the relevant forces along a single state variable and can make vacancies, tightness, and the hiring mix appear tightly mapped to y even when the net effect on unconditional volatility is muted by the offsetting duration and replacement margins. By contrast, in the joint specification the same productivity level is associated with multiple turnover states, so conditioning on y averages over turnover risk. This averaging can attenuate the apparent sensitivity of equilibrium objects to y in productivity-conditioning plots even as unconditional volatility rises sharply. Taken together, Table 7.4 shows that introducing an independent separation regime is the most effective way to generate large business-cycle fluctuations in unemployment, vacancies, and the market–referral hiring mix, precisely because it adds an autonomous replacement-demand channel on top of productivity-driven movements in flow surplus.

Table 3.6: Business-cycle volatility explained across different shock specifications

Variable	Data σ	Prod. only	Linked ($\xi < 0$)	Joint (s, d)
Quarterly (CPS/JOLTS/BEA), HP $\lambda = 1600$				
u	0.227	0.014 (6%)	0.051 (22%)	0.126 (56%)
v	0.096	0.065 (68%)	0.047 (49%)	0.088 (92%)
v/u	0.286	0.079 (28%)	0.097 (34%)	0.094 (33%)
f^M	0.130	0.022 (17%)	0.026 (20%)	0.030 (23%)
q^M	0.059	0.028 (48%)	0.035 (59.3%)	0.038 (64%)
y	0.017	0.013 (76%)	0.013 (76%)	0.013 (76%)
Annual (SCE), HP $\lambda = 100$ **(model annualized by averaging 4 quarters)**				
Ω^M	0.097	0.027 (27%)	0.051 (53%)	0.079 (81%)
$1 - \Omega^M$	0.110	0.026 (23%)	0.048 (44%)	0.073 (66%)
γ^M	0.136	0.014 (10%)	0.017 (12%)	0.014 (11%)
γ^R	0.110	0.009 (8%)	0.012 (11%)	0.013 (11%)
y	0.014	0.016 (116%)	0.016 (116%)	0.016 (116%)

Notes: Each model cell reports the model-implied standard deviation of the HP-filtered log cycle, with the fraction of data volatility explained in parentheses, $100 \times \sigma_{\text{model}}/\sigma_{\text{data}}$. Quarterly data SDs are taken from Table 3.1 and annual SDs from Table 3.2. In the annual panel, model series are annualized by averaging four consecutive quarters before applying the HP filter with $\lambda = 100$.

8 Conclusion

Job search has received substantial attention in the literature, whereas firms' hiring decisions—and in particular the choice between market hiring and referral hiring—have received comparatively less. This paper brings the hiring-channel margin to the forefront in a stochastic search-and-matching environment and studies how firms optimally reallocate hiring across market and referral hiring over the business cycle. In the calibrated steady state, roughly 50% of positions are filled through each channel in the U.S. over 2013–2021, consistent with the data and with existing evidence in the literature. When the economy is driven only by labor productivity shocks, the model reproduces the observed procyclicality and countercyclicality of optimal market and referral hiring rates by tracing cyclical movements in hiring back to a shifting quantity–quality–cost trade-off. Quantitatively, productivity shocks explain about 23–27% of the observed hiring volatility in the U.S., and 1.3 times the volatility in Greece's market hiring and about 19.5% of the volatility in Greece's referral hiring.

A central message of the paper is that matching observed hiring volatility requires not only productivity-driven movements in surplus, but also cyclical movements in *match durability*. To quantify this margin, I introduce separation-rate shocks and study how turnover risk reshapes firms' incentives to allocate hires across channels. I consider a linked separation regime—in which

separations are negatively correlated with productivity—so that turnover risk moves systematically with the aggregate state. Introducing state-dependent separations preserves the qualitative ranking of outcomes across expansions and recessions from the productivity-only benchmark, but it strengthens the reallocation mechanism by making continuation values and expected match duration more state dependent. Quantitatively, in my calibrated economy this extension generates the largest fluctuations in the market versus referral hiring shares (roughly $45 - 61\%$ of the observed volatility in the U.S. and about 50% of the referral hiring volatility and all of the market hiring volatility in Greece).

I also study a joint specification in which separation risk follows its own stochastic process, so that turnover varies independently of contemporaneous productivity. Relative to the linked regime, this environment delivers *larger unconditional fluctuations* in labor-market outcomes—including greater model-implied variation in tightness and hiring shares—but can produce *weaker* productivity-conditioning relationships for two complementary reasons. First, in the linked regime productivity simultaneously shifts flow surplus and expected match duration: high-productivity states feature both higher surplus and lower separation risk, while low-productivity states feature both lower surplus and higher turnover. Because vacancy creation and the market–referral allocation respond to both margins, this co-movement concentrates the relevant forces into a single state variable and can generate sharp, sometimes non-linear movements in productivity-conditioning plots, especially near the tails of the productivity distribution where implied separation risk changes discretely on a finite grid. In the joint regime, by contrast, turnover does not systematically reinforce productivity. At a given productivity level, some histories imply high separation risk (high replacement demand) while others imply low separation risk (high expected duration). This weakens the one-to-one mapping from productivity into tightness and channel allocations: conditioning on productivity averages over multiple turnover realizations, mechanically attenuating the sensitivity of vacancies, tightness, and hiring composition to productivity. Second, with a parsimonious discretization of the joint process, this within-productivity averaging is especially pronounced and further smooths the response of equilibrium objects in productivity-conditioning figures even as unconditional volatility rises.

Quantitatively, the joint specification generates about 81% of the market hiring volatility, 66% of the referral hiring volatility, and 33% of the volatility in tightness. While allowing turnover risk to move independently is informative about the role of replacement demand and match durability, the model's tightness volatility remains below its data counterpart even after adding separations. This

suggests that a complete quantitative account of vacancy creation and market tightness may require additional aggregate drivers beyond productivity and turnover risk alone—for example, shocks to matching efficiency, vacancy opening costs, screening technology, or forces that shift surplus-sharing and recruiting intensity over the cycle.

Future work can use this framework to study aggregate regimes in which productivity, screening technology, network homophily, separations, and the magnitude of referral preference bias co-move endogenously or are subject to distinct shocks. This would sharpen the empirical mapping from observed labor-market volatility to the underlying sources of aggregate uncertainty, and would further clarify how hiring composition, match quality, and tightness jointly respond when both technology-driven and preference-driven forces vary over the business cycle.

Appendix A.1 - List of Figures

Labor Productivity Shocks

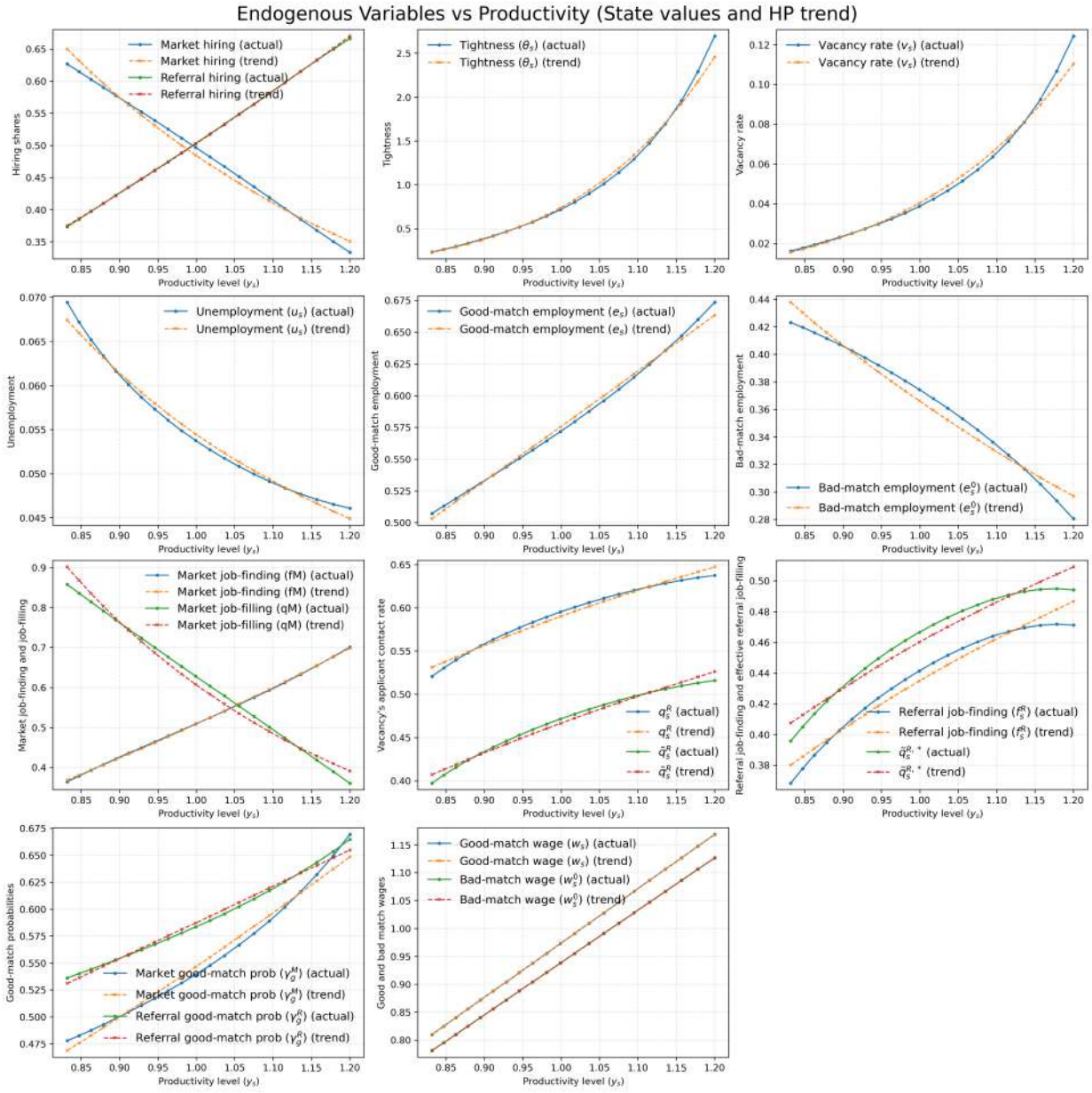


Figure 6.3.2: Actual and Trend Fit of the endogenous variables.

Notes: The figure plots each endogenous variable (level) against per-state productivity y_s on the model's 21-state, first-order Markov grid (no time path). Circles show the per-state values z_s sorted by y_s ("actual"). The dashed line with "x" markers is the HP trend of $\log z_s$ with $\lambda = 1600$, exponentiated back to levels to provide a smooth fit across states. Dots are state grid points, not simulated realizations. z_s denotes a state value of plotted variable z.

Labor Productivity and Negatively Correlated Separation-Rate Shocks

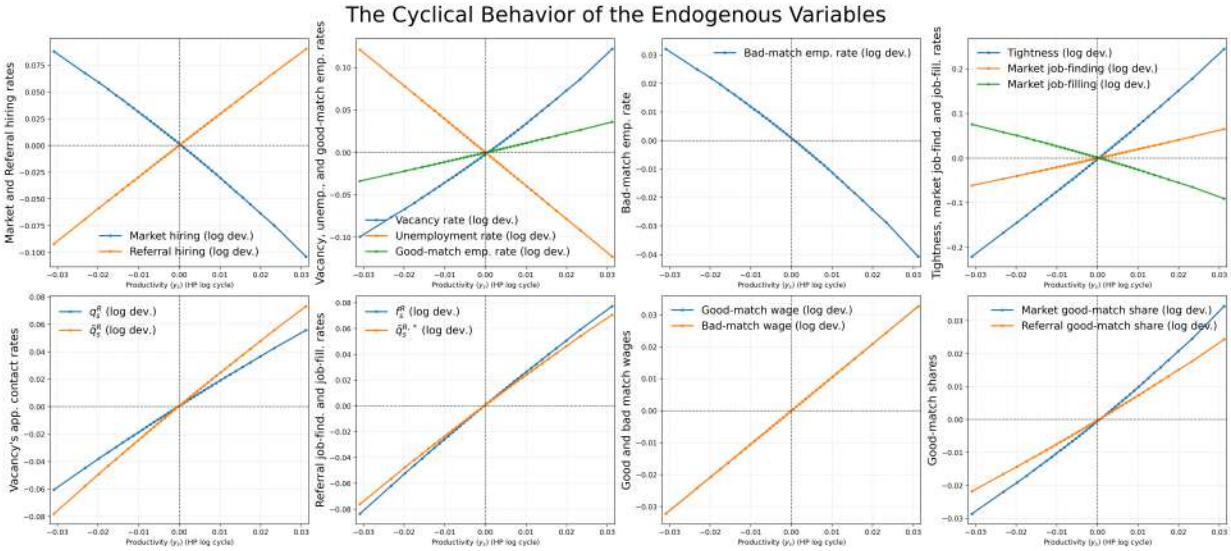


Figure 7.1.1: Log deviations from trend of endogenous variables — linked separations ($\xi < 0$).

Notes: Each variable is plotted against the labor-productivity cycle using HP-filtered log deviations ($\lambda = 1600$) computed along a long simulated path. We sort observations by the productivity cycle, partition them into equal-frequency (quantile) bins, and plot bin means $(\bar{x}_b, \bar{z}_b)$ connected by lines. Productivity follows a 21-state Markov chain.

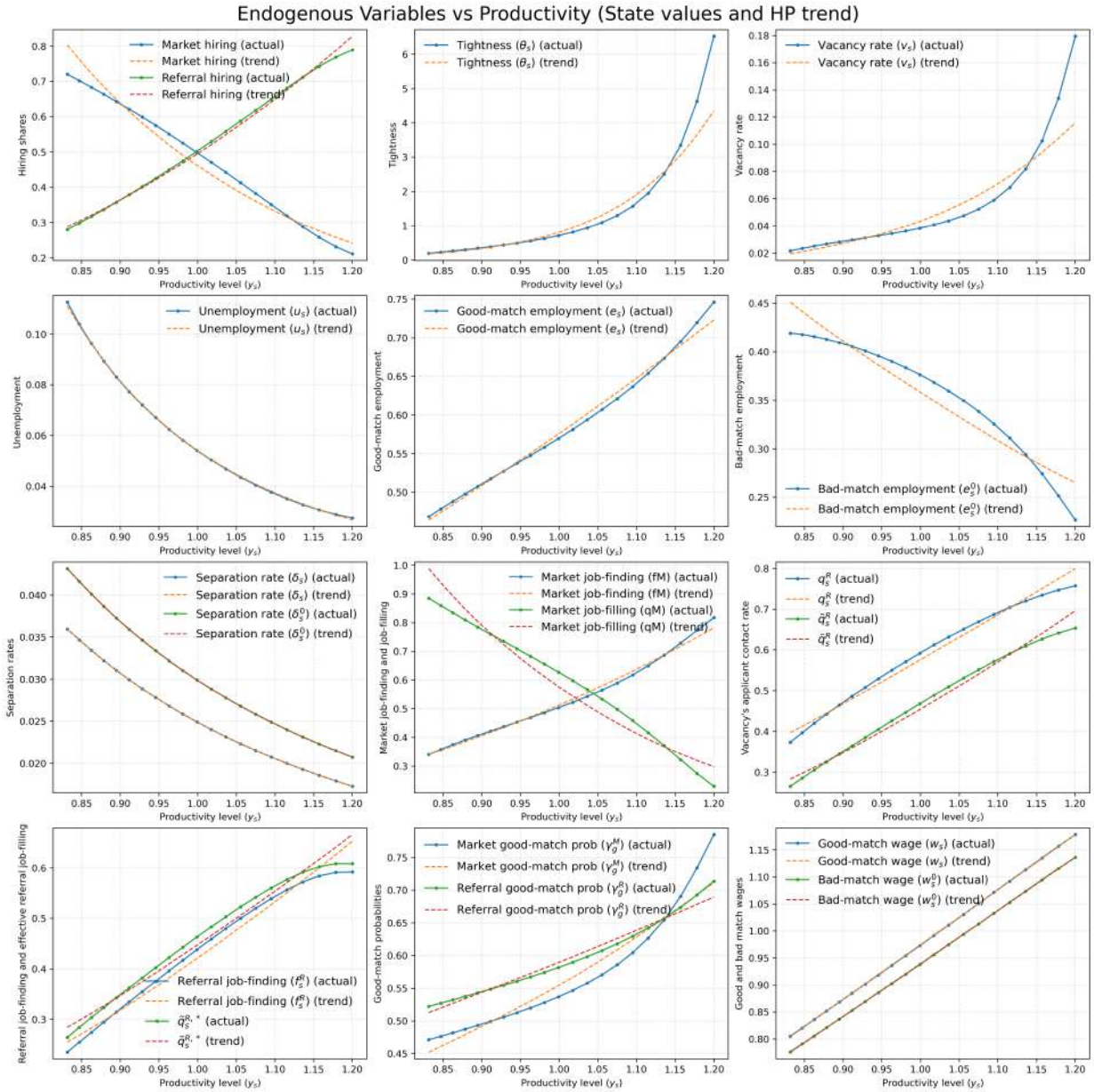


Figure 7.1.2: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 21-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels. z_s denotes a state value of plotted variable z.

Jointly Distributed Labor Productivity and Separation-Rate Shocks

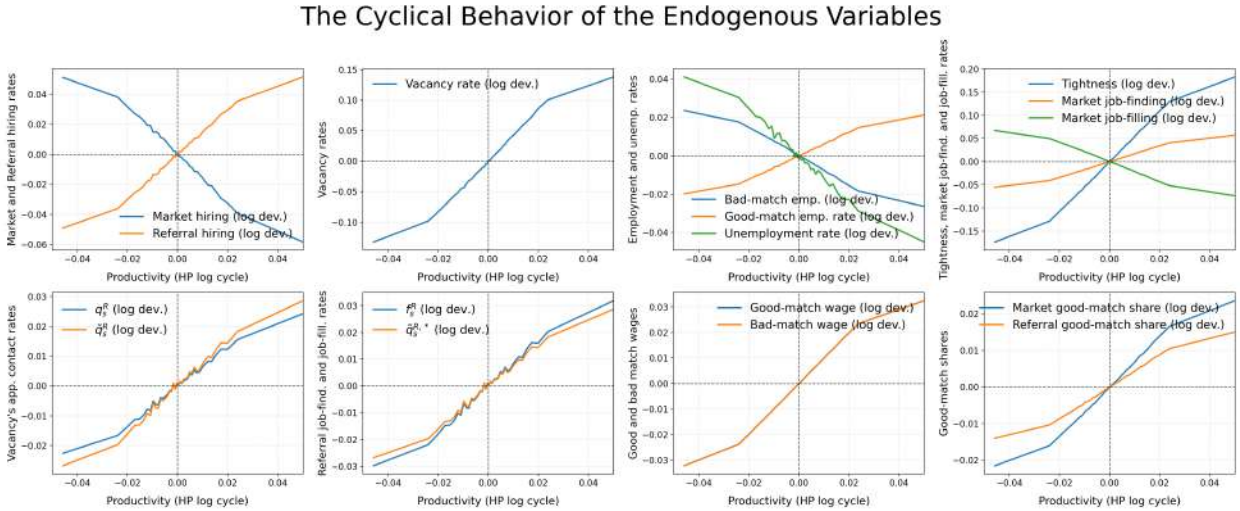


Figure 7.2.1: Log deviations from trend of endogenous variables in the joint-shock regime (y, z).

Notes: Each variable is plotted against the labor-productivity cycle using HP-filtered log deviations ($\lambda = 1600$) computed along a long simulated path from the joint state process (y, z). Observations are sorted by the productivity cycle, partitioned into equal-frequency (quantile) bins, and plotted as bin means connected by lines. The underlying state space consists of 10 productivity states and 10 separation-rate states, so the figure conditions on the productivity component on the horizontal axis while the endogenous outcomes reflect the full joint realization of both shocks.

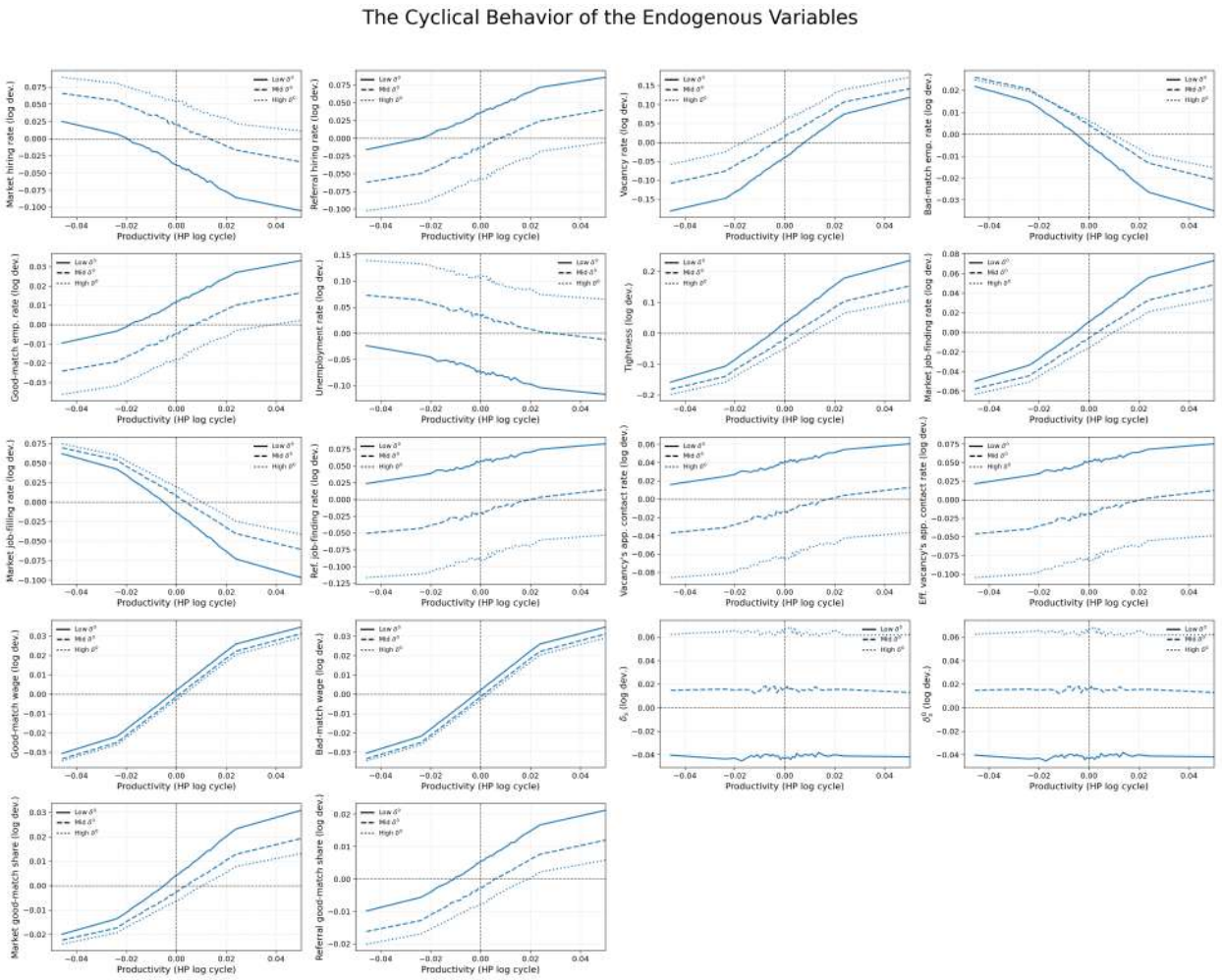


Figure 7.2.1: Log deviations from trend of endogenous variables by separation-rate regime — joint state space (y, d).

Notes: Each subplot reports HP-filtered log deviations from trend ($\lambda = 1600$) computed along a long simulated path of the joint state space. The horizontal axis is the labor-productivity cycle. Rather than plotting raw time-series pairs, I sort observations by the productivity cycle, partition them into equal-frequency bins, and plot binned conditional means. Within each subplot, line styles correspond to low, medium, and high regimes of the bad-match separation rate δ^0.

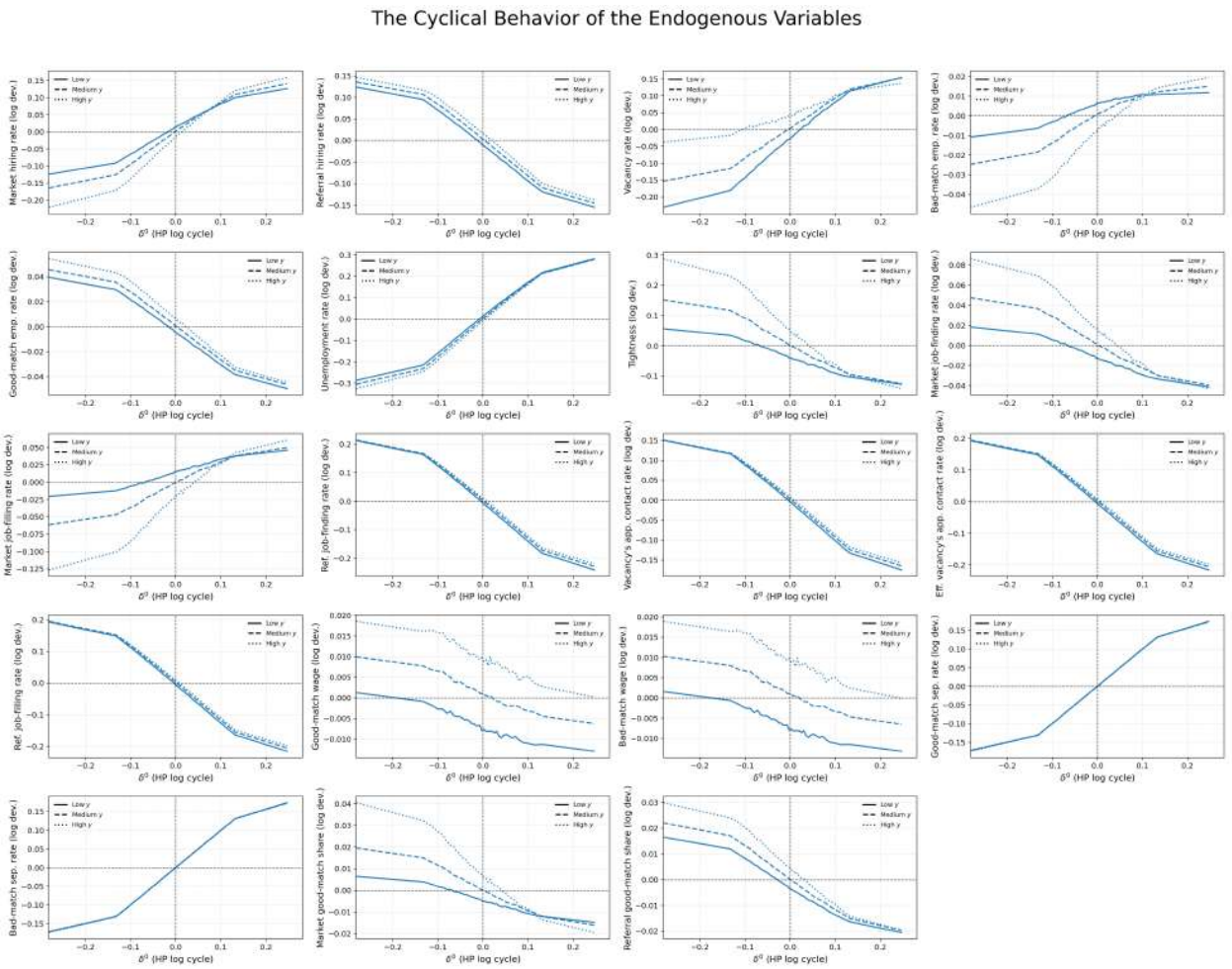


Figure 7.2.2: Log deviations from trend of endogenous variables by productivity group against the separation-rate cycle — joint state space (y, d).

Notes: Each subplot reports HP-filtered log deviations from trend ($\lambda = 1600$) computed along a long simulated path of the joint state space. The horizontal axis is the HP-filtered log cycle of the bad-match separation rate δ^0. States are grouped into low, medium, and high productivity categories according to terciles of the productivity grid, and line styles identify these productivity groups. Each curve is constructed from equal-frequency bins of the separation-rate cycle and plots binned conditional means rather than raw observations, so the figure summarizes the average co-movement between each endogenous variable and the separation-rate cycle across productivity groups.

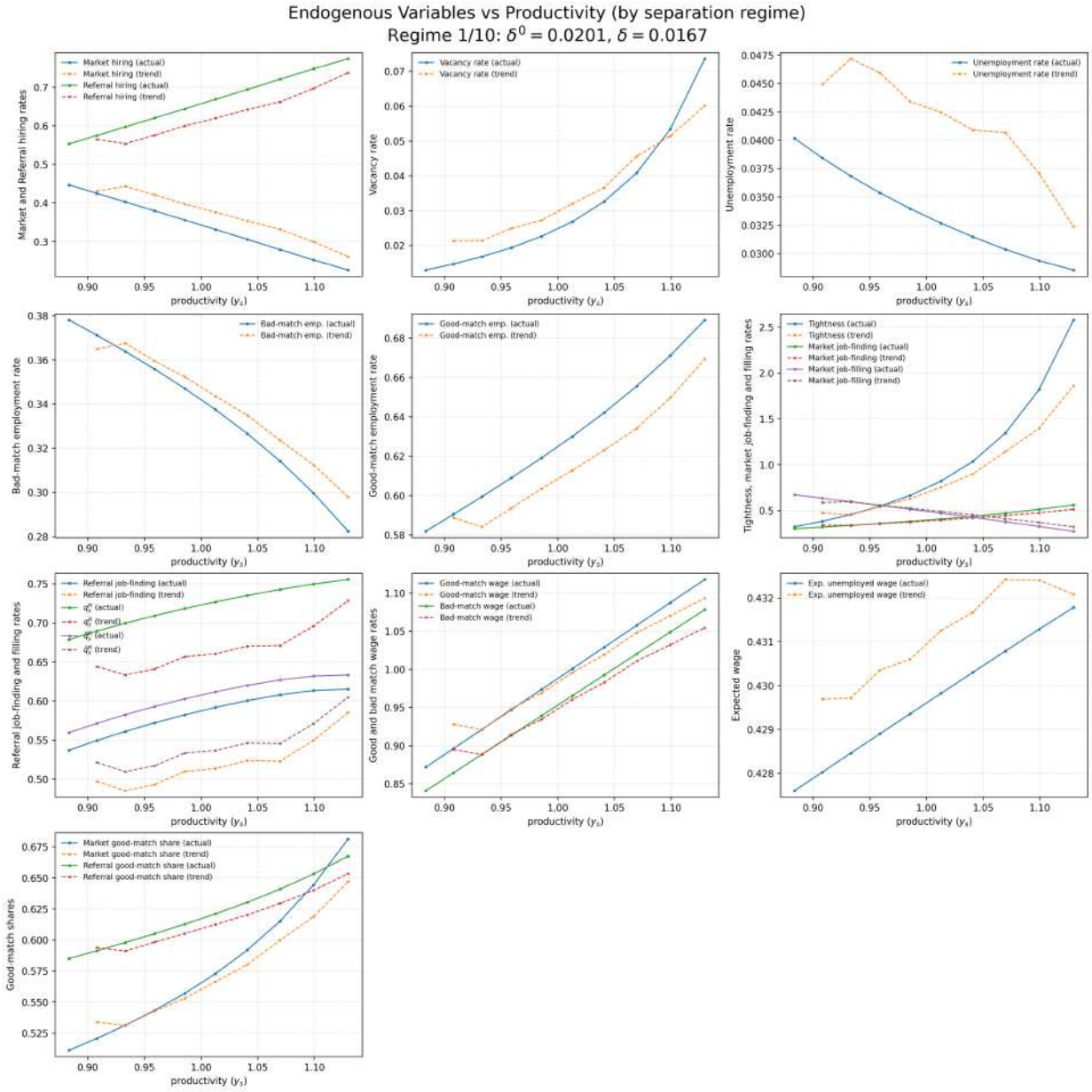


Figure 7.2.1.1: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 21-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

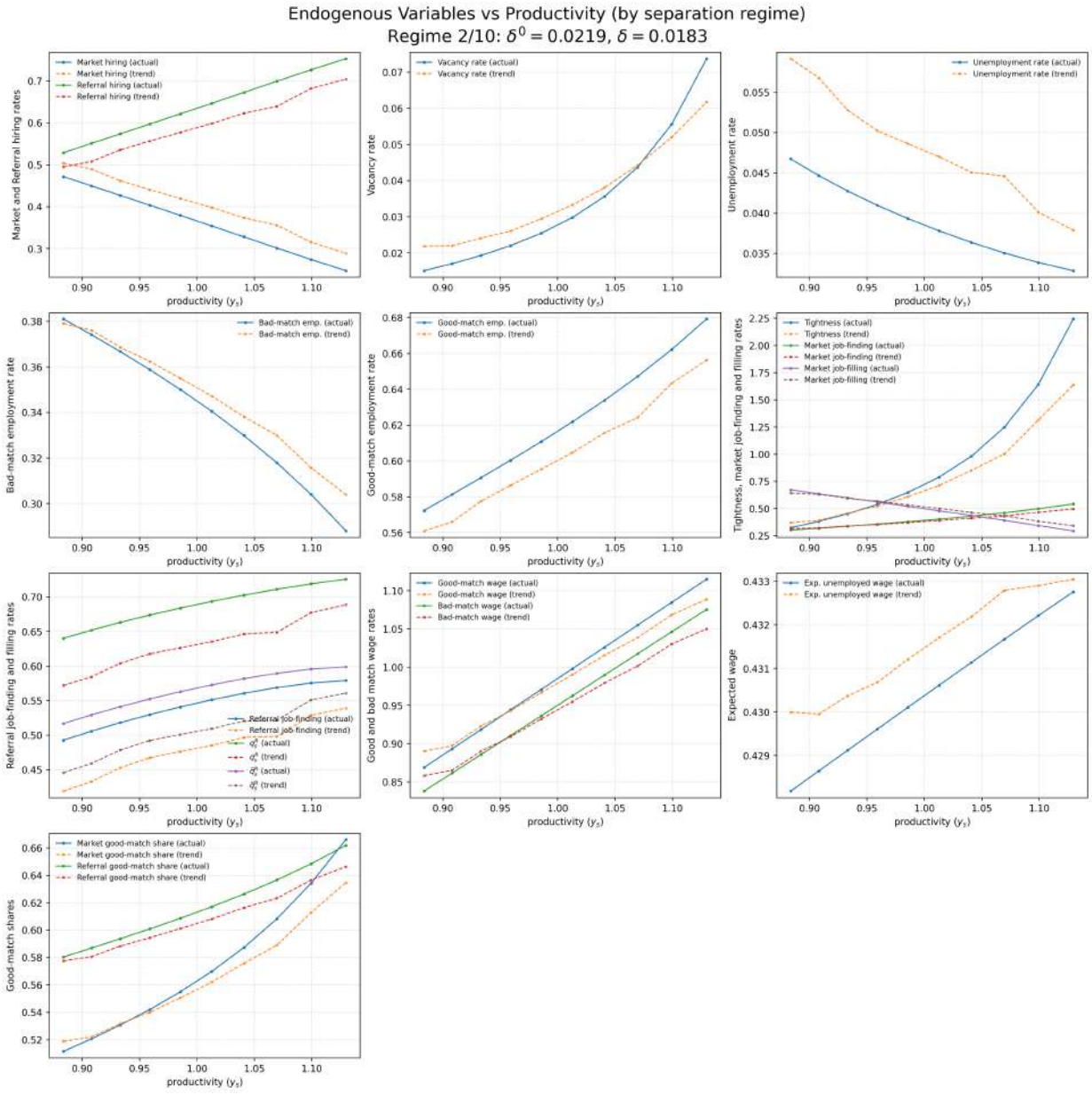


Figure 7.2.1.2: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 21-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

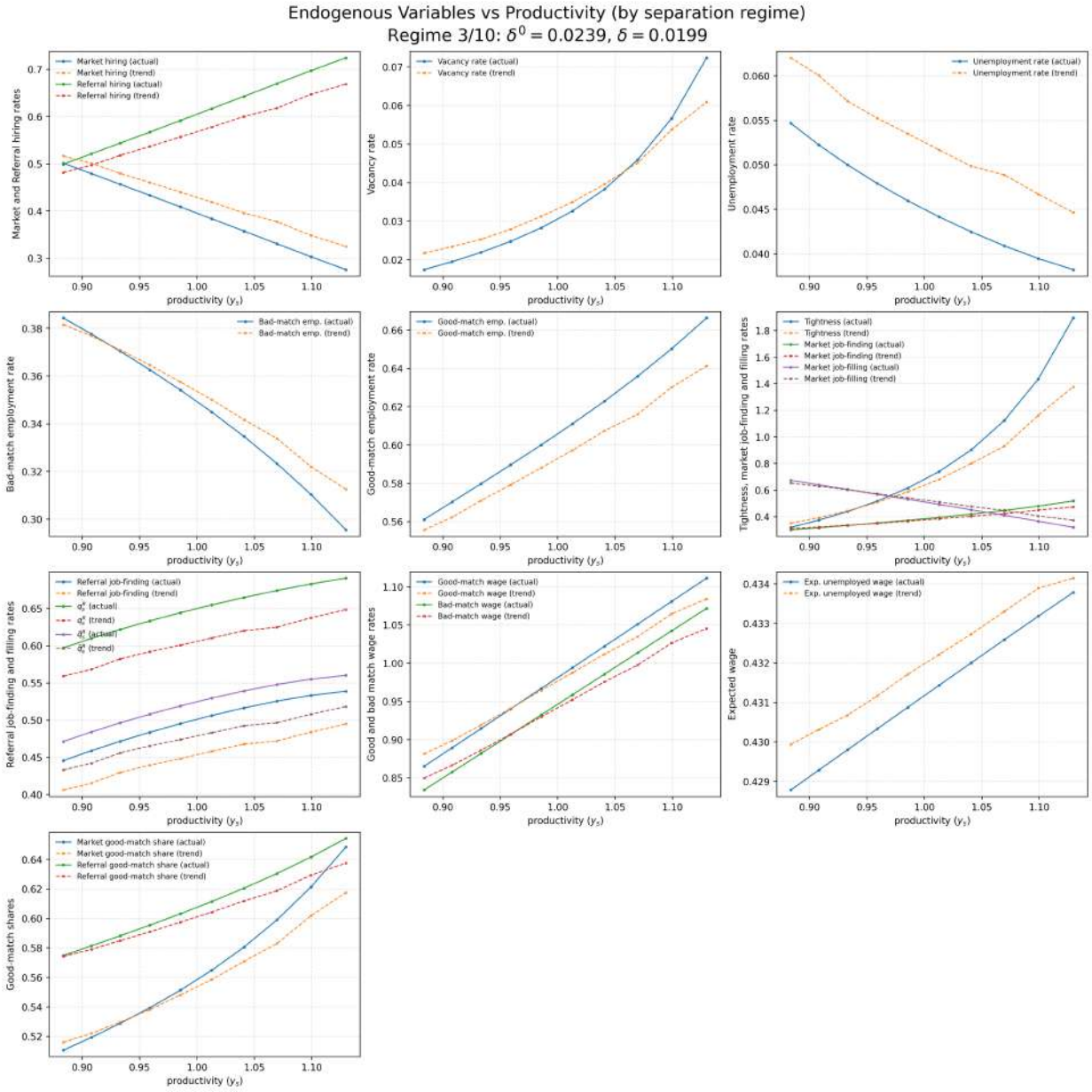


Figure 7.2.1.3: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

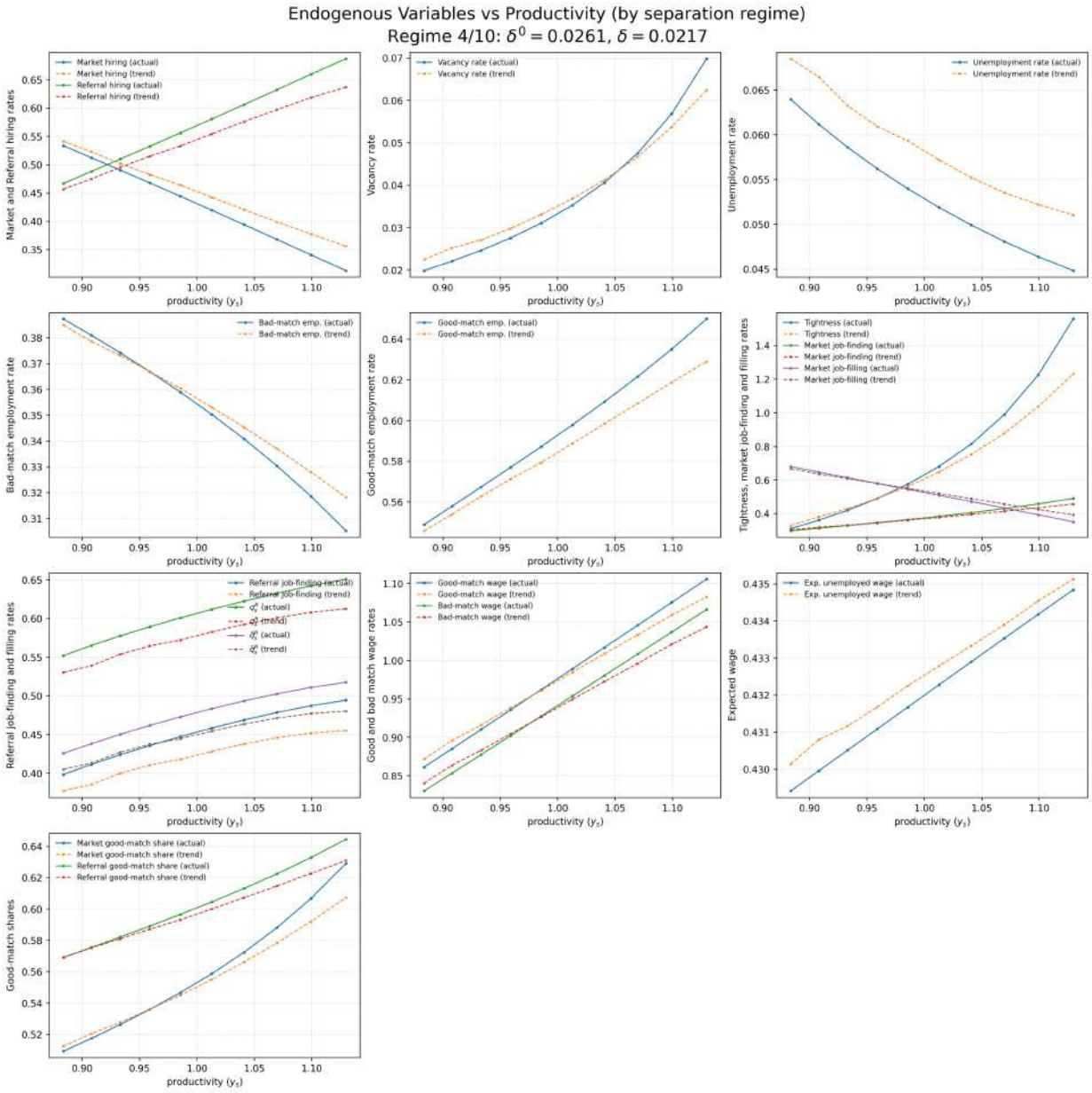


Figure 7.2.1.4: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

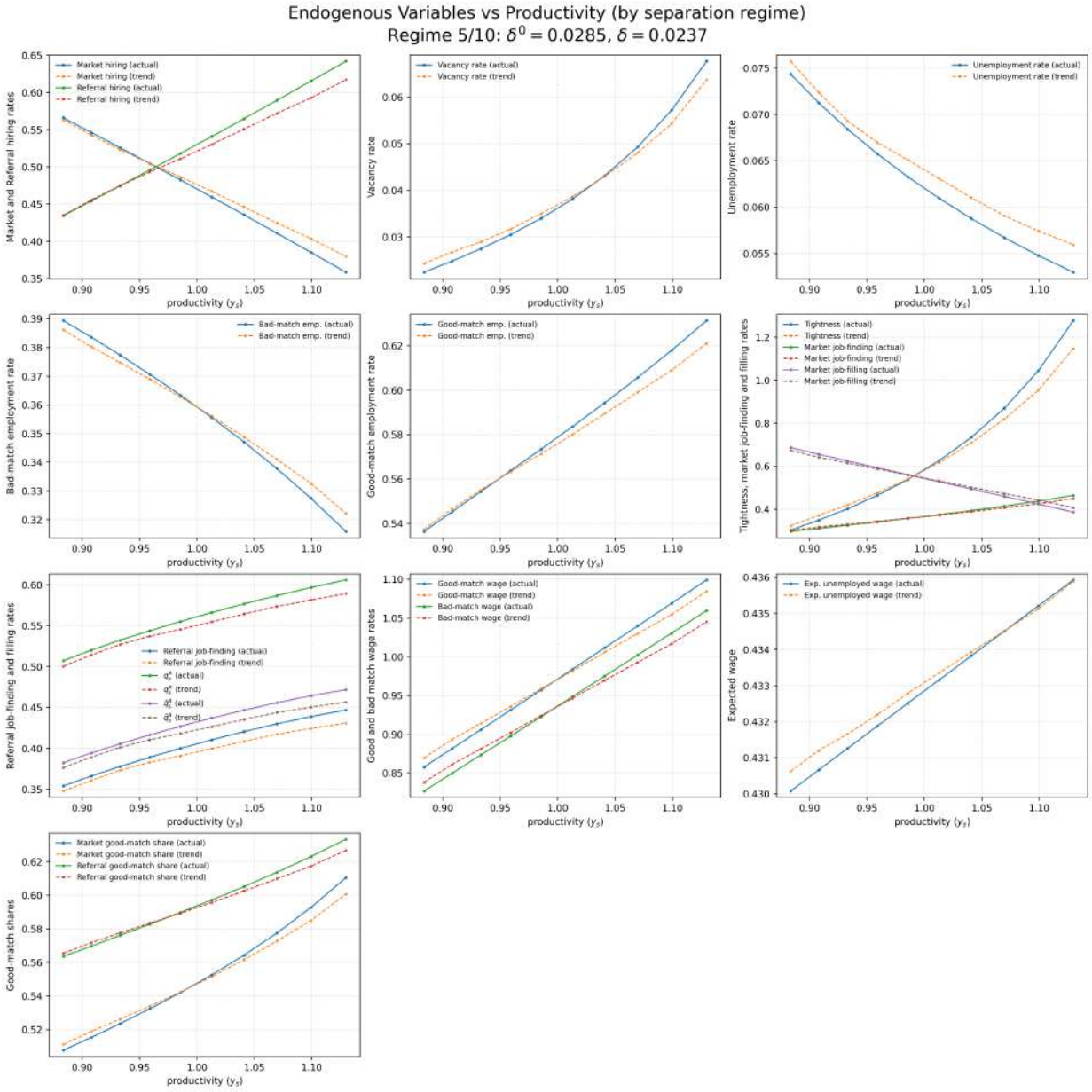


Figure 7.2.1.5: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

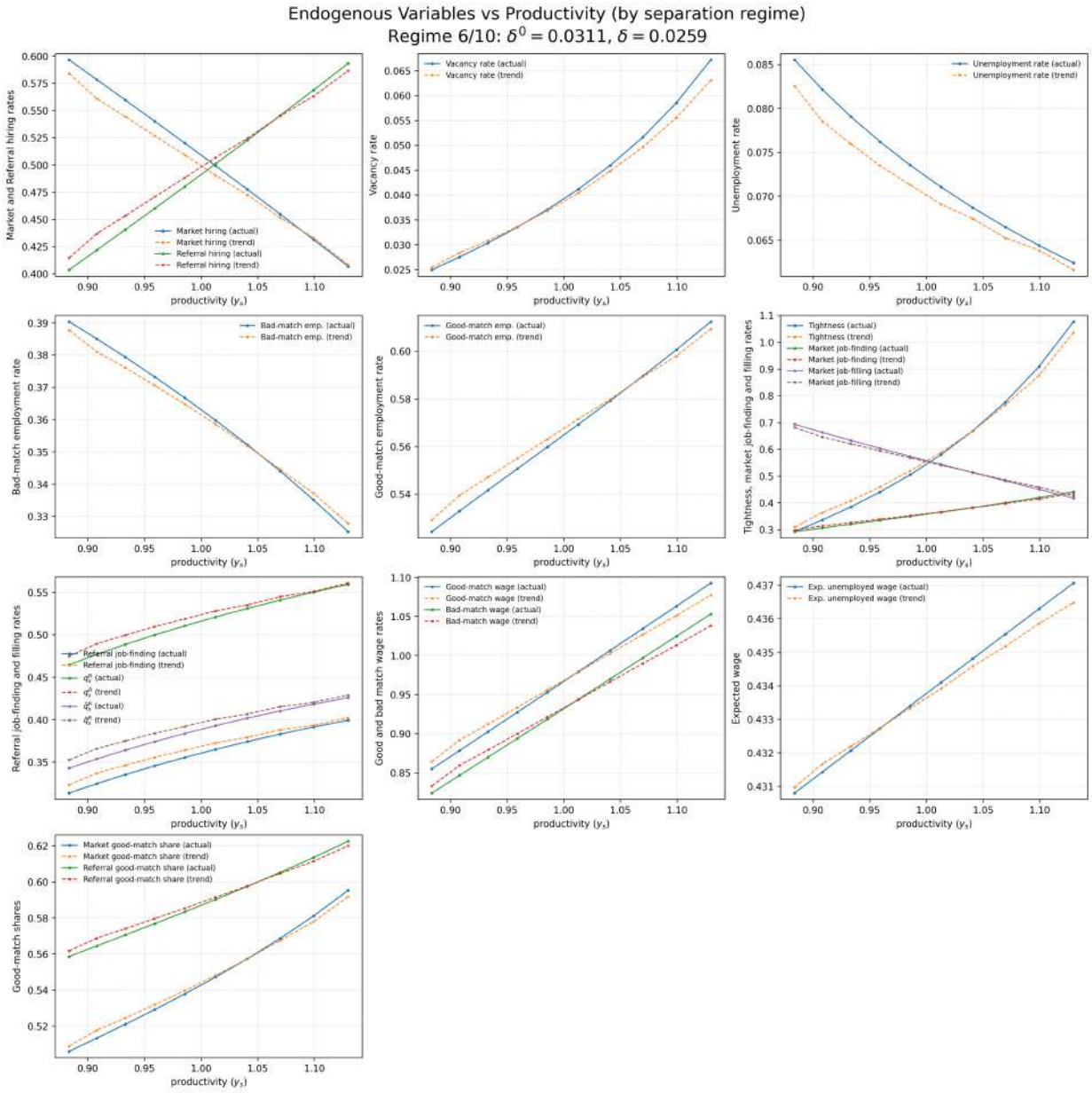


Figure 7.2.1.6: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

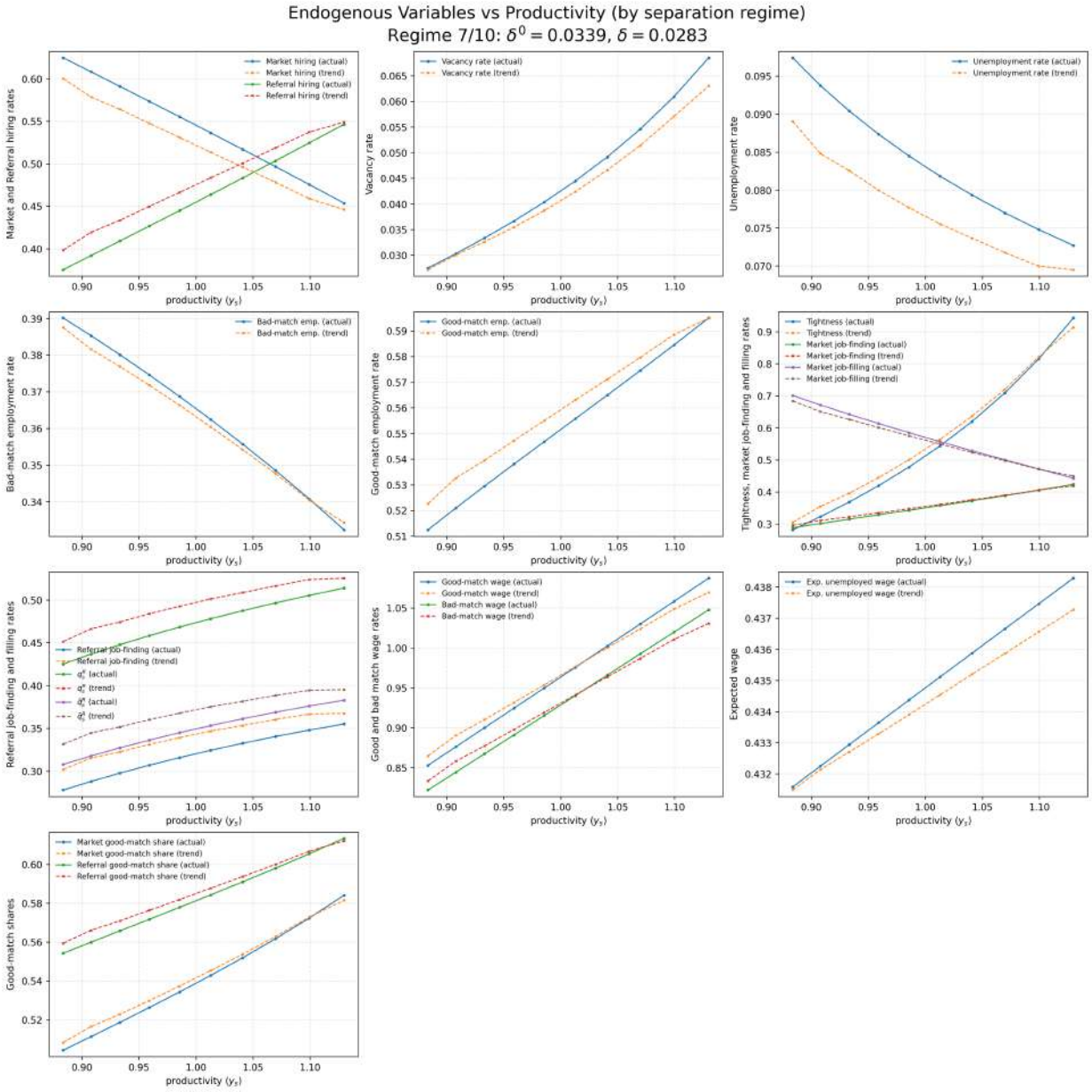


Figure 7.2.1.7: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

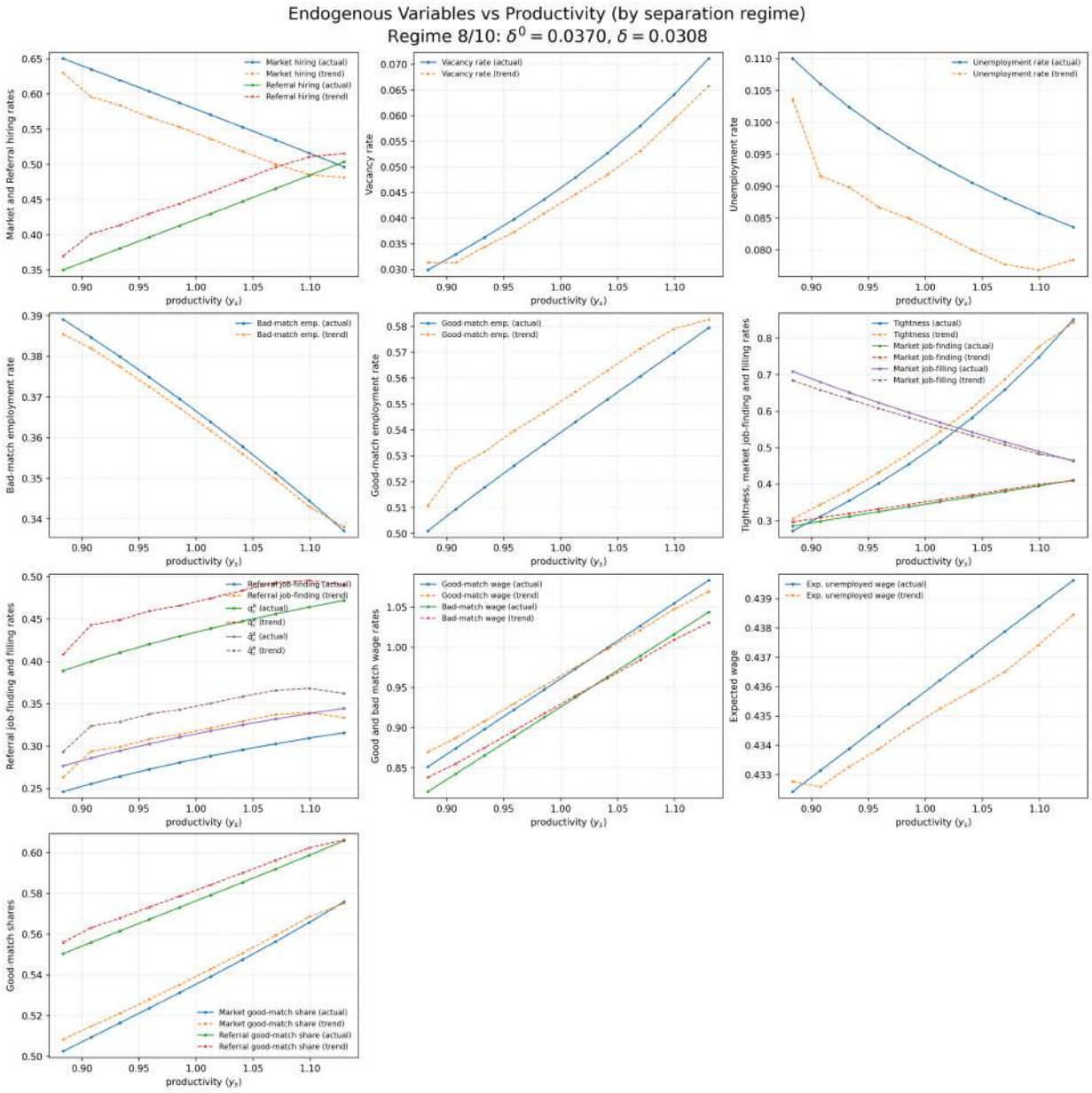


Figure 7.2.1.8: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

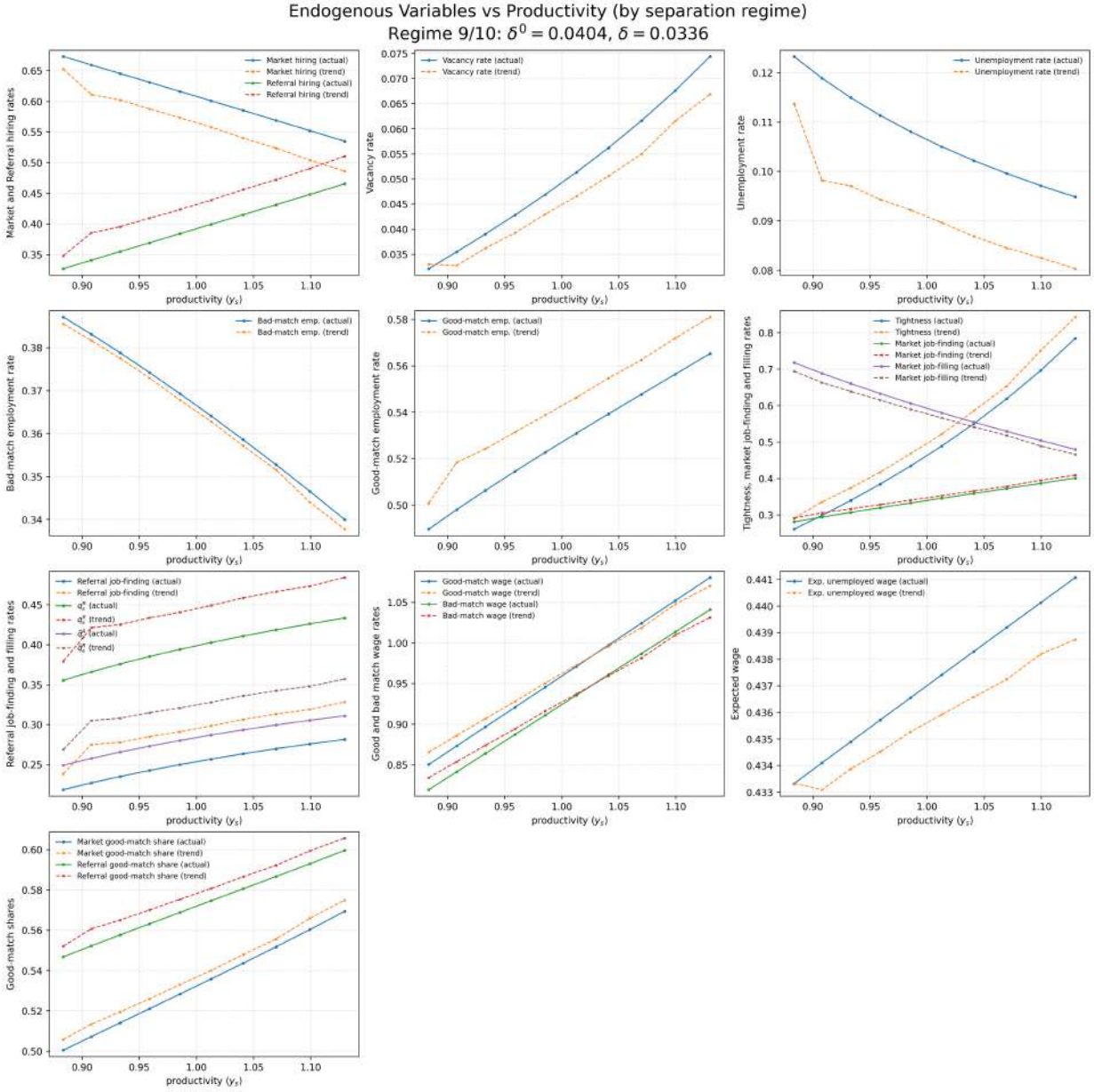


Figure 7.2.1.9: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

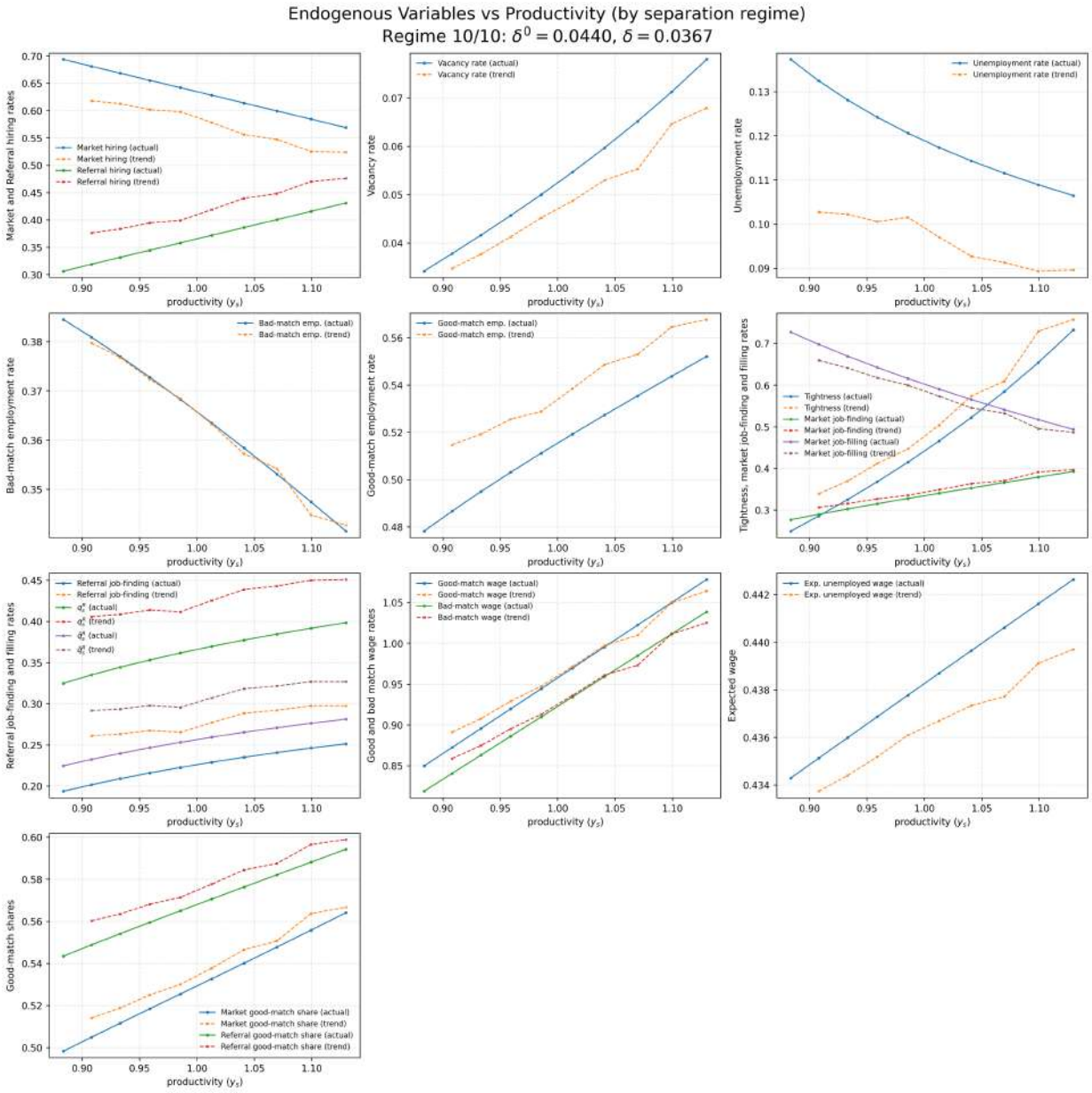


Figure 7.2.1.10: Actual and Trend Fit of the endogenous variables.

Notes: Circles show per-state values z_s plotted against productivity y_s on the 10-state Markov grid (sorted by y_s). The dashed line is the HP trend of $\log z_s$ ($\lambda = 1600$), exponentiated back to levels.

Appendix - List of Tables

Labor Productivity and Negatively Correlated Separation-Rate Shocks

Table 7.1.1: Parameters — labor productivity and linked separation rate shocks

Description	Parameter	Value
Internally Calibrated Parameters		
market matching scale	A	0.803
market match quality elasticity	ψ	0.320
per-hire costs	c^M, c^R	0.430, 0.301
network size	n	22.120
Shock Parameters		
productivity AR(1) for $\log y$	ρ^y, σ^y	0.970, 0.002
separation AR(1)	ρ^d, σ^d	0.900, 0.057
grid sizes	N^y, N^d, N	21, 1, 21
target/achieved σ(HP cycle of $\log y$)	$\sigma^{y,\text{target}}, \sigma^{y,\text{actual}}$	0.013, 0.013
target/achieved σ(HP cycle of $\log \delta^0$)	$\sigma^{d,\text{target}}, \sigma^{d,\text{actual}}$	0.057, 0.026
mean separations (stationary)	$E[\delta], E[\delta^0]$	0.025, 0.030
Externally Calibrated and Preset Parameters		
discount factor	β	0.980
unemployment benefit	b	0.420
bargaining power	ϕ	0.700
homophily rate	h^R	0.9
ref. wedge	ζ	-0.500
vacancy posting cost	k	0.140
market screening technology	λ^M	0.450
market matching elasticity	η	0.400

Table 7.1.2: Competitive Equilibrium — labor productivity and negatively linked separation rate shocks

Endogenous Variables	**Model**	**Data**	**Targeted**
Market and Referral hiring rates $(\Omega^M, 1-\Omega^M)$	0.483, 0.517	0.507, 0.493	**Y**
Vacancy rate (v)	0.054	0.041	**Y**
Unemployment rate (u)	0.059	0.054	**Y**
Market good-match prob. (γ_g^M)	0.565	0.540	**Y**
Labor market tightness $(\theta = v/u)$	0.910	0.74	**N**
Market job-finding rate (f^M)	0.530	0.298	**N**
Market job-filling rate (q^M)	0.600	0.591	**N**
Good and Bad match shares (e, e^0)	0.582, 0.358	–	**N**
Ref. good-match prob. (γ_g^R)	0.594	0.672	**N**
Vacancy's applicant contact rates $(q^R, \tilde{q}^R)$	0.583, 0.466	–	**N**
Ref. job-filling rate $(\tilde{q}^{R,*})$	0.457	–	**N**
Ref. job-finding rate (f^R)	0.432	–	**N**
Wages (w, w^0)	0.980, 0.945	–	**N**
Per-hire profits (Π^M, Π^R)	0.206, 0.162	–	**N**

Table 7.1.3: Summary statistics — labor productivity and negatively linked separation rate shocks

Quarterly series (HP $\lambda = 1600$)						
	u	v	v/u	f^M	q^M	y
Standard Deviation	0.051	0.047	0.097	0.026	0.035	0.013
Quarterly Autocorrelation	0.718	0.717	0.718	0.718	0.718	0.718
Correlation Matrix						
u	1.000	-0.966	-0.992	-0.997	0.975	-1.000
v	—	1.000	0.991	0.982	-0.999	0.964
v/u	—	—	1.000	0.999	-0.995	0.991
f^M	—	—	—	1.000	-0.988	0.997
q^M	—	—	—	—	1.000	-0.974
y	—	—	—	—	—	1.000

Annual series (annualized from model; HP $\lambda = 100$)					
	Ω^M	$1 - \Omega^M$	γ^M	γ^R	y
Standard Deviation	0.051	0.048	0.017	0.012	0.016
Annual Autocorrelation	0.583	0.584	0.582	0.584	0.584
Correlation Matrix					
Ω^M	1.000	-0.974	-0.999	-0.998	-0.982
$1 - \Omega^M$	—	1.000	0.968	0.987	0.999
γ^M	—	—	1.000	0.996	0.976
γ^R	—	—	—	1.000	0.992
y	—	—	—	—	1.000

Notes: Quarterly variables are HP-filtered in log space with $\lambda = 1600$. Annual variables are constructed by averaging four consecutive quarters of the model series, then HP-filtered in log space with $\lambda = 100$. Correlations are computed on the corresponding HP cycles.

Jointly Distributed Labor Productivity and Separation-Rate Shocks

Table 7.2.1: Parameters — joint (y, d) shocks

Description	Parameter	Value
Internally Calibrated Parameters		
market matching scale	A	0.564
market match quality elasticity	ψ	0.320
per-hire costs	c^M, c^R	0.498, 0.349
network size	n	21
Shock Parameters		
productivity AR(1) for $\log y$	ρ^y, σ^y	0.970, 0.002
separation AR(1)	ρ^d, σ^d	0.900, 0.057
grid sizes	N^y, N^d, N	10, 10, 100
target/achieved σ(HP cycle of $\log y$)	$\sigma^{y,\text{target}}, \sigma^{y,\text{actual}}$	0.013, 0.013
target/achieved σ(HP cycle of $\log \delta^0$)	$\sigma^{d,\text{target}}, \sigma^{d,\text{actual}}$	0.057, 0.073
mean separations (stationary)	$E[\delta], E[\delta^0]$	0.02500, 0.03000
Externally Calibrated and Preset Parameters		
discount factor	β	0.980
unemployment benefit	b	0.420
bargaining power	ϕ	0.700
homophily rate	h^R	0.9
ref. wedge	ζ	-0.500
vacancy posting cost	k	0.140
market screening technology	λ^M	0.450
market matching elasticity	η	0.400

Table 7.2.2: Competitive Equilibrium — joint productivity and separation rate shocks (conditional on separation rate)

Endogenous Variables	**Model**	**Low δ^0**	**Mid δ^0**	**High δ^0**	**Data**	**Targeted**
Market and Referral hiring rate $(\Omega^M, 1-\Omega^M)$	0.488, 0.512	0.435, 0.565	0.487, 0.513	0.534, 0.466	0.507, 0.493	**Y**
Vacancy rate (v)	0.038	0.032	0.037	0.045	0.041	**Y**
Unemployment rate (u)	0.068	0.053	0.067	0.082	0.054	**Y**
Labor market tightness (θ)	0.585	0.630	0.576	0.554	0.851	**Y**
Market job-finding rate (f^M)	0.363	0.370	0.362	0.358	0.298	**Y**
Good-match prob. (Market) (γ^M)	0.546	0.551	0.546	0.543	0.540	**Y**
Good-match prob. (Ref.) (γ^R)	0.591	0.599	0.591	0.585	0.672	**N**
Market job-filling rate (q^M)	0.549	0.536	0.551	0.558	0.591	**N**
Vacancy's applicant contact rate (q^R)	0.539	0.607	0.541	0.479	–	**N**
Eff. vacancy's applicant contact rate $(\tilde{q}^R)$	0.413	0.480	0.413	0.355	–	**N**
Ref job-filling rate $(\tilde{q}^{R,*})$	0.413	0.480	0.413	0.355	–	**N**
Ref. job-finding Rate (f^R)	0.385	0.455	0.386	0.326	–	**N**
Fraction of good and bad matches (e, e^0)	0.572, 0.360	0.591, 0.356	0.573, 0.361	0.556, 0.362	–	**N**
Good match wage (w)	0.970	0.967	0.967	0.974	–	**N**
Bad match wage (w^0)	0.935	0.932	0.932	0.939	–	**N**
Per-hire profits (Π^M, Π^R)	0.076, 0.064	0.062, 0.076	0.076, 0.065	0.088, 0.053	–	**N**

Notes: Model moments are computed using the stationary distribution over joint states. Low/Mid/High columns report stationary-weighted conditional means by regimes of δ^0.

Table 7.2.3: Competitive Equilibrium — joint productivity and separation rate shocks (conditional on productivity)

Endogenous Variables	**Model**	**Low y**	**Mid y**	**High y**	**Data**	**Targeted**
Market and Referral hiring rate $(\Omega^M, 1-\Omega^M)$	0.488, 0.512	0.510, 0.490	0.487, 0.513	0.472, 0.528	0.507, 0.493	**Y**
Vacancy rate (v)	0.038	0.031	0.037	0.046	0.041	**Y**
Unemployment rate (u)	0.068	0.069	0.067	0.069	0.054	**Y**
Labor market tightness (θ)	0.585	0.461	0.568	0.703	0.851	**Y**
Market job-finding rate (f^M)	0.363	0.338	0.361	0.385	0.298	**Y**
Good-match prob. (Market) (γ^M)	0.546	0.531	0.545	0.560	0.540	**Y**
Good-match prob. (Ref.) (γ^R)	0.591	0.582	0.591	0.599	0.672	**N**
Market job-filling rate (q^M)	0.549	0.596	0.550	0.508	0.591	**N**
Vacancy's applicant contact rate (q^R)	0.539	0.538	0.543	0.536	–	**N**
Eff. vacancy's applicant contact rate $(\tilde{q}^R)$	0.413	0.414	0.416	0.409	–	**N**
Ref job-filling rate $(\tilde{q}^{R,*})$	0.413	0.414	0.416	0.409	–	**N**
Ref. job-finding rate (f^R)	0.385	0.386	0.389	0.382	–	**N**
Good and Bad match shares (e, e^0)	0.572, 0.360	0.561, 0.370	0.572, 0.361	0.581, 0.350	–	**N**
Good match wage (w)	0.970	0.928	0.967	1.007	–	**N**
Bad match wage (w^0)	0.935	0.894	0.932	0.971	–	**N**
Per-hire profits (Π^M, Π^R)	0.076, 0.064	0.081, 0.058	0.076, 0.064	0.072, 0.068	–	**N**

Notes: Model moments are computed using the stationary distribution over joint states. Low/Mid/High columns report stationary-weighted conditional means by regimes of productivity y.

Table 7.2.4: Competitive Equilibrium — jointly distributed labor productivity and separation rate shocks

Endogenous Variables	**Model**	**Data**	**Targeted**
Market and Referral Hiring rates $(\Omega^M, 1-\Omega^M)$	0.488, 0.512	0.507, 0.493	**Y**
Vacancy rate (v)	0.038	0.041	**Y**
Unemployment rate (u)	0.068	0.054	**Y**
Market good-match prob. (γ_g^M)	0.546	0.540	**Y**
Labor market tightness $(\theta = v/u)$	0.564	0.74	**N**
Market job-finding rate (f^M)	0.363	0.298	**N**
Market job-filling rate (q^M)	0.549	0.591	**N**
Good and Bad match shares (e, e^0)	0.572, 0.360	–	**N**
Referral good-match prob. (γ_g^R)	0.591	0.672	**N**
Vacancy's applicant contact rates $(q^R, \tilde{q}^R)$	0.539, 0.413	–	**N**
Ref. job-filling rate $(\tilde{q}^{R,*})$	0.41	–	**N**
Ref. job-finding rate (f^R)	0.385	–	**N**
Wages (w, w^0)	0.970, 0.935	–	**N**
Per-hire profits (Π^M, Π^R)	0.076, 0.064	–	**N**

Table 7.2.5: Summary statistics — labor productivity and separation-rate shocks (jointly distributed)

Quarterly series (HP $\lambda = 1600$)								
	u	v	v/u	f^M	q^M	y	δ	δ^0
Standard Deviation	0.126	0.088	0.094	0.030	0.038	0.013	0.073	0.073
Quarterly Autocorrelation	0.695	0.704	0.707	0.707	0.706	0.718	0.695	0.695
Correlation Matrix								
u	1.000	0.666	-0.717	-0.718	0.712	-0.130	0.988	0.988
v	—	1.000	0.043	0.041	-0.047	0.622	0.760	0.760
v/u	—	—	1.000	1.000	-0.998	0.756	-0.613	-0.613
f^M	—	—	—	1.000	-0.996	0.761	-0.614	-0.614
q^M	—	—	—	—	1.000	-0.742	0.609	0.609
y	—	—	—	—	—	1.000	0.004	0.004
δ	—	—	—	—	—	—	1.000	1.000
δ^0	—	—	—	—	—	—	—	1.000

Annual series (annualized from model; HP $\lambda = 100$)					
	Ω^M	$1-\Omega^M$	γ^M	γ^R	y
Standard Deviation	0.079	0.073	0.014	0.013	0.016
Annual Autocorrelation	0.505	0.505	0.549	0.525	0.585
Correlation Matrix					
Ω^M	1.000	-0.980	-0.840	-0.963	-0.340
$1-\Omega^M$	—	1.000	0.806	0.954	0.339
γ^M	—	—	1.000	0.942	0.776
γ^R	—	—	—	1.000	0.575
y	—	—	—	—	1.000

Notes: Quarterly variables are HP-filtered in log space with $\lambda = 1600$. Annual variables are constructed by averaging four consecutive quarters of the model series, then HP-filtered in log space with $\lambda = 100$. Correlations are computed using the corresponding HP cycles.

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