Heterogeneity in Self-employment and Labor Market Risk :Role of the "Gig Economy"

Kisan Choi*

November 4, 2024

Click here for the most recent version

Abstract

This paper investigates the gig economy as a novel form of self-employment that addresses labor market risks. By employing a quantitative model that highlights its distinct features—such as easy entry and exit and lower earnings—this study finds that the gig economy effectively reduces unemployment rates, particularly benefiting low-skilled and asset-poor workers. Welfare analysis indicates aggregate gains, especially for unemployed individuals who are ineligible for unemployment insurance. Additionally, the gig economy's impact is closely tied to traditional labor market policies. Counterfactual analysis reveals that generous unemployment insurance benefits can discourage gig participation, resulting in greater welfare losses due to diminished insurance effects. Conversely, the gig economy may help mitigate the negative welfare impacts of higher firing costs by increasing gig participation.

*Department of Economics, University of Washington, Seattle 98195. Email: kisanc@uw.edu. I would like to thank Fabio Ghironi, Andrei Zlate, and Brian Greaney for their invaluable guidance and support throughout this project. All errors are mine.

1 Introduction

The issue of low-quality self-employment is particularly pronounced in developing economies, where such work is often informal and lacks social security protections. Poorer individuals frequently turn to self-employment as a means of survival, driven by subsistence concerns (Poschke, 2013; Herreño and Ocampo, 2023). In contrast, advanced economies typically feature more robust social security measures, such as unemployment insurance, which support formal, established businesses that tend to be larger in scale.

The rise of digital labor platforms, such as Uber and DoorDash, has significantly transformed the landscape of self-employment. The emergence of the "gig economy" has created new opportunities for income generation, particularly during periods of unemployment. As noted by Jackson (2022), many unemployed individuals in the U.S. are increasingly turning to gig work as a means to navigate their unemployment spells. Furthermore, data from the Survey of Consumer Finances highlights a growing polarization in self-employment across income percentiles, with a marked increase in low-earning self-employed workers in recent years. For example, recent surveys from 2016 and 2019 show that the self-employment rate for the bottom 10% of income percentiles (24%) is higher than its long-run average of 18.4%. Empirical studies suggest that this rise in low-earning self-employment may be linked to the emergence of the gig economy (Boeri et al., 2020; Henley, 2023).

This paper investigates the role of the gig economy in mitigating labor market risks and its potential to provide alternative income sources during unemployment. Although gig work is classified as a form of self-employment, it has unique features that differentiate it from traditional self-employment. The barriers to entry for gig work are relatively low, as participants do not require substantial initial investments and can efficiently access job opportunities through digital platforms. This allows individuals to generate income during adverse economic conditions and effectively serves as a additional layer of insurance against income shocks. As a result, individuals with lower skill levels, financial constraints, and higher earning risks—who may have previously pursued traditional self-employment or remained unemployed—may be better off by opting for gig work. From a firm's perspective, gig employment also influences job creation by affecting labor market conditions and profitability.

To analyze these dynamics, I construct a quantitative model that captures the empirical characteristics of heterogeneous self-employment and examines the effects of the gig economy on labor markets and welfare. The model accounts for agents' heterogeneity in productivity and wealth, along with labor market risks that drive transitions among employment statuses.

Specifically, it incorporates earning risks from idiosyncratic productivity shocks and labor market shocks within an incomplete market framework, akin to the Bewley-Huggett-Aiyagari (BHA) model. Additionally, to gain a comprehensive understanding of labor market effects, I employ a Diamond-Mortensen-Pissarides (DMP) style search and matching framework. Calibrated to reflect the U.S. economy, the model successfully captures selection patterns between two types of self-employment, the concentration of gig employment within the lower earnings distribution, and transitions across various occupations.

My quantitative analysis, utilizing two calibrated models—one with and one without gig components—reveals that the introduction of the gig economy reduces the unemployment rate, particularly benefiting low-skilled and asset-poor individuals drawn to gig work as an alternative income source. Furthermore, while workers experience wage increases due to improved bargaining positions supported by gig working option, this leads to a decrease in job vacancies within corporate firms. Welfare analysis, measured through the consumption equivalence approach, indicates aggregate welfare gains across demographics, especially for the unemployed ineligible for unemployment insurance. The gig economy functions as an effective insurance mechanism, mitigating risks related to productivity and labor market fluctuations, particularly benefiting those with lower skill levels and assets.

Furthermore, the potential role of the gig economy is intertwined with labor market policies, such as unemployment insurance and dismissal regulations, designed to protect employment and offer temporary relief to the unemployed. Through a counterfactual analysis, the findings reveal that while both policies incur welfare costs due to reduced job creation, the effects of the gig economy differ. Generous UI benefits discourage participation in gig work, leading to greater welfare losses than in an economy without gig options. This occurs because the positive insurance offered by UI benefits is offset by reduced insurance from smaller gig participation, resulting in an overall welfare effect dominated by the negative impact of reduced job creation. In terms of firing restrictions, while higher firing costs result in fewer job openings and diminished welfare, the gig economy may provide mitigating effects. Unlike in the case of generous UI, gig participation increases as non-employed individuals are less likely to find a job due to stricter firing restrictions.

The effects of flexibility-enhancing labor market reforms may also be influenced by labor market innovations. Easing regulations in high-regulation countries can significantly lower unemployment rates and boost welfare, particularly with the gig economy providing an additional insurance channel.

Related Literature While earlier research on self-employment primarily focused on entrepreneurship, a growing body of literature examines the heterogeneity within self-employed individuals, particularly in subsistence self-employment. Levine and Rubinstein (2017) disaggregates self-employed individuals into incorporated and unincorporated types, explaining their motivations. Recent studies highlight the role of labor market risks in this selection process; Poschke (2024) demonstrates that these risks explain cross-country differences in occupational composition, while Garcia-Cabo and Madera (2019) shows that lifetime earnings risk influences the decision to enter self-employment. Additionally, Herreño and Ocampo (2023) extends this analysis by modeling subsistence self-employment in the context of unemployment risk and financial frictions. This study contributes to the literature by presenting a distinct selection mechanism for a new type of self-employment with uninsurable earning risks and labor market frictions, using a dynamic general equilibrium model that facilitates occupational transitions.

The welfare implications of self-employment are significant. Research by Quadrini (2000) and Cagetti and De Nardi (2006) quantifies how financial frictions distort the scale of firms and contribute to wealth concentration through occupational choice models. Lee (2021) finds that self-employment incurs higher welfare costs during business cycles due to its inherent volatility. Recent studies have examined self-employment policies and their welfare outcomes (Humphries, 2021; Herreño and Ocampo, 2023), further extending the literature by addressing distributional implications. This study investigates the welfare implications of heterogeneous self-employment for the overall economy, as well as for different groups with varying skill sets and wealth levels.

The economic impact of the gig economy as a new form of self-employment is particularly relevant to this analysis. Empirical studies have identified various benefits associated with gig work, such as increased productivity (Cramer, Krueger, et al., 2016) and greater economic surplus (Chen et al., 2019), primarily driven by improved efficiency in labor matching and enhanced flexibility. Research by Koustas (2018) and Jackson (2022) shows that gig work can help participants manage income fluctuations and play a crucial role in addressing unemployment by providing flexible job opportunities that enable workers to recover some of their lost income. This study represents the first attempt to analyze the general equilibrium effects of the gig economy by examining occupational dynamics.

This research also contributes to the literature on labor market policies, particularly regarding the effects of unemployment insurance (Baily, 1978; Chetty, 2006; Mortensen and Pissarides, 1994) and firing restrictions (Hopenhayn and Rogerson, 1993; Lazear, 1990). It aligns with research examining policy effects in contexts where labor market risks are not perfectly insurable (Krusell et al., 2010; Alvarez and Veracierto, 2001; Cozzi and Fella, 2016; Lalé, 2019). For instance, Krusell et al. (2010) analyzes the effects of unemployment insurance using a general equilibrium model that incorporates the Bewley-Huggett-Aiyagari incomplete markets and a search and matching framework, while Setty and Yedid-Levi (2021) further extends this work by introducing exogenous heterogeneity among worker types. However, many studies overlook self-employment as an occupational choice, which presents distinct implications for labor market dynamics. An exception is Audoly (2024), which considers self-employment but primarily focuses on unemployment insurance benefits for self-employed individuals. My work extends this line of research by incorporating two forms of heterogeneous self-employment and reexamining conventional labor market policies and reforms.

2 Data

This section summarizes the characteristics of gig employment, distinguishing it from traditional self-employment. Commonly used household and labor force surveys, such as the U.S. Current Population Survey (CPS), often fail to capture recent developments in self-employment, as noted by Abraham, Haltiwanger, et al. (2021) and OECD, ILO, and EU (2023). These surveys can be prone to inaccuracies in self-reported data due to ambiguities around dependent versus independent employment and multiple job holding. Therefore, this study utilizes microdata from the Survey of Household Economics and Decisionmaking (SHED), an annual survey initiated by the Federal Reserve Board in 2013.[1] The SHED addresses various topics relevant to financial well-being, including employment, housing, credit access, and education, and has included specific questions on the gig economy since 2016. To construct a panel dataset, only responses with two consecutive years are included, spanning from 2016 to 2020.[2] The sample consists of 14,084 respondents, weighted using the Federal Reserve's official sampling weights.

[1] While tax return data is available, changes in taxpayer reporting behavior make it challenging to interpret self-employment accurately (Garin et al., 2024). For other regions, surveys like the 2017-2018 COLLEEM, covering 15 European countries, provide comparable data focused on platform work (Pesole et al., 2018). Additionally, Eurostat has recently piloted survey data on digital platform workers as part of its official labor force survey in 2023.

[2] In 2021, major revisions to the survey limited the gig economy questions to a narrower set.

2.1 Characteristics of Gig Workers

In the dataset, 28.6% of individuals in the U.S. and 32.7% in the labor force engage in gig activities during the surveyed month.[3] I categorize these individuals into three groups based on their motivations for gig work: primary gig workers, secondary gig workers, and others. Primary gig workers rely on gig activities as their main income source, while secondary gig workers engage in gig activities for additional income or to support their families. Others pursue gig activities for skill development, selling items, or personal interests.

Table 1 shows that the majority of gig participants are secondary gig workers, comprising 17.0% of the labor force, while primary gig workers make up 5.6%. Despite their smaller numbers, primary gig workers exhibit distinct demographic and economic characteristics that set them apart from other gig workers and traditional self-employed individuals. On average, primary gig workers tend to be younger, predominantly male, and have completed less higher education (Table 2) than secondary gig workers or traditional self-employed individuals.

Table 1: Gig Participation Rate (%)

	All gig workers	Primary gig	Secondary gig	Other
Among all adults	28.6	4.5	14.3	9.8
Among labor force	32.7	5.6	17.0	10.1

Table 2: Demographic Characteristics

	Gig Workers			Traditional	All Adults
	All	Primary	Secondary	Self-Employed	
Age (mean)	42.2	37.1	41.3	48.7	47.0
Higher Education[1](%)	33.8	18.0	34.6	29.8	30.2
Female Share (%)	45.6	39.7	44.9	35.5	44.3

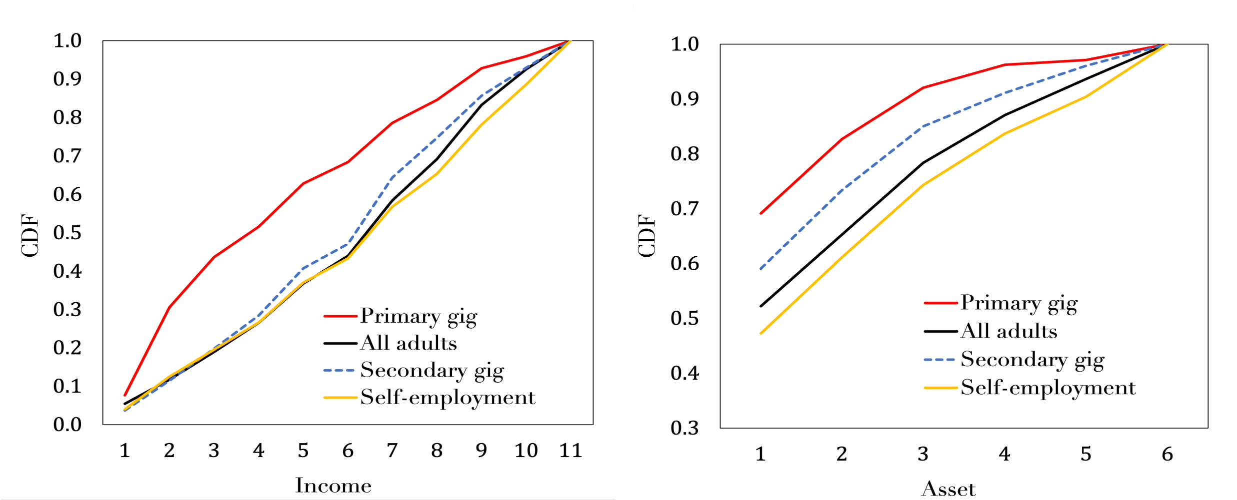
[1] Bachelor's degree or higher

Furthermore, primary gig workers are typically in a more financially disadvantaged situation. They show a strong concentration in lower income and wealth categories, unlike secondary gig workers, who display little deviation from the general population or traditional self-employment (see Figure 1). Notably, 32% of primary gig workers reported a lack of confidence in their financial circumstances, more than double the rate observed in the general population (15%). A comparable pattern emerges concerning the proportion experiencing credit denial (17% vs. 8%).

[3] The average gig participation rate for each year of the SHED from 2016 to 2020 was 29.0%.

This paper primarily focuses on primary gig workers, who engage in gig activities for income and possess distinctive demographic and economic characteristics. This focus aligns with the paper's objective of studying the selection into gig employment compared to other forms of employment and its relationship with major economic variables.

Figure 1: Income and Wealth Distribution of Gig Workers



The horizontal axis represents income and asset intervals as specified in the survey. Income intervals range from a minimum of $0 to a maximum of $200,000 or higher. Asset intervals span from a minimum of $50,000 or less to a maximum of $1,000,000 or greater.

2.2 Employment Status

Table 3 illustrates that primary gig workers are predominantly categorized as paid employees, but a significant portion are also classified as self-employed or unemployed. This finding aligns with prior research highlighting the ambiguous status or potential misclassification of gig workers, as demonstrated in studies by Abraham, Haltiwanger, et al. (2021), Bracha and Burke (2021), and Bracha and Burke (2023).

Table 3: Reported Employment Status of Gig Workers (%)

	All Gig			All Adults
		Primary	Secondary	
Paid Employment	76.6	55.2	79.9	82.7
Traditional Self-Employment	14.5	23.9	13.6	10.0
Unemployment	9.0	20.9	6.5	7.2

Numbers represent the share of each employment status in the labor force in percent.

New Employment Categorization To investigate occupational choices related to gig work, I redefine employment status by designating primary gig workers as a separate employment category. After isolating the 5.6% of primary gig workers in the labor force, the share of paid employment decreases by 3.1 percentage points, while the shares of self-employment and unemployment drop by 1.3 and 1.2 percentage points, respectively. This result aligns with Bracha and Burke (2023), who find a higher employment share (including self-employment) when considering gig work.[4]

Table 4: Employment Status Composition (%)

	Current	New	Difference
Paid Employment	82.7	79.6	-3.1
Traditional Self-Employment	10.0	8.7	-1.3
Unemployment	7.2	6.1	-1.2
Gig Employment (Primary)	-	5.6	5.6

Numbers represent the share of each employment status in the labor force in percent.

It is evident that a significant portion of the data showing subsistence self-employment can be attributed to the presence of gig workers. This can be seen in Figure 2, which illustrates a significant decrease in the share of self-employment within the bottom decile of the income distribution following a revised categorization.[5] This decline is primarily a result of the substantial representation of primary gig workers within that decile. **Transition Rates:**

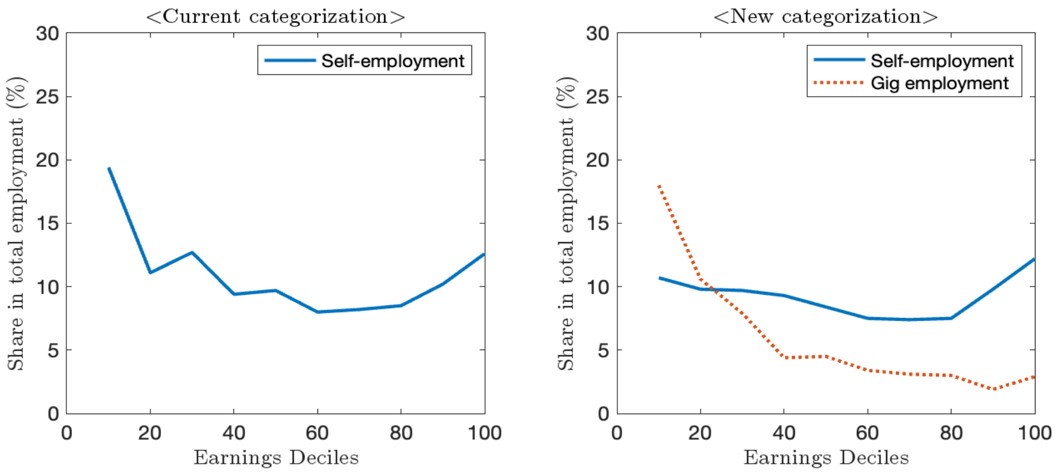
Table 5 presents transition rates between employment statuses, including gig workers, after one year. Traditional self-employed (S_T) and unemployed (U) individuals are more likely to transition into gig work (S_G) in the following year than paid employees (E), as indicated in the last column. This implies that primary gig employment is often chosen by individuals who were previously unemployed or engaged in subsistence self-employment, seeking a basic income, rather than by salaried employees seeking better opportunities. Additionally, the rate of remaining in the same employment status in the following year is lowest for gig workers, reflecting the flexibility and low entry and exit barriers associated with the gig economy.[6]

[4]Bracha and Burke (2023) find that the employment-to-population ratio would have been 0.25 to 1.1 percentage points higher over the 2015–2022 period under conservative estimates and as much as 5.1 percentage points higher under more generous estimates in the CPS data.

[5]The underrepresentation of self-employment in the top decile of the income distribution in the SHED data may be due to the absence of oversampling wealthy households, a feature typically present in household surveys like the survey of consumer finance (SCF).

[6]A limitation here is that the data only records annually, which may not reflect the short-period movement nature of gig work. For example, Uber drivers have high turnover and, on average, work only part of the year (an average of three months) Mishel (2018).

Figure 2: Self-employment and Gig Employment Rate



The figure depicts the distribution of self-employed individuals and gig workers among all employed individuals for deciles of the earnings distribution. The left panel represents the existing categorization that does not account for gig workers, while the right panel illustrates the new categorization that isolates primary gig employment.

Table 5: Transition Rates Between Employment Status

		$(t+1)$			
		E	S_T	U	S_G
(t)	E	94.0	2.0	1.8	2.2
	S_T	15.6	72.6	2.3	9.5
	U	38.8	3.5	48.2	9.5
	S_G	53.2	14.1	14.4	18.3

3 Model

This section introduces a general equilibrium model that captures labor market transitions between various employment arrangements, including two types of self-employment. The model is built upon the framework established by Krusell et al. (2010), incorporating the Bewley-Huggett-Aiyagari (BHA) incomplete markets framework alongside Diamond-Mortensen-Pissarides (DMP) search and matching mechanisms.[7] Self-employment is included as an occupational option, as discussed in Herreño and Ocampo (2023).

3.1 Environment

Demographics and Preferences Time is continuous, and the economy consists of a unit mass of infinitely-lived workers. Each worker can be in one of the following labor market states: paid employment (E), traditional self-employment (S_T), gig self-employment (S_G), or unemployment (U). Paid employees receive wage income, while the two types of self-employed workers earn profits from their businesses. Unemployed individuals receive unemployment insurance benefits but lose eligibility after a certain period, thus they can be divided into two groups: UI eligible (U_1) and UI ineligible (U_0). Workers are risk-averse, and a worker i's utility at time t is derived from consumption c_{it} and is represented by the utility function:

$$u(c_{it}) = \frac{c_{it}^{1-\gamma}}{1-\gamma} \tag{1}$$

Workers supply labor inelastically. For simplicity, individual and time subscripts i and t are omitted unless necessary.

Production Technology Production occurs in two types of firms: (1) corporate firms and (2) self-employed firms.

Corporate Firms: A continuum of risk-neutral corporate firms acts competitively, with each firm maintaining a single job position. Each job position generates output according to a Cobb-Douglas production function:

$$y(z,k) = zk^{\alpha}\bar{l}^{1-\alpha} \tag{2}$$

where z is the idiosyncratic productivity of the hired worker, which evolves stochastically,

[7] A note by Bardóczy (2017) presents the continuous-time version of the model proposed by Krusell et al. (2010).

following a Markov process.[8] Each hired worker provides a fixed labor endowment, $\bar{l}$, and is compensated with a wage $w(a,z)$. Capital k is rented at the market rate r.

Self-Employed Firms: Self-employed firms, operated without any hiring, are heterogeneous in the technologies they utilize:

$$y^{S_j}(z,k) = e_j(z)(k^{\alpha}\bar{l}^{1-\alpha})^{\nu} \quad \forall j \in \{T, G\} \tag{4}$$

Here, S_T denotes traditional self-employment sector, and S_G represents gig sector. The idiosyncratic productivity of the self-employed worker, z, is directly linked to the firm's production efficiency through $e_j(z) = \bar{e}_j z^{\theta_j}$. The scale parameter $\bar{e}_j$ and the productivity relevance factor θ_j are assumed to be higher for traditional self-employment compared to gig work. The parameter ν, which represents the span of control as introduced by Lucas (1978), is less than 1, reflecting diminishing managerial efficiency or returns as inputs increase.

Labor Market Corporate firms with vacant jobs and job seekers are randomly matched in the labor market according to an aggregate matching function:

$$M(u,g,v) = \chi(u+\eta g)^{\psi} v^{1-\psi} \tag{5}$$

The number of matches depends on the matching efficiency ($\chi > 0$), the total number of job vacancies (v), and the total job search efforts given by ($u+\eta g$), where u is the unemployment rate and g is the share of gig workers. Agents who are unemployed or gig workers search for paid employment, but time allocation for gig workers toward searching is less efficient than that of unemployed workers; thus, their search efforts are only a fraction $\eta \in (0,1)$ of those of the unemployed. Labor market tightness is defined as the ratio of vacancies to total search effort:

$$\theta = \frac{v}{u+\eta g} \tag{6}$$

Therefore, the probability that a vacancy finds a worker is given by

$$q(\theta) = \frac{M(u,g,v)}{v} = \chi\theta^{-\psi}$$

[8]Specifically, the logarithm of productivity evolves according to an Ornstein–Uhlenbeck process, which serves as the continuous-time analogue of an AR(1) process:

$$d\log z_t = -\tilde{\rho}_z \log z_t \, dt + \sigma_z dW_t \tag{3}$$

where $\tilde{\rho}_z$ represents the persistence, σ_z is the volatility, and W_t is a standard Brownian motion.

and the probability that a job seeker finds a job is

$$f(\theta) = \frac{M(u, g, v)}{u + \eta g} = \chi \theta^{1-\psi}$$

If a match dissolves or self-employment terminates, agents become job seekers. A matched position dissolves exogenously at a rate λ_E or endogenously at a rate $\tilde{\lambda}_E$, through a firing decision by the firm or a quitting decision by workers. Self-employed businesses may end exogenously at a rate λ_S. Additionally, gig workers have the option to end their work at will, at a rate of $\tilde{\lambda}_S$.

Borrowing and Saving Markets are incomplete, as described in Aiyagari (1994). Workers can partially insure against labor market and productivity risks by holding two types of assets: capital (a production input) and equity (a claim to the firm's profits). A no-arbitrage condition ensures that the returns on capital, $r - \delta$, and the returns on equity, $\frac{d}{p}$, are equal, where δ is the capital depreciation rate, d is the dividend, and p is the price of equity. Total asset holdings for a worker are defined as:

$$a = s(k)k + s(p)p. \tag{7}$$

Here, s represents the portfolio weight for each asset, allowing a to be treated as a single state variable for assets for each worker. Additionally, there is a borrowing constraint $\underline{a}$.

Government Policy The model incorporates two main labor market policies: unemployment insurance (UI) benefits and firing restrictions. Under the UI system, the government provides financial support to laid-off workers, offering benefits as a fraction of their previous wage for a limited time. However, workers transitioning from self-employment do not qualify for these benefits. This UI system, structured as in Setty and Yedid-Levi (2021), is defined by a replacement rate b and a benefit cap $\bar{B}$. Accordingly, UI benefits are calculated as:

$$\min\{b\bar{w}(z), \bar{B}\}, \tag{8}$$

where benefits are a fraction of the average wage $\bar{w}(z)$ for employed workers with productivity z, capped by $\bar{B}$. For the unemployed who are not eligible for UI benefits, the government offers a flat amount of social security, B_0. Funding for UI and social security benefits comes from taxes on labor income, self-employment income, and the benefits themselves, with the tax rate adjusted to maintain a balanced budget.

The model also accounts for firing restrictions imposed on corporate firms, which are required to pay a firing cost F upon terminating employees. These firing costs represent an administrative expense borne by the firm, following the approach described in Cacciatore and Fiori (2016).

3.2 Workers' Problem

Let $W^o(a,z)$ represent the present value for individuals in employment status o, with asset holdings a and productivity z. The employment status o includes five different states: paid employment (E), traditional self-employment (S_T), gig self-employment (S_G), and two types of unemployment, UI eligible (U_1) and UI ineligible (U_0).

3.2.1 Paid Employment

The value of a paid-employed worker satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$\begin{aligned}
\rho W^E(a,z) = & \max_c u(c) + W_a^E(a,z)\dot{a} + \lambda^E \left[W^{U_1}(a,z) - W^E(a,z)\right] \\
& + \tilde{\lambda}^E \max\left\{W^{U_1}(a,z) - W^E(a,z), 0\right\} + W_z^E(a,z)\mu(z) + \frac{1}{2}W_{zz}^E(a,z)\sigma^2(z) \\
\text{s.t.} \quad & \dot{a} = (1-\tau)w(a,z) + (r-\delta)a - c \\
& a \geq \underline{a}
\end{aligned} \tag{9}$$

Workers earn after-tax labor income $(1-\tau)w(a,z)$, where τ is a flat tax on labor income. Wage rates are determined through negotiations with the corporate firm and are functions of both asset levels and individual productivity. Employment is subject to an exogenous job separation shock that occurs at a rate λ^E, and workers have the option to voluntarily quit their jobs if the value of unemployment exceeds the value of paid employment at a rate $\tilde{\lambda}^E$.[9] The worker's value is also influenced by the idiosyncratic productivity process, where $\mu(z)$ represents the drift term and $\sigma(z)$ the volatility term in the stochastic productivity dynamics.

[9]The sign $\sim$ denotes the arrival rate for endogenous transition opportunities throughout the paper. Exogenous transitions do not carry the $\sim$ sign.

3.2.2 Unemployment

The value of an unemployed agent is described by the following HJB equation:

$$\begin{aligned}
\rho W^{U_k}(a,z) = & \max_c u(c) + W_a^{U_k}(a,z)\dot{a} + f(\theta)[W^E(a,z) - W^{U_k}(a,z)] \\
& + \mathbb{1}_{k=1}\lambda^U[W^{U_0}(a,z) - W^{U_k}(a,z)] + \sum_{j=\{T,G\}} \tilde{\lambda}^j \max\left\{W^{S_j}(a,z) - W^{U_k}(a,z), 0\right\} \\
\text{s.t.} \quad & \dot{a} = (1-\tau)B_k(z) + (r-\delta)a - c, \quad \forall k \in \{0,1\}, \quad \forall j \in \{T,G\} \\
& a \geq \underline{a}
\end{aligned} \tag{10}$$

Unemployed workers receive income B_k, where $k \in \{0,1\}$. UI-eligible individuals receive UI benefits B_1 as specified in equation (8). Non-UI eligible individuals receive social security benefits B_0. It is important to note that idiosyncratic productivity remains fixed during unemployment spells, meaning that the base wage for UI benefits is not affected by productivity shocks. UI eligibility expires after a certain period, with λ^U denoting the arrival rate of this eligibility expiration. Unemployed workers can transition into paid employment when they find a job in the labor market with a probability of $f(\theta)$. Alternatively, they can switch to both types of self-employment at will, albeit with different arrival rates for these opportunities, denoted by $\tilde{\lambda}^j$.

3.2.3 Self-Employment

The value of a self-employed agent is described by the following HJB equation:

$$\begin{aligned}
\rho W^{S_j}(a,z) = & \max_c u(c) + W_a^{S_j}(a,z)\dot{a} + \lambda^S[W^{U_0}(a,z) - W^{S_j}(a,z)] \\
& + \mathbb{1}_{\{j=G\}}\left[\tilde{\lambda}^G \max\left\{W^{U_0}(a,z) - W^{S_j}(a,z), 0\right\} + \eta f(\theta)[W^E(a,z) - W^{S_j}(a,z)]\right] \\
& + W_z^{S_j}(a,z)\mu(z) + \frac{1}{2}W_{zz}^{S_j}(a,z)\sigma^2(z) \\
\text{s.t.} \quad & \dot{a} = (1-\tau)\pi^{S_j}(z,k) + (r-\delta)a - c \\
& \pi^{S_j}(z,k) = \max_{k^{S_j} \leq \zeta a} y^{S_j}(z,k) - rk^{S_j}, \quad \forall j \in \{T,G\} \\
& a \geq \underline{a}
\end{aligned} \tag{11}$$

Self-employed workers operate in either the traditional sector (T) or the gig sector (G), generating profits by utilizing capital from the capital market and supplying their own labor, which is fixed at $\bar{l}$. As outlined in equation (4), profits from traditional and gig self-employment differ due to variations in the technologies employed. A collateral constraint limits the amount of capital self-employed workers can access, proportional to their asset holdings.

When self-employed individuals terminate their business, they transition to being unemployed and non-UI eligible. Traditional self-employment can only terminate exogenously at a rate λ^S. The second line in equation (11) accounts for additional transitions for gig self-employed individuals, who can quit gig work endogenously with opportunities arriving at a rate $\tilde{\lambda}^G$. This endogenous exit is assumed only for gig workers, reflecting the ease with which workers in the gig sector can exit their work. They can also be hired by a corporate firm with a job finding rate of $\eta f(\theta)$.

3.3 Corporate Firm's Problem

The value of a filled job for a corporate firm, $J(a, z)$, is defined by the following HJB equation:

$$\begin{aligned}(r-\delta)J(a,z) = {} & y(z,k) - w(a,z) - rk + J_a(a,z)\dot{a} + \lambda^E[V - J(a,z)] \\ & + \tilde{\lambda}^E \max\{V - F - J(a,z), 0\} + J_z(a,z)\mu(z) + \frac{1}{2}J_{zz}(a,z)\sigma^2(z)\end{aligned} \tag{12}$$

The firm's flow profits are derived from production revenue $y(z, k)$, net of labor costs $w(a, z)$ and capital costs rk. The matched worker's asset dynamics $\dot{a}$ also affect the firm's values, as firms take workers' saving decisions as given. The variable V represents the value of maintaining a job vacancy. A worker-job match dissolves exogenously at a rate λ^E, and the firm can dismiss the worker and post a vacancy with this opportunity arriving at a rate of $\tilde{\lambda}^E$, similar to the worker's quitting decision. In this case, the firm incurs a firing cost F.

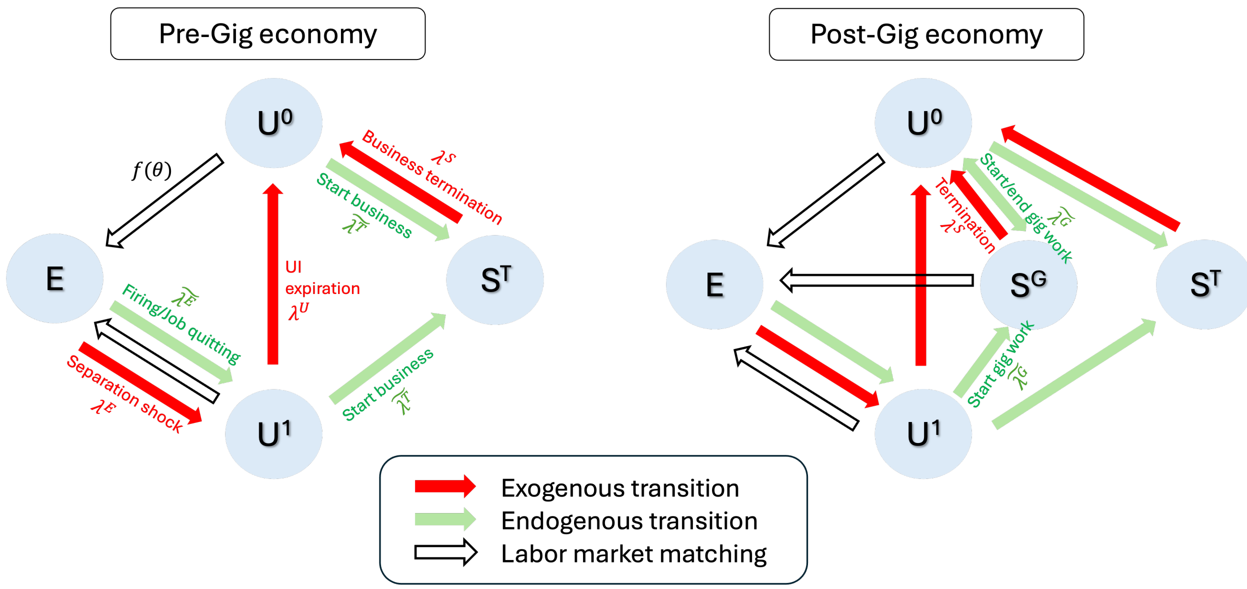
The value of maintaining a vacancy, V, is the solution to the following HJB equation:

$$(r-\delta)V = -\,\xi + q(\theta)\int_z\int_a \frac{d^U(a,z) + \eta d^{S_G}(a,z)}{u+\eta g}\left[J(a,z) - V\right] da dz \tag{13}$$

The vacancy is filled with a worker at the rate $q(\theta)$, randomly selected from the distribution of all job seekers. The term ξ represents the job posting cost. The expression $\frac{d^U(a,z)+\eta d^{S_G}(a,z)}{u+\eta g}$ reflects the weighted density of job seekers drawn from both the unemployed and gig employed pools. Given the free entry of firms, the value of holding a vacant position must equate to zero:

$$\xi = q(\theta)\int_z\int_a \frac{d^U(a,z) + \eta d^{S_G}(a,z)}{u+\eta g} J(a,z) da dz \tag{14}$$

Figure 3: Occupational transitions



3.4 Wage Setting

Wages are determined through Nash bargaining, as is standard in search-and-matching models.

$$w(a,z) = \text{argmax}\left[\left(\widetilde{W}^E(w,a,z) - W^{U_1}(a,z)\right)^{\psi}\left(\widetilde{J}(w,a,z) - (V-F)\right)^{1-\psi}\right] \tag{15}$$

The worker's outside option in this negotiation is represented by the value of receiving UI benefits, $W^{U_1}(a,z)$. This is because UI benefits are designed to exert upward pressure on wages throughout the employment period, following the reasoning presented by Lalé (2019).

The incumbent worker (E)'s threat point during bargaining is their ability to claim $W^{U_1}(a,z)$ if they lose their job. For newly hired workers who were previously receiving UI benefits (U_1), $W^{U_1}(a,z)$ continues to serve as the relevant outside option when negotiating with an employer. Conversely, for new workers coming from ineligibility for UI benefits (U_0) or gig employment (S_G), one could theoretically use $W^{U_0}(a,z)$ as the outside option at the start of employment. However, the marginal benefits of doing so are outweighed by the additional computational cost of introducing an extra state variable. Notably, the self-employment option $W^{S_j}(a,z)$ is not explicitly included as a threat point, as it does not represent a direct destination for paid employees and is already reflected in $W^{U_1}(a,z)$. Therefore, $W^{U_1}(a,z)$ is consistently used as the outside option for all workers in the model.

One advantage of the continuous-time setup is that it allows for the expression of wages in a readily computable form based on the value and policy functions; the detailed derivation is shown in the Appendix. The optimal wage $w^*(a,z)$ can be expressed as:

$$w^*(a,z) = \psi \frac{S_{firm}}{1 - J_a(a,z)(1-\tau)} - (1-\psi)\frac{S_{worker}}{W_a^E(a,z)(1-\tau)} \tag{16}$$

where

$$\begin{aligned} S_{firm} &= y(z,k) - rk + J_a(a,z)\big((r-\delta)a - c^E(a,z)\big) + (\lambda + r - \delta)F \\ &\quad + J_z(a,z)\mu(z) + \frac{1}{2}J_{zz}(a,z)\sigma^2(z) \\ S_{worker} &= u(c^E(a,z)) - \rho W^{U_1}(a,z) + W_a^E(a,z)\big((r-\delta)a - c^E(a,z)\big) + W_z^E(a,z)\mu(z) + \frac{1}{2}W_{zz}^E(a,z)\sigma^2(z) \end{aligned}$$

The optimal wage function $w^*(a,z)$ reflects the equilibrium wage that balances the interests of both the firm and the worker. It comprises two key components: the surplus to the firm S_{firm}, calculated as the firm's revenue from production $y(z,k)$ minus costs, and the surplus to the worker S_{worker}, which encompasses their utility from consumption and the value of being unemployed. The bargaining power of the worker, represented by the parameter ψ, plays a crucial role in determining the outcome of negotiations; higher values indicate greater worker strength and influence over wage setting.

The terms $1 - J_a(a,z)(1-\tau)$ and $W_a^E(a,z)(1-\tau)$ are adjustment factors ensuring direct comparisons between the after-tax values of the firm and worker. Specifically, W_a^E measures the marginal value of a dollar to the worker, while $1 - J_a$ captures the marginal value of a dollar to the firm. If the worker transfers an additional dollar to the firm, it results in a direct one-dollar increase in the firm's value, along with an indirect impact from the worker's asset accumulation $(-J_a)$.

Furthermore, unemployment insurance benefits enhance workers' outside options, decreasing S_{worker} while simultaneously exerting upward pressure on wages. Firing costs, on the other hand, create job security that empowers workers and increases S_{firm} during negotiations. Individual characteristics, such as asset holdings and productivity, also shape the optimal wage; these factors influence both the worker's reservation wage and the firm's surplus from hiring, ultimately affecting the wage-setting dynamics.

3.5 Distribution of Workers

The distribution of workers across each employment status d^o for $o \in \{E, U_0, U_1, S_T, S_G\}$ evolves according to a set of Kolmogorov Forward (KF) equations. Let $\Phi^E(a,z)$ denote the match separation decision of workers and firms, which equals 1 if the match is dismissed and 0 otherwise. The terms $\Phi^{U_k S_j}(a,z)$ represent entry decisions from unemployment to self-employment for each type of unemployment ($k \in \{0,1\}$) and self-employment ($j \in \{T, G\}$). Specifically, $\Phi^{S_G U_0}(a,z)$ indicates the decision of gig workers to transition into unemployment.

The evolution of the distribution of workers can be expressed by the following set of equations:

$$
\begin{aligned}
\dot{d}^E(a,z) =& -\partial_a\left[\dot{a}^E(a,z)d^E(a,z)\right] - \{\lambda^E + \tilde{\lambda}^E\Phi^E(a,z)\}d^E(a,z) + f(\theta)d^{U_1}(a,z) \\
&+ \eta f(\theta)d^{S_G}(a,z) - \partial_z[\mu(z)d^E(a,z)] + \frac{1}{2}\partial_{zz}\left[\sigma^2(z)d^E(a,z)\right] \\
\dot{d}^{U_0}(a,z) =& -\partial_a\left[\dot{a}^{U_0}(a,z)d^{U_0}(a,z)\right] - \{f(\theta) + \tilde{\lambda}^T\Phi^{U_0S_T}(a,z) + \tilde{\lambda}^G\Phi^{U_0S_G}(a,z)\}d^{U_0}(a,z) \\
&+ \{\lambda^S + \tilde{\lambda}^G\Phi^{S_GU_0}(a,z)\}d^{S_G}(a,z) + \lambda^S d^{S_T}(a,z) + \lambda^U d^{U_1}(a,z) \\
\dot{d}^{U_1}(a,z) =& -\partial_a\left[\dot{a}^{U_1}(a,z)d^{U_1}(a,z)\right] - \{f(\theta) + \tilde{\lambda}^T\Phi^{U_1S_T}(a,z) + \tilde{\lambda}^G\Phi^{U_1S_G}(a,z)\}d^{U_1}(a,z) \\
&+ \{\lambda^E + \tilde{\lambda}^E\Phi^E(a,z)\}d^E(a,z) \\
\dot{d}^{S_T}(a,z) =& -\partial_a\left[\dot{a}^{S_T}(a,z)d^{S_T}(a,z)\right] - \lambda^S d^{S_T}(a,z) + \tilde{\lambda}^T[\Phi^{U_0S_T}(a,z)d^{U_0}(a,z) \\
&+ \Phi^{U_1S_T}(a,z)d^{U_1}(a,z)] - \partial_z[\mu(z)d^{S_T}(a,z)] + \frac{1}{2}\partial_{zz}\left[\sigma^2(z)d^{S_T}(a,z)\right] \\
\dot{d}^{S_G}(a,z) =& -\partial_a\left[\dot{a}^{S_G}(a,z)d^{S_G}(a,z)\right] - \{\eta f(\theta) + \lambda^S + \tilde{\lambda}^G\Phi^{S_GU_0}(a,z)\}d^{S_G}(a,z) \\
&+ \tilde{\lambda}^G[\Phi^{U_0S_G}(a,z)d^{U_0}(a,z) + \Phi^{U_1S_G}(a,z)d^{U_1}(a,z)] \\
&- \partial_z[\mu(z)d^{S_G}(a,z)] + \frac{1}{2}\partial_{zz}\left[\sigma^2(z)d^{S_G}(a,z)\right] \qquad (17)
\end{aligned}
$$

$$
1 = \sum_{o \in \{E, S_T, S_G, U_0, U_1\}} \int_z \int_a d^o(a,z)\,da\,dz \qquad (18)
$$

In this analysis, I consider a stationary equilibrium wherein the distributions remain invariant over time, leading to the condition $\dot{d}^o(a,z) = 0$ for all o.

3.6 Equilibrium

A stationary equilibrium consists of the following components: value functions and consumption policy functions for each employment status, $W^o(a,z)$ and $c^o(a,z)$; value functions for corporate firm positions, $J(a,z)$ and V; capital demands from corporate firms and self-employed firms, represented as $k(z)$, $k^{S_T}(z)$, and $k^{S_G}(z)$; the density of state variables $d^o(a,z)$; and equilibrium prices, including the wage w, interest rate r, equity price p, and tax rates τ. These components must satisfy the following conditions:

1. Given prices and job-finding probability $f(\theta)$, agents optimize their choices, ensuring that the value and policy functions satisfy the equations from (9) to (11). The optimal consumption for each occupation is derived from the first-order condition of the worker's problem:

$$c^o(a,z) = \partial_c u^{-1}\left(\partial_a W^o(a,z)\right) \tag{19}$$

The capital demand for self-employed firms is determined by solving the flow profit maximization problem:

$$k^{S_j}(z) = \underset{k \leq \zeta a}{\text{argmax}}\ y^{S_j}(z,k) - rk^{S_j} \quad \forall j \in \{T, G\} \tag{20}$$

2. Given prices, tightness, and the distribution $d^o(a,z)$, the corporate firm's capital demand k solves the firm's optimization problem:

$$k(z) = \underset{k}{\text{argmax}}\ y(z,k) - w(a,z) - rk \tag{21}$$

This is accompanied by the corresponding value functions $\{J(a,z), V\}$ and the free entry condition.

3. The wage function $w(a,z)$ is determined through Nash bargaining.

4. The asset market clears according to the following condition:

$$\int\int \left[k(z)d^E(a,z) + k^{S_T}(z)d^{S_T}(a,z) + k^{S_G}(z)d^{S_G}(a,z)\right] dadz + p = \sum_o \int\int ad^o(a,z)dadz \tag{22}$$

5. The dividend paid to equity owners each period is the sum of flow profits from the corporate firm, net of expenditures on vacancies:

$$d = \int_z \int_a \left[\left(y(z,k) - w(a,z) - rk\right) d^E(a,z) - \xi v\right] dadz \tag{23}$$

6. The government balances the budget, ensuring that total tax revenues equal total

expenditures:

$$\tau \int_z \int_a \left[w(a,z)\, d^E(a,z) + \pi^{S_T}(z,k)\, d^{S_T}(a,z) + \pi^{S_G}(z,k)\, d^{S_G}(a,z) + B^{U_1}\, d^{U_1}(a,z) + B^{U_0}\, d^{U_0}(a,z) \right] da dz$$
$$= \int_z \int_a \left[B^{U_1}\, d^{U_1}(a,z) + B^{U_0}\, d^{U_0}(a,z) \right] da dz \tag{24}$$

7. The density of state variables $d^o(a,z)$, for $o \in \{E, S_T, S_G, U_0, U_1\}$, is consistent with individuals' optimal behavior.[10]

4 Parameterization

To parameterize the model, I adopt commonly used values from the literature and calibrate key parameters to match empirical moments related to labor market frictions and self-employment. Given the limited availability of data on the gig economy, I employ a two-step calibration process. First, I simplify the model by excluding gig employment, calibrating key parameters using data from a period before the gig economy became a significant employment option. Specifically, I focus on the period from 1994 to 2013, utilizing data from the Current Population Survey (CPS) and the Survey of Consumer Finances (SCF) to calibrate traditional self-employment dynamics.[11] In this setup, workers dismissed from paid employment can either transition to traditional self-employment or remain unemployed while actively searching for jobs.[12] This simplified model is also used later for counterfactual analyses.

In the second step, gig economy-specific parameters in the full model are calibrated using data from the Survey of Household Economics and Decisionmaking (SHED), which captures gig employment between 2016 and 2020. I utilize the parameter values from the simplified model for traditional self-employment while calibrating the gig parameters to match these more recent data moments.[13] Tables 6 and 7 summarize the externally and internally calibrated parameters, respectively.

[10]Since the model lacks a closed-form solution, it is solved using numerical methods. A detailed explanation of the numerical algorithm and the behavior of the resulting policy functions can be found in the Appendix.

[11]While reliable datasets such as the CPS and SCF are extensive, they do not specifically distinguish gig workers from traditional self-employed individuals. In recent years, the advent of digital labor platforms has resulted in mixed coverage for self-employment, making it unsuitable for directly matching parameters related to both types of self-employment.

[12]This setup corresponds to $j = T$ in the self-employed worker's HJB equation (11).

[13]Here, I assume that the parameters related to traditional self-employment maintain their values regardless of the introduction of the gig economy.

4.1 Externally Calibrated Parameters

Externally calibrated parameters are grounded in existing literature. The coefficient of relative risk aversion (CRRA), γ, is set to 1.5, following Attanasio et al. (1999). The discount rate, ρ, corresponds to an annual rate of 4%, which implies a quarterly rate of 1%. The capital share in production, α, is set at 0.3, a standard value in macroeconomic models. The parameter for self-employment returns to scale, ν, is set at 0.85, following Midrigan and Xu (2014). The persistence and volatility of idiosyncratic productivity shocks, ρ_z and σ_z^2, are taken from Floden and Lindé (2001).

Labor market parameters, such as the elasticity of matching, ϕ, and workers' bargaining power, ψ, are both set to 0.72, consistent with the calibration used in Shimer (2005). I assume that the arrival rate for gig entry and exit occurs on a monthly basis. This is reasonable, as typical ridesharing driver applications take less than a few weeks, although individuals in rural areas may find it harder to access gig work. The arrival rate of traditional self-employment opportunities is set to occur less frequently compared to the monthly arrival of gig employment opportunities. The unemployment benefit replacement rate is set to 45%, with the arrival rate of benefit expiration set to 0.45, allowing benefits to expire after 26 weeks, in line with U.S. policy. Firing costs are assumed to be zero in the context of the U.S. economy. The collateral constraint parameter for self-employed individuals, τ, is set to 1.86, matching the debt-to-equity ratio observed in the SCF, while labor supply is normalized to 1.

Table 6: Externally calibrated parameters

	Parameter	Value	Source
γ	CRRA curvature	1.5	Attanasio et al. (1999)
ρ	Discount rate	0.01	Annual discount rate, 4%
α	Capital share	0.3	Standard literature
ν	Returns to scale	0.85	Midrigan and Xu (2014)
ρ_z	Productivity persistence	0.978	Floden and Lindé (2001)
σ_z^2	Productivity volatility	0.103	Floden and Lindé (2001)
ϕ	Elasticity of matching	0.72	Shimer (2005)
ψ	Worker's bargaining power	0.72	Shimer (2005)
$\tilde{\lambda}^E$	Endogenous job separation	3	Monthly arrival
$\tilde{\lambda}^G$	Gig entry/exit opportunity	3	Monthly arrival
F	Firing costs	0	Baseline (U.S.)
b	Unemployment benefit	0.45	Replacement rate (U.S.)
λ^U	UI expiration	0.45	26 weeks (U.S.)
ζ	Collateral constraint	1.86	Debt-to-equity ratio for the self-employed (SCF)
$\bar{l}$	Labor supply	1	Normalization

4.2 Internally Calibrated Parameters

Internally calibrated parameters are fine-tuned to match key labor market and self-employment outcomes, with parameters related to employment transitions (excluding gig employment) relying on CPS data from 1994 to 2013. The exogenous separation rate for paid employment, λ^E, is calibrated to match the average unemployment rate during this period, which is 6.2%. The entrepreneurial opportunity arrival rate for the unemployed, λ^T, is set at 0.18 to match the transition rate from unemployment to self-employment in the data, which is 5.2%. The self-employment termination rate is set at 0.06, aligned with the transition rate from self-employment to unemployment, which is 2.7%. For search effort among gig workers, I set the rate at 0.15, indicating they exert 85% less effort than the unemployed, which matches the transition rate from gig employment to paid employment in SHED data, 21.9%. The matching efficiency parameter, χ, is calibrated to 1.79 to replicate a long-run monthly job-finding rate of 45%, consistent with literature such as Shimer (2005).

Parameters relevant to self-employment production differ between traditional and gig sectors. The productivity scale parameters, $\bar{e}^T$ and $\bar{e}^G$, are set to match the level of self-employment income relative to paid employment income in the SCF and SHED, respectively. These parameters are crucial in determining the potential income that workers in each sector can generate. The traditional self-employment sector, associated with higher average productivity, typically requires more skills, capital, and experience, which is reflected in a higher value for $\bar{e}^T$. In contrast, the gig economy is characterized by lower average productivity, as gig workers generally perform less skill-intensive tasks, justifying the lower value for $\bar{e}^G$. The parameters θ^T and θ^G capture the extent to which an individual's inherent productivity impacts their income in each sector. θ^T is set to match the self-employment share of the top 20% income percentile, reflecting higher participation among affluent groups. Conversely, θ^G is calibrated to match the overall gig income share of total income. Notably, θ^G is smaller than θ^T, indicating that self-employment production efficiency across individual ability is flatter for the gig sector compared to the traditional sector. In the traditional sector, individual skills and productivity play a more significant role in determining earnings, as workers operate businesses where personal expertise directly influences success. Conversely, the lower value of θ^G in the gig economy reflects that individual productivity is less decisive, as gig work often involves standardized tasks or is heavily influenced by external factors, such as the platform's structure or the availability of gigs.

Finally, the maximum unemployment insurance (UI) benefit, $\bar{b}$, is calibrated to match 50% of the average wage generated by the model, while social security benefits for UI-ineligible unemployed individuals are set to a 5% replacement rate, consistent with U.S. data.

Table 7: Internally Calibrated Parameters

	Parameter	Value	Target
Labor Market and transitions			
λ^E	Exogenous job separation	0.09	Unemployment rate, 6.2%
$\tilde{\lambda}^T$	Business opportunity arrival	0.18	Unemp. to Self-emp. transition rate, 5.2%
λ^S	Self-employment termination	0.06	Self-emp. to Unemp. transition rate, 2.7%
η	Search efforts for the gig-employed	0.15	Gig to Paid emp. transition rate, 21.9%
χ	Matching efficiency	1.79	Monthly job-finding rate, 45%
ξ	Vacancy posting cost	0.19	Labor market tightness $(\theta) = 1$
Self-employment production			
$\bar{e}^T$	Production scale (traditional)	1.23	Self-emp. to Paid emp. income ratio, 1.24
θ^T	Productivity relevance (trad.)	1.26	Self-emp. share of top 20% income, 14.6%
$\bar{e}^G$	Production scale (gig)	1.07	Gig to Paid emp. income ratio, 0.45
θ^G	Productivity relevance (gig)	1.22	Gig income share, 2.9%
Policy and others			
$\bar{b}$	Maximum UI benefit	1.0	50% of mean wage
b^0	Social security (UI ineligible)	0.1	5% replacement rate
δ	Depreciation	0.02	Investment-output ratio, 20%

4.3 Results

Table 8 presents the model's predictions for labor market and economic outcomes, comparing them with data from the SHED. The model closely replicates the observed labor force composition: gig employment constitutes 5.6% of the labor force in both the model and the data, and. the shares of traditional self-employment and paid employment align closely with the data.[14]

In terms of wealth and income, the model estimates a median wealth ratio of 0.85 for gig workers relative to paid employees, which falls within the data range of 0.7–0.8.[15] This finding indicates that gig workers generally possess lower wealth than their counterparts in paid employment, reflecting a broader economic vulnerability associated with gig work. For the bottom 40% income group, the model predicts a gig-to-paid employment ratio of 0.147,

[14]The model's higher unemployment rate partly reflects differences between the SHED and CPS data sources used in the calibration. SHED data indicates a higher baseline unemployment rate compared to CPS data, which calibrated the model's pre-gig economy period.

[15]In SHED data, wealth and income are reported in intervals, limiting precision in calculating median values. The median wealth for gig workers relative to paid employees is estimated by identifying the wealth interval closest to the 50th percentile of the SHED sample distribution. Income data is provided with more granular intervals, allowing for a more accurate estimate of the income distribution.

closely aligning with the observed value of 0.135. These result suggest that gig work is particularly prevalent among low-income and low-asset individuals, a trend consistent across both the model and the data.

Transition rates, detailed in Table 8, further illustrate the dynamics of gig workers.[16] The model captures larger inflows from traditional self-employment and unemployment into gig work compared to transitions from paid employment. However, the model underestimates the transitions between gig and traditional self-employment, likely due to its simplified structure that lacks transitions between the two forms of self-employment. Furthermore, the model underestimates the outflow from gig employment to unemployment, which may stem from the assumption that gig and traditional self-employment share the same exogenous termination rate, failing to account for the unique and often volatile demand fluctuations in gig work. In practice, these demand changes can lead to higher exit rates from gig employment.

Table 8: Comparison of Unmatched Moments Between Model and Data

	Model	**Data[1] (SHED)**
Labor Force Share		
Gig Employment (S_G)	5.6%	5.6%
Traditional Self-employment (S_T)	8.6%	8.7%
Paid Employment (E)	81.3%	79.6%
Unemployment[2] (U)	4.6%	6.1%
Transition Rates		
S_G to U	4.1%	8.8%
S_G to S_T	0.3%	6.9%
U to S_G	10.9%	5.7%
S_T to S_G	1.8%	4.8%
E to S_G	1.0%	0.9%
S_G to S_G (Retention)	73.0%	62.3%
Other Ratios		
S_G to E Median Wealth Ratio[3]	0.85	0.7–0.8
S_G to E Employment Ratio for Bottom 40% Income	0.147	0.135

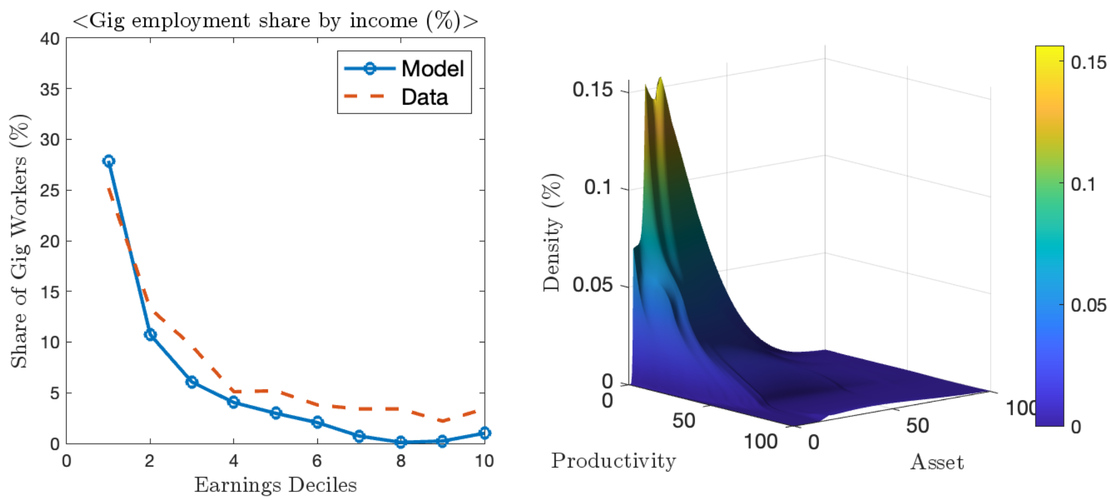
[1] SHED data is reclassified for primary gig employment as in Section 2. The SHED data is annual, while the model operates quarterly, necessitating adjustments for comparison.
[2] The model's higher unemployment rate partly reflects calibration strategies. SHED data indicates a higher unemployment rate compared to CPS data, even for the post-gig period.
[3] SHED wealth and income data are provided in intervals. Median wealth is estimated from the closest interval to the 50th percentile. Income data has finer intervals, allowing for a more accurate estimate.

Figures 4 visually represent the distribution of gig workers. The left panel shows gig employment share across income deciles, with model predictions represented by the solid blue line and data by the dashed red line. The model successfully captures the concentration of gig workers in the lower income deciles, particularly in the first decile, where approximately

[16]SHED data is collected annually and reflects job market conditions at a specific point in time, potentially capturing fluctuations in unemployment not accounted for in the model's quarterly framework.

30% of workers engage in gig work. This share declines sharply in higher deciles, indicating that gig work is predominantly occupied by lower-income individuals. However, there are discrepancies in the middle deciles, where data indicates a marginally higher proportion of gig workers than the model. The right panel illustrates the density of gig workers across asset holdings and productivity levels, showing that most gig workers cluster in the lower ranges of asset holdings, with productivity levels generally below the average. This suggests that gig workers tend to have lower asset holdings and productivity, further supporting the model's representation of gig work.

Figure 4: Distribution of Gig Workers



5 Effects of the Introduction of the Gig Economy

In this section, I conduct a quantitative analysis to evaluate the impact of the gig economy on the labor market and overall welfare. This analysis utilizes two calibrated model versions introduced in the previous section: the "pre-gig model," which excludes gig work options, and the "gig model," which incorporates them. In the pre-gig model, workers not employed by corporate firms and opting for self-employment can only engage in traditional self-employment.

5.1 Labor Market Response

Table 9 compares key labor market indicators from the pre-gig and gig models, illustrating how the inclusion of gig work influences labor market dynamics.

Table 9: Effects of the Gig Economy on Labor Market and Macro Outcomes

	Pre-Gig Model	Gig Model	Difference (%)
Employment Status			
Unemployment Rate	6.3%	4.6%	-1.7%
UI Ineligible	1.5%	0.9%	-0.6%
UI Eligible	4.8%	3.7%	-1.1%
Paid Employment Share	82.8%	81.2%	-1.6%
Self-Employment Share	10.9%	8.6%	-2.3%
Gig Employment Share	0.0%	5.6%	5.6%
Labor Market			
Job Separation Rate	4.5%	4.1%	-0.4%
Job Finding Rate	45.0%	46.2%	1.2%
Vacancies	100.0	98.0	-2.0%
Labor Market Tightness	100.0	113.9	13.9%
Average Wage	100.0	102.3	2.3%
Median Wage	100.0	100.9	0.9%
Macro Outcomes			
Output per Worker	100.0	99.3	-0.7%
Aggregate Consumption	100.0	101.2	1.2%
Assets	100.0	101.0	1.0%

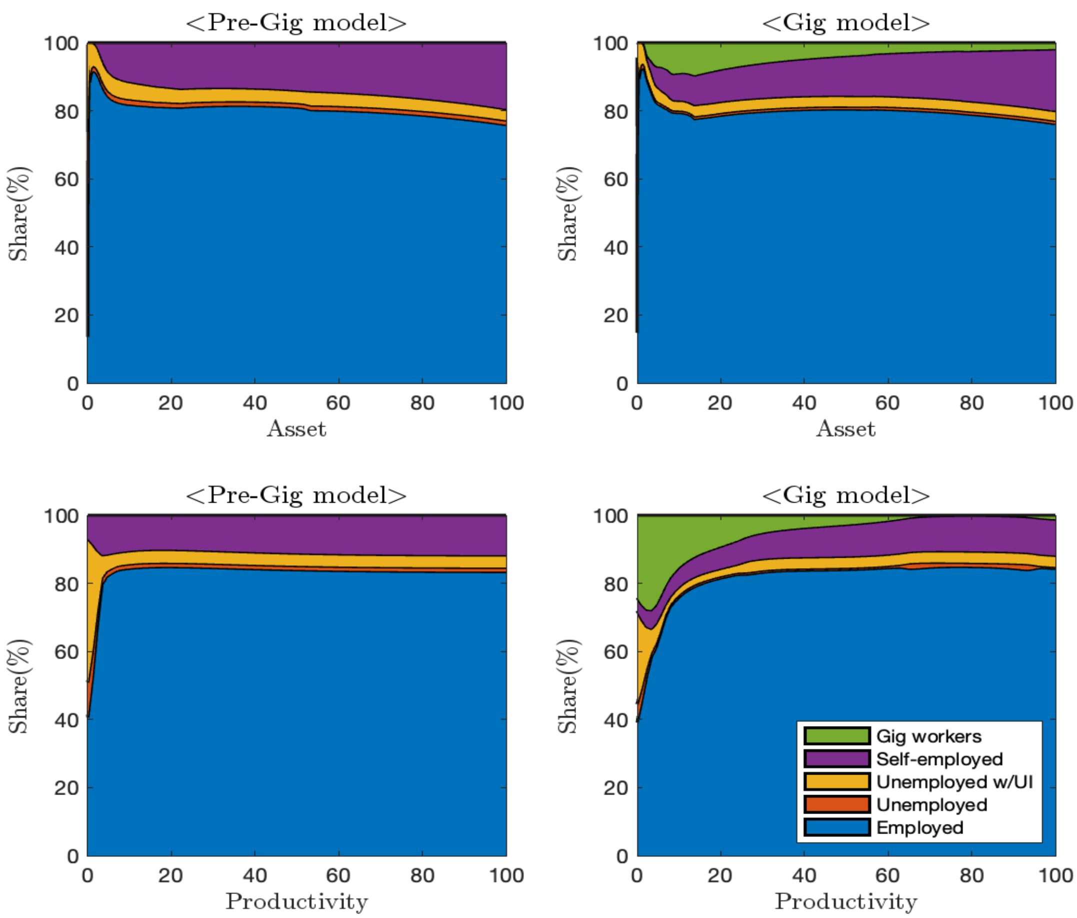
Employment Composition The introduction of gig work results in a significant reduction in the unemployment rate, decreasing from 6.2% to 4.7% (see Table 9).[17] Notably, a substantial portion of this reduction occurs among workers ineligible for unemployment insurance (UI), whose unemployment rate falls from 1.5% to 0.9%. This suggests that the gig economy provides alternative income opportunities for individuals who might otherwise face prolonged unemployment. This finding aligns with the research of Jackson (2022), which indicates that gig work can serve as a temporary solution for those experiencing extended job searches. Figure 5 illustrates the shift in employment composition, revealing that the decline in unemployment primarily affects low-skilled and asset-poor individuals, who are more inclined to pursue gig work. However, it is important to note that the lowest asset groups are less likely to engage in gig work due to the capital requirements (such as owning a car) that must be met, as these assets serve as collateral for loans.

Additionally, gig entrants are often drawn from self-employment, evidenced by a decrease in the self-employment rate from 10.9% to 8.6%. Figure 6 highlights that this decline primarily occurs among poorer and low-skilled individuals. In the absence of other earning opportunities, unemployed workers who face challenges in securing paid employment may

[17]While conclusive evidence from official labor market surveys on the gig economy's direct impact on unemployment rates is lacking, it is plausible that many gig workers are classified as "unemployed" rather than "employed" in official statistics. The SHED data indicates that approximately 16% of the unemployed engage in primary gig work.

resort to subsistence self-employment, as noted by Herreño and Ocampo (2023). The availability of gig work allows these individuals to more readily secure income while continuing their search for paid employment.

Figure 5: Share of Employment Status by Productivity and Asset



Labor Market The introduction of the gig economy yields higher wages, a decrease in job vacancies, and tighter labor market conditions. Wages rise because gig work provides an alternative income source for unemployed individuals, enhancing their bargaining power during wage negotiations. Consequently, average wages increase by 2.3%, particularly benefiting those most likely to transition into gig work, as illustrated in Figure 7.

The impact of the gig economy on job creation within paid employment can be understood by decomposing the firm's expected value from posting a vacancy, as shown in equation (13):

Figure 6: Self-employment Share by Productivity and Asset

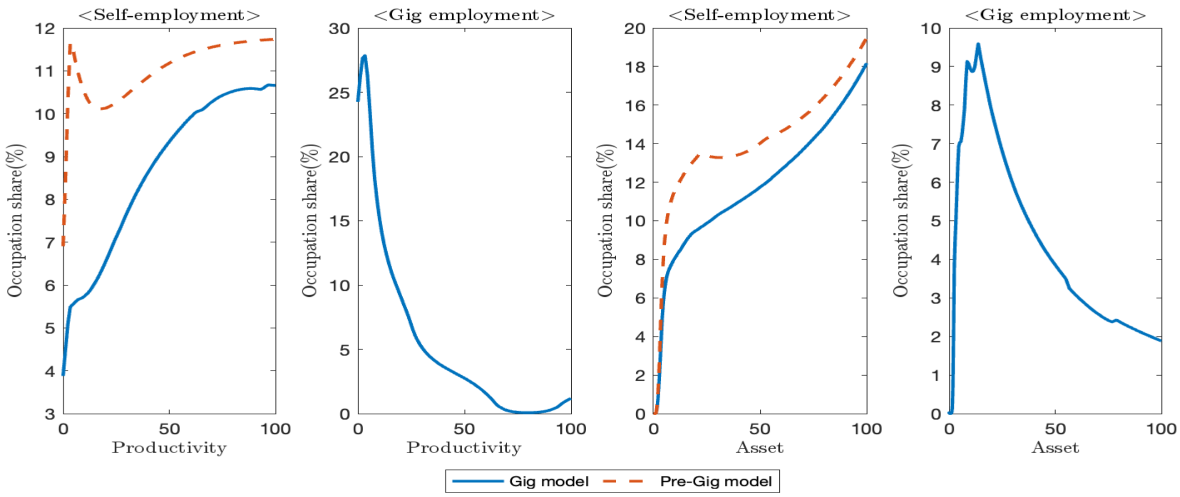
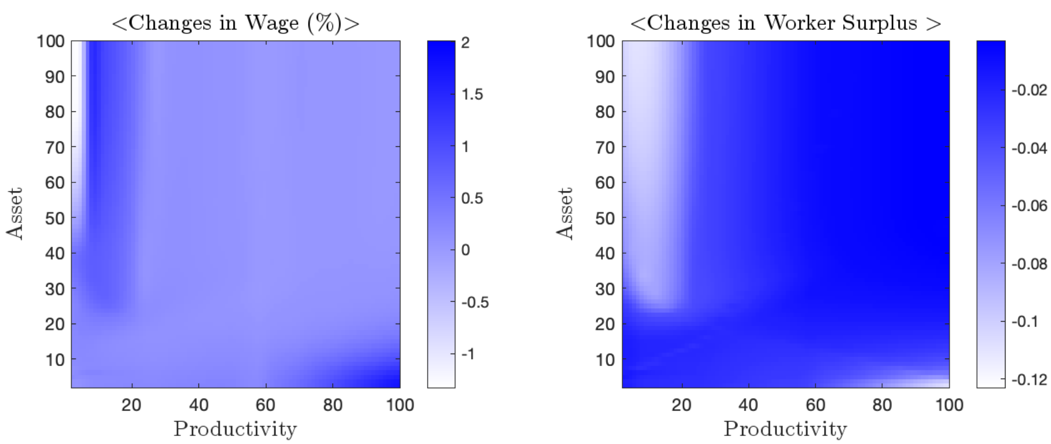


Figure 7: Changes in Wage and Worker Surplus



$$\text{From equation (13): } \underbrace{q(\theta)}_{(2)} \int_z \int_a \underbrace{\frac{d^U(a,z) + \eta d^{S_G}(a,z)}{u + \eta g}}_{(1)} \underbrace{\max\{J(a,z) - V, 0\}}_{(3)} dadz$$

(1) As more low-skilled individuals opt for gig work, the average productivity of the job seeker pool increases, enhancing the value of posting a vacancy. (2) However, the reduction in the pool of available job seekers, as gig workers exhibit lower search intensity than the unemployed, complicates firms' efforts to fill vacancies. (3) Additionally, the wage increase diminishes the expected profits associated with filling job positions. The second and third effects outweigh the first, leading to an overall reduction in job vacancies by 2.0%. Despite this decrease, the labor market tightens by 13.9% due to a more significant decline in the number of job seekers.

Aggregate consumption increases by 1.2%, and asset accumulation rises by 1.0% as a result of the additional earning opportunities presented by gig work.[18] However, output per worker declines by 0.7% in the gig model. This decrease is attributed to shifts in the production sector's composition, as lower-productivity gig jobs replace higher-productivity roles in the corporate sector.

5.2 Welfare

Welfare is assessed using the consumption equivalence (CE) measure, calculated at the individual level based on each person's asset and productivity. These values are then aggregated using the distribution from the pre-gig economy to derive an overall welfare measure. Specifically, for an individual with given assets and productivity in each employment status, CE represents the percentage change in consumption required across all future states and dates to render them indifferent between the stationary equilibria before and after the gig economy's introduction:

$$W^o_{NG}((1 + CE^o(a,z)) \times C^o_{NG}(a,z)) = W^o_G(C^o_G(a,z)) \tag{25}$$

In this equation, W^o denotes the value functions corresponding to each employment status, where $o \in \{E, S_T, U_0, U_1\}$ in equations (9)–(11). The variable C represents consumption

[18] The addition of insurance through gig work options may reduce precautionary savings in an incomplete market. However, since gig work requires capital to produce services, these effects are offset. When the gig production function is considered solely a function of labor input, as in Choi (2023), aggregate assets decrease due to reduced precautionary savings.

in each state, with superscripts NG and G indicating the pre- and post-gig economies, respectively. Given the utility function, $CE(a, z)$ can be directly computed from the value functions:

$$CE(a, z) = \left(\frac{W_G(a, z)}{W_{NG}(a, z)} \right)^{\frac{1}{1-\gamma}} - 1$$

The aggregate CE is obtained by integrating over the stationary distribution in the non-gig model:

$$\overline{CE} \equiv \sum_{o \in \{E, S_T, U_0, U_1\}} \int_z \int_a d^o_{NG}(a, z) CE^o(a, z) \, da \, dz \tag{26}$$

The introduction of the gig economy leads to a moderate increase in overall welfare. Table 10 presents welfare measures across different demographic groups, revealing an aggregate welfare increase of 0.47% compared to the pre-gig economy. This welfare improvement occurs across various individual states, with particularly pronounced benefits for low-skilled and asset-poor individuals, who experience increases of 0.53% for both groups. By employment status, the largest gains are observed among the unemployed who are ineligible for unemployment insurance (UI), with a 0.54% increase.

Table 10: Effects of Gig Economy on Welfare (%)

	Productivity			**Assets**			All
	Low	Medium	High	Poor	Medium	Wealthy	
Unemployment - UI ineligible	0.62	0.57	0.42	0.60	0.56	0.45	0.54
Unemployment - UI eligible	0.59	0.54	0.42	0.58	0.54	0.44	0.52
Paid Employment	0.53	0.46	0.40	0.52	0.47	0.40	0.47
Traditional Self-employment	0.52	0.45	0.39	0.51	0.46	0.39	0.46
All	0.53	0.46	0.40	0.53	0.48	0.40	0.47

[1] Welfare is assessed as a consumption equivalent, expressed in percentage terms, for each state and aggregated based on the pre-gig distribution.
[2] The classifications for productivity and asset groups are as follows: Low/Poor represents the bottom 33% of the distribution, Medium, 34% to 66%, and High/Wealthy, top 33%.

To further explore the gig economy's role as an insurance mechanism, I break down the welfare effects into two components: insurance effects and market effects, as suggested by Mukoyama (2013) and Setty and Yedid-Levi (2021). The insurance effects assume that wages, interest rates, equity prices, and job-finding rates for paid employment remain constant at pre-gig levels. This scenario reflects the intrinsic value of gig work as an additional insurance channel against productivity and labor market shocks for workers in various employment statuses before any market adjustments occur. The market effects represent the residual impact of the total effect, where prices and job-finding rates undergo adjustments.

Figure 8 illustrates the welfare gains from insurance effects in the upper panels and total effects in the lower panels, categorized by asset holdings. The welfare gain is expressed as a percentage using the consumption equivalence measure. The left panel presents results by employment status, indicating that while insurance effects are predominantly positive for all groups, they are most significant for those most affected and open to gig opportunities—specifically, the unemployed without unemployment insurance (UI) benefits and those with relatively low assets. The right panel highlights the effects based on individual productivity levels, showing that low-skilled individuals derive the greatest benefit from the added insurance of gig employment, although overall effects are generally positive.

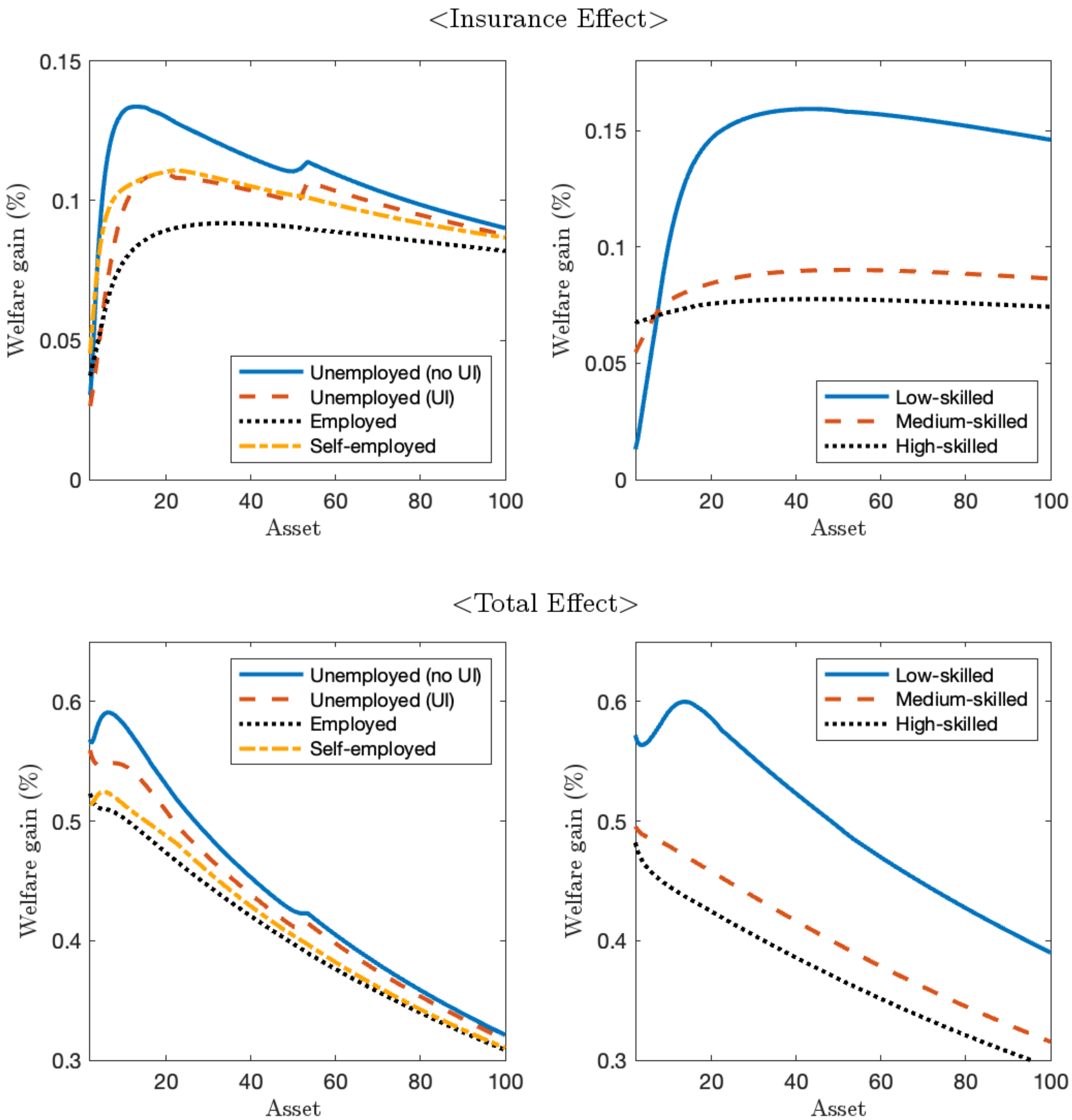
The total effects illustrate increased welfare attributed to wage growth, benefiting asset-poor and low-skilled workers, as well as enhanced job-finding rates that help the unemployed. However, a decrease in interest rates partially offsets the welfare gains for asset-rich individuals.

6 Policy Analysis

This section examines the effects of conventional labor market policies, specifically unemployment insurance (UI) and firing restrictions, while considering two types of self-employment. By varying the UI replacement rate and firing costs while keeping other parameters constant, I conduct a counterfactual analysis. To ensure realistic policy implications, I begin with labor market policy data from various countries. Figure 9 illustrates the average levels of the UI replacement rate and the employment protection strictness index among OECD countries from 2008 to 2019.[19] It reveals a general trend indicating that countries with higher UI replacement rates tend to have stricter employment protections, with rates ranging from 28% in Australia to 85% in Luxembourg. The strictness index for employment protection concerning individual and collective dismissals ranges from 1.0 in the U.S. to 3.3 in the Netherlands. Western and Southern European nations, such as the Netherlands and Portugal, cluster in the top-right quadrant, indicating robust UI benefits alongside strict worker protections. In contrast, English-speaking countries, such as New Zealand and the United States, occupy the bottom-left quadrant, characterized by both low UI benefits and

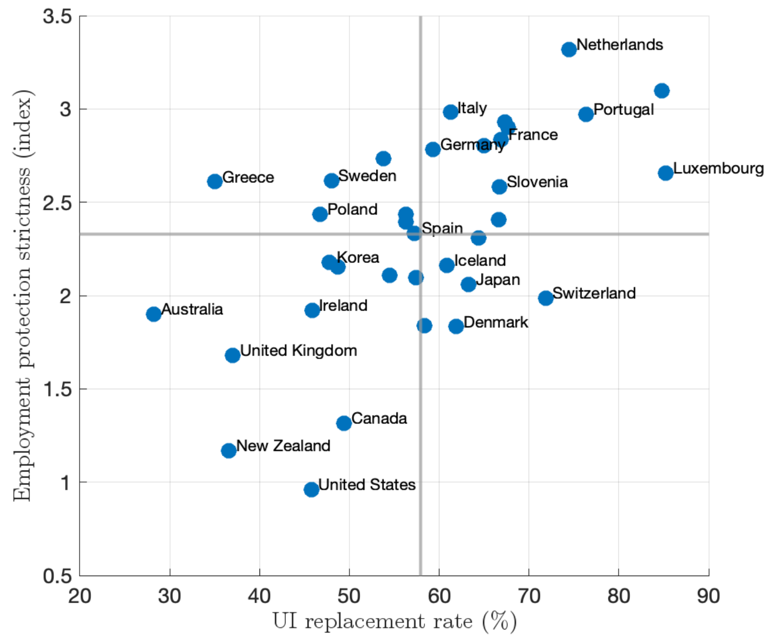
[19] The OECD employment protection strictness index assesses job dismissal regulations in terms of procedural requirements prior to notification, notice periods and severance pay, and regulations and enforcement for unfair dismissals OECD (2020).

Figure 8: Effect of the Gig Economy on Welfare



less stringent employment protection. The baseline calibration of the model in this study, which aligns with U.S. data, reflects a low to medium level of UI replacement and the least strict employment protection.

Figure 9: UI Benefits and Firing Restrictions



Note: The figure illustrates the relationship between UI replacement rates and employment protection strictness, categorizing countries into four quadrants based on these metrics.

6.1 Unemployment Insurance

I analyze deviations from the baseline UI replacement rate (45% for the U.S.) to explore alternative scenarios: a lower rate of 30%, a slightly higher rate of 50%, and a higher rate of 80%. UI provides essential support for individuals facing income fluctuations due to job loss, aiding in consumption smoothing while unemployed. However, it can also raise the reservation wage, potentially discouraging job search efforts. Increased wage demands stemming from a strengthened bargaining position for workers may hinder job creation by firms. While literature presents various solutions for determining the optimal UI benefit level, models incorporating search and matching frictions and incomplete asset markets, such as those by Krusell et al. (2010), suggest that the negative impacts of reduced employment outweigh the positive effects of UI as a safety net.

Table 11 presents the findings. The results indicate that, regardless of the presence of gig employment, reducing UI leads to lower unemployment rates and higher aggregate welfare, primarily due to an increase in job vacancies. For instance, when the replacement rate decreases to 30%, the unemployment rate drops from 6.3% to 5.7%, yielding a 0.13% increase in aggregate welfare in the pre-gig model. Similarly, in the gig model, the unemployment rate decreases from 4.6% to 4.0%, resulting in a 0.11% welfare gain. These findings are consistent with Krusell et al. (2010). The positive effects of UI reductions are less pronounced for low-skilled and asset-poor groups, adversely impacting the welfare of those receiving UI benefits, reflecting a redistributive effect as noted by Mukoyama (2013). Traditional self-employment declines with less generous UI benefits, as unemployed individuals are less likely to pursue self-employment when more job openings in paid employment are available, as indicated by Garcia and Hansch (2021).

When considering heterogeneous types of self-employment, a notable difference emerges: the welfare costs associated with generous UI benefits can be more pronounced within a gig economy context. For example, increasing the UI replacement rate to 80% results in a welfare loss of 0.58% in the pre-gig model, compared to 0.80% in the gig economy. This discrepancy arises from the shared characteristics of unemployed and gig-employed individuals, who tend to be low-skilled and asset-poor, acting as substitutes for one another. Consequently, changes in UI benefits influence the size of unemployment and gig employment in opposing directions. As UI benefits rise, non-paid workers may opt for unemployment while searching for paid jobs and receiving UI benefits instead of engaging in gig work, even in the face of fewer job openings. This behavior contrasts with traditional self-employment, which is predominantly chosen by higher-skilled and wealthier individuals. Thus, the additional insurance effects from generous UI benefits are offset by the diminished insurance effects due to a reduced size of gig employment, resulting in more severe overall negative effects.

6.2 Firing Restrictions

Table 12 presents the effects of varying firing costs—expressed as percentages of monthly wages for the lowest productivity—on labor market outcomes and welfare measures in both pre-gig and gig economy scenarios. Increasing firing costs have a limited impact on the unemployment rate, as they deter dismissals while simultaneously reducing job vacancies. When firing costs increase from 0 to 50% of monthly wage, the unemployment rate increases 0.1 percentage point (6.3% to 6.4%) in the pre-gig scenario, and decrease 0.1 percentage point (4.6% to 4.5%) in the gig scenario. Although the number of individuals receiving

Table 11: Effects of UI policy

Replacement Rate (%)	Pre-Gig model 30	Pre-Gig model 45 (Base)	Pre-Gig model 50	Pre-Gig model 80	Gig model 30	Gig model 45 (Base)	Gig model 50	Gig model 80
Unemployment rate	5.7	6.3	6.4	8.1	4.0	4.6	5.1	7.2
UI ineligible	1.3	1.5	1.5	2.0	0.8	0.9	1.0	1.4
UI eligible	4.4	4.8	4.9	6.1	3.2	3.7	4.1	5.9
Paid Employment	83.4	82.8	82.6	80.5	81.4	81.2	80.9	79.0
Self-employment	10.8	10.9	11.0	11.4	8.0	8.6	8.8	9.7
Gig Employment	0.0	0.0	0.0	0.0	6.6	5.6	5.2	4.0
Job separation rate	4.2	4.5	4.5	5.3	3.9	4.1	4.3	5.2
Job finding rate	46.9	45.0	44.5	41.5	48.0	46.2	45.4	41.9
Vacancies (base =100)	111.0	100.0	96.5	87.8	111.2	100.0	98.4	89.6
Aggregate Welfare	0.13	0.00	-0.03	-0.58	0.11	0.00	-0.11	-0.80
Low-skilled	0.09	0.00	-0.01	-0.46	0.07	0.00	-0.10	-0.71
Asset poor	0.09	0.00	-0.02	-0.53	0.06	0.00	-0.10	-0.78
U_1 & poor	-0.03	0.00	0.03	-0.27	-0.09	0.00	-0.07	-0.54

Note: All values except Welfare are in percentage points or indexed at 100. Welfare is measured in terms of consumption equivalent.

unemployment insurance (UI) decreases due to fewer firings by corporate firms, the pool of UI-ineligible individuals grows as reemployment becomes more challenging.

The welfare effects present two opposing forces. On one hand, higher firing costs lower the productivity threshold at which firms dismiss employees, leading to a decreased separation rate as firms are less likely to fire lower productivity workers. This retention allows low-skilled workers to keep their jobs. Conversely, higher firing costs diminish firms' expected returns on vacancies, since every filled position now entails the burden of potential future dismissal costs. Weaker bargaining power for firms can also lead to increased wages, further reducing the attractiveness of posting vacancies. Consequently, this situation results in fewer job openings, decreasing the probability of job seekers finding employment. Here, the negative effect of reduced job creation predominates, leading to a decline in welfare as firing costs increase, applicable to both pre-gig and gig economy contexts. This aligns with findings in the literature using incomplete market setups with search and matching frictions, such as Lalé (2019) and Näf et al. (2022), and others, where higher employment protection lead to increased unemployment and less job creation.

Traditional self-employment tends to rise when reemployment opportunities diminish, as individuals seek alternative income sources. Unlike generous UI benefits, which also correlate with smaller job vacancies, gig employment increases under stronger firing restrictions. This occurs because unemployed individuals without generous UI benefits are more likely to opt for gig work. The two scenarios show similar trends in unemployment and welfare; however, the composition within self-employment varies. Traditional self-employment increases less in the gig model than in the pre-gig model, as individuals with lower assets and skills tend to prefer gig work over traditional self-employment. The insurance effects of the gig economy partially mitigate the welfare costs of firing restrictions: when firing costs increase to 50% of monthly wages, aggregate welfare decreases by 0.54% in the pre-gig model but only by 0.41% in the gig model.

Table 12: Effects of Firing Costs

	Pre-Gig Model				Gig Model			
Firing Cost (% of Monthly Wage)	**0 (Base)**	**10**	**30**	**50**	**0 (Base)**	**10**	**30**	**50**
Unemployment Rate	6.3	6.2	6.4	6.4	4.6	4.6	4.6	4.5
UI Ineligible	1.5	1.5	1.7	1.9	0.9	0.9	1.0	1.1
UI Eligible	4.8	4.7	4.7	4.5	3.7	3.7	3.6	3.5
Paid Employment	82.8	82.3	80.7	79.2	81.2	80.8	79.9	78.4
Self-employment	10.9	11.5	13.0	14.5	8.6	8.9	9.5	10.4
Gig Employment	0.0	0.0	0.0	0.0	5.6	5.7	6.0	6.7
Job Separation Rate	4.5	4.2	4.0	3.7	4.1	3.9	3.6	3.4
Job Finding Rate	45.0	43.5	40.1	37.1	46.2	44.6	41.5	38.4
Vacancies (base =100)	100.0	83.6	58.6	41.0	100.0	84.3	60.1	42.4
Aggregate Welfare	0.00	-0.06	-0.31	-0.54	0.00	-0.06	-0.21	-0.41
Low Skilled	0.00	-0.09	-0.42	-0.72	0.00	-0.09	-0.30	-0.56
Asset Poor	0.00	-0.09	-0.41	-0.71	0.00	-0.09	-0.30	-0.55
U_1 & low-skilled	0.00	-0.14	-0.60	-1.04	0.00	-0.15	-0.51	-0.92
E & low-skilled	0.00	-0.09	-0.40	-0.70	0.00	-0.08	-0.29	-0.54

6.3 Labor Market Reform

Overly stringent labor market regulations have been identified as a significant factor contributing to poor job creation and high unemployment rates, particularly in many European countries (Cacciatore and Fiori, 2016). In response, international institutions such as the OECD have called for labor market reforms aimed at enhancing flexibility. These reforms may include easing hiring and dismissal regulations for regular workers and increasing the incentives for the non-employed to find jobs by reducing the level or duration of unemployment benefits (Boeri et al., 2015).[20]

In this section, I revisit these flexibility-enhancing labor market reforms, or deregulation, by evaluating their welfare effects while considering heterogeneous self-employment. I assume two hypothetical countries: one with a high level of regulations (such as the Netherlands and Portugal) and another with a mid-level of regulations (such as Spain and South Korea).

[20] In the aftermath of the global financial crisis, several countries—including Greece and Portugal—relaxed strict dismissal regulations for regular workers (OECD, 2020).

For the high-regulation scenario, I set firing costs (F) at 50% and the UI replacement rate at 80%, while for the mid-regulation scenario, I set F at 30% and the UI replacement rate at 50%. I compare the labor market responses and welfare outcomes when the strictness of regulations is reduced. In the high-regulation case, I decrease the parameters to mid-level regulations (from F=50% and UI=80% to F=30% and UI=50%), and for the mid-level case, I further reduce them to lower levels (from F=30% and UI=50% to F=0% and UI=30%), akin to countries like the U.S. and New Zealand. This analysis utilizes both the pre-gig and gig models to compare the results, as presented in Table 13.

The analysis reveals that in the high-regulation case, unemployment rates decrease, and paid employment increases significantly due to increased job creation and higher job finding rates. Aggregate welfare also rises with the improved labor market conditions. Traditional self-employment declines as workers shift toward more stable employment opportunities. These effects are particularly pronounced in the gig model. With the gig work option, as UI benefits become less generous, a greater proportion of UI-receiving unemployed individuals transition into gig employment. This is evident in Table 13, where the UI-eligible unemployment rate decreases by 1 percentage point in the gig model, compared to a reduction of just 0.5 percentage points in the pre-gig model. This shift is especially significant for low-skilled individuals, where gig density is high, as illustrated in Figure 10. Thus, the welfare effects from gig employment contribute to a larger overall welfare benefit of deregulation.

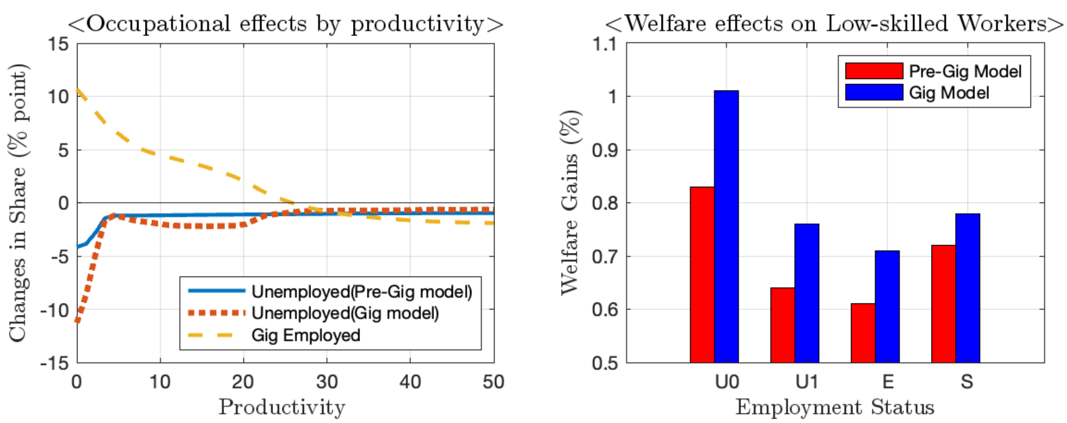
In contrast, the mid-regulation scenario exhibited smaller effects than the high-regulation scenario. The decrease in the unemployment rate and the associated welfare gains were more modest in both the pre-gig and gig models. This is primarily due to the fact that as firing costs are eliminated, firms find it easier to dismiss low-productivity employees. Moreover, as UI benefits are reduced to a minimal level, their insurance effects diminish. With the gig economy, the welfare gains are even smaller than in the pre-gig model. When gig work options are available, lower UI benefits prompt non-employed workers to opt for gig work for immediate earnings rather than engaging in job searches. This behavior results in a smaller increase in paid employment, which could potentially lead to higher earnings in the future. Consequently, output per worker declines as the low-productivity gig sector begins to replace higher-productivity paid employment opportunities. This negative effect is less pronounced in the pre-gig model, where UI-receiving low-skilled workers are largely limited to entering traditional self-employment, which typically requires substantial assets to start, thus benefiting from the greater opportunity to transition into paid employment.

Table 13: Effects of Labor Market Reforms on Employment and Welfare

	Case 1: High F, High UI		Case 2: Mid F, Mid UI	
	Pre-Gig Model	Gig Model	Pre-Gig Model	Gig Model
Unemployment Rate	-1.2	-1.4	-0.8	-0.8
UI Ineligible	-0.6	-0.4	-0.5	-0.3
UI Eligible	-0.5	-1.0	-0.3	-0.5
Paid Employment	3.1	3.4	3.0	1.6
Self-Employment	-1.9	-2.3	-2.2	-1.7
Gig Employment	-	0.3	-	0.9
Job Finding Rate	6.1	6.8	7.4	7.1
Vacancies	80.5	85.5	99.8	92.7
Aggregate Welfare	0.67	0.74	0.49	0.37
Aggregate Consumption	0.97	1.19	0.37	0.27
Output per Worker	0.16	0.24	0.12	-0.05

Note: Each cell represents the change in the variable value compared to before the reform was implemented. The top panel variables are expressed in percentage point changes, while the bottom panel shows percentage changes.

Figure 10: Effects of deregulation by productivity, high-regulation case



7 Conclusion

This paper explores self-employment in a frictional labor market, focusing on the gig economy as a novel form of self-employment. Using a quantitative model that captures employment transitions and labor market dynamics, I illustrate how gig work helps mitigate labor market risks, especially for low-skilled individuals with limited assets. The model is calibrated to address the challenges posed by the limited data on the gig economy, employing a two-step process that integrates traditional and gig self-employment.

The introduction of gig employment reduces the unemployment rate and traditional subsistence self-employment but adversely affects job creation in paid employment and overall productivity. Adding gig work options to the economy improves overall welfare through its insurance benefits and wage increases, with the extent of these gains varying among demographic groups.

The effects of labor market policies—specifically unemployment insurance and firing restrictions—are altered by the interplay with the gig economy. Generous unemployment benefits may discourage gig work participation, potentially leading to greater welfare losses than an economy without gig opportunities. In contrast, stringent firing restrictions, which might impose welfare costs by reducing job creation, could be partially offset by the gig economy, as more job seekers turn to gig work for additional income. This suggests that policymakers should consider the unique characteristics of the gig economy when designing labor market regulations.

Despite these insights, further research is necessary to address various policy issues and the evolving labor market environment. One example is recent movements to classify gig workers as dependent employees, allowing them access to unemployment insurance and healthcare protections.[21] While such policies may attract more individuals to gig work, they could also negatively impact labor market flexibility and job creation.

[21] The EU's Platform Workers Directive 2024 seeks to enhance protections for gig workers by presuming their employment status and providing workers' rights, and the UK's Supreme Court ruling in 2021 classified Uber drivers as workers entitled to minimum wage and holiday pay.

References

Abraham, K. G., Haltiwanger, J. C., et al. (2021). Reconciling survey and administrative measures of self-employment. *Journal of Labor Economics*, *39*(4), 825–860.

Aiyagari, S. R. (1994). Uninsured idiosyncratic risk and aggregate saving. *The Quarterly Journal of Economics*, *109*(3), 659–684.

Alvarez, F., & Veracierto, M. (2001). Severance payments in an economy with frictions. *Journal of Monetary Economics*, *47*(3), 477–498.

Attanasio, O. P., Banks, J., Meghir, C., & Weber, G. (1999). Humps and bumps in lifetime consumption. *Journal of Business & Economic Statistics*, *17*(1), 22–35.

Audoly, R. (2024). Self-employment and labor market risks. *International Economic Review*.

Baily, M. N. (1978). Some aspects of optimal unemployment insurance. *Journal of Public Economics*, *10*(3), 379–402.

Bardóczy, B. (2017). Labor-market matching with precautionary savings.

Boeri, T., Cahuc, P., & Zylberberg, A. (2015). The costs of flexibility-enhancing structural reforms: A literature review.

Boeri, T., Giupponi, G., Krueger, A. B., & Machin, S. (2020). Solo self-employment and alternative work arrangements: A cross-country perspective on the changing composition of jobs. *Journal of Economic Perspectives*, *34*(1), 170–195.

Bracha, A., & Burke, M. A. (2021). How big is the gig? the extensive margin, the intensive margin, and the hidden margin. *Labour Economics*, *69*, 101974.

Bracha, A., & Burke, M. A. (2023). *Informal work and official employment statistics: What's missing?*

Cacciatore, M., & Fiori, G. (2016). The macroeconomic effects of goods and labor markets deregulation. *Review of Economic Dynamics*, *20*, 1–24.

Cagetti, M., & De Nardi, M. (2006). Entrepreneurship, frictions, and wealth. *Journal of Political Economy*, *114*(5), 835–870.

Chen, M. K., Chevalier, J. A., Rossi, P. E., & Oehlsen, E. (2019). The value of flexible work: Evidence from uber drivers. *Journal of Political Economy*, *127*(6), 2735–2794.

Chetty, R. (2006). A general formula for the optimal level of social insurance. *Journal of Public Economics*, *90*(10-11), 1879–1901.

Choi, K. (2023). Macroeconomic effects of the rise of the "gig economy". *Working Paper*.

Cozzi, M., & Fella, G. (2016). Job displacement risk and severance pay. *Journal of Monetary Economics*, *84*, 166–181.

Cramer, J., Krueger, A. B., et al. (2016). Disruptive change in the taxi business: The case of uber. *American Economic Review*, *106*(5), 177–182.

Floden, M., & Lindé, J. (2001). Idiosyncratic risk in the united states and sweden: Is there a role for government insurance? *Review of Economic Dynamics*, *4*(2), 406–437.

Garcia, S. C., & Hansch, M. (2021). The effect of unemployment insurance benefits on (self-)employment: Two sides of the same coin?

Garcia-Cabo, J., & Madera, R. (2019, November). *The self-employment option in rigid labor markets: An empirical investigation* (No. 1264).

Garin, A., Jackson, E., & Koustas, D. (2024, April). *New gig work or changes in reporting? understanding self-employment trends in tax data* (Working Paper No. 32368). National Bureau of Economic Research.

Henley, A. (2023). Is rising self-employment associated with material deprivation in the uk? *Work, Employment and Society*, *37*(5), 1395–1418.

Herreño, J., & Ocampo, S. (2023). The macroeconomic consequences of subsistence self-employment. *Journal of Monetary Economics*, *20*, xx–xx.

Hopenhayn, H., & Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. *The Journal of Political Economy*, *101*(5), 915–938.

Humphries, J. E. (2021). *The Causes and Consequences of Self-Employment over the Life Cycle.*

Jackson, E. (2022). Availability of the Gig Economy and Long Run Labor Supply Effects for the Unemployed. *Working Paper*, (November), 74.

Koustas, D. K. (2018). Consumption Insurance and Multiple Jobs: Evidence from Rideshare Drivers. *Working Paper.*

Krusell, P., Mukoyama, T., & Şahin, A. (2010). Labour-market matching with precautionary savings and aggregate fluctuations. *The Review of Economic Studies*, *77*(4), 1477–1507.

Lalé, E. (2019). Labor-market frictions, incomplete insurance, and severance payments. *Review of Economic Dynamics*, *31*, 411–435.

Lazear, E. P. (1990). Job security provisions and employment. *The Quarterly Journal of Economics*, *105*, 699–726.

Lee, Y. (2021). *Excessive firm turnover in the shadow of unemployment* [Unpublished manuscript].

Levine, R., & Rubinstein, Y. (2017). Smart and illicit: Who becomes an entrepreneur and do they earn more? *The Quarterly Journal of Economics*, *132*(2), 963–1018.

Lucas, R. E. (1978). On the size distribution of business firms. *The Bell Journal of Economics*, *9*(2), 508–522.

Midrigan, V., & Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review*, *104*(2), 422–458.

Mishel, L. (2018). Uber and the labor market: Uber drivers' compensation, wages, and the scale of uber and the gig economy.

Mortensen, D., & Pissarides, C. A. (1994). Job creation and job destruction in the theory of unemployment. *Review of Economic Studies*, *61*(3), 397–415.

Mukoyama, T. (2013). Understanding the welfare effects of unemployment insurance policy in general equilibrium. *Journal of Macroeconomics*, *38*, 347–368.

Näf, A., Stucki, Y., & Thomet, J. (2022). The effects of firing costs on labour market dynamics. *Economica*, *89*, 461–488.

OECD. (2020). *Oecd employment outlook 2020.*

OECD, ILO, and EU. (2023). *Handbook on measuring digital platform employment and work.*

Pesole, A., Brancati, M. U., Macias, E. F., Biagi, F., & Vazquez, I. G. (2018). Platform workers in europe: Evidence from the colleem survey.

Poschke, M. (2013). Who becomes an entrepreneur? labor market prospects and occupational choice. *Journal of Economic Dynamics and Control*, *37*(3), 693–710.

Poschke, M. (2024). Wage employment, unemployment and self-employment across countries. *Journal of Monetary Economics*, 103684.

Quadrini, V. (2000). Entrepreneurship, Saving, and Social Mobility. *Review of Economic Dynamics*, *3*(1), 1–40.

Setty, O., & Yedid-Levi, Y. (2021). On the provision of unemployment insurance when workers are ex-ante heterogeneous. *Journal of the European Economic Association*, *19*(1), 664–706.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, *95*(1), 25–49.