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Job Finding Rate and Female Labor Supply- A Heterogeneity Perspective: Evidence from Pakistan

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Abstract

The notion of job finding rate (JFR) is important in modern labor economics since it describes the job search and assesses the labor market's employment potential. In light of this, economists have lately begun to track labor movements between three states: employment, unemployment, and inactivity. The study uses cross-sectional data from the PSLM for the year 2013-14 to calculate female labor supply (FLS) in Pakistan, taking into account labor market flows and JFRs. The study's main goal is to include heterogeneity into the FLS model. As a result, the study assesses FLS, contemplating endogenous household JFRs as well as female non-participation. It includes both theoretical and empirical analyses to demonstrate how the job search rate impacts FLS. In this research, a divergent set of control variables has been added to capture the composition and dispersion effects of the labor market. The major result emphasizes the importance of adding the inactive group when determining the rate of job search and the unobserved variability of female decision-making. If this isn't done, the relevance of other factors influencing aggregate participation and unemployment rates will be skewed. The findings suggest that policymakers examine the relevant flows in order to promote woman employment in the country.

Keywords: PSLM, Job finding rate, inactivity, female labor force participation (FLFP), heterogeneity.
JEL Codes: B54, E24, J21, J64

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1 Introduction

The conventional definition of JFR is the chance of a job seeker finding work in a certain amount of time (Hall & Schulhofer-Wohl, 2018). It is a crucial topic in understanding labor market turnover because changes in the JFR have a mechanical impact on aggregate contribution and unemployment rates. This link is further supported by the compositional heterogeneity and dispersion effect (Barnichon & Figura, 2015). The non-employed pool is traditionally defined by the former heterogeneity, which occurs as individual traits change over time, making job search more or less likely. The latter results from labor market dispersion, which occurs when a tight labor market coexists with a slack labor market. In this sense, heterogeneity is important for a better job search and accurate assessment of workers' employment prospects.

Despite the fact that there is a strong link between JFR and participation in the labor force, research on assessing and analyzing JFR is yet in its early stages, and the difference between modern and old approaches still persists. For the calculation of the JFR, classic search models solely use flows linked to unemployment and employment. As a result, a large body of literature distinguishes between job searchers and inactive segments, as the former serves as the primary predictor of the unemployed pool. However, according to recent studies, the possibility of inactive people finding work cannot be ruled out. This means that new workflows can be filled not just by the unemployed, but also by the inactive population (Sedlacek, 2016). As a result, search models attempting to explain employment patterns should take into account changes in the labor market caused by inactivity movements (Choi et al., 2012). This has given us a starting point for our research.

Another viable justification for this research is the fact that FLFP in Pakistan has numerous distinguishing characteristics. According to a recent study from Pakistan's Labor Force Survey (LFS), females have a crude participation rate of 14.5 percent, while males have a rate of 48.3 percent. In the year 2107- 18, the refined rates showed the same scenario, with females accounting for 20.1 percent and men accounting for

60.8 percent. Despite the fact that females account for 49.2% of the overall population, the employment rate for females has been falling in recent years (Pakistan Economic Survey, 2018-19). In addition, women had a greater unemployment rate (8.3%) than males (5.1%) in 2017-18 (LFS, 2017-18). Overall, falling participation rates and ambiguous unemployment rates for women show that female involvement in the labor market is still insufficient. The causes of this problem have yet to be determined. As a result, despite its vast scope, the notion of determining FLS in Pakistan remains an academic curiosity.

As a result, concerns about quantifying the job search rate and falling FLFP in Pakistan have led to the creation of this research. This research aims to calculate Pakistan's FLS, with the goal of including an endogenous JFR in the labor supply model. This research also employed a unique set of independent variables that took into account compositional variability and dispersion effects. Furthermore, the study's concept is based on the possible benefits offered by search models of job-seeking by Kudlyak and Lange (2017) and Choi et al. (2012).

The following is the outline of the paper. Section 2 compares and contrasts different search theories in order to explain the traditional and relevant theoretical models of job seeking in the labor market. Section 3 looks at a variety of research on unemployment and employment, both on a global and national scale. The conceptual viewpoint for the study's empirical model has been enhanced as a result of this review. Section 4 lays out the study's conceptual framework and methodology discussing extraction of worker flows, and JFR calculation using other pertinent variables' data. The major results are presented in Section 5, and the conclusion is presented in Section 6.

2 The Study's Theoretical Background

The Basic Search Model starts with a discrete-time0 design in which a person looks for a job under certain market conditions. This model presupposes a frictionless job market in which a worker may accept work at the given salary right away. The loosening of such severe norms allows search models to make diverse predictions regarding salaries and unemployment.

The equilibrium models of unemployment are believed to start with Stigler's (1961) Simple Model of Job Search. He developed a static model and worked through economic issues to demonstrate certain key elements of economic organization, resulting in a novel job search implication. Furthermore, McCall (1970), Mortensen (1970), and Gronau (1971) were the first to propose the Sequential Search Theory. These fundamental search models, on the other hand, are unable to address a variety of labor market challenges such as worker transitions, estimating unemployment length, determining reservation wages, and so on.

The Worker Turnover Model, on the surface, seems to generalize the flow of people from employment to unemployment. When examining salaries, tenure, and separation rates, the model assumes certain exogenous reasons for transitioning to unemployment. It is predicated on the fact that a worker would stay in a job for a long period before finding a better one.

Pissarides (1985, 2000) used Random Matching in search to define employment entrance rates, salaries, and match creation and destruction, i.e., Matching Technology, spawned a prominent area of research. This technology is meant to represent the fundamental idea that in the labor market, companies and employees take time to get to know one another. This is a similar concept from the production function, which states that output is a function of capital and labor. By addressing the decision-making of companies (which is endogenous) to publish a job with a requirement of free entrance, the concepts of matching and bargaining are integrated. The Single Agent Model, on the other hand, indicates that growth in unemployment benefits leads employees to increase reserve wages, reducing search intensity (Rogerson et al., 2005).

Mortensen and Pissarides (1994) utilized an endogenous job separation rate that took into account on-the-job pay changes. Endogenous flows into and out of unemployment were captured by the authors' paradigm. Although these flows change over time from nation to country, this allows one to analyze the reasons that contribute to these variances. Shimer (2005) used and extended this paradigm. In this literature, there is also a component that introduces heterogeneous companies and workers. Shimer and Smith (2000), Mortensen and Pissarides (1999), and Acemoglu (2001) are examples of these investigations. Caballero and Hammour (1996) and Barlevy (2002) investigated the ramifications of this concept.

The Dynamic Search Model is a one-of-a-kind solution. It enables jobless employees to forecast their pay and the unemployment-to-vacancy ratio. According to the concept, a surge of unemployment layoffs allows a worker to take a risk in exchange for greater compensation. As a result, businesses wind up providing higher pay but fewer jobs. It primarily clarifies the matching procedure and wages setting. The inadequacy of Dynamic Models to describe why employees do not negotiate for various wages with firms in a decentralized market is a possible disadvantage (Rogerson et al., 2005). As a result, Shimer (2008) presented and modified the dynamic search model, including the addition of heterogeneity to account for pay disparity among heterogeneous employees.

The Random Matching and Posting Theories of search are combined in the Modern Theory of Wage Dispersion. This pay theory's philosophy aims to comprehend the role of worker heterogeneity in the search process. In this context, two dispersion models based on job search and worker heterogeneity have been suggested (Rogerson et al., 2005). The On-the-Job-Search Model accounts for pay while ignoring employment histories, whereas heterogeneous models address worker employment histories while ignoring wage. As demonstrated by Bontemps et al. (1999), an integrated model may account for both viewpoints, and hence the field offers the prospective for theoretical and empirical study.

Based on the theories presented in this part, it is clear that different search models highlight distinct constraints, but there is no one canonical model that addresses all job-search difficulties. Thus, in section 4, the framework for this research is constructed by analyzing commonalities of various search models with the help of a complete literature survey, but with a few fundamental differences. In the next part, we will examine relevant research that has been evaluated to include relevant aspects that may be used for the empirical estimate.

3 Review of Related Research

Hall and Schulhofer-Wohl (2018) calculated matching efficiency with heterogeneous job searchers using sixteen labor-market statuses. The authors used the CPS and the JOLTS to create an efficiency index for each category of job seeker from 1999 to 2015, and then used a fractional logit model to calculate monthly JFRs. Furthermore, dummy factors were used to adjust these rates for overall labor market tightness. From 2001 to 2013, the research found an overall drop in matching efficiency, and it concluded that ignoring heterogeneity among job searchers.

Kudlyak and Lange (2017) divided the labor market into three labor force statuses (LFS), observing individual histories and JFRs heterogeneity. The sample is made up of four-month longitudinal panels from the Current Population Survey (CPS) for the years 1994 to 2016, using a linear probability model including gender, age, education, and race. The research offered a novel strategy for employed, including the jobless and the inactive. Inactive people had a better probability of getting a job than job seekers, according to the findings.

Sedlacek (2016) used data from the CPS and the JOLTS from December 2000 to June 2013. While evaluating job searchers from employment, unemployment, and inactivity, the author used the Variable approach to estimate an aggregate matching function (that links new hires, job vacancies, and job seekers). The author discovered that employment and inactivity flow filled the US labor market. Importantly, in empirical studies of the US labor market, the unobserved group of inactive persons was frequently overlooked.

Bachmann et al. (2015) analyzed labor market movements in a wide number of European nations using microdata. Using a multinomial logit model, the research explored how these flows were influenced by the recent financial and economic crisis during its early stages, from 2008 to 2010. Before the crisis, females experienced greater unemployment inflows than males, according to the authors, but this disparity was sharply reversed in 2008. The research found that the crisis had varied effects on different age groups, and that these heterogeneities were to blame for the labor market's development.

Barnichon and Figura (2015) presented a two-stage estimate technique using matching technology in the expanded version. Stage 1 calculated JFRs for various market groups using microdata from CPS to reflect the influence of worker attributes. To compute the matching function elasticity during the period 1976–2007, the second stage combined the first stage data with the Help Wanted Online (HWOL) data. Over the period 1976–2012, the results revealed that heterogeneous labor and labor market segmentation increased the aggregate JFR. The authors claimed that worker heterogeneity and labor markets are important aspects of unemployment variations.

Through field research in Multan's districts, Faridi and Rashid (2014) investigated the variables influencing the decision to work for an educated woman. However, factors such as geography, being a married educated woman, having an educated father, the status of work of her husband as well as income, district headquarters' distance from the house, as well as ownership of assets were all factors that reduced FLFP.

Bashir et al. (2013) conducted a survey in Bahawalnagar's district to determine the reasons for unemployment among Bahawalnagar's educated young. The authors were concerned about the importance of technical education for women because it was marginally significant, with a negative coefficient for educated but jobless women.

Shimer (2012) re-examined the ins and outs of unemployment in the United States, calculating job-finding and job-exit probability from 1948 to 2010. Shimer discovered that finding probability is more important than job exit probabilities in explaining unemployment swings, and hence the latter probabilities are quantitatively unimportant.

Choi et al. (2012) used monthly CPS data to track worker movement span from January 1976 to July 2010. they separated samples of females and males. These researchers calculated life-cycle probabilities by adjusting for age, gender, and race while considering the three labor market conditions. To estimate the profiles, the Seemingly Unrelated Regressions (SUR) technique was used, which included equations for unemployment and participation rates. The research's major result is that inactivity is an important component that should be incorporated in classic search models.

Ejaz (2011) utilized IV regression utilizing PSLM data for the year 2006-07 to estimate the supply of female labor in Pakistan's rural and urban districts. FLS and birth rate, as well as pay disparities, were found to have an indirect and statistically significant link. On the other hand, a direct link was found between FLS and a number of factors including the usage of appliances, domestic labor, asset ownership, and the joint family arrangement.

Using logistic regression analysis, Ahmad and Azim (2010) calculated youth employment probability. To integrate the heterogeneity prognosis for Pakistan, the author used microdata from the LFS 2006-07. Gender, age, marital status, training, education level, migration, geography, and family factors were all shown to be substantially linked with young employment in Pakistan. Furthermore, under Pakistan's labor employment regulations, the variety of jobless individuals must be taken into account.

For the period 1993-2003, Fabrizi and Mussida (2009) used a Markov chain method using a multinomial logit model. The authors looked at the movement of workers between employment, unemployment, and idleness. In light of the current situation of unemployment, the research discovered that male employees transitioned from unemployment to employment more quickly than female job seekers. Furthermore, due to the possibility of a discouragement impact, female employees were more likely to become inactive after experiencing unemployment.

Da Rocha and Fuster (2006) created a model to link female work involvement with fertility preferences using survey data from the Panel Research on Income Dynamics (PSID) from 1972 to 1993. The authors argued that during employment disruptions, females look for jobs with an exogenous likelihood and discount human capital. Females must also determine how they will divide their time among different professional and non-professional activities.

Arif et al. (2002) used longitudinal data to capture the labor market trends in Pakistan for both men and women. The author based his findings on data from two Pakistan Socio-Economic Surveys (PSES) conducted in 1998-99 and 2000-01. Through Bivariate and Logistic Regression Analysis, the findings of the research indicated that the transition from unemployment to employment was sluggish, with half of the entire jobless pool experiencing short-term unemployment. The remaining five control variables were also found to be significant. Furthermore, the findings failed to explain any differences in outcomes across male and female groups. According to the findings, labor market absorption has been declining in Pakistan over time, and policymakers should be concentrating more on labor market flows as job vacancies increase.

Arellano and Meghir (1992) devised a unique technique for developing a model for job search consistency with FLS. The Family Expenditure Survey and the UK Labor Force Survey for 1983 were merged by the authors. Age, education, demography, and income all have a significant impact on working hours, according to the findings.

A complete assessment of the emerging worldwide research on JFR focuses on altering search models, whereas national literature is primarily focused on studies on women that look at schooling and household issues.

4 Methodology

4.1 The Study's Conceptual Framework

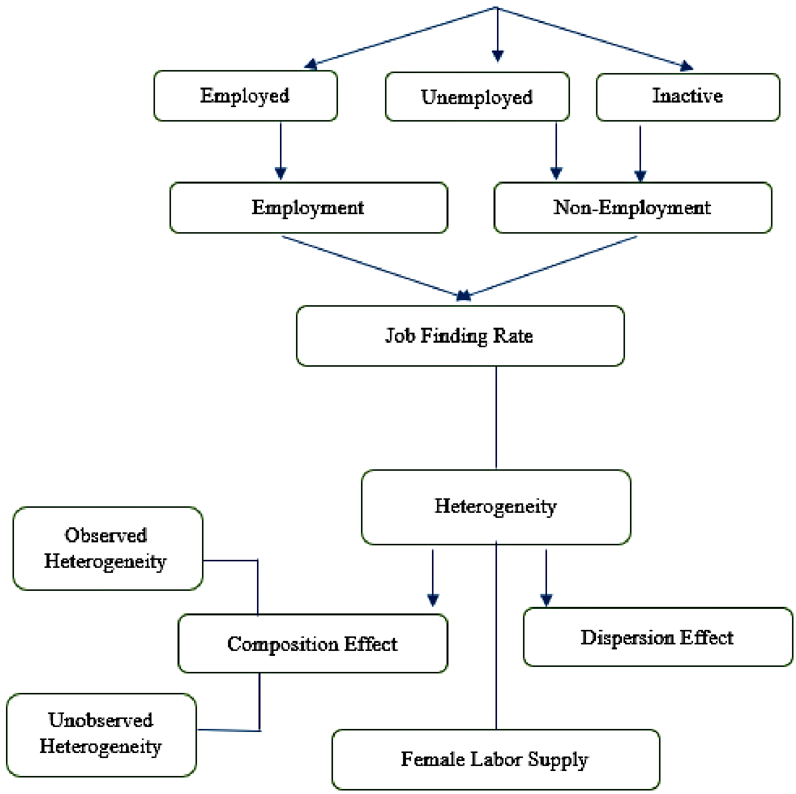
The research's conceptual model posits that the labor market is distributed differently across employed, jobless, and inactive working-age people. As a result, if a female belongs to the working-age population, her job status (past and present) should be included while observing labor market results. This concept has given rise to an intuition for calculating the JFR using female labor market flows between the three labor market states and her optimal labor market status choice. The research's concept (Figure 4.1) simply suggests that heterogeneity allows a woman to choose between working and being inactive. Furthermore, observable, and unobserved variability is linked to a female's decision to participate in the labor market. Alternatively, given the variability of composition and dispersion impact, the conceptual framework of this research gives a reasonable basis for associating the JFR with FLS.

The composition effect is used in this research to detect observable and unobserved variability by including relevant worker and family factors into the model. Females' personal and household characteristics represent observable variability, whereas female decision-making captures unobserved heterogeneity for education, employment, and non-employment.

To address labor market disruptions for women in Pakistan, the dispersion impact of the labor market has been considered. As a result, with the idea of a single market for females ruled out, geographical differences and pay disparities are critical for the research. Furthermore, the dispersion of females in the labor market provides a chance to analyze how the labor market in Pakistan supports female employees. The dispersion effect is examined in this research in relation to female location, regionalism through province status, and pay disparities. In light of these findings, it's reasonable to assume that the indirect relationship between dispersion effect and JFR is linked to ore dispersion for females, which has a direct impact on total participation rate.

In this research, a female's ideal answer is her involvement in the job market. The model's parameters show that a FLFP is influenced by the JFR. Furthermore, a woman's choice to enter the labor force will be immediate, and her labor market position will be determined by heterogeneity that varies from woman to woman, family to household, and exclusively across urban-rural and provincial labor markets.

Figure 4.1
Conceptual Framework of the Research



Source: Authors' Illustration

4.2 Data

Because this is the most recent data set, the researchers used data from the Pakistan Standard of Living Measurement (PSLM) for 2013-14 to create flows of females from the decision-making module.

The JFR is calculated using female labor market flows (aged 15 to 65 years) and results in nine female worker flows across three labor market states. To be more specific, these nine flows are computed by integrating information on a female's labor market position in a particular year, such as 2013-14, with information on her labor market status in the previous year to produce yearly flows (Bachmann et al. 2015). Mathematically, letting jf as the task flow from state to A ∈ {E, U, I} to state B ∈ {E, U, I};

$$jf = \prod \Gamma_B S_A = \begin{pmatrix} ee & eu & ei \\ ue & uu & ui \\ ie & iu & ii \end{pmatrix} \quad (1)$$

Where SA is a vector of the female's labor market state in the previous year, and B is a vector of the same female's labor market status in the observed year. Only six flows are used to compute the JFR, which is the ratio of new hires to the unemployed pool, ignoring a female's labor market persistence. Given a female's age limitation and market flow, JFR is defined as follows:

$$Job\ Finding\ Rate = New\ Hires/NonEmployed\ Pool$$

The new hire pool comprises labor market flows from unemployment and inactivity to employment (ue, ie), while the non-employed pool includes the remaining four flows (eu, ei, ui, iu) from the previous year to 2013-14. As a result, the household job-finding rate is computed as follows:

$$jfr = \sum_i^N \frac{nhi}{nei} \quad (2)$$

Table 1 has a full overview of the variables.

Table 1
Variable Descriptions for the Main Model

	Dependent Variable	
	Variable	**Description**
	Female Labor Supply **(fls)**	A ratio between total females employed and total employment
	Control Variables	
	Variable	**Description**
Women's Attributes	Age (**age**)	Respondent's age
	Experience **(exp6)**	Age - years of education -6

	Education **(hedu)**	Highest year of education of female
Labor Market Characteristics	Wage Differential **(wd)**	The difference between current year income (cyi) and previous year income (pyi) of the female respondent
	Location **(loc)**	1=Rural, 2= Urban
	Region **(reg)**	1=Khyber Pakhtunkhwa, 2=Punjab, 3= Sindh, 4= Balochistan
Household Attributes	Household head education **(hhedu)**	Highest years of education of the household head
	Family income **(fi)**	Sum of Monthly income of the family in a year
	Family size (**fsize)**	Total number of family members in the household
Endogenous Variable	Job Finding Rate **(jfr)**	A ratio between new hires to non-employed pool
Instrumental Variables	**Unobserved heterogeneity of Education (uhedu)**	The decision to get education depends on 1=female's decision, 2= female and household head combine decision and 3= household head decision
	Unobserved heterogeneity of Employment (**uhemp)**	The decision to work or search depends on 1=female's decision, 2= female and household head combine decision and 3= household head decision

	Unobserved heterogeneity of non-employed (**uhnemp)**	The decision of remaining economically inactive relies on 1= Personal attributes of female, 2= household attributes of female and 3= labor market rigidities

Source: Compiled by Authors

4.3 Estimation Strategy

4.3.1 Stage I:

The JFR is identified as endogenous in the research since it is determined by observable and unobserved heterogeneity. This enables the addition of worker and family characteristics (observed heterogeneity); female decision making (unobserved heterogeneity) aged 15 to 49; and labor market dispersion. The model for first stage estimate is shown in Equation 2.

$$jfr_i = \alpha_0 + \alpha_1 age_i + \alpha_2 exp6_i + \alpha_3 fsize_i + \alpha_4 wd_i + \alpha_5 fi_i + \alpha_6 hedu_i + \alpha_7 hhedu_i + \alpha_8 reg_i + \alpha_9 loc_i + \alpha_{10} uhedu_i + \alpha_{11} uhemp_i + \alpha_{12} uhnemp_i + \epsilon_i \quad (3)$$

In the second stage, the estimated FLS equation is utilized to determine the FLS rate.

4.3.2 Stage II:

The second step enables the job-finding rate to be linked to the FLS. Equation 3 outlines the research's formal model.

$$fls_i = \beta_0 + \beta_1 jfr_i + \beta_2 age_i + \beta_3 exp6_i + \beta_4 fsize_i + \beta_5 wd_i + \beta_6 fi_i + \beta_7 hedu_i + \beta_8 hhedu_i + \beta_9 reg_i + \beta_{10} loc_i + \varepsilon_i \quad (4)$$

Furthermore, the 2SLS approach necessitates specification checks for job discovery rate endogeneity and overidentification.

5 Results of the Estimation

5.1 FLS and JFR Coefficient Estimates

The findings of a two-stage estimate approach that explicitly took into consideration the functional connection between JFR and FLS are presented in Table 2. The positive impact of the core variable on FLS demonstrates that the movement of females into work from inactivity and unemployment improves estimates of FLS in Pakistan. This conclusion contradicts the widely held belief, which has been supported by several worldwide research, that job separation rates are more important than JFRs. Meanwhile, the results are uniform with prediction of Shimer (2012).

According to the descriptive evidence from data, 85.9% of females had converted from inactivity to employment, whereas just 7.2 percent of "New Hires" indicated transitions from unemployment to work.

Table 2

Estimates of Coefficients in Two-Step Estimation

	jfr			fls		
	Coefficient	**t value**	**P>t**	**Coefficient**	**z**	**P>z**
Jfr	-	-	-	0.036537	5.82	0.000
Age	0.0068178	3.83	0.000	0.0001665	2.35	0.019
exp6	-0.0083996	-4.74	0.000	-0.0001142	-1.54	0.125
Hedu	-0.0072395	-2.96	0.003	-4.51E-07	-0.01	0.996
Fsize	0.0133566	3.38	0.001	-0.001281	-8.51	0.000
Fi	-1.23E-06	-2.33	0.02	2.55E-08	1.45	0.146
Hhedu	0.00045	0.18	0.856	-0.0001371	-1.69	0.091
Wd	0.000014	4.93	0.000	3.20E-07	2.75	0.006
Reg						
1	-	-	-	-	-	-
2	0.0282313	0.91	0.362	-0.0008049	-0.83	0.409
3	0.1826327	4.17	0.000	-0.0009008	-0.51	0.608
4	0.0273599	0.54	0.592	-0.0047172	-3.42	0.001
Loc						
1	-	-	-	-	-	-
2	-0.1214493	-5.09	0.000	-0.0040424	-3.38	0.001
Uhedu						
1	-	-	-	-	-	-

2	-0.1072362	-1.87	0.062	-	-	-
3	-0.1043202	-2.28	0.023	-	-	-
Uhemp						
1	-	-	-	-	-	-
2	0.0836586	1.21	0.227	-	-	-
3	0.0201399	0.39	0.697	-	-	-
Uhnemp						
1	-	-	-	-	-	-
2	-0.157742	-5.95	0.000	-	-	-
3	-0.0360533	-0.97	0.331	-	-	-
_cons	0.0948105	1.15	0.248	0.0133831	6.13	0.000
Number of Observation		6144		**Number of Observation**		6144
F(17, 6126)		12.2		**Wald hi2 (12)**		473.86
Prob >F		0.000		**Prob > chi2**		0.000
R-squared		0.0552		**R-squared**		0.3482
Adj R-squared		0.0526				
Root MSE		0.9482		**Root MSE**		0.03149

Source: Estimated by Authors

When it comes to flows to "non-employment," employment to unemployment accounts for 17.87 percent of the total, whereas inactivity to unemployment accounts for 34.71 percent. Females in work to inactivity flowed at a relatively low rate (0.80 percent), while unemployment to inactivity flowed at 8.62 percent. It is important to note that the remaining proportion of flows was reduced due to the age-specific condition of females in the 15-49 age group. These findings give important information regarding the focused labor market category in Pakistan, namely the inactive females. A further segmentation of these data to define these flows according to the age of female employees would complement the research methodology. Choi et al. (2012) and a subsequent companion research by Kudlyak and Lange (2017) support these findings.

As a result, the positive and substantial relationship between JFR and FLS leads to two pathways. For starters, labor market flows are critical for assessing changes in the FLS. Second, owing to unobserved heterogeneity, the potentially important ‘inactive' portion of the labor market may change, and it is a crucial parameter for the estimation of the JFR (Jones & Riddell, 1998). As a result, a proper economic interpretation of the functional relationship between JFR and FLS necessitates a division of the overall effect into composition and dispersion effects.

5.2 Estimates of the Composition Effect Coefficients

When it comes to worker attributes, female age is found to be positively related to FLS and JFR. It is compelling because, beyond a certain age, women choose to work or look for work for a variety of reasons. To begin with, it's likely that the relevant girl had completed her studies and was now looking for work (Morikawa, 2015). Second, it is possible that a woman decides to re-enter the labor market after a period of inactivity owing to fertility and child-raising (Choi et al., 2012). Third, the "additional worker impact" occurs when a woman returns to work after a period of inactivity owing to the loss of her husband's employment and becomes the family's income earner (Mankart & Oikonomou, 2017). When a female's work experience is taken into account, the variable has a negative influence on the JFR, showing that experience gives employment security to a woman and she does not look for another job. Bashir et al. (2013), justify the negative relationship between schooling and employment. According to the authors, highly educated women choose to obtain better quality jobs with decent compensation and so continue to look for them, or they temporarily abandon the labor market or remain inactive due to discouragement. The variable, on the other hand, has no bearing on the availability of female labor in Pakistan. This conclusion contradicts Faridi and Rashid (2014), Ahmad and Azim (2010), and Kanjilal-Bhaduri and Pastore (2018).

In terms of home features, the presence of more family members stimulates a female to enter the labor market in order to improve her quality of life. In the second stage, however, the outcome might be linked to the fact that the home has a sufficient amount of money, preventing a female from entering the job market. The inverse relationship between family income and JFR suggests that higher-income households limit women's participation in-home tasks such as housework, child-raising, and so on (Albanesi and Prados, 2017; Bredtmann et al., 2017). Despite the notion that a small body of work has shown that income has a negative but considerable impact on FLS, this household variable has been proven to be negligible for FLS. According to Blau and Kahn (2007), this is attributable to improvements in female career orientation, shifting societal norms and expectations, and female job commitments. In theory, a home head with education allow female to be the part of the labor force. Above conclusion, however, is insufficient to describe the JFR. However, we discovered that household head education had a favorable and substantial influence on FLS, confirming the theoretical hypothesis.

Another reason for the disparities in JFRs between employed and unemployed people is the unobserved heterogeneity of the decision-making module. Due to familial resistance, large results of unobserved variability in education and non-employment occur (Todd, 2013). It is challenging to give labor market incentives to lure prospective females from inactivity to employment or job searching, presuming that household opposition is connected to cultural rules and male-controlled setup (Tanaka & Muzones, 2016). As a result, FLFP is restricted, making her a stigmatized portion of society. This measure is found to be negligible in explaining the JFR due to the unobserved heterogeneity of employment. Keeping this unimportant variable, however, has been evaluated to prevent omitted variable bias (Angrist & Krueger, 2001).

It's possible to view these findings as a manifestation of the prejudice that those women face at home. Despite the increasing opportunities for women to contribute financially through employment, persistent societal restrictions continue to force women to stay at home. Although it is true that girls have greater difficulty finding work than males, the patriarchal system continues to play a significant role in determining females' employment decisions in Pakistan.

5.3 Estimates of the Dispersion Effect Coefficients

Female wage differentials have a positive relationship with both the pace of job search and the supply of female labor.

This gives important insight into how a salary rise not only drives females to seek better occupations but also attracts the idle and jobless to seek higher-paying positions. This might also be a sign of improved labor market results for women, such as higher-paying employment and more flexible work schedules. According to the results of the regional dummy for JFR and FLS, a tight labor market may coexist with a slack labor market (Barnichon & Figura, 2015). According to the results of the location dummy, females in urban areas have a harder time finding work owing to unfavorable associations. This is due to rural-urban migration, which has created a demand-supply imbalance, placing pressure on urban labor markets (Zulifquar & Chaudhary, 2007). This might also be attributed to a shift in female employment patterns away from agriculture and toward non-agricultural pursuits (Mustafa Kemal & Naci, 2009).

Table 3 shows the findings of the endogeneity test, whereas table 4 shows the results of the instrumental regression overidentification constraints.

Table 3
Test of Endogeneity

Test of Endogeneity		
H0: Variable is exogenous		
Robust score chi2(1)	4.42201	(p-value=0.0355
Robust Regression F (1,6130)	4.4134	(p-value=0.0357

Source: Estimated by Authors

Table 2's estimations confirmed the endogeneity of the JFR, whereas table 3 demonstrated the validity of the instrument variables included in the model.

Table 4
Over-identification Restrictions Test

Sargan Test of Over identifying Restrictions		
Score chir2 (5)	8.15511	(p-value=0.1479)

Source: Estimated by Authors

6 Conclusion

Using data from the PSLM Survey 2013-14, this research estimates female labor force supply, creating age-specific conditional streams of female employees between Pakistan's three labor market states. This approach generates a stable set of flows from which we can determine the rate of job search by age group. Differences in contribution rates can be ascribed to the migration of employees from inactive and unemployment to employment, according to estimates of JFRs. Despite the fact that two-state labor market (employment and unemployment) models may give a decent match to unemployment statistics, the research emphasizes that they are insufficient to undertake counterfactual experiments for policy analysis.

The primary result was based on the labor supply model's inclusion of inactivity, endogenous JFR, and unobserved heterogeneity. If this isn't done, other factors affecting participation and unemployment, as well as aggregate participation and unemployment rates, will be skewed. The research's findings suggest that policymakers take into account relevant flows in order to enhance female unemployment and employment rates. The implementation of such measures, rather than depending on present policies, may be more successful.

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