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Employment Dynamics by Gender in Pennsylvania since the Great Recession *

Yaya Sissoko[a] and Brian W. Sloboda[b]

[a]*Department of Economics, Indiana University of Pennsylvania, USA*
[b]*University of Maryland University College, Largo, MD, USA*

Abstract: This paper examines the effects of the Great Recession on employment by gender in Pennsylvania. Using the Quarterly Workforce Indicators (QWI) in the Longitudinal Employer-Household Dynamics (LEHD) data set from the Census Bureau, we examine the employment dynamics for Pennsylvania by gender from Q1 of 1997 to Q4 of 2013. We investigate the impacts of the Great Recession on male and female employment in the Pennsylvania economy in the manufacturing, construction, healthcare, and retail sectors by investigating the net job gains by gender using a vector error correction model (VECM).

Keywords: VECM, gender employment, Quarterly Workforce Indicators, Great Recession, Pennsylvania
JEL Codes: J16, J21, D00, C32

1. INTRODUCTION

When the Great Recession began after the Financial Crisis of 2008, Pennsylvania had a lower peak unemployment rate than the U.S. as a whole: 8.7 versus 10.0 percent. As pointed out by Hall and Greene (2013), Pennsylvania's labor market recovery has been uneven across sectors. Notably, the sectors of trade, transportation, and utilities have not fully recovered to their pre-Great Recession levels, and the construction and manufacturing sectors have 14 percent fewer jobs than before the Great Recession. On the other hand, the following sectors experienced the greatest net job gains since 2007: education and health services; leisure and hospitality; professional and business services; and mining and logging. Given these uneven improvements in the labor market across sectors in Pennsylvania, how did these changes differ between men and women? In this paper, we examine changes in the labor market for Pennsylvania by gender from 1997 through 2013. This period covers pre- and post-Great Recession years. We investigate the dynamic relationships for men and women in separate specifications to examine any changes in employment patterns between the pre- and post-Great Recession years. The focus of this paper is to analyze the long-run behavior of employment patterns of men and women in Pennsylvania via co-integration and a vector error correction model (VECM). A co-integration relationship indicates that there are no fundamental distortions of employment patterns by gender in Pennsylvania. If one is found, the detailed short-run

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Sissoko is an Associate Professor of Economics at Indiana University of Pennsylvania, Indiana, PA. Sloboda is a faculty member at the University of Maryland University College, Largo, MD. *Corresponding Author:* brian.sloboda@faculty.umuc.edu

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properties of the relationship among variables are obtained from the estimation of the VECM and analyzed.

Our paper is organized as follows. Section 2 reviews the existing literature pertaining to the LEHD model. We describe the longitudinal employer-household dynamics data analysis in Section 3, and Section 4 discusses our methodology and sources of the data. In Section 5, we discuss our empirical results. Finally, we provide concluding remarks in Section 6.

2. EXISTING RESEARCH

In the United States, the recent availability of employer-employee data has led to increased research about the labor interactions of firms and workers. The long history of the examination of worker-based data has revealed the fundamental heterogeneity of worker outcomes, even with good data on worker characteristics. Faberman (2006) compiled infrastructure files, using multiple imputation methods to impute missing data and statistical techniques to assure data quality. In addition, Faberman (2006) used statistical models to improve administrative data. He also described enhancements and limitations imposed by data and legal constraints concerning the use of the microdata. Using the QWI developed by Faberman (2006), Davis, Faberman, and Haltiwanger (2006) found that Pennsylvania's economy has been slower than the national average when recovering from the recession of 2001, even though the 2001 recession had a less severe impact on Pennsylvania than it did on the nation as a whole. In fact, some of Pennsylvania's largest sectors are still struggling to recover from this recession. The annual rate of job growth for the three largest sectors has decelerated almost 25 percent since before the recession. Such slow economic growth is preventing a more rapid recovery in Pennsylvania.

Fallick and Fleischman (2004) used the matched models of Mortensen and Pissarides (1994) to capture the dynamics of the labor market. More specifically, they followed several studies, e.g., Davis and Haltiwanger (2001), Petrongolo and Pissarides (2001), and Eriksson and Gottfries (2005), by using more recent models and data to include a role for on-the-job search. Specifically, they show that 2.6 percent of employed persons change employers each month; two -fifths of the new jobs started between 1994 and 2003. Employer-to-Employer (EE) flows are markedly pro-cyclical, with cyclicality concentrated around the recession. The EE flows did not increase as the labor market tightened in 1994-2000, but they dropped sharply as the labor market loosened from 2001 to 2003.

Abowd et al. (2005) used Davis, and Haltiwanger's (1990, 1992) approaches to study job flows in past recessions. They conclude that larger losses occurred during the most recent recession because of its jobless recovery. Since the 1991 recession, employment growth has slowed. Following the 2001 recession, job destruction returned quickly to pre-recession levels, but there was still a large decline in job creation. The results from Abowd et al. (2005) concurred with Groshen and Potter's (2003), as they showed a recovery from the 2001-2003 recession also brought no growth in jobs.

Abowd and Vilhuber (2011) developed a consistent measure of gross worker and job flow. They used gross flows of workers in and out of employment to investigate the composition of flows in nonrecessionary periods as well as in the period of the Great Recession. They also used gross flows at highly detailed geographic and demographic levels to determine if particular demographic groups are less affected by the sharp changes in gross flows during recessions.

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They found that workers with an education that is less than a high school diploma have a worker reallocation rate that is nearly twice that of workers with a bachelor's degree or higher. Also, their results suggest that worker reallocation rates are three times as large as job reallocation rates.

Schaal (2012) used a dynamic search model of heterogeneous firms with decreasing returns to labor to allow for endogenous separations, entry and exit of firms, and job-to-job transitions. His results revealed that productivity and uncertainty shocks significantly improved the ability of search models to predict output, hiring, and layoffs. The model tended to predict large fluctuations in the entry/exit dimensions. The results also showed that there is a large dispersion in wages and a realistic size-wage differential.

Hyatt and McEntarfer (2012) used linear models to demonstrate how measures of flows across jobs constructed from linked employer-employee data can shed light on employment and wage dynamics as well as provide new information about the economy. This paper also provides some new evidence on labor turnover and earnings dynamics during the Great Recession. From their assessment, a sharp drop occurred in job mobility during the Great Recession. The dramatic decrease in mobility was present across all age groups, but the largest decrease was among younger workers. In addition, they also found higher earnings penalties for job transitions with an intervening non-employment spell.

Bjelland et al. (2011) used new data sources, such as the Business Employment Dynamics (BED), the Job Openings and Labor Turnover Survey (JOLTS), and the Longitudinal Employer-Household Dynamics (LEHD), to provide a strong empirical foundation for the flow approach to labor market analysis. They found that the pace of employer-to-employer (E-to-E) flows is high, representing about 4 percent of employment and 30 percent of separations each quarter. In fact, the pace of E-to-E is highly procyclical, and it varies across the characteristics of the worker, job, and employer. Their assessment of the E-to-E suggested that for workers obtaining new jobs, these new jobs were generally better jobs. Surprisingly, they also found there are strong patterns of these E-to-E flows from industry to industry. More specifically, at least half of the workers making the E-to-E switch occurred frequently even at the highest level of aggregation of North American Industrial Classification System (NAICS) industries or one digit NAICS.

In summary, the availability of the link between employer-employee data and the availability of microdata in the U.S. has led to greater research about the labor interactions of firms and workers in U.S. labor markets. Employer-employee data, such as the LEHD and JOLTS, informs researchers about which employees are employed by which firms in a quarter and also provides some basic demographic characteristics of those employees. Consequently, these links between employers and employees allow us to follow the movement of workers between firms and in and out of the labor market over time.

3. LONGITUDINAL EMPLOYER-HOUSEHOLD DYNAMICS DATA ANALYSIS

The Quarterly Workforce Indicators (QWI) within the Longitudinal Employer–Household Dynamics (LEHD) is the data source used in this analysis. The LEHD data were created through a partnership between the Census Bureau and U.S. states to provide local labor market information and to improve the Census Bureau's economic and demographic data programs. The LEHD data are comprised of different administrative sources, primarily

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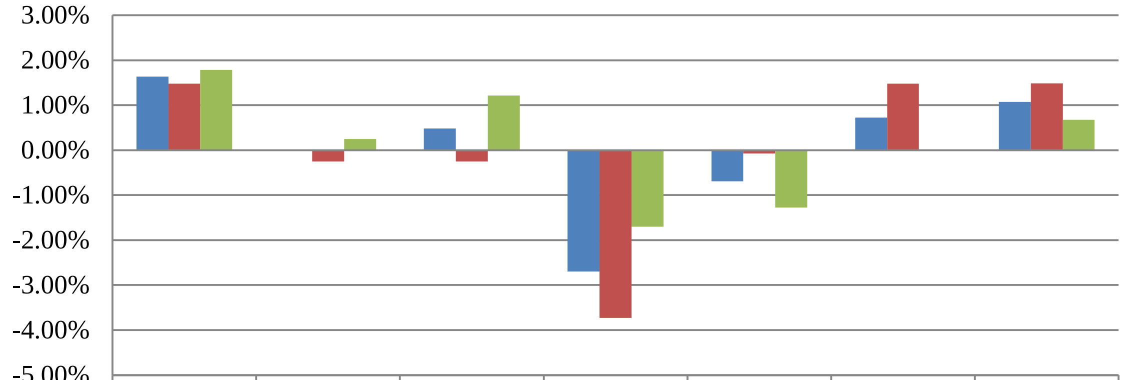
Figure 1. Year-over-Year Change in Employment, Pennsylvania



	2006	2007	2008	2009	2010	2011	2012
All Workers	1.6%	0.0%	0.5%	-2.7%	-0.7%	0.7%	1.1%
Men	1.5%	-0.3%	-0.3%	-3.7%	-0.1%	1.5%	1.5%
Women	1.8%	0.2%	1.2%	-1.7%	-1.3%	0.0%	0.7%

Unemployment Insurance (UI) earnings data and the Quarterly Census of Employment and Wages (QCEW), as well as censuses and surveys. Firm and worker information are combined to create job level quarterly earnings history data, data on where workers live and work, and data on firm characteristics such as industry.

Employment for both men and women steadily increased in 2006 in Pennsylvania, as shown in Figure 1, with small increases for women and declines for men thereafter and through 2008. As the recession deepened in 2009, both men and women experienced dramatic year-over-year job losses. Men fared far worse than women, losing 90,806 jobs (-3.7 percent) compared with the women's decline of 42,611 jobs (-1.7 percent). As the recovery began in the fourth quarter of 2009, men lost 1,752 jobs (-0.1 percent) while women experienced a decline of 31,420 jobs (-1.3 percent) in 2010. As the economy of Pennsylvania improved, modest job gains began for women through 2011, but the job gains for men were greater. In 2012, men gained 35,351 jobs (1.5 percent) while women also experienced a job gain of 16,411 jobs (0.7 percent). In 2013, men and women made more substantive job gains; men gained 52,593 jobs (2.2 percent) while women gained 68,323 jobs (2.8 percent).

4. THE METHODOLOGY AND THE DATA SOURCES

4.1 The Data Sources

The model for the net job gains by gender for Pennsylvania is contingent on labor market variables. The general model is given by:

(1) $FRMJBC_D = f(\ Tax, Employ, Capital, GDP\ of\ Pennsylvania)$

where $FRMJBC_D$ is the net gain of jobs in Pennsylvania; *Tax* is the general tax revenue collected by the Commonwealth of Pennsylvania; *Employ* is the employment by gender in Pennsylvania; *Capital* represents capital stock in Pennsylvania; and *GDP of Pennsylvania* is the amount of gross domestic product in Pennsylvania. The FRMJBC variable simply subtracts the job gains

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Table 1: Data Sources and Description

Variable Name	Description	Source
Net Job Gains (*FRMJBC*)	The net job gains in Pennsylvania on the firm level	Quarterly Workforce Indicators (QWI), Longitudinal Employer-Household Dynamics (LEHD), Bureau of the Census
Employment (*Employ*)	The total employment in Pennsylvania on the firm level for the quarter by gender	Quarterly Workforce Indicators (QWI), Longitudinal Employer-Household Dynamics (LEHD), Bureau of the Census
Gross Domestic Product (*GDP*) of Pennsylvania	A measure of GDP for Pennsylvania from the National Income and Product Accounts (NIPA)	Bureau of Economic Analysis
Capital Stock (*K*)	A measure of capital stock from the National Income and Product Accounts (NIPA) based on fixed capital	Bureau of Economic Analysis
Taxes (*Tax*)	General tax revenues for the Commonwealth of Pennsylvania	Bureau of Revenue, Commonwealth of Pennsylvania

and job losses for men and women in the same time period. That is, it is not a first difference with respect to changes over time. The data are given on a quarterly basis from Q1 of 1997 to Q4 of 2013 and are expressed in natural logarithms. The data sources are provided in Table 1.

4.2 The Methodology: Vector Error Correction Model (VECM)

We use a vector error correction model (VECM) in this paper. A VECM is a restricted vector autoregressive (VAR) model designed for use with nonstationary series that are known to be co-integrated. The VECM has co-integration relations built into the specification; consequently, it restricts the long-run behavior of the endogenous variables to converge to their co-integrating relationships while allowing for dynamics in the short run. This co-integration term is the error correction term since the deviation from long-run equilibrium is corrected through partial short-run adjustments. Thus, we have the following VECM specification:

$$(2)\quad \Delta Z_t = \Gamma_1 \Delta Z_{t-1} + \ldots + \Gamma_{k-1}\Delta Z_{t-k+1} + \Pi Z_{t-k} + u_t$$

where Z_t is the vector of the endogenous variables containing *Tax*, *Employment*, *Capital*, and *GDP* of Pennsylvania and where all variables are I(1), and $\Gamma_1, \ldots .\Gamma_{k+1}$ are (4×4) matrices of the short-run parameters, **Π** is a (4×4) matrix of the long-run parameters, and u_t is the white-noise stochastic error term. Equation 3 shows the speed of adjustment in the VECM:

$$(3)\quad \mathbf{\Pi} = \boldsymbol{\alpha\beta}'$$

where vector α represents the speed of adjustment to disequilibrium and $\boldsymbol{\beta}$ is a vector that represents up to (n-1) co-integrating relationships among the nonstationary variables. Trace and maximum eigenvalue statistics are used to test for co-integration. After Equation 1 is estimated, we test for weak exogeneity for the linear restrictions on $\boldsymbol{\beta}$. The terms of vector $\boldsymbol{\alpha}$ (factor loading

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matrix) measure the speed at which the variables adjust towards the long-run equilibrium after a price shock. The α vector of the weakly exogenous variable equals zero. To find the direction of the Granger causality between the net job flows by gender in Pennsylvania, restrictions are tested on the $\boldsymbol{\alpha}$ vector.

Selecting the optimal lag is performed before estimating the VECM from the results of VAR model. The stationary properties of the time series for each of the variables are then analyzed.

After determining the presence of unit roots, we investigate the existence of co-integration. More specifically, Engle and Granger (1987) indicate that a linear combination of two or more nonstationary series may be stationary. Consequently, if such a stationary linear combination exists, then the nonstationary time series may be co-integrated. Such a stationary linear combination is called a *co-integrating equation* and can be interpreted as a long-run equilibrium relationship among the variables. Johansen and Juselius's (1988, 1990) maximum likelihood method was applied to investigate whether there is more than one co-integration relationship via the trace and maximum eigenvalue statistics.

Johansen and Juselius's method estimates Π using an unrestricted VAR model to test whether we can reject the restrictions implied by the reduced rank of Π and estimate the characteristic roots of Π. Once the characteristic roots are calculated, we then proceed to the λ_{max} and λ_{trace} tests, which are two tests used to determine the number of co-integrating vectors. That is, the rank of Π equals the count of its nonzero characteristic roots, i.e., the number of co-integrating vectors. The λ_{trace} test tests for the null hypothesis that the distinct number of co-integrating vectors is less than or equal to r versus the alternative hypothesis that the distinct number of co-integrating vectors is greater than r. The λ_{max} test tests the null hypothesis that the distinct number of co-integrating vectors is r versus the alternative hypothesis that the distinct number of co-integrating vectors is greater than $r+1$. Johansen and Juselius's co-integration procedure is based upon estimating the vector error correction model as specified in Equation 2.

5. EMPIRICAL RESULTS

The first step is the development of the unrestricted vector autoregressive model (VAR) to determine the optimal lag length for estimating subsequent models. The results are presented in Table 2A for men and Table 2B for women.

According to Schwarz's Information Criterion (SIC), the best lag length is two. From the VAR Lag Order Selection, Tables 2A and 2B generally seem to point to a lag of 4 or 5, which is fairly typical for deseasonalized quarterly data. Better results were obtained using only two lags, and undoubtedly in part because a four-period lag poses a degrees-of-freedom problem.

The Augmented Dickey-Fuller (ADF) test was used to determine the order of integration by testing the unit root hypothesis in the level of variables and in their first differences. The null hypothesis is the presence of a unit root. The ADF is used in the stationarity analysis. Lag lengths are decided by evaluating Akaike's Information Criterion (AIC) and Schwarz's Information Criterion (SIC). Table 3 summarizes the results from the ADF tests.

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Table 2A: VAR Lag-Order Selection Criteria: Men Employment

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	323.064	NA	3.32e-11	-9.936	-9.598	-9.805
1	707.538	683.509	3.69e-16	-21.350	-20.160	-20.882
2	816.782	176.873	2.59e-17	-24.025	-21.984*	-23.222
3	853.154	53.114	1.89e-17	-24.386	-21.494	-23.249
4	900.915	62.166*	9.99e-18*	-25.108*	-21.366	-23.637*
5	918.912	20.568	1.44e-17	-24.886	-20.294	-23.080

Note: The lag length selected was two per the Schwarz Information Criterion (SIC). * indicates the lag order selected by the criterion. LR = the Sequential modified LR test statistic; FPE = the Final Prediction Error; AIC = Akaike Information Criterion; SIC = Schwarz Information Criterion; and HQ = Hannan Quinn Information Criterion.

Table 2B: VAR Lag-Order Selection Criteria: Women Employment

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	309.227	NA	5.15e-11	-9.4993	-9.159	-9.365
1	686.188	670.152	7.27e-16	-20.672	-19.482	-20.204
2	801.918	187.374	4.16e-17	-23.553	-21.512*	-22.750
3	844.192	61.732	2.51e-17	-24.101	-21.210	-22.964
4	897.638	69.566*	1.11e-17*	-25.004*	-21.262	-23.533*
5	915.978	20.960	1.58e-17	-24.793	-20.200	-22.987

Note: The lag length selected was two per the Schwarz Information Criterion (SIC). * indicates the lag order selected by the criterion. LR = the Sequential modified LR test statistic; FPE = the Final Prediction Error; AIC = Akaike Information Criterion; SIC = Schwarz Information Criterion; and HQ = Hannan Quinn Information Criterion.

5.1 Cointegration Tests

The number of co-integrating vectors (CVs) is determined from the trace and maximum eigenvalue tests with an initial (null) hypothesis that there is a lack of a co-integrated vector in the system. As seen in Table 4A, the trace statistic (93.02) is greater than the critical value of 69.82 at the 5 percent level, thus rejecting the null hypothesis of a lack of long-run co-integration between the variables. This result is confirmed by testing a second null hypothesis that there is at most one co-integrated vector, and as seen in Table 4A, the hypothesis was not rejected at the 5 percent level of significance. Table 4B confirms the results from Table 4A using the maximum eigenvalue test.

The co-integration models were then estimated for the variables *Net Gain Job Gains-Women* and *Employment for Women*. The trace statistic (89.37) shown in Table 5A is greater than the critical value of 69.82 at the 5 percent level, thus rejecting the null hypothesis of a lack of long-run co-integration between the variables. This result is confirmed by testing a second null hypothesis that there is at most one co-integrated vector and, as seen in Table 5A, the hypothesis was not rejected at the 5 percent level of significance. Table 5B confirms the results from Table 5A using the maximum eigenvalue test.

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Table 3: Augmented Dickey-Fuller Tests

Variables log (levels)	Included in regression	Test Statistic	1% Critical Value	5% Critical Value	Lag Length	Conclusion
Capital Stock	Constant	-2.284	-3.530	-2.906	1	No Unit Root
Capital Stock	Constant, Linear Trend	-3.104	-4.103	-3.479	1	No Unit Root
Employment - Men	Constant	-1.216	-3.553	-2.908	4	Unit Root
Employment - Men	Constant, Linear Trend	-1.820	-4.110	-3.482	4	Unit Root
Employment -Women	Constant	-1.499	-3.553	-2.908	4	No Unit Root
Employment-Women	Constant, Linear Trend	.331	-4.110	-3.482	4	No Unit Root
Net Job Gains - Men	Constant	-9.904	-3.531	-2.909	0	Unit Root
Net Job Gains - Men	Constant, Linear Trend	-8.989	-4.100	-3.478	0	Unit Root
Net Job Gains -Women	Constant	-7.689	-3.531	-2.905	0	Unit Root
Net Job Gains - Women	Constant, Linear Trend	-7.930	-4.110	-3.478	0	Unit Root
GDP of Pennsylvania	Constant	-2.438	-3.531	-2.905	0	No Unit Root
GDP of Pennsylvania	Constant, Linear Trend	-2.496	-4.100	-3.478	0	No Unit Root
Tax	Constant	-1.013	-3.538	-2.908	4	Unit Root
Tax	Constant, Linear Trend	-1.953	-4.110	-3.482	4	Unit Root
log (1st difference)						
Δ (Capital Stock)	Constant	-1.226	-3.533	-2.906	0	Not Stationarity
Δ (Capital Stock)	Constant, Linear Trend	-1.880	-4.103	-3.479	0	Not Stationarity
Δ (Employment-Men)	Constant	-.333	-3.538	-2.908	3	Not Stationarity
Δ (Employment-Men)	Constant, Linear Trend	-.963	-4.110	-3.482	3	Not Stationarity
Δ (Employment-Women)	Constant	-1.329	-3.538	-2.908	3	Not Stationarity
Δ (Employment-Women)	Constant, Linear Trend	-2.272	-4.110	-3.482	3	Not Stationarity
Δ (Net Job Gains-Men)	Constant	-10.275	-3.536	-2.907	2	Stationarity
Δ (Net Job Gains-Men)	Constant, Linear Trend	-10.174	-4.107	-3.481	2	Stationarity
Δ (Net Job Gains-Women)	Constant	-8.934	-3.536	-2.907	2	Stationarity
Δ (Net Job Gains-Women)	Constant, Linear Trend	-8.864	-4.107	-3.481	2	Stationarity
Δ (GDP of PA)	Constant	-7.497	-3.533	-2.906	0	Stationarity
Δ (GDP of PA)	Constant, Linear Trend	-7.754	-4.103	-3.479	0	Stationarity
Δ (Tax)	Constant	-5.382	-3.538	-2.908	3	Stationarity
Δ (Tax)	Constant, Linear Trend	-5.205	-4.110	3.482	3	Stationarity

Note: For the regression equations without a linear trend, the critical values were derived from MacKinnon (1996). The unit root tests were estimated using EViews 8.0.

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Table 4A: Unrestricted Co-integration Rank Test (Trace), Male Employment

Hypothesized #. of CE(s)	Eigenvalue	Trace statistic	.05 critical value	*p*-value**
None *	0.563	93.015	69.819	.000
At most 1	0.292	39.961	47.856	.223
At most 2	0.206	17.811	29.797	.580
At most 3	0.046	3.078	15.495	.963
At most 4	0.000	0.032	3.841	.858

Note: Trace test indicates one co-integrating equation at the 0.05 level or better (lower) via EViews 8.0. * denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values are provided.

Table 4B: Unrestricted Co-integration Rank Test (Maximum Eigenvalue), Male Employment

Hypothesized #. of CE(s)	Eigenvalue	Max eigen statistic	.05 critical value	*p*-value**
None *	0.563	53.053	33.877	.000
At most 1	0.293	22.150	27.584	.213
At most 2	0.206	14.733	21.132	.308
At most 3	0.047	3.046	14.265	.944
At most 4	0.000	0.032	3.841	.858

Note: The maximum eigenvalue test indicates one co-integrating equation at the 0.05 level or better (lower) via EViews 8.0. * denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) p-values are provided.

Table 5A: Unrestricted Co-integration Rank Test (Trace), Female Employment

Hypothesized # of CE(s)	Eigenvalue	Trace statistic	.05 critical value	*p*-value**
None *	0.541	89.366	69.819	.000
At most 1	0.271	38.692	47.856	.273
At most 2	0.153	18.114	29.797	.558
At most 3	0.065	7.301	15.495	.543
At most 4	0.045	2.995	3.841	.084

Note: Trace test indicates one co-integrating equation at the .05 level or better (lower) via EViews 8.0. * denotes rejection of the hypothesis at the .05 level. **MacKinnon-Haug-Michelis (1999) p-values are provided.

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Table 5B: Unrestricted Co-integration Rank Test (Maximum Eigenvalue), Female Employment

Hypothesized # of CE(s)	Eigenvalue	Max eigen statistic	0.05 critical value	*p*-value**
None *	0.541	50.674	33.877	.000
At most 1	0.271	20.578	27.584	.303
At most 2	0.153	10.813	21.132	.666
At most 3	0.064	4.305	14.265	.823
At most 4	0.045	2.996	3.841	.084

Note: The maximum eigenvalue test indicates one co-integrating equation at the .05 level or better (lower) via EViews 8.0. * denotes rejection of the hypothesis at the .05 level. **MacKinnon-Haug-Michelis (1999) p-values are provided.

5.2 Results from the Vector Error Correction Model (VECM)

A VECM was used to estimate the net job gains for men, and we report the results from the net job gains for male employment in Table 6. Earlier, it was determined by the trace tests in Table 4A that there is one co-integration equation. Normalizing the co-integrating vector with respect to *Net Gains for Men*, the long-run equilibrium relationships are given as

$$Net\ Gains\ Men_{t-1} = \underset{(23.493)}{134.232} * \text{Employ Men}_{t-1} + \underset{(21.664)}{71.097} * Capital\ Stock_{t-1} + \underset{(57.292)}{148.32} * \text{GDP Penn}_{t-1} + \underset{(7.396)}{18.599} * Tax_{t-1}$$

The standard errors are given in parentheses below each coefficient in the normalized co-integration equation. In both of the normalized co-integration equations, each independent variable is significant. The signs of the effects are also of the expected sign. There is a relationship between the net gains of jobs and employment. This relationship is positive if employment is increasing and negative if employment is declining. As a result, if employment is increasing, this increase indicates that more people are working, which results in greater contributions to the GDP of Pennsylvania. Consequently, more people working means there are more people paying taxes, resulting in an increase in fiscal revenues to the Commonwealth of Pennsylvania. In addition, the expansion of the economy, as indicated by a rising GDP in Pennsylvania, enables firms to generate more profits and enhance state tax coffers. As for capital stock, the positive relationship with net gains is likely due to the fact that firms have more resources to invest and the firm can purchase more capital resources for their business that generates additional jobs.

From Table 6, the error correction terms represent the long-run impact of one variable on the other, while the changes in the lagged independent variable describe the short-run causal impact. Furthermore, the reported coefficients indicate that the net job gains for men react to changes in the variables and to deviations from the equilibrium path of the system. The value of the error correction coefficient for the first term (-0.67) suggests that 67 percent of the disequilibrium is corrected in the next quarter. More specifically, the dynamics of the error correction model suggest the employment moves heavily back towards the long-run equilibrium. Another important finding from the model is that the error correction terms are statistically significant.

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Earlier, it was determined by the trace tests in Table 5A that there is one co-integration equation for the net gains for women. Normalizing the co-integrating vector with respect to *Net Gains for Women*, the long-run equilibrium relationship is given as

$$\underset{}{Net\ Gains\ Women_{t-1}} = \underset{(3.988)}{11.267 * \text{Employ Women}_{t-1}} + \underset{(3.72)}{7.95 * Capital\ Stock_{t-1}} + \underset{(10.522)}{22.095 * \text{GDP Penn}_{t-1}} + \underset{(1.77)}{6.08 * Tax_{t-1}}$$

Standard errors are reported in parentheses. In the normalized co-integration equations, each independent variable is significant. From this normalization, the signs are as expected. The interpretation of the relationships of each of the independent variables and the net gains for women is analogous to the interpretation under the normalization of the co-integrating vector with respect to *Net Gains for Men.*

Table 6: Results from the Vector Error Correction Model for Male Employment

Vector Error Correction Model: Short-Run Dynamics			
	Δ (Net job gains)	Standard error	Test statistic
Error Correction Term	-0.668	0.207	-3.219*
Δ *Net Gains*$^{t-1}$	-0.184	0.173	-1.056
Δ *Net Gains*$^{t-2}$	0.115	0.125	0.921
Δ *Emp*$^{t-1}$	-22.254	7.840	-2.838*
Δ *Emp*$^{t-2}$	5.734	7.400	0.775
Δ *GDP of Pennsylvania*$^{t-1}$	-7.320	16.810	-0.435
Δ *GDP of Pennsylvania*$^{t-2}$	20.609	17.527	1.176
Δ *Capital Stock*$^{t-1}$	-0.481	246.493	-0.001
Δ *Capital Stock*$^{t-2}$	108.786	231.097	0.470
Δ *Tax*$^{t-1}$	3.079	0.953	2.230*
Δ *Tax*$^{t-2}$	2.502	1.061	2.357*
Finance 2008 (Binary Variable)	0.005	0.477	0.011
Constant	-0.976	0.525	-1.860
R^2	.740		
Adjusted R^2	.678		
Sum square of residuals	39.603		
S.E. equation	0.873		
F-statistic	12.318		
Log likelihood	-76.128		
Akaike AIC	2.7424		
Schwarz SIC	3.177		
Mean of the Dependent Variable	-0.003		
Standard Deviation of the Dependent Variable	1.542		

Note: The VECM was estimated in EViews 8.0. The dependent variable is the net job gains for men. Other equations of the VECM are not presented to preserve space. * indicates statistical significance at the 5 percent level.

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Table 7: Results from the Vector Error Correction Model for Female Employment

Vector Error Correction Model: Short-Run Dynamics			
	Δ (Net job gains)	Standard error	Test statistic
Error Correction Term	-0.862	0.301	-2.865
Δ *Net Gains*$^{t-1}$	-0.056	0.251	-0.223
Δ *Net Gains*$^{t-2}$	-0.092	0.210	-0.441
Δ *Net Gains*$^{t-3}$	-0.152	0.161	-0.945
Δ *Tax*$^{t-1}$	5.334	3.013	1.770
Δ *Tax*$^{t-2}$	3.226	1.508	2.138*
Δ *Tax*$^{t-3}$	1.338	2.602	0.514
Δ *Emp*$^{t-1}$	18.930	12.902	1.467
Δ *Emp*$^{t-2}$	35.568	13.074	2.720*
Δ *Emp*$^{t-3}$	18.242	13.692	1.332
Δ *GDP of Pennsylvania*$^{t-1}$	-23.379	28.096	-0.832
Δ *GDP of Pennsylvania*$^{t-2}$	-7.624	27.663	-0.275
Δ *GDP of Pennsylvania*$^{t-3}$	-26.344	24.346	-1.082
Δ *Capital Stock*$^{t-1}$	-380.227	332.664	-1.143
Δ *Capital Stock*$^{t-2}$	-557.792	485.731	-1.148
Δ *Capital Stock*$^{t-3}$	386.760	348.143	1.110
Finance 2008 (Binary Variable)	1.412	0.682	2.069*
Constant	4.227	1.594	2.651*
R^2	.587		
Adjusted R^2	.434		
Sum square of residuals	61.229		
S.E. equation	1.1537		
F-statistic	3.8437		
Log likelihood	-89.396		
Akaike AIC	3.356		
Schwarz SC	3.963		
Mean dependent	0.016		
S.D. dependent	1.533		

Note: The VECM was estimated in EViews 8.0. The dependent variable is the net job gains for women. Other equations of the VECM are not presented to preserve space. * indicates statistical significance at the 5 percent level.

From Table 7, the error correction terms represent the long-run impact of one variable on the other while the changes of the lagged independent variable describe the short-run causal impact. The significance of the error correction coefficients for the error correction term confirms the existence of a co-integration relationship between the variables. Moreover, it indicates that the net job gains for women react to changes in the variables and to deviations from the equilibrium path of the system. The value of the error correction coefficient for the first

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term (-0.862) suggests that 86.20 percent of disequilibrium is corrected in the next quarter. More specifically, the dynamics of the error correction model suggest the employment moves heavily back towards the long-run equilibrium. Also, another important finding from the model is that the error correction term is statistically significant at the 5 percent level of significance.

5.3 Testing the Robustness of the Vector Error Correction (VECM) Model

For the VECM for men, the multivariate Lagrange Multiplier (LM) statistics showed that the residuals are not auto-correlated since the *p*-value is greater than the generally accepted level of significance of .05, and for the VECM for women, the residuals are not auto-correlated because its *p*-value also exceeds normally accepted levels of significance of 0.05. The multivariate Jarque-Bera test confirms that the residuals for the VECMs for both men and women were not nearly normally distributed because the multivariate test of skewness show that the residuals are somewhat skewed while the test for kurtosis indicates a problem with kurtosis. Finally, VECM Residual Heteroscedasticity Tests were also applied to both VECM models, and the tests show there is no problem with VECM residuals with regards to heteroscedasticity since the *p*-values are greater than 0.05.

5.4 Granger Causality/Block Exogeneity Wald Test

After estimating the long-run VECM model, we estimate the short-run causality model. Under co-integration, the dynamics should be phased into the vector error correction term. This allows us to assess both long- and short-run causality on the χ^2 -test of the lagged first differenced terms for each right-hand-side variable and the *t*-test of the error correction term. The results of the test are presented in Table 8 for men and Table 9 for women, and the discussion follows below.

If the variable *x* "Granger causes" variable *y*, then the time series of variable *x* necessarily contains information that leads to the prediction of variable *y*. In other words, Granger causality is a statistical concept that shows the predictive power of past values in the determination of the accuracy of forecasts. In fact, Granger causality may be indicative of the existence or nonexistence of short-run relationships between variables. From Tables 8 and 9, those independent variables that are statistically significant exhibit Granger causality, while statistically insignificant variables do not. The significance of the coefficient of the error correction term of *Δ (Net Gains)* shows that there is a long-run relationship between the net gains for men, the net gains for women, and their associated independent variables. In addition, the disequilibrium in net gains for employment by men and women would be corrected after any external shocks to employment. Intuitively, the mechanics of the VECM imply that the net job gains for men and women are initial receptors of exogenous changes to the long-run equilibrium. The remaining independent variables must bear the burden of the short-run adjustment exogenously in different proportions to return the system to the long-run equilibrium.

6. CONCLUSION

This paper examines the effects of the Great Recession on workers in Pennsylvania. Using a vector error correction model, we investigate the impacts of the Great Recession on male and female employment in the Pennsylvania economy in the manufacturing, construction, healthcare, and retail sectors using Longitudinal Employer-Household Dynamics data from the first quarter of 1997 to the final quarter of 2013. We find a long-run relationship between the net

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Table 8: VECM Granger Causality/Block Exogeneity Wald Tests, Male Employment

Dependent Variables	Independent Variables					
	Δ Net Gains	Δ Tax	Δ Employment	Δ Capital	Δ GDP of PA	EC Term
Δ Net Gains	___	14.265*	10.853*	3.073	1.491	-0.668*
		[.008]	[.004]	[.215]	[.474]	(-3.210)
Δ Tax	34.230*	___	1.16	1.166	4.139	-.0140*
	[.000]		[.558]	[0.558]	[.126]	(-0.848)
Δ Employment	9.549*	33.568*	___	0.033	7.910*	.0006
	[.008]	[.000]		[.983]	[.019]	(0.170)
Δ Capital	6.13*	0.277	4.45	___	0.1749	0.0003*
	[.046]	[.871]	[.108]		[.916]	(3.140)
Δ GDP of	.8727	3.05	6.528*	.460	___	.0019
Pennsylvania	[.646]	[.217]	[.038]	[.794]		(1.233)

Note: The *p*-values are in brackets, and the *t*-statistics are given in parentheses. The *p*-values and test statistics denoted with * are significant at the 5 percent level.

Table 9: VECM Granger Causality/Block Exogeneity Wald Tests, Female Employment

Dependent Variables	Independent Variables					
	Δ Net Gains	Δ Tax	Δ Employment	Δ Capital	Δ GDP of PA	EC Term
Δ (Net Gains)	___	7.671	7.441	13.396*	1.608	-.862*
		[.053]	[.0591]	[.0039]	[.657]	(-2.865)
Δ (Tax)	25.046*	___	21.177*	21.363*	6.464	-0.057*
	[.000]		[.0001]	[.0001]	[.091]	(-4.54)
Δ (Employment)	1.625	1.979	___	1.980	5.335	0.002
	[.6573]	[.576]		[.576]	[.148]	(.518)
Δ (Capital)	10.585*	9.566*	3.536	___	1.771	-0.0002*
	[.014]	[.023]	[.316]		[.6211]	(-2.118)
Δ (GDP of	6.786	0.889	4.749	1.687	___	0.0002
Pennsylvania)	[.0790]	[.827]	[.1911]	[.639]		(.127)

Note: The *p*-values are in brackets, and the *t*-statistics are given in parentheses. The *p*-values and test statistics denoted with * are significant at the 5 percent level. The Granger Causality/Block Exogeneity Wald Tests in Tables 8 and 9 were estimated with EViews 8.0.

job gains and employment for men and women using Johansen's co-integrating technique. The net job gains for women react strongly to changes in the variables and to deviations from the equilibrium path of the system in comparison to the net job gains for men. We suspect that this can be attributed to the strong improvements in the education and health services and leisure and hospitality sectors that generally employ more women. Our findings further suggest that the disequilibrium is corrected in the next quarter regardless of gender.

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