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Do Race and Ethnicity Determine Employment in Certain Occupations? A VECM Approach

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Abstract

The social sciences literature is replete with microeconomic models on racial discrimination of minority employment. This paper contributes to the empirics by testing the hypothesis of short run and long run employment relationships among racial groups in the U.S. labor market. The author employs a VECM model using national quarterly BLS data for years 2000 to 2023 to test for short-run and long-run Granger causality between employment among racial groups in 5 broad occupational categories: management and professional; services; sales and office; natural resources, construction, and maintenance; and production, transportation, and material moving.

The results overwhelmingly reject the hypothesis of independence in employment among the racial groups. Among other findings, there is evidence to suggest that employment of African Americans in the natural resources, construction, and maintenance occupations Granger cause employment in the White and Latino communities in the short run. This short run burst of African American employment in these occupations may be a sign of forthcoming economic downturn. In this same group of occupations, Latin employment Granger causes Asian and White employment, while Asian employment Granger causes White and Latin employment. GDP and these racial groups Granger cause White and Latin employment in the long run.

Keywords: Labor markets; Employment; Cointegration; Granger causality; Vector Error-Correction Model

JEL Codes: J11, J15, J71

1. Introduction and literature Search

Much of the literature has focused on the differences in the unemployment rates among races – in particular, the difference between long-run unemployment between Blacks and Whites in the United States. In particular, the largest strand of the literature has a microeconomics approach to analyzing the statistical differences. (Zatzick & Alvira, 2002) took an empirical approach by analyzing a sample of 8918 employees from a financial firm during the early 1990s to determine if race played a role in layoffs over a three-year period. Controlling for race, tenure, job category, and other relative characteristics, their results indicated that not only did race play a role in layoffs, but it also played a role in promotions, evaluations, salary increases, performance ratings. Among the races, Blacks were negatively impacted the worst.

Peterson et al. (2005) took a similar approach to determine if gender and race affected a firm's hiring practice. Analyzing the hiring practice of a large firm in the service industry they conducted a logit model to estimate the probability of hiring applicants by race and race. Their results varied in accordance with occupation. They found little to negligible difference between men and women but found a large statistical difference when it comes to race. Controlling for various factors, Blacks had approximately 25% lower probability of being hired. When controlling for language, the bias against other racial employees were reduced.

As is somewhat evident in the literature, racial disparities are not homogeneous across all industries and occupations. As the two papers above have shed light on, gender and race are treated differently, depending on the occupation, as well as the industry. (Bloch, 2003) peered into the construction occupation to observe racial employment differences – specifically employment levels and salaries. The interesting fact about the construction industry is that they are impacted by the Davis-Bacon Act. Functioning as a minimum wage law for the construction industry, the act requires federally funded projects to pay the prevailing wage to construction workers. This is a natural control for wages among racial employment groups. Holding everything else constant, if wages are equalized among the races, then any difference in the employment levels can be attributed to a bias. Analyzing salary and employment data from the Current Population Survey over 162 metropolitan counties over a period of 1986-1994, the author finds a strong negative wage effect on minority laborers and employment. He finds that the efficiency wage paid to construction workers has a relatively small difference in employment levels overall, but that it produces large wage employment elasticities for minorities. This captures the racial biasness of employers in the construction industry.

To determine if any patterns exist among racial, age, genders groups, (Hoyne et al., 2012) looked at employment rate decreases among the groups. Using the Bureau of Labor Statistics for the recessionary periods from 1979 through 2011, they found that employment declines were greatest during the Great Recession. Moreover, they found that the magnitude of the decreases in employment rates varied across demographics in the labor market. Younger workers, males, lower-educated, Hispanics, and blacks experienced the steepest declines compared to their counterparts who were white, female, or more educated.

To the best of our knowledge, the first macroeconomic time series analysis was conducted by (Coupet, 2022). Using BLS data for African Americans and whites from 1989 to 2020, he employed a vector error correction model to conduct short-run and long-run causality tests on racial employment data. Using both annual data and quarterly data and not controlling for occupation, he found that African American employment Granger causes white employment in the short run. Moreover, GDP and African American employment explain White employment in the long run.

This paper extends the causality analysis by controlling for occupation and including other races (Asians and Latinos) in the analysis. This method retains the macroeconomic approach while also drilling down to the occupation level. As we have encountered in the literature, various laws, cultures, and biases may affect the hiring practices of employers.

The remainder of this paper will proceed with sections on methodology and data, followed by a discussion of the results. We conclude with a brief connection to future research opportunities and policy implications.

2. Methodology

Let:

$$Y_{i,t} = A_{i,t}{}^{\gamma} K_{i,t}{}^{\alpha} H_{i,t}{}^{\beta} \left(L_{i,t}\right)^{1-\gamma-\alpha-\beta} \tag{1}$$

be the production of a typical firm competing in the ith sector of the economy at a point in time. Firms are free to hire anyone in the labor market of any race. Therefore, each firm's labor force is the sum of its employees of all races:

$$L_{i,t} = L_{i,t}{}^{AA} + L_{i,t}{}^{W} + L_{i,t}{}^{L} + L_{i,t}{}^{O} \qquad (2).$$

We can substitute equation (2) into equation (1) above. We further assume that employees are perfect substitutes for each other, and their marginal products are equal.

This leads to:

$$Y_{i,t} = A_{i,t}{}^{\gamma} K_{i,t}{}^{\alpha} H_{i,t}{}^{\beta} \left(L_{i,t}{}^{AA} + L_{i,t}{}^{W} + L_{i,t}{}^{L} + L_{i,t}{}^{O}\right)^{1-\gamma-\alpha-\beta} \qquad (3)$$

At the margin, the temporal dynamic of the firm's production function can be expressed as

$$\frac{\dot{Y}_{i,t}}{Y_{i,t}} = \gamma \frac{\dot{A}_{i,t}}{A_{i,t}} + \alpha \frac{\dot{K}_{i,t}}{K_{i,t}} + (1-\gamma-\alpha-\beta)\left(\frac{\dot{L}^{AA}}{L_{i,t}} + \frac{\dot{L}^{W}}{L_{i,t}} + \frac{\dot{L}^{L}}{L_{i,t}} + \frac{\dot{L}^{O}}{L_{i,t}}\right) + \beta \frac{\dot{H}_{i,t}}{H_{i,t}} \qquad (4)$$

We can use this dynamic expression to determine the short-run marginal effect of employment of any employee of any race. For example, the proportional change in employment of an African American laborer could be represented as:

$$\frac{\dot{L}^{AA}}{L} = \frac{1}{(1-\gamma-\alpha-\beta)} \frac{\dot{Y}_{i,t}}{Y_{i,t}} - \frac{\gamma}{(1-\gamma-\alpha-\beta)} \frac{\dot{A}_{i,t}}{A_{i,t}} - \frac{\alpha}{(1-\gamma-\alpha-\beta)} \frac{\dot{K}_{i,t}}{K_{i,t}} - \frac{\dot{L}^{W}}{L_{i,t}} - \frac{\dot{L}^{L}}{L_{i,t}} - \frac{\dot{L}^{o}}{L_{i,t}} - \frac{\beta}{(1-\gamma-\alpha-\beta)} \frac{\dot{H}_{i,t}}{H_{i,t}} \qquad (5)$$

Let us assume that the firm is at its short-run equilibrium in output. An increase in the number of white employees would require a reduction in the employment level of African Americans. Ceteris paribus, the only way to change the racial makeup of the firm's labor force is to increase output and capital structure or reduce employment in any racial community it employs. This employment model allows us to understand the firm's employment decision at the margin, but it doesn't provide us with any potential hiring patterns of the firm. Is there a preference or long run relationship in the pattern of hiring? Do firms hire in an unbiased way? Does the industry that the firm competes in matter? More specifically, is employment in any occupation race-specific?

Empirically, one way to analyze this is to look at the long run relationship between the output and racial employment of firms. Let's constrain the firm's stylized production function to the following:

$$Y_{i,t} = f\left(L_{i,t}^{AA}, L_{i,t}^{W}, L_{i,t}^{L}, L_{i,t}^{A}\right) \qquad (6)$$

We will further assume that the hiring decision is completely endogenous. To determine if there is a long-run relationship in a firm's hiring practice, we test to see if the employment levels among the races are cointegrated. (Engle& Granger, 1987; Enders, 1995) defines cointegration as the linear combination of nonstationary variables. Given two random nonstationary series of variables, {x} and {y}, a system of two cointegrated variables can be written as:

$$\Delta x_t = \theta_1 + \alpha_x (y_{t-1} - \beta x_{t-1}) + \sum a_{11}(i)\Delta x_{t-i} + \sum b_{12}(i)\Delta y_{t-i} + e_{x,t}$$

$$\Delta y_t = \theta_2 + \alpha_y (y_{t-1} - \beta x_{t-1}) + \sum a_{12}(i)\Delta x_{t-i} + \sum b_{22}(i)\Delta y_{t-i} + e_{y,t} \quad (7)$$

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$(y_{t-1} - \beta x_{t-1})$ is the error correction term. If their coefficients are statistically significant, then the variables are cointegrated, and the dependent variables are caused by the independent variables in the long run. Deviation of the dependent variables from their long run equilibrium in the previous period will be corrects in the magnitude of the $\alpha_y(y_{t-1} - \beta x_{t-1})$. Also, notice that the coefficient is also the speed of the adjustment from disequilibrium --the higher the value-- the quicker, the error is corrected. The error terms, $e_{x,t}$and $e_{y,t}$ are white noise.

If the coefficient of error correction term in either equation is statistically significant, then there is long-run Granger causality. If the coefficient of the error term is not statistically different from zero, then the equations default to a vector autoregressive model (VAR), and there is no long run relationship in the variables. In that case, only short-run causal relationships can be established. In the case where all coefficients are statistically insignificant, then there is no relationship among the variables.

To test the hypothesis that the employment levels among the racial groups are related – that is, not randomly distributed and are independent, we shall proceed in the following manner: 1) Using the employment levels in each of the five occupation categories, we use a battery of tests for the existence of a unit root. As stated before, cointegration requires nonstationarity of the variables in their levels and stationarity in their first difference. 2) Given the results of the previous step, we conduct the Johansen cointegration test to determine if there is a long-run relationship among the endogenous variables and, if this condition is true, the number of error correction equations that exist.3) If the variables are cointegrated, we estimate the error correction models. If none exists, we proceed by estimating vector autoregression models for short run relationships. 4) We conclude with short-run Granger causality tests using the Chi-square tests. This joint test of the lagged coefficients will categorically determine if there is a short run Granger causality among the variables.

3. Data

All employment data are extracted from the Bureau of Labor Statistics (BLS). This quarterly employment data is disaggregated into 5 broad occupation levels: management and professional; services; sales and office; natural resources, construction, and maintenance; and production, transportation, and material moving, from Q12000 to Q12023. There is a series for Black or African American, White, Asian, and Latino. As is usually the case, the series for Latino is not necessarily race specific – so the sum of all racial employment identities does not equal the total employment -- in any given year. The quarterly GDP data from the Bureau of Economic Analysis, taken over the same period.

A cross section of the broad level occupations can be found in Table 1 below for the year 2021. A few salient points can be gleaned from this table. Among the management and professional occupations, 42% of total employment work in those occupations. Whites are proportionally represented at 43%, while Black and Latinos are significantly underrepresented. More than half of total Asian employment (58%) is in these occupations. They are strikingly overrepresented in those occupations. African Americans and Latinos are overrepresented in the service occupations. When it comes to the natural resources, construction and maintenance occupations, African Americans and Asians are underrepresented while Latinos are overrepresented.

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Table 1. National Employment Levels, 2021

Occupation	Total Labor	White Emp		Black Emp		Latino Emp		Asian	
Management, professional, and related	42%	50,695 K	43%	6,345 K	34%	6,733 K	25%	5,827 K	58%
Services	16%	17,765 K	15%	4,026 K	22%	6,272 K	23%	1,440 K	14%
Sales and Office	20%	23,499 K	20%	3,982 K	21%	5,189 K	19%	1,538 K	15%
Natural resources, construction, and maintenance	9%	12,047 K	10%	1,033 K	6%	4,662 K	17%	321 K	3%
Production, transportation, and material moving	13%	14,289 K	12%	3,340 K	18%	4,576 K	17%	908 K	9%
Total	100%	118,295K	100%	18,727 K	100%	27,432 K	100%	10,034 K	100%

4. Results

Units root tests are conducted on the data series. We conduct widely accepted stationarity tests: the Augmented Dickey-Fuller; the Dickey-Fuller with GLS, and the Phillips Perron. The results are found in Table A1 of the Appendix. For each variable, the three tests are conducted on the levels, followed by their first differences. For the Dickey-Fuller and Phillips-Perron tests, we accept the null hypothesis of the presence of a unit root if the Z score is smaller than the critical values at the 1% level. We reject the null hypothesis of a unit root with the DF-Fuller test if the Tau score is statistically significant at the 1% level as well. To account for various sensitivity levels of the tests, we require rejection of the unit root on at least two tests. As a necessary condition for cointegration and vector autoregression analyses, we find the series to be nonstationary in their levels, but are stationary in the first differences [I(1)]. We can then state that the variables are CI(1,1).

4.1 Management and Professional Occupations

The results of a battery of information criteria and likelihood ratio tests suggest an optimal lag length of 5 for the Johansen Cointegration tests. The results of the trace, max, SBIC, and HQIC in Table A2A suggest that we accept the null hypothesis of maximum rank of 1 at the 5% level. This result strongly recommends that there is one cointegrating relationship among the variables identified in the model. We shall use this result to estimate the Vector Error Correction Model (VECM) among the variables. The results of the VECM are found in Table 2 below.

The statistical significance of the error correction coefficients of the White employment equations indicates that employment levels of other races explain White employment levels in the long run. The coefficient of the error correction model for the White employment equation is -.824, statistically significant at the 5 % level. This indicates that lags of employment level changes of White, African American, Latino, Asian and GDP explain employment changes of whites in the long run. Specifically, 82.4% of the errors in estimating White employment changes were corrected in the previous quarter. There is a strong long-term relationship between GDP and employment of other races and White employment within management and professional occupations.

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A close look at the first VECM model of African American employment allows us to reject the null hypothesis that white employment, Latino employment, Asian employment, and GDP Granger-cause employment of African Americans in the management and professional occupations. We arrive at this conclusion because the error correction coefficient is statistically insignificant at the 5% level. However, increases in Latino employment and GDP increases Granger-cause African American employment in the short-run. Specifically, an increase of 1000 in the Latino sector in the previous quarter will result in the additional employment of 410 African Americans in the current quarter. Likewise, an increase in gross domestic product (GDP) in that same quarter will also generate a spurt of African American employment of 204. However, when we test for joint significance of the coefficients of lagged Latino employment variables, we cannot generally state that Latino employment Granger Causes African American employment in the short run (refer to Table 3). Contrarily, we reject the null hypothesis that the coefficients of the lagged GDP coefficients are zero at the 1% level. We can thus say that GDP Granger-causes African American in the short run in this set of occupations.

An overall assessment of the results after triangulating among the various VECM and Granger causality functions for the management and professional occupation, we can make the following statements regarding relationships among the races. Employment increases among whites positively affect Asian employment in the following quarters. African American and Latino employment bring about a decline in Asian employment the following year. Apart from Asian employment, economic growth has a positive effect on all employment.

The LaGrange Multiplier tests reject the existence of serial autocorrelation of the residuals (p-values range from 18% to 85%).

Table 2. Management and Professional Occupations Vector Error Correction Model (VECM)

	ΔAA_Emp_t	$\Delta White\_Emp_t$	$\Delta Latin\_Emp_t$	$\Delta Asian\_Emp_t$	ΔGDP_t
ce_{t-1}	-.200	-0.824**	-0.201*	0.349***	0.311
	(.115)	(.360)	(.119)	(.083)	(.262)
ΔAA_Emp_{t-1}	-0.346**	0.325	0.147	-0.293**	-0.719*
	(.165)	(.514)	(.169)	(.118)	(.373)
ΔAA_Emp_{t-2}	-0.3028*	0.664	0.330*	-0.057	-0.143
	(.160)	(.519)	(.171)	(.119)	(.378)
ΔAA_Emp_{t-3}	-0.041	0.525	0.158	-0.061	0.293
	(.160)	(.500)	(.165)	(.115)	(.364)
ΔAA_Emp_{t-4}	0.137	0.332	0.119	-0.039	-0.170
	(.138)	(.432)	(.142)	(.099)	(.314)
$\Delta White\_Emp_{t-1}$	-0.073	-0.779***	-0.056	0.107***	-0.168
	(.056)	(.174)	(.057)	(.040)	(.127)
$\Delta White\_Emp_{t-2}$	-0.058	-0.740***	-0.027	0.136***	-0.181
	(.055)	(.171)	(.056)	(.039)	(.124)
$\Delta White\_Emp_{t-3}$	-0.067	-0.543***	-0.103*	0.166***	-0.067
	(.054)	(.169)	(.056)	(.039)	(.123)
$\Delta White\_Emp_{t-4}$	-0.010	0.222	0.037	0.131***	-0.128
	(.052)	(.161)	(.053)	(.037)	(.117)
$\Delta Latin\_Emp_{t-1}$	0.273	1.559***	-0.237	-0.391***	-0.074
	(.167)	(.521)	(.172)	(.120)	(.379)
$\Delta Latin\_Emp_{t-2}$	0.410**	0.999*	-0.195	-0.560***	0.105
	(.189)	(.591)	(.195)	(.136)	(.430)
$\Delta Latin\_Emp_{t-3}$	0.147	0.707	0.067	-0.606***	-0.419
	(.172)	(.535)	(.177)	(.123)	(.340)
$\Delta Latin\_Emp_{t-4}$	0.262	0.566	-0.002	-0.208*	0.416
	(.158)	(.494)	(.163)	(.114)	(.359)
$\Delta Asian\_Emp_{t-1}$	0.003	-0.392	0.094	0.078	0.421
	(.181)	(.567)	(.187)	(.130)	(.412)

$\Delta Asian\_Emp_{t-2}$	0.005 (.180)	-0.530 (.562)	0.032 (.185)	0.233 (.129)	0.618 (.409)
$\Delta Asian\_Emp_{t-3}$	-0.339 (.186)	-0.283 (.580)	-0.186 (.191)	0.311** (.133)	-0.038 (.422)
$\Delta Asian\_Emp_{t-4}$	-0.104 (.168)	0.451 (.525)	0.359** (.173)	0.418*** (.121)	-0.180 (.382)
ΔGDP_{t-1}	0.071 (.063)	0.593*** (.195)	0.092 (.064)	0.076* (.045)	0.069 (.142)
ΔGDP_{t-2}	0.204*** (.061)	0.711*** (.189)	0.068 (.062)	0.010 (.044)	0.311 (.138)
ΔGDP_{t-3}	0.128* (.066)	0.725*** (.207)	0.244*** (.068)	-0.065 (.048)	0.151 (.150)
GDP_{t-4}	0.053 (.073)	0.244 (.227)	-0.032 (.075)	-0.089* (.052)	0.136 (.165)
Constant	5.266 (25.888)	16.219 (80.797) (72.418)	40.40 (26.641)	-13.558 (18.588)	87.612 (58.789)
Jarque-Berra Normality test Prob > X^2 All Equations= 0.01	0.18	0.01	0.06	0.84	0.10
LM Test of autocorrelation $H_o: No\ autocorrelation =>$ res_{-1}: Prob>$X^2 = .85$; res_{-2}: Prob>$X^2 = .20$; res_{-3}: Prob>$X^2 = .18$; res_{-4}: Prob>$X^2 = .32$					

*10% level of significance
**5% level of significance
***1% level of significance

Table 3. Management and Professional Occupations Short-run Granger Causality Tests

	AA_Emp_t	$White\_Emp_t$	$Latin\_Emp_t$	$Asian\_Emp_t$	GDP_t
AA_Emp_t		0.76	0.43	0.00	0.05
$White\_Emp_t$	0.57		0.06	0.00	0.49
$Latin\_Emp_t$	0.19	0.06		0.00	0.20
$Asian\_Emp_t$	0.35	0.62	0.07		0.41
GDP_t	0.01	0.00	0.00	0.16	

P-value of the Wald (Chi-Square) test that the row variable short-run Granger causes the respective column variable; Prob > $X^2 = a$

4.2 Service Occupations

Using the suggested lag length of 7 from the information criteria tests, the Johansen Tests for cointegration in Table A2B provide mixed results. The Trace statistic points to a rank of 3. This is offset by the Max statistics and SBIC that accept the null hypothesis of one cointegrating equation. The HQIC and AIC point to 4 and 5, respectively. So, we used one cointegrating equation to model the VECM for Service occupations. All the vector error correction models in Table 4 accept the null hypothesis that there is no long-run Granger causality, as all the coefficients are either positive or statistically insignificant at the 5% level. Additionally, except for African American employment in the first quarter Granger causing Asian employment there is no short-run causality among the other races. This is a stark difference from the management and professional occupations models in the previous section.

The Granger causality tests in Table 5 confirm this conclusion. All the results of the Chi-square test lagged coefficients do not reject the null hypothesis that lagged coefficients of other variables are not statistically different from zero. The LaGrange multiplier tests accept the null hypothesis of no serial autocorrelation of the lagged residuals of the models – a great outcome for the quality of the model. Except for the African American and white employment ECMs, the residuals exhibit white noise. For the most part, we can conclude from these models that employment activity of the racesTable 4. Service Occupations

Table 4. Vector Error Correction Model is independent in the services occupations.

	ΔAA_Emp_t	$\Delta White\_Emp_t$	$\Delta Latin\_Emp_t$	$\Delta Asian\_Emp_t$	ΔGDP_t
ce_{t-1}	-0.018	0.434*	0.062	0.043	0.148
	(.060)	(.256)	(.106)	(.035)	(.099)
ΔAA_Emp_{t-1}	-0.274	-0.039	-0.009	0.061**	-0.380
	(.178)	(.762)	(.317)	(.105)	(.296)
ΔAA_Emp_{t-2}	-0.120	0.452	0.181	0.199	-0.185
	(.182)	(.781)	(.325)	(.107)	(.303)
ΔAA_Emp_{t-3}	-0.259	-0.151	-0.248	-0.025	-0.466
	(.173)	(.740)	(.308)	(.102)	(.287)
$\Delta White\_Emp_{t-1}$	0.018	-0.182	0.029	-0.017	-0.081
	(.067)	(.287)	(.119)	(.039)	(.111)
$\Delta White\_Emp_{t-2}$	-0.043	-0.546***	0.046	0.007	0.200
	(.050)	(.213)	(.089)	(.029)	(.083)
$\Delta White\_Emp_{t-3}$	-0.037	-0.243	0.071	0.004	-0.169
	(.065)	(.279)	(.116)	(.038)	(.108)
$\Delta Latin\_Emp_{t-1}$	-0.008	-0.525	-0.519*	0.081	-0.128
	(.161)	(.690)	(.287)	(.010)	(.268)
$\Delta Latin\_Emp_{t-2}$	-0.075	-0.814	-0.705***	-0.081	-0.884***
	(.170)	(.727)	(.302)	(.100)	(.282)
$\Delta Latin\_Emp_{t-3}$	0.168	-0.235	-0.559*	-0.024	-0.171
	(.170)	(.731)	(.304)	(.100)	(.284)
$\Delta Asian\_Emp_{t-1}$	-0.170	3.084*	0.758	-0.385	0.510
	(.405)	(.1.737)	(.722)	(.239)	(.674)
$\Delta Asian\_Emp_{t-2}$	-0.279	1.487	0.333	-0.491***	0.089
	(.368)	(1.578)	(.656)	(.217)	(.613)
$\Delta Asian\_Emp_{t-3}$	0.210	2.689*	0.954	-0.025	0.063
	(.350)	(1.497)	(.622)	(.206)	(.581)
ΔGDP_{t-1}	0.141	-0.353	-0.028	-0.010	0.135
	(.108)	(.462)	(.192)	(.063)	(.179)
ΔGDP_{t-2}	0.142	0.704*	0.158	0.044	0.431***
	(.100)	(.427)	(.177)	(.059)	(.166)
ΔGDP_{t-3}	-0.031	0.049	0.145	0.009	0.345*
	(.108)	(.463)	(.192)	(.064)	(.180)
Constant	-29.088	-26.196	33.555	3.866	58.174
	(28.547)	(122.446) (72.418)	(50.907)	(16.827)	(47.535)
Jarque-Berra Normality test Prob > X^2 All Equations= 0.00	0.00	0.03	0.48	0.71	0.33
LM Test of autocorrelation $H_o: No\ autocorrelation =>$ res_{-1}: Prob>$X^2 = .61$; res_{-2}: Prob>$X^2 = .22$; res_{-3}: Prob>$X^2 = .67$;					

Table 5. Service Occupations Short-run Granger Causality Tests

	AA_Emp_t	$White\_Emp_t$	$Latin\_Emp_t$	$Asian\_Emp_t$	GDP_t
AA_Emp_t		0.91	0.71	0.24	0.31
$White\_Emp_t$	0.63		0.90	0.91	0.01
$Latin\_Emp_t$	0.62	0.70		0.55	0.00
$Asian\_Emp_t$	0.53	0.21	0.42		0.85
GDP_t	0.21	0.39	0.67	0.89	

P-value of the Wald (Chi-Square) test that the row variable short-run Granger causes the respective column variable; Prob > $X^2 = a$

4.3 Sales and Office Occupations

Using the sales and office employment series and a maximum lag of 4 determined by information criteria, 4 of 5 of the Johansen cointegration tests suggest accepting the null hypothesis of a maximum rank of 1 (Table A2C). We will estimate a system of vector error correction models with 1 error correction equation in Table 6.

The coefficient of the error correction variable for the African American equation is statistically significant, negative, and less than one. This indicates that white employment, Latino employment, Asian employment, and real GDP Granger causes African American employment in the long run. Moreover, 37.1% of deviations from this long run equilibrium are corrected in the first quarter. The coefficient of the second lag of the white employment variable is negative, and statistically significant. A 1,000 unit increase in white employment in the second quarter, on average, leads to a reduction of 170 employees in the African American community, holding GDP and employment in the other communities constant. This is corroborated by the Chi square coefficient in the short run Granger causality Table 7, albeit at the 10% level of significance. The null hypothesis of serial correlation of the three lags of the residuals is accepted. However, the results of Chi-square tests of the Jarque-Berra reject the null hypothesis of normality in the residuals.

We can conclude from these results that among sales and office related occupations, there is some evidence of a negative relationship between white and African American communities. Increased white employment in the labor market typically leads to a reduction in employment of African Americans.

Table 6. Sales and Office Occupations Vector Error Correction Model

	ΔAA_Emp_t	$\Delta White\_Emp_t$	$\Delta Latin\_Emp_t$	$\Delta Asian\_Emp_t$	ΔGDP_t
ce_{t-1}	-0.371**	-0.091	-0.194	0.096	1.077***
	(.146)	(504)	(.154)	(.085)	(.301)
ΔAA_Emp_{t-1}	-0.199	0.172	0.271	0.088	-0.384
	(.158)	(.547)	(.167)	(.092)	(.327)
ΔAA_Emp_{t-2}	-0.493***	-0.620	-0.035	0.053	-0.687**
	(.147)	(.508)	(.155)	(.085)	(.303)
ΔAA_Emp_{t-3}	-0.407***	-0.466	-0.087	-0.004	-0.372
	(.136)	(.468)	(.143)	(.079)	(.279)
$\Delta White\_Emp_{t-1}$	-0.000	-0.226	-0.013	0.045	0.268*
	(.079)	(.272)	(.083)	(.046)	(.162)
$\Delta White\_Emp_{t-2}$	-0.170**	-0.597**	-0.121	-0.051	0.044
	(.076)	(.261)	(.080)	(.044)	(.156)
$\Delta White\_Emp_{t-3}$	-0.052	-0.100	-0.088	-0.001	0.170
	(.075)	(.260)	(.079)	(.044)	(.155)

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$\Delta Latin\_Emp_{t-1}$	-0.120	0.798	-0.260	0.128	0.616*
	(.171)	(.591)	(.180)	(.100)	(.353)
$\Delta Latin\_Emp_{t-2}$	0.144	0.474	-0.244	0.076	0.388
	(.164)	(.566)	(.173)	(.095)	(.338)
$\Delta Latin\_Emp_{t-3}$	0.003	0.095	-0.122	0.061	0.178
	(.163)	(.562)	(.172)	(.094)	(.336)
$\Delta Asian\_Emp_{t-1}$	-0.261	0.679	-0.021	-0.332**	1.219**
	(.281)	(.972)	(.297)	(.163)	(.580)
$\Delta Asian\_Emp_{t-2}$	-0.317	-0717	-0.280	-0.424***	-0.236
	(.252)	(.870)	(.266)	(.146)	(.519)
$\Delta Asian\_Emp_{t-3}$	0.021	0.187	0.027	-0.266**	-0.058
	(.228)	(.787)	(.240)	(.132)	(.470)
ΔGDP_{t-1}	0.153	-0.272	-0.002	-0.137**	-0.638***
	(.093)	(.322)	(.098)	(.054)	(.193)
ΔGDP_{t-2}	0.347***	0.643*	0.183*	0.076	-0.060
	(.099)	(.342)	(.104)	(.058)	(.200)
ΔGDP_{t-3}	0.153	0.133	0.127	0.022	-.060
	(.097)	(.335)	(.102)	(.056)	(.200)
Constant	-18.288	-239.552**	21.398	-22.618	-20.628
	(32.342)	(111.694)	(34.106)	(18.771)	(66.684)
Jarque-Berra Normality test Prob > X^2 All Equations= 0.00	0.00	0.00	0.08	0.00	0.11
LM Test of autocorrelation $H_o: No\ autocorrelation =>$ res_{-1}: Prob>$X^2 = .56$; res_{-2}: Prob>$X^2 = .31$; res_{-3}: Prob>$X^2 = .11$;					

Table 7. Sales & Office Occupations Short-run Granger Causality Tests

	AA_Emp_t	$White\_Emp_t$	$Latin\_Emp_t$	$Asian\_Emp_t$	GDP_t
AA_Emp_t		0.40	0.21	0.76	0.14
$White\_Emp_t$	0.10		0.35	0.25	0.34
$Latin\_Emp_t$	0.61	0.54		0.60	0.32
$Asian\_Emp_t$	0.50	0.43	0.62		0.04
GDP_t	0.01	0.09	0.24	0.01	

P-value of the Wald (Chi-Square) test that the row variable short-run Granger causes the respective column variable; Prob > $X^2 = a$

4.4 Natural Resources, Construction & Maintenance Occupations

Four of five Johansen tests for cointegration among the series fail to reject the null hypothesis of zero max rank among the matrices. This suggests that there is no long-run relationship among the variables. However, the series are nonstationary in their levels as determined in Table 1. This rejects the likelihood of cointegration among the variables, leading to a vector autoregressive (VAR) model to determine short-run relationships among the variables. Table A2D contains these results. Guided by information criteria tests, we use 6 lags of variables in the system of equations.

The VAR results are found in Table 8. The fourth lag of employment in African American employment Granger causes (positively) white and Latino employment. Albeit with oscillating signs, coefficients of three of six lags of the white employment variables are statistically significant in the African American employment equation. Additionally, an increase in employment in the African American community can be seen as a precursor to increases in employment in white and Latino employment – but a decrease in future employment in the

Asian community. An interesting causal outcome can be seen between Asian and Latino employment. Albeit with toggling signs of the coefficients, four of 6 lags of Latino employment Granger-causes Asian employment. This is corroborated with rejection of the null hypothesis of all six coefficients jointly equally zero with a 0.00 p-value of the Chi square in Table 9. Indeed, Latino employment Granger causes Asian employment in these occupations.

Conversely, the first three lags of the coefficients of the Asian employment variables are statistically significant – the first lag significant only at the 10% level. The short-run Granger causality in Table 10 also corroborates this result. So, there is feedback between these two employment communities in these occupations. An increase in employment in the Latino community is met with an increase in employment in the Asian community. The same occurs if the increase in employment begins in the Asian community. However, an increase in the second previous quarter results in a decrease in employment in the other community. Employment in these two communities is not independent of employment in the other -- astonishing!

Diagnostically, this VAR system of equations is sound. There is no sign of serial autocorrelation of the residuals and the Jarque-Berra Chi square tests do not reject the null hypothesis of white noise in the residuals.

Table 8. Natural Resources Construction & Maintenance Vector Autoregression Model (VAR)

	AA_Emp_t	$White\_Emp_t$	$Latin\_Emp_t$	$Asian\_Emp_t$	GDP_t
AA_Emp_{t-1}	0.208*	-0.888	-0.519	-0.046	-0.418
	(.121)	(.629)	(.343)	(.049)	(.606)
AA_Emp_{t-2}	-0.078	0.711	0.443	0.115**	-0.440
	(.120)	(.624)	(.341)	(.049)	(.601)
AA_Emp_{t-3}	-0.084	-0.202	-0.500	-0.149***	-0.231
	(.118)	(.615)	(.336)	(.048)	(.593)
AA_Emp_{t-4}	0.202*	2.673***	1.509***	0.056	2.647***
	(.117)	(.611)	(.333)	(.048)	(.588)
AA_Emp_{t-5}	-.107	-0.149	-0.280	0.002	-0.111
	(.126)	(.659)	(.359)	(.052)	(.634)
AA_Emp_{t-6}	0.233**	-0.507	-0.371	-.002	-0.427
	(.116)	(.604)	(.330)	(.047)	(.582)
$White\_Emp_{t-1}$	0.122***	0.599***	0.068	-0.026*	-0.231
	(.036)	(.186)	(.101)	(.015)	(.179)
$White\_Emp_{t-2}$	-0.028	0.164	0.190	0.019	0.212
	(.045)	(.236)	(.129)	(.019)	(.228)
$White\_Emp_{t-3}$	-0.014	0.181	-0.065	-0.032**	-0.038
	(.038)	(.200)	(.109)	(.016)	(.193)
$White\_Emp_{t-4}$	0.100***	0.429**	0.150	0.029*	0.044
	(.037)	(.195)	(.106)	(.015)	(.187)
$White\_Emp_{t-5}$	-0.118***	-0.136	-.169	0.005	0.371*
	(.038)	(.199)	(.109)	(.016)	(.192)
$White\_Emp_{t-6}$	-0.015	-0.216	0.029	-0.004	0.109
	(.039)	(.204)	(.111)	(.016)	(.197)
$Latin\_Emp_{t-1}$	-0.103	0.064	0.670***	0.105***	0.225
	(.077)	(.401)	(.219)	(.032)	(.386)
$Latin\_Emp_{t-2}$	0.114	-0.455	-0.489**	-0.092**	0.275
	(.094)	(.488)	(.266)	(.038)	(.470)
$Latin\_Emp_{t-3}$	-0.005	0.927*	0.902***	0.156***	0.198
	(.092)	(.479)	(.261)	(.038)	(.461)
$Latin\_Emp_{t-4}$	-0.152	-1.076**	-0.709***	-0.092**	-0.749
	(.095)	(.497)	(.271)	(.039)	(.479)
$Latin\_Emp_{t-5}$	0.157	0.516	0.391	0.005	-0.833*
	(.091)	(.474)	(.259)	(.037)	(.457)

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$Latin\_Emp_{t-6}$	-0.064	-0.638	-0.503**	-0.026	-0.708
	(.089)	(.468)	(.255)	(.037)	(.451)
$Asian\_Emp_{t-1}$	0.051	0.668	1.240*	0.287***	-0.534
	(.252)	(.1.312)	(.716)	(.103)	(1.264)
$Asian\_Emp_{t-2}$	0.013	-2.659*	-1.570**	-0.124	0.628
	(.279)	(1.454)	(.793)	(.114)	(1.400)
$Asian\_Emp_{t-3}$	0.295	3.220**	1.676**	0.279**	0.326
	(.272)	(1.416)	(.773)	(.111)	(1.364)
$Asian\_Emp_{t-4}$	0.232	-1.654	-0.469	0.041	0.960
	(.251)	(1.309)	(.715)	(.103)	(1.261)
$Asian\_Emp_{t-5}$	-0.145	-0.065	-0.309	-0.027	-3.067**
	(.241)	(1.257)	(.686)	(.099)	(1.211)
$Asian\_Emp_{t-6}$	0.065	-3.054**	-0.975	-0.173*	-0.288
	(.235)	(1.225)	(.669)	(.096)	(1.180)
GDP_{t-1}	0.110	0.034	-0.009	.010	0.827***
	(.030)	(.155)	(.085)	(.012)	(.149)
GDP_{t-2}	-0.034	0.285	0.110	0.008	0.129
	(.035)	(.181)	(.099)	(.014)	(.174)
GDP_{t-3}	0.052	-0.292*	-0.244***	-0.026**	-.044
	(.032)	(.167)	(.091)	(.013)	(.161)
GDP_{t-4}	-0.087***	-0.279	0.063	0.003	0.013
	(.034)	(.176)	(.096)	(.014)	(.170)
GDP_{t-5}	0.019	-0.267	-0.137	-0.010	0.153
	(.037)	(.195)	(.106)	(.015)	(.187)
GDP_{t-6}	0.055*	0.628***	0.345***	0.029**	0.217
	(.031)	(.162)	(.089)	(.013)	(.156)
Constant	-276.624	-154.737	-1900.128*	219.648	-4887.647
	(385.258)	(2006.327)	(1094.884)	(157.729)	(1932.142)
Jarque-Berra Normality test Prob > X^2 All Equations= 0.75	0.37	.64	.54	1.00	.27

LM Test of autocorrelation
$H_o: No\ autocorrelation =>$
res_{-1}: Prob>$X^2 = .19$;
res_{-2}: Prob>$X^2 = .19$;
res_{-3}: Prob>$X^2 = .42$;
res_{-4}: Prob>$X^2 = .69$
res_{-5}: Prob>$X^2 = .72$

Table 9. Natural Resources, Construction, & Maintenance Occupations Granger Causality Tests

	AA_Emp_t	$White\_Emp_t$	$Latin\_Emp_t$	$Asian\_Emp_t$	GDP_t
AA_Emp_t		0.00	0.00	0.04	0.00
$White\_Emp_t$	0.00		0.27	0.27	0.02
$Latin\_Emp_t$	0.07	0.32		0.00	0.00
$Asian\_Emp_t$	0.71	0.03	0.05		0.21
GDP_t	0.08	0.00	0.00	0.00	

P-value of the Wald (Chi-Square) test that the row variable short-run Granger causes the respective column variable; Prob > $X^2 = a$

The impulse response functions in Figure 1 provide a graphical illustration of the dynamic relations among the variables. Owing to the low-level effects of shocks running from Latino employment to Asian employment, the graph in the first column, row four appears to be a relatively flat line. On the other hand, the relationship between Latino employment and White employment can be seen in the graph located in row 4 and column 6.

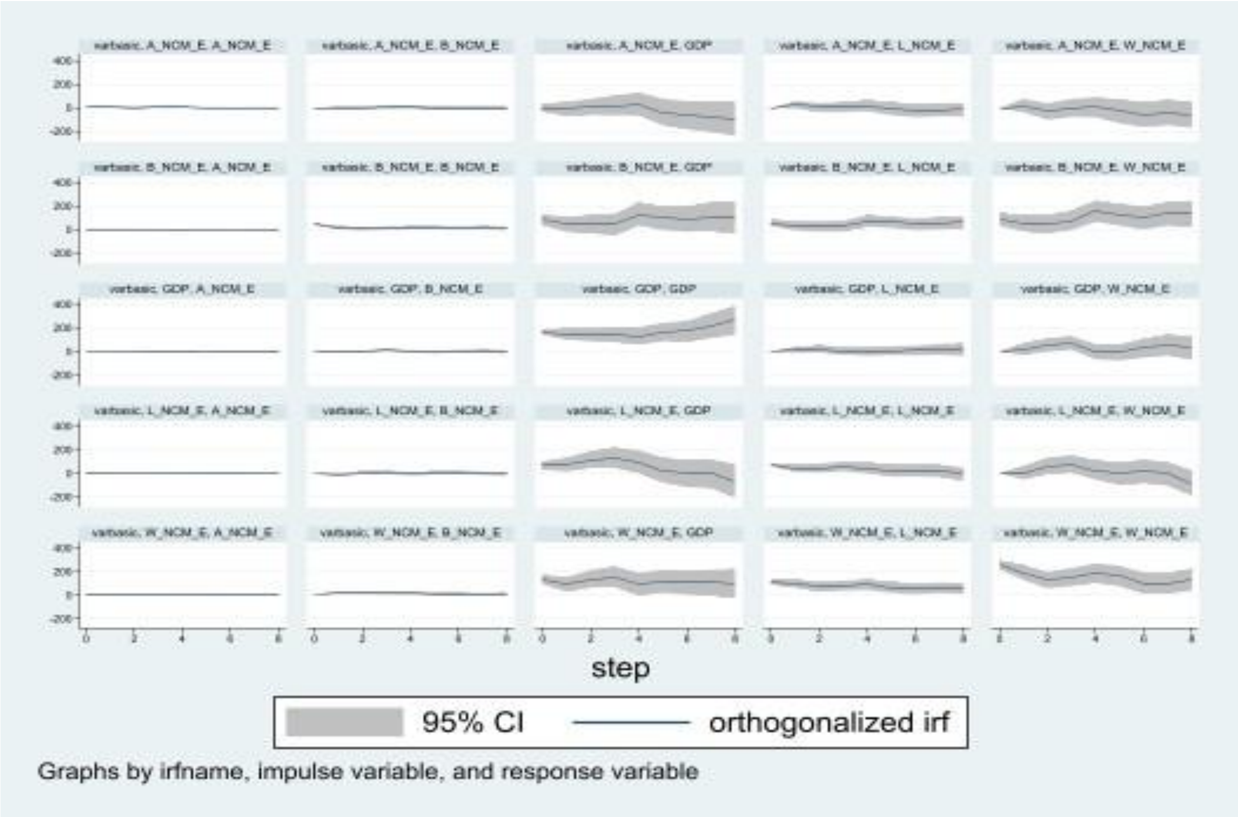

Figure 1. Impulse Response Function -- Natural Resources, Production, and Maintenance

4.5 Production, Transportation & Material Moving Occupations

We accept the null hypothesis of no cointegration among the variables, as suggested by three of the Johansen cointegration tests. The VAR model is in Table 10 and Granger causality tests in Table 11. African American employment Granger causes white and Latino employment in these occupations. There is also feedback running from white employment to African American employment. We also note that Latino and Asian employment affect African American employment in the short run as well. Except for the Asian employment market, there is a great deal of interaction between the races in the production, transportation, and materials movement labor market. The residuals in the models are normally distributed and serially uncorrelated.

Table 10. Production, Transportation (Employment Sector) Vector Autoregression Model (VAR)

	AA_Emp_t	$White\_Emp_t$	$Latin\_Emp_t$	$Asian\_Emp_t$	GDP_t
AA_Emp_{t-1}	0.445***	0.691**	0.200	0.110*	-0.133
	(.101)	(.346)	(.133)	(.062)	(.294)
AA_Emp_{t-2}	0.059***	0.822**	0.216	0.041	0.934***
	(.110)	(.377)	(.145)	(.068)	(.320)
AA_Emp_{t-3}	-0.099	-0.086	0.098	0.012	-0.308
	(.110)	(.377)	(.145)	(.068)	(.320)
AA_Emp_{t-4}	0.376***	-0.574*	-0.144	-0.053	0.024
	(.096)	(.328)	(.126)	(.059)	(.279)
$White\_Emp_{t-1}$	0.032	0.151	-0.076	-0.061**	-0.364**
	(.050)	(.172)	(.066)	(.031)	(.146)
$White\_Emp_{t-2}$	0.130**	0.320*	0.071	0.067*	0.270*
	(.056)	(.190)	(.073)	(.034)	(.162)
$White\_Emp_{t-3}$	0.053	0.260	0.013	-0.011	0.021
	(.055)	(.187)	(.072)	(.034)	(.159)

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$White\_Emp_{t-4}$	-0.204***	-0.057	0.000	-0.016	-0.217*
	(.049)	(.168)	(.065)	(.030)	(.143)
$Latin\_Emp_{t-1}$	-0.316***	-0.846**	0.073	-0.130*	-0.709**
	(.121)	(.415)	(.160)	(.075)	(.353)
$Latin\_Emp_{t-2}$	0.056	-0.065	-0.160	-0.010	0.610
	(.128)	(.439)	(.169)	(.079)	(.373)
$Latin\_Emp_{t-3}$	-0.301**	-0.494	-0.033	-0.003	-0.266
	(.130)	(.445)	(.171)	(.080)	(.378)
$Latin\_Emp_{t-4}$	0.652***	0.750*	0.183	-0.021	1.047***
	(.124)	(.424)	(.163)	(.076)	(.31)
$Asian\_Emp_{t-1}$	0.139	-0.984	-0.424*	0.478***	-0.552
	(.179)	(.614)	(.236))	(.111)	(.522)
$Asian\_Emp_{t-2}$	-0.474**	0.404	0.260	-0.036	0.189
	(.198)	(.677)	(.261)	(.122)	(.575)
$Asian\_Emp_{t-3}$	0.661***	.355	0.194	0.094	-0.131
	(.198)	(.676)	(.260)	(.122)	(.573)
$Asian\_Emp_{t-4}$	-0.087	0.230	0.077	0.351***	-0.051
	(.182)	(622)	(.239)	(.112)	(.528)
GDP_{t-1}	0.189***	0.806	0.264***	.088***	1.459***
	(.047)	(.161)	(.062)	(.029)	(.137)
GDP_{t-2}	-0.087	-0.556**	-0.108	-0.070*	-0.359*
	(.068)	(.232)	(.089)	(.042)	(.197)
GDP_{t-3}	0.007	-0.251	-0.058	-0.020	-.101
	(.061)	(.210)	(.081)	(.038)	(.178)
GDP_{t-4}	-0.103**	-0.011	-0.031	0.012	-0.091
	(.048)	(.164)	(.063)	(.030)	(.140)
Constant	-208.446	4687.604***	1209.391**	545.617*	2112.195
	(460.399)	(1574.340)	(606.028)	(283.330)	(1337.124)
Jarque-Berra Normality test Prob > X^2 All Equations= 0.00	0.12	.73	.92	.60	.00
LM Test of autocorrelation $H_o: No\ autocorrelation =>$ res_{-1}: Prob>$X^2 = .52$; res_{-2}: Prob>$X^2 = .67$; res_{-3}: Prob>$X^2 = .94$; res_{-4}: Prob>$X^2 = 1.00$					

Table 11. Production, Transportation, & Material Moving Occupations Short-run Granger Causality Tests

	AA_Emp_t	$White\_Emp_t$	$Latin\_Emp_t$	$Asian\_Emp_t$	GDP_t
AA_Emp_t		0.00	0.05	0.22	0.06
$White\_Emp_t$	0.00		0.77	0.17	0.02
$Latin\_Emp_t$	0.00	0.09		0.46	0.01
$Asian\_Emp_t$	0.01	0.53	0.29		0.74
GDP_t	0.00	0.00	0.00	0.05	

P-value of the Wald (Chi-Square) test that the row variable short-run Granger causes the respective column variable; Prob > $X^2 = a$

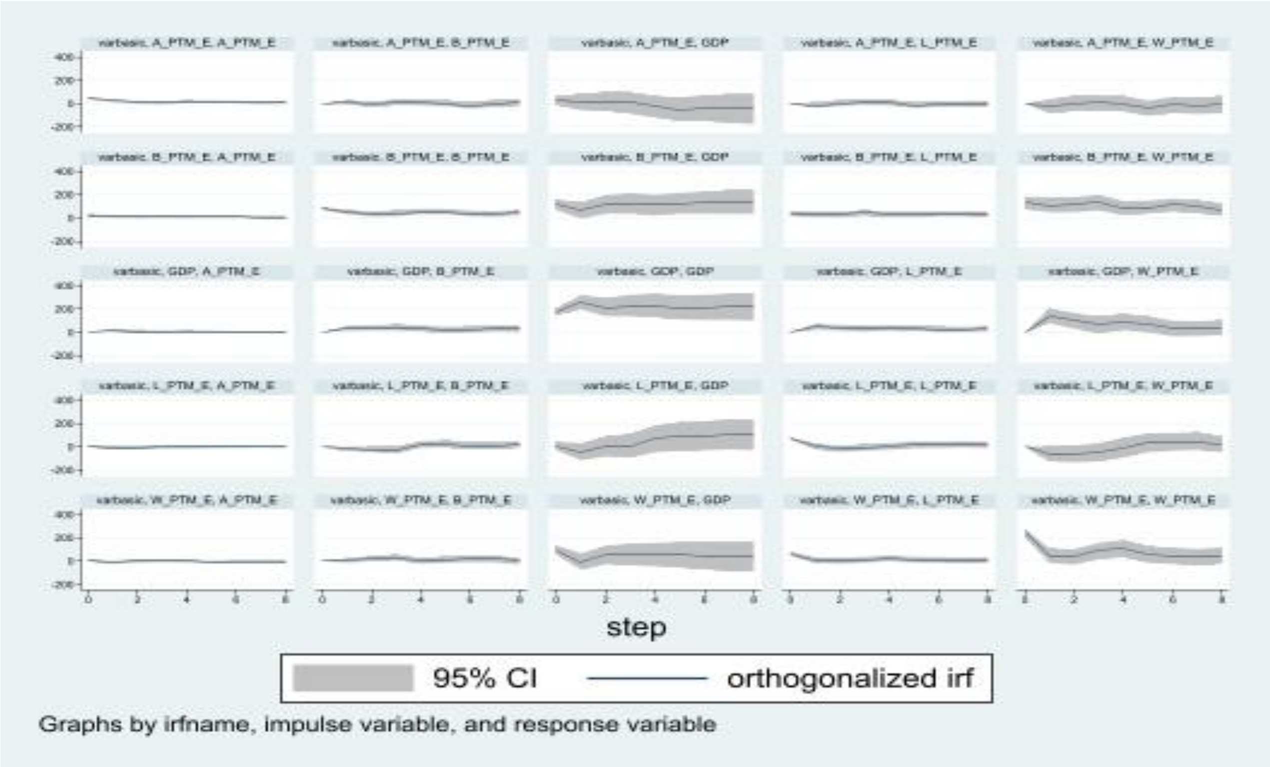

Figure 2 Impulse Response Function- Production, Transportation, & Material Moving Occupations

Table 12 summarizes the results of the VECM, VAR and Granger Causality tests from the previous sections. The five occupational categories are designated by their respective letters. This is either followed by superscript of + or – to indicate a conclusive positive effect or a negative causality. In cases where the direction is inconclusive, a sign is omitted. When it comes to short run Granger causality, racial employment is occupationally dependent. Racial employment relationship exists in the three broad racial occupations: Management and professional; natural resources, construction, and maintenance occupations; and production, transportation, and material movement occupations. Contrary to a priori expectations, there does not appear to be much racial employment relationship in the sales and office occupations and Services occupations.

Table 12. Summary of Granger Causality Tests All Occupations

	AA Emp	White Emp	Latino Emp	Asian Emp	GDP
AA Emp	--	N^+,P^+	N^+,P^+	M^-,N	M,N^+
White Emp	N^+, P	--	--	N^-, M^+	S,N ,P
Latino Emp	P	N^-	--	M^-,N	S,N^+,P
Asian Emp	P	N	N	--	N^-, Sa^+
GDP	M,Sa^+ ,P	Sa^+,N^+,P^-	M,N ,P^+	Sa^-,N ,P^+	--

M = Management and professional occupations
S = Services occupations
Sa = Sales and Office occupations
N = Natural resources, construction, and maintenance occupations
P = Production, transportation, and material movement

We can see from the table that not only does African American employment Granger causes white, and Latino employment in the Natural resource, construction, and maintenance occupations, but it does so in a positive way. Within this occupation, when African American employment increases, it results in an increase in employment of Whites and Latino workers the following year (4 quarters). This resoundingly refutes the zero-relationship assumption. An increase in African American employment will not only lead to an increase in Latino and white employment in the following year, it results in economic expansion, holding all else constant. We can view African American employment as a leading indicator for economic growth. This is an interesting outcome, given that the economy employs the fewest workers in that industry (9%) and only 6% of all African American workers.

We can also glean from Table 12 that in the short run, African American employment in production, transportation, and maintenance is most dependent on the employment of whites, Latinos, and Asians. And in the opposite direction, an increase in African American employment leads to unambiguous increases in employment of whites and Latinos in the short run.

In the production, transportation and material moving occupations, African American employment also positively Granger causes White and Latino employment in the short run. It is a relatively interesting outcome that Latino employment does not Granger cause employment of Whites in any occupation. This is also true in reverse – whites do not Granger cause Latino employment in any occupation.

In management and professional occupations, White employment Granger cause Asian employment in the short run. In this view, Asian employees can be thought of as good substitutes for white employment.

5. Conclusion

There are many models that explain employment levels differences of African Americans relative to other racial groups. Whatever barriers that firms face as reasons for not hiring members of a racial group, we know that if a firm is operating efficiently at its optimal level of output, the only way to change the racial makeup of its labor force is to either increase output; alter the technology employed; change its capital structure; or alter the proportion of other racial groups the firm employs. While this reality exists at the micro level for each firm, there are not many empirical studies that have identified dynamic racial relationships within the U.S. labor force. This paper adds to this void by employing VECM and VAR models to test for Granger causality among the racial groups in broad occupations in the United States.

We discovered that there is an unambiguous relationship in the employment of racial groups in the labor market – it is a function of the occupation. While relationships are ubiquitous among racial groups within most occupations, the most pronounced is the relationship in employment between African American and other racial groups in the natural resources, construction, and maintenance occupations. Revealing occupational employment patterns among racial groups is a great start. This will go a long way toward implementing policy to rectify this. Towards that end, it would be useful to determine if these patterns are universal, geographical, or even by locale. This leaves plenty of research opportunities toward that end. Until such a time, we can conclude for now with some degree of confidence that the hiring/employment practice of firms is not a stochastic process – it matters on the occupation.

6. Appendix

Appendix A1. Unit Root Analysis

Management, Professional, & Other Occupations

Variable	Dickey Fuller, Z(t)	DFGLS, (Tau)	Phillips-Perron, Z(t)
GDP	1.794	-0.251	2.338
ΔGDP	-2.986**	-6.094***	-10.126***
AA Emp	2.246	-0.324	2.889
ΔAA Emp	-2.230	-2.337	-12.790***
L Emp	1.728	-1.224	1.880
ΔL Emp	-4.786***	-7.657***	-12.073***
White Emp	1.044	-1.860	1.195
ΔWhite Emp	-3.980***	-3.991***	-11.665***
Asian Emp	1.560	-0.961	1.707
ΔAsian Emp	-3.039**	-2.185	-10.641***

Service Occupations

Variable	Dickey Fuller, Z(t)	DFGLS, (tau)	Phillips-Perron, Z(t)
AA Emp	-1.375	-2.427	-1.948
ΔAA Emp	-4.293***	-9.295***	-10.933***
L Emp	-1.155	-2.337	-1.578
ΔL Emp	-5.119***	-8.919***	-12.733***
White Emp	-2.478	-1.685	-3.593***
ΔWhite Emp	-5.337***	-2.996**	-12.945***
Asian Emp	-1.153	-2.839	-1.646
ΔAsian Emp	-4.170***	-9.926***	-13.739***

Sales and Office Occupations

Variable	Dickey Fuller, Z(t)	DFGLS, (tau)	Phillips-Perron, Z(t)
AA Emp	-2.405	-2.191	-3.700***
ΔAA Emp	-4.539***	-4.874***	-11.196***
L Emp	-1.402	-2.348	-1.050
ΔL Emp	-3.828***	-9.365***	-10.249***
White Emp	-0.118	-1.976	-0.316
ΔWhite Emp	-3.805***	-4.058***	-10.308***
Asian Emp	-1.250	-2.289	-3.032**
ΔAsian Emp	-4.470***	-8.475***	-15.095***

Natural Resources, Construction, & Maintenance Occupations

Variable	Dickey Fuller, Z(t)	DFGLS, (tau)	Phillips-Perron, Z(t)
AA Emp	-1.517	-1.617	-4.361***
ΔAA Emp	-4.706***	-4.216***	-15.089***
L Emp	-1.348	-1.608	-1.412
ΔL Emp	-3.314**	-2.812*	-11.161***
White Emp	-2.397	-2.197	-2.565
ΔWhite Emp	-2.978**	-4.197***	-11.604***
Asian Emp	-2.735*	-2.757*	-6.427***
ΔAsian Emp	-4.553***	-1.954	-16.018***

Production, Transportation, & Material Moving Occupations

Variable	Dickey Fuller, Z(t)	DFGLS, (tau)	Phillips-Perron, Z(t)
AA Emp	0.164	-1.078	-0.421
ΔAA Emp	-3.382***	-3.042**	-11.523***
L Emp	-2.042	-1.014	0.295
ΔL Emp	-4.195***	-10.959***	-15.141***
White Emp	-2.607*	-0.786	-2.752*
ΔWhite Emp	-3.686***	-9.948***	-13.877***
Asian Emp	-0.885	-1.226	-2.067
ΔAsian Emp	-4.426***	-8.460***	-14.794***

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Appendix A2. Johansen Cointegration Tests

Table A2A. Management and Professional Occupation Johansen Tests for Cointegration

Max Rank	Parms	LL	Eigen	Trace Stat	5% CV	Max Stat	5% CV	SBIC	HQIC	AIC
0	105	-2827		83.03	68.52	40.46	33.46	69.60	67.83	66.64
1	114	-2807	0.369	42.57	47.21	20.25	27.07	69.59	67.68	66.38
2	121	-2798	0.206	22.32	29.68	10.63	20.97	69.72	67.69	66.31
3	126	-2791	0.114	11.69	15.41	7.72	14.07	69.85	67.74	66.31
4	129	-2788	0.084	3.97	3.76	3.97	3.76	69.92	67.75	66.29
5	130	-2786	0.044					69.92	67.74	66.26
N= 88		Lags =5		Trend = constant						

Table A2B. Services Occupation Johansen Tests for Cointegration

Max Rank	Parms	LL	Eigen	Trace Stat	5% CV	Max Stat	5% CV	SBIC	HQIC	AIC
0	155	-2661		99.75	68.52	44.17	33.46	69.92	67.28	65.50
1	164	-2639	0.402	55.58	47.21	23.99	27.07	69.87	67.08	65.19
2	171	-2627	0.243	31.59	29.68	16.79	20.97	69.96	67.04	65.08
3	176	-2619	0.117	14.80	15.41	12.14	14.07	70.02	67.02	65.00
4	179	-2613	0.132	2.65	3.76	2.65	3.76	70.03	66.98	64.93
5	180	-2611	0.030					70.06	66.99	64.92
N= 86		Lags =7		Trend = constant						

Table A2C. Sales and Office Occupations Johansen Tests for Cointegration

Max Rank	Parms	LL	Eigen	Trace Stat	5% CV	Max Stat	5% CV	SBIC	HQIC	AIC
0	155	-2858		87.74	68.52	44.17	33.46	66.27	65.36	64.74
1	64	-2833	0.438	35.94	47.21	23.99	27.07	66.15	65.09	64.37
2	71	-2823	0.189	17.00	29.68	16.79	20.97	66.29	65.11	64.31
3	76	-2818	0.114	6.07	15.41	12.14	14.07	66.41	65.15	64.30
4	79	-2815	0.062	0.28	3.76	2.65	3.76	66.50	65.19	64.31
5	80	-2815	0.003					66.55	65.22	64.32
N= 90		Lags =3		Trend = constant						

Table A2D. Natural Resources, Construction, & Maintenance Occupations Johansen Tests for Cointegration

Max Rank	Parms	LL	Eigen	Trace Stat	5% CV	Max Stat	5% CV	SBIC	HQIC	AIC
0	130	-2516		70.94	68.52	27.38	33.46	64.51	62.30	60.82
1	139	-2502	0.270	43.56	47.21	19.58	27.07	64.65	62.30	60.71
2	146	-2492	0.202	23.98	29.68	15.29	20.97	64.79	62.31	60.65
3	151	-2485	0.161	8.70	15.41	6.77	14.07	64.87	62.31	60.59
4	154	-2481	0.075	1.93	3.76	1.93	3.76	64.94	62.33	60.58
5	155	-2480	0.022					64.97	62.35	60.58
N= 87		Lags =6		Trend = constant						

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Table A2E. Production, Transportation, and Material MovingvJohansen Tests for Cointegration

Max Rank	Parms	LL	Eigen	Trace Stat	5% CV	Max Stat	5% CV	SBIC	HQIC	AIC
0	80	-2719		65.92	68.52	28.90	33.46	65.14	63.80	62.90
1	89	-2705	0.277	37.02	47.21	16.24	27.07	65.26	63.78	62.78
2	96	-2696	0.167	20.79	20.68	11.87	20.97	65.44	63.83	62.75
3	101	-2690	0.125	8.92	15.41	6.37	14.07	65.55	63.87	62.73
4	104	-2687	0.069	2.54	3.76	2.54	3.76	65.63	63.90	62.73
5	105	-2696	0.028					65.66	63.90	62.72
N= 89		Lags = 4		Trend = constant						

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