THE ROLE OF BUSINESS CYCLE IN INTERNAL MIGRATION: A PANEL VAR APPROACH*

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Abstract This paper provides new evidence for the procyclicality of the state-to-state migration within the United States. Applying the current CPS panel data to a novel panel VAR framework, we confirm the findings of previous literature that internal migration rises during economic boom and declines during contraction. Procyclicality is found for both in and out migration flow.

Keywords: Business cycle; Internal migration; Panel VAR; Difference GMM

I. INTRODUCTION

Historically, high internal mobility has always been a hallmark of the U.S. population. From the westward expansion in the 19th century to the most recent urban collapse of Detroit, a vast number of Americans decide to leave their hometown and migrate to a different part of the country. According to the Current Population Survey (CPS) in 2014, 11.5% of the U.S. population lived in a different residence a year ago, and of those, 13.1% are from a different state.[1]

The possible determinants of internal migration have been extensively studied by economists and sociologists for over half a century. Early studies such as Tiebout (1956) suggest the important role of public policy using the famous consumer-voter model. The model states that the choice process of individuals, jurisdictions and residents will determine an equilibrium provision of local public goods, thereby sorting the population into optimum communities. Meanwhile, factors such as the cyclical behavior of real wages and unemployment have also been widely popular. For example, Barsky and Solon (1989) find evidence for the procyclicality of real wages in the U.S. Their analysis of longitudinal income data reveals substantial cyclicality in nationwide average wages since WWII. Despite the large number of empirical contributions made examining both migration and the cyclical properties of the labor market in general, it is indeed surprising that the linkage between internal migration in the U.S. and the business cycle has received so little attention thus far. This study tries to shed new light on this topic through the use of advanced panel data analysis.

The omission in the mainstream labor economics literature of cyclical properties of migration is unexpected because migration, as an important aspect of the labor market, offers advantages in business cycle and labor market studies. First of all, migration theory offers a direct and well-established framework for identifying the

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* This paper is a shortened version of the final dissertation of the same title. The work presented in this paper only addresses a fraction of the original proposal and the results shown are subject to future changes.

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[1] Source: 2014 CPS ASEC sample estimates https://www.census.gov/hhes/migration/data/cps.html.

effect of the business cycle on the geographic reallocation of the labor force. The maximization of personal well-being is the driving force of migration including a preference for amenities or the pursuit of economic opportunity. Given that personal preferences are unrelated to the business cycle, any correlation between migration and the business cycle is only driven by changes in the economic benefits of moving. The other advantage is that migration data is easily accessible and available for a significant time range, which allows us to observe more business cycles and more variations.

The question the present study raises is whether and how the business cycle correlates with internal migratory flows. It is a reasonable assumption that internal migration is strongly cyclical on a state level because across state migration is frequently accompanied by a change of local labor market conditions, a new employer-employee match or a change in labor force status (Saks and Wozniak 2011). Ergo, as a proxy for labor reallocation, migration is closely associated with fluctuations of the labor market, which is a reflection of the business cycle.

In light of the lack of related studies using panel data, I attempt to seek the answer by applying a panel vector autoregression (PVAR) model using aggregate level Current Population Survey (CPS) data. This currently untapped empirical tool combines the traditional VAR approach, which treats all variables of the system as endogenous, with new estimation techniques for panel data. Therefore, it enables us to look at the question from a new angle of both temporal and spatial variations. The use of panel VAR is considered a significant enrichment to the current literature due to the fact that while traditional VAR models in time series analysis are a common standard, the incorporation with panel data in the field of labor economics is relatively scarce.

The empirical results that we present confirm the findings of previous literature that there is procyclicality within the U.S. internal migration. We show that the state-to-state migration is positively correlated with the local business cycle for both in and out migration flow. Specifically, a 1 standard deviation increase in unemployment growth rate will result in a decrease of 0.249 in gross in-migration rate per 1000 residents and a 1 standard deviation increase in unemployment gap will on average result in a 0.482 fall in gross out-migration rate per 1000 residents. We interpret these results as evidence that the net benefit of migration fluctuates over the business cycle.

The remainder of the paper proceeds in five sections. In Section II, I first briefly introduce the literature on the general determinants of migration. Then I discuss further in detail previous migration studies related to both the business cycle and the panel VAR technique. I address a debate of different views on the role of migration at the end of this section. In Section III, I present the theoretical framework used for this research. A data overview and empirical design are presented in Section IV, which includes the model specification, preliminary test results and a brief discussion of the estimation method. Section V presents the estimation results. Section VI concludes this paper.

II. LITERATURE REVIEW

The field of interregional migration has been widely studied. Greenwood (1975) provides a thorough review of the earlier migration research. At the same time, studies on the cyclical properties of labor market variables other than geographic flows have also been fruitful and detailed. Studies such as Barsky and Solon (1989) reveal substantial cyclicality of real wages in the U.S. since WWII through their analysis of longitudinal data on industry real average wages. What is truly striking about the prior literature is the fact that cyclicality in migration has escaped a satisfactory examination for such a long time. Empirically, modern studies on cyclical behaviors of migration using panel data modelling remain both scarce and inconclusive.

1. Determinants of migration

The classic literature has considered a variety of determinants and modelling techniques for both gross and net migration volume. Early studies such as Tiebout (1956) suggest the important role of public policy using the famous consumer-voter model. The model states that the choice process of individuals, jurisdictions and residents will determine an equilibrium provision of local public goods, thereby sorting the population into optimum communities. Later research has examined both economic and non-economic incentives including climate (Conway and Houtenville 1998; Conway and Houtenville 2001; Cebula 2007), housing prices (Cebula 2007), tax burdens (Tiebout 1956; Cebula 1990; Hsing 1995; Cebula 2007), education attainment (Winson 1930), per capita income (Sommers et al. 1973; Wadycki 1974; Meyer et al. 2001), employment opportunities (Sommers et al. 1973; Wadycki 1974; Meyer et al. 2001) and personal characteristics such as age and race (Greenwood et al. 1971; Gius 2011). For example, Gabriel et al. (1993) examine the determinants of regional migration in the 1980s using a place-to-place logistic model. Their results suggest that migration decisions depend importantly on both wage and unemployment rate differentials. Hsing (1995) finds that higher employment growth, more sunshine and a higher percentage of metropolitan area population attract in-migration. Preuhs (1999) observes that state policy factors are significant determinants: low taxation levels, high investment-consumption ratios and more liberal ideologies are associated with larger population growth via migration. Conway and Houtenville (2003) give us an insight in the migration behavior of the elderly. Their result shows that "all elderly age groups avoid moving to states with high estate/inheritance/gift taxes". Younger elderly prefer destinations with temperate climate and favorable public policy towards income tax and welfare spending. Older elderly on the other hand are likely to be driven by lower cost of living and lower income and property taxes.

International migration patterns have also been a popular research topic. Karemera et al. (2000) apply a linear gravity model incorporating immigration regulations and various characteristics of the origin and destination countries. The study covers migration flows to Canada and the United States from 70 countries between 1976 and 1986. Their results show that the income of destination countries and the population of origin countries are two major determinants of migration to North America. In another application of the gravity model, Gallardo-Sejas et al. (2006) examine the determinants of international labor migration in 13 European destination countries from 139 origin countries in 2000. Their evidence suggests that the population of origin countries, welfare, cultural proximity and trade relations are important explanatory factors. Later, Clark, Hatton and Williamson (2007) find that income differentials as well as the stock of previous immigrants play an important role in migration decisions.

2. Cyclicality of migration

Even though the question of the cyclicality of migration is yet to be answered thoroughly, related studies have offered evidence that migratory flows are positively correlated with the business cycle.

Pissarides and Wadsworth (1989) use data from the British Labor Force Survey to examine the relation between unemployment and the probability of individual interregional migration. Under a linear probability framework, they use the gap between regional and national unemployment rates as an explanatory variable with other personal characteristics. The same regressions are estimated for both 1976 and 1983 data. They discover that the propensity to migrate is reduced at a higher level of unemployment and regional unemployment differentials encourage mobility. Apart from geographic migration, Blanchard and Diamond (1990) provide some interesting findings on the cyclical behavior of gross flows between labor force status: employment, unemployment and "not in the labor force" of U.S. workers. Applying a single-equation dynamic panel with 1968-86 CPS data, they observe sharp differences between the cyclical behavior of employment to unemployment flows and employment to not in labor force flows. In particular, they find that the flow from employment to unemployment increases in a recession while the employment to not in labor force flow decreases. They also find that the unemployment to employment flow increases during a recession, while the not in labor force to employment flow decreases. Fallick and Fleischman (2004) find procyclicality in employer-to-employer (EE) flows for the United States, although the cyclicality is only found concentrated around recessions. EE flows dropped sharply as the labor market loosened in 2001-2003, but did not increase as the labor market tightened between 1994 and 2000.

More recently, Saks and Wozniak (2011) provide stronger evidence that long distance migration within the U.S. is positively correlated with the national business cycle using a static panel model. They creatively employ the nationally representative IRS data on both state and metropolitan level from 1975 to 2008 to assess the cyclical pattern. They define gross migration volume between regions by the change in number of tax exemptions filed. This clever use of data however does not confine migration to job-related moves. Three measures are used for the business cycle: the employment gap, the unemployment rate and the unemployment insurance claim rate. Based on the results of the static linear regression on the state level, all three measures confirm that migration is higher when relative employment and income level are better in the destination state and lower when these conditions are better in the origin state. Specifically, a one standard deviation improvement in national economic conditions is associated with a 2.5% increase in the migration flow. On metropolitan level, the findings suggest that in-migration is more cyclical than out-migration. A one standard deviation improvement in national economic conditions is associated with 1.5% increase in in-migration and a 1% increase in out-migration. To sum up, both levels show that the net benefit of moving rises during booms, the migration flow is associated with geographic variation of job opportunities and is not related to local economic conditions but rather to factors that are common to all locations. Moreover, they apply an individual level linear probability model with CPS micro-data to determine which segment of the population is most sensitive to business cycle conditions. The evidence shows that magnitude of the procyclical behavior is the strongest for the young migrants group. A one standard deviation change in the national business cycle leads to a 17% to 47% change in individual migration probabilities. Other interesting findings include the fact that migration decisions of individuals who are not in the labor force are acyclical; home-ownership has no important impact on the cyclicality of migration; and female heads of household have more cyclical migration patterns than males. Although this recent work provides substantial evidence and exploits both aggregate and micro-level data, the limitations of a static linear regression model remain. For one, local economic conditions are reversely affected by migration, which makes economic conditions potentially endogenous. Without a proper choice of an instrument variable, there is the possibility of inaccurate estimation. The other limit of a static specification is that it does not take full advantage of the panel data and fails to provide a dynamic view through time. Despite the shortcomings, we will use the Saks-Wozniak approach as a benchmark approach for future comparison.

3. *Use of panel VAR*

Although the use of panel VAR is not yet very common in migration studies, I find in recent papers some interesting applications of this methodology. Alecke, Mitze and Untiedt (2009) analyze the influence of regional labor market disparities on internal migration behavior between East and West Germany during the period 1991-2006. Using a panel VAR model as the empirical method, they choose the net migration rate as the dependent variable and include the real wage and the unemployment rate of both regions as explanatory variables. A human capital index, labor productivity and labor participation are also included as additional controls. As for estimation, they apply a first-difference transformation to the multiple-equation generalized method of moments (GMM) framework and use lagged differences as instrumental variables. The impulse response of migration to a unit shock in unemployment proves to be negative with most of the migration response absorbed in six years. The response to a shock in the regional wage rate differential is positive and fades out more rapidly. The migration responses to labor productivity and human capital shocks turn out to be positive and show a higher degree of persistence. This general picture is also supported by the variance decomposition analysis. In the short run, a shock in the unemployment rate has the biggest effect on net migration. In the long run, most of the forecast error variance in net migration is due to labor productivity and human capital shocks.

The work of Boubtane, Coulibaly and Rault (2012) is another case where panel VAR techniques are applied. Using annual net migration data for 22 major OECD host countries over the period 1987-2009, they study the interaction between immigration and host country economic conditions. The economic activity level of the host country is measured by real GDP per working age population and the unemployment rate for both native and foreign-born residents. They show through impulse response functions that immigration has a positive impact on the host economy's GDP per working age population and a negative impact on aggregate unemployment, native and foreign-born unemployment rates. Furthermore, immigration flows are also influenced by the host country economic conditions, immigration responds positively and significantly to the host GDP per working age population and negatively to the host aggregate unemployment rate. These findings are in line with previous literature on bilateral migration flows. The variance decomposition shows that GDP per working age population and the aggregate unemployment rate of the host country explain approximately 8% and 5% of the fluctuations in migration. Migration explains approximately 5% of changes in GDP per working age population, 6% of the fluctuations of the unemployment rate and 4% of the changes in the employment rate of the host country. Native and foreign-born unemployment rates explain 5% and 4% of the forecast variance in migration. Migration explains 2% of the fluctuations in the native unemployment rate and 7% of the changes in the foreign-born unemployment rate.

4. The debate

There are divergent views regarding whether migration is merely a response to asymmetric demand shocks or it is also a source of shock in the labor market. One commonly held opinion is that short-term fluctuations in U.S. migration are primarily responses to labor demand shocks. Blanchard and Katz (1992) argue that labor mobility is the dominant adjustment mechanism rather than job creation to transitory fluctuations in unemployment and wages. Migration arbitrages away wage and unemployment differentials caused by uneven spatial distribution of demand in a rapid speed, they find that the unemployment rate returns to its original level in about seven years after a shock. However, Rowthorn and Glyn (2003) question this result by arguing that migration adjustment alone does not fully equilibrate regional disparities. They conclude that migration, as an adjustment mechanism to employment shocks, has been rather weak from the 1970s to the 2000s in the U.S.

Partridge and Rickman (2006) address this debate in much more detail. Applying a structural VAR to the U.S. migration time-series data from the 1970s to the 1990s for the lower 48 states, they reveal that less than one-half of innovations in migration flows are responses to labor-demand shocks. For the short-term forecast horizon, on average about 46% of the first-year migration forecast error variance is due to own-innovations in migration, while only about 28% is due to labor-demand shocks. In the long run, as lagged migration responses to demand accumulate, labor-demand shocks slightly overtake migration shocks in significance. This challenges migration’s role in arbitraging macroeconomic fluctuations. One possible explanation is that migration induced by the demand of location-specific amenities is subject to short-term shocks if the attractiveness of amenities fluctuates. Their results also show that in the first year, the average employment response to a positive one standard-deviation demand shock is over 0.6%, whereas the migration response is approximately 0.2%. Cumulative employment growth exceeds the initial response, peaking in the sixth year before declining. The migration response peaks at the ninth year before stabilizing. Their findings suggest that U.S. labor market flexibility is enhanced in the short run by changes in unemployment. Migration plays the dominant role in equilibrating asymmetric demand shocks in the medium to long run. However, it is also evident that migration innovations result from a combination of factors and cannot be solely characterized as a simple response to demand shocks or as primarily own shocks.

The role of migration can be tested as a supplement of our discussion by variance decomposition analysis over medium to long run forecast horizons. The proportion of the migration forecast variance attributable to labor demand shocks and migration (labor-supply) shocks can be quantified under the PVAR framework. The result of this analysis helps determine whether migration innovations are simply a response to demand shocks, which implies migration's role as an equilibrator, or primarily due to its own shocks.

III. THEORETICAL FRAMEWORK

Consider a simple human capital model in migration (Sjaastad 1962). Migration occurs if the return in the investment in migration, that is the relatively increased earnings, exceeds the cost of relocating, which includes the forgone earnings and the direct out-of-pocket costs. Thus, workers move from locations with relatively low return on their individual skills to markets where the return is relatively high. Furthermore, geographic differences in relative return to skills and therefore local economic conditions determine migration behavior. To better understand how aggregate economic conditions may affect migration behavior, I adopt the optimal search model by Kennan and Walker (2011). Although the role of aggregate variables is not explicitly included, the dynamic angle this model inventively contributes will help us better grasp the role of the business cycle in the migration process.

Within the neoclassical migration framework, in accordance with the human capital model of investment, a representative agent under a rational behavior assumption will migrate if this action improves his welfare relative to not migrating. Kennan and Walker (2011) improve this traditional static problem by incorporating dynamic sequences of migration choices. At any given time, the individual must choose whether to stay in the current location or go somewhere else. The individual acts so as to maximize the expected present value of the realized payoffs, net of moving costs (Kennan and Walker 2011). Thus, the migration problem evolves into a labor search problem where a worker's goal is to find the market that provides the highest income relative to the cost of migrating.

For simplicity, the basic assumption of Kennan and Walker's (2011) model is that the individual knows the wage in his current location as well as locations he visited in the recent past but will have to move to a new location in order to determine the wage in that market. Furthermore, "wages are local prices of individual skill bundles", which reflects an individual's earning power and in turn determines his utility. They also introduce a location-specific shock to capture any other factors that are independent across locations.

The individual's migration decision is based on the following recursive utility maximization problem:

$$V(x,\zeta) = max_j[v(x,j) + \zeta_j]$$

Where

$$v(x,j) = u(x,j) + \beta E[v(x'|x,j)]$$

Workers are to maximize their overall utility flow from choosing location j,

$v(x,j)$ plus a shock specific to location j, ζ_j[2]. x is the state vector which includes the individual's wage, preference information, age and current location. The overall utility flow $v(x,j)$ is a function of the current utility from choosing location j, $u(x,j)$ plus the discounted value of the expected utility if the individual transits to a new state vector x' in the next period, given location j is chosen.

Kennan and Walker (2011) specify the utility function $u(x,j)$ as follows:

$$u(x,j) = \alpha w_j + \Gamma Y_j - c(x,j) + \zeta_j$$

Where w_j is the wage in location j, Y_j is the amenity vector in j, $c(x,j)$ is the transportation cost occurred during migration, and ζ_j is a location specific utility shock.

Given the framework above, how the aggregate economic cycle functions in a migration process becomes straightforward. There are several channels through which economic conditions may affect migration: wage rate, moving cost and cyclical shocks. Firstly, when economic conditions change, individuals can quickly adapt their expected market wage rate w_j, and would be more likely for them to migrate if the expected wage rate of an alternative location increases relative to their current residence. Moreover, in economic upswings, individuals may take advantage of their high earnings to "purchase" migration, given migration is a normal good. Secondly, moving cost $c(x,j)$ is subject to cyclical fluctuations, hence rendering migration behavior procyclical. Moving cost may vary in a number of ways. The cost of job searching is significantly lower during booms since the probability of finding a desirable match is much higher. In addition, reasons such as a lower cost of selling and buying a house during an economic boom will also facilitate migration. Lastly, other factors, which may be unrelated to the labor market, can appear as a cyclical shock, ζ_j, to the utility function, which consequentially will cause the propensity of migration to fluctuate alongside the business cycle.

In conclusion, cyclical fluctuations will cause alternating rises and falls in migratory flow. In times of prosperity and economic expansion, migration level will rise according to our theoretical model and vice versa.

IV. EMPIRICAL DESIGN

The primary objective of the present study is to uncover the underlying linkages between economic conditions and the internal migration flow among U.S. states. This paper utilizes a PVAR approach on the state level as the main empirical methodology.

1. *Data description*

In order to establish the correlation between internal migration and aggregate economic conditions, we need an accurate representation of the geographical flow. In this study, I use the gross migration rate instead of net migration for the state-level panel VAR study because the gross migration rate is the meaningful way to reflect the individual decision-making process that is elaborated in our theoretical discussion. The data source available at hand is the Current Population Survey (CPS)-Annual Social

[2] ζ_j is a random variable that is assumed to be independent and identically distributed across locations and periods and independent of the state vector x. (Kennan and Walker 2011)

and Economic Supplement (ASEC)[3] data from 1962 to 2015 for all 50 states plus the District of Columbia. The survey asks respondents about their current state of residence and whether they have changed residence in the past year. Those who are living in the same house as a year ago are considered non-movers and no further questions about migration are asked. Movers are asked about the city, county and state or foreign country where they resided one year ago. The primary reason for moving is also asked of movers. To my knowledge, ASEC provides the longest time series data on annual migration in the U.S. However, since state level internal migration constitutes a measure of geographic reallocation of the labor force, we need to further restrict the migration data to labor market related moves, causing our sample size to shrink down to 1999-2015[4].

The raw data collected from the CPS-ASEC is survey responses on an individual level grouped by household. Therefore, further data aggregation is applied to obtain the gross migration rate. Table 1 presents the summary statistics of the gross migration rate by state from CPS data.

Table 1. Descriptive Statistics of Gross Internal Migration Rate by State

State	In-migration rate				Out-migration rate			
	Mean*	Standard Deviation	Max	Min	Mean*	Standard Deviation	Max	Min
Alabama	8.49	3.72	14.97	0.64	8.89	5.07	23.48	3.83
Alaska	23.95	6.68	35.14	14.06	23.31	18.97	60.87	0.62
Arizona	11.77	5.73	20.75	2.36	9.44	4.12	15.25	3.68
Arkansas	10.26	3.59	16.22	3.01	8.67	4.59	17.87	0.75
California	4.96	1.26	7.62	2.80	5.59	0.97	7.12	3.97
Colorado	17.47	6.28	34.90	8.77	10.93	3.16	16.35	4.25
Connecticut	7.01	3.50	13.22	2.06	6.55	2.79	11.99	1.84
Delaware	5.90	3.75	13.56	0.83	10.21	11.38	35.26	0.00
District of Columbia	18.83	3.78	25.13	11.80	23.40	13.55	48.18	0.00
Florida	9.13	4.20	16.37	2.23	7.23	2.29	12.52	3.28
Georgia	13.34	4.29	20.46	5.68	10.21	5.26	26.42	3.32
Hawaii	14.37	6.94	25.07	5.24	19.06	9.19	35.88	6.87
Idaho	12.60	6.31	24.15	3.03	13.05	7.54	26.36	1.81
Illinois	5.88	1.78	9.28	3.41	7.23	2.17	11.25	3.51
Indiana	7.21	3.58	14.06	0.70	7.41	3.15	13.20	2.03
Iowa	8.50	3.87	18.01	1.87	9.48	5.15	18.87	0.59
Kansas	13.75	4.64	21.71	8.16	15.04	5.50	26.19	4.09
Kentucky	11.03	5.61	22.42	5.15	9.34	5.09	21.47	0.10
Louisiana	8.46	3.70	14.32	2.69	8.38	5.68	22.21	0.52
Maine	6.18	2.59	9.11	1.60	7.88	5.75	17.91	1.28
Maryland	9.22	4.58	18.94	4.30	10.06	4.72	18.81	3.49
Massachusetts	4.80	3.01	12.47	0.72	6.12	2.53	10.17	1.88

[3] ASEC is a supplemental survey conducted in March since 1948 as a complement to CPS with supplement topics including income, health insurance coverage, mobility, fertility, veteran information, etc.
[4] "Reason for move" category is not included in the CPS-ASEC until 1999.

Table 1. Continued

State	In-migration rate				Out-migration rate			
	Mean*	Standard Deviation	Max	Min	Mean*	Standard Deviation	Max	Min
Michigan	4.30	2.13	10.83	2.03	5.97	1.80	9.97	4.28
Minnesota	6.74	3.75	16.66	2.08	5.73	2.95	13.28	1.43
Mississippi	6.19	4.01	12.96	1.51	10.76	3.39	16.36	4.43
Missouri	7.49	3.81	17.05	1.74	7.65	4.13	17.58	2.08
Montana	11.55	4.26	20.70	5.14	13.03	7.13	28.54	0.82
Nebraska	11.14	3.98	18.68	4.48	10.76	7.73	34.58	3.19
Nevada	17.36	6.68	25.64	6.69	12.16	6.83	30.24	3.87
New Hampshire	6.96	3.14	15.84	3.74	6.43	6.95	28.22	0.50
New Jersey	4.05	1.83	7.56	0.85	6.12	3.27	13.69	0.83
New Mexico	12.06	5.97	20.82	1.50	9.33	4.74	19.45	2.18
New York	3.47	1.26	5.65	1.41	5.87	1.64	9.36	3.24
North Carolina	11.75	5.38	21.50	2.51	9.86	3.74	16.38	1.83
North Dakota	11.34	6.13	25.74	1.88	15.52	13.85	46.62	0.00
Ohio	4.97	2.55	11.57	1.96	6.26	2.60	10.66	1.85
Oklahoma	11.63	4.00	17.06	3.39	10.90	4.34	19.90	4.30
Oregon	11.67	4.66	20.75	3.22	11.31	5.91	22.48	3.22
Pennsylvania	5.31	1.61	8.83	3.27	6.50	2.20	10.07	1.95
Rhode Island	7.09	2.85	13.07	4.18	7.71	5.63	20.93	0.00
South Carolina	8.02	4.76	17.97	1.75	8.41	3.91	15.98	2.85
South Dakota	11.94	4.54	21.10	4.29	14.46	9.44	33.41	1.57
Tennessee	10.07	2.71	15.67	5.40	8.77	3.58	14.70	3.55
Texas	7.73	2.01	11.20	4.36	6.97	2.80	13.70	3.46
Utah	10.41	4.78	19.84	2.81	14.70	7.67	31.79	4.14
Vermont	8.21	2.94	17.27	4.58	8.56	7.19	24.06	1.88
Virginia	12.58	5.17	24.11	5.64	10.60	4.73	24.51	4.90
Washington	13.88	5.23	27.23	8.17	11.15	3.83	17.94	4.62
West Virginia	5.71	3.40	13.65	0.23	9.05	5.94	20.25	0.00
Wisconsin	6.37	3.69	13.86	1.58	5.79	2.28	9.14	1.72
Wyoming	21.67	7.18	35.41	14.34	22.27	12.58	45.99	5.19

*average over years observed 1999-2015, estimated per 1000 residents.

Source: U.S. Census Bureau, Current Population Survey-Annual Social and Economic Supplement 1999-2015

2. *Historical evidence from CPS data*

Based on the estimates from Current Population Survey (CPS)-Annual Social and Economic Supplement (ASEC) data from 1995 to 2015, Table 2 gives a historical overview of the annual geographical mobility rate, which is calculated as the fraction of migration volume over total population aged 1 year and over, by type of movement.

Table 2. Annual Geographical Mobility Rates, By Type of Movement: 1995-2015 (Percent)

Mobility Period	Total, 1 year and over	Same residence(non-movers)	Total Movers	Different residence in the U.S.					Movers from abroad
				Total	Same county	Different County			
						Total	Same State	Different State	
2015	100.0	88.4	11.6	11.1	7.3	3.8	2.1	1.6	0.5
2014	100.0	88.5	11.5	11.2	7.6	3.6	2.1	1.5	0.4
2013	100.0	88.3	11.7	11.4	7.5	3.8	2.3	1.6	0.3
2012	100.0	88.0	12.0	11.6	7.7	3.9	2.2	1.7	0.4
2011	100.0	88.4	11.6	11.2	7.7	3.5	1.9	1.6	0.4
2010	100.0	87.5	12.5	12.1	8.6	3.5	2.1	1.4	0.3
2009	100.0	87.5	12.5	12.1	8.4	3.7	2.1	1.6	0.4
2008	100.0	88.1	11.9	11.5	7.8	3.7	2.1	1.6	0.4
2007	100.0	86.8	13.2	12.8	8.6	4.2	2.5	1.7	0.4
2006	100.0	86.3	13.7	13.3	8.6	4.7	2.8	2.0	0.4
2005	100.0	86.1	13.9	13.2	7.9	5.3	2.7	2.6	0.6
2004	100.0	86.3	13.7	13.3	7.9	5.3	2.8	2.6	0.4
2003	100.0	85.8	14.2	13.7	8.3	5.4	2.7	2.7	0.4
2002	100.0	85.2	14.8	14.2	8.5	5.7	2.9	2.8	0.6
2001	100.0	85.8	14.2	13.5	8.0	5.6	2.7	2.8	0.6
2000	100.0	83.9	16.1	15.4	9.0	6.4	3.3	3.1	0.6
1999	100.0	84.1	15.9	15.4	9.4	5.9	3.1	2.8	0.5
1998	100.0	84.0	16.0	15.6	10.2	5.4	3.0	2.4	0.5
1997	100.0	83.5	16.5	16.0	10.5	5.5	3.0	2.4	0.5
1996	100.0	83.7	16.3	15.8	10.3	5.6	3.1	2.5	0.5
1995	100.0	83.6	16.4	16.1	10.8	5.3	3.1	2.2	0.3

Source: U.S. Census Bureau, Current Population Survey https://www.census.gov/hhes/migration/data/cps/historical.html

As shown in the table, migration dropped sharply in both 2001 and 2007, the latter did not start recovering until 2009. According to NBER's designation, a peak occurred in the U.S. economy in March 2001 and December 2007, while June of 2009 is a trough of the U.S. economy due to the mortgage default crisis- "…A peak is thus a determination that the expansion that began in March 1991 ended in March 2001 and a recession began…The trough marks the end of the recession that began in December 2007 and the beginning of an expansion."[5] In fact, the most recent drop began years ahead of the previous peak of December 2007, probably due to the housing market decline in 2006, which elicited falling home price or rising interest rates that could "lock-in" people to their homes, reducing, not raising mobility (Ferreia, Gyourko and Tracy 2010). Although a falling house price may not necessarily induce a mobility drop, a rising interest rate certainly can by causing the inability for a household to afford a new loan for the purchase of a new residence.

Table 3 gives the annual geographical mobility rate by tenure from 2005 to 2015 in addition to the type of move. As the table suggests, renters are more inclined to

[5] NBER Announcement Memo by Business Cycle Dating Committee, http://www.nber.org/cycles.html

migrate than home owners.

Table 3. Annual Geographical Mobility Rates, By Tenure: 2005-2015 (Percent)

Mobility Period	Total	Same residence(non-movers)	Total Movers	Different residence in the U.S.					Movers from abroad
				Total	Same county	Different County			
						Total	Same State	Different State	
2015									
Owner	100.0	94.9	5.1	5.0	3.2	1.8	1.0	0.8	0.1
Renter	100.0	76.0	24.0	22.8	15.3	7.5	4.2	3.3	1.3
2014									
Owner	100.0	95.0	5.0	4.9	3.2	1.7	1.0	0.6	0.2
Renter	100.0	75.5	24.5	23.7	16.3	7.5	4.2	3.3	0.8
2013									
Owner	100.0	94.9	5.1	5.0	3.1	1.9	1.1	0.8	0.1
Renter	100.0	75.1	24.9	24.1	16.4	7.7	4.5	3.1	0.8
2012									
Owner	100.0	95.3	4.7	4.6	2.9	1.7	1.1	0.7	0.1
Renter	100.0	73.3	26.7	25.8	17.5	8.3	4.6	3.7	0.9
2011									
Owner	100.0	95.3	4.7	4.6	2.9	1.7	0.9	0.7	0.1
Renter	100.0	73.9	26.1	25.3	17.9	7.4	4.0	3.3	0.8
2010									
Owner	100.0	94.8	5.2	5.0	3.4	1.7	1.0	0.7	0.1
Renter	100.0	71.5	28.5	27.7	20.2	7.5	4.5	3.1	0.7
2009									
Owner	100.0	94.8	5.2	5.0	3.3	1.7	1.0	0.8	0.2
Renter	100.0	70.8	29.2	28.3	20.1	8.3	4.8	3.4	0.8
2008									
Owner	100.0	94.6	5.4	5.2	3.3	1.9	1.1	0.8	0.1
Renter	100.0	72.3	27.7	26.7	18.7	8.1	4.6	3.5	1.0
2007									
Owner	100.0	93.4	6.6	6.4	4.1	2.4	1.4	1.0	0.2
Renter	100.0	70.7	29.3	28.4	19.7	8.7	5.4	3.3	1.0
2006									
Owner	100.0	92.9	7.1	6.9	4.2	2.7	1.7	1.0	0.2
Renter	100.0	69.8	30.2	29.1	19.3	9.8	5.5	4.3	1.1
2005									
Owner	100.0	92.5	7.5	7.3	4.1	3.2	1.7	1.5	0.2
Renter	100.0	69.5	30.5	28.7	17.8	10.9	5.4	5.5	1.8

Source: U.S. Census Bureau, Current Population Survey https://www.census.gov/hhes/migration/data/cps/historical.html

Table 4 shows the composition of movers by the reason for move from 1999 to 2015. Housing related moves appear to be the largest component of migration followed by family related and employment related moves. The present study will focus on the employment related moves due to the inherent linkage between internal migration and the labor market. Unlike short-range movements, long distance migration patterns, in this case relocation across states, constitutes an indicator of worker reallocations since it is frequently accompanied by a change of local labor markets. Therefore, studying the cyclical properties of geographic reallocations of the labor force helps identify labor market adjustment over the business cycle (Saks and Wozniak 2011).

Table 4. Reason for Move: 1999-2015 (Percent)

Mobility Period	Total Movers 1 year and over	Change in marital status	To establish own household	Other family reason	New job or job transfer	To look for work or lost job	To be closer to work/easier commute	Retired	Other job related reason	Wanted own home, not rent	Wanted new or better home/apartment	Wanted better neighborhood /less crime	Wanted cheaper housing	Foreclosure/eviction*	Other housing reason	To attend or leave college	Change of climate	Health reasons	Natural disaster**	Other reasons
2015	100.0	5.8	11.0	14.3	10.6	1.6	4.9	1.1	2.3	5.3	15.3	2.9	7.5	0.7	14.4	0.3	0.2	0.3	-	1.5
2014	100.0	4.9	11.1	13.4	9.7	2.1	6.2	0.7	2.0	5.6	15.8	3.0	9.4	1.3	12.8	0.5	0.1	0.4	0.0	1.0
2013	100.0	5.1	10.5	14.8	9.0	2.1	5.4	0.7	2.3	5.8	14.8	3.2	8.3	1.8	14.0	0.6	0.1	0.4	0.0	1.3
2012	100.0	6.3	10.7	12.3	9.5	1.8	5.5	0.5	2.1	4.7	15.9	3.4	8.9	2.2	14.4	0.5	0.0	0.3	0.2	0.9
2011	100.0	5.5	9.5	12.8	8.0	2.6	5.9	0.3	1.5	4.4	16.2	3.9	10.5	1.2	8.7	2.6	0.4	1.6	0.1	4.1
2010	100.0	7.3	11.2	11.8	7.8	2.5	4.2	0.5	1.3	4.6	15.4	4.1	10.8	-	8.7	2.7	0.6	1.5	0.3	4.4
2009	100.0	5.4	9.5	11.5	8.7	2.7	5.0	0.4	1.0	5.5	14.5	5.0	11.1	-	9.7	2.6	0.5	1.6	0.4	4.8
2008	100.0	5.7	10.5	14.4	8.4	2.3	6.2	0.4	3.7	5.8	13.8	5.1	8.2	-	7.2	2.5	0.6	1.3	0.2	3.9
2007	100.0	5.9	9.8	14.4	9.8	1.7	4.8	0.6	4.0	5.9	15.8	5.5	8.0	-	6.8	1.9	0.4	1.4	0.5	2.9
2006	100.0	6.0	8.5	13.2	8.7	1.6	3.6	0.4	4.0	8.6	17.8	4.4	6.2	-	9.2	2.7	0.4	1.3	1.7	1.7
2005	100.0	7.1	7.8	12.2	10.4	1.9	3.4	0.5	1.4	9.3	17.8	4.0	6.6	-	9.4	3.2	0.6	1.6	-	2.6
2004	100.0	6.2	7.0	11.2	9.2	2.4	3.7	0.3	1.4	9.3	21.1	4.7	7.3	-	10.3	2.9	0.6	1.0	-	1.5
2003	100.0	6.7	7.0	12.6	8.8	1.9	3.2	0.3	1.4	10.2	19.8	3.8	6.5	-	11.0	2.5	0.4	1.4	-	2.5
2002	100.0	6.1	7.6	12.0	10.5	2.3	3.0	0.6	1.6	10.5	18.8	4.0	5.9	-	10.4	2.7	0.6	1.2	-	2.1
2001	100.0	6.0	7.5	13.7	10.3	2.1	3.1	0.6	1.1	10.1	17.6	3.9	5.5	-	10.8	3.0	0.6	1.3	-	2.8
2000	100.0	6.1	7.2	13.3	10.4	1.7	3.4	0.4	1.3	11.0	17.8	4.3	5.3	-	11.2	2.5	0.7	1.1	-	2.2
1999	100.0	6.5	7.7	11.6	9.5	1.6	3.1	0.6	2.0	7.8	20.8	3.9	6.0	-	11.1	2.0	0.8	1.1	-	4.1

*The foreclosure/eviction reason for move was added to the survey in 2012. The 2011 estimate was created from write-in responses.

**The natural disaster reason for move was added in 2006.

Source: U.S. Census Bureau, Current Population Survey https://www.census.gov/hhes/migration/data/cps/historical.html

Finally, Table 5 presents the comparison between the inflow and outflow of migration in metropolitan areas versus non-metropolitan areas from 2006 to 2014. As one can see, there has been a significant trend of negative net migration from both principle cities and non-metropolitan areas, and positive net migration to both suburban areas and metropolitan areas. The underlying migration path is then from non-metro area to metro area[6], principal cities[7] to suburbs.

Table 5. In-migration, Out-migration and Net Migration for Metropolitan Areas: 2006-2014 (Numbers in thousands)

Mobility Period and Metropolitan status	In-migrants	Out-migrants	Net migration	Movers from abroad	Net migration including movers from abroad
2014					
Metropolitan areas	1,486	1,035	451*	1,095	1,546*
Principal cities	3,455	5,198	-1,744*	515	-1,229*
Suburbs	5,487	3,292	2,195*	580	2,775*
Nonmetropolitan areas	1,035	1,486	-451*	38	-413*
2013					
Metropolitan areas	1,460	1,034	426*	971	1,397*
Principal cities	3,272	5,421	-2,150*	549	-1,601*
Suburbs	5,807	3,231	2,576*	422	2,998*
Nonmetropolitan areas	1,034	1,460	-426*	65	-361*
2012					
Metropolitan areas	1,260	1,118	141	1,078	1,219*
Principal cities	3,206	5,420	-2,213*	580	-1,633*
Suburbs	5,648	3,294	2,354*	498	2,852*
Nonmetropolitan areas	1,118	1,260	-141	76	-65
2011					
Metropolitan areas	1,118	1,022	96	1,032	1,128*
Principal cities	3,074	4,882	-1,809*	595	-1,214*
Suburbs	5,104	3,200	1,905*	437	2,342*
Nonmetropolitan areas	1,022	1,118	-96	52	-44
2010					
Metropolitan areas	1,151	977	175*	922	1,097*
Principal cities	3,054	5,416	-2,361*	434	-1,927*
Suburbs	5,614	3,079	2,536*	488	3,024*
Nonmetropolitan areas	977	1,151	-175*	63	-122
2009					
Metropolitan areas	1,316	1,008	309*	1,022	1,331*

[6] Metropolitan areas (metro areas) are geographic entities delineated by the Office of Management and Budget (OMB) for use by Federal statistical agencies in collecting, tabulating, and publishing Federal statistics. A metro area contains a core urban area of 50,000 or more population. Each metro area consists of one or more counties and includes the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core.

[7] Principal cities for each Core Based Statistical Area are defined by the Office of Management and Budget as the largest incorporated place in a CBSA with a population of at least 10,000 people.

Table 5. Continued

Mobility Period and Metropolitan status	In-migrants	Out-migrants	Net migration	Movers from abroad	Net migration including movers from abroad
Principal cities	3,171	5,278	-2,108*	576	-1,532*
Suburbs	5,497	3,081	2,416*	447	2,863*
Nonmetropolitan areas	1,008	1,316	-309*	65	-244*
2008					
Metropolitan areas	1,259	1,118	141	1,054	1,196*
Principal cities	3,039	5,052	-2,013*	631	-1,382*
Suburbs	5,297	3,143	2,154*	423	2,577*
Nonmetropolitan areas	1,118	1,259	-141	91	-51
2007					
Metropolitan areas	1,335	1,255	80	1,109	1,189*
Principal cities	3,496	5,372	-1,876*	613	-1,263*
Suburbs	5,566	3,610	1,956*	496	2,452*
Nonmetropolitan areas	1,255	1,335	-80	82	2
2006					
Metropolitan areas	1,475	1,320	155	1,176	1,331*
Principal cities	3,769	5,845	-2,076*	643	-1,433*
Suburbs	6,040	3,809	2,231*	532	2,763*
Nonmetropolitan areas	1,320	1,475	-155	120	-35

* Net flow significantly different from zero at the 90-percent confidence level.

Source: U.S. Census Bureau, Current Population Survey https://www.census.gov/hhes/migration/data/cps/historical.html

3. *Panel unit root tests*

Since we are working with macro-level panel data, the non-stationarity issue may occur. We therefore perform the panel unit root tests for the variables in levels. There are a number of popular tests based on the asymptotic behavior of the time-series dimension T and the cross-sectional dimension N.

The general structure used by most panel unit root tests is the Augmented Dickey-Fuller (ADF) regression:

$$\Delta y_{it} = \alpha_i d_{it} + \rho_i y_{it-1} + \sum_{l=1}^{p_i} \emptyset_{il} \Delta y_{it-l} + \varepsilon_{it}$$

Where the d_{it} are the deterministic components (constant and trend). $\rho_i = 0$ means the process has a unit root for individual i, while $\rho_i < 0$ means that the process is stationary around the deterministic part.

Levin-Lin-Chu Test

Levin, Lin and Chu (2002) propose a test with the following hypotheses:

H_0: each time series contains a unit root

H_1: each time series is stationary

The null hypothesis is $\rho_i = 0$. Since LLC test assumes a common ρ_i across all panels, this test does not allow for the possibility that some states contain unit roots while other states do not. In order for the asymptotic theory to hold, a necessary condition for the LLC test is $\sqrt{N_T}/T \to 0$, which requires that the number of time periods grow more quickly than the number of panels so the ratio of panels to time periods tends to zero. In practice, we select the number of lags used in the ADF regression based on the AIC with at most 4 lags. According to Levin, Lin and Chu (2002), the statistic performs well when N lies between 10 and 250 and when T lies between 5 and 250. Our application (N=51, T=17) fits in this range.

Im-Pesaran-Shin Test

The IPS test is not as restrictive as LLC test, since it allows for heterogeneous coefficients. The test assumption is that T is the same for all cross-section units hence IPS is applied only for balanced panel data. IPS test also requires $N/T \to 0$ for $N \to \infty$. The null hypothesis is that all individuals follow a unit root process $\rho_i = 0$. The alternative allows some but not all of the individuals to have unit roots.

The results of both tests for gross migration rate, pair-wise migration rate and business condition measurements that we use in our study are given in table 6. In our tests, d_{it} contains only panel-specific means with no time trend.

Table 6. Test statistics and p-values of panel unit root test for variables in levels

Specification	LLC test		IPS test	
	Statistic	p-value	Statistic	p-value
Gross in-migration rate	-10.3581	0.0000	-8.6505	0.0000
Gross out-migration rate	-15.2850	0.0000	-12.7044	0.0000
State unemployment rate	-7.6751	0.0000	-5.0050	0.0000
Unemployment growth rate	-7.8392	0.0000	-13.7142	0.0000
Unemployment gap	-8.4150	0.0000	-4.2545	0.0000
UI claim rate	-7.0597	0.0000	-9.1029	0.0000
Median household income	-6.9230	0.0000	-5.5664	0.0000
Income growth rate	-22.5165	0.0000	-22.8400	0.0000

Note: 1. N=51 and T=17 in our application. 2. The number of lags to include is selected based on the AIC with at most 4 lags. 3. Use 5% significance level.

Results from both tests suggest we should reject the null hypothesis and conclude that the series for all variables tested are stationary. These results confirm our theoretical conjectures that migration and labor market variables typically follow a stationary process.

4. *State level panel VAR approach*

As the primary empirical methodology for our research, I use a state level panel VAR model to examine the underlying cyclicality of migration patterns. A general panel VAR representation of the relationship between business cycle and migration rate can be written as follows:

$$\begin{pmatrix} gm_{it} \\ c_{it} \\ I_{it} \end{pmatrix} = \begin{pmatrix} \delta_i^1 \\ \delta_i^2 \\ \delta_i^3 \end{pmatrix} + \sum_{s=1}^{p} \begin{pmatrix} \varphi_{11}^s & \varphi_{12}^s & \varphi_{13}^s \\ \varphi_{21}^s & \varphi_{22}^s & \varphi_{23}^s \\ \varphi_{31}^s & \varphi_{32}^s & \varphi_{33}^s \end{pmatrix} \begin{pmatrix} gm_{it-s} \\ c_{it-s} \\ I_{it-s} \end{pmatrix} + \begin{pmatrix} \varepsilon_{it}^1 \\ \varepsilon_{it}^2 \\ \varepsilon_{it}^3 \end{pmatrix}$$

Here, the gross migration rate is calculated separately to measure both the inflow and outflow of migration. The gross in/out-migration rate gm_{it} of state i at any given year is defined as the proportion of individuals who indicate in the CPS ASEC March survey (1999-2015) that they moved to/from state i in the past 12 months, estimated per 1000 residents.

$$Gross\ In/Out\ Migration\ Rate = 1000 * \frac{migration\ inflow/outflow\ of\ state\ i}{state\ i\ population}$$

The regional economic condition c_{it} is measured by three scales: The first is state level unemployment growth rate, which is calculated as the percentage change in the annual unemployment rate[8] published by the U.S. Bureau of Labor Statistics. This measurement has been widely used to describe business cycles in other studies and it is available for a wide time range from 1948 to 2015. The second measure is the number of unemployment insurance claimants[9] relative to total covered employment, which is called the UI claims rate (Saks and Wozniak 2011). This measure is available for all states and for our entire sample period. The last measure is the unemployment gap, which is calculated as the difference between the state unemployment rate and the national natural rate[10] of unemployment provided by the U.S. Congressional Budget Office. Income level I_{it} is represented by median household income of state i at year t. The hypothesis we are interested to test for the state level model is whether business cycle Granger-causes migration, that is whether parameters φ_{12}^{s} and φ_{13}^{s} are jointly zero.

5. *Difference GMM estimation of panel VAR*

To look more closely at the dynamic panel VAR system, we can write the j[th] equation as (for simplicity, we use panel VAR of order 1 as an example):

$$y_{it}^{j} = \beta_1^{j} y_{it-1}^{j} + \Gamma^{j} X_{it-1}^{j} + \delta_i^{j} + u_{it}^{j}$$

Where for i=1,…, S cross-sectional dimension (states) and t=1,…, T time dimension (years), y_{it}^{j} is the dependent variable and y_{it-1}^{j} is the one period lagged value. X_{it-1}^{j} is a vector of one period lagged values of y_{it-1}^{j} for i≠s. δ_i^{j} is the unobservable state fixed effect and u_{it}^{j} is the remainder error term.

One immediate problem with our empirical design is that y_{it-1}^{j} is correlated with the unobserved panel-level fixed effects, which are essentially part of the error term. This gives rise to "dynamic panel bias". One commonly used solution is the first-difference transformation, which gives the name "difference GMM". First-difference transformation removes the state fixed effect δ_i^{j} from the equation.

$$(y_{it}^{j} - y_{it-1}^{j}) = \beta_1^{j}(y_{it-1}^{j} - y_{it-2}^{j}) + \Gamma^{j}(X_{it-1}^{j} - X_{it-2}^{j}) + (u_{it}^{j} - u_{it-1}^{j})$$

The next problem we need to tackle is that $(u_{it}^{j} - u_{it-1}^{j})$ is again correlated with

8 To be consistent with the timing of the CPS data, the annual unemployment rate is calculated as the average of monthly rates in a single year.

9 The number of unemployment insurance (UI) claimants is the total number of the first unemployment insurance check issued to each claimant during his or her benefit year. In States with a variable benefit year (different beginning and ending dates for each claimant), most claimants are issued only one first payment during a calendar year. In States with a uniform benefit year (the same beginning and ending dates for all claimants), it is possible for a relatively few claimants to be issued two first payments during a calendar year.
Source: U.S. Department of Labor ET Financial Data Handbook 394
http://workforcesecurity.doleta.gov/unemploy/hb394/gloss.asp#(23)

10 An alternative of using the national natural rate is to use state level average annual unemployment rate.

$\left(y_{it-1}^{j}-y_{it-2}^{j}\right)$. This can be solved by instrumenting lagged differences with differences and levels from earlier periods. Anderson & Hsiao (1981) are among the first to propose an estimator following the first-difference transformation by introducing instrumental variables based on the past values of the lagged endogenous variables. The instrument can either be in levels y_{it-2}^{j} , or lagged differences $\left(y_{it-2}^{j}-y_{it-3}^{j}\right)$. Both y_{it-2}^{j} and Δy_{it-2}^{j} are mathematically related to Δy_{it-1}^{j} but not to the error term Δu_{it}^{j}, as long as the error terms are not serially correlated. The simplest way to incorporate either instrument is with two stage least squares (2SLS). However, an omnipresent problem in empirical work is heteroskedasticity, which will render the standard 2SLS estimates of the standard errors inconsistent. A popular approach when facing heteroskedasticity of unknown form is to apply the generalized method of moments (GMM), which makes use of the orthogonality conditions to achieve efficient estimation. The advantages of GMM over 2SLS are clear: if heteroskedasticity is present, the GMM estimator is more efficient than the simple 2SLS, whereas if heteroskedasticity is not present, the GMM estimator is no worse asymptotically than the 2SLS estimator (Baum et al. 2003). It is also important to note that instrumenting with levels y_{it-2}^{j} instead of lagged differences Δy_{it-2}^{j} seems preferable for maximizing sample size. $\Delta y_{it-2}^{j}$is generally not available until t=4, whereas $y_{it-2}^{j}$is available at t=3. The underlying orthogonality conditions for this approach are then:

$$E\left(y_{it-2}^{j}\Delta u_{it}^{j}\right)=0 \text{ or } E\left(\Delta y_{it-2}^{j}\Delta u_{it}^{j}\right)=0$$

To improve efficiency, Arellano & Bond (1991) take the Anderson-Hsiao approach further using all valid lags of the untransformed dependent variable as additional instruments. The orthogonality conditions are as follows:

$$E\left(y_{it-s}^{j}\Delta u_{it}^{j}\right)=0 \text{ for t=3,…, T and s}\geqslant 2$$

Since in our panel VAR system, error terms are likely to be correlated across equations, ΔX_{it-1}^{j} is also endogenous hence it needs a separate set of instrumental variables. Applying the Arellano-Bond approach to both sets of IVs, the full instrument set for the first differenced model is then:

$$\mathbf{Z_i^j}=(\mathbf{Z_i^{j,y}},\mathbf{Z_i^{j,x}})$$

Where $\mathbf{Z_i^{j,y}}$ is the $(T-2)\times m$ instrument matrix given below, m=0.5(T-1)(T-2).

$$\mathbf{Z_i^{j,y}}=\begin{bmatrix} y_{i1}^{j} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & y_{i1}^{j} & y_{i2}^{j} & \dots & 0 & \dots & 0 \\ . & . & . & \dots & . & \dots & . \\ 0 & 0 & 0 & \dots & y_{i1}^{j} & \dots & y_{i(T-2)}^{j} \end{bmatrix}$$

Similarly for the set of pre-determined explanatory variables ΔX_{it-1}^{j}:

$$\mathbf{Z_i^{j,x}}=\begin{bmatrix} X_{i1}^{j} & 0 & 0 & \dots & 0 & \dots & 0 \\ 0 & X_{i1}^{j} & X_{i2}^{j} & \dots & 0 & \dots & 0 \\ . & . & . & \dots & . & \dots & . \\ 0 & 0 & 0 & \dots & X_{i1}^{j} & \dots & X_{i(T-2)}^{j} \end{bmatrix}$$

The complete moment conditions can now be written as:

$$E\left(\mathbf{Z'^j_i}\Delta\mathbf{u_i^j}\right)=0$$

Where $\Delta\mathbf{u_i^j}$ is the (T-2) vector$(\Delta u_{i3}^{j},\Delta u_{i4}^{j},\dots,\Delta u_{iT}^{j})'$.

The GMM estimator under these moment conditions minimizes the quadratic distance $(\Delta\mathbf{u'^j}\mathbf{Z^j}\mathbf{A_N}\mathbf{Z'^j}\Delta\mathbf{u^j})$ for some $m\times m$ metric $\mathbf{A_N}$, where $\mathbf{Z'^j}$ is the $m\times N(T-2)$ matrix $(\mathbf{Z'^j_1},\mathbf{Z'^j_2},\dots,\mathbf{Z'^j_N})$ and $\Delta\mathbf{u'^j}$ is the N(T-2) vector

$(\Delta\mathbf{u'}^{\mathbf{j}}_{\mathbf{1}}, \Delta\mathbf{u'}^{\mathbf{j}}_{\mathbf{2}}, \dots, \Delta\mathbf{u'}^{\mathbf{j}}_{N})$. The GMM estimator is then given by:

$$\widehat{\Phi^{J}_{GMM}} = (\mathbf{X'^{j}Z^{j}A_{N}Z'^{j}X^{j}})^{-1}\mathbf{X'^{j}Z^{j}A_{N}Z'^{j}Y^{j}}$$

Where $\Phi^{j}_{GMM} = (\beta^{j}_{1}, \Gamma^{j})'$. $\mathbf{X^{j}}$ is the $N(T-2)\times 2$ matrix of both endogenous regressors Δy^{j}_{it-1} and ΔX^{j}_{it-1}. $\mathbf{Y^{j}}$ is simply the (T-2) vector $(\Delta y^{j}_{i3}, \Delta y^{j}_{i4}, \dots, \Delta y^{j}_{iT})$ stacked across N individuals. In general, the optimal weights are given by:

$$\mathbf{A_{N}} = (\mathrm{N}^{-1}\textstyle\sum_{\mathbf{i=1}}^{\mathbf{N}} \mathbf{Z'^{j}_{i}}\widehat{\Delta\mathbf{u}^{\mathbf{j}}_{\mathbf{i}}}\,\widehat{\Delta\mathbf{u'}^{\mathbf{j}}_{\mathbf{i}}}\mathbf{Z^{j}_{i}})^{-\mathbf{1}}$$

$\widehat{\Delta\mathbf{u}^{\mathbf{j}}_{\mathbf{i}}}$ here are residuals from an initial consistent estimator, which according to Arellano & Bond (1991) is equivalent to the following when u^{j}_{it} are i.i.d.:

$$\mathbf{A_{N}} = (\mathrm{N}^{-1}\textstyle\sum_{\mathbf{i=1}}^{\mathbf{N}} \mathbf{Z'^{j}_{i}H\,Z^{j}_{i}})^{-\mathbf{1}}$$

Where

$$\mathbf{H} = \begin{bmatrix} 2 & -1 & 0 & \dots & 0 \\ -1 & 2 & -1 & \dots & 0 \\ 0 & -1 & 2 & \dots & 0 \\ . & . & . & \dots & . \\ 0 & 0 & 0 & \dots & 2 \end{bmatrix}$$

Arellano and Bover (1995) argue that estimators in first differences can be poorly behaved since lagged levels only provide weak instruments. To address this problem, they proposed that instead of transforming the regressors to remove the fixed effects, differencing the instruments to make them exogenous to the fixed effects is also viable. In other words, lagged differences could be possible instruments for equations in levels. The moment conditions of this approach is then:

$$E\left(\Delta y^{j}_{it-1}u^{j}_{it}\right) = 0$$

Finally, Blundell and Bond (1998) formalize a GMM estimator based on a stacked system comprising the equations in both first differences and in levels. This approach is known as the system GMM. System GMM is treated as a single-equation estimation problem because the same linear relationship with the same coefficients is applied to variables in both first-differences and levels. The instrument matrix for the system GMM can be written as:

$$\mathbf{Z^{j,sys}_{i}} = \begin{bmatrix} \mathbf{Z^{j}_{i}} & 0 & 0 & \dots & 0 \\ 0 & \Delta y^{j}_{i2} & 0 & \dots & 0 \\ 0 & 0 & \Delta y^{j}_{i3} & \dots & 0 \\ . & . & . & \dots & . \\ 0 & 0 & 0 & \dots & \Delta y^{j}_{i(T-1)} \end{bmatrix}$$

Where $\mathbf{Z^{j}_{i}}$ is the same instrument matrix used in the Arellano-Bond specification. The additional instruments are chosen according to Arellano and Bover (1995) for equations in levels. The calculation of the system GMM estimator is analogous to what is described above. For the empirical estimation of our panel VAR model, we apply the system GMM for each equation in our PVAR system.

V. EMPIRICAL RESULTS

We present the estimation results of the PVAR(1) model of our specification for both gross in-migration and out-migration as suggested by Alecke, Mitze and Untiedt (2009). First, we discuss in detail the estimation output for our PVAR system. We focus on the evidence that reveals the correlation between business cycle and internal migration and compare them to the findings of existing literature. Then, we take a closer look at the post estimation tests to ensure the efficiency of our estimation method and the validity of our chosen instruments. Our IV selection is guided by the J statistic of Hansen (1982). Here we don’t use the Sargan or Basmann test for overidentifying restrictions because neither the Sargan nor the Basmann statistics is valid in the presence of heteroskedasticity. In fact, Arellano & Bond (1991) show that the one-step Sargan test overrejects when there is heteroskedasticity present. Furthermore, we check for the joint significance of key coefficients, the presence of heteroskedasticity in the system as well as autocorrelation in the first-differenced errors.

The empirical results of our PVAR(1) model comes from a two-step robust system GMM estimation. Table 7 reports the coefficient estimates together with the post estimation test results for both gross in-migration rate and out-migration rate.

Table 7. Estimation results for state level PVAR(1)

Dep. Var.	Ind. Var. (in lag)	Coef.	Std. Err. (Robust)	P-value	Hansen's J statistics	A-B test for autocorrelation	Wald test for joint significance
Gross in rate	Gross in rate	0.613***	0.0431	0.000	50.01 (1.000)	1.29 (0.197)	57.56 (0.000)
	Unemp. growth rate	-1.247*	0.7038	0.077			
	Med. hh. income	6.45e-05***	8.50e-06	0.000			
Gross in rate	Gross in rate	0.618***	0.0429	0.000	49.91 (1.000)	1.34 (0.181)	60.50 (0.000)
	UI claim. rate	-1.948	7.0540	0.782			
	Med. hh. income	6.56e-05***	1.49e-05	0.000			
Gross in rate	Gross in rate	0.616***	0.0456	0.000	49.07 (1.000)	1.31 (0.190)	64.01 (0.000)
	Unemp. gap	-0.033	0.0705	0.638			
	Med. hh. income	6.35e-05***	8.89e-06	0.000			
Gross out rate	Gross out rate	0.364***	0.0490	0.000	48.96 (1.000)	1.74 (0.082)	88.43 (0.000)
	Unemp. growth rate	-0.707	0.9217	0.443			
	Med. hh. income	1.09e-04***	1.17e-05	0.000			
Gross out rate	Gross out rate	0.364***	0.0501	0.000	49.47 (1.000)	1.73 (0.084)	88.88 (0.000)
	UI claim. rate	-4.539	12.7418	0.722			
	Med. hh. income	1.17e-04***	2.51e-05	0.000			
Gross out rate	Gross out rate	0.349***	0.0476	0.000	45.49 (1.000)	1.68 (0.093)	102.14 (0.000)
	Unemp. gap	-0.240**	0.1041	0.021			
	Med. hh. income	1.16e-04***	1.16e-05	0.000			
No. of obs. per equation		816					
No. of instruments		405					
White test for heteroskedasticity	Gross in migration	51.76 (0.00)					
	Gross out migration	36.60 (0.00)					

Note: ***, **, * denote significance at the 1%, 5%, 10% level. Standard errors are computed using Windmeijer (2005) bias-corrected robust VCE. P-values are in parentheses.

The table above focuses on the coefficient estimates for the migration equations in our PVAR system. The results show that out of the three measurements of regional economic conditions, only two of them turn out to be statistically significant and of expected signs. For the gross in-migration rate, unemployment growth rate is the only significant measurement of economic conditions and it has a significant negative effect. In standardized terms, an increase of 1 standard deviation in unemployment growth rate will result in a decrease of 0.249 in gross in-migration rate per 1000 residents. This result confirms the findings of Saks and Wozniak (2011) that migration within the United States has a procyclical pattern, that is, migration activity is lower during economic downturns and vice versa. This is further validated through the coefficient of the median household income. An increase of a thousand dollars in annual median household income will bring about 0.0645 increase in in-migration rate per 1000 residents. We can interpret this correlation between local business cycle and migration as evidence that the net benefits are higher during an economic boom and vice versa. On the gross out-migration side, we see a similar trend. Unemployment gap is the only significant measurement with a negative impact. An increase of 1 standard deviation in unemployment gap, which is the difference between the state unemployment rate and the national natural rate, will on average result in a 0.482 fall in gross out-migration rate per 1000 residents. This means that the deeper the recession, the lower the out-migration, which is yet another proof of the procyclicality of migration in the U.S. If we take another look at the effect of median household income, an increase of a thousand dollars in median household income will raise the out-migration rate per 1000 residents by 0.116. At first glance, one may think of the positive sign counterintuitive. However, the positive correlation between out-migration and income level is exactly what one should expect because that is the very evidence of the procyclicality that we are seeking: in times of prosperity and economic expansion, both in and out migration level will rise. One explanation for the positive sign is that procyclical fluctuations in income level can generate procyclical migration by allowing credit-constrained individuals to finance moves to new markets (Saks and Wozniak 2011). Individuals may take advantage of their high earnings to "purchase" migration, given migration is a normal good. Gregg, Machin, and Manning (2004) suggest that speculative moves in search of work by the unemployed are extremely rare in the U.K., given the costs of moving and the difficulty of obtaining accommodation if one is without work.

If we turn to the post-estimation tests, the results from Hansen's (1982) test present strong evidence in favor of the null hypothesis that the overidentifying restrictions are valid for both in and out migration regression. Next, we take a look the Arellano-Bond test for autocorrelation in the first-differenced errors. Based on the test results there is no serial correlation in the first-differenced errors at an order higher than 1, which implies that moment conditions used by system GMM are valid. For the Wald test of joint significance, we test whether the coefficients of the core variables, economic conditions and income level, are jointly zero. The test shows that for both in and out-migration model, business cycle condition and income level are jointly significant. Finally, from the White's general test for heteroskedasticity, we reject the null hypothesis of homoscedasticity, which renders the normal Sargan test invalid.

VI. CONCLUSION

This paper aims to evaluate the linkage between cyclical economic fluctuations and U.S internal migration. There are references to the cyclicality of internal migration in the existing literature, however none has taken a panel VAR strategy to analyze the problem and a lack of thorough investigation of this relationship in a large economy such as the United States is still a limitation. My paper sheds new light on this topic through the use of a dynamic panel data model.

We found evidence of procyclical migration patterns in state-to-state migration using aggregate level CPS panel data. Specifically, a 1 standard deviation increase in unemployment growth rate will result in a decrease of 0.249 in gross in-migration rate per 1000 residents and a 1 standard deviation increase in unemployment gap will on average result in a 0.482 fall in gross out-migration rate per 1000 residents. We interpret these results as evidence that the net benefit of migration fluctuates over the business cycle.

By studying the labor market fluctuations through the lens of migration using a novel PVAR approach, we offer yet another evidence of the procyclicality in the labor market. This paper also provides useful alternatives to the limited number of measurements of labor market conditions.

Despite the finding that there is a positive correlation between migration and business cycle, our analysis is still preliminary and has a lot of potential. This paper has yet to address how migration fluctuations interact with labor market fluctuations. One common view of labor economic research is that labor migration can equilibrate regional markets that are exposed to asymmetric demand shocks since labor can migrate to less adversely affected areas, reducing the aggregate unemployment rate (Archibald 1969). According to this view, migration is often considered an adjustment mechanism, smoothing away labor demand differentials across locations (Blanchard and Katz 1992). The other theory suggests that it serves as a source of regional growth differentials in employment and population and becomes an additional source of labor market fluctuations itself (Partridge and Rickman 2006). Through the variance decomposition analysis of the PVAR framework, one can answer the question of whether “migration only reflects responses to demand shocks” or “migration also serves as supply innovations”.

Whether regional disparities of local business cycles play a role is also an interesting follow-up question that deserves further investigation. For this particular problem, the same PVAR approach can be utilized but requires concentration on migration between pairs of origins and destinations of which economic conditions differ. According to neoclassical theory, regions with relatively low unemployment and high income levels should attract in-migration from regions with less opportunities.

The additional questions mentioned above will be answered in the continuation of this study. This paper is meant to be a starting point for further studies on the cyclical properties of labor market and it offers a good reference on how to incorporate business cycle theories into the study of migration.

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