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Immigration and Economic Performance
Across Fifty U.S. States from 1980-2015

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The fifty US states experienced diverse increases in immigration since 1980 but shared a similar institutional framework, which allows us to assess the impact of immigration on several macro-level variables of economic performance. We use data from a variety of public sources and the popular shift-share instrument to isolate exogenous variation in migration by state and decade since 1980. Although the overall correlation between immigration and performance variables is positive, analysis of regional and time variation reveals a negative *growth* relationship between the foreign-born share of the labor force and GDP, per-capita GDP, employment, native employment, and per-capita income. Most of those effects dissipate in *level* regressions that assess longer-term impacts.

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1. Introduction

When exploring the economic effect of immigration, are we missing the forest for the trees? Among four papers in the Fall 2016 issue of the *Journal of Economic Perspectives* with competing perspectives, one (Dustman, Shönberg, and Stuhler, 2016) showcased the confusion with its very title: "The Impact of Immigration: Why Do Studies Reach Such Different Results?" One of the reasons is that the same method applied to the same microdata can yield different results simply based on how the data are aggregated. Dustman et al. (2016) show that the same underlying microdata can be vulnerable to conflicting interpretations based on how the data is aggregated into subgroups. For example, should you use three education categories or five when comparing subgroups? Four skill levels or one? Those decisions will affect the results of microdata inquiries, and simple trends can easily be missed.

Immigration skeptics routinely cite George Borjas (2003, 2015). Advocates for the benefits of immigration cite the work of Giovanni Peri (2012). Yet both scholars tend to use microdata as the basis of empirical work. As background, publicly available microdata involves individual-level observations, in contrast to macro data which tends to include regional averages. The macro data for the USA tells us that 3.8 percent of the labor force is unemployed, whereas the microdata tells us exactly which individuals are unemployed.

This paper explores the forest, not the trees, with data on all fifty states in the USA over many decades using what is known as the spatial-correlation approach. Spatial-correlation studies typically exploit geographical variation over time to analyze the effects of one variable on another, and usually the dependent variable in immigration studies is the native-born population (e.g. Altonji and Card, 1991; Borjas, Freeman and Katz, 1996; Card and Lewis, 2007; Peri, 2012). We aim to explore whether there are causal relationships between immigration and economic performance from 1980 to the present. By using multiple decades of data across fifty states, rates of change can be compared over four different time periods. We consider state-by-state economic performance in terms of GDP levels, GDP growth, per-capita GDP, personal income, and the employment to population ratio (overall as well as native-born).

Our study is somewhat unique because we conduct a spatial-correlation study with macro-level outcome variables that are provided by public entities. Often in the immigration literature, data is generated from individual-level samples and corresponding sample weights to manually construct weighted averages at the regional level. Spatial-correlation studies are sometimes extended by grouping individuals into skill groups based on education and work experience (see Basso and Peri, 2015; Borjas, 2003; and Card and DiNardo, 2000), but as mentioned above, these types of studies can be sensitive to the way the groups are defined.

One of the main obstacles to estimating a causal effect of immigration through a spatial-correlation study is overcoming the endogeneity of the immigrant variable. Since immigration tends to be correlated with unobservables that affect macro-level outcome variables, OLS estimates may suffer from omitted variables bias. We are aware of this issue and address it through the use of instrumental variables.

Various instruments have been used in the literature including the “past-settlement” instrument (Altonji and Card, 1991) as well as the popular “shift-share” instrument that uses a measure of lagged immigration and adjusts it by a national immigration growth rate (Peri and Sparber, 2009; Basso and Peri, 2015). Others include the “gravity-approach” instruments where the number of immigrants leaving the sending country are predicted using a variety of supply-push factors from the sending country. These predicted numbers are summed up over all sending countries and are then used as an instrument for the immigrant population in the receiving country (e.g. Ortega and Peri, 2014; Jamotte, Koloskova and Saxena, 2016). More recently, Peri (2012) uses the distance from the center of mass from each US state to the Mexican border as well as a Mexican border dummy as instruments for measures of state-level immigration.

Other studies have attempted to use natural experiments to identify exogenous variation in the number of immigrants. Most notable is David Card’s paper on the Mariel Boatlift which uses the sudden shock of Cuban immigrants to Florida in 1980 (Card, 1990). Card’s natural experiment uses a difference-in-difference approach which compares pre and post Miami to other cities around that time that did not experience labor-supply shocks. Card finds that this sudden inflow of lower-skilled immigrants generally did not harm native workers. Recently, both Borjas and Peri revisited the same data surrounding the Mariel Boatlift using different subsamples of individuals (which is another potential pitfall when using microdata) and synthetic control groups for comparison. Borjas claims to have overturned Card’s findings, while Peri finds results that are consistent with Card’s (Borjas, 2017; Peri, 2017). This lack of consensus continues to drive the debate on immigration. On top of this general disagreement, there are only a handful of studies that look at the effect of immigration on aggregate variables like per capita income or the employment to population ratio,

Among the studies that look at macro-level outcomes, we are only aware of one other that uses state-level GDP to analyze the effects of immigration in the United States (i.e. Peri, 2012). However, Peri (2012) focuses on total factor productivity which must be estimated after making assumptions about the aggregate production technology; whereas our paper relies on readily observable measures of economic performance.

We find that the baseline relationship between immigration and economic growth is positive, meaning that the U.S. states with larger immigration shares tend to have higher per capita GDP and per capita GDP growth. Hancock and McIntosh (2016) report a similar relationship among OECD countries. It is unclear whether immigration leads to faster growth or if growth induces more immigration. There could even be an unknown variable driving both. This paper attempts to determine which of these three avenues is the most plausible.

2. Data

The main immigration variable used in this study is the foreign-born as a share of the civilian labor force in 50 states during the years 1980, 1990, 2000, 2010, and 2015. This series is published by the Migration Policy Institute (2017) and is based on data from the U.S. Census Bureau's American Community Survey (ACS) and the decennial U.S. Census.

Gross domestic product (GDP) is our main measure of economic performance, though the data is complicated by a fundamental shift in how it was defined by the U.S. Bureau of Economic Analysis (BEA) in 1997. The BEA publishes state and municipal figures for gross domestic product (GDP) under its regional data series in current dollars as far back as 1963. However, BEA cautions about a discontinuity in 1997 when "the data change from SIC industry definitions to NAICS industry definitions. This discontinuity results from many sources. The NAICS-based statistics of GDP by state are consistent with U.S. gross domestic product (GDP) while the SIC-based statistics of GDP by state are consistent with U.S. gross domestic income (GDI)." Although the correlation in the BEA's two 1997 definitions of GDP is 0.999, we took two approaches to make a continuous GDP measure. First, we focused on growth, which obviates the level discontinuity. Second, we transitioned the pre-1997 GDP levels up by a constant percentage of 1.538 percent (this was the average upshift across all fifty states between the two BEA 1997 series). Because the BEA reports data back to the year 1980 in current dollars only, we also applied a GDP deflator to create a real measure. Finally, we created a new GDP per capita series by dividing each state's reported GDP level by the Census estimate of state population annually back to 1980.

Personal income is another major series published by the BEA, though it suffers no 1997 discontinuity. This measure includes all income whether it is taxed (such as wages, capital gains, and rent), partly taxed (such as social security benefit payments), or tax-exempt (such as transfer payments, and Medicare, Medicaid, and welfare benefit payments). The BEA reports its per-capita series in nominal terms only, which we adjusted using the consumer price index (CPI) to calculate state-level growth rates in real personal income per capita.

Rather than focus on unemployment rates, for our main labor measure we used total state employment as a ratio of state population, known as EPOP. Moreover, we constructed a native-only employment/population rate. Constructing a measure of statewide native-born employment involves gathering data on statewide employment as well as the labor force, then adjusting each with estimates of the foreign-born share of employment as well as the labor force. As a result, we considered two EPOP variables. The first is an overall EPOP as normally understood. The second is EPOP for natives, which uses the employment level of natives only in the numerator and the population of natives only in the denominator. The BLS provides monthly statewide data in its Local Area Unemployment Statistics (LAUS) dataset, which is available online. We used the figures for January of each year.

Table 1. Overview of Main Variables

LEVEL	1980	1990	2000	2010	2015
GDP (2009 $m, real)	6,830,449	9,453,524	13,730,330	16,150,679	17,925,143
GDP per capita ($)	30,150	37,895	48,661	52,209	55,474
Real Personal Income per capita ($)	28,260	33,333	39,272	40,277	44,680
Immigrant Share of Labor Force	4.3%	4.7%	7.0%	8.5%	9.0%
GROWTH (annual average)					
GDP		3.9%	4.0%	1.8%	1.1%
GDP per capita		2.6%	2.4%	0.7%	0.6%
Real Personal Income per capita		1.8%	1.8%	0.3%	1.1%

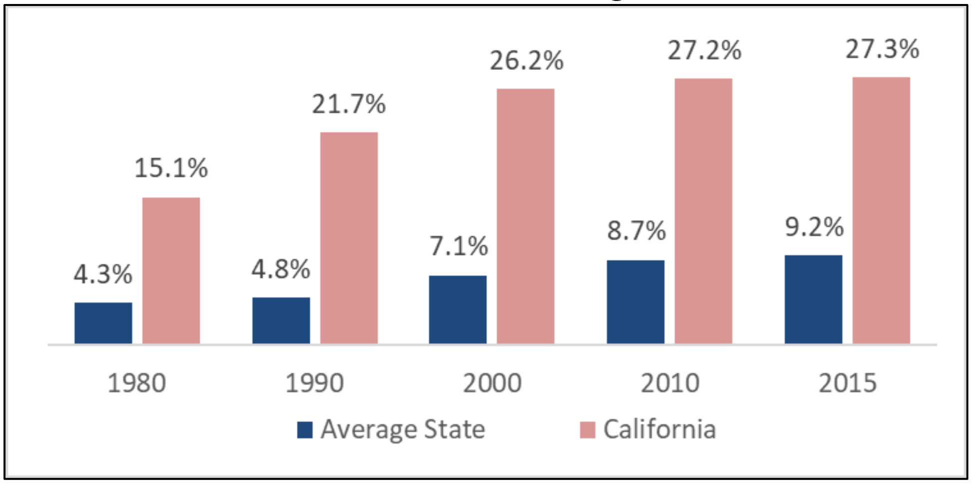
2.1 Immigration Trends in the Fifty States

In general, immigration levels have been rising since 1980, but the increase during the decade of the 1990s was extraordinary, roughly double the subsequent pace and quadruple the previous pace. Likewise, real incomes surged during the 1990s. Personal income growth was highest in northern states while lowest in many high-immigration states, particularly along the Mexican border. Nevada, Arizona, New Mexico, and Florida experienced real income growth of around 1 percent per year from 1980-2015, but in northern states from Massachusetts to the Dakotas, real income growth averaged twice as high. The decade average rate across all fifty states was 1.7 to 2.0 percent annually except for the 2000s when the average was 0.6 percent per year.

California has the highest share of population born outside of the United States. This foreign-born share includes all immigrants, legal and illegal. It includes Holocaust survivors as well as tourists who overstayed their visas. Some immigrants became citizens half a century ago, and some will never become citizens. The foreign-born share of the civilian labor force is highly correlated with the foreign-born share of the population, but is distinct because southern states that experienced recent surges in immigration tend to also have children (who are in the population but not in the labor force).

In 1980, which serves as the baseline year in this analysis, California's immigrant share of the population was 15.1 percent (Figure 1). The average state had an immigrant share of 4.3 percent, but seventeen states had an immigrant share of less than 2 percent. Immigrant shares increased rapidly during the past three and a half decades, but the changes varied across states and decades. By 2015, California's immigrant share had almost doubled, whereas only one state (West Virginia) still had an immigrant share of less than two percent. Half of the immigrant surge nationally occurred during the 1990s.

Figure 1. Immigrant Share of the Population: California vs. Average State
N=50 for State Averages



Growth in immigration was initially concentrated in a few states in the 1980s and 1990s, but became more evenly spread after 2000 (Figure 2a). For example, during the 1980s there were only eleven states that saw immigration shares rise by more than one percentage point, spiking particularly high in California, Nevada, New York, New Jersey, Florida, and Texas. The Midwest and Southeast saw only small immigrant share increases in the 1990s and 2000s. The standard deviation of changing immigrant shares across all 50 states was 1.3 percent in the 1980s, 1.6 percent in the 1990s, then dropped (that is, became more evenly spread) to just 0.9 percent in recent decades. It is this variation in immigration shares that enables us to explore whether the high growth of immigration nationally in the 1990s is related to strong income growth during that same time. When compared to growth rates across the 50 states, ranked from fastest to slowest each decade (Figure 2b), the variation in immigrant flows is much higher than the more equal distribution of growth rates.

Figure 2a. Change in Foreign-Born Share of Labor Force Across 50 States, Ranked

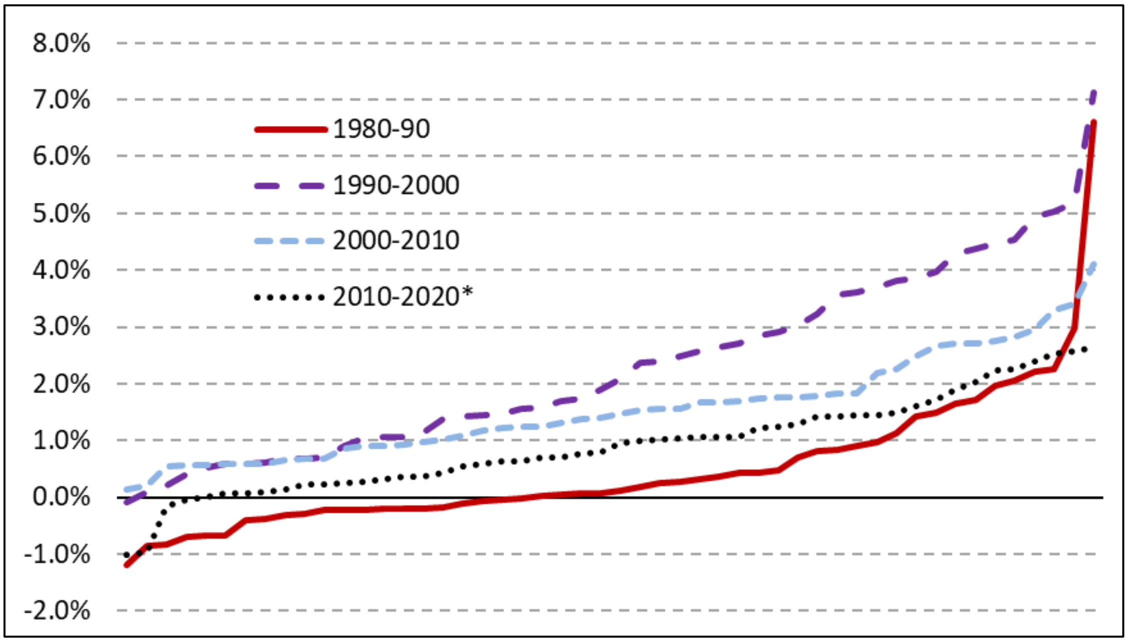
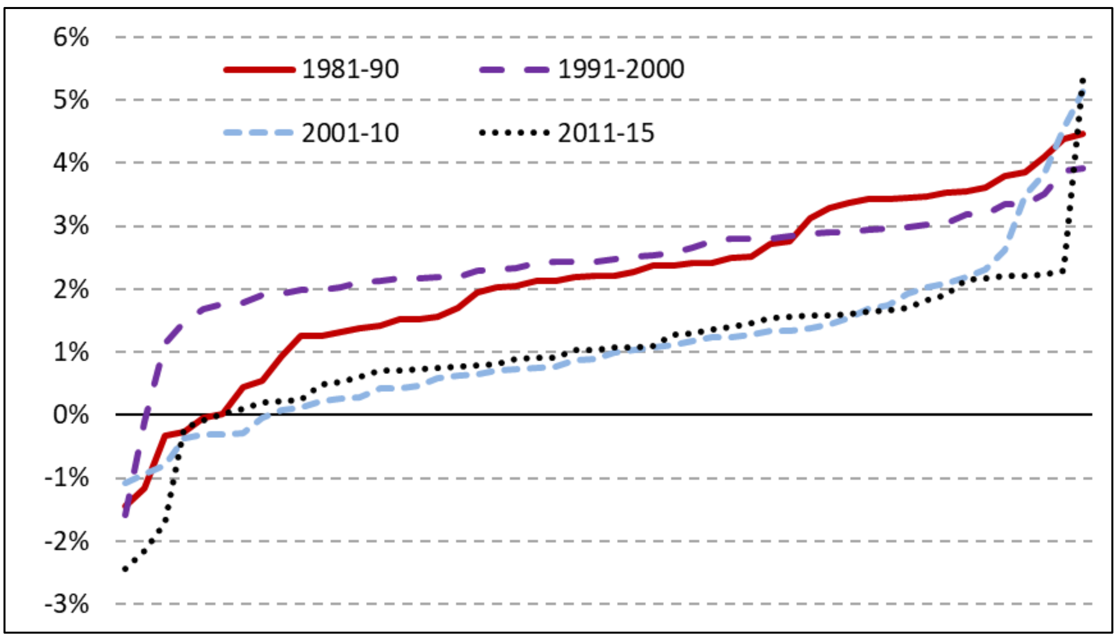


Figure 2b. Annual Average Growth of Real GDP Across 50 States, Ranked



2.2 Simple Relationships

The share of immigrants is positively correlated with the overall GDP levels, per-capita GDP, and per-capita income. However, the relationship between immigrants and the change of these macro variables has a small negative correlation. In addition, the immigrant share is also negatively correlated with the employment/population ratio of native-born citizens.

Table 2. Correlations (N=250 for level variables, N=200 for change variables)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	M	1.00											
(2)	ΔM	0.53	1.00										
(3)	Log real GDP	0.58	0.43	1.00									
(4)	Log per-capita real GDP	0.53	0.34	0.35	1.00								
(5)	Log per-capita income	0.59	0.30	0.41	0.92	1.00							
(6)	GDP growth	-0.01	0.25	0.02	-0.02	-0.04	1.00						
(7)	Per-capita GDP growth	-0.17	0.02	-0.01	-0.08	-0.04	0.87	1.00					
(8)	Per-capita income growth	-0.14	-0.28	-0.03	0.03	0.15	0.51	0.66	1.00				
(9)	EPOP	-0.11	0.03	-0.21	0.25	0.26	0.44	0.42	0.32	1.00			
(10)	ΔEPOP	-0.23	-0.38	-0.11	-0.32	-0.22	0.35	0.46	0.62	0.39	1.00		
(11)	Native EPOP	-0.32	-0.07	-0.32	0.11	0.12	0.43	0.44	0.34	0.97	0.43	1.00	
(12)	Δ Native EPOP	-0.26	-0.46	-0.13	-0.31	-0.21	0.32	0.43	0.63	0.38	0.99	0.42	1.00

Looking at a scatterplot of the fifty states at five time periods in Figure 3, we can see that states with higher immigrant shares tend to have higher GDP. This relationship persists after taking the first difference (see Figure 4) indicating that states that experienced an increase in the share of immigrants also experienced larger increases in GDP over four time periods (i.e., changes between 1990 and 1980, 1980 and 1970, and so on).

If we instead look at GDP growth rates, then states experiencing larger increases in the share of immigrants also tend to have larger GDP growth overall (Figure 5), but this strong positive correlation fades to neutral once we look at per-capita GDP growth (Figure 6).

There is a small negative relationship between the native employment-to-population ratio and the immigrant share (Figure 7). That the relationship becomes more pronounced once we take the first difference (Figure 8). These simple relationships may not hold once important factors of time, place, and additional influences are included, which we will address below.

Figure 3. Real Log GDP vs. Immigrant Share (N=250)

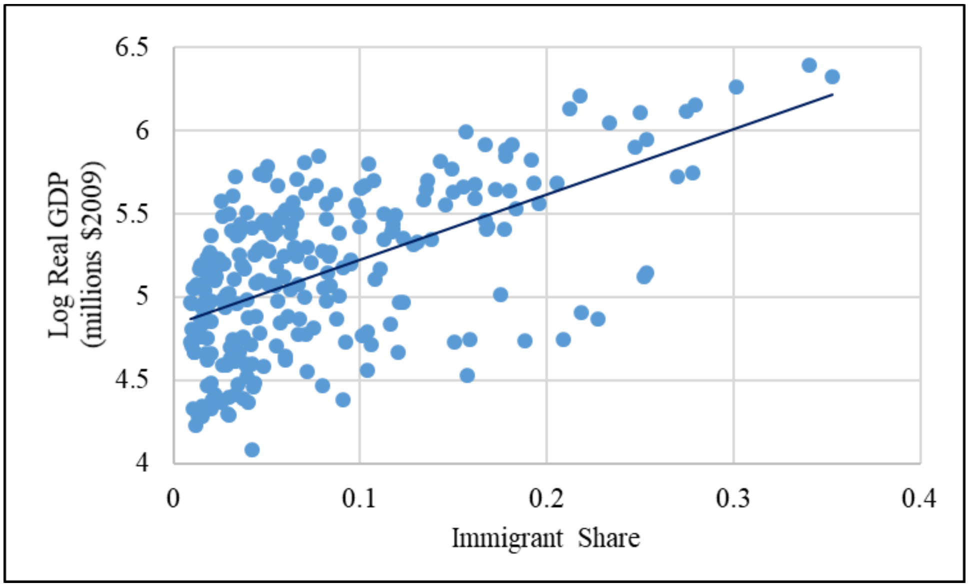


Figure 4. Change in Real GDP vs. Change in Immigrant Share (N=200)

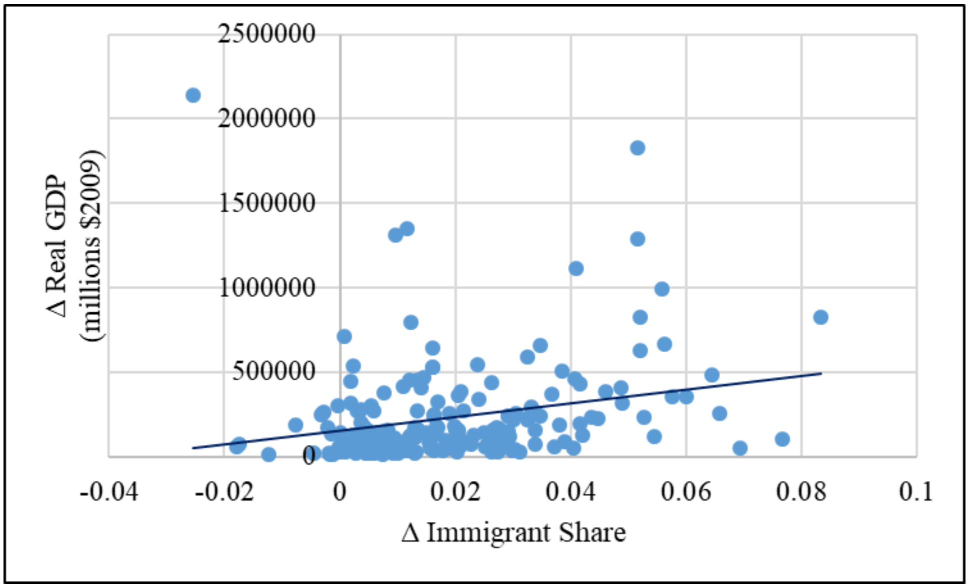


Figure 5. Growth in GDP vs. Change in Immigrant Share (N=200)

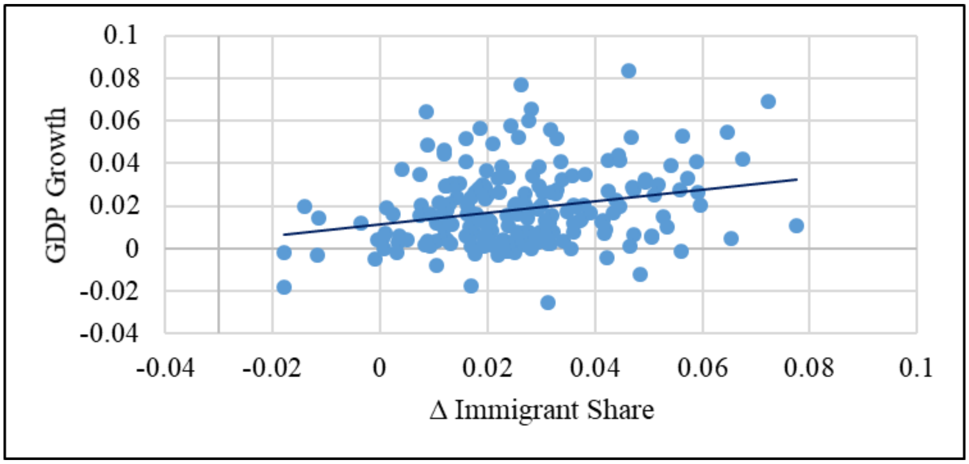


Figure 6. Per-Capita GDP Growth vs. Change in Immigrant Share (N=200)

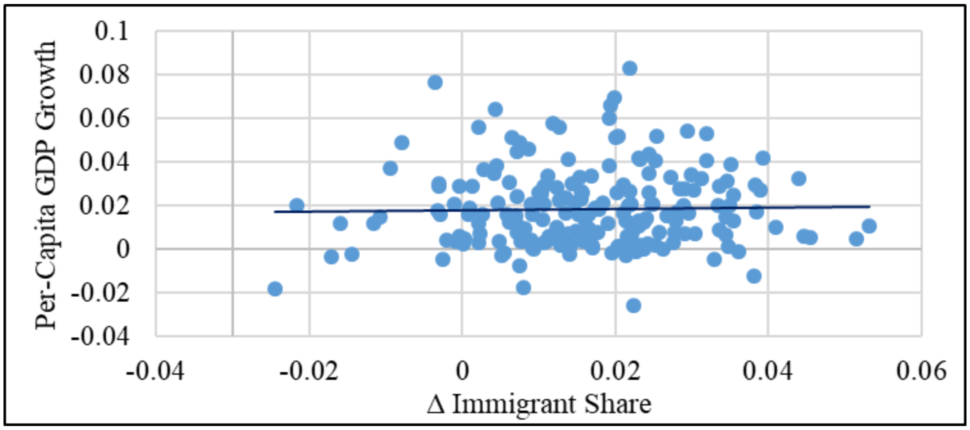


Figure 7. Native Employment to Population Ratio vs. Immigrant Share (N=250)

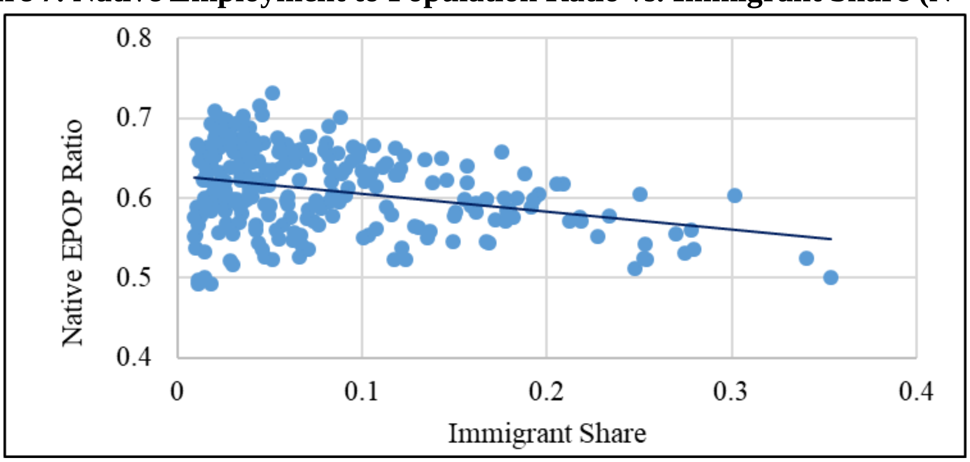
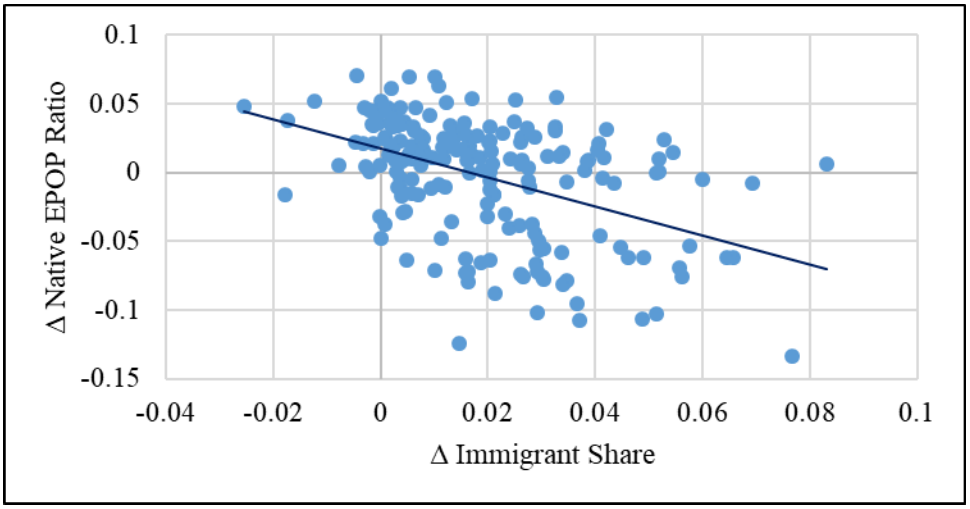


Figure 8. Change in Native E/Pop vs. Change in Immigrant Share (N=200)



3. Methodology

In order to estimate the causal effect of immigration on economic outcomes in the U.S., we use the fixed-effects panel data models depicted below. Our baseline OLS model (1) is used when the outcome variable is in levels. We use model specification (2) when the outcome variable is a first-difference or a growth rate such as the GDP growth or the change in the employment to population ratio. The main difference between (1) and (2) is the main regressor of interest. In specification (1) we use the immigrant share, but in specification (2) we use the change in the immigrant share. Consider the following

(1) $Y_{st} = \beta_0 + \beta_1 M_{st} + \beta_3 U_{st} + \varphi_t + \rho_s + \varepsilon_{st}$

(2) $\Delta Y_{st} = \Gamma_0 + \Gamma_1 \Delta M_{st} + \Gamma_2 \Delta U_{st} + \varphi_t + \rho_s + \varepsilon_{st}$

where M_{st} is the share of immigrants in state s at time t and Δ is the first-difference operator (t=1980, 1990, 2000, 2010, 2015). U_{st} is only used in the employment models and is the unemployment insurance exhaustion rate. The variables φ_t are time fixed effects, and ρ_s are state fixed effects.

In order to address the issue of endogeneity, we utilize two different instrumental variables to try to exploit exogenous variation in the share of immigrants. For each OLS model we run, we also estimate a separate IV model using a single shift-share instrument as well as a shift-share instrument interacted with a Mexican border dummy variable. The IV models use either equation (3) or (4) in the first stage, depending on the outcome variable we are examining. All of our models use standard errors that are clustered at the state level.

(3) $M_{st} = \alpha_0 + \alpha_1 Z_{st} + \alpha_2 Z_{st} \cdot D_s + + \alpha_3 U_{st} + \varphi_t + \rho_s + \varepsilon_{st}$

(4) $\Delta M_{st} = \alpha_0 + \alpha_1 \Delta Z_{st} + \alpha_2 \Delta Z_{st} \cdot D_s + + \alpha_3 \Delta U_{st} + \varphi_t + \rho_s + \varepsilon_{st}$

The first instrument we utilize is Z_{st} which is the popular shift share instrument. This adapts the work of Bartik (1991) to an immigration setting. In this case, our shift-share instrument is generated by taking the number of immigrants from each birthplace in each state in a period prior to our analysis (1970) and multiplies it by the subsequent national growth factor of immigrants from each birthplace which gives us the projected number of immigrants from each birthplace in each state based on a national growth rate. Then we sum up the projected number of immigrants from all places of birth for each state and year, and use the number of projected immigrants to construct the projected share of immigrants for each state in each year.

(5) $\hat{I}_{st} = \sum_b I_{b,s,1970} \frac{I_{b,n,t}}{I_{b,n,1970}}$

(6) $Z_{st} = \frac{\hat{I}_{st}}{\hat{I}_{st} + N_{st}}$

where $\hat{I}_{st}$ is the projected number of immigrants in state *s* at time *t*, $I_{b,s,1970}$ is the number of immigrants from birthplace *b* in state *s* in 1970 and $I_{b,n,t}$ is the number of immigrants from birthplace *b* nationally, and N_{st} is the observed number of natives in state *s* at time *t*. The idea behind the instrument is that the variation in the share of immigrants is driven by national factors that are independent of demand-pull factors that are specific to each state which may potentially cause the OLS estimates to be biased. We also interact the shift-share instrument with the variable D_s which is a dummy variable for states that border Mexico.

The coefficients of interest are β_1 and Γ_1. The interpretation of β_1 is that a one percentage point increase in the share of immigrants causes a β_1 percent increase in the outcome variable if the outcome variable is in log form (such as log GDP) or a β_1 percentage point increase in the outcome variable if the outcome variable is a share (such as the employment to population ratio). The interpretation of Γ_1 is that a one percentage point increase in the share of the foreign-born labor force causes a 0.01x Γ_1 increase in the dependent variable.

4. Regression Results

We ran a series of panel data regressions to determine how GDP, income, immigration, and labor markets are interrelated. All of the results presented here include state and year fixed effects unless otherwise noted. In the IV models, the immigrant share is instrumented by the shift-share instrument as well as the shift-share instrument interacted with a Mexican border dummy variable which has an entry of 1 if the state shares a border with Mexico. The first stage F-statistics are all over 20 which exceeds the generally accepted criteria of 10.

4.1 Gross Domestic Product and Per-Capita Income

We begin with an analysis of GDP growth rates in order to highlight how the statistical significance collapsed under different treatments. Table 3 shows several OLS models estimating equation (2) where the dependent variable is the real GDP growth rate. Column (A) has no dummies, column (B) includes year dummies, and column (C) includes both year and state dummies. What is a statistically significant relationship in columns (A) and (B) becomes insignificant in column (C) once both state and year fixed effects are controlled. So the simple correlations and figures described earlier are affirmed at first: an increasing share of immigrants is linked to faster economic growth rates. But once we control for the effect of specific states, the link is not statistically significant.

Table 3. GDP Growth Regressions with Different Controls

	(A) GDP Growth	(B) GDP Growth	(C) GDP Growth
$\triangle$M	0.233***	0.237***	0.110
	(0.000)	(0.000)	(0.314)
N	200	200	200
R^2	0.021	0.276	0.282

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

All results we present hereafter include both state and year fixed effects. This increases the likeliehood that significant coefficients represent causality because these fixed effects control for time-invariant unobservables that are specific to each state as well as unobservables common to all states that vary over time. Table 4 shows the relationship between the change in the share of immigrants and the growth of GDP, per-capita GDP, and per-capita income using both OLS and IV for comparison (i.e., models 2 and 4).

Since the independent variable here is the change in the immigration share, a change in the independent variable of 0.01 represents a one percentage point increase in the state labor force that is foreign born. A one percentage point increase in the state labor force is associated with a Γ_1 percentage point increase in each of the dependent variables in Table 4. Although the OLS results show an insignificant, positive relationship for overall GDP growth, the shift-share results show a significant, negative relationship. The shift-share results are significant and negative for per-capita GDP growth and per-capita income growth as well. The implication is that a one percentage point increase in the state labor force that is foreign born causes a 0.32 percentage point decrease in GDP growth, a 0.28 percentage point decrease in per-capita GDP growth, and a 0.30 percentage point decrease in per-capita income growth.

Table 4. Change-Change Regressions

	(1) (OLS) GDP Growth	(2) (IV) GDP Growth	(3) (OLS) Per-Cap GDP Growth	(4) (IV) Per-Cap GDP Growth	(5) (OLS) Per-Cap Income Growth	(6) (IV) Per-Cap Income Growth
$\triangle$M	0.110	-0.319**	-0.039	-0.281***	-0.068	-0.300***
	(0.314)	(0.031)	(0.649)	(0.005)	(0.124)	(0.000)
N	200	200	200	200	200	200
R^2	0.282	0.199	0.249	0.208	0.405	0.333

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5. Level-Level Regressions

	(1) (OLS) Log GDP	(2) (IV) Log GDP	(3) (OLS) Log Per-Cap GDP	(4) (IV) Log Per-Cap GDP	(5) (OLS) Log Per-Cap Income	(6) (IV) Log Per-Cap Income
M	1.266***	0.093	0.053	-0.053	-0.677**	-0.742
	(0.000)	(0.811)	(0.793)	(0.854)	(0.045)	(0.102)
N	250	250	250	250	250	250
R^2	0.919	0.900	0.858	0.857	0.911	0.911

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Turning now to levels instead of growth rates, results in Table 5 isolate the effect of immigration shares on log GDP, log per-capita GDP, and log per-capita income. Here, higher immigration levels are associated with an increase in GDP and per-capita GDP but a decrease in per-capita income. However, the statistical significance is wanting. After estimating the model with instrumental variables, the results become insignificant across the board. We caution against interpreting the OLS results as causal due to the potential endogeneity of the immigrant variable. Econometric theory suggests that we should generally expect the OLS results to be biased upwards since immigration is plausibly correlated with unobservable labor demand pull factors that are likely positively correlated with GDP and income. The results from all of the IV estimates in tables 4 and 5 support this notion, either less positive or more negative relative to the OLS results.

The interpretation overall implies a new and potentially valuable insight, which is that the effect of higher immigration *levels* on GDP, per capita GDP, and personal income is negligible, whereas there is a *negative transition effect* during the decade in which immigration surges. So on the one hand, the longest term data of 35 years shows an unambiguous positive correlation between GDP and immigration. Once the data is cut into decades – allowing us to control for both time and state effects – the positive relationship in levels becomes neutral whereas a short-term transition negative is revealed.

4.2 Employment

We found a consistently negative relationship between the share of immigrants and the employment-to-population ratio (Table 6). We hypothesized that immigrants may create an immediate displacement that would be invisible in macro data for a fluid labor market but visible in the presence of welfare programs that are conditional on non-work. The immigration displacement effect may then show up because of the so-called poverty trap of generous social safety nets such as unemployment insurance. To test that hypothesis, we included a variable for the exhaustion rate of unemployment insurance (columns 3, 4, 7, and 8). As we predicted, a high rate of people exhausting their unemployment benefits is associated with lower employment. And indeed, its inclusion in our regressions led to loss of significance for immigration share as the driver of lower E/Pop ratios.

Table 6. Employment Regressions

	(1) (OLS) EPOP	(2) (IV) EPOP	(3) (OLS) EPOP	(4) (IV) EPOP	(5) (OLS) △ EPOP	(6) (IV) △ EPOP	(7) (OLS) △ EPOP	(8) (IV) △ EPOP
M	-0.249***	-0.184	-0.197**	-0.113				
	(0.008)	(0.161)	(0.040)	(0.426)				
UIXR			-0.564***	-0.618***				
			(0.003)	(0.003)				
△M					-0.273*	-0.542***	-0.178	-0.299
					(0.081)	(0.001)	(0.257)	(0.124)
△UIXR							-0.732***	-0.717***
							(0.000)	(0.000)
N	250	250	250	250	200	200	200	200
R^2	0.751	0.749	0.773	0.769	0.774	0.769	0.813	0.812

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

4.3 Native Employment

In order to look at the effect of immigration on the native workforce, we examine the effect on E/Pop of native-born workers (Table 7). As a reminder, the "Native EPOP" variable was carefully constructed using modified measures of employment in the numerator and population in the denominator for each state by removing the foreign-born employment and population estimates respectively. The results here show a statistically negative effect of immigration on the employment of natives for all specifications used. The negative impact of immigration on native employment stays statistically significant whether we include or exclude the unemployment insurance variable. The results indicate that a one percentage point increase in the share of immigrants causes a 0.38 to 0.52 percentage point decrease in the employment to population ratio of the native-born.

Table 7. Native Employment Regressions

	(1) (OLS) Native EPOP	(2) (IV) Native EPOP	(3) (OLS) Native EPOP	(4) (IV) Native EPOP	(5) (OLS) △ Native EPOP	(6) (IV) △ Native EPOP	(7) (OLS) △ Native EPOP	(8) (IV) △ Native EPOP
M	-0.469***	-0.440***	-0.421***	-0.378**				
	(0.000)	(0.002)	(0.000)	(0.015)				
UIXR			-0.515***	-0.543***				
			(0.004)	(0.008)				
△M					-0.527***	-0.742***	-0.440***	-0.516**
					(0.001)	(0.000)	(0.005)	(0.020)
△UIXR							-0.672***	-0.663***
							(0.000)	(0.000)
N	250	250	250	250	200	200	200	200
R^2	0.806	0.806	0.820	0.820	0.803	0.800	0.832	0.831

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

4.4 Reverse Causality

Perhaps the direction of causality is in the opposite direction from what is explored above, for example the possibility that faster-growing states cause a higher inflow of migrants. To study the possibility of reverse causality, we reran regressions for all of the models in tables 3-7 with the only difference being to swap the immigration variable with the relevant dependent variable. Full results of the IV regressions are presented as tables 4R, 5R, 6R, and 7R in Appendix I.

There was no evidence of a significant effect of economic growth on immigrant flows (table 4R), in contrast to the significant negative effect of changing immigration patterns on GDP growth, GDP per capita growth, and personal income growth. On the other hand, we did find significant reverse relationships in levels (table 5R) *in contrast to the earlier finding*. That is, the level of immigration was significantly and positively affected by the levels of real GDP and personal income. What this means is that a short-term surge in GDP growth is not linked to higher immigration flows, but a long-term increase in the level of GDP does tend to draw in a higher level of immigrants. Putting this with the earlier result, it seems that immigrants cause a negative shock to economic performance, but no long-term impact, whereas economic vitality does serve as a long-term term draw to immigrants as well. Both findings align with textbook economics of how a dynamic labor market functions.

A higher EPOP ratio is also associated with a lower level of immigration, but the growth-on-growth effect was not significant (table 6). The same relationship was observed in EPOP for natives, which had a negative level effect on immigration but also negative in growth rates (table 7). The latter result suggests that a state experiencing an increased employment rate of natives leads to a slower inflow of migrants. The economic story here is murky. Although it could be that surging native employment crowds-out migrant opportunities – perhaps a reflection of labor differentiation in some states – this finding could also simply be an echo of normal causality.

The best way to resolve this puzzle is to examine data of shorter periods which is a different scope than this study. However, we were curious to see if Granger-causality regressions shed any light on our decade-length variables. Appendix II presents eight additional tables using the nomenclature "table #G" for Granger regressions of lagged immigration variables on performance and "table #GR" for the Granger regressions in reverse. What we found in essence is that the direction of causality is significant in both directions: one-decade lagged immigration is causing current-decade relatively weaker GDP growth, per capita GDP growth, personal income growth, per capita GDP levels, and personal income levels (table 4G and 5G). In the reverse, growth performance variables do not Granger cause immigration flows to change (table 4GR), however higher economic performance levels lagged by one decade do Granger cause current-decade immigration levels to be higher. As for employment, lagged EPOP has an insignificant impact on immigration flows and levels (tables 6GR and 7GR), in contrast to significant and far stronger Granger-caused negative impact of immigration flows on EPOP (table 6G) level and growth, as well as on EPOP of natives (table 7G).

We conducted these additional tests to assess whether our main results were robust, and indeed the findings were consistent. We would caution that a full exploration of Granger causality must be done with a larger set of data with annual observations that will allow for a longer lag structure. It is not our goal here to provide a definitive answer to causal interactions. We hope future papers that look into annual data will not face the scope and measurement continuity issues that bind this study.

5. Conclusion

By looking at the forest and not the trees, we have tried to identify relationships between immigration and economic performance in the United States since 1980, a period of surging immigration. Instead of focusing on micro-level data, we used macro-level state variables. We confirmed a positive national relationship between immigration and GDP growth in the overview, but a deeply nuanced and sometimes negative interaction using more sophisticated statistical techniques.

Once state and time fixed effects are controlled for, we exploit exogenous variation in the immigrant share of the workforce by using the shift-share instrument, allowing us to show three interesting impacts. First, a surge in immigration causes a transitional setback to *growth* of state GDP, GDP per capita, and personal income relative to other states/decades. A one percentage point increase in the foreign born share of a state's labor force causes a 0.32 percentage point decrease in GDP growth, a 0.28 percentage point decrease in per-capita GDP growth, and a 0.30 percentage point decrease in per-capita income growth during the decade. Second, that effect dissipates, which we know because the effect of a higher *level* of immigration has no significant effect on the levels of GDP, GDP per capita, or personal income. It may well be that the negative short-term growth finding is driven by the relative poverty of the migrants who eventually upskill and integrate, but our data cannot clarify that conjecture. Our third finding is that immigration causes a slight but real decline in growth and level of the employment of locals who are native-born, again relative to other states/decades.

Although the US certainly benefits from immigrants who start businesses, fill labor shortages, and add value to the economy and society through other channels, the evidence here suggests that there are some short-term negative impacts of immigration during the past 35 years.

There are at least three data limitations to our study. No data, micro or macro, can tell us what the impact of immigration has been at the most aggregate level of all: the national level. It could well be that the surge of immigration to the United States during the past century led to a higher baseline *national* growth rate. Or a lower growth rate. This we cannot know. Second, we are constrained by a relatively long time span compared to other studies but short relative to what we would prefer. That is, the timespan limits our scope to only four periods, but also limits the variety of immigrants that arrived during the period (e.g. primarily poor migrants from Latin America, compared to largely European immigrants in the previous half century). A longer series would almost certainly provide significance to the levels analysis and bolster the positive view. A third limitation is that we were unable to look at interstate native migration. Could it be that Ohioans are displacing Floridians? That question is vital to truly understand the relative impact of foreign-born migration.

A fourth potential limitation to our study is that econometric tools dealing with endogeneity are imperfect. Our use of the shift-share instrument is, we hope, best practice. Yet a recent working paper (Jaeger, et al., 2018) criticizes the shift-share instrument because it may lead to biased estimates if the distribution of immigrants from the same origin are highly serially correlated. They propose the use of multiple shift-share instruments to correct this issue, which is beyond the scope of this paper. It is our hope that this paper does, however, add insights to the discussion that Jaeger, et al. began.

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Appendix I – Reverse Causality

Table 4R

Outcome Variable $\Longrightarrow$	(1) $\triangle$M	(2) $\triangle$M	(3) $\triangle$M
GDP Growth	0.0689		
	(0.313)		
Per-Capita GDP Growth		-0.036	
		(0.657)	
Per-Capita Income Growth			-0.152
			(0.241)
N	200	200	200
R^2	0.455	0.451	0.456

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5R

Outcome Variable $\Longrightarrow$	(1) M	(2) M	(3) M
Log Real GDP	0.168***		
	(0.000)		
Log Per-Capita Real GDP		0.012	
		(0.787)	
Log Per-Capita Income			-0.082**
			(0.042)
N	250	250	250
R^2	0.758	0.693	0.710

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6R

Outcome Variable $\Longrightarrow$	(1) M	(2) M	(3) $\triangle$M	(4) $\triangle$M
EPOP	-0.450***	-0.380**		
	(0.002)	(0.021)		
UIXR		0.387*		
		(0.055)		
$\triangle$EPOP			-0.0824	-0.065
			(0.168)	(0.355)
$\triangle$UIXR				0.074
				(0.335)
N	250	250	200	200
R^2	0.727	0.733	0.463	0.466

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7R

Outcome Variable $\Longrightarrow$	(1) M	(2) M	(3) $\triangle$M	(4) $\triangle$M
EPOPN	-0.661***	-0.637***		
	(0.000)	(0.000)		
UIXR		0.147		
		(0.381)		
$\triangle$EPOPN			-0.150**	-0.147*
			(0.022)	(0.053)
$\triangle$UIXR				0.016
				(0.836)
N	250	250	200	200
R^2	0.788	0.789	0.494	0.494

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix II – Granger Causality and Reverse Granger Causality

Table 4G

Outcome Variables $\Longrightarrow$	(1) GDP Growth	(2) GDP Growth	(3) Per-Capita GDP Growth	(4) Per-Capita GDP Growth	(5) Per-Capita Income Growth	(6) Per-Capita Income Growth
Lagged GDP Growth	-0.180	-0.175				
	(0.174)	(0.148)				
Lagged Per-Capita GDP Growth			-0.258**	-0.275***		
			(0.016)	(0.006)		
Lagged Per-Capita Income Growth					-0.178	-0.205**
					(0.104)	(0.032)
Lagged $\triangle$M		-0.599***		-0.483***		-0.441***
		(0.002)		(0.001)		(0.000)
N	150	150	150	150	150	150
R^2	0.405	0.485	0.364	0.444	0.553	0.669

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5G

Outcome Variables $\Longrightarrow$	(1) Log GDP	(2) Log GDP	(3) Log Per-Cap GDP	(4) Log Per-Cap GDP	(5) Log Per-Cap Income	(6) Log Per-Cap Income
Lagged Log GDP	0.247***	0.243***				
	(0.000)	(0.000)				
Lagged Log Per-Cap GDP			0.003	-0.009		
			(0.835)	(0.497)		
Lagged Log Per-Cap Income					0.028	0.002
					(0.211)	(0.927)
Lagged M		0.025		-0.420**		-1.015***
		(0.916)		(0.012)		(0.002)
N	200	200	200	200	200	200
R^2	0.905	0.905	0.835	0.844	0.874	0.894

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6G

Outcome Variables ⟹	(1) EPOP	(2) EPOP	(3) $\triangle$ EPOP	(4) $\triangle$ EPOP
Lagged EPOP	0.266***	0.190**		
	(0.008)	(0.029)		
Lagged M		-0.169***		
		(0.007)		
Lagged $\triangle$EPOP			-0.703***	-0.713***
			(0.000)	(0.000)
Lagged $\triangle$M				-0.391**
				(0.026)
N	200	200	150	150
R^2	0.787	0.798	0.816	0.821

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7G

Outcome Variables ⟹	(1) EPOPN	(2) EPOPN	(3) $\triangle$ EPOPN	(4) $\triangle$ EPOPN
Lagged EPOPN	0.360***	0.149*		
	(0.000)	(0.067)		
Lagged M		-0.335***		
		(0.000)		
Lagged $\triangle$EPOPN			-0.707***	-0.734***
			(0.000)	(0.000)
Lagged $\triangle$M				-0.506***
				(0.008)
N	200	200	150	150
R^2	0.824	0.849	0.839	0.846

p-values in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4GR

Outcome Variable $\Longrightarrow$	(1) $\triangle$M	(2) $\triangle$M	(3) $\triangle$M	(4) $\triangle$M
Lagged $\triangle$M	-0.145	-0.148	-0.137	-0.134
	(0.543)	(0.514)	(0.559)	(0.573)
Lagged GDP Growth		0.112		
		(0.240)		
Lagged Per-Capita GDP Growth			0.0833	
			(0.453)	
Lagged Per-Capita Income Growth				0.182
				(0.278)
N	150	150	150	150
R^2	0.475	0.487	0.480	0.483

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5GR

Outcome Variable $\Longrightarrow$	(1) M	(2) M	(3) M	(4) M
Lagged M	0.690***	0.616***	0.734***	0.729***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Log Real GDP		0.055***		
		(0.001)		
Lagged Log Per-Capita Real GDP			0.012***	
			(0.001)	
Lagged Log Per-Capita Income				0.012***
				(0.000)
N	200	200	200	200
R^2	0.928	0.936	0.935	0.935

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6GR

Outcome Variable ⟹	(1) M	(2) M	(3) △M	(4) △M
Lagged M	0.690***	0.703***		
	(0.000)	(0.000)		
Lagged EPOP		0.048		
		(0.287)		
Lagged △M			-0.145	-0.139
			(0.543)	(0.559)
Lagged △EPOP				0.045
				(0.513)
N	200	200	150	150
R^2	0.928	0.929	0.475	0.478

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7GR

Outcome Variable ⟹	(1) M	(2) M	(3) △M	(4) △M
Lagged M	0.690***	0.736***		
	(0.000)	(0.000)		
Lagged EPOPN		0.093*		
		(0.059)		
Lagged △M			-0.145	-0.141
			(0.543)	(0.554)
Lagged △EPOPN				0.0156
				(0.809)
N	200	200	150	150
R^2	0.928	0.930	0.475	0.495

p-values in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$