Impact of Immigration Policy Changes on Labor Force Participation Rates and Economic Growth (GDP)

Danish Khan
Faculty mentors: Linda Dynan
Economics

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Danish Khan

Danish Khan is a senior at Northern Kentucky University pursuing a Bachelor of Science in Data Analytics & Statistics and Economics, with an expected graduation in May 2026. He maintains a 3.87 GPA. Danish was grateful for the opportunity to work with his mentor, Dr. Linda Dynan, on this project. He is actively involved on campus as a Haile Ambassador, a Statistical Consultant at the Burkardt Consulting Center, and a Math, Statistics, and Economics Tutor.

Abstract

This study examines the relationship between immigration policy changes and their effects on labor force participation rates (LFPR) and economic growth (GDP) in the United States from 1980 to 2022. It uses the ratio of deportations to legal immigrants (R/L) as a proxy for immigration policy strictness and employs regression analysis to evaluate how fluctuations in enforcement intensity influence labor market dynamics and overall economic performance. By analyzing key labor and economic indicators, the research aims to provide insights into how immigration policies may shape workforce participation and long-term economic trends. This study contributes to ongoing debates about the role of immigration in the U.S. economy and offers a data-driven perspective to inform future policy decisions.

Introduction

Immigration policy affects various aspects of society, from economic well-being to social integration, with significant implications for labor markets. The debate about whether immigrants displace native-born workers or help fill crucial gaps in the workforce remains ongoing. However, understanding how shifts in immigration policies influence labor market dynamics is essential. This study examines the impact of immigration policy changes on labor force participation rates and Gross Domestic Product (GDP), seeking to understand how variations in immigration laws, sometimes more open, other times more restrictive, can influence the number of people who enter or remain in the labor market. The primary aim is to assess how changes in immigration policy affect the labor force participation rate (LFPR), defined as the proportion of individuals over 16 years of age who are either employed or actively seeking work, alongside GDP growth.

Much research contributes valuable insights into issues around immigration and its effect on labor markets. Edwards and Liu (2018), for example, analyzed data from the American Community Survey (ACS) from 2005 to 2016 and found a positive correlation between native employment rates and a higher share of foreign-born workers. Their difference-in-differences approach suggests that immigrant labor can stimulate overall economic activity, challenging the common belief that immigration negatively impacts native employment.

Similarly, Holzer (2019) summarizes numerous studies and policy reports, reinforcing the argument that immigration fosters economic growth by alleviating employment shortages, particularly in areas with a scarcity of native labor. Holzer's comprehensive review provides an understanding of both the benefits and challenges that immigration presents to labor markets. He highlights how immigrant workers often fill essential roles in sectors that experience labor shortages, such as agriculture and low-skill manufacturing, thereby enabling these industries to remain competitive. However, Holzer also acknowledges the potential for wage suppression in certain industries, especially when immigration policies lead to an oversupply of labor in particular regions or sectors.

Building on this, Orrenius, Zavodny, and Gullo (2020) employed data from the ACS to examine the labor market impact of immigration. Their findings show that immigrants often occupy roles complementary to native-born workers, rather than competing directly with them. This suggests that both native and immigrant workforces stand to benefit when immigration policies align with labor market needs.

Emerson (2007) conducted a sector-specific analysis of the agricultural labor market, demonstrating that a substantial portion of agricultural workers are foreign-born. According to Emerson, changes in immigration policy directly influence labor availability and wages in this sector, highlighting the concrete effects of immigration policy on industries that depend heavily on immigrant labor.

International evidence further enriches the discussion. Fromentin's (2013) study on immigration and unemployment in France indicates that immigrant workers often experience higher unemployment rates compared to their native-born counterparts. This disparity is likely because of issues such as discrimination and mismatches in qualifications, underscoring the fact that the way immigration laws are drafted can have a big impact on how successfully immigrants integrate into the workforce.

Peri (2012) offers additional insights with a study on U.S. states, where he found that immigration has no negative effect on native workers' employment or hours worked. Instead, immigrants contributed to increased total factor productivity and worker income, suggesting that immigration can enhance overall economic efficiency and competitiveness, regardless of employment levels.

Recent political developments further underscore the relevance of this research. Policies such as mass deportations, particularly under the Trump administration, have reignited debates about the economic impacts of immigration on labor markets. This study examines how stringent immigration policies, including mass deportations and aggressive enforcement, decrease immigrant labor force participation, potentially due to fear, uncertainty, and legal challenges to employment. While native-born workers might fill some of these vacancies, industries that rely on immigrant labor could face labor shortages, wage shifts, and disruptions in economic productivity. Therefore, I hypothesize that stricter immigration policies reduce the LFPR and hinder economic growth.

Methods

This study empirically tests the hypothesis that stricter immigration policies reduce the LFPR and that these shifts in labor market behavior have broader economic implications for economic growth. Basically, our goal is to understand how policy changes affect employment behavior over time, as well as how these changes impact the GDP. The analysis uses simple regression models to capture both the direct effect on LFPR and the subsequent impact on GDP.

Labor market information, including the LFPR, unemployment rate, and wage growth, is drawn from the Federal Reserve Economic Data and the Office of Homeland Security. Economic indicators such as GDP and recession status are included to capture broader macroeconomic conditions. Since a direct immigration policy variable is not present in the dataset, I will use the ratio of deportations to legal immigrants (R/L) as a proxy for immigration policy stringency. Higher values of this ratio will be interpreted as representing more restrictive immigration environments, while lower values suggest less restrictive periods.

The primary dependent variables are the LFPR and GDP. The LFPR is the percentage of individuals aged 16 and over who are either employed or actively seeking work. The economic outcome is reflected by a primary indicator, the GDP. The key independent variable is the ratio of deportations to legal immigrants (R/L). Other independent variables include: Unemployment Rate, Wage Growth, Recession Indicator, and Time.

I begin the analysis by generating descriptive statistics for each key variable. Next, I create visualizations such as scatter plots that will show the relationship between LFPR and R/L, R/L and Time and between GDP and R/L. These visuals will help illustrate overall trends and guide the regression analysis. The core of the analysis involves two regression models. The first model estimates the direct effect of immigration policy stringency on labor force participation rate. The second model tests how labor force participation, shaped by immigration enforcement, impacts GDP.

The models are specified as follows:

Model 1

$$LFPR_t = \beta_1(R/L)_t + \beta_2(Unemployment\ Rate_1) +$$

$$\beta_3(Recession_t) + \beta_4(Wage\ Growth_t) + \varepsilon_t$$

In this equation, $LFPR_t$ represents the labor force participation rate at time t, while all terms on the right-hand side (*(R/L), Unemployment Rate, Recession Indicator, Wage Growth*, and *Time*) are independent variables. The ratio of deportations to legal immigrants (R/L) serves as a proxy for immigration policy stringency. The coefficient β_1 captures the average change in LFPR associated with increased immigration enforcement, and ε_t represents the error term that accounts for unobserved influences on $LFPR_t$.

The second part of the analysis evaluates the broader economic implications by examining how changes in labor force participation rate, influenced by immigration policy, affect GDP.

The following regression model is used:

Model 2

$$GDP_t = \alpha_1(LFPR_t) + \alpha_2(R/L)_t + \alpha_3(Unemployment\ Rate_t) +$$

$$+\alpha_4(Recession_t) + \alpha_5(Time_t) + \upsilon_t$$

In this model, GDP_t represents the level of economic output at time t. The independent variables include LFPR, the R/L ratio, unemployment rate, recession indicator, and time. The coefficient α_1 reflects the direct effect of labor force participation on GDP, while α_2 measures the direct impact of immigration policy stringency. The υ_t is the error term accounting for other unobserved factors that may affect GDP.

Together, these two models provide a comprehensive framework for evaluating the labor market and economic effects of immigration enforcement over time.

Analysis

My dataset includes Labor Force Participation Rate (LFPR), the ratio of deportations to legal immigrants (R/L), Unemployment Rate, Wage Growth, Recession Indicator, Gross Domestic Product (GDP) and Time. The dataset includes 43 observations for each variable.

Now I present the descriptive statistics of my data covering the time period from 1980 to 2022 in Table I.

The *LFPR* has a mean of 65.02%, indicating that, between 1980 and 2022 on average, 65.02% of the working-age population is employed or actively seeking employment. The values range from a minimum of 61.70% to a maximum of 67.10%, with a variance of 2.77, showing moderate variation across the dataset. The ratio of deportations to legal immigrants (*R/L*) has a mean of 0.18, meaning that, on average, for every 100 legal immigrants, there are 18 deportations. This ratio ranges from a minimum of 0.02 to a maximum of 0.44, with a variance of 0.02, indicating relatively stable fluctuations.

Unemployment Rate has a mean of 6.07%, with a minimum of 3.50% and a maximum of 10.80%. Its variance of 3.06 suggests some fluctuation in joblessness across the data time. *Wage Growth* has a mean of 4.24% reflecting an average 4.24% increase in wages, though it ranges from (1.80%) to a maximum of 6.30%. *GDP* shows an average of 11508 (in billions), with a wide range from 2857 (in billions), to 26,007 (in billions). The

Table I. Descriptive Statistics

Variable	Total Count	Mean	SD	Variance	Min.	Med.	Max.
LFPR	43	65.02	1.67	2.77	61.70	65.60	67.10
R/L	43	0.18	0.14	0.02	0.02	0.18	0.44
Unem-ployment Rate	43	6.07	1.75	3.06	3.50	5.70	10.80
Recession	43	0.19	0.39	0.16	0.00	0.00	1.00
Wage Growth	43	4.24	1.17	1.37	1.80	4.10	6.30
GDP	43	11508	6317	39902183	2857	10582	26007
Time	43	22.00	12.56	157.67	1.00	22.00	43.00

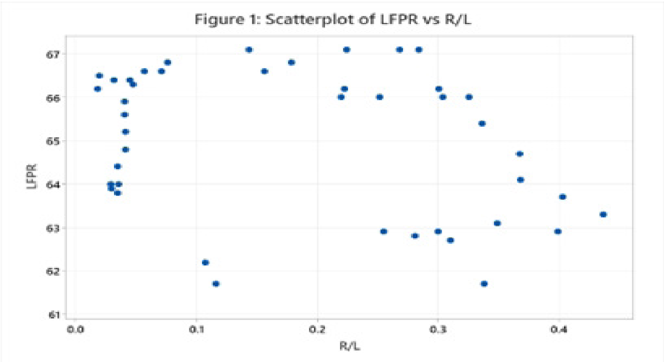

Figure 1. LFPR vs R/L ratio.

data points span 43 time periods, from 1980-2022. About 19% of the observations are from periods of recession.

Figure 1 is a graph of LFPR against the R/L. It shows a negative relationship between LFPR and R/L—as R/L increases, LFPR decreases. Most data points cluster at lower R/L values, with LFPR stable between 64-66. As R/L rises above 0.2, LFPR declines, with more variability at higher R/L value. The graph suggests a concave relationship so we might include a squared term for the R/L variable in our regression model.

Figure 2 is a graph of LFPR against Time. The scatterplot shows the non-linear relationship between LFPR and Time. LFPR starts around 63, rises to a peak at time = 20, and then declines. This pattern suggests that labor force participation increased for some time, possibly due to favorable economic conditions, before decreasing, possibly due to factors like economic recessions or demographic changes. The graph suggests a concave relationship so we might include a squared term for the time variable in our regression model.

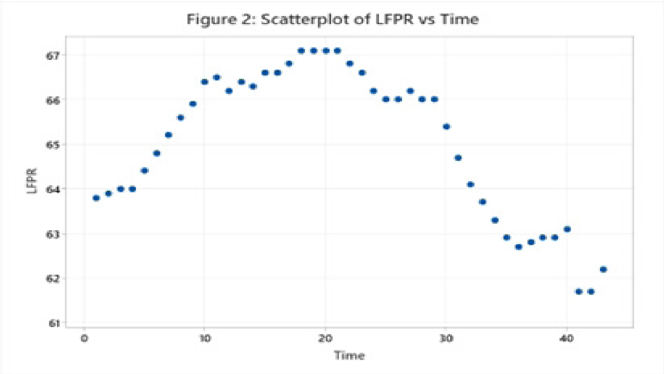

Figure 2. LFPR vs time. (1980 = 0)

The scatter plot of GDP vs. R/L (Figure 3) shows a positive linear relationship. As R/L increases, GDP also increases, indicating that higher ratio of deportations to legal immigrants is associated with a rise in economic output (GDP).

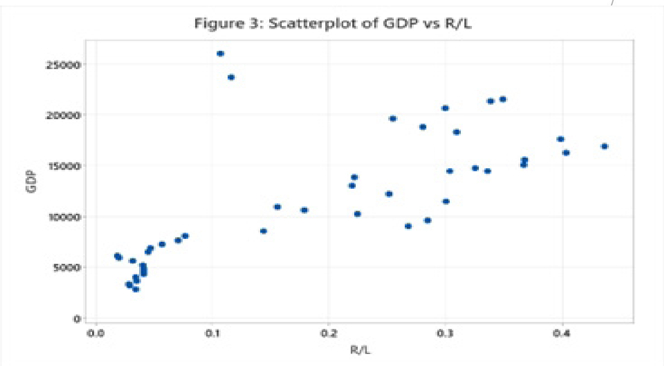

Figure 3. GDP vs R/L ratio.

Results

Model 1

The correlation matrix (Table II) highlights a few key relationships of concern. The R/L ratio has a strong negative correlation with *Wage Growth* (-0.791) and a strong positive correlation with *Time* (0.788). The strong negative correlation between R/L and *Wage Growth* (-0.791) implies that as the ratio of deportations to legal immigration increases, wage growth tends to decline significantly. This may reflect economic pressures linked to stricter immigration enforcement. Additionally, *Wage Growth* and *Time* are also strongly negatively correlated (-0.677). These strong correlations suggest potential multicollinearity, particularly between R/L and the other variables. Upon examining the variance inflation factor (VIF) values, which are reported alongside the coefficient estimates in Table IV, these relationships were found not to be statistically significant, indicating that multicollinearity was not a concern in the model.

Upon looking at the overall model, the regression appears to be statistically significant. The ANOVA results in Table III show an F-value of 153.51 with a corresponding p-value of 2.44×10^{-24}, which is far below the common significance level of 0.05. This indicates that the model explains a significant portion of the variation in the dependent variable.

The standard error (S) is 0.323970, which measures the typical distance between the observed LFPR values and the predicted values—lower values suggest better model fit. The R-squared (R^2) is 96.21%, meaning that approximately 96.21% of the

Table II. Model 1 Correlation Matrix

	R/L	Unem-ployment Rate	Recession	Wage Growth
Unemployment Rate	-0.109	--	--	--
Recession	-0.082	0.480	--	--
Wage Growth	-0.791	-0.075	0.253	--
Time	0.788	-0.399	-0.178	-0.677

Table III. Model 1 ANOVA Results

	df	SS	MS	F	P-Value
Regression	7	112.7851	16.11216	153.5126	2.44×10^{-24}
Residual	35	3.673481	0.104957	--	--
Total	42	116.4856	--	--	--

variation in the LFPR is explained by the model.

Regression Equation:

$$LFPR = 61.070 - 0.0468(Unemployment\ Rate) +$$
$$0.239(Recession) + 0.361(Wage\ Growth) - 2.00(R/L)^2 -$$
$$0.45(R/L) + 0.4465(Time) - 0.010942(Time^2)$$

The regression equation estimates the LFPR using seven variables: *(R/L), Unemployment Rate, Recession, Wage Growth, Time*, the square of *(R/L)*, and the square of *Time*. The constant term is 61.070, representing the baseline LFPR when all predictors are zero. The coefficient for *(R/L)* is -0.45, indicating that a one percentage point increase in the ratio of deportations to legal immigrations leads to a 0.45 percentage point decrease in LFPR. The squared term of (R/L) has a coefficient of -2.00, suggesting that while increases in (R/L) initially reduce LFPR, this effect diminishes as (R/L) increases further. However, both (R/L) and $(R/L)^2$ are not statistically significant with p-values of 0.857 and 0.724, respectively.

Wage Growth significantly affects LFPR, with a coefficient of 0.361, meaning that one percentage point increase in wage growth leads to a 0.361 percentage point increase in LFPR ($p = 0.002$). Time also plays a crucial role, showing that LFPR declines by 0.010942 percentage points per year ($p < 0.001$), indicating a long-term downward trend in LFPR. The

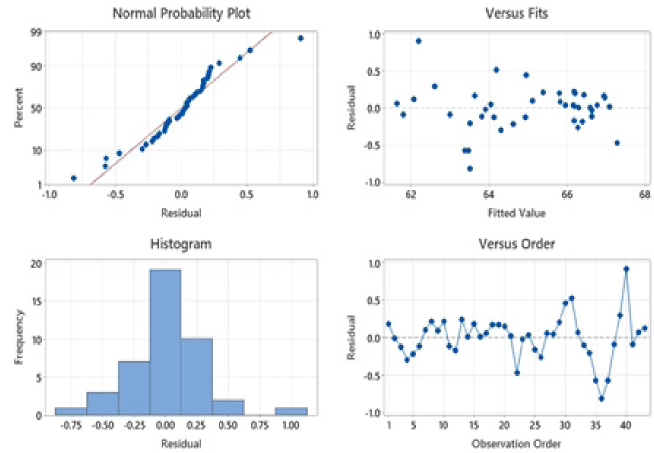

Figure 4. Normality diagnostics of residuals for Model 1 LFPR.

Unemployment Rate has a negative coefficient (-0.0468), suggesting that higher unemployment may reduce LFPR, but this effect is not statistically significant ($p = 0.394$). Similarly, the *Recession* variable has a small positive effect (0.239), but with a high p-value (0.192), it is not significant. Overall, the model shows that LFPR is most strongly and significantly influenced by wage growth and time.

After evaluating the normality of the residuals shown in Figure 4, the results suggest that the assumption of normally distributed error terms is met. The normal probability plot shows that the residuals roughly follow a straight line, with only minor deviations, particularly at the tails. The versus fit plot displays no clear pattern, indicating a reasonably consistent spread of residuals across fitted values. Additionally, the histogram of residuals appears relatively symmetric, supporting the assumption of normality for the residuals.

Model 2

The correlation matrix in Table V shows the strength and direction of linear relationships among the explanatory variables. The most notable correlation in the matrix is the

Table IV. Model 1 Regression Coefficients

Term	Coefficient	SE Coefficient	95% CI	T-value	P-value	VIF
Constant	61.070	0.940	(59.163, 62.977)	65.00	0.000	--
Unemployment Rate	-0.0468	0.0542	(-0.1567, 0.0632)	-0.86	0.394	3.59
Recession	0.239	0.180	(-0.126, 0.603)	1.33	0.192	2.00
Wage Growth	0.361	0.106	(0.145, 0.577)	3.40	0.002	6.21
$(R/L)^2$	-2.00	5.61	(-13.39, 9.40)	-0.36	0.724	38.55
R/L	-0.45	2.50	(-5.53, 4.62)	-0.18	0.857	4.66
Time	0.4465	0.0310	(0.3836, 0.5095)	14.40	0.000	6.71
$Time^2$	-0.010942	0.000527	(-0.012012, -0.009873)	-20.77	0.00	23.05

Table V. Model 2 Correlation Table

	LFPR	R/L	Unemployment Rate	Recession
R/L	-0.293	_	_	_
Unemployment Rate	-0.044	-0.109	_	_
Recession	-0.074	-0.082	0.480	_
Time	-0.503	0.788	-0.399	-0.178

Table VI. Model 2 ANOVA Results

	df	SS	MS	F	P-Value
Regression	5	1.66E+09	3.33E+08	1028.916	1.29E-38
Residual	37	11967007	323432.6	--	--
Total	42	1.68E+09	--	--	--

strong positive relationship between *R/L* and *Time* (0.788), suggesting that the ratio of deportations to legal immigrations has increased over time. Additionally, *LFPR* and *Time* show a moderate negative correlation (-0.503), indicating a decline in labor force participation as time progresses. Upon examining the VIF values, which are reported alongside the coefficient estimates in Table VII, these relationships were found not to be statistically significant, indicating that multicollinearity was not a concern in the model.

Upon looking at the overall model for GDP, the regression appears to be statistically significant. The ANOVA table (Table VI) shows an F-value of 1028.92 with a corresponding p-value of 1.29×10^{-38}, which is far below the common significance level of 0.05. This indicates that the model explains a significant portion of the variation in GDP.

The Standard Error of this regression model is 568.711 indicating the average deviation of observed values from predicted values. The adjusted R-squared (R^2) is 99.19%. The model accounts for 99.29% of the variability in GDP, indicating an outstanding fit.

Regression Equation:

$$GDP = 36376 - 522.6(LFPR) - 4389(R/L) - 163.9(Unemployment\ Rate) + 476(Recession) + 492.1(Time)$$

This equation and the values from the regression reported in Table VII suggest that GDP is influenced by these variables: *LFPR, R/L, Unemployment Rate*, and *Time*. For one percentage point increase in *LFPR*, GDP decreases by 522.6 units (in billions), holding other factors constant. For one percentage point increase in *R/L*, GDP decreases by 4,389 units (in billions), suggesting that higher ratio of deportations to legal immigration negatively impacts GDP. For one percentage point increase in the *Unemployment Rate*, GDP decreases by 163.9 units (in billions). As *Time* progresses by one year, GDP increases by 492.1 units (in billions), indicating economic growth over time.

The constant is 36,376 (in billions), which is the estimated GDP when all predictor variables are zero. The coefficient for *LFPR* is -522.6, and the p-value is 0.000, making it highly statistically significant. This shows that LFPR negatively impacts GDP. The coefficient for *R/L* is -4,389, and the p-value is 0.001, indicating a statistically significant negative relationship between R/L and GDP. The coefficient for *Unemployment Rate* is -163.9, with a p-value of 0.026, meaning this is statistically significant, suggesting that higher unemployment negatively impacts GDP. The coefficient for *Time* is 492.1, with a p-value of 0.000, making it highly statistically significant, indicating that time is a strong predictor of GDP growth.

Table VII. Model 2 Regression Coefficients

Term	Coefficient	SE Coefficient	95% CI	T-value	P-value	VIF
Constant	36376	4758	(59.163, 62.977)	7.64	0.000	-
LFPR	-522.6	68.3	(-661.1, -384.2)	-7.65	0.000	1.68
R/L	-4389	1197	(-6814, -1963)	-3.67	0.001	3.47
Unemployment Rate	163.9	70.7	(-307.1, -20.7)	-2.32	0.026	1.98
Recession	476	255	(-41, 993)	1.86	0.070	1.31
Time	492.1	16.3	(459.1, 525.2)	30.14	0.000	5.46

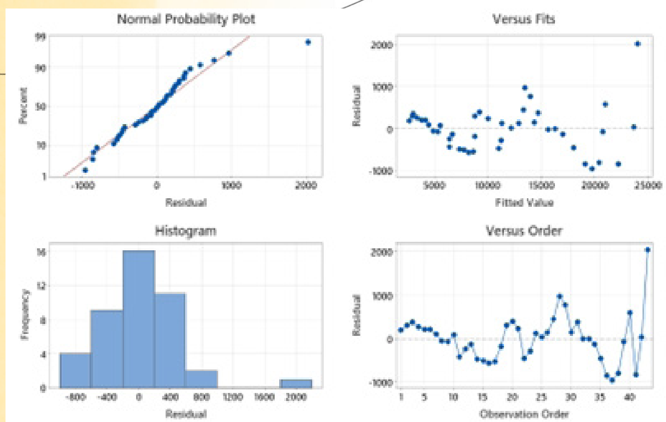

Figure 5. Normality diagnostics of residuals for Model 2 GDP.

After evaluating the normality of residuals shown in Figure 5, I obtained the following results.

The residuals roughly follow a straight line, indicating that they are approximately normally distributed. This suggests that the assumption of normality for the residuals is met. From the versus fit plot, we can see that the residuals are randomly scattered around zero with no clear pattern. This suggests that the model fits the data well and that the variance of residuals is constant.

Discussion and Conclusions

This study explored the relationship between immigration enforcement intensity and its economic implications, particularly through the Labor Force Participation Rate (LFPR) and Gross Domestic Product (GDP). The regression analysis revealed that Time and Wage Growth were the most significant predictors of LFPR. While the ratio of deportations to legal immigration (R/L) had a negative coefficient, it was not statistically significant, suggesting no strong direct effect on LFPR. Similarly, unemployment and recession variables were also not significant in predicting LFPR. Therefore, the first part of the hypothesis, that stricter immigration policies reduce LFPR, was not fully supported by the statistical evidence.

In contrast, the GDP regression model strongly supported the second part of the hypothesis. LFPR had a statistically significant negative effect on GDP, as did R/L and the unemployment rate. Meanwhile, time was a strong positive predictor of GDP growth. These results align with the expectation that shifts in labor force dynamics, driven by immigration policy can impact broader economic productivity.

The findings align closely with Edwards and Liu (2018), who emphasized the positive role of immigrant labor in enhancing overall employment and economic activity. Holzer (2019) and Orrenius et al. (2020) also support the idea that immigrant labor is often complementary to native employment and necessary for economic efficiency. Although this study did not directly observe sector-level impacts, the broader decline in LFPR is consistent with Emerson's (2007) concern that immigration enforcement can negatively affect industries dependent on immigrant labor. Furthermore, the observed productivity-related outcomes support Peri's (2012) conclusion that immigration enhances total factor productivity, even if not always reflected in short-term employment changes.

In summary, this study contributes to the growing body of research highlighting the economic trade-offs of strict immigration policy. While LFPR itself may not be directly and significantly impacted by enforcement metrics, the broader implications on GDP are substantial. The evidence suggests that over time, stricter immigration enforcement could undermine economic growth by disrupting labor availability, particularly in sectors where immigrant workers play a key role.

This study has several important limitations. First, while the ratio of deportations to legal immigration (R/L) was used as a proxy for immigration enforcement, it may not fully reflect the breadth and nuance of immigration policies. Elements such as visa regulations, policy discretion at state and local levels, and the role of undocumented immigration are not captured by this metric, potentially limiting the validity of R/L as a comprehensive measure of enforcement intensity. Second, the LFPR model showed that R/L and its squared term were statistically insignificant, which may indicate either a lack of true effect or model misspecification. It's possible that labor force behavior is influenced by more granular or indirect effects of immigration policy—such as fear of deportation or reduced inflow of immigrant labor, which this model could not account for. Third, the small sample size ($n = 43$) reduces the statistical power of the regression analysis, especially for detecting smaller or more complex effects. This limits the generalizability of the findings and may increase the likelihood of Type II errors.

Future research should aim to overcome these limitations in several ways. First, using state-level or sector-specific data could better reveal the heterogeneous effects of immigration policies across industries and geographic areas. Second, including more refined policy indicators, such as E-Verify mandates, sanctuary policies, or visa issuance trends, would allow for a more nuanced evaluation of policy strictness. Third, disaggregating the labor force by skill level, age, or immigration status may clarify how specific subgroups are affected by policy changes. Finally, longitudinal designs that track pre- and post-policy implementation periods could help establish causal links between immigration enforcement and labor market or GDP outcomes more convincingly. By exploring these areas, future research could provide a more comprehensive understanding of how immigration policy shapes the labor market and broader economic outcomes.

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Disclosure: I used AI assistance for paraphrasing and organizing ideas to improve clarity and structure. While the core analysis and arguments are my own, AI helped refine the wording and ensure coherence.