Deciphering the H-1B Visa Approvals Impact on U.S. Wages: A Comprehensive Panel Data Study (2019-2022)

Group.9

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Abstract

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This study examines the impact of H1B visas on the U.S. local wage levels in the United States. Using data from 2019 to 2023, we employ a panel data model that considers factors including region, occupational category, prevailing wages, job demand, and the Trump administration's H1B policy. The analysis results show that the number of H1B visa approvals has no significant impact on local wages in the short term, but H1B wages are positively correlated with local wages. In addition, job demand has a positive impact on the U.S. local salary levels. It is worth noting that the Trump administration's H1B policy has a negative correlation with local wage levels. These findings shed light on the complex relationship between H1B visas and the labor market and provide useful insights for policymakers regarding immigration and labor market policies.

1. Introduction

The H-1 visa program, established under the Immigration and Nationality Act, enables employers to hire foreign workers for specialty occupations that require a higher education degree. This program has evolved and called H1B visa now. The annual caps have varied over time from its inception to 2004. The annual cap is 65,000 new visas each fiscal year now.

The establishment of the H1B visa program served with varying perspectives. Proponents assert that the program enables employers to access specialized skills possessed by H-1B workers, who are often in high demand for expertise in technology, engineering, or scientific research. By hiring these workers, employers can gain a competitive edge and drive innovation. H-1B workers also help fill talent gaps that may be challenging to fulfill with domestic workers alone, thereby enhancing the efficiency of business operations. Additionally, the presence of a diverse range of cultural perspectives and experiences brought by foreign workers can help companies and peers gain a better understanding of diversity, serve diverse customer bases, and promote cross-cultural collaboration in the workplace.

Critics of the program argue that the H-1B visa program may harm U.S. workers by creating competition for jobs. They believe that foreign workers are seizing opportunities that would have been otherwise available to domestic workers. However, proponents of the program counter that foreign workers are often hired for specialized skills that are in short supply in the U.S. workforce. They also contend that these high-skilled workers can help create jobs and drive innovation in the economy, ultimately benefiting U.S. workers as well. Furthermore, the presence of skilled foreign workers may enhance the workplace environment and culture, thereby benefiting both domestic and foreign workers.

The mechanism might be complex. We are curious if the approval of H1B visas have an impact on the local US labor market over time.

2. Literature Review

Before constructing a model, let's summarize and generalize the previous relevant research. Two aspects that have been widely mentioned in previous research include the impact of foreign labor or immigration on the wages/income of native workers and the impact on labor productivity and innovation.

2.1 Impact of immigration on wages and employment of native workers

The results are differentiated. First, some researchers have attempted to demonstrate that immigration has negative wage and employment shocks based on an intuition that immigration increases labor supply and lowers wages. For example, in a study by Yu et al. (2021), researchers found that, across Canada, immigration crowds out job opportunities for natives and negatively affects wages. Borjas (1999) in their study of the United States and Mexico, and Friedberg and Hunt (2018) in their study of the United States, find that immigration leads to lower native wages, which also lead to unemployment for some native workers. Bound et al. (2017) supported this perspective through an empirical analysis of U.S. H-1B visa information. They discovered that when the demand for highly skilled professionals decreases, an influx of foreign highly skilled workers can displace and reduce salaries for their American counterparts. While the innovative contributions of these highly skilled workers may diminish, it is not sufficient to counterbalance the displacement effect.

On the other hand, some researchers refute this assertion. For example, Peri (2015) constructs a natural experiment based on random H-1B visa rationing that occurred in April 2007 and April 2008 due to excess demand relative to quota. Peri's (2015) empirical study demonstrates that skilled immigration does not negatively affect the wages or unemployment rate of native workers. Specifically, the research analyzes the reactions of computer-related employers, showing that when their intended foreign hires were denied H-1B visas, these employers did not increase their hiring of local workers. Instead, employment and wages of native workers in comparable roles remained unchanged at best. This suggests that H-1B workers do not replace, but rather supplement, native employees in computer-related occupations. Similarly, Peri et al. (2014) found that when the number of H-1B-driven STEM workers in a city increased, there was a significant rise in wages for college-educated local workers. Wage increases for non-college-educated natives were also notable, albeit smaller. The core logic of this argument is that immigrants and skilled workers from other places bring local production efficiency improvements and bring more business income to drive expansion and labor demand. Based on the above analysis, a first research hypothesis was developed: **Hypothesis 1: Foreign labor immigration has a negative impact on wage levels.**

2.2 Impact of Immigration on labor productivity and Innovation

Most studies consider high-skilled immigration can drive innovation positively. In detail, high-skilled immigration—through patents and innovations—promotes knowledge and productivity generation, thereby pushing the production possibility frontier(PPF) outward and increasing total factor productivity(TPF)(Freeman, 2006). In line with this perspective, Hunt and Gauthier-Loiselle (2010) evaluate the degree to which skilled immigration fosters innovation in the United States. They do so by investigating personal patenting activities and the factors at the national level that influence patenting. The empirical research shows that for every percentage point increase in the share of university graduate immigrants in the population, the number of patents per capita increases by 6%; this figure increases to 15% after controlling for the effect of natives. In other words, immigrants have more than twice the impact on innovation than natives.

However, there are also studies that show that highly educated immigrants seem to be competing with the local highly educated labor force, leading to a decline in investment in education by residents and weakening growth momentum (Peri, 2016). But empirical studies refute this assertion and support the hypothesis that higher education or highly skilled immigrants increase local productivity. For example, Peri et al. (2014) estimates the change in TFP due to the total number of STEM workers and show that foreign STEM has a significant positive effect on TFP growth in the average US city between

1990 and 2010. In addition, the empirical research of Bound et.al (2017) shows that foreign workers, especially high-skilled workers, have a positive impact on innovation and bring additional consumer benefits to a certain extent. Therefore, it is justified to develop a second hypothesis: **Hypothesis 2: Foreign immigration is positively related to labor productivity.**

2.3 Research Gap

Taking the above into account, existing research details the impact that immigration can have on labor markets, including wages and employment levels, human capital, and innovation. On the one hand, regarding innovation and total factor productivity, the conclusions of existing studies are basically consistent. In contrast, the discussion of wages and employment is inconsistent: this creates a research gap. In this regard, it is necessary to limit the discussion to specific types of immigrants or regions. On the other hand, most of the existing research focuses on immigration in STEM fields, and the computer science industry. In order to fill this research gap, the following content will develop a study involving the impact of H1B visa bands in diverse industries.

3. Data and Sample

The data for this study are obtained from the U.S. Department of Labor (DOL) through its Office of Foreign Labor Certification (OFLC) and are gathered through the Labor Condition Application (LCA) process, which is a prerequisite for U.S. employers to hire a foreign worker on an H-1B visa. It provides detailed information on the foreign workers, their sponsoring employers, and the jobs they perform. In our study, we opted to choose the information of applicants whose worksite is in the United States and have an H-1B visa decision date from October 2019 to December 2022 with a total of 202762 observations.

As the dataset we got is observations of multiple applicants with different job titles, different visa certified statuses, and different units of wages, to make it quantitatively and comparable, we firstly converted visa-certified status into a dummy variable, taking the value one if the visa is certified by the DOL and zero otherwise. We also classified our soc title into nine job categories and transformed all wage levels into hourly wages. After cleaning the data and dropping outliers in wages, we selected the variables to be used in our model and aggregated our data to the “State X Job category X year/month” level. This aggregation results in multiple observations for the same states and job categories over time, creating a panel dataset. ***What's importantly, all dummy variables were expressed as percentages within states, periods, and job categories.***

In our study, we will utilize six variables in our model, as in Table1.

Table 1

Variable definition

Dependent variable	Variable Definition
Prevailing wage set for H1B workers ($/Hour)	It is defined as the average wage paid to similarly employed workers in a specific occupation in the area of intended employment, according to U.S. Department of Labor. (2023).
Independent variable	
The share of H1B visas that have been approved (%)	Share of H1B visas that have been approved within states, periods, and job categories.
Instrument variable	
One period lagged variable of the share of approved H1B visas	The variable is created by shifting the independent variable one time period back.
Controlled variables	
Actual wage for H1B workers ($/Hour)	Actual wage paid to nonimmigrant workers at the worksite location.
Total number of job openings	Total number of foreign workers the Employer needed about their job position.
Trump's visa freeze policy dummy (%)	Share of all applicants have a decision date after June 2020 within states, periods, and job categories.

It is worth noting that prevailing wage is the minimum wage rate that an employer must offer to pay a foreign worker, ensuring that foreign workers are not hired at wages that are lower than what would be paid to a similarly employed U.S. worker, which could potentially undercut U.S. wages and job opportunities. Thus, in our study, we set the prevailing wage as the dependent variable, representing the U.S. national wages that we aim to estimate. As for the instrument variable, we adopted one period lagged variable of the share of approved H1B visas as our instrument variable, chosen because it satisfies the instrument variables' properties of relevance and exogeneity, according to section C. of Aydemir, A., & Borjas, G. J. (2011). To be more specific, it is correlated with the current share of approved H1B visas but not correlated with current prevailing wages. Additionally, considering the former U.S. president Donald Trump ordered a ban on the issuance of new green cards, H-1B, L-1, J-1, and other temporary work visas for skilled workers, managers on June 22nd, 2020 to protect the jobs of American workers during the pandemic, we add the effect of Trump's visa freeze policy into our model as a controlled variable.

Table 2

Corresponding soc title for each job category

Job Category	Corresponding SOC_TITLE
Arts, Media & Entertainment	Commercial and Industrial Designers, Graphic Designers…
Business, Finance, and Management	Business Intelligence Analysts, Management Analysts, Accountants and Auditors, Computer Systems Analysts…
Education & Social Services	Secondary School Teachers, Elementary School Teachers…
Healthcare & Life Sciences	Physicians and Surgeons, Medical Scientists, Therapists…
Legal and Compliance	Lawyers, Legal Support Workers, Financial Examiners…
Science, Technology, Engineering, and Mathematics (STEM)	Statisticians, Industrial Engineers, Data Scientists, Computer Systems Engineers, Mechanical Engineers…
Social Services & Community	Social Workers, Farm and Home Management Advisors
Technology & Information Systems	Software Developers, Hospitalists, Computer Occupations
Others	Chefs and Head Cooks, Economists, Astronomers, Dentists, Geographers, Logisticians, Sociologists, Veterinarians…

By conducting descriptive statistics, we observed that the positive relationship between the labor demand and the prevailing wages is not clear, and "Legal and Compliance" and "Others" job categories tend to have higher certified visa shares and higher salaries, as illustrated in Figure.1 and Figure.2. Regarding figure 3, we noted that states with a higher proportion of top-paying jobs generally have a higher mean hourly wage; however, there are exceptions, such as Virgin Islands (VI). We can also conclude that Maine (ME) and West Virginia (WV) are the two states with the highest mean hourly wages.

Figure1 *Distribution of Mean Hourly Wages and Job Openings by Job Category*

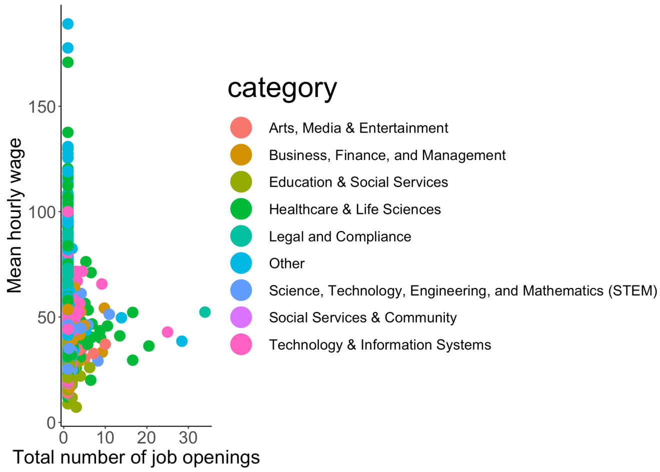


Figure2 *Mean Hourly Wages and Job Openings by Job Category*

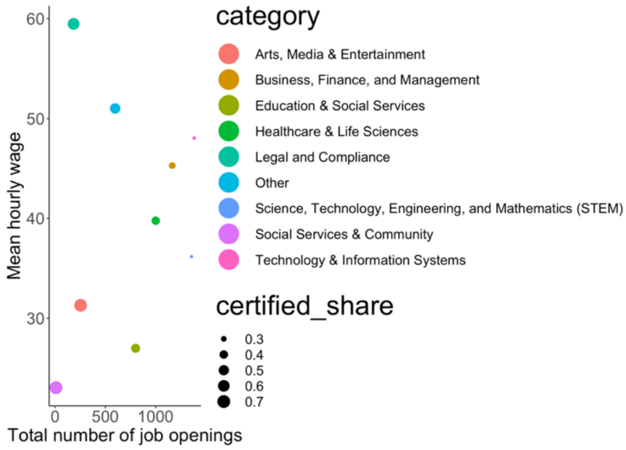
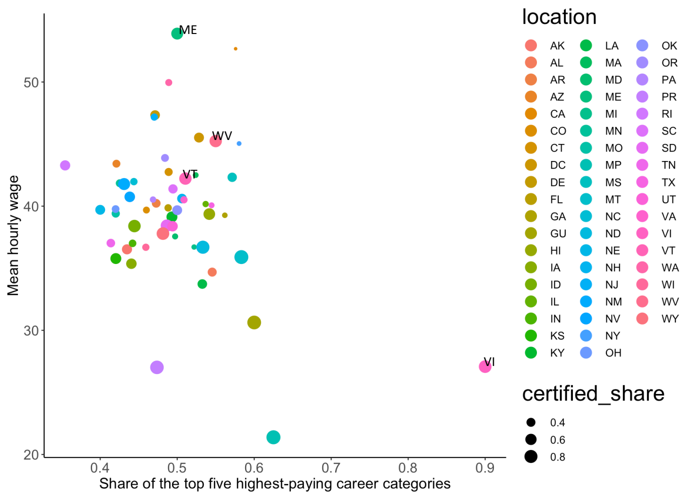


Figure 3 *Visualizing H1B Visa Approvals and Wages across U.S. States*



4. Model Specification

First, run a pooled OLS to see the results:

$$log(Prevailing\ wage) = \beta_0 + \beta_1 log(Actual\ wage) + \beta_2 certified\ dummy + \beta_3 total\ positions + \beta_4 policy\_dummy + \varepsilon$$

	Dependent variable:
	log(prevailing_wage)
log(foreign_wage_level)	0.722***
	(0.007)
certi_dummy	-0.023***
	(0.006)
total_positions	0.007**
	(0.003)
policy_dummy	-0.027*
	(0.014)
Constant	0.882***
	(0.029)
Observations	5,978
R^2	0.662
Adjusted R^2	0.662
F Statistic	2,923.780*** (df = 4; 5973)
Note:	*p<0.1; **p<0.05; ***p<0.01

It seems that all variables are significant at least 10% level, and main variables like $certified\ dummy$, which stands for the share of approved H1b visas is having a negative impact on the $Prevailing\ wage$. However, these results can be biased that it is ignoring all the possible individual specific effects that brought by states and categories. Now, we can fit a panel data model and do a F test compared to OLS to see if there is a presence of common effect in our regression:

F test for individual effects
F = 6.988, df1 = 54, df2 = 5919, p-value < 2.2e-16

The test result has p-value close to zero, rejecting the null that there is no individual-specific effect in the model, and conclude that we should consider a panel data model the account for the heterogeneity by individual specific effects.

In addition to a based pooled OLS model, a fixed effect panel model can be considered:

$$log(Prevailing\ wage)_{i,t} = \beta_1 log(Actual\ watge)_{i,t} + \beta_2 certified\ dummy_{i,t} + \beta_3 total\ positions_{i,t} + \beta_4 policy\ dummy_{i,t}$$
$$+\gamma_i + \lambda_t + \varepsilon_{i,t}$$

In this model, all i denotes the individual with the location(states) x category (job types) pairs within a specific time t. γ_i and λ_t represents the unobserved individual specific and time-specific factors that affect our dependent variables and that need to be controlled. The generated result is in the second column:

	Dependent variable:	
	log(prevailing_wage)	
	(1)	(2)
log(foreign_wage_level)	0.722***	0.706***
	(0.007)	(0.007)
certi_dummy	-0.023***	-0.014**
	(0.006)	(0.006)
total_positions	0.007**	0.005*
	(0.003)	(0.003)
policy_dummy	-0.027*	-0.024*
	(0.014)	(0.014)
Constant	0.882***	
	(0.029)	
Observations	5,978	5,978
R^2	0.662	0.647
Adjusted R^2	0.662	0.644
F Statistic	2,923.780*** (df = 4; 5973)	2,714.630*** (df = 4; 5919)
Note:		*p<0.1; **p<0.05; ***p<0.01

Comparing the fixed effects model with the classic OLS result, after accounting for individual specific effects, the general sign of the effects by the variables did not change, while $certified\ dummy$ and $total\ positions$ are becoming less significant. Other than a fixed effects model, a random effect model is worth considering:

$$log(Prevailing\ wage)_{i,t} = \beta_1 log(Actual\ watge)_{i,t} + \beta_2 certified\ dummy_{i,t} + \beta_3 total\ positions_{i,t} + \beta_4 policy\ dummy_{i,t}$$

$$+ \upsilon_{i,t} + \varepsilon_{i,t}$$

The result from this model is in the third column:

	Dependent variable:		
	log(prevailing_wage)		
	(1)	(2)	(3)
log(foreign_wage_level)	0.722***	0.706***	0.709***
	(0.007)	(0.007)	(0.007)
certi_dummy	-0.023***	-0.014**	-0.016***
	(0.006)	(0.006)	(0.006)
total_positions	0.007**	0.005*	0.005*
	(0.003)	(0.003)	(0.003)
policy_dummy	-0.027*	-0.024*	-0.024*
	(0.014)	(0.014)	(0.014)
Constant	0.882***		0.925***
	(0.029)		(0.029)
Observations	5,978	5,978	5,978
R^2	0.662	0.647	0.799
Adjusted R^2	0.662	0.644	0.799
F Statistic	2,923.780*** (df = 4; 5973)	2,714.630*** (df = 4; 5919)	11,160.050***
Note:			*p<0.1; **p<0.05; ***p<0.01

By running a Hausmann test to see which of the panel model is more appropriate in our case:

Hausman Test
chisq = 9.2566, df = 4, p-value = 0.055

We do not reject the null, meaning that the random effect is consistent and efficient, but the p-value is on the 0.05 borderline, we need another test to check for its validity. Here is the Breusch-Pagan LM test for random effect:

Lagrange Multiplier Test - (Breusch-Pagan)
chisq = 1076.2, df = 1, p-value < 2.2e-16

We reject the null and conclude that there is a random effect. So, in this model, the existing fixed effects are uncorrelated with the predictors, and in turn individual characteristics like states and job categories do not affect the dependent variables. This statement is against common sense. Generally, individuals working in different cities get paid differently, for example, for someone in Detroit cannot be paid the same as they are in New York, which is the same for different job types.

Random effect model is preferred to fixed effect model can be counterintuitive, the reason is from the data wrangling process. Since the original data set is not strictly panel data because a panel data requires same individual's information across different years, which is unlikely in the case of H1B certification process. Later, the original data is grouped by *location*, *category*, and *decision date,* and other variables selected are averaged for those three groups to create the new panel date set. In other words, a fixed effect model will estimate the individual specific effects for each variable that is specified as fixed effects, while the data is averaged within each group, so the individual effect is already being estimated. Thereby, both Hausman test and BPLM test are indicating random effect is better.

With our final random effect model, we can test for possible autocorrelation and heteroscedasticity that might affect our model:

Breusch-Godfrey/Wooldridge test for serial correlation
chisq = 60.585, df = 10, p-value = 2.808e-09
studentized Breusch-Pagan test
BP = 667.59, df = 4, p-value < 2.2e-16

Based on both tests, the rejected results showed that there are serial correlation and heteroscedasticity which can lead to inefficient estimate and wrong standard errors, so these two problems need to be dealt with. To account for heteroscedasticity, a robust standard error can be used. As for autocorrelation, the random effect model can include a lagged $certified\ dummy$ as Instrument to account for the possible autocorrelation in our model, after that, autocorrelation test result is:

Breusch-Godfrey/Wooldridge test for serial correlation
chisq = 19.083, df = 8, p-value = 0.01442

The result becomes less significant, than before, but there is still autocorrelation exits. Combining with heteroscedasticity robust standard error, our final model is:

	Dependent variable:				
	log(prevailing_wage)				
	panel			*coefficient*	
	linear			*test*	
	(1)	(2)	(3)	(4)	(5)
log(foreign_wage_level)	0.722^{***}	0.706^{***}	0.709^{***}	0.709^{***}	0.707^{***}
	(0.007)	(0.007)	(0.007)	(0.021)	(0.025)
certi_dummy	-0.023^{***}	-0.014^{**}	-0.016^{***}	-0.016	-0.014
	(0.006)	(0.006)	(0.006)	(0.011)	(0.012)
total_positions	0.007^{**}	0.005^{*}	0.005^{*}	0.005^{*}	0.007^{**}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
policy_dummy	-0.027^{*}	-0.024^{*}	-0.024^{*}	-0.024^{*}	-0.038^{***}
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Constant	0.882^{***}		0.925^{***}	0.925^{***}	0.942^{***}
	(0.029)		(0.029)	(0.077)	(0.092)
Observations	5,978	5,978	5,978		
R^2	0.662	0.647	0.799		
Adjusted R^2	0.662	0.644	0.799		
F Statistic	$2,923.780^{***}$ (df = 4; 5973)	$2,714.630^{***}$ (df = 4; 5919)	$11,160.050^{***}$		
Note:			*p<0.1; **p<0.05; ***p<0.01		

In this table, the model (4) is the random effect model with heteroscedasticity consistent standard error, and the model (5) is the random effect model that both autocorrelation and heteroscedasticity are considered.

5. Estimation Results

Using a panel data model with random effect, model number (5) will yield the best result. Comparing all the models, the variable of interest, $certified\ dummy$, from significant at a 0.01 level with coefficient -0.023 to non-significant value -0.014. Other control variables, like *log(actual_wage)*, which is the salary paid to H1B holders, is always having a positive relationship with the *prevailing_wage*. 1% H1B pay level is associated with 0.7% increase in native wage level. *Total positions*, as the demand for certain type of worker, its result on the changes of *prevailing_wage* doesn't vary much between the models; 1 unit change in will have a 0.7% increase in *prevailing_wage*. As for the *policy_dummy* representing the Trump's H1B policy, changes from 0.1 level of significance to 0.01 level, with a general negative impact on *prevailing_wage* level: with Trump' policy, on average, there is 3.8% drop in the native worker's average wage level.

Going back to the research hypothesis 1 postulated, numerous economists believe that introduction of high-skilled immigrant employees tends to have an adverse effect on local wage level due to their competition with domestic employees, while some of others believe certain types of careers like STEM related occupations might benefit local workers with a college or above degree, thanks to the potential production efficiency improvement.

In our analysis, number of H1B approved do not have significant impact on the local level wages based on the four years (2019 to 2023) of data. H1B's short term influence on the local-level pay is slightly negative yet non-significant. In addition, H1B wage level is having a positive relationship with local wage, meaning, with compensation for non-immigrant(H1B) workers going up, the level going up for local workers as well. The proxy for demand, total positions request, brings positive effect on the local wage level, which support the theory that as the demand for workers increases, employers may offer higher pay to attract and retain workers. The Trump policy having a negative relationship with local wage level is unexpected. Trump's H1B policy aims at protecting American workers and promote domestic hiring. Possible explanations can be with restriction on H1B labor force, with less options, employers are having less incentive to offer high salaries, a sign of reduced competition. Or there are possible decline in innovation and productivity, leading to drop in wages.

6. Conclusion

In this study, we analyze the impact of H1B visas on local wage levels. The results show that the number of H1B visa approvals has no significant effect on local wage levels in the short run. H1B wages are positively correlated with local wages, suggesting that as wages for nonimmigrant workers increase, wages for local workers also rise. This reflects the potential positive effect of highly skilled and well paid H1B workers on the overall productivity and competitiveness of the labor market, which ultimately benefits local workers. In addition, the positive impact of job demand on local wages suggests that as demand for workers increases, wages offered by employers to attract and retain talents rise. This finding is consistent with economic theory and provides evidence for the importance of labor demand in determining wage levels. Finally, the negative relationship between Trump's H1B policy and local wages is an interesting and unexpected finding. This suggests that restrictions on the H1B workforce could lead to unintended consequences, such as reduced competition for jobs or reduced innovation and productivity, leading to lower wage levels for local workers. This highlights the complexity of the relationship between immigration policy and labor market outcomes and reminds us of the need to consider the full range of possible impacts when formulating relevant policies.

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