

How High-Skill Immigration Restrictions Eroded Regional Productivity: Evidence from the 2017 BAHA Policy

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ABSTRACT: This paper examines how limiting high-skill immigration affects the economy at the regional level, using the 2017 “Buy American, Hire American” (BAHA) executive order as a quasi-experimental shock. This restrictive policy significantly increased the difficulty of obtaining H-1B visas, which high-skilled foreign workers primarily rely on to work in the United States. As a result, denial rates for new H-1B applications rose from 7% to 17%, and STEM-specific rejections jumped to an all-time high of 31%. Employing a difference-in-differences method, this study finds that from 2018 to 2020, states with high reliance on H-1B labor experienced a 2.8% drop in economic output compared to states with lower H-1B exposure. In total, this decline translates to an estimated productivity loss of \$218 billion for the most affected regions in 2018 alone. While job counts and wages generally remained stable during this period, likely supported by tax cuts and deregulation, overall productivity was negatively impacted because of restrictions on skilled foreign talent. Thus, this study suggests that policies that only focus on conventional employment metrics may overlook the “hidden” costs of immigration restrictions to economic performance, particularly the impact on innovation and productivity.

KEYWORDS: Economics, Labor Economics, H-1B Visas, Innovation and Productivity, Immigration Policy Shock.

■ Introduction

One of the most widely contested questions within labor economics is whether foreign workers substitute or complement native workers. This issue lies at the heart of United States immigration policy: if policymakers believe that foreign-born workers heighten labor market competition and depress outcomes for native workers, they may pursue restrictive policies to limit foreign labor supply. But if skilled immigrants are viewed as sources of specialized expertise that foster innovation and provide knowledge spillovers, policymakers may take more balanced approaches to facilitate their entry to support economic growth. This paper examines these competing perspectives through the lens of the H-1B visa program, which enables employers to access skilled foreign talent. The 2017 BAHA policy shock is used as a quasi-natural experiment, which allows for identifying the causal effects of immigration restrictions on economic outcomes.

Economists have long argued about the labor market impacts of high-skilled immigration, evidenced by a large body of such studies. Borjas estimates that a 10% increase in the historical immigration supply reduced native wages by 3–4%,¹ which implies that immigrants and natives with similar backgrounds, such as education and experience, are close substitutes. However, this viewpoint is challenged by many subsequent studies. Card finds little evidence that immigration significantly depresses native wages,² and Ottaviano and Peri similarly suggest that immigrants and natives are imperfect substitutes who specialize in different areas.³ In addition, Kerr and Lincoln and Kerr, Kerr, and Lincoln show that skilled immigrants increase innovation and boost science and engineering employment,^{4,5} and Hunt identifies them as job-creating entrepreneurs.⁶

High-skill immigrants are also catalysts for total factor productivity (TFP) and innovation. STEM immigrants are associated with higher rates of patenting and overall productivity increases.^{7,8} Furthermore, research by Akcigit, Grigsby, and Nicholas and Peri, Shih, and Sparber elucidates how foreign-born workers drive U.S. innovation because of their complementarity with native workers.^{9,10}

Despite this evidence, the H-1B program has become an ever more difficult system to navigate after the annual visa cap reverted from 195,000 to 65,000 in 2004. Since the early 2000s, the H-1B policy has been revised multiple times under different presidential administrations. For instance, in 2007, the first-ever computer-generated lottery was implemented for H-1B selection due to unprecedented demand. Although some studies find no significant impacts from H-1B visa lotteries at the firm level,¹¹ many other analyses show that policy-induced shifts in H-1B supply can greatly affect innovation and productivity across cities and states.^{5,10} Recent work by Glennon identifies an “offshoring” phenomenon: when U.S. policy became more restrictive towards immigration, many multinational firms chose to relocate R&D operations to foreign affiliates in China and India.¹² This substantiates the idea that H-1B restrictions can diminish domestic value added, a measure of labor productivity defined as the total value of goods and services produced minus the input cost, without necessarily lowering aggregate employment. That cost was reflected in the estimated \$100 billion decline in market valuation following the 2020 visa suspensions made to combat COVID-19.¹³

The April 2017 BAHA executive order introduced a significant disruption to the H-1B program. The policy increased H-1B denial rates sharply; the two main factors contributing to this were tightened eligibility standards and increased “Re-

quests for Evidence" (RFEs), which caused average rejection rates to rise from 5% (2010–2016) to over 11% by 2018. The shock affected new STEM applications the most, with nearly one in three cases being rejected. Figure 1 shows that each state has a different reliance on the H-1B visa program prior to the BAHA period; this variation creates a unique setting to measure the heterogeneous regional effects of BAHA restrictions on high-skill immigration.

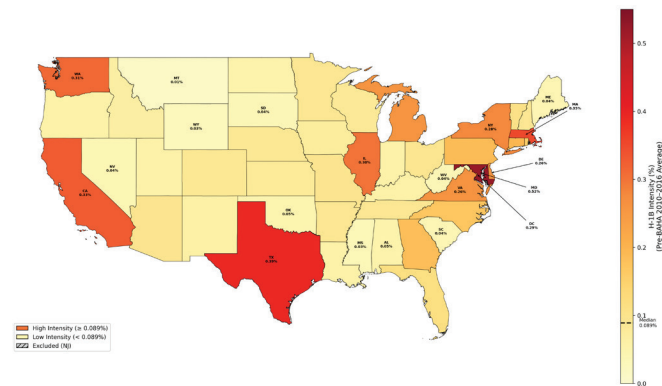


Figure 1: Pre-BAHA H-1B Intensity by State. H-1B exposure varies across states, with many coastal states showing relatively high reliance on H-1B workers. New Jersey is excluded from this analysis (see Methods section for details). Map generated by the author in Python using the pre-policy H-1B intensity data.

To determine how BAHA affects states with different levels of H-1B reliance, this study analyzes state-level immigration and labor productivity data from 2010 to 2020 and divides states into two groups based on their average H-1B share of total employment (H-1B intensity) prior to 2017. Using a difference-in-differences approach, the analysis compares the effect of BAHA on labor market outcomes in high H-1B intensity states relative to low-intensity states. The results show that states with high H-1B intensity experienced a 2.8% relative drop in value-added output ($\beta = -0.028$, $p = 0.049$), which equates to an estimated \$218 billion productivity loss across the ten most exposed states in 2018 alone. Notably, these productivity losses occurred despite tax cuts and deregulation implemented during the same period to spur business activity, prompting firms to maintain strong labor demand. This indicates that although these stimulative policies may have kept labor quantity stable, they were unable to offset the “quality-of-labor” drain induced by BAHA. In short, regional productivity contracted without a material change in aggregate employment.

While previous work has mostly examined firm-level responses to high-skill immigration policy changes, such as Doran, Gelber, and Isen using H-1B visa lotteries,¹¹ the broader implications to regional economies were not clearly evaluated. The 2017 BAHA order caused a significant aggregate contraction in the supply of high-skilled labor, providing a natural setting to evaluate complementarities and knowledge spillovers that may not be visible in firm-level data. In this sense, our study builds on productivity and innovation literature while complementing more recent work on policy-driven shocks.^{5,7,10,12,13}

Collectively, these findings suggest that restrictive policies focused solely on employment outcomes may fundamentally underestimate the overall economic effects of lost productivity on value-added output.

■ Methods

This study identifies the impact of the 2017 BAHA order using a difference-in-differences (DiD) framework together with an event-study analysis used to assess the validity of the DiD assumptions. This policy serves as a natural experiment because it was a sharp, discrete policy shift that provides a clean break for identification, and its uniform federal application means that “treatment” intensity is determined by a state’s pre-existing H-1B reliance rather than the policy itself. This method ensures that the shock is exogenous to state-level economic shifts.

There are other common methods used in immigration literature, such as instrumental variables (IV) or regression discontinuity (RD). However, identifying a truly valid instrument for H-1B exposure is widely debated in the literature. In addition, the BAHA policy did not establish a clear geographical or numerical threshold suitable for the RD approach. As a result, the DiD and event-study approaches are better suited, as this framework leverages longitudinal data to compare the effects of the policy shock across states with different levels of pre-policy H-1B reliance.

Data Sources and Selection:

The primary datasets used in this study include Labor Condition Application (LCA) filings, H-1B petition data, and labor productivity measures from 2010 to 2020.

LCA filings were sourced from the Department of Labor as a primary measure of employer demand for H-1B talent,¹⁴ following the approach of Kerr and Lincoln.⁵ H-1B supply-side records (approvals and denials) were obtained from the U.S. Citizenship and Immigration Services (USCIS) Data Hub files.¹⁵ STEM records, representing the bulk of H-1B petitions, were proxied using NAICS sectors 51 (Information) and 54 (Professional, Scientific, and Technical Services). Labor productivity metrics (e.g., employment, hours worked, hourly compensation, and value-added output) were pulled from the U.S. Bureau of Labor Statistics (BLS) State and Regional Labor Productivity data files.¹⁶ The labor productivity metrics sourced are for all private non-farm sectors, but did not have NAICS sector codes to further differentiate STEM-specific metrics.

Raw datasets cover 2010 through 2024, but this study excludes years beyond 2020 for the DiD and event-study analyses for two reasons: several Trump-era immigration mandates were reversed in 2021, effectively offsetting the original policy treatment; the 2021–2024 window is heavily confounded by the COVID-19 recovery and the introduction of a new H-1B electronic registration system. By ending the analysis in 2020, the study can better isolate the impact of the BAHA order.

Within the 2010–2020 window, the pre-treatment period is 2011–2016, and the post-treatment period is 2018–2020. 2017 was excluded because the BAHA was signed in April 2017. In

addition, the year 2010 serves as the base year for year-over-year calculations and is not included in those calculations. New Jersey was also dropped from the dataset because several major IT outsourcing firms are headquartered there but deploy workers to other states.

The final dataset covers 2010 to 2020, including 49 states plus the District of Columbia (50 in total) and 9 years for a total of 450 state-year observations.

Empirical Trends and Policy Shocks:

This section analyzes immigration trends before and after the 2017 BAHA policy shock. Table 1 shows that LCA filings continued to grow and certification (approval) rates remained stable over the years, indicating growing demand for foreign talent. However, H-1B denial rates surged from 4.9% on average from 2010 to 2016 to 11.5% in 2018, essentially limiting the supply of foreign labor. This means an increasing demand-supply gap due to BAHA.

Table 1: LCA and H-1B Summary Statistics (average across states). LCA filing increased over time, but BAHA caused a significant “denial shock” to H-1B petitions, especially to STEM categories.

Labor Demand vs. Supply	Variable	Pre-BAHA (2010-2016)	2018	2019	2020
		Mean	Mean	Mean	Mean
Demand	LCA Total Filings	8,357	11,501	11,901	12,562
	LCA Certification Rate (%)	82.0	85.5	87.8	92.1
	STEM LCA Total	5,299	7,607	7,918	7,709
	STEM LCA Certification Rate (%)	83.0	86.2	89.1	91.9
Supply	H-1B Total	5,173	6,989	8,146	8,307
	H-1B Denial Rate (%)	4.93	11.5	11.34	7
	H-1B New Employment Denial Rate (%)	7.2	17.1	15.8	9.6
	STEM H-1B Denial Rate (%)	6.3	19.6	18.2	12.8
	STEM H-1B New Employment Denial Rate (%)	8.7	31.4	27.0	17.6

As illustrated in Figure 2 below, this denial shock was not uniform. Denial rates for renewals (continuations of employment) remained stable throughout the decade, but new employment petitions saw denial rates jump from 7.2% to over 17.1% in 2018. STEM-specific new employment petitions saw an even more pronounced rise from 8.7% to 31.4%. This surge in rejections for new employment filings significantly tightened the new talent pipeline.

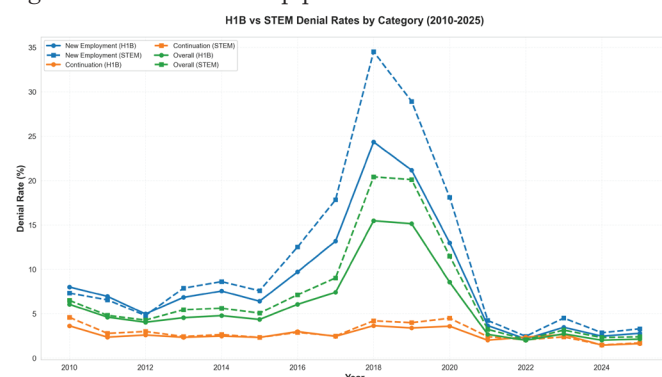


Figure 2: National-level H-1B and STEM Denial Rates. H-1B and STEM denial rates remained stable and low from 2010 to 2016. Post-BAHA denial rates spiked significantly for new employment petitions and STEM-specific categories. Figure generated by the author using the USCIS H-1B and STEM denial rate data.

Treatment Variables:

H-1B intensity is the treatment variable to measure cross-state variation in H-1B dependence during the pre-BAHA period. For each state, this variable is defined as:

$$H1B_{Intensity} = \left(\frac{H1B_{Approvals}_{s,2010-2016}}{Employment_{s,2010-2016}} \right) \times 100 \quad (1)$$

After calculating H-1B intensity, states are split into two groups using the median value of 0.089% across all states. 25 states, such as Maryland, Texas, and California, with a high concentration of technology, biotech, and finance sectors, are in the high-intensity group. The other 25 states, such as Montana, Alaska, and Wyoming, with high exposure to agriculture and natural resources, are in the low-intensity group. New Jersey was excluded from the dataset, as explained in Data Sources and Selection. Because the H-1B intensity values are computed using pre-policy data, it is predetermined relative to the policy shock, thereby minimizing reverse causality concerns. The binary treatment indicator is:

$$HighH1B = 1 \text{ if } H1B \text{ Intensity} \geq \text{median}; 0 \text{ otherwise}$$

Outcome Variables:

Four variables are used to track labor market outcomes: employment, hours worked, real hourly compensation, and value-added output. Since the distribution of these variables is heavily right-skewed, we transform them into natural logarithms. This step reduces skewness by more than 90% while still allowing for an intuitive interpretation of the result as percentage changes (Table 2).

Table 2: Labor Market Outcome Variables Distribution and Transformations. Log transformation reduces skewness by 94-98%.

Variable	N	Mean	Std Dev	Skewness (Raw)	Kurtosis (Raw)	Skewness Improvement (Log)
Employment (K)	750	2,568	2,923	2.58	7.72	0.04 98.4%
Hours Worked (M)	750	4,389	5,024	2.59	7.64	0.04 98.5%
Real Hourly Comp (\$/hr)	750	38.10	4.50	0.95	1.13	~0 >95%
Value-Added Output (M, 2012\$)	750	317,633	433,301	3.32	13.67	0.2 94.0%

Difference-in-Differences Model Specification:

The DiD model uses the following equation:

$$\log Y_{st} = \alpha + \beta_1 HighH1B_s + \beta_2 Post_t + \beta_3 (HighH1B_s \times Post_t) + \lambda (HighH1B_s \times t) + \delta_s + Y_t + \epsilon_{st} \quad (2)$$

where Y_{st} represents the outcome variable (employment, hours worked, real hourly compensation, or value-added output) in state s and year t ; $HighH1B_s$ is the binary treatment indicator for high-treatment states; $Post_t$ equals one for years 2018 and later (the BAHA period); $HighH1B_s \times Post_t$ is the interaction term that captures the treatment effect of BAHA on high-H1B states in the post period, relative to low-H1B states; δ_s and Y_t are state and year fixed effects; and $HighH1B_s \times t$ is a state-specific linear time trend that reflects the pre-existing trend of high-H-1B states relative to the low-H-1B states.

β_1 represents the baseline difference between the high- and low-H1B groups, and β_2 is the common post-BAHA shift effect for both groups. β_3 identifies the causal effect of the BAHA policy on the states with high H-1B exposure, under the parallel trends assumption. The DiD approach compares the states in the high-intensity group to their own pre-policy history and to the control group (low-intensity states). Since a log specification is used, multiplying β_3 by 100 is the estimated percentage effect. Finally, standard errors ϵ are clustered

by state to account for serial correlation over time, to ensure robustness for significance testing across 50 clusters.

As stated in the above section, the pre-treatment period is defined as 2011–2016. The DiD model estimates the policy impacts over three post-treatment periods (2018 only, 2018–2019, and 2018–2020) in order to evaluate how firms were able to adjust to the new policy over time.

Identification Strategy:

Three conditions are key to ensuring that β_3 captures a causal relationship rather than a simple correlation of variables. First, high- and low-intensity states should have parallel or similar trends before the BAHAs policy shock. This assumption can be validated by examining the coefficients of each labor outcome variable in the pre-policy period (see Event Study Specification). As explained in Results and Discussion, pre-policy coefficients for two labor variables, employment and real hourly compensation, hover near zero, suggesting parallel trends. However, the other two variables, value-added output and hourly worked, show non-parallel upward trends, necessitating the use of state-specific linear time trends (λ). Second, it is important to ensure exogenous treatment. This study uses the average H-1B intensity from 2010 to 2016 as a pre-determined metric to meet this condition. Finally, this analysis uses state and year fixed effects to control for unobserved confounders, which absorb permanent state differences and other factors, such as the Tax Cuts and Jobs Act (TCJA) of 2017.

Event Study Specification:

Event study tests the pre-policy parallel trends assumption to complement the static DiD approach, using the following specification:

$$\log Y_{st} = \alpha + \beta_1 \text{HighH1B}_s + \sum_{k \neq 2016} \theta_k 1\{t=k\} + \sum_{k=2011, k \neq 2016}^{2020} \beta_k (\text{HighH1B}_s \times 1\{t=k\}) + \epsilon_{st} \quad (3)$$

Where β_1 is the baseline difference between the high- and low-intensity states in the reference year (2016, the full year prior to the BAHAs order); θ_k is the year effect in year k (relative to 2016) common to both groups; β_k is the key coefficient that measures the difference between the two groups in year k , relative to the reference year; and $1\{t=k\}$ is indicator for k from 2011 to 2020, with 2016 set at zero.

The pre-2016 coefficients (β_{2011} through β_{2015}) directly test the parallel trends assumption: if these coefficients were close to zero, then high- and low-intensity states were on similar trends prior to BAHAs. The post-2017 coefficients (β_{2018} through β_{2020}) reveal the magnitude of the impact after the BAHAs policy was implemented.

Results and Discussion

DiD Model Estimates:

β_3 in Table 3 highlights the DiD results. The most significant result is a 2.8% relative decline in value-added output across high-intensity states in 2018 ($\beta_3 = -0.028$, $p = 0.0498$). The effect continued on this path through 2020, suggesting that the "productivity shock" persisted as the policy was enforced. The state-specific trend control (λ) was essential for identi-

fying the true β_3 , because high-intensity states were growing faster annually ($\lambda = 0.0109$ in Table 3) relative to low-intensity states before BAHAs; omitting this control would have masked the true magnitude of the policy's negative impact. In contrast, the result also reveals a discrepancy: while economic output dropped significantly, labor input (employment, hours worked, and real hourly compensation) showed minimal movement ($p > 0.15$). This suggests that the policy dealt a blow to work efficiency rather than labor quantity or wages.

β_1 and β_2 are absorbed by the state and year fixed effect terms in the DiD model in Equation 2 and hence dropped from the final DiD model estimates. Table 3 shows model estimates for β_3 .

Table 3: DiD Model Results. β_3 for Value-Added Output consistently shows statistical significance across the periods. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. SE (cluster) is associated with β_3 .

Post-BAHA Periods	Outcome	β_3 (DiD)	SE (cluster)	t-stat	p-value	Sig	$\beta_3 \times 100$ (t=)	trend λ	95% CI
1-Yr Post (2018)	log(Employment)	0.0078	0.0059	1.317	0.1879		0.78	0.0021	[-0.0038, 0.0194]
	log(Hours Worked)	0.0004	0.0077	0.048	0.9616		0.04	0.0044	[-0.0148, 0.0155]
	log(Real Hourly Comp)	0.0072	0.0088	0.811	0.4173		0.72	(0.0036)	[-0.0102, 0.0245]
	log(Value-Added Output)	-0.0281	0.0143	-1.962	0.0498	**	-2.81	0.0109	[-0.0561, 0.0000]
2-Yr Post (2018-19)	log(Employment)	0.0076	0.0062	1.234	0.2173		0.76	0.0021	[-0.0045, 0.0197]
	log(Hours Worked)	-0.0024	0.0083	-0.287	0.7742		-0.24	0.0042	[-0.0186, 0.0138]
	log(Real Hourly Comp)	0.0126	0.0092	1.371	0.1705		1.26	(0.0032)	[-0.0054, 0.0306]
	log(Value-Added Output)	-0.0290	0.0151	-1.914	0.0556	*	-2.90	0.0109	[-0.0586, 0.0007]
3-Yr Post (2018-20)	log(Employment)	0.0070	0.0063	1.108	0.2678		0.70	0.0015	[-0.0054, 0.0194]
	log(Hours Worked)	-0.0029	0.0084	-0.345	0.7305		-0.29	0.0037	[-0.0194, 0.0136]
	log(Real Hourly Comp)	0.0130	0.0092	1.418	0.1551		1.30	(0.0028)	[-0.0050, 0.0310]
	log(Value-Added Output)	-0.0286	0.0152	-1.879	0.0602	*	-2.86	0.0113	[-0.0584, 0.0012]

Event Study Evidence (Validating the DiD Assumptions):

Figure 3 shows the coefficients of pre- and post-policy trends of high-intensity states, relative to low-intensity states. As shown in this graph, pre-treatment coefficients for employment and real hourly compensation oscillate near zero, affirming that these two variables followed similar trajectories before the policy. Post-2017 coefficients for these variables also remain insignificant.

However, value-added output and hours worked show clear upward trends prior to 2016 and violate the parallel trends assumption. This violation confirms the need for the inclusion of a state-specific linear trends term (λ) in Equation 2 to address the pre-policy trends and separate the policy's impact from the baseline growth trend differences.

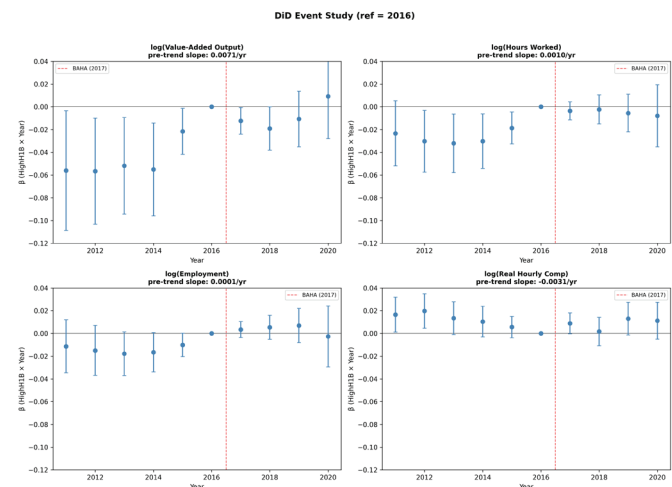


Figure 3: Event Study DiD Coefficients. Pre-2016 coefficients for employment and real hourly compensation are near zero, while value-added output and hours worked show non-parallel upward trends. Graph generated by the author in Python using event study DiD regression estimates.

The subsequently detrended graph (Figure 4) shows that the state-specific trends term (λ) effectively handles the parallel trends assumption violation issue. After subtracting the pre-treatment linear trend from the entire series, the pre-period slope is centered around zero for all four outcome variables. This ensures that post-2017 coefficients are a true representation of the policy shock effects, not continuations of prior trends.

The detrended post-treatment coefficients for value-added output remain negative and statistically significant. This verifies that the economic output drop in high-intensity states was a distinct break caused by the BAHHA order. By comparison, the other three variables show no significant upward or downward patterns away from zero. This reinforces our conclusion that the impact of the BAHHA maneuvered through a decline in productivity as opposed to labor quantity or wages.

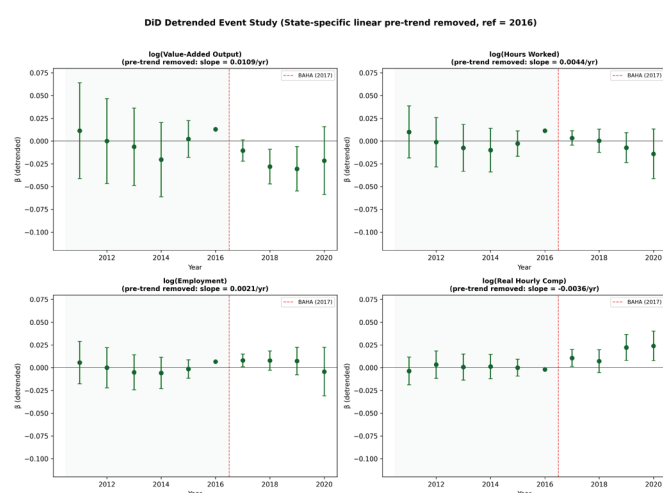


Figure 4: Detrended Event Study DiD Estimates. Detrended pre-policy coefficients for all four outcome variables are around zero, thereby satisfying the parallel trends assumption. Figure generated by the author in Python using detrended event study DiD regression estimates.

2017 is retained as the reference/boundary year in Equation 3 and in Figures 3 and 4, where it marks the transition point between the pre- and post-policy periods on the event-study timeline.

Robustness Checks:

Several robustness checks were conducted to confirm the validity of the DiD model results (Table 4).

The first check is a placebo test, run by estimating the model using only pre-BAHHA data (2011–2016) and assigning a fictitious policy shock to 2014. As expected, the result was statistically insignificant and actually moved in the opposite direction of the main findings ($\beta_{\text{placebo}} = +0.023$). The fact that no “phantom” effect appeared in the years leading up to the policy corroborates that the post-2017 decline is a causal shift.

The second test swapped the general H-1B intensity variable with a STEM-specific metric, which identifies the loss of technical talent as the main factor behind the drop in productivity. Nearly identical results were found ($\beta_3 = -0.027$).

The third test evaluated whether states with “middle-of-the-road” H-1B reliance were diluting the results, using an

extreme-tercile comparison which divides the dataset into three equal thirds. Comparing only the top and bottom thirds of the sample and omitting the middle third, the negative impact on value-added output nearly doubled to -4.3% ($p = 0.014$). This suggests that the baseline -2.8% estimate is likely conservative. More importantly, it suggests that the productivity drain was directly proportional to how much a state’s economy relied on H-1B talent.

Finally, two additional specification checks (Test 4 and 5 in Table 4) were conducted to confirm that the findings were not driven by outliers or pre-policy trends. Test 4 shows the coefficient holds relatively steady ($\beta_3 = -0.031$) after excluding the three largest H-1B states. Test 5 tests the impact of removing the state-specific linear time trends from the model; β_3 result becomes insignificant, which validates that we must account for pre-existing growth trend to identify the policy’s real impact. It is important to note that the central finding rests on the assumption that the diverging pre-2017 growth trajectories of high-intensity states would have continued linearly in the absence of the BAHHA policy. This linear extrapolation is a standard and defensible approach in DiD designs facing non-parallel pre-trends, but it is an assumption rather than an observed counterfactual.

Table 4: Robustness Checks Results for Value-Added Output. These checks confirmed the validity of the DiD model results. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Specification	Treatment	1-Yr Post β_2	p-value	Sig	2-Yr Post β_2	p-value	Sig	3-Yr Post β_2	p-value	Sig
Primary DiD Model	Binary (50 states/DC)	-0.0281	0.049	**	-0.0290	0.055	*	-0.0286	0.060	*
(1) Placebo (2014)	Binary (50 states/DC)	+0.0231	0.203							
(2) STEM Treatment	Binary + STEM-specific (50 states/DC)	-0.0269	0.061	*	-0.0283	0.062	*	-0.0280	0.066	*
(3) Extreme Tercile	Binary (34 states/DC)	-0.0428	0.014	**	-0.0429	0.020	**	-0.0422	0.024	**
(4) Drop CA, TX, NY	Binary (47 states/DC)	-0.0309	0.032	**	-0.0316	0.039	**	-0.0311	0.043	**
(5) No State-specific Linear Trends Term	No trend control	+0.0211	0.293		+0.0253	0.251		+0.0334	0.185	

Interpretation:

This study points to a clear “decoupling” observation of labor quantity and economic output. Following the BAHHA order, firms in high-intensity states appear to have maintained their headcounts by replacing denied H-1B talent with domestic workers. But this replacement was likely associated with contemporaneous policy stimuli, most prominently the TCJA of 2017 and overall federal deregulation.

However, this replacement carried a steep, covert cost. Domestic backfills were inherently imperfect substitutes for H-1B workers, oftentimes lacking the STEM expertise or niche human capital of the H-1B workers that they replaced. As a result, work efficiency suffered. Essentially, the 2017–2020 fiscal stimulus successfully preserved the number of workers, but the immigration restrictions likely eroded the quality of that labor.

While our analysis does not directly measure innovation or firm-level productivity, these findings align with the work of Peri, Shih, and Sparber,¹⁰ who argue that reductions in high-skill (especially STEM) immigrant concentration can diminish knowledge spillovers, specialization, and innovation, all of which are key drivers of total factor productivity. As an illustrative calculation, applying the 2.8% decline to the 2018 value-added output of the top ten H-1B-intensive states suggests a potential productivity gap of \$218 billion (95%

Confidence Interval: approximately \$1 billion to \$437 billion), relative to an extrapolated counterfactual trend (Table 5). This figure should be treated as an estimate rather than a precise effect, since it applies the average effect across all high-intensity states to the top ten states and is subject to substantial estimation uncertainty.

Table 5: Estimated Value-Added Gap in the Top 10 H-1B-Intensive States (2018). This \$218 billion gap is estimated as the 2018 Value-Added Output multiplied by 0.028 (where $\beta_3 = -0.028$ applies to each state).

Rank	State	H-1B Intensity (%)	2018 Value-Added Output (\$M)	Implied 2.8% Gap (\$M)
1	Maryland	0.523	291,815	8,171
2	Texas	0.392	1,527,024	42,757
3	Massachusetts	0.351	464,671	13,011
4	California	0.329	2,342,527	65,591
5	Washington	0.313	454,680	12,731
6	Illinois	0.300	722,516	20,230
7	District of Columbia	0.290	91,277	2,556
8	New York	0.279	1,432,581	40,112
9	Virginia	0.261	396,841	11,112
10	Delaware	0.260	60,409	1,691
Total			7,784,341	217,962

■ Conclusion

The 2017 BAHA policy shock provides a natural experiment to quantify how the effects of sudden restrictions on high-skill immigration can ripple through regional economies. Our study finds that the states relying most on H-1B talent experienced a 2.8% relative drop in value-added output; for the ten most H-1B-intensive states alone, this represents an estimated \$218 billion productivity loss in 2018. Meanwhile, no significant shifts in employment or wages were identified during the post-policy period, which suggests that labor replacement alone does not offset the impact of severing the supply of specialized foreign talent on total factor productivity and knowledge spillovers.

The results thus indicate that measuring immigration policy solely based on "headcount" or "jobs saved" may be insufficient. Doing so crucially risks ignoring the hidden economic toll of losing highly specialized expertise. To understand these costs more thoroughly, further work should investigate whether this talent drain slows patenting and R&D investment.

Building upon these findings, an important direction for future research is to analyze how alternative high-skill immigration policy frameworks interact with ongoing technological change. For example, studies could evaluate whether technological breakthroughs will continue to increase demand for highly skilled STEM workers or substitute for certain specialized tasks. Understanding these interactions would help policymakers assess whether future productivity shocks resulting from immigration restrictions are likely to be amplified or offset by advanced technologies. Studies should also examine whether uncertainty in U.S. immigration policy is driving international students and STEM talent away from the U.S. and towards competing technology hubs in other countries.

In addition, future studies can move from empirical diagnosis to actual policy recommendations. We can leverage the baseline foundation from this paper to build and test concrete policy ideas, such as fast-tracked application paths for high-demand fields, to help mitigate these productivity losses.

As for long-term effects, the economic burden of these restrictions does not end when a specific executive order is revoked. The U.S. regulatory stance frequently shifts, and this "on-again, off-again" nature of immigration policy is exemplified by the 2021 BAHA reversal and the introduction of a \$100,000 supplemental payment requirement for new, non-exempt H-1B petitions filed after September 2025. This continual volatility may be one of the most lasting and costly burdens to long-run economic growth.

A political economy perspective may help explain why restrictive high-skill immigration policies persist, despite evidence of aggregate economic costs. While the results indicate a decline in regional productivity following reduced access to H-1B talent, these effects are distributed across states and firms broadly and may be less immediately visible to the public. In contrast, potential benefits, such as reduced perceived competition in specific occupations or greater prioritization of domestic hiring, are more concentrated and more salient to affected groups. As a result, different stakeholders may perceive or experience the policy's costs and benefits unevenly, contributing to differing policy preferences. Public opinion may also play a role, as views on immigration policy often reflect concerns about job opportunities, wage dynamics, and fairness in labor markets, even when empirical evidence points to broader productivity effects. These considerations suggest that future research could examine how distributional dynamics and voter perceptions interact with aggregate economic outcomes in shaping the policies.

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