Dynamic Effects of H-1B and Section 127 Policy on Higher Education

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Abstract

Section 127 of the United States Internal Revenue Code provides for a tax deduction to employers that provide financial assistance to help employees pay for education. Counterintuitively, enrollment in higher education slowed around the creation of Section 127. Further, a simple regression of the inflation-adjusted tax-deductible limit on education enrollment indicates a significant negative correlation. These findings raise concerns about omitted variables bias. After taking extensive steps to account for dynamic economic conditions and various policy effects, analysis robustly identifies positive marginal employer assistance effects on enrollment. The linear and total effects of interest remain negative over the main period of analysis from 1992 through 2017. Controlling for H-1B policy effects leads unexpectedly to the identification of H-1B policy as a comparatively preferred policy tool. Results are validated using vector autoregression (VAR), dynamic ordinary least squares (DOLS), and instrumental variable (IV) analysis.

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1. Introduction

The passage of Public Law 95-600 in 1978 created Section 127[1]. Section 127 provides for a limited employer tax deduction for the transfer of money to an employee for educational purposes. This paper tests the hypothesis that the causal effect of Section 127 employer assistance on total university enrollment is positive. Results show that employer assistance has a positive marginal effect on enrollment and negative linear and total effects. H-1B visa policy is a comparatively effective policy instrument for enrollment, national student loan debt, and the price of education.

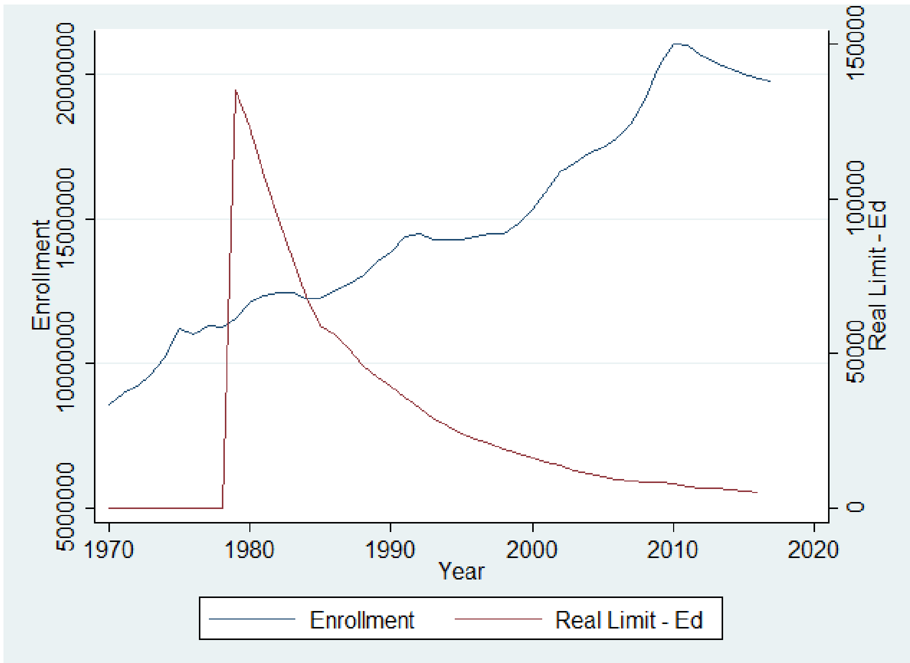
Figure 1 illustrates university enrollment over time and the real maximum deductible amount for Section 127 educational assistance. Here, education-specific inflation informs the real assistance limit. This paper hypothesizes that the apparent inverse relation is a superficial result of variable omission. Analysis in this paper controls extensively for dynamic policy and economic variation. The use of multiple specifications ensures the robustness of findings. In one specification, vector autoregression (VAR) provides evidence on Granger causality.

The failure of several simple theories to successfully explain the observation of enrollment slowdown in the late 1970s and 1980s further motivates the present study.

1.1. Simple Supply-Side Explanations

One hypothesis is that there is an adjustment period between the creation of Section 127 and widespread employer provision of the newly deductible benefit. Allowing for a 3 or 5 year lag around the passage of Public Law 95-600 fails to harmonize observed enrollment slowdown with the expected increase to demand. Across the eight five-year periods from 1970 to 2010, the five-year public enrollment growth rate was above 9 percent half of the time. Two of the four low-growth intervals occurred immediately after the 1978 creation of Section 127. The period just prior, from 1970-1975, saw the highest growth in enrollment across those eight periods.

Figure 1: Enrollment and Real Assistance Over Time



Surveys of employers provide further data on employer provision of educational assistance over time. Cappelli identifies three employer surveys from 1992 and 1993, which indicate that at least 86 percent of surveyed employers provided educational assistance[2]. These early surveys consist of samples of convenience. Nevertheless, further considerations lead Cappelli to conclude that a substantial majority of employers offered such plans over his period of analysis from about 1990 to 2004. The provision of this kind of benefit remains common in later years. In 2013, SHRM reported that 61 percent of employers offer tuition assistance[3]. In 2017, World at Work found that 85 percent of employers offered such a benefit, with another 7 percent offering non-reimbursement tuition assistance, such as upfront tuition discounts[4]. In summary, the simplistic hypothesis of lagged or bottlenecked employer support for Section 127 fails to solve the problem.

1.2. *Simple Demand-Side Explanations*

A simple regression of real employer assistance on enrollment may yield a significant negative correlation wholly due to consumer effects. The factual claim of decreasing market demand is consistent with observation, but it began before the passage of Section 127. Falling average tuition and fees are observed for all institutions from 1972 to 1980. The college-age enrollment percent does not increase substantially from 1970 to 1980. Higher education prices increase after 1980, as do the college-age enrollment percentage and total enrollment.

Because the decline in demand predates the passage of Section 127, the cause of decline must be located elsewhere, at least in part. Simplistic demand-side identification of the effects of employer assistance fails due to omitted variable bias. Important omitted variables include controls for inflation, the price of education, and relevant policy changes. Immigration, veteran education, and federal lending policy undergo fundamental changes in proximity to 1978 and in years later. Sufficient identification of the effect of Section 127 must account for changes in these variables over time.

2. Empirical Model

This paper takes multiple steps to ensure robustness and analytical completeness. The final results are consistent across three empirical specifications. In addition to the variable of interest, this paper tests two other left-hand variables. Testing these two secondary dependent variables of interest improves confidence in the theoretical and applied soundness of the conclusion.

Total postsecondary enrollment in the United States is the dependent variable. The Section 127 policy effect is the right-hand parameter of interest in the first two specifications. Equation 1 is the first specification of interest. This model is an ordinary least squares model. Here, α is a $1 * k$ vector of coefficients, and V is a $k * 1$ vector of annually observed independent variables.

$$Y_t = \alpha V_t + u_t \tag{1}$$

Policy variables exist for federal lending policy, veteran education benefits, and H-1 Visa policy. Two additional non-policy variables include time, in years, and the real price of university tuition plus mandatory fees.

Equation 2a describes the next specification. This model follows the Anderson–Hsiao pattern[5] with the lagged variable of interest as an instrument. This specification investigates concerns of potential endogeneity in the dependent variable. It is both an instrumental variable model and also a dynamic ordinary least squares (DOLS) model.

$$\Delta Y_t = \beta W_t + Bz_t + e_t \tag{2a}$$

$$z_t = \delta W_t + DY_{t-2} + g_t \tag{2b}$$

Here, β is a $1 * l$ vector of coefficients, and W is an $l * 1$ vector of annually observed independent variables. z is the instrument, and it is a projection of lagged enrollment derived from twice-lagged enrollment. Equation 2b explicitly derives z.

l is a transformation of k from Equation 1. l contains five variations of each variable in k. The first variation is the non-transformed value. The other variations include the first and second lags and differences for each variable in k.

The third specification is a vector autoregression (VAR) model. Six related models follow the general reduced form described in Equation 3c. This first model following this functional form is a two-variable case. This first model is similar to the previous non-VAR specifications because it identifies the effect of real employer assistance on total enrollment. A second model follows the same form, but the independent variable is H-1B visa issuance, instead of Section 127 assistance.

$$v_t = \alpha_0 + \alpha_1 v_{t-1} + \alpha_2 v_{t-2} + ... + \alpha_i v_{t-i} + u_t \tag{3a}$$

$$V_t = \alpha_0 + \alpha_1 v_{1,t-1} + \alpha_2 v_{2,t-1} + ... + \alpha_{ik-1} v_{k-1,t-i} + \alpha_{ik} v_{k,t-i} + u_t \tag{3b}$$

$$Y_t = \sigma_k V_{kt} + e_t \tag{3c}$$

Equation 3a is a univariate autoregression. Dependent and independent variables are uniformly represented by v_t. An ordinary least squares function of i lags explains the current-period value of the variable in the univariate regression. Equation 3b extends this operation to k variables. Notice that V_t is not a collection of univariate v_t. Instead, it is a $k * k$ vector, a constant, and an error term.

Equation 3c obtains V_t as specified in Equation 3a for all variables in k, then fits an ordinary least squares model across $V_k t$ to explain the current-period dependent variable, Y_t. Section 127 effects turn out to be insignificant in the specification described by Equation 3c, but H-1B effects are significant. As a result, all four remaining VAR equations use H-1B issuance as the independent variable.

Two of the four remaining models are three-variable extensions of the prior specification. These two models extend Equation 3c by adding a second stage response. In the first case, the second-order response is federal student loan debt. In the second case, the second-order response is the price of higher education. David Schenk suggests Cholesky decomposition as a method of generating an ordered impulse-response function from a VAR[6]. Equations 4a and 4b describe Cholesky identification.

$$e_t = B u_t \tag{4a}$$

$$\Sigma = E(e_t e_t') = E(B u_t u_t' B') = BE(u_t u_t')B' = BB' \tag{4b}$$

The left-hand error term in Equation 4a, e_t, is the same as in Equation 3c. The right-hand of Equation 4a defines B, which is the coefficient matrix for u_t.

Structural, or uncorrelated, errors are defined as u_t. Endogenous error in B allows us to estimate the effects of arbitrary innovation in some variable in V_k.

The reduced form BB' in Equation 4b matches many matrices. There does exist a unique lower-triangle matrix which satisfies the equality statement with Σ, the covariance matrix of the errors. Selecting the lower-triangle solution is isomorphic to stipulating a causal direction of effect on the variables in the VAR. The order imposed during the VAR calculation process is called a Cholesky ordering. This paper selects theoretically-grounded Cholesky orderings. Measures of the fitness of the resulting models are considered evidence about Granger causality.

The last two models in the six-model VAR family are also simple two-factor VAR models. These models test the hypothesis that enrollment effects are extraneous to the effects of H-1B policy on student loans and the price of higher education. The form of these models follows the specification in Equation 3c, but the independent and response variables are different. H-1B issuance is the independent variable. The response variable is federal student loan debt in one case. The price of higher education is the response variable in the other case.

3. Data

Information on total enrollment for all degree-granting postsecondary institutions in the United States is provided by the National Center for Education Statistics (NCES)[7]. Enrollment figures are for the fall semester of the school year. The values that NCES provides for years after 2018 are projections. The present study does not use any of the projected values. Other data sources and policy considerations constrain the period of interest to the 27 years from 1990 to 2016.

Personal Consumption Expenditures (PCE) data is a measure of inflation provided by the U.S. Bureau of Economic Analysis (BEA)[8]. NCES data allows the calculation of education-specific inflation[9]. NCES data is the average tuition and required fees for full-time undergraduate students across all degree-granting postsecondary institutions. NCES provides nominal values and values adjusted for the consumer price index (CPI) for tuition. Cost information does not include the price of room and board. 2016 is the base year for each measure of inflation.

Nominal Section 127 limits are a matter of public law. Section 127 took effect beginning after December 31, 1978, with a nominal assistance limit of 5,000 dollars[1]. In October 1986, Pub. L. 99–514 increased the nominal assistance limit to 5,250 dollars[10]. Combining nominal assistance over time with CPI and education-specific inflation data yields two real measures of inflation.

Changes to veteran education benefits are also a matter of public law. A categorical state variable represents veteran education benefits from 1970 to 2020 and allows for five different states. The Servicemen's Readjustment Act of 1944 is also called the G.I. Bill. This bill is the first relevant case of veteran benefits, but it precedes the period of interest for this study.

The original bill expired in 1956[11]. This expired state is the first state represented by the veteran education state variable. The Veterans Educational Assistance Program (VEAP) passed in 1981[12]. The third period of interest begins in 1984 with the enactment of the Montgomery GI Bill[13]. The fourth period of interest begins in 2009 with the Post-9/11 GI Bill.

Finally, many benefits from the Forever GI Bill became effective in 2018, with additional provisions taking effect in 2020 and 2022[14]. This fifth policy state is too recent to be included in the period of interest. The recent changes in veteran education benefits are a critical caveat for any attempt at forecasting or prediction outside of the period of study.

Due to constraints on the availability of other right-hand variable data, the main period of regression analysis ranges from 1990 to 2016. Veteran education benefits exhibit only one change during this period, but this factor proves to be significant in the preferred model.

Stafford loan data is another critical component of the analysis. Stafford loan limits impact the supply of loanable funds, which indirectly modifies demand for education. Stafford data also broadly proxies non-military federal student aid policy. There are two variables for Stafford loans. The first variable is the nominal loan limit for undergraduates. The second variable is a dummy variable. The dummy variable indicates whether the undergraduate loan limit is the combined limit for undergraduate and graduate loans. A policy change in 1993 grouped these limits. FinAid provides the Stafford loan data used in this study[15].

Visa policy is a complex issue. The number of H-1B visas issued each year is an essential variable in this study. The Immigration Act of 1990 decomposed the existing H-1 visa into distinct H-1A and H-1B categories. Later legislation established the H-1B1, H-1C, and many other visa classifications, but these are mostly inapplicable to the present research. The H-1B visa is most relevant for this study because it relates explicitly to the undergraduate degree. The Immigration Act of 1990 makes available the H-1B classification for specialized workers, or workers in a specialty occupation. That legislation formally defines a specialty occupation as "an occupation that requires...attainment of a bachelor's or higher degree..."

H-1 visas are a subgroup of nonimmigrant visas. Nonimmigrant visa award data by classification from 1987 to 2019 is provided by the Bureau of Consular Affairs within the United States State Department[16]. This paper exclusively uses the most relevant H-1B visa award numbers, but reanalysis with other visa classifications could yield statistically significant findings. The prior H-1 visa was also a merit worker visa, but it had no formal definition of merit. It is plausible that the college-educated effect informally existed before the 1990 legislation. One might also find small but significant effects by looking into visas outside the H-1 family. Besides the number of actual visa awards, an analyst could look for visa cap effects or visa policy state effects. For example, the Pew Research Center notes that the American Competitiveness in the 21st Century Act of 2000 exempts certain entities from the H-1B cap[17].

The last data source of interest is on actual federal loans. Actual federal loans stand in contrast to loan limits, which are represented by the Stafford loan limit variable. Loan limits are a policy choice, but after correcting for loan limits, the actual amount of loans made primarily represents a demand effect. As such, we would not want to correct for actual loans. That would wipe out the effect of interest, which is the demand effect attributable to various policies, and Section 127 employer educational assistance in particular.

Loan data generates results as a left-hand variable of secondary interest, rather than as an independent variable. The variable I use in this regard is total federal undergraduate loans. College Board provides loan data. College Board also gives the additional context in a report which is related to the loan data[18]. The additional context suggests that an analysis that decomposes federal loans by type could yield preferred statistical results[19].

4. Results

4.1. Multiple Regression Results

The key independent variable is H-1B visa issuance, but at the outset, there are two potential left-hand variables available. Ordinary least squares (OLS) multiple regression of visa effects, time, and tuition was run against both total enrollment and public university enrollment. Total enrollment was more predictable than public university enrollment, so this was selected as the preferred enrollment variable.

With total enrollment as the explained variable, a kitchen sink multiple regression was used to select the most influential factor from among each factor group. The total number of visas issued across classification is not significant. Stafford loan limit variables were also identified as insignificant. The long regression of interest has higher unadjusted explanatory power compared to kitchen sink regression. Measures of tuition were identified as insignificant. Table 1 is a table of regressions which helps illustrate that, somewhat surprisingly, real measures of employer assistance capture price and inflation effects in a preferred way compared to using a more direct measure of tuition.

Tuition is insignificant in model 1. Replacing tuition with PCE and education-deflated employer assistance in model 2 identifies the latter with significance at

Table 1: Table of Multiple Regression on Total Enrollment, Selected Variables

	1	2	3	4
Montgomery GI	-1.059e+06++	-1.080e+06++	-1.076e+06**	-9.604e+05++
	(4.195e+05)	(4.093e+05)	(2.668e+05)	(3.533e+05)
Real Limit - Ed and PCE		-9.659e+02+		
		(5.198e+02)		
Real Limit - Ed	1.162e+03**	1.231e+03**		-4.416e+02
	(2.171e+02)	(2.260e+02)		(3.092e+02)
Real Limit - Ed^2			3.534e-02**	5.906e-02**
			(8.705e-03)	(7.304e-03)
Real Limit - Ed^3			-4.752e-07*	-8.301e-07**
			(1.564e-07)	(9.794e-08)
Tuition CPI	7.422e+02			
	(4.638e+02)			
H-1 Visa	-7.820e+01*	-7.702e+01*	-2.646e+01	
	(2.284e+01)	(2.214e+01)	(1.938e+01)	
H-1B Visa	-4.667e+01+	-5.077e+01+		-1.731e+01++
	(2.516e+01)	(2.496e+01)		(7.763e+00)
$H\text{-}1B^2$	9.363e-04++	9.944e-04++	8.564e-05	4.266e-05
	(4.065e-04)	(4.015e-04)	(6.804e-05)	(3.394e-05)
H-1 Non-H-1B	1.273e+02*	1.238e+02*	5.289e+01	
	(3.918e+01)	(3.778e+01)	(3.295e+01)	
Year	4.169e+08*	4.094e+08*	2.365e+08**	2.478e+08**
	(1.236e+08)	(1.130e+08)	(2.720e+07)	(3.236e+07)
$Year^2$	-1.037e+05*	-1.018e+05*	-5.875e+04**	-6.155e+04**
	(3.077e+04)	(2.814e+04)	(6.756e+03)	(8.022e+03)
R-sqr	0.9973	0.9975	0.9970	0.9965

Standard errors in parentheses

+ $p < 0.10$, ++ $p < 0.05$, * $p < .01$, ** $p < .001$

the 0.1 level and also improves the overall explanatory power of the model. Real employer education assistance which is solely corrected for the price of education is eventually preferred to the multiple-deflated measure. This makes the education-deflated real employer assistance limit the preferred Section 127 variable. After deciding on this variable as the preferred measure, quadratic, cubic, and interaction transformations are investigated. The interaction of Section 127 policy and visa effects turns out to be small in magnitude, low significance, and in possession of a sign which is sensitive to specification.

Model 4 is preferred out of the models presented in Table 1. While model 1 has the highest r-squared value, model 4 has an adjusted r-squared equal to model 1. Model 4 is the result of a thorough nonlinear investigation, while models 1 and 2 are not. Model 3 is technically stronger but difficult to interpret. For example, interpreting the H-1B visa policy effect is not straightforward, both because a linear effect is missing in the model and also because other H-1 variables are present which make pure H-1B effect attribution impossible.

All four models are technically very strong, but model 4 makes interpretation simple. The linear effect of real Section 127 assistance is insignificant and negative with low confidence. The marginal effect is highly significant and positive but decreasingly positive. The total effect in the relevant range is also positive[1]. This indicates that a real increase to Section 127 assistance would further boost enrollment, but such increases would be decreasingly effective.

H-1 visa effects are complex and important across specifications. The preferred model identifies a significant negative linear effect on enrollment from H-1B visa issuance. There is an insignificant positive marginal effect and a total negative effect. While the preferred model focuses on H-1B effects, analysis shows this is largely generalizable to the H-1 family. In fact, substituting H-1

[1]Elimination of nonlinear effects from the preferred model acts as a robustness check, identifies the direction of the total effect in the relevant range, and maintains significance for all factors. The real Section 127 assistance coefficient has a point estimate of 623 in such a model, and the H-1B visa issuance coefficient takes a value of about -15.

total issuance for the linear H-1B variable improves linear visa effect significance, although it does not improve raw or adjusted explanatory power for the model overall. That move also is not preferred because the linear effect and the marginal visa effects would then correspond to different measures.

Time is the most consistently significant variable across multiple regressive models. Time, measured in years, intuitively possesses a positive linear effect and a negative marginal effect on total enrollment. The total effect of time over the period of the analysis is also strongly positive. A simple regression of time on total enrollment has an adjusted r-squared of about .95. Analysis using specifications that are explicitly dynamic is motivated in part by early identification of such important time effects.

4.2. Dynamic Ordinary Least Squares Results

Dynamic ordinary least squares (DOLS) models supplement multiple regressive analysis in at least two ways. First, autocorrelation can be removed using lagged variables in an Anderson–Hsiao adjustment[5]. Second, atemporal marginal effects can be tested against marginal effects in a dynamic context, which improves model utility in an applied context.

Table 2 compares selected variables from two models of interest. Selected variables include any variable which appears in both models. The first model of interest is the preferred multiple regression with an Anderson-Hsiao adjustment. The Anderson-Hsiao adjustment involves three changes that allow an analyst to address an issue of actual or potential autocorrelation in the dependent variable. The first step in the adjustment is to leverage an instrumental variable regression instead of an ordinary least squares regression. The second step is to pick a particular instrumental variable, often called the Anderson-Hsiao estimator. The Anderson-Hsiao estimator is a twice lagged first difference of the dependent variable. The third step is to replace the dependent variable with the first difference of itself. After taking these three steps, the model is removed from overlapping periods, which contribute to autocorrelation over time. The second model of interest is the preferred DOLS model.

Table 2: Table of DOLS Regression on Total Enrollment, Selected Variables

	5	6
H-1B^2	-4.217e-06	7.578e-04++
	(5.768e-05)	(3.354e-04)
H-1B^3		-2.086e-09++
		(9.547e-10)
Real Limit - Ed	3.359e+02	-2.202e+02+
	(5.214e+02)	(1.014e+02)
Real Limit - Ed^2	-4.256e-04	5.406e-03++
	(1.294e-02)	(2.026e-03)
Year^2	-2.064e+04	-5.706e+01*
	(1.633e+04)	(1.489e+01)
R-sqr	0.5172	0.9252

Standard errors in parentheses

+ $p < 0.10$, ++ $p < 0.05$, * $p < .01$, ** $p < .001$

The preferred dynamic OLS model obtains an adjusted r-squared of about 0.85. In contrast, the simple adjustment to the preferred multiple regression obtains an adjusted r-squared of about 0.26. A surprising result is that the Anderson-Hsiao estimator is insignificant across various specifications, including the preferred DOLS model ($p = 0.51$). Time effects are independently significant in the model. These results indicate that the apparent autocorrelation is due to independent effects which are effectively proxied with the measure of time included in the data set.

While the Anderson-Hsiao estimator is insignificant, dropping that variable and running an ordinary regression reduces adjusted r-squared to 0.82, but all independent factors retain significance. This demonstrates comparative model robustness over the preferred multiple regression. For this reason, the preferred DOLS model, with or without instrumentation, is preferred to the preferred multiple regression identified as model 4 in Table 1.

Lagged employer assistance effects are insignificant when explaining the first difference in total enrollment. The first and second differences are significant. The current period linear and marginal effects are also significant. The first difference and the current period marginal effects are both significant and positively signed. This indicates that raising assistance within-period and between periods are both expected to boost enrollment at the margin. Both marginal effects follow an Inada-like pattern, where the marginal effect is decreasingly positive. The linear effect on employer assistance is significant and negative.

I now calculate the total effect of employer assistance. Model 6, the preferred model, is fit to the years 1992 through 2017. The average values for the relevant independent variables over this period include an average real assistance limit of 13942.22, an average squared assistance limit of $2.56x10^8$, an average first difference in assistance of -1228.18, and an average second difference of 122.87. Based on these values, the total effect of employer assistance over the model period is a decrease in enrollment by about 3.34 million[2]. Suppose a steady-state, where

[2]The total effect is the rounded result of solving $X = -220.1953 * 13942.22 + (2.56 * 10^8) *$

Section 127 assistance has been constant for more than three periods. In this situation, a \$1,000 increase over the next period would result in a value of \$1,000 for the first and second differences. In this situation, the effect of a dynamic \$1,000 real increase to employer assistance would be to increase enrollment by about 7.45 million[3].

First-difference, lagged, and current H-1B visa effects are all significant, but linear visa effects are not significant. DOLS specification reveals significant lagged marginal effects and positive lagged cubic effects. The lagged linear effect is isomorphic to the first difference in this specification, and the first difference is positive. The total lagged effect indicates that as lagged period visa count increases, the expected change in current period visa issuance is both positive and eventually increasingly positive.

Other than lagged effects, dynamic visa effects are consistent with an insightful refinement of visa effects identified under multiple regression analysis. For example, an insignificant positive quadratic effect is identified in the preferred ordinary multiple regression. In the preferred DOLS, a positive marginal effect is identified with significance. Moreover, a negative first difference is also identified with significance. It makes sense that forcing these related and opposing marginal effects into a single variable would lead to insignificance in a non-dynamic specification.

Using a dynamic specification, we can see that marginal effects are stable, but they move in different directions when issuance is increased with and without respect to time. Moreover, both of these factors face marginal effects that have an attenuating higher-order counterpart. The positive static marginal effect is attenuated by a negative cubic effect. The negative dynamic static marginal effect is attenuated by a positive and significant second-difference coefficient.

It is important to note that DOLS models explain a slightly smaller period

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$.0054062 + 1314.489 * -1228.18 - 355.0654 * 122.87$.

[3]The period-over-period effect from a steady-state is computed as $X = -220.1953 * 1000 + .0054062 * 1000 * 1000 + 1314.489 * 1000 - 355.0654 * 1000$.

of analysis because of the use of lagged variables. While the preferred multiple regression covers 27 annual samples from 1990 to 2016, the preferred DOLS model obtains a sample size of 25 over the period from 1992 to 2016.

In summary, DOLS analysis demonstrates non-robustness in the preferred non-dynamic model, then provides an alternative model that is significantly more robust, although it achieves a slightly lower level of explanatory power. DOLS analysis addresses concerns of potential autocorrelation, finding that autocorrelation is not an important concern. DOLS also provides rudimentary causal findings by identifying changes that are associated with results in the following period.

4.3. Vector Autoregression Results

Dynamic ordinary least squares provide rudimentary causal findings, but vector autoregression provides deeper analysis in this regard. Vector autoregression (VAR) improves on DOLS for the specific purpose of identifying potential natural or policy instruments. Difference and lag effects of the first and second orders were arbitrarily selected for investigated using DOLS. In contrast, VAR lag selection techniques involve rigorous selection criteria. Vector autoregression is also relatively straightforward with many periods of interest.

Employer assistance, visa, and time effects are the only factors in the preferred dynamic model. Prior analysis ruled out the significance of an interaction variable between visa and employer assistance effects. As a result, the two initial VAR models are both simple, two-variable models.

For the employer assistance model, an extended sample of 43 observations over the period from 1974 to 2016 is used. For the H-1B model, 24 samples over the period from 1994 to 2017 are used. Ivanov and Kilian find that the Schwarz Information Criterion, also called Schwarz's Bayesian information criteria (SBIC), is the most accurate selection criterion for sample sizes less than 120[20]. For that reason, I prefer this criterion. Fortunately, all significant selection criteria provided by STATA unanimously agreed in the case of lag selection for both models. Such criteria included SBIC, the likelihood ratio (LR), the final prediction error (FPE), Akaike Information Criterion (AIC), and Hannan-Quinn Information Criterion (HQIC). For both models, the optimal lag length is identified at two periods. The p-value for the optimal lag was less than 0.001 for both models.

VAR results for employer assistance are directionally consistent with prior analysis. A positive shock to employer assistance is associated with a downward parabola curve response. The response, however, is not significant for any period, even when using a 60 percent confidence interval.

VAR results for an H-1B policy impulse are significant. A positive shock to H-1B issuance is also associated with a downward parabola curve response. The effect is insignificant at the 0.5 level for the first two periods, but it reaches a significant positive effect in the third period. The positive effect plateaus in the seventh period, then it reverses and reaches a permanent zero effect in the eleventh period.

Increased enrollment reflects an increase in demand which is associated with increased tuition and debt both theoretically and in the present data[4]. From a policy perspective, increasing enrollment may not be desirable. Higher education has a great return from an individual perspective, but there are several concerns from a social perspective. Examples include concerns about grade inflation, credential inflation, experience inflation, and the social return to education spending abound. For example, Forbes magazine recently pointed out that the price of college is increasing almost eight times faster than wages[21]. Edvisors notes that the average tuition inflation rate is double the average CPI-U[22]. Many in the media consider the size of federal student loan debt to be a crisis. Because H-1B policy is an enrollment instrument, and enrollment is directly related to loans and real tuition, further analysis investigates a downstream effect

[4] A simple regression of total enrollment on total federal loans yields a positive coefficient with a p-value less than 0.001 and an adjusted r-squared of 0.973. A simple regression of total enrollment on CPI-adjusted real tuition yields a positive coefficient with a p-value less than 0.001 and an adjusted r-squared of 0.915.

of H-1B policy on loans or real tuition.

A short regression of three variables on total enrollment identifies a positive but insignificant (p ¡ 0.2) interaction between tuition and loans significantly interact. The independent variables include total loans, CPI-adjusted tuition, and an interaction variable. It is plausible that more sophisticated analysis may prove some kind of interaction exists, but even supposing significance, the correct Cholesky ordering is non-obvious. Based on the lack of interaction, further analysis scopes loans and tuition to separate models.

Figure 2: H-1B VAR Results

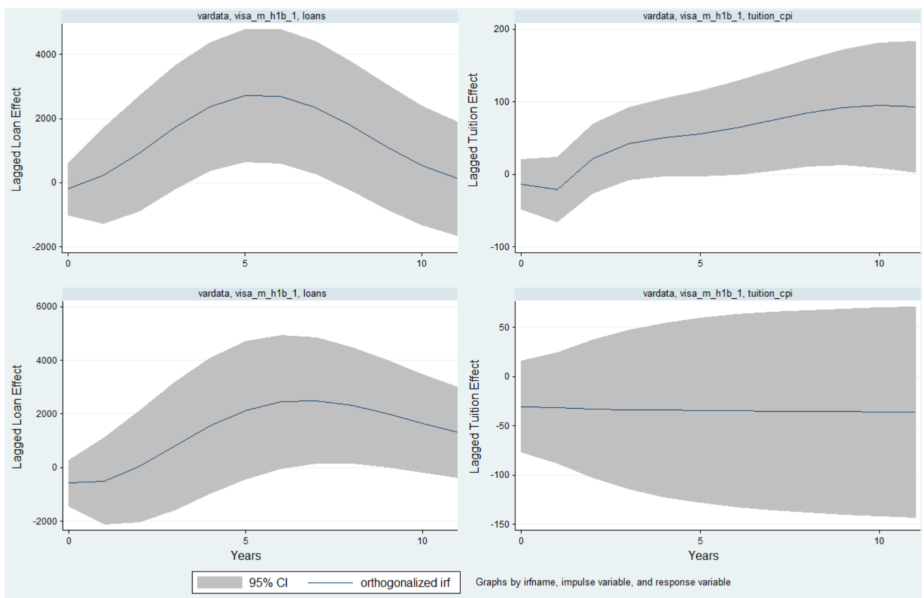

Figure 2 is a graphical representation of the VAR model results. The top row contains three-variable models of interest. In these models, an H-1B impulse generates a first-order enrollment response. The bottom row contains two-variable specifications that omit the intermediary enrollment response. On the left are the loan models, and on the right are the tuition models.

The figure makes the three-variable model preference clear for tuition, but some model statistics make the case stronger with respect to the loan models. In the two-variable loan VAR, the r-squared for the visa variable is less than 0.89, and the r-squared for the loan variable is less than 0.988. In the three-variable specification, the r-squared for the visa variable is greater than 0.913, and the r-squared for the loan variable is greater than 0.989. This confirms that the enrollment effect is model-improving rather than extraneous complexity.

Both three-variable models achieve significance at the 0.05 level. Both three-variable models are optimized for two lags based on the SBIC selection criterion. As previously discussed, I prefer the Schwarz Information Criterion because these models involve small sample sizes. The loan model has a sample size of 25 over the years from 1993 to 2017. The CPI-adjusted tuition model has a sample size of 25 over the years from 1992 to 2016.

The loan model anticipates a temporary increase in total loans, followed by an eventual return to zero. The tuition model allows for the same, but it also indicates the potential establishment of a new normal of high real tuition prices. It does not seem to be the case that a real-world shock would result in one or the other effect. Instead, a real-world H-1B shock would be expected to cause both effects. The interaction between loans and higher tuition effects is weak, as previously noted, but it is positively signed. These models understate the effects of interest if some positive interaction does obtain.

In summary, vector autoregression confirms H-1B visa issuance as a Granger-causal policy instrument. H-1B policy stimulus directly impacts enrollment and has further indirect effects on aggregate student loans and the real price of tuition. The dynamic response of enrollment and other dependent variables to employer assistance impulse is insignificant.

5. Conclusions

A surprising slowdown in enrollment is observed around the time Section 127 was created. Cappelli constrains a simple slow employer adoption hypothesis by demonstrating widespread adoption as early as 1993. Demand-side explanations do a fair job of explaining low enrollment until about 1980. From about

1980 until about 1993, several important economic and policy variations are identified.

References

[1] Vol. 92 STAT. 2763, 95th Congress, 1978. [link].
URL https://www.govinfo.gov/content/pkg/STATUTE-92/pdf/STATUTE-92-Pg2763.pdf

[2] P. Cappelli, Why do employers pay for college?, Journal of Econometrics 121 (1-2) (2004) 213–241.

[3] T. Cherry, Rejuvenating tuition reimbursement programs, HR Magazine 59 (6) (2014).

[4] TalentCulture, What does tuition assistance look like in 2018? (May 2018).
URL https://talentculture.com/tuition-assistance-look-like-2018/

[5] T. W. Anderson, C. Hsiao, Estimation of dynamic models with error components, Journal of the American statistical Association 76 (375) (1981) 598–606.

[6] D. Schenck, Structural vector autoregression models (Sep 2016).
URL https://blog.stata.com/2016/09/20/structural-vector-autoregression-models/

[7] N. National Center for Education Statistics, Table 303.10, total fall enrollment in degree-granting postsecondary institutions, by attendance status, sex of student, and control of institution: Selected years, 1947 through 2028 (2019).
URL https://nces.ed.gov/programs/digest/d18/tables/dt18_303.10.asp

[8] U. B. o. E. A. BEA, Personal consumption expenditures (Feb 2020).
URL https://fred.stlouisfed.org/series/PCE

[9] N. National Center for Education Statistics, Table 330.10, average undergraduate tuition and fees and room and board rates charged for full-time students in degree-granting postsecondary institutions, by level and control of institution: Selected years, 1963-64 through 2016-17 (2017).
URL https://nces.ed.gov/programs/digest/d17/tables/dt17_330.10.asp

[10] Vol. 100 STAT. 2510, 99th Congress, 1986. [link].
URL https://www.govtrack.us/congress/bills/99/hr3838/text

[11] A. Glass, Roosevelt signs the gi bill of rights into law, june 22, 1944 (Jun 2010).
URL https://www.politico.com/story/2010/06/roosevelt-signs-the-gi-bill-of-rights-into-law-june-22-1944-038814

[12] D. o. Veterans Affairs, Veterans educational assistance program (veap) (Mar 2017).
URL https://www.benefits.va.gov/gibill/veap.asp

[13] R. Powers, Learn about the gi bill for post-9/11 active duty service members (Dec 2018).
URL https://www.thebalancecareers.com/gi-bill-for-the-21st-century-3347143

[14] D. o. Veterans Affairs, Forever gi bill - harry w. colmery veterans educational assistance act (Jan 2020).
URL https://www.benefits.va.gov/GIBILL/FGIBSummaries.asp

[15] FinAid, Loans: Historical loan limits (2020).
URL https://www.finaid.org/loans/historicallimits.phtml

[16] C. A. Bureau of, Nonimmigrant visa statistics, nonimmigrant visas by individual class of admission (e.g. a1, a2, etc.) (2020).
URL https://travel.state.gov/content/travel/en/legal/visa-law0/visa-statistics/nonimmigrant-visa-statistics.html

[17] N. G. Ruiz, Key facts about the us h-1b visa program, Washington, DC: Brookings (2017).

[18] T. College Board, Trends in student aid 2019 excel data, table 2_ug (2019). URL https://research.collegeboard.org/xlsx/trends-student-aid-excel-data.xlsx

[19] T. College Board, Trends in student aid 2019 (2019). URL https://research.collegeboard.org/trends/student-aid

[20] V. Ivanov, L. Kilian, A practitioner's guide to lag order selection for var impulse response analysis, Studies in Nonlinear Dynamics & Econometrics 9 (1) (2005).

[21] C. Maldonado, Price of college increasing almost 8 times faster than wages, Forbes Magazine Online (2018).

[22] Edvisors, Why do tuition rates rise faster than inflation? (Dec 2019). URL https://www.edvisors.com/plan-for-college/saving-for-college/tuition-inflation/