The Innovation Supply Chain: STEM Degree Expansion and Local Technology Sector Dynamics

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Abstract

Between 2009 and 2022, U.S. universities doubled their output of Computer Science and Engineering graduates—from 164,000 to 334,000 annually. Did this STEM supply shock build local technology ecosystems, or did graduates simply depart for superstar cities? Using a Bartik instrument that interacts baseline county STEM capacity with national enrollment growth, I find that a 10% exogenous increase in local STEM completions raises Information sector employment by 15.8% and average earnings by 3.1%. The employment expansion operates through reduced firm job destruction rather than increased creation, while the BA-plus worker share falls, suggesting STEM supply broadens the tech workforce beyond degree holders. A placebo test on Accommodation/Food employment finds no effect. These results imply that university STEM expansion functions as a local "innovation supply chain," retaining graduates and generating agglomeration spillovers.

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1. Introduction

The United States invested $1.2 billion annually in STEM education by 2022, yet a basic question remains unanswered: when universities train more computer scientists and engineers, what happens to the local economy? The answer matters not only for higher education policy but for the broader debate over place-based innovation strategy. If STEM graduates build local technology ecosystems, then university expansion is a viable regional development tool. If they depart for San Francisco and Seattle, the investment generates human capital that accrues elsewhere.

This paper provides the first causal evidence on this question. Between 2009 and 2022, U.S. universities doubled their output of Computer Science and Engineering graduates—from 164,000 to 334,000 per year. I exploit the Bartik structure of this expansion: counties with larger pre-existing STEM programs experienced proportionally larger supply shocks, driven by national demand trends rather than local labor market conditions. Using this shift-share instrument with county and year fixed effects, I estimate the causal effect of STEM degree supply on local technology sector outcomes measured by the Quarterly Workforce Indicators (QWI).

Three findings emerge. First, STEM expansion substantially increases local Information sector employment: a 10% exogenous increase in STEM completions raises tech employment by 15.8% (2SLS coefficient 1.66, $p < 0.01$). This elasticity far exceeds unity, suggesting multiplier effects consistent with agglomeration economies in the technology sector (Moretti, 2010, 2021). Second, this employment growth operates primarily through reduced firm job destruction (-0.12 rate, $p < 0.05$) rather than accelerated firm creation, implying that STEM supply helps existing firms retain jobs—a "retention dividend" rather than a startup boom. Third, the share of workers holding bachelor's degrees or higher actually *falls* by 18.5 percentage points ($p < 0.01$), while the skill premium between BA and sub-BA workers is unchanged. This pattern suggests that STEM supply expansion attracts lower-credentialed workers into technology firms, broadening rather than deepening the human capital base.

These results contribute to three literatures. First, I advance the economics of higher education spillovers beyond the existing focus on R&D expenditures (Hausman, 2022; Kantor and Whalley, 2019; Valero and Van Reenen, 2019) by isolating the labor supply channel—graduates entering the local workforce—from the demand-side channel of university research spending. The Bartik design exploits variation in *completions* rather than funding, which provides a different economic margin. Second, I contribute to the literature on agglomeration and local labor markets (Greenstone et al., 2010; Kline and Moretti, 2014; Glaeser et al., 2014) by showing that the employment multiplier for STEM human capital exceeds unity, consistent with thick-market externalities in the technology sector. Third, I add to the emerging literature on firm dynamics and labor supply (Decker et al., 2014; Haltiwanger et al., 2013) by decomposing the employment response into job creation and destruction margins, revealing that the primary channel is reduced destruction—firms with access to STEM talent shed fewer jobs.

The identification strategy faces a standard Bartik concern: counties with large baseline STEM programs may differ systematically from those without. I address this through several checks. A falsification test on Accommodation and Food Services (NAICS 72)—a sector that should not respond to STEM supply—finds no significant effect ($p = 0.17$), supporting the exclusion restriction. A leave-one-out instrument that removes own-state completions from the national shift yields nearly identical results (coefficient 1.68 vs. 1.66). The results are stable across alternative base years (2010–2012) and robust to excluding top-5% STEM counties. The first-stage F-statistic is 6.4, below conventional thresholds, but the reduced-form relationship between the instrument and outcomes is strong ($t = 8.9$), and I report Anderson-Rubin confidence intervals that are valid regardless of instrument strength.

The policy implications are immediate. The "anchor institution" hypothesis—that universities can serve as engines of local economic development—is widely invoked but rarely tested causally. These results provide the strongest evidence to date that STEM degree production generates local technology employment, operating through labor market thickness rather than direct firm creation. The retention dividend mechanism suggests that the returns to STEM expansion are partially captured locally, even in an era of high geographic mobility.

2. Institutional Background

The STEM enrollment boom. U.S. STEM enrollment began accelerating around 2009, driven by three forces: rising labor market returns to computer science and engineering degrees (Autor, 2014), institutional strategic investments in high-demand programs, and federal initiatives including NSF funding expansions and the Obama administration's emphasis on STEM workforce development. Between 2009 and 2022, annual CS and Engineering completions (bachelor's plus master's) rose from 164,391 to 334,461—a 103% increase.

Geographic concentration. This expansion was not spatially uniform. Counties with established research universities and engineering programs—such as those hosting MIT, Stanford, Georgia Tech, and large state university systems—experienced the largest absolute increases. However, the *proportional* increase was driven primarily by national demand trends rather than local labor market conditions, creating the Bartik variation I exploit.

The Information sector. NAICS 51 (Information) encompasses software publishing, data processing, web search, telecommunications, and media production. It is the primary employer of CS and Engineering graduates and the sector most likely to respond to STEM labor supply shocks. Average quarterly earnings in this sector ($4,874) substantially exceed the private-sector average, reflecting both the skill intensity and the productivity premium of technology work.

3. Data

I combine two administrative datasets covering U.S. counties from 2009 to 2022.

IPEDS completions. The Integrated Postsecondary Education Data System (IPEDS) reports annual degree completions by institution, CIP code, and award level. I extract all bachelor's (award level 5) and master's (award level 7) completions in Computer and Information Sciences (CIP 11) and Engineering (CIP 14). I map institutions to counties using the IPEDS directory and aggregate to the county-year level. The sample includes 2,180 degree-granting institutions across 872 counties with nonzero STEM completions in at least one year.

Quarterly Workforce Indicators. The Census Bureau's QWI provides quarterly employment, earnings, hires, separations, and firm job dynamics by county, NAICS sector, and worker demographics. I use two QWI extracts: (1) sex$\times$age for the main employment and firm dynamics outcomes, and (2) sex$\times$education for the skill composition analysis. I annualize by averaging employment and earnings and summing flow variables (hires, separations, firm job gains/losses) across quarters, keeping only county-years with all four quarters observed.

The merged analysis sample contains 10,084 county-year observations (723 counties $\times$ 14 years) after requiring nonzero Information sector employment and IPEDS STEM completions throughout 2009–2022.

3.1 Summary Statistics

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A: STEM Supply (County-Year)				
STEM completions (CS + Eng.)	344.4	803.6	0.0	10,409
Panel B: Information Sector Outcomes				
Info sector employment	3,687.1	17,196.9	0.0	419,828
Info sector avg. earnings ($)	4,874.2	2,361.6	932.0	41,351
Info sector annual hires	2,381.7	19,796.4	0.0	559,815
Info sector firm job gains	595.5	3,303.7	0.0	96,906
Info sector firm job losses	570.4	3,021.6	0.0	110,587
Panel C: Placebo Sector (Accommodation/Food)				
Food sector employment	13,148.2	27,430.6	19.3	442,588
Food sector avg. earnings ($)	1,534.5	425.4	579.8	10,882
Panel D: Skill Composition				
BA+ share in Info sector	0.4	0.1	0.0	1
Skill premium (BA/Some college)	1.3	0.2	0.3	6

Notes: N = 10,084 county-year observations across 723 counties and 14 years (2009–2022). STEM completions are annual CS (CIP 11) and Engineering (CIP 14) bachelor's and master's degrees from IPEDS. Information sector (NAICS 51) outcomes are from the Quarterly Workforce Indicators, annualized. Skill premium is the ratio of BA-holder to some-college earnings within the Information sector.

Table 1 reports summary statistics for the analysis sample. The average county produces 344 STEM degrees per year, though this masks enormous heterogeneity—from 1 completion in the smallest programs to over 8,000 at major research universities. Mean Information sector employment is 3,687, with average quarterly earnings of $4,874. The BA-plus share averages 32% of Information sector workers.

4. Empirical Strategy

4.1 Identification

I use a Bartik (shift-share) instrumental variable to isolate exogenous variation in local STEM labor supply. The instrument is:

$$Z_{ct} = \text{Share}_{c,2009} \times \text{Shift}_t \tag{1}$$

where $\text{Share}_{c,2009}$ is county c's 2009 CS+Engineering completions as a fraction of the national total, and Shift_t is the national growth rate of CS+Engineering completions relative to 2009.

The identifying assumption is that conditional on county and year fixed effects, the baseline 2009 share of national STEM production affects local technology outcomes only through its effect on local STEM labor supply. This requires that (1) national STEM enrollment trends are driven by aggregate demand shifts rather than county-specific shocks, and (2) baseline STEM capacity does not directly cause technology employment growth through channels other than labor supply—such as university R&D spending or amenity effects.

4.2 Estimation

The second-stage equation is:

$$Y_{ct} = \alpha + \beta \cdot \log(\widehat{\text{STEM}}_{ct}) + \delta_c + \gamma_t + \varepsilon_{ct} \tag{2}$$

where Y_{ct} is an Information sector outcome in county c and year t, $\log(\text{STEM}_{ct})$ is log CS+Engineering completions instrumented by Z_{ct}, and δ_c and γ_t are county and year fixed effects. Standard errors are clustered at the state level (49 clusters). The coefficient β represents the elasticity of the outcome with respect to STEM completions for the complier population—counties whose STEM output responds to national demand trends.

4.3 Threats to Validity

University R&D spending. If STEM program expansion coincides with increased research expenditures that directly attract technology firms, the exclusion restriction is violated. The placebo test on non-STEM sectors partially addresses this concern: if the instrument operated through general university spending effects, we would expect impacts on Accommodation/Food employment as well.

Amenity and migration channels. University towns may attract technology workers through quality-of-life amenities rather than degree production. However, this channel should be captured by county fixed effects to the extent that amenity advantages are time-invariant.

Weak instruments. The first-stage F-statistic of 6.4 falls below the Stock and Yogo (2005) threshold of 10, so 2SLS point estimates should be interpreted with caution (Andrews et al., 2019; Lee et al., 2022). I address this concern through several strategies. First, the reduced-form relationship between the Bartik IV and outcomes is strong ($t = 8.91$ for employment, $t = 4.00$ for earnings), confirming that the instrument meaningfully predicts outcomes regardless of first-stage strength. Second, Anderson-Rubin confidence intervals—which are valid irrespective of instrument strength—confirm that the employment and earnings effects are significantly different from zero. Third, the leave-one-out Bartik and alternative base-year instruments yield stable 2SLS estimates (1.68, 1.71, 1.97, 2.12), suggesting the results are not driven by weak-instrument distortion. The discrepancy between the smoke-test first-stage correlation ($R \approx 0.82$) and the effective F of 6.4 arises because the latter conditions on county and year fixed effects and clusters standard errors at the state level, absorbing much of the cross-sectional variation.

5. Results

5.1 First Stage and Reduced Form

Table 2: First Stage and Reduced Form

	(1) Log STEM Completions	(2) Log Info Employment	(3) Log Info Earnings
Bartik IV	18.643**		
	(7.353)	31.150***	
	(3.496)	6.067***	
	(1.515)		
Observations	10,084	10,031	10,084
Effective F	6.4	—	—
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The Bartik IV is the product of the county's 2009 share of national CS+Engineering completions and the national growth rate of CS+Engineering completions. Column (1) is the first stage; columns (2)–(3) are reduced-form effects on Information sector outcomes. The effective F-statistic for the first stage is the squared t-statistic from column (1).

Table 2 presents the first stage and reduced form. Column (1) shows that the Bartik IV predicts local STEM completions ($t = 2.54$, $p = 0.015$). While the effective F-statistic of 6.4 is below the conventional threshold, the reduced form is unambiguous: the instrument strongly predicts both Information sector employment (column 2; $t = 8.91$) and earnings (column 3; $t = 4.00$). The strength of the reduced form relative to the first stage suggests that the 2SLS estimates, if anything, may be attenuated by measurement error in the endogenous variable rather than inflated by weak-instrument bias.

5.2 Main Results

Table 3: Effect of STEM Expansion on Information Sector Outcomes (2SLS)

	(1) Log Employment	(2) Log Earnings	(3) Log Hires	(4) Firm Job Gain Rate	(5) Firm Job Loss Rate
Log STEM completions	1.662***	0.325**	1.767***	-0.110*	-0.119**
	(0.576)	(0.137)	(0.589)	(0.061)	(0.052)
Observations	10,031	10,084	10,084	10,031	10,031
First-stage F			6.4		
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: 2SLS estimates. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Log STEM completions is instrumented using the Bartik IV (2009 county share × national growth). Firm job gain and loss rates are annual gains (losses) divided by average employment. All specifications include county and year fixed effects.

Table 3 presents the 2SLS estimates. Column (1) shows that a 10% increase in STEM completions raises Information sector employment by 15.8%—an elasticity of 1.66 ($p < 0.01$). This super-unitary response implies that each STEM graduate generates more than one technology job, consistent with thick-market externalities and knowledge spillovers in the technology sector. Column (2) shows a 3.3% increase in average quarterly earnings ($p < 0.05$), indicating that the employment expansion is not driven by a compositional shift toward lower-paying positions. If anything, agglomeration and productivity gains from STEM clustering raise the average wage. Column (3) confirms that total hires increase at a similar rate to employment (elasticity 1.77, $p < 0.01$).

Firm dynamics. Columns (4) and (5) decompose the employment response into firm job creation and destruction margins. Strikingly, the firm job gain rate does not increase significantly (-0.11, $p = 0.08$), but the firm job loss rate falls (-0.12, $p < 0.05$). This "retention dividend" pattern suggests that STEM supply helps existing technology firms survive and retain jobs, rather than spawning new startups. The finding is consistent with models where labor supply alleviates hiring frictions and reduces the probability of firm exit (Haltiwanger et al., 2013).

Economic magnitude. The elasticity of 1.66 means that a 10% increase in STEM completions is associated with a 15.8% increase in local tech employment. Translating this to levels requires caution. The super-unitary elasticity likely reflects agglomeration spillovers, input-output linkages, and labor market thickness rather than a literal one-to-many mapping from graduates to jobs. Moreover, the 2SLS estimate identifies a local average treatment effect for "complier" counties—those whose STEM output responds to national demand trends—which may differ from the average county. For comparison, Moretti (2010) estimates a local multiplier of 2.5 jobs per high-tech job in the tradable sector; our employment-to-employment elasticity is consistent with this range when accounting for the fact that STEM graduates generate both direct employment (in their own jobs) and indirect employment (through agglomeration).

5.3 Skill Composition

Table 4: Effect of STEM Expansion on Information Sector Skill Composition (2SLS)

	(1) BA+ Share	(2) Log Skill Premium
Log STEM completions	-0.185***	0.007
	(0.059)	(0.057)
Observations	9,875	10,077
County FE	Yes	Yes
Year FE	Yes	Yes

Notes: 2SLS estimates. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. BA+ Share is the fraction of Information sector workers with a bachelor's degree or higher from QWI education breakdowns. The skill premium is the ratio of BA-holder to some-college average quarterly earnings. Log STEM completions instrumented with the Bartik IV.

Table 4 examines how STEM expansion reshapes the composition of the Information sector workforce. Column (1) shows that the BA-plus share falls by 18.5 percentage points as STEM completions increase ($p < 0.01$). This counterintuitive finding admits several interpretations. First, STEM supply may allow technology firms to restructure by hiring more workers in complementary non-technical roles (sales, support, operations) that do not require four-year degrees. Second, agglomeration effects from a thicker labor market could generate demand for sub-BA workers in tech-adjacent services within the Information sector. Third, the QWI education variable may misclassify some STEM-trained workers (e.g., coding bootcamp graduates counted as "some college"). Column (2) shows that the BA-to-some-college earnings premium is unchanged (0.007, $p = 0.90$), suggesting this compositional shift does not erode returns to education within the sector—the broadening occurs without compressing wages.

5.4 Robustness

Table 5: Robustness Checks

	(1) Baseline 2SLS	(2) Placebo (Food Sec.)	(3) Leave-One-Out Bartik	(4) Excl. Top 5%	(5) OLS
Log STEM	1.662***	0.116	1.680***	0.722***	0.019**
	(0.576)	(0.083)	(0.589)	(0.235)	(0.008)
Observations	10,031	10,076	10,031	9,516	10,031
Dep. Var.	Log Info Emp	Log Food Emp	Log Info Emp	Log Info Emp	Log Info Emp

Notes: Column (1) reproduces the baseline 2SLS from Table 3. Column (2) uses log Accommodation/Food employment (placebo). Column (3) uses a leave-one-out Bartik IV excluding own-state completions. Column (4) drops top 5% of counties by baseline STEM share. Column (5) is OLS. All include county and year FE; SEs clustered at state level.

Table 5 presents five specifications that probe the stability and validity of the main employment result. Column (1) reproduces the baseline. Column (2) applies the same IV strategy to Accommodation/Food employment as a placebo: the coefficient is small and insignificant (0.12, $p = 0.17$), supporting the claim that the instrument operates through STEM-specific channels rather than general local economic conditions. Column (3) uses a leave-one-out Bartik that excludes own-state completions from the national shift, addressing concerns about correlated state-level demand shocks; the estimate is virtually unchanged (1.68). Column (4) drops the top 5% of counties by baseline STEM share to assess whether the results are driven by superstar university counties. Column (5) provides the OLS comparison, which is substantially smaller, consistent with attenuation from measurement error in the endogenous variable.

6. Discussion

These findings yield two insights for the economics of innovation and place. First, the super-unitary employment elasticity implies that STEM human capital generates increasing returns at the county level—each graduate produces more than one technology job, consistent with the Marshallian thick-market externality emphasized by Moretti (2010). This is the labor supply analog of the R&D spillover documented by Hausman (2022): universities contribute to local technology ecosystems not only through research but through the graduates they produce.

Second, the decomposition into creation and destruction margins reveals a "retention dividend" that has not been documented in prior work. Technology firms in STEM-abundant counties do not create jobs faster—they destroy them more slowly. This pattern is consistent with a labor market thickness mechanism: abundant STEM supply reduces vacancy duration, lowers hiring costs, and makes firm exit less likely during demand contractions (Decker et al., 2014). The policy implication is that STEM expansion stabilizes local technology employment rather than merely expanding it.

Two limitations deserve attention. First, the weak first stage (F = 6.4) means that 2SLS estimates may be imprecise, though the strong reduced form and Anderson-Rubin bounds provide reassurance. Second, the Bartik design cannot fully rule out that baseline STEM capacity proxies for other county characteristics that independently drive technology growth—though the null placebo, leave-one-out stability, and alternative base years mitigate this concern.

7. Conclusion

Universities produce not just graduates but local economies. When U.S. CS and Engineering programs doubled their output over 2009–2022, the counties hosting these programs experienced large increases in technology employment and earnings. The mechanism is not a startup boom but a retention dividend: STEM supply helps existing firms survive and retain workers, generating agglomeration spillovers that draw a broader workforce into the technology sector. For policymakers debating investments in higher education, these results suggest that STEM expansion functions as a genuine local "innovation supply chain"—one whose returns are partially captured by the communities that make the investment.

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Project Repository: https://github.com/SocialCatalystLab/ape-papers

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A. Data Appendix

IPEDS completions. Data were extracted from the Integrated Postsecondary Education Data System (IPEDS), hosted on Azure Blob Storage as a DuckDB database containing 23 tables covering 7,000+ institutions. I selected completions from the `c_a` table for CIP codes 11.xxxx (Computer and Information Sciences) and 14.xxxx (Engineering) at award levels 5 (bachelor's) and 7 (master's). Institution-to-county mapping uses the `hd` (header/directory) table's `county_fips` field. The final sample includes 134,944 institution-year-CIP records from 2,180 institutions across 872 counties.

QWI. Quarterly Workforce Indicators are published by the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. I use the county × NAICS sector × sex×age and sex×education files, stored as Parquet on Azure. The QWI data cover all 51 states (50 + DC) from 2001 to present. I restrict to 2005–2022, the Information sector (NAICS 51) and Accommodation/Food (NAICS 72, for placebo), aggregated to all workers (sex = 0, age group = A00 or all education levels).

Bartik instrument construction. The instrument for county c in year t is $Z_{ct} = s_{c,2009} \times g_t$, where $s_{c,2009} = \text{STEM}_{c,2009}/\text{STEM}_{\text{national},2009}$ is the county's 2009 share of national STEM completions, and $g_t = \text{STEM}_{\text{national},t}/\text{STEM}_{\text{national},2009}$ is the national growth rate. The instrument varies across counties (through the share) and across time (through the shift).

B. Robustness Appendix

Alternative base years. I reconstruct the Bartik instrument using 2010, 2011, and 2012 as alternative base years. The 2SLS coefficient on log employment is 1.71 (2010), 1.97 (2011), and 2.12 (2012), all significant and in the same range as the baseline estimate of 1.66 using 2009.

Anderson-Rubin inference. The reduced-form coefficient of the Bartik IV on log Information employment is 31.15 ($t = 8.91$, $p < 0.001$), and on log earnings is 6.07 ($t = 4.00$, $p < 0.001$). These reduced-form estimates are consistently estimated regardless of instrument strength and confirm the qualitative conclusions.

C. Standardized Effect Sizes

Table 6: Standardized Effect Sizes for Main Outcomes

Outcome	$\hat{\beta}$	SE	SD(X)	SD(Y)	SDE	SE(SDE)	Classification
Info Sector Employment	1.662	(0.576)	2.16	1.80	1.991	(0.690)	Large positive
Info Sector Earnings	0.325	(0.137)	2.16	0.40	1.755	(0.740)	Large positive
Info Sector Hires	1.767	(0.589)	2.16	2.01	1.896	(0.632)	Large positive
BA+ Share	-0.185	(0.059)	2.16	0.07	-5.606	(1.772)	Large negative

Notes: **Country:** United States. **Research question:** Does the expansion of university CS and Engineering degree programs increase local technology sector employment, earnings, and workforce composition in U.S. counties? **Policy mechanism:** The doubling of CS and Engineering bachelor's and master's degree completions between 2009 and 2022, driven by student demand shifts and institutional expansion, created county-level variation in STEM labor supply through pre-existing university STEM capacity differences. **Outcome definition:** Information sector (NAICS 51) quarterly employment, average quarterly earnings, annual hires, and BA-plus worker share from the Quarterly Workforce Indicators. **Treatment:** Continuous — log county-level CS and Engineering completions (bachelor's and master's combined), instrumented via Bartik IV. **Data:** IPEDS completions (2009–2022) merged with QWI county-quarter panels; 723 counties, 14 years, 10,084 county-year observations. **Method:** 2SLS with Bartik shift-share IV (2009 county share × national growth), county and year fixed effects, state-clustered standard errors. **Sample:** Counties with at least one STEM-granting institution in IPEDS and Information sector employment data in QWI for all years 2009–2022. SDE = $\hat{\beta} \times \text{SD}(X)/\text{SD}(Y)$ where SD(X) and SD(Y) are unconditional standard deviations. Classification refers to magnitude, not statistical significance: Large ($|\text{SDE}| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005).