The Effects of Place-Based Policies on Innovation and Entrepreneurship: Evidence from 3D Printing

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ABSTRACT: What is the impact of place-based policies on the direction of technological development and innovation solving grand challenges, and what firms benefit most? In 2012 the U.S. government announced the establishment of the first National Additive Manufacturing Innovation Institute (NAMII) in Youngstown, Ohio, which was a pilot institute for a broader network to address the grand challenges of modernizing American manufacturing, including promoting technological sovereignty and sustainability. We track U.S. patents by government contractors, universities, and other organizations from 2006 to 2019, and using a difference-in-differences design, we find large increases in annual patenting for 3D-printing technology compared to other patenting by the same organizations post-NAMII. The largest gains occurred in upstream portions of the value chain and in 3D-printing inventions classified as "green", suggesting policy success. The initiative intended to attract both public and private participation, including incumbent and new firms; however, we find greater increases for established U.S.-government contractors than for other organizations post-policy, regardless of their proximity to Youngstown. Startups experienced a net decline in patenting post-policy, with the sharpest negative effects concentrated among those near the Youngstown hub. This is consistent with local crowding out by large incumbents. Early-mover startups active in 3D printing before NAMII were the most displaced. Simultaneously, universities, including U.S.-contractor universities, were unaffected. These results imply that place-based policy can achieve its technological goals, but disadvantages the local entrepreneurial ecosystem it was designed to stimulate. Our findings have implications for value capture in sectors where innovation cycles are long and path-dependent, and thus tend to be targets of policy interventions.

JEL: B52, O33, O34, O38

Keywords: patents; place-based policy; innovation sustainability, additive manufacturing; 3D printing, grand challenges

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While states can fund innovation, it is unclear whether they are effective in stimulating it (Pavitt and Walker, 1976; Romer, 2000; Jaffe *et al.*, 2001; Furman, Murray and Stern, 2012; Radicic, 2019; Krieger and Zipperer, 2022; Howell, 2024). There's a long history of programs that failed to generate real impact, especially in technologies with long development cycles or complex commercialization timelines (Fabre and Straub, 2023). Nevertheless, governments continue to enact place-based policies designed to foster agglomeration economies and encourage technological spillovers (Kline and Moretti, 2014), particularly ones that may help solve large societal and environmental problems that otherwise lack private-sector participation. What is the impact of place-based policy on entrepreneurship and innovation for technologies aimed to solve so-called 'grand challenges', and what firms—incumbents or new entrants—capture the most value?

In complex interventions involving several actors, the risk is that public interventions reinforce the positions of incumbent firms who withhold information or disincentivize innovation and efficiency (Laffont and Tirole, 1993). This concern is especially acute for digital technologies. Digital technologies are characterized by high sunk costs, giving them a natural monopoly nature. Digital technologies also scale differently from physical ones, often more rapidly, conferring early advantages to firms with strong network effects. Who benefits and what kind of innovation gets produced from place-based policy has long-term implications for the competitive dynamics of nascent technology markets solving grand challenges (Fabre and Straub, 2023).

This paper examines one such intervention: the 2012 launch of the first U.S. National Additive Manufacturing Innovation Institute (NAMII) based in Youngstown, Ohio. The pilot institute targeted additive manufacturing (also known as 3D printing) as a key technology to

modernize U.S. manufacturing. This sector, both historically "dirty" and politically salient, has long been a focus of public policy. Rebranded 'America Makes', the U.S. government aimed to stimulate applied R&D, reduce development risk, and build the 3D-printing ecosystem by funding public-private collaborations under a larger, national network. We examine whether the 'America Makes' initiative changed patterns of innovation, and for whom, using a difference-in-differences empirical design and U.S. patent data from 2006 to 2019. Uncertainty surrounding policy effectiveness is even more pressing considering how the green agenda is unfolding alongside digitization. This "twin transition" introduces new complications. The global, interconnectivity of digital technology raises questions about the incompatibility of standards, supply chains, and infrastructure for artificial intelligence, high-performance computing, manufacturing, and energy, for example, with implications for national security (Greenstein, 2019; Crespi *et al.*, 2021; Edler *et al.*, 2023; Edler, 2024).[1]

Results show that yearly patenting in additive manufacturing increased on average for U.S.-government contractors, universities, and private firms after the 2012 federal funding of 'America Makes'. The effect is heterogenous across firms. U.S.-government contractors were more likely to increase their patenting per year in 3D-printing subclasses as compared to other patent classes than non-U.S. government contractors, with the largest gains concentrated in upstream, "green" technologies, which is consistent with policy goals. However, the benefits were captured almost entirely by established U.S. government contractors, regardless of their proximity to the Youngstown hub. Startups experienced a net decline in patenting post-policy,

[1] Twin transition innovation policy with technological sovereignty components involves more than stimulating R&D through one-time grants or procurement projects. Instead, many countries have enacted large-scale industrial and innovation policy that combine multiple, overlapping interventions, often with a place-based component or involving public-private partnerships, for grand challenges that address simultaneous environmental and societal needs (Howell, 2024).

with the sharpest negative effects concentrated among startups near the policy hub, which is consistent with local crowding out once incumbent contractors entered the regional ecosystem. Universities, which are often key enablers of basic science, were minimally affected by 'America Makes', and universities who are U.S.-government contractors did not differ in their patent filings compared to non-contractor universities. These findings suggest that place-based policy can achieve its technological goals while simultaneously displacing the local entrepreneurs it was designed to help.

This paper contributes to ongoing debates about the design and impact of place-based policy. While many studies investigate the effectiveness of policies encouraging innovation input or R&D (Baghana and Mohnen, 2009; Ientile and Mairesse, 2009; Foreman-Peck, 2013) and ARPA-model innovation policy on patents or publications (Bonvillian, 2018; Azoulay et al., 2019), few studies look at the direction of this innovation. Even less attention has been paid to place-based policy for 'grand challenges', which addresses complex problems whose solutions in the form of new technologies and products are critical to addressing the public sector's unmet needs (Furman, Murray and Stern, 2012; Mowery, 2012; Agarwal, Kim and Moeen, 2021). One potential by-product of our findings is the potential for patent thickets around foundational, upstream 3D-printing innovation by existing U.S.-government contractor firms. Future research should investigate incumbent-startup collaboration as a solution: could startups have avoided displacement by partnering with incumbent government contractors? Findings are particularly relevant for industries where innovation cycles are long, resource-intensive, and implicate technological sovereignty, such as artificial intelligence, biotech, semiconductors, and space.

Theory Development

Early entry to nascent markets can result in the competitive dominance of some firms (Anderson and Tushman, 1990; Sorenson, 2000). Investigating entry strategies, such as whether and when firms should enter nascent markets, is the focus of much scholarly work (*see* Eggers and Moeen, 2021). Firms may hesitate to enter nascent markets when the costs of research and development (R&D) or scaling production are prohibitively high for a new technology. Certain critical societal and environmental goals, such as sustainable manufacturing, twin transition, technological sovereignty, or climate change mitigation, involve large-scale, high-risk, and long-term investment with uncertain payoffs. These characteristics reduce private sector incentives to address them without government involvement (Agarwal, Kim and Moeen, 2021). Markets alone often fail to internalize social benefits fully or act quickly enough in response to time-sensitive needs. The U.S., UK, EU, and OECD countries leverage new policy instruments in cases of such market failure (Armitage, Bakhtian and Jaffe, 2024). Public-private collaboration in the form of place-oriented policy becomes crucial in these contexts (George *et al.*, 2016; Agarwal, Kim and Moeen, 2021; Howell, 2024).

Place-based policies differ from more traditional person-based policies in that they target specific geographic areas for treatment, from substitutes to public investment, as opposed to taxpayers or households. This is particularly useful when regions or nations exhibit areas of underdevelopment. Place-based policies are a popular form of industrial policy where the government aims to (1) provide public amenities (e.g., safety); (2) address labor market frictions (e.g., when unemployment is disproportionately high); (3) solve missing insurance or credit constraints (e.g., external shocks prevent consumption); or (4)

solve a pre-existing distortion (e.g., disparity in income or minimum wage) (Kline and Moretti, 2014). When it comes to technology, place-based policies also target agglomeration economies, or investment in innovation in a certain industrial location with the hope that its byproducts will spillover to create a broader ecosystem for that technology. Additive manufacturing is a nascent technology with large economic and transformative potential, but with little actual impact on value creation in the private sector, leading to inconsistent investment and adoption across geographies and industries (Martinelli, Mina and Moggi, 2021; Hahn and Massini, 2024).[2] This explains why it became a target for place-based policy in 2012.

The setting for this paper is the additive manufacturing or 3D-printing industry. The U.S. government established the National Additive Manufacturing Innovation Institute (NAMII) as a pilot institute in August of 2012 in Youngstown, Ohio. This policy was expanded and formalized under the National Network of Manufacturing Innovation (rebranded 'America Makes') as part of the FY2013 national budget, which began the prioritization of standard-setting and federal funding of basic science and development of additive manufacturing technology. 'America Makes' and future Institutes of Manufacturing Innovation leverage supply-side policy tools (Edler and Georghiou, 2007) to fund public-private partnerships.[3] The goals of 'America Makes' are to (1) advance additive manufacturing technology; (2) grow the 3D-printing workforce; and (3) expand the additive manufacturing ecosystem to promote U.S. competitiveness. The 30M USD initial

[2] One possible explanation for the underwhelming adoption of 3D printing is its numerous constraints.
[3] Public procurement is a trivial element of 'America Makes'. For example, NASA awarded the small firm 'Made In Space' a Phase III Sole Source contract to build a 3D printer to send to the International Space Station (ISS) as part of the First ISS National Lab Research Flight on September 30, 2013. Today, the ISS is equipped with a 3D bioprinter capable of printing human tissue, as well as a 3D printer for metal.

award by the U.S. Department of Defense was matched by a consortium of 40 companies, 9 universities, 5 community colleges, and 11 non-profits from 'America Makes', and later joined by 45M USD by five federal agencies: the departments of Defense, Energy, and Commerce, the National Science Foundation, and NASA. Awards to 'America Makes' are ongoing.

3D-printing technology has the ability address two major grand challenges simultaneously: sustainability goals in manufacturing (Ghisetti *et al.*, 2017; Krieger and Zipperer, 2022) and derisking global supply chains critical to national defense or economic growth (Chan *et al.*, 2018; Chen and Tang, 2024). As energy demands rise for critical technologies, twin transition policies, which prioritize environmental sustainability and digitization together, has gained increasing attention (Diodato *et al.*, 2023). Traditional manufacturing is characterized by its high energy consumption and pollution generation relative to other industries, making it ripe for sustainability targets. By contrast, additive manufacturing significantly reduces the energy consumption and hazardous industrial waste. The U.S. Department of Energy (USDOE) estimates up to a 50 percent energy savings in applications where additive manufacturing is competitive (USDOE, 2012).[4] At the firm-level, however, incentives are not always aligned with the 'paradigm shift' necessary to adopt radically different digital, decarbonized, and nationally-secure business models (Vermeulen and Pyka, 2024). This leaves room for place-based policy intervention around a U.S. hub for additive manufacturing.

[4] Additive manufacturing applications are vast. 3D printing has been used by contractors to build an entire neighborhood of homes in Texas (Garcia, 2024) and by astronauts to create spare parts and metal tools in space (Corless, 2024). A wide range of materials can be used as inputs to 3D printers, including metals, plastics, polymers, and food ingredients, which is why some scholars consider 3D printing a disruptive technology (Rayna and Striukova, 2016; Beltagui, Rosli and Candi, 2020).

Data and methods

This analysis uses data on patent applications linked to granted patents issued by the United States Patent and Trademark Office (USPTO) from 1986[5] to 2024, with the primary sample covering filing years from 2006 through 2019. We focus on patents with at least one U.S.-based assignee to enable matching to the National Establishment Time Series (NETS) database, which provides covariates including industry, employment, sales, and government contractor status.[6] We start with the set of all 3D-printing patents, defined as those classified in CPC subclass B33Y. We then collect all other patents that belong to assignees who filed at least one 3D-printing patent through the end of 2019.[7]

The primary outcomes of interest are the organization-level patent counts in the 3D manufacturing patent class. Patent applications have long been used as a measure of innovation output, particularly in manufacturing sectors (Griliches, 1990). The choice of patent class is made during the examination process, and the USPTO uses a special patent class for technology related to 3D printing or additive manufacturing (CPC Subclass B33Y). In this way, patents—unlike patent citations—are unlikely to be strategic; rather, determined by examiner. The 3D patent class contains 11 subgroups that identify different technical and commercial aspects of 3D printing, which are used in investigations of the direction of innovation. Patent classification data also identifies inventions related to

[5] The first 3D printing U.S. patent, 4,575,330, was filed in 1984 and granted in 1986. All patent data are obtained from the December 2024 version of the PatentsView database, available at www.patentsview.org.

[6] The NETS database is based on data from Dun & Bradstreet, and uses the "dunsnumber" identifier. This identifier is required for all organizations seeking U.S. government contracts, and thus ensures accurate tracking of contractors in our analysis.

[7] We end our primary sample in 2019 to limit the effects of truncation bias, and to avoid the impact of the COVID-19 epidemic in subsequent years.

"green" technology and climate change; specifically, we use CPC subclass Y02P to identify such inventions.

The paper compares a treatment sample of patents in additive manufacturing against a control group of patents unrelated to the additive manufacturing industry (all other patent classes), focusing on variation within the same organization. We use a stacked-regression setup, with shared coefficients across all covariates except $post_t$ and, where applicable, its interactions. The dependent variable tracks the counts of patent filings by organization and patent category (3D printing vs. all other classes in our main specifications, and other comparisons for extended analyses) from 2006–2019. The model below estimates the difference-in-differences equation:

$$patent_count_{ict} = \beta_0 X_{ict} + \beta_1 treat_{ic} + \beta_2 post_t + \beta_{12} (treat_{ic} * post_t) + \gamma_i + \delta_t + \varepsilon_{ict} \quad (1)$$

The dependent variable *patent_count* is the number of patents filed by firm *i* for patent category *c* in year *t*. Patent category is binary: either additive manufacturing (CPC Subclass B33Y) or all other patents; thus, the treatment group ($treat_{ic}$) tracks organization-year counts of 3D-printing patents, while the control observation consists of the same organization-year's count of all patents that do not include any CPC classes related to 3D printing. $Post_t$ is a dummy variable equal to 1 for filing years on or after 2013, corresponding to the policy event. The coefficient on the interaction term is β_{12} is the variable of interest, and it measures the change in patenting in additive manufacturing patent classes after the policy event in 2013, relative to the change in patenting for all other patent classes by firm. Firm and year fixed effects are represented by γ_i and δ_t, respectively.

Subsequent models use U.S.-government contractor status as a moderator to the treatment effect, and extended analyses explore subsets of 3D-printing patents, including

comparisons of upstream-vs-downstream inventions in terms of the 3D-printing value chain, and 3D-printing patents that are cross-listed (or not) with green technologies and those related to climate change mitigation.

[Figures 1-2; Tables 1-3]

We also investigate differences in patenting by incumbent firms compared to startup firms. Startup firms are defined as a firm with fewer than 500 employees and less than 5 years of age as of 2012, the year before the America Makes policy launched. Startup status is fixed and held constant across the panel. We also investigate patterns of new entrants. A firm is classified as a new entrant if it filed its first 3D-printing patent between 2011 and 2013. New entrants are firms that entered the additive manufacturing patenting space at or around the policy launch. This creates four groups: Established Contractor, Established Non-Contractor, New Entrant Contractor, and New Entrant Non-Contractor. The outcome is mean annual 3D-printing patent count per firm.

[Figures 3-5]

Finally, we investigate the place-based component of the 'America Makes' policy. We calculate distance to Youngstown, OH (the location of the America Makes hub) using patent-level geocoordinates from the USPTO disambiguated assignee file, merged to firm headquarters via DUNS number. Distance in miles is computed using the "geodist" command (latitude 41.0998, longitude −80.6495). Firms are classified as "close" if their mean distance falls at or below the median among 3D-printing filers in 2012, and "far" otherwise. This binary variable is crossed with new entrant status to produce four groups: Established Far, Established Close, New Entrant Far, and New Entrant Close.

[Figure 6]

Current State of Paper and Future Analyses

While we have a full working paper draft, there are a variety of future analyses we would like to incorporate going forward that align closely with this Call for Papers. The 'America Makes' place-based policy was designed to attract entrepreneurship in additive manufacturing both locally within Youngstown, OH, and nationally in the U.S. The results suggest that startups close to Youngstown were more active in 3D printing before 'America Makes' launched, suggesting they were early movers in the local ecosystem. After the policy, they experienced a sharper decline than startups far away, as much as three times larger for close firms (-3.03***) than for far firms (-1.25**). This looks like a crowding out story similar to what we find in other nascent industries, such as in AR/VR (Bradley and Kolev, 2026). One explanation is that once 'America Makes' channeled resources and contracts toward large established contractors, local startups near the hub faced more competition (where the policy was most active). Given these results, we would like to conduct follow-on analyses that ask: Could startups avoid negative effects by partnering with larger or incumbent firms? We can answer this question by exploring collaboration among startup and established firms and co-authorship teams in patenting. Finally, the results suggest that both established and startup contractors benefited from the policy, but established contractors benefited more. By contrast, for non-contractors, the established firms got a small boost even as there was a small negative impact on startups. Overall, this story is consistent with partial mediation: established firms are the primary beneficiaries even though they are late-comers to the technology, and contractor-status is a big part of the mechanism driving the result. This has a variety of implications for managers and entrepreneurs (e.g., startups might invest in joining federal contractor lists to benefit from policies related to directed technological change) that we hope to explore further.

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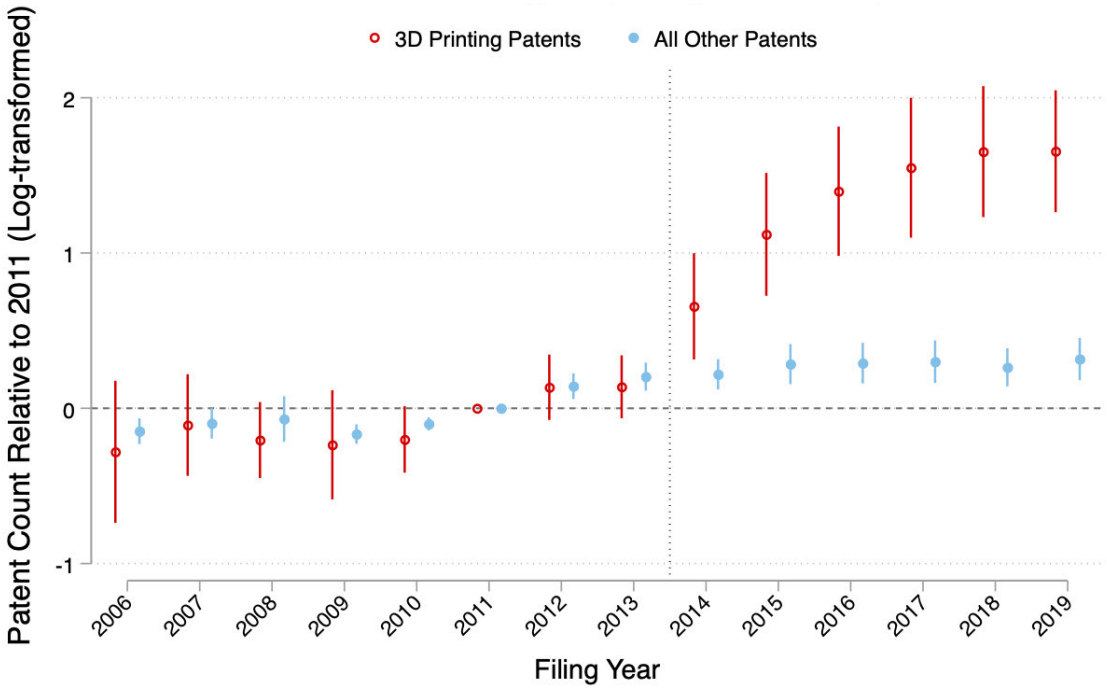
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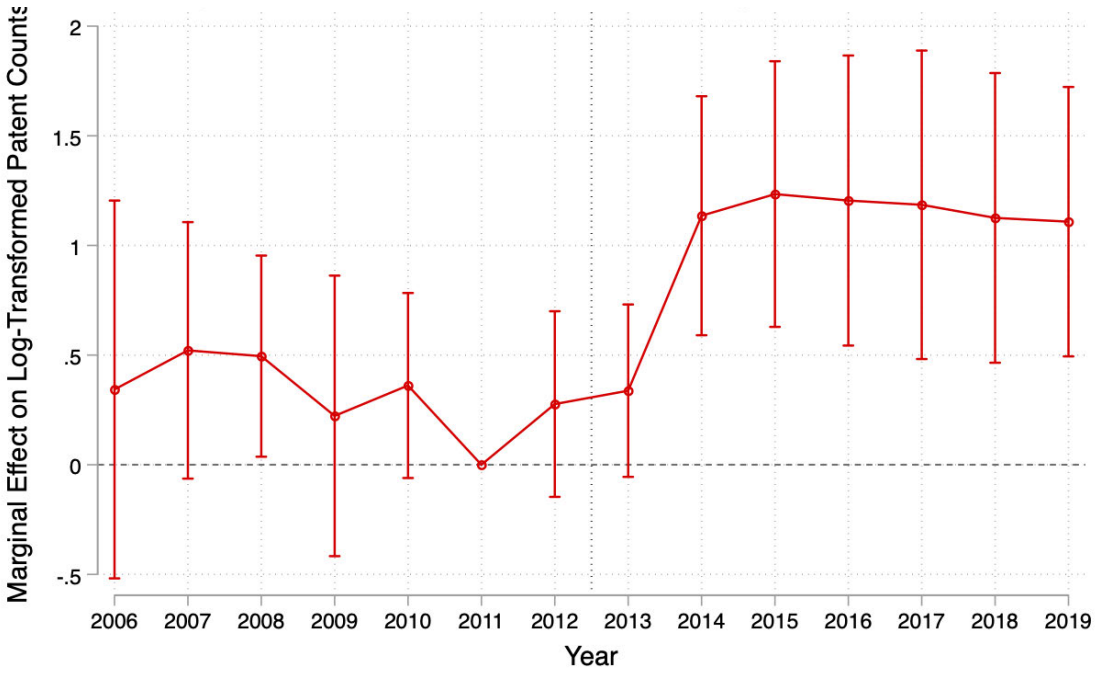
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Figure 1: Trends in U.S. Patenting: 3D Printing vs. All Other Patent Classes (2006-2019)



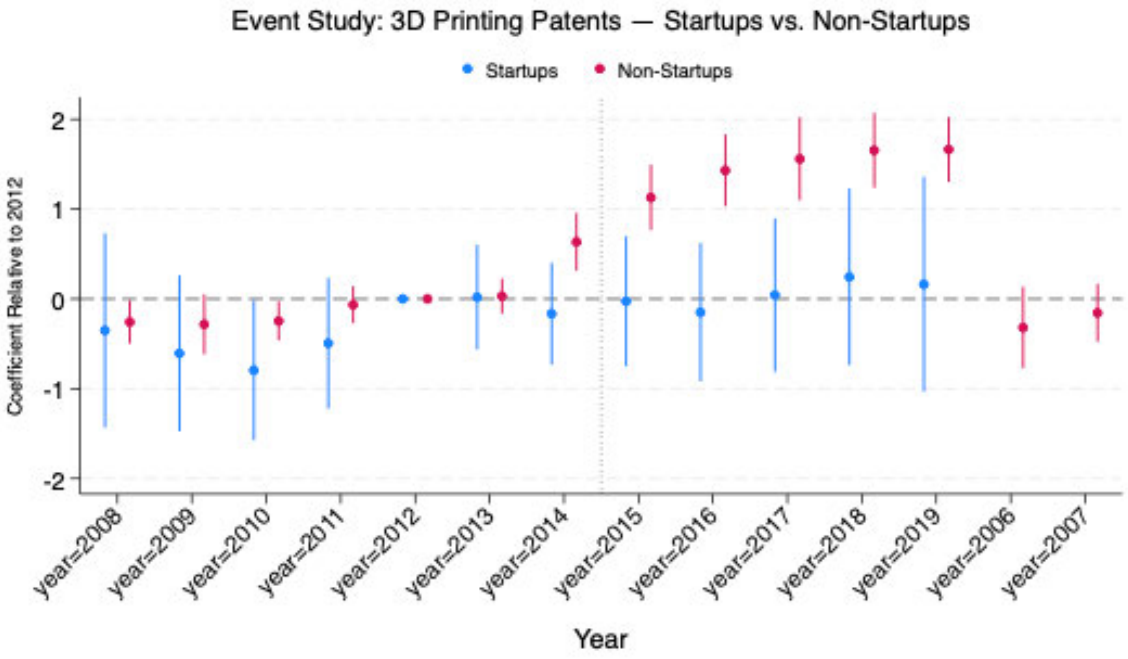
Note: The figure above plots trends in average patenting per year before and after 'America Makes' (2013) by organization within Additive Manufacturing (CPC Class B33) (red) compared to the same organizations patenting in all other classes (blue).

Figure 2: Marginal Effect of Contractor Status on 3D Printing Patent Counts (2006-2019)



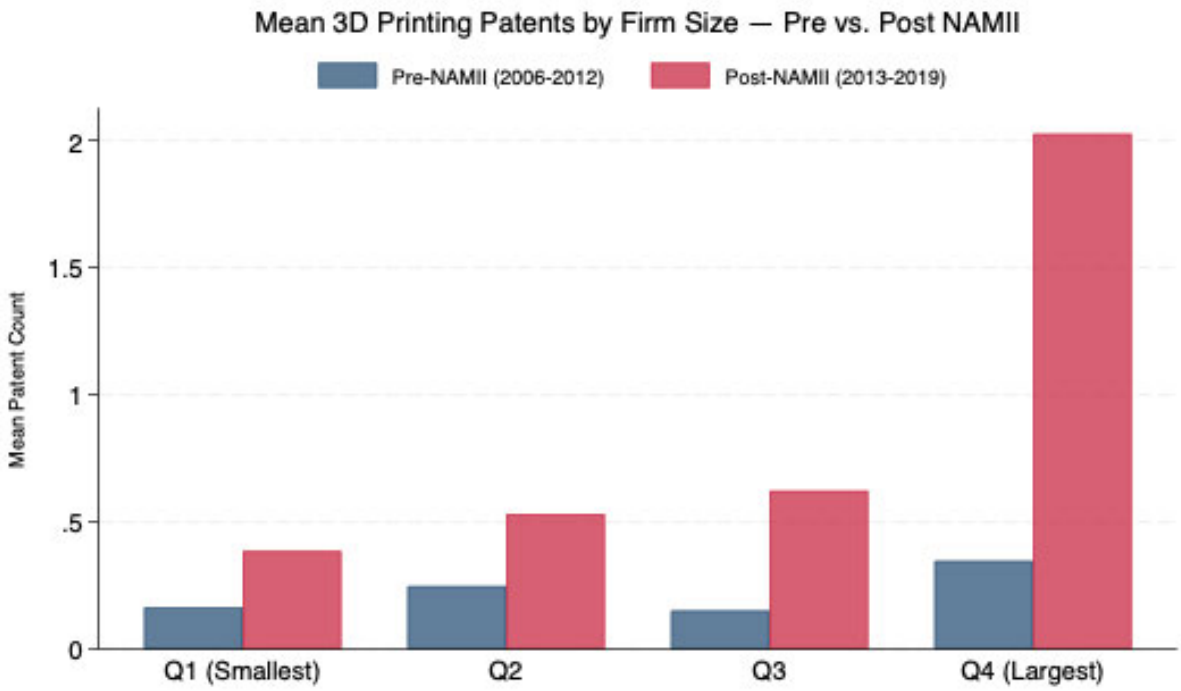
Note: The figure plots average marginal effects of 'America Makes' initiative on U.S. patents filed within the Additive Manufacturing category (CPC Class B33) by U.S. government contractors per year compared to non-U.S. government contractors per year.

Figure 3. 3D Printing Patents Startups vs. Non-Startups



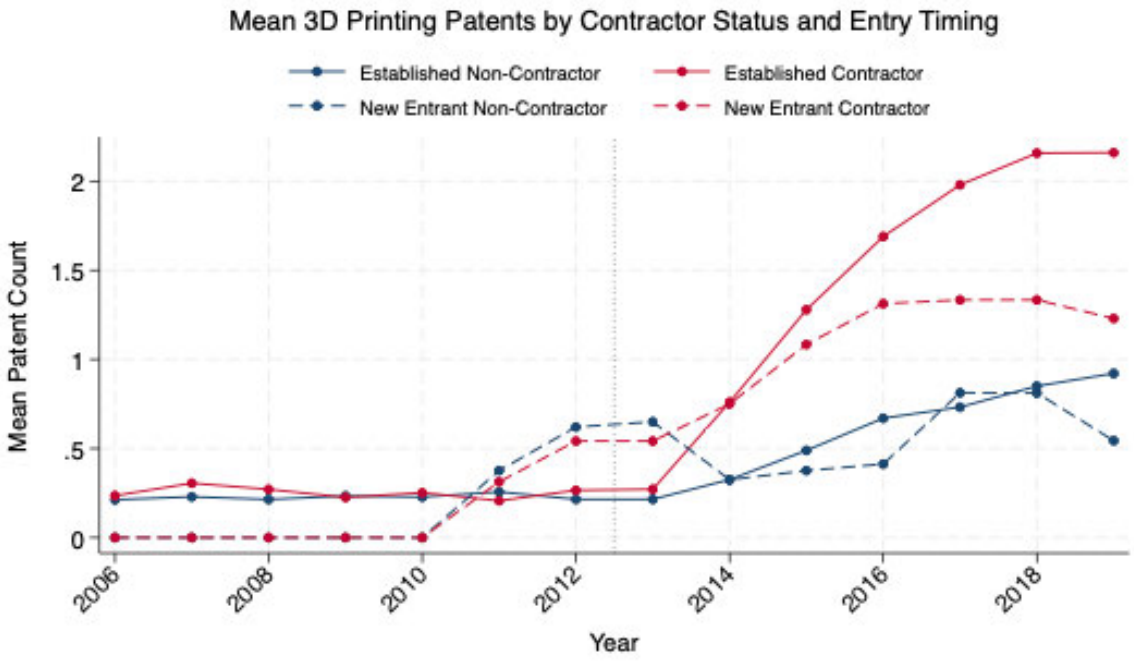
Note: Two separate random-effects Poisson models are estimated on the sample of 3D-printing patent filers (var_3d = 1) for 2006–2019, using 2012 as the base year. Each model includes year fixed effects and controls for firm age, ownership type, log employment, log sales per employee, 2-digit NAICS fixed effects, patent history, contractor status, and university affiliation. Standard errors are clustered by firm. This model compares startups only (is_startup = 1) with non-startups (is_startup = 0). Coefficients on year dummies are plotted as an event study, showing annual patenting relative to the 2012 baseline. Post-policy, non-startups show a sustained and significant increase in 3D-printing patenting, while startup coefficients remain near or below zero throughout the post-period. This difference indicates 'America Makes' primarily benefited established firms, with startups showing no significant patenting response.

Figure 4. 3D Printing Patents by Firm Size



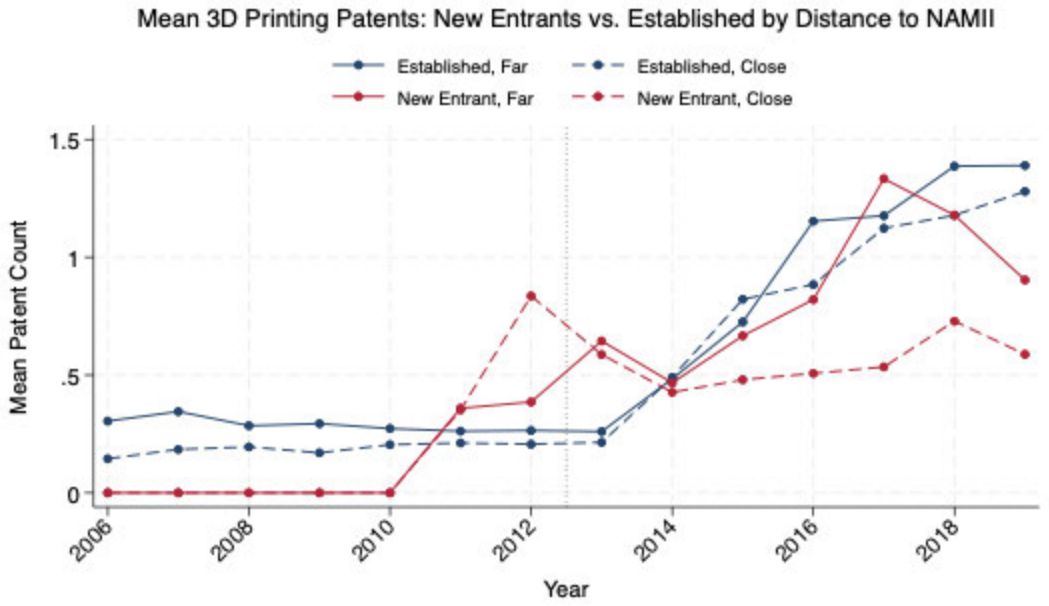
Note: Firm size is measured by log employment in 2012 and divided into quartiles (Q1 smallest to Q4 largest). Quartile assignment is fixed using the 2012 cross-section and carried forward across the panel. Mean patent count per firm is computed separately for the pre-NAMII period (2006–2012) and post-NAMII period (2013–2019) within each quartile. In this descriptive chart, the sample is restricted to 3D-printing patent filers (var_3d = 1). Mean patents per firm-year are collapsed by size quartile and period, then plotted as grouped bars (blue = pre-NAMII, red = post-NAMII). Firm size is binned into employment quartiles as of 2012. Regression results are similar: the triple-difference interaction (treat*event*log_emp) from the firm size moderator regression is positive and significant ($\beta = 0.163$, $p<0.01$), indicating larger firms captured disproportionately more post-policy patenting gains. The direct DiD term (treat*event) is near zero and insignificant ($\beta = -0.088$, $p>0.1$) when size is included, meaning the aggregate policy effect is fully mediated by firm size. Patent gains are thus concentrated in Q4 (largest) firms, consistent with incumbent value capture.

Figure 5. 3D Printing Patents by Contractor Status and Entry Timing



Note: This is a descriptive trends plot. The sample is restricted to 3D-printing filers (var_3d = 1) for 2006–2019. Mean patents are collapsed by year and group, then plotted as connected lines with a vertical dotted line at 2012 marking policy launch. Contractor status equals 1 if a firm held a U.S. government contract during 2006–2011; new entrant equals 1 if first 3D patent was filed in 2011–2013. The four-way interaction (treat*event*contractor*new entrant) is positive but insignificant ($\beta = 0.975$, $p>0.1$), while the contractor-only DiD (treat*event*contractor) is positive and significant ($\beta = 0.694$, $p<0.05$). This suggests that established contractors drove post-policy patenting gains regardless of entry timing. New entrants alone show no significant DiD effect ($\beta = 0.072$, $p>0.1$), indicating entry timing without contractor status confers no advantage.

Figure 6. 3D Printing Patents by Contractor Status and Distance from Youngstown, OH



Note: This is a descriptive trends plot. The sample is restricted to 3D-printing patent applicants for 2006–2019. Mean patents are collapsed by year and group. Established firms (close and far) both increase patenting steadily post-policy and converge to similar levels. New entrants close to the hub show an initial uptick followed by decline. This suggests local crowding out by incumbents once policy resources concentrated in the region. Notably, a t-test confirms that contractors and non-contractors are statistically indistinguishable in their distance to Youngstown (means of 1,207 vs. 1,177 miles; $p = 0.687$), meaning proximity does not explain the contractor advantage.

Table 1: Patenting for 3D printing (2006-2019): Difference-in-differences analysis

VARIABLES	(1)	(2)	(3)	(4)	(5)
	DV=patent_count; Specification: Poisson				
	Treat=3D patent subclass; Control=all other subclasses				
is_contractor	-0.613***	-0.439***	-0.265*		
	(0.144)	(0.146)	(0.157)		
is_univ	-0.0476	-0.0477	-0.0477		
	(0.270)	(0.266)	(0.267)		
treat	-5.714***	-5.714***	-5.191***	-5.714***	-5.191***
	(0.168)	(0.168)	(0.310)	(0.168)	(0.310)
treat*post	1.208***	1.208***	0.795***	1.208***	0.795***
	(0.162)	(0.162)	(0.165)	(0.162)	(0.165)
is_contractor*treat			-0.948***		-0.948***
			(0.364)		(0.364)
is_contractor*post			-0.285**		-0.285**
			(0.119)		(0.119)
is_contractor*treat*post			0.756**		0.756**
			(0.296)		(-0.296)
post	0.148***				
	(0.0454)				
firm_age	0.0255***	0.000971	0.00109	0.0402***	0.0558***
	(0.00598)	(0.00174)	(0.00175)	(0.00570)	(0.00922)
corp_01	-0.744***	-0.804***	-0.810***		
	(0.147)	(0.143)	(0.144)		
public_01	0.824***	0.695***	0.699***		
	(0.207)	(0.189)	(0.189)		
foreignown_01	0.721***	0.437**	0.443**		
	(0.195)	(0.177)	(0.178)		
log_emp	-0.0346	0.112***	0.113***		
	(0.0348)	(0.0259)	(0.0259)		
log_sales_per_emp	0.260***	0.249***	0.249***		
	(0.0664)	(0.0625)	(0.0626)		
log_pat_history	0.640***	0.675***	0.677***		
	(0.0453)	(0.0384)	(0.0385)		
ln_alpha	0.934	0.781	0.785		
	(0.931)	(0.949)	(0.950)		
Constant	1.499**	1.487**	1.356*		
	(0.755)	(0.713)	(0.719)		
Firm FE	NO	NO	NO	YES	YES
Year FE	NO	YES	YES	YES	YES
NAICS-2 FE	YES	YES	YES	NO	NO
Observations	32,360	32,360	32,360	30,662	30,662
Number of firm_id	1,420	1,420	1,420	1,335	1,335

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Patenting for 3D printing: Upstream vs. downstream technology

VARIABLES	(1) Upstream-3D vs. non-3D	(2) Upstream-3D vs non-3D	(3) Downstream-3D vs. non-3D	(4) Downstream-3D vs. non-3D	(5) Upstream vs. Downstream	(6) Upstream vs. Downstream
	DV=patent_count (upstream-3D/downstream-3D/non-3D) Specification: Poisson					
is_contractor	-0.431***	-0.258	-0.423***	-0.251	-0.201	-0.648**
	(0.150)	(0.160)	(0.150)	(0.160)	(0.156)	(0.296)
is_university	0.00623	0.00555	-0.0284	-0.0297	-0.497*	-0.499*
	(0.276)	(0.276)	(0.268)	(0.269)	(0.273)	(0.261)
treat	-7.229***	-6.604***	-6.195***	-5.725***	-1.034***	-0.879***
	(0.243)	(0.401)	(0.168)	(0.314)	(0.213)	(0.324)
treat*post	2.071***	1.614***	0.182	-0.186	1.890***	1.800***
	(0.223)	(0.263)	(0.143)	(0.178)	(0.200)	(0.275)
is_contractor*treat		-1.199**		-0.831**		-0.368
		(0.469)		(0.367)		(0.377)
is_contractor*post		-0.286**		-0.288**		0.692***
		(0.119)		(0.119)		(0.252)
is_contractor*treat*post		0.901**		0.651**		0.250
		(0.390)		(0.265)		(0.353)
firm_age	0.00134	0.00146	0.00181	0.00191	-0.00460***	-0.00479***
	(0.00177)	(0.00178)	(0.00184)	(0.00185)	(0.00147)	(0.00150)
corp_01	-0.844***	-0.850***	-0.936***	-0.938***	-0.245	-0.247
	(0.149)	(0.149)	(0.151)	(0.152)	(0.172)	(0.170)
public_01	0.717***	0.721***	0.771***	0.773***	-0.240	-0.244
	(0.190)	(0.190)	(0.189)	(0.189)	(0.239)	(0.239)
foreignown_01	0.477***	0.484***	0.542***	0.546***	-1.110***	-1.118***
	(0.180)	(0.180)	(0.181)	(0.181)	(0.191)	(0.193)
log_emp	0.117***	0.118***	0.129***	0.129***	0.0191	0.0186
	(0.0261)	(0.0262)	(0.0265)	(0.0265)	(0.0401)	(0.0401)
log_sales_per_emp	0.280***	0.280***	0.278***	0.278***	-0.0652	-0.0674
	(0.0662)	(0.0664)	(0.0647)	(0.0649)	(0.0693)	(0.0692)
log_pat_history	0.677***	0.679***	0.679***	0.681***	0.428***	0.425***
	(0.0391)	(0.0392)	(0.0395)	(0.0396)	(0.0434)	(0.0428)
ln_alpha	0.929	0.932	1.014	1.018	0.594	0.597
	(0.956)	(0.956)	(0.967)	(0.967)	(1.688)	(1.661)
Constant	1.129	1.002	1.158	1.037	-0.780	-0.481
	(0.755)	(0.762)	(0.738)	(0.745)	(0.871)	(0.871)
Year FE	YES	YES	YES	YES	YES	YES
NAICS-2 FE	YES	YES	YES	YES	YES	YES
Observations	32,360	32,360	32,360	32,360	32,360	32,360
Number of firm_id	1,420	1,420	1,420	1,420	1,420	1,420

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Patenting for 3D printing: Green vs. non-green technology (Y02P)

VARIABLES	(1) Green 3D vs. non-3D	(2) Green 3D vs. non-3D	(3) non-green 3D vs. non-3D	(4) non-green 3D vs. non-3D	(5) green 3D vs. nongreen 3D	(6) green 3D vs. nongreen 3D
	DV=patent_count (green-3D/nongreen-3D/non-3D) Specification: Poisson					
is_contractor	-0.423***	-0.251	-0.438***	-0.263*	-0.213	-0.904***
	(0.152)	(0.162)	(0.147)	(0.158)	(0.155)	(0.300)
is_university	0.0103	0.00945	-0.0390	-0.0396	-0.507**	-0.514**
	(0.275)	(0.276)	(0.267)	(0.268)	(0.251)	(0.239)
treat	-8.189***	-8.025***	-5.802***	-5.252***	-2.387***	-2.774***
	(0.229)	(0.339)	(0.170)	(0.312)	(0.189)	(0.199)
treat*post	2.546***	2.277***	0.909***	0.556***	1.637***	1.721***
	(0.220)	(0.230)	(0.149)	(0.167)	(0.182)	(0.218)
is_contractor*treat		-0.257		-1.012***		0.754**
		(0.463)		(0.365)		(0.333)
is_contractor*post		-0.288**		-0.286**		0.693***
		(0.119)		(0.119)		(0.261)
is_contractor*treat*post		0.429		0.655**		-0.226
		(0.393)		(0.284)		(0.330)
firm_age	0.00166	0.00177	0.00124	0.00135	-0.00481***	-0.00502***
	(0.00181)	(0.00182)	(0.00176)	(0.00177)	(0.00144)	(0.00147)
corp_01	-0.928***	-0.932***	-0.821***	-0.827***	-0.287*	-0.288*
	(0.151)	(0.152)	(0.147)	(0.148)	(0.174)	(0.171)
public_01	0.762***	0.765***	0.710***	0.714***	-0.112	-0.115
	(0.190)	(0.190)	(0.189)	(0.189)	(0.235)	(0.234)
foreignown_01	0.535***	0.540***	0.457**	0.464***	-0.949***	-0.956***
	(0.181)	(0.181)	(0.179)	(0.179)	(0.183)	(0.184)
log_emp	0.130***	0.130***	0.113***	0.114***	0.0246	0.0241
	(0.0264)	(0.0265)	(0.0262)	(0.0262)	(0.0391)	(0.0392)
log_sales_per_emp	0.283***	0.283***	0.262***	0.262***	-0.0793	-0.0822
	(0.0668)	(0.0670)	(0.0627)	(0.0629)	(0.0739)	(0.0740)
log_pat_history	0.676***	0.678***	0.678***	0.680***	0.422***	0.418***
	(0.0398)	(0.0399)	(0.0386)	(0.0387)	(0.0421)	(0.0416)
ln_alpha	1.017	1.021	0.862	0.866	0.446	0.450
	(0.962)	(0.962)	(0.951)	(0.951)	(1.659)	(1.631)
Constant	1.097	0.969	1.341*	1.215*	-0.436	-0.00634
	(0.762)	(0.769)	(0.716)	(0.722)	(0.901)	(0.886)
Year FE	YES	YES	YES	YES	YES	YES
NAICS-2 FE	YES	YES	YES	YES	YES	YES
Observations	32,360	32,360	32,360	32,360	32,360	32,360
Number of firm_id	1,420	1,420	1,420	1,420	1,420	1,420

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1