

POLITICAL POLARIZATION AND INVENTOR PRODUCTIVITY: EVIDENCE FROM LOCAL TELEVISION MARKETS IN THE US

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ABSTRACT. Innovation depends on collaboration across people with different perspectives, yet little is known about whether political polarization disrupts this process. We study how the partisan homogenization of local television affects inventor productivity by exploiting the staggered expansion of the Sinclair Broadcast Group (SBG) across U.S. media markets between 2003 and 2023. Comparing inventors at the same firm in the same year who live in different media markets, we find that SBG entry makes inventors' collaboration networks more ideologically homogeneous and leads to persistent declines in inventive output. Patent applications fall by 1.6% and forward citations by 5.8%, indicating that partisan media affects the quality of invention more than its quantity. The effects are concentrated entirely among inventors with high pre-treatment exposure to ideologically diverse collaborators while inventors with homogeneous networks are unaffected. The failure to form new collaborations explains the decline in invention more than the deterioration of existing collaborations. After SBG entry, the formation of new ideologically distant ties falls more than three times as much as the formation of ideologically similar ties. Partisan media reduces innovation by narrowing the pool of collaborators from whom inventors draw new ideas.

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1. INTRODUCTION

Innovation is a collective enterprise. The overwhelming majority of patents are produced by teams, and the most influential inventions typically combine knowledge from collaborators who bring different training, experience, and perspectives to a problem (Wuchty et al., 2007; Uzzi et al., 2013). Such collaborations depend not only on technical complementarities, but also on inventors' willingness to search for, trust, and work with people unlike themselves. At the same time, the United States has experienced a sharp rise in affective polarization, with partisans increasingly distrusting, avoiding, and discriminating against members of the opposing party in settings far removed from politics, including hiring, dating, and everyday economic exchange (Iyengar and Westwood, 2015; Iyengar et al., 2019; McConnell et al., 2018).

There is increasing importance of team collaboration in the production of knowledge (Wuchty et al., 2007), yet this collaboration across group lines is fragile. Collaboration for the production of knowledge requires that individuals can disagree without losing respect and trust one another. Partisan polarization undermines these conditions. For example, political disagreement can turn a productive task conflict into a damaging relationship conflict (Simons and Peterson, 2000; Amason, 1996; Jehn and Bendersky, 2003). Partisans also distrust and discriminate against out-party members in economic interactions (Iyengar and Westwood, 2015; McConnell et al., 2018; Gift and Gift, 2015; Kempf and Tsoutsoura, 2021; Dagostino et al., 2023), while negative stereotypes discourage interaction and the formation of new ties (Iyengar et al., 2019; Klar, 2018; Huber and Malhotra, 2017; Ahler and Sood, 2018). Together, conflict, distrust, and avoidance imply that polarization can weaken productive collaboration even without changing individuals' abilities or opportunities. We argue that partisan local television generates such polarization and show that it disrupts collaborative networks enough to reduce aggregate innovation.

If political polarization shapes whom individuals trust and with whom they are willing to associate, its effects may extend to the formation of productive relationships. Yet we know little about whether such trend changes intellectual workers' collaborative relationships. In particular, we focus on U.S. patent inventors because their output, which accumulates into technological progress, can be quantified and their co-inventor network is observable.¹ This paper studies whether political polarization reshapes inventor collaboration and, ultimately, innovative activity that is critical for firm value and economic growth.

¹These inventor data have been widely used to study team formation, knowledge flows, and innovation. Prior work documents the rise of team-based invention (Wuchty et al., 2007; Jones, 2009), links co-inventor networks to invention quality and breakthrough discoveries (Fleming et al., 2007; Singh and Fleming, 2010; Gao et al., 2025), maps how knowledge diffuses across technology fields through patent citations (Acemoglu et al., 2016), models innovation as arising from interactions among heterogeneous inventors (Akcigit et al., 2018), and shows that early exposure to inventor networks predicts entry into invention (Bell et al., 2019).

A growing literature attributes the escalating polarization to partisan news media. We study the influence of political polarization in the context of local television, which throughout our sample period was the leading source of news for American adults, drawing a larger audience than cable or national network news, and is among the most trusted news sources in the country (Pew Research Center, 2025b,a, 2026). In particular, we focus on the expansion of the Sinclair Broadcast Group (SBG), the largest owner of local television stations in the country. SBG stations are required to air centrally produced “must-run” segments that replace part of locally produced political coverage with nationally coordinated, conservative-leaning commentary, and prior work documents that SBG acquisitions shift local newscasts toward national politics and a more conservative slant (Martin and McCrain, 2019; Levendusky, 2022; Martin et al., 2024). Because stations are retransmitted throughout an entire Designated Market Area (DMA), an acquisition changes the information environment for every household an inventor in the market at once.

Our data combine the universe of USPTO patent applications with the disambiguated inventor file, which allows us to follow individual inventors over time, locate them in a DMA using the county of residence reported on their filings, and reconstruct their co-inventor networks year by year. We measure inventive output using patents and citations and characterize collaboration networks by their ideological diversity. We proxy inventors’ political orientation using pre-treatment county-level presidential vote shares and measure both ideological dispersion among collaborators and their ideological distance from the inventor. We measure inventive output using patents and citations and characterize collaboration networks by their ideological diversity. We proxy inventors’ political orientation using pre-treatment county-level presidential vote shares and measure both ideological dispersion among collaborators and their ideological distance from the inventor. Our identification exploits the staggered entry of SBG across media markets. Because inventors’ residential DMA determines exposure, we can compare inventors working for the same firm and year but exposed to different local media environments, while also accounting for state $\times$ year shocks. We estimate cohort-specific treatment effects using Sun and Abraham (2021). Event-study estimates show no evidence of differential pre-trends, and the results are robust to the sensitivity analysis of Rambachan and Roth (2023).

We establish four sets of results. First, SBG entry makes inventors’ collaboration networks more ideologically homogeneous. Both ideological dispersion and ideological distance decline significantly after entry, and the decline grows over the post-treatment period. Inventors in treated markets increasingly collaborate with co-inventors who resemble them politically.

Second, this homogenization is accompanied by persistent declines in inventive output. Patent applications fall by 1.6% and forward citations by 5.8%; the weighted analogues fall by 1.2% and 4.1%. The citation effect is roughly four times the patent effect, a pattern

that recurs throughout the paper and indicates that partisan media reduces the quality and influence of invention more than its quantity. The estimates are stable across alternative staggered difference-in-differences estimators (Wooldridge, 2023; Dube et al., 2023), outcome transformations, and sample definitions. They also exhibit a clear dose-response relationship: exploiting variation in the channel position of acquired stations, which historically determines visibility and viewership, we find that moving from the least to the most prominent channel position is associated with a 2.5% decline in patents and a 9.0% decline in citations.

Third, the productivity losses are concentrated entirely among inventors who were exposed to ideologically diverse collaborators before treatment. We construct a pre-treatment index of cross-partisan network exposure and split inventors at its median. For the high-exposure group, patents fall by 2.0% and citations by 9.4%; for the low-exposure group, the effects are small and statistically indistinguishable from zero on every outcome. The low-exposure group consisting of inventors working with more politically homogeneous co-inventors thus serves as a within-sample placebo. Any post-entry shock common to all inventors in treated markets, such as local economic conditions or changes in patent-office practice, would affect both groups; the differential between them, which is significant at the 1% level, isolates the component of the treatment effect that operates through the ideological composition of collaboration networks.

Fourth, we identify the margin along which the network mechanism operates. A natural explanation is that partisan media erodes existing cross-partisan collaborations. Our evidence, however, does not support this mechanism. Using pre-2012 collaboration networks, we track never-treated inventors whose collaborators become exposed to SBG, and we track inventor-co-inventor pairs at the dyad level once one member’s market is acquired. Existing collaborations do not deteriorate: ideologically distant pairs are no more likely than ideologically similar pairs to reduce their joint output, and the interaction between direct treatment and network exposure is indistinguishable from zero. Instead, the effect operates on the new ties. After SBG entry, the number of new co-inventor ties formed each year falls by roughly 11%, with the decline concentrated in cross-ideological collaborations. New ties with ideologically similar co-inventors fall only modestly, while those with ideologically distant co-inventors decline by more than three times as much. Partisan media thus does not primarily disrupt existing collaborations; it prevents ideologically diverse ones from forming.

Taken together, these findings support a simple account of how partisan media affects innovation. Local television shapes not only what viewers believe about national politics but also whom they trust and are willing to work with. When a market’s local news becomes more ideologically uniform, the cost of reaching across partisan lines to initiate a new collaboration rises, and inventors respond by forming ties with people more like themselves. Because the most novel ideas often arise from the recombination of distant knowledge, this narrowing of

the collaborator pool lowers the impact of what inventors produce even when it changes the number of inventions only modestly. The concentration of the effect among inventors who previously drew on diverse networks, the absence of any effect on established ties, and the sharp decline in new cross-partisan ties are all consistent with this account and difficult to reconcile with alternatives based on firm-level shocks, local demand conditions, or general declines in inventor effort, none of which predicts that the effect should depend on the political composition of an inventor’s collaborators.

The rest of the paper is organized as follows. Section 2 reviews the related literature and discusses our contribution. Section 3 provides background on local television markets in the United States, SBG’s expansion, and the data we use. Section 4 explains the empirical strategy. Section 5 presents the main results on inventor networks, ideological diversity, and inventor productivity, together with robustness checks. Section 6 shows that the effects concentrate on inventors with high pre-treatment cross-partisan exposure. Section 8 documents network spillovers and isolates the extensive margin of new cross-partisan tie formation. Section 9 concludes.

2. RELATED LITERATURE

This paper connects four streams of the economics literature that have developed largely in isolation: the economics of networks and collaborations, the economics of innovation, the economics of media and persuasion, and the economic consequences of political polarization.

First, we add new insights to the literature on collaboration networks and innovation. Innovation has become an increasingly collaborative activity, and team composition matters for what teams produce. [Wuchty et al. \(2007\)](#) and [Jones \(2009\)](#) document the rise of teams in science and invention showing how important is collaboration on high-impact research due to the growing specialization required by an expanding knowledge frontier; [Uzzi et al. \(2013\)](#) show that the highest-impact work combines conventional and atypical knowledge; and [Hong and Page \(2004\)](#) and [Berliant and Fujita \(2011\)](#) provide theoretical foundations for the value of cognitively diverse collaborators. Empirically, the loss of a key collaborator permanently reduces co-authors’ output ([Azoulay et al., 2010](#); [Jaravel et al., 2018](#)) and locally contracts the diffusion of the affected inventor’s knowledge ([Balsmeier et al., 2023](#)). Homophily along ethnic lines lowers the impact of scientific work ([Freeman and Huang, 2015](#)), while diversity of co-inventors lead to more influential inventions ([Gao et al., 2025](#); [Mack et al., 2025](#)). Moreover, knowledge flows are strongly mediated by personal and geographic proximity ([Jaffe et al., 1993](#); [Singh, 2005](#); [Breschi and Lissoni, 2009](#); [Agrawal et al., 2006](#); [Moretti, 2021](#)). Our contribution is to show that the ideological composition of collaboration networks is a distinct margin along which diversity affects inventive output, and to identify a media shock that shifts this margin. Whereas most of the network literature studies

the persistence or disruption of existing ties, our dyad-level and new-tie results isolate tie formation as the operative channel.

Second, our paper contributes to the innovation economics literature by showing a new, non-pecuniary determinant of inventor productivity, which shows that inventors respond to features of their environment beyond financial incentives. Perceived pay unfairness reduces effort (Card et al., 2012; Mas, 2017), and pay transparency raises inventor output (Gao et al., 2025). Psychological states and traits, including mood, overconfidence, and risk appetite, also shape creativity and innovation (Isen et al., 1987; Hirshleifer et al., 2012; Sunder et al., 2017). We add the local information environment to this list. Unlike compensation or personality, which operate at the individual or firm level, media slant is a market-level shock that alters the social fabric within which inventors search for collaborators, and it therefore affects even inventors whose own incentives and dispositions are unchanged.

Third, we contribute to the surging literature shows that partisan media changes political beliefs and behavior. DellaVigna and Kaplan (2007) document that the entry of Fox News into cable markets raised Republican vote share, and Martin and Yurukoglu (2017) estimate a structural model of cable news persuasion in which viewer choice and channel slant reinforce one another; see also Gentzkow (2006), Gentzkow and Shapiro (2010), Enikolopov et al. (2011), and Ash et al. (2022). Our setting builds on a smaller set of papers that study SBG specifically. Martin and McCrain (2019) show that SBG acquisitions shift local news content away from local politics toward national politics and a rightward slant; Levendusky (2022) finds that exposure to SBG stations moves viewers' attitudes on national issues; Miho (2024) estimates effects on presidential vote shares; Mastrorocco and Ornaghi (2025) show that the resulting decline in local coverage reduces police accountability; and Martin et al. (2024) compare SBG with other conglomerate acquirers and find that its content changes are distinctive. Closest to us in spirit is Berger et al. (2026), who use the same staggered SBG expansion to study bank deposits, lending, and local labor markets. We extend this literature from political and financial outcomes to the production of knowledge, and we show that the relevant channel runs through the structure of social ties rather than through beliefs about national politics alone.

Finally, we present novel evidence to the literature on the economic consequences of political polarization. Political scientists have documented that partisanship in the United States has become a salient social identity that governs interpersonal trust and behavior outside politics: partisans discriminate against out-party members in hiring and economic games (Iyengar and Westwood, 2015; Gift and Gift, 2015), select politically similar partners (Huber and Malhotra, 2017), and trade at worse terms with co-partisans of the other side (McConnell et al., 2018); Iyengar et al. (2019) survey this evidence. Economists have begun to trace the consequences of this affective polarization for economic decisions: credit analysts'

ratings (Kempf and Tsoutsoura, 2021), loan pricing (Dagostino et al., 2023), investor beliefs (Cookson et al., 2020), household spending (Mian et al., 2023), executive teams (Fos et al., 2022), and entrepreneurship (Engelberg et al., 2022). While these studies typically take polarization as given and examine its economic consequences, we identify a causal link from a specific source of polarization, partisan local television, to the formation of economically productive relationships. We further show that this effect operates through the formation of new relationships rather than the dissolution of existing ones.

3. BACKGROUND AND DATA

3.1. Local television markets and Sinclair Broadcast Group. Television remains the primary source of news for most Americans, with local television continuing to attract a larger audience than either cable or national network news. To regulate broadcasting, the Federal Communications Commission (FCC) divides the country into 210 non-overlapping Designated Market Areas (DMAs), geographic media markets that encompass several counties and often cross state borders. Television stations require FCC licenses to broadcast and typically combine locally produced news with syndicated programming. Because cable providers retransmit local stations throughout the entire DMA, households within a market are broadly exposed to the same local television content. Within this institutional setting, changes in station ownership can alter the information environment experienced by all viewers in a DMA.

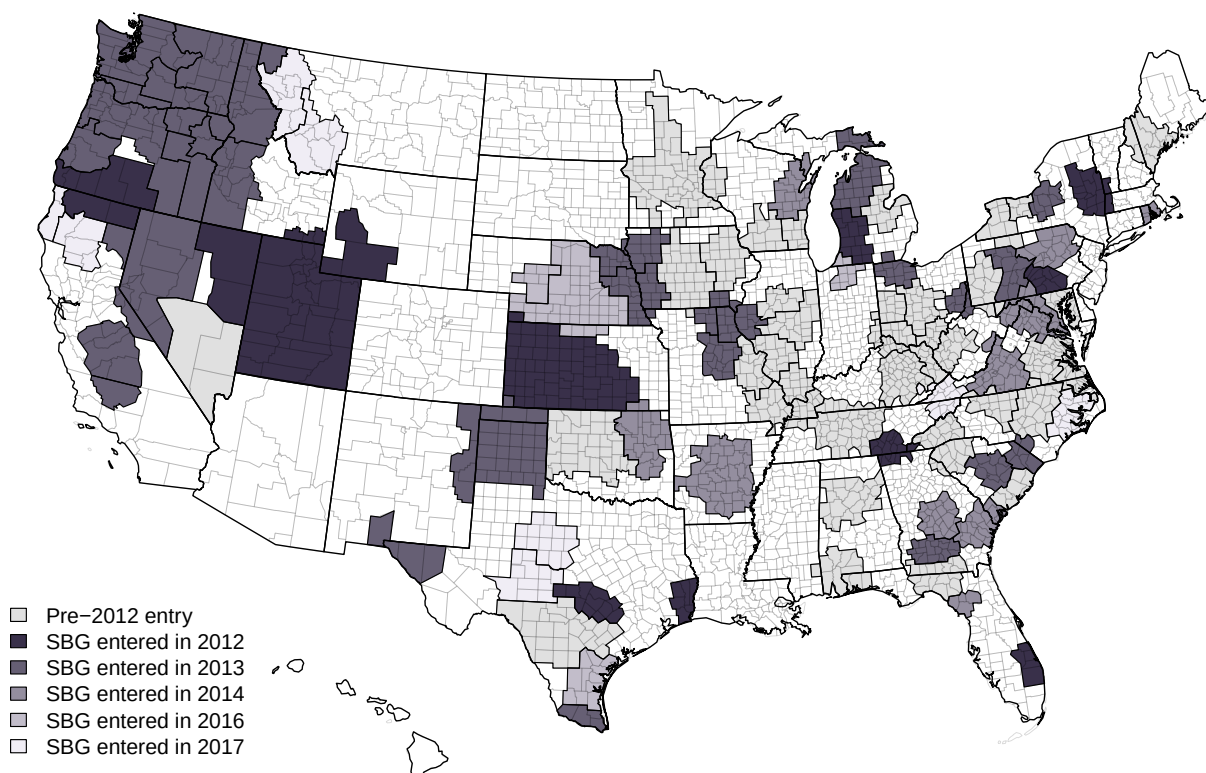
Sinclair Broadcast Group (SBG) is the largest television station owner in the United States, currently owning and operating more than 185 stations nationwide. The company has been widely documented as providing a conservative slant in its programming (Martin and McCrain, 2019). In particular, the company requires its stations to air centrally produced “must-run” segments that replace part of local political coverage with nationally coordinated conservative commentary, reducing ideological diversity across affected markets.

Beginning in 2012, SBG rapidly expanded through a series of staggered acquisitions, entering 57 additional DMAs between 2003 and 2023. Figure 1 illustrates the geographic distribution of these acquisitions. Because each acquisition changes the television content available throughout the corresponding DMA, this staggered expansion generates plausibly exogenous variation in local media exposure across markets and over time. We exploit this variation by comparing inventors in DMAs following Sinclair’s entry with those in markets where Sinclair had not yet entered or never entered to estimate the effect of increased conservative media slant on inventor productivity.

3.2. Individual inventor panel. Our primary data come from the USPTO patent database. We construct an inventor-year panel by linking USPTO patent records to the disambiguated inventor dataset, which identifies unique inventors across patent applications.

Each inventor is assigned to a Designated Market Area (DMA) using the county of residence reported in patent filings and is matched to the DMA where the majority of their patent applications were filed. The resulting panel spans patent application years from 2003 through 2023.

FIGURE 1. SBG market entry across 210 US Designated Market Areas, 2003–2023



Notes: This map presents the spatial distribution of SBG market entry dates across the 210 US Designated Market Areas (DMAs). Each DMA is shaded by the year in which SBG first acquired a TV station in that market. White areas represent DMAs where SBG never operated or operated before 2003.

We impose three sample restrictions. First, we retain only inventors observed in at least two years, excluding one-time patentees. Second, because collaboration is central to the mechanisms we study, we restrict the sample to inventors employed at firms with at least two co-inventors. Third, we impose the support conditions required for staggered difference-in-differences estimation. Treated inventors must be observed both before and after Sinclair’s

entry into their assigned DMA, while never-treated inventors must have observations on both sides of the first treatment year (2012).

We study two dimensions of inventor productivity: the quantity of inventive output, measured by patent applications, and the impact of inventive output, measured by forward citations. For each dimension, we construct both raw and fractional measures. The raw measures assign one patent (or its associated citations) to each listed inventor, whereas the fractional measures weight each patent and its citations by the inverse of the number of co-inventors, thereby allocating equal credit across collaborators. We estimate all specifications using both the natural logarithm of $(x + 1)$ and the inverse hyperbolic sine (IHS) transformation to accommodate the highly right-skewed distribution of innovation outcomes and the large share of inventor-years with zero output.

3.3. Ideological network measures. To characterize the ideological composition of inventors’ collaboration networks, we construct two measures based on county-level political preferences. We proxy ideology using the county-level average Democratic presidential vote share in the 2004–2010 elections, assigning each inventor a fixed ideology score based on the modal county in which they filed patents during the pre-treatment period.

The first measure, *ideological dispersion*, is the standard deviation of ideology scores across an inventor’s co-inventors in a given year, capturing within-network ideological heterogeneity. The second, *ideological distance*, is the absolute difference between an inventor’s own ideology score and the average ideology of their co-inventors, capturing how far an inventor collaborates across the political spectrum. These outcomes allow us to examine whether exposure to partisan local media is associated with greater ideological sorting within inventor collaboration networks.

4. EMPIRICAL STRATEGY

Our identification strategy exploits the staggered timing of Sinclair Broadcast Group’s (SBG) expansion across local television markets. We compare inventors in DMAs following SBG’s entry with inventors in DMAs that had not yet been treated or were never treated. Identification relies on the assumption that, absent SBG entry, inventor productivity would have followed parallel trends across treated and control markets. Because treatment is staggered over time, a conventional two-way fixed effects (TWFE) estimator may produce biased estimates when treatment effects are heterogeneous. [Goodman-Bacon \(2021\)](#) shows that TWFE combines multiple 2×2 difference-in-differences comparisons, including “forbidden comparisons” that use already-treated units as controls for units treated later. We therefore use the interaction-weighted estimator of [Sun and Abraham \(2021\)](#), which estimates cohort-specific average treatment effects on the treated (CATTs) using only valid control groups for each treatment cohort. Specifically, we estimate:

$$(4.1) \quad \tilde{Y}_{it} = \alpha_i + \alpha_{ft} + \sum_{\substack{k=-5 \\ k \neq 0}}^7 \beta_k SBG_j \times \mathbf{1}(\text{Entry}_t = k - 1) + \varepsilon_{it}$$

Following [Borusyak et al. \(2024\)](#), $\tilde{Y}_{it}$ denotes the pre-residualized outcome. We first regress the outcome on state-by-year fixed effects using only never-treated inventors and use the resulting residuals in all subsequent estimations. This procedure removes state-level innovation shocks without requiring the inclusion of high-dimensional state-by-year fixed effects in the main specification. An inventor is considered treated in all years following SBG's entry into their assigned DMA ($SBG_j = 1$). We assign treatment according to the inventor's residential DMA, defined as the DMA in which the inventor filed the majority of their patents. Never-treated inventors are those located in DMAs where SBG never acquired a station during the sample period and they serve as the primary control group, while inventors in not-yet-treated DMAs provide additional controls for each treatment cohort.

Because treatment is assigned according to an inventor's residential DMA rather than the firm's headquarters, inventors employed by the same firm in the same year may face different media environments. This within-firm-year variation allows us to include firm-by-year fixed effects, thereby absorbing any organizational shocks common to all inventors within a firm-year (α_{ft}). The event-time indicators $\mathbf{1}(\text{Entry}_t = k - 1)$ equal one when year t is $k - 1$ years relative to SBG's entry into market j . We normalize the year immediately preceding entry ($k = 0$) to zero, so all coefficients measure effects relative to the last pre-treatment year. We bin event times outside the estimation window by grouping all periods earlier than $k = -5$ and later than $k = 7$. Finally, inventor fixed effects, α_i , absorb time-invariant inventor characteristics, and we cluster standard errors at the DMA level (210 markets).

The CATT coefficients β_k for each event-time period k are then aggregated to a single post-entry average treatment effect:

$$(4.2) \quad \hat{\beta} = \sum_g \omega_g \hat{\beta}^g$$

where weights ω_g are proportional to cohort size. Identification relies on the assumption that, in the absence of SBG entry, potential outcomes would have evolved similarly across treatment and control groups, as verified by the absence of pre-trends in the event-study plots.

5. RESULTS

The empirical analysis proceeds in three steps. We first examine the effects of SBG entry on inventor collaboration networks and their ideological composition. We next estimate its

effects on inventor productivity. Finally, we evaluate the robustness of the results to alternative estimators, functional forms, sample definitions, and measures of treatment intensity.

TABLE 1. Effect of SBG entry on ideological diversity of inventor networks

	Ideological Dispersion		Ideological Distance	
	IHS (1)	Ln (2)	IHS (3)	Ln (4)
<i>Panel A: Abraham & Sun (2021)</i>				
SBG $\times$ After Entry	-0.002*** (0.001)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)
N	4,307,727	4,307,727	4,307,726	4,307,726
<i>Panel B: TWFE</i>				
SBG $\times$ After Entry	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)
N	4,307,727	4,307,727	4,307,726	4,307,726
Inventor FE	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓

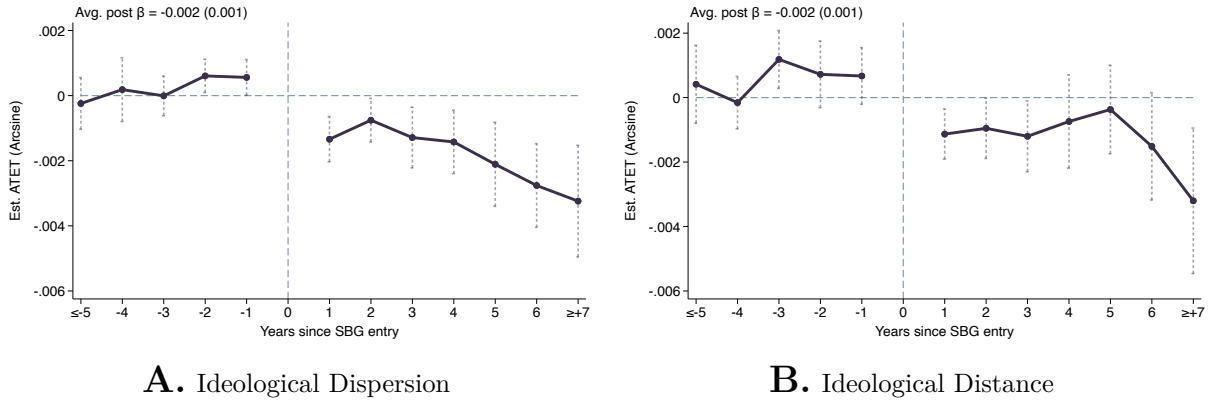
Notes: The outcome is the standard deviation of ideology scores across co-inventors (Ideological Dispersion, columns 1–2), or the absolute difference between the inventor’s ideology and the network’s average ideology (Ideological Distance, columns 3–4). All specifications use the pre-residualized outcome $\tilde{Y}_{it}$: state $\times$ year fixed effects are removed in a first step by regressing the outcome on state $\times$ year dummies using only never-treated inventors; residuals are used as the outcome in all regressions shown. Panel A: Abraham & Sun (2021) estimator. Panel B: TWFE on the same pre-residualized outcome, shown for comparison. Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.1. Effects on Ideological Composition of Inventor Networks. We begin by examining the impact of SBG entry on collaborative inventor networks. Partisan media may reduce cross-ideological interaction, fragmenting collaborative networks and narrowing the diversity of knowledge sources available to inventors. Table 1 reports Sun and Abraham (2021) estimates of SBG entry on the two measures of ideological composition introduced in Section 3: (1) the ideological dispersion across an inventor’s co-inventors, and (2) the ideological distance between an inventor’s own ideology and the average ideology of their network. Both measures decline following SBG entry, with point estimates of approximately -0.002 that are statistically significant at the 1% level under both the IHS and log transformations. Panel B reports conventional TWFE estimates using the same pre-residualized outcome. The point estimates are nearly identical, although the Abraham and Sun estimator yields slightly more conservative standard errors. Overall, these results indicate that inventors in SBG-treated markets collaborate with ideologically more similar co-inventors, reducing the ideological diversity of their collaborative networks.

Figure 2 presents the corresponding event-study estimates. For both outcomes, the estimated coefficients are close to zero and statistically indistinguishable from zero prior to

treatment, providing no evidence of differential pre-trends. Following SBG entry, the estimated effects become increasingly negative over the post-treatment periods, indicating that the reduction in ideological diversity strengthens over time. Together, these findings indicate that SBG entry leads inventors to form increasingly ideologically homogeneous collaborative networks and are consequently exposed to a narrower range of ideas and perspectives. In the next section, we examine whether these changes in network composition translate into lower inventor productivity.

FIGURE 2. Event study: ideological diversity of inventor networks



Notes: Event-study plots using the Abraham & Sun (2021) estimator. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Corresponding plots using the $\ln(x + 1)$ transformation are provided in Figure A.1 of the Appendix.

5.2. Inventor Productivity. Having established that SBG entry leads to smaller and more ideologically homogeneous collaborative networks, we now examine how this network fragmentation translates into changes in inventor productivity.

Table 2 reports our main estimates. Each pair of columns presents the IHS and log transformations of a different patent outcome using the Abraham and Sun (2021) estimator. Panel B reports the corresponding TWFE estimates for comparison.

The results indicate that SBG entry reduces both the quantity and quality of inventive output. Total patenting declines by approximately 1.6% ($100 \times (e^{-0.016} - 1)$), statistically significant at the 1% level. The effects are substantially larger for innovation quality since the citation index falls by roughly 5.8%, nearly four times the decline in patent output. This pattern suggests that partisan media primarily affects the quality rather than the quantity of innovation, consistent with inventors drawing on a narrower set of ideas and knowledge sources following the fragmentation of collaborative networks. Moreover, the weighted outcomes point to the same conclusion. Weighted patent output declines by approximately 1.2%, while weighted citations fall by about 4.1%, with all estimates statistically significant

at the 1% level. Taken together, these findings indicate that SBG entry not only reduces inventive activity but has an even stronger effect on the influence and quality of the resulting innovations.

TABLE 2. Effect of SBG entry on inventor productivity

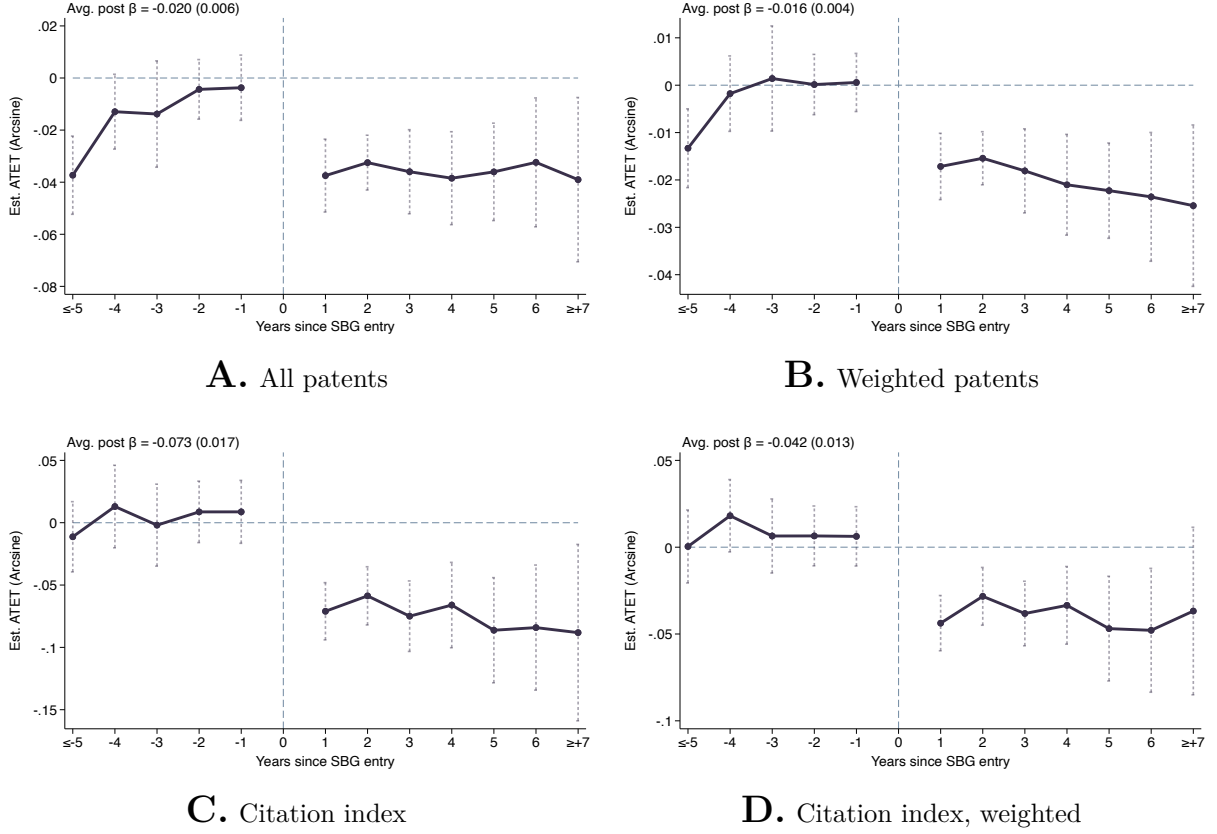
	All patents		Citations		Wt. patents		Wt. citations	
	IHS	Ln	IHS	Ln	IHS	Ln	IHS	Ln
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A: Abraham & Sun (2021)</i>								
SBG $\times$ After Entry	-0.020*** (0.006)	-0.016*** (0.005)	-0.073*** (0.017)	-0.060*** (0.015)	-0.016*** (0.004)	-0.012*** (0.003)	-0.042*** (0.013)	-0.033*** (0.011)
N	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727
<i>Panel B: TWFE</i>								
SBG $\times$ After Entry	-0.021*** (0.007)	-0.016*** (0.005)	-0.073*** (0.017)	-0.060*** (0.015)	-0.016*** (0.005)	-0.012*** (0.004)	-0.043*** (0.015)	-0.034*** (0.013)
N	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727	4,307,727
Inventor FE	✓	✓	✓	✓	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is inventor-level all-patent count (cols. 1–2), citation index (3–4), inverse-inventor-weighted patent count (5–6), or inverse-inventor-weighted citation index (7–8), each transformed by inverse hyperbolic sine (IHS) and $\ln(x + 1)$ (Ln). All specifications use the pre-residualized outcome $\tilde{Y}_{it}$: state $\times$ year fixed effects are removed in a first step by regressing on state $\times$ year dummies using only never-treated inventors (Borusyak et al., 2024); residuals are the outcome in all regressions. Panel A: Abraham & Sun (2021) cohort-specific estimator. Panel B: TWFE on the same pre-residualized outcome, shown for comparison only. Standard errors clustered at the DMA level (210 markets). Sample: inventors with observations in 2003–2023 appearing more than one year; treated cohorts entering 2003 or later.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3 presents the event-study estimates for patent quantity and citation quality, respectively. Across all outcomes, the estimated coefficients remain close to zero and statistically insignificant before treatment, providing no evidence of differential pre-trends. Following SBG entry, the effects become progressively more negative over time, indicating that the impact of partisan media strengthens as exposure accumulates. While patent output declines modestly, the deterioration in citation quality is substantially larger throughout the post-treatment period, reinforcing the conclusion that partisan media affects the quality of innovation more strongly than its quantity. Figures A.2 and A.3 replicate these results using the $\ln(x + 1)$ transformation and produce nearly identical dynamic patterns.

FIGURE 3. Event study: effect of SBG entry on innovation



Notes: Event-study plots using the Abraham & Sun (2021) estimator. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Panels (a) and (b) report effects on patent output, while Panels (c) and (d) report effects on citation-based measures of innovation quality. Corresponding plots using the $\ln(x + 1)$ transformation are provided in Figures A.2 and A.3 of the Appendix.

5.3. Robustness. We assess the robustness of our findings across alternative estimators, specifications, and measures of innovative activity, and examine their sensitivity to potential violations of the identifying assumptions.

5.3.1. Robustness to Parallel Trends Violations. We assess the sensitivity of our results to potential violations of the parallel trends assumption using the Honest DiD procedure of Rambachan and Roth (2023). Rather than imposing exact parallel trends, this approach allows for bounded deviations in pre-treatment trends and constructs confidence sets for the average treatment effect under progressively weaker identifying assumptions. Following Rambachan and Roth (2023), we evaluate a range of values for the sensitivity parameter $\bar{M}$,² where larger values permit greater departures from parallel trends. Appendix Figures A.7–A.12 report the resulting confidence sets for each outcome and post-treatment horizon.

²Formally, the restriction is $|\Delta_t^{\text{pre}}| \leq \bar{M} |\Delta_{t-1}^{\text{pre}}|$, where Δ_t^{pre} denotes the change in the pre-trend between consecutive periods. As $\bar{M}$ increases, larger deviations from parallel trends are permitted.

Across all outcomes, the estimated effects remain negative even under relatively large values of $\bar{M}$, and the corresponding confidence sets continue to exclude zero throughout the post-treatment period. These results indicate that our findings are robust to moderate departures from the parallel trends assumption and are unlikely to be driven by differential pre-treatment trends between treated and control markets.

5.3.2. Treatment Intensity: Channel Position. Our baseline specification treats SBG entry as a binary event, implicitly assuming a homogeneous treatment effect across markets. However, the influence of a local television station is likely to depend on its prominence and audience reach. To capture this heterogeneity, we exploit variation in the channel positions of acquired stations. In U.S. television markets, lower channel numbers have historically enjoyed greater visibility and viewership than higher-numbered channels. We therefore construct a continuous treatment intensity measure that maps each station’s channel position onto the unit interval, assigning a value of one to the most prominent position (channel 2) and zero to the least prominent (channel 45).³

5.3.3. Alternative Staggered DiD Estimators. Tables A.1 and A.2 examine the robustness of the network and inventor productivity results to alternative recently developed staggered DiD estimators and outcome transformations. Panel A reports estimates using the IHS transformation under four estimators: Abraham and Sun (2021), TWFE, Wooldridge (2021), and Local Projection DiD (Dubé et al., 2023). Panel B repeats the analysis using the outcomes in levels and, for the productivity measures, additionally reports Poisson quasi-maximum likelihood estimates. Across all specifications, the estimated effects are remarkably stable in both magnitude and statistical significance, indicating that the choice of estimator or outcome transformation does not drive our findings and conclusions.

5.3.4. Fixed Effects Specification. Table A.3 examines the sensitivity of the productivity results to the fixed-effects specification by replacing the baseline Firm $\times$ Year fixed effects with standard firm fixed effects. The estimated effects remain negative and statistically significant across all outcomes but are substantially larger in magnitude under the less restrictive specification. For example, the Abraham and Sun (2021) estimate for total patents declines from -0.143 under firm fixed effects to -0.020 in the baseline specification.

This pattern suggests that the less restrictive specification captures firm-level shocks that vary over time and are absorbed by the baseline model, such as changes in R&D investment, managerial turnover, or firm-specific technological cycles, that could otherwise be correlated with SBG’s expansion. Identification in the baseline specification therefore comes from

³Formally, we replace the binary treatment indicator with the continuous measure $\text{Rank}_j = 1 - (\text{ChannelPos}_j - 2)/(45 - 2)$, where ChannelPos_j denotes the primary channel number of the SBG-acquired station in DMA j . By construction, $\text{Rank}_j \in [0, 1]$, with higher values corresponding to more prominent channel positions.

comparisons among inventors working in the same firm and year but exposed to different local media environments because of their geographic location. The Firm $\times$ Year specification is also more demanding in terms of identification, as it requires within-firm-year variation and consequently excludes firm-year singletons. This reduces the estimation sample from 4.84 million to 4.31 million inventor-year observations. Although this restriction reduces the sample size, it provides a more conservative identification strategy by controlling for potential time-varying firm-level confounders.

5.3.5. Sample Robustness. Our baseline sample requires that treated inventors have at least one pre-treatment observation and that control inventors are observed both before and after 2012. Table A.4 replicates the main results without these restrictions, retaining the full universe of inventors. The A&S and TWFE estimates are nearly identical in sign, magnitude, and significance to those in Tables 1 and 2, confirming that the sample restrictions do not drive the results. Moreover, Figures A.4–A.6 present the corresponding event-study estimates for the full inventor sample using the IHS transformation. The dynamic patterns are virtually identical to those reported in the main text, with no evidence of differential pre-treatment trends and progressively more negative post-treatment effects. This confirms that the baseline sample restrictions do not affect either the identifying assumptions or the dynamic evolution of the treatment effects.

Table A.5 reports the corresponding estimates. Consistent with our baseline results, the effects become stronger as treatment intensity increases. Moving from the least to the most prominent channel position is associated with a 2.5% decline in patent output and a 9.0% decline in citation quality, with negative and statistically significant coefficients across all outcomes. These findings provide evidence of a clear dose-response relationship: markets exposed to more prominent SBG stations experience larger declines in innovative activity. This monotonic pattern strengthens the interpretation that the observed effects are driven by differential exposure to partisan media rather than by the mere timing of SBG acquisitions. Moreover, as expected, the TWFE estimator performs poorly under this specification, with coefficient signs reversing because of the forbidden-comparison bias discussed in Section 4.

6. HETEROGENEITY BY CROSS-PARTISAN NETWORK EXPOSURE

The preceding results point to a network mechanism through which partisan media affects innovation. SBG entry reduces the ideological diversity of inventor networks, and these changes are accompanied by lower inventive output and citation quality. If partisan media reduces innovation by limiting exposure to ideologically diverse collaborators, inventors with greater pre-existing cross-partisan exposure should experience the largest productivity declines. Inventors whose networks were already ideologically homogeneous, in contrast, should be comparatively unaffected through this channel.

To test this prediction, we construct a measure of pre-treatment cross-partisan network exposure. Specifically, we average two standardized variables computed prior to SBG entry: (i) the ideological diversity within an inventor’s collaboration network and (ii) the ideological distance between the inventor and the average ideology of their collaborators. The first captures the ideological heterogeneity of an inventor’s network, while the second measures the extent to which inventors themselves collaborate across ideological lines. Averaging the two measures provides a more comprehensive proxy for cross-partisan exposure while reducing measurement noise relative to either measure alone. We then partition inventors at the median of this index into low- and high-exposure groups.

To estimate heterogeneous treatment effects, we employ the exact saturated estimator of Wooldridge (2023), since the Abraham and Sun (2021) estimator requires a binary treatment indicator and does not extend naturally to settings with continuous treatment intensity or within-group heterogeneity. The estimator fully interacts treatment cohorts with calendar years separately for each subgroup, thereby accommodating staggered treatment timing while avoiding the forbidden-comparison bias of conventional TWFE estimators. Let $\tilde{Y}_{it}$ denote the transformed outcome after pre-residualizing state-by-year fixed effects using never-treated inventors, and let $G_i \in \mathcal{G}$ denote the treatment cohort. We then estimate subgroup-specific cohort-by-year effects using the following specification:

$$(6.1) \quad \tilde{Y}_{it} = \underbrace{\sum_{g \in \mathcal{G}} \sum_{t \geq g} \delta_{gt}^{Lo} D_{igt}^{Lo}}_{\text{low-exposure cells}} + \underbrace{\sum_{g \in \mathcal{G}} \sum_{t \geq g} \delta_{gt}^{Hi} D_{igt}^{Hi}}_{\text{high-exposure cells}} + \alpha_i + \psi_{ft} + \varepsilon_{it},$$

where $D_{igt}^s \equiv \mathbf{1}\{G_i = g\} \cdot \mathbf{1}\{\text{year} = t\} \cdot \mathbf{1}\{S_i = s\}$ identifies observations belonging to treatment cohort g , calendar year t , and exposure group $s \in \{Lo, Hi\}$; α_i is an inventor fixed effect; and ψ_{ft} is a firm $\times$ year fixed effect. Subgroup ATTs are then

$$\hat{\beta}^s = \sum_{g, t \geq g} \frac{N_{gt}^s}{N^{s+}} \hat{\delta}_{gt}^s, \quad s \in \{Lo, Hi\}.$$

We also estimate the difference in treatment effects, $\hat{\beta}^{Hi} - \hat{\beta}^{Lo}$, to formally test whether the response differs across the two exposure groups. The low-exposure group serves as a within-sample placebo: because these inventors had limited pre-treatment cross-partisan exposure, the proposed homogenization mechanism has little scope to operate, implying treatment effects close to zero.

Table 3 reports the heterogeneous treatment effects by pre-treatment cross-partisan exposure. Consistent with our hypothesis, the estimated effects for the low-exposure group are small and statistically indistinguishable from zero across all four measures of inventor productivity. By contrast, the effects for the high-exposure group are negative and statistically significant at the 1% level for every outcome. Total patenting declines by 2.0%, citation

quality by 9.4%, weighted patent output by 1.7%, and weighted citations by 6.5%. These estimates are comparable to, and in some cases larger than, the baseline results, suggesting that the average effect largely reflects the response of inventors with high pre-treatment cross-partisan exposure.

TABLE 3. Effect of SBG Entry by Pre-Treatment Cross-Partisan Network Exposure

	Inventor Productivity			
	All pat. (1)	Citations (2)	Wt. pat. (3)	Wt. cit. (4)
<i>Heterogeneity by pre-2012 cross-partisan network exposure index (Wooldridge 2021)</i>				
SBG $\times$ After (Low exposure)	0.022* (0.013)	0.041 (0.032)	−0.000 (0.007)	0.032 (0.022)
SBG $\times$ After (High exposure)	−0.020*** (0.007)	−0.099*** (0.018)	−0.017*** (0.004)	−0.067*** (0.012)
Differential (High − Low)	−0.042*** (0.011)	−0.140*** (0.026)	−0.017*** (0.006)	−0.099*** (0.018)
N	4,307,727	4,307,727	4,307,727	4,307,727
Inventor FE	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓

Notes: All outcomes transformed by IHS. Estimates follow the Wooldridge (2021) saturated estimator with inventor, state $\times$ year, and firm $\times$ year fixed effects. Inventors are partitioned at the median of a pre-treatment cross-partisan network exposure index, which combines the ideological diversity within an inventor’s co-author network and the ideological distance between the inventor and the average ideology of their collaborators, both measured in the years prior to SBG entry. The *Differential* row reports the difference between the two group estimates. Standard errors clustered at the DMA level (210 markets). $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

The differences in treatment effects between the two exposure groups are themselves statistically significant at the 1% level across all outcomes, with estimated differentials ranging from 4.1 percentage points for total patenting to 13.1 percentage points for citation quality. The comparison between the two exposure groups is especially informative because it nets out shocks that are common to all treated inventors. Any post-entry shock common to all treated inventors, such as macroeconomic conditions, changes in patent-office practices, or sectoral technology cycles, would affect both exposure groups and therefore be differenced out in this comparison. The remaining differential isolates the component of the treatment effect associated with pre-treatment cross-partisan network exposure. The fact that the estimated effects for the low-exposure group are indeed statistically indistinguishable from zero strengthens the interpretation that the productivity losses observed among high-exposure inventors operate through the network mechanism rather than through confounding shocks common to all treated inventors.

7. EFFECTS ON COLLABORATION

Homogenizing the local media environment can reshape innovation by altering inventors' collaboration patterns. In particular, two changes in how inventors interact with their collaborators can account for the direct productivity losses documented in Section 5.2. The first operates through existing ties or changes in an inventor's productivity with co-authors with whom she had already collaborated before Sinclair's arrival. The second operates through new ties, that is, collaborations that she would otherwise have formed after Sinclair's entry but that now fail to materialize.

TABLE 4. Collaboration with old coinventors

	Excl. same county		Excl. same DMA	
	Pat. w/ old (IHS) (1)	Cites w/ old (IHS) (2)	Pat. w/ old (IHS) (3)	Cites w/ old (IHS) (4)
<i>Panel A: Old = past 3 years</i>				
SBG $\times$ After Entry	−0.006 (0.004)	0.002 (0.008)	−0.019*** (0.004)	0.002 (0.005)
N	4,307,727	4,307,727	4,307,727	4,307,727
<i>Panel B: Old = past 5 years</i>				
SBG $\times$ After Entry	−0.001 (0.004)	0.009 (0.009)	−0.016*** (0.004)	0.010* (0.005)
N	4,307,727	4,307,727	4,307,727	4,307,727
<i>Panel C: Old = past 10 years</i>				
SBG $\times$ After Entry	0.004 (0.004)	0.013 (0.009)	−0.013*** (0.004)	0.012** (0.006)
N	4,307,727	4,307,727	4,307,727	4,307,727
Inventor FE	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓

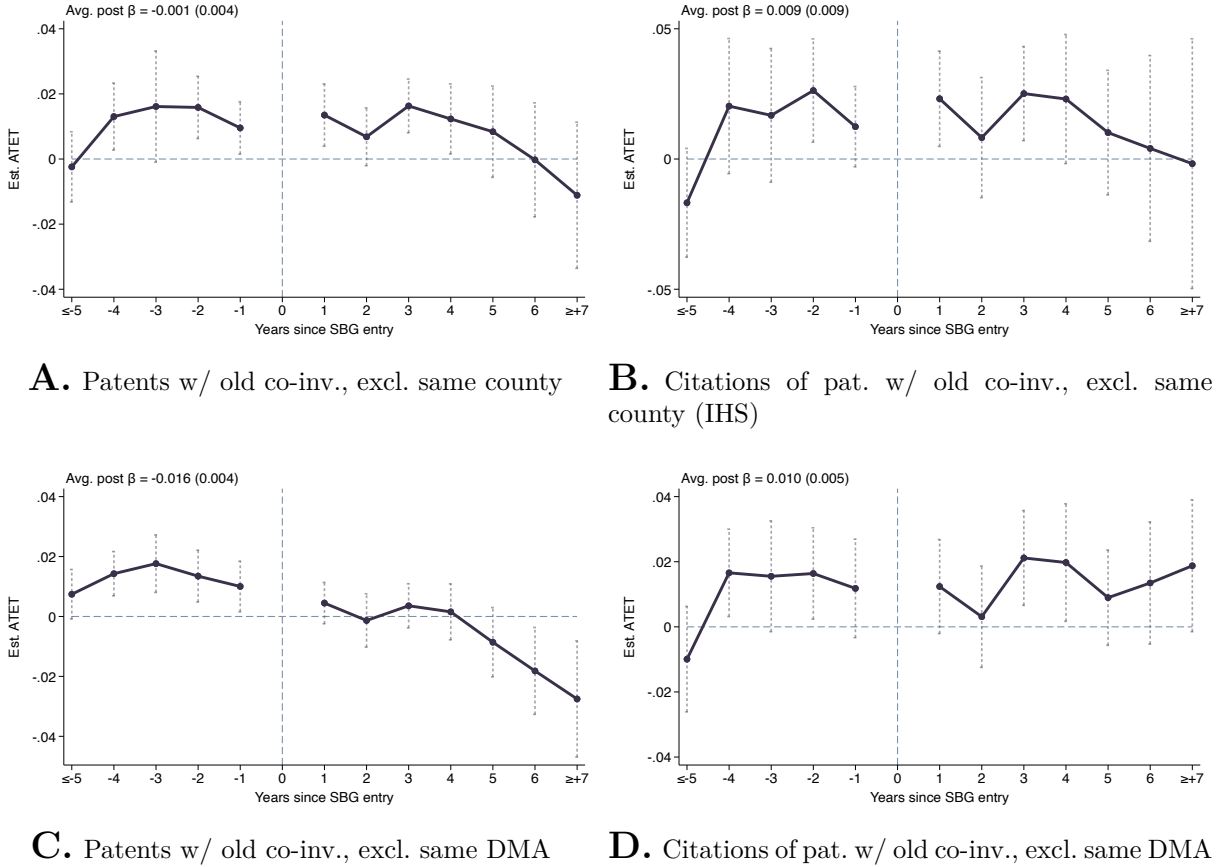
Notes: Columns (1)-(2) drop coinventors ever located in the same county as the focal inventor in year t ; columns (3)-(4) drop coinventors ever located in the same DMA as the focal in year t . Each panel varies the definition of an old coinventor as a coauthor with whom the focal filed a joint patent within the previous $N \in \{3, 5, 10\}$ years. Dependent variables in columns (1) and (3) count of focal inventor's patents in year t co-authored with at least one retained old coinventor. Dependent variables in columns (2) and (4) sum of citations of those patents. All variables are transformed by inverse hyperbolic sine (IHS). All specifications use the pre-residualized outcome $\tilde{Y}_{it}$: state $\times$ year fixed effects are removed in a first step using never-treated inventors (Borusyak, Jaravel, and Spiess, 2014). Estimates use the Abraham & Sun (2021) interaction-weighted estimator with cohort = SBG entry year and control cohort = never-treated inventors. Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7.1. Existing ties. We first evaluate whether SBG's entry reduces an inventor's output from collaborations with existing co-inventors. To do so, for each inventor-year, we define an *old* collaborator as a co-inventor with whom the focal inventor filed a joint patent within

the previous N years, with $N \in 3, 5, 10$. We then track both the number of patents filed jointly with these prior collaborators and the citations those patents receive.

A concern with these outcomes is contamination through geography. An old co-inventor who resides in the same DMA as the focal inventor is exposed to the same Sinclair shock, so a decline in their joint output could reflect co-treatment rather than a change in how the focal inventor draws on her existing network. To isolate the collaboration channel from this common shock, we exclude co-inventors who reside in the same location as the focal inventor, implementing two geographic exclusions. First, we exclude any old co-inventor with a reported location in the focal inventor's own county. Second, we exclude any old co-inventor with a reported location in the focal inventor's own DMA. We determine location using the co-inventor's full set of reported patent locations in year t .

FIGURE 4. Event study: joint output with old co-inventors ($N = 5$)



Notes: Event-study plots using the Abraham & Sun (2021) estimator. Outcomes are the count of the focal inventor's patents in year t co-authored with at least one old co-inventor and the sum of citations those patents receive. Panels A and B exclude old co-inventors ever located in the focal inventor's own county ; Panels C and D exclude old co-inventors ever located in the focal's own DMA. $k = -0$ is the omitted base period; dashed lines are 95% confidence intervals with standard errors clustered at the DMA level.

Table 4 reports the results applying the Abraham and Sun (2021) interaction-weighted estimator explained in the section 4. When we exclude same-county co-authors, the estimates for both joint patents and citations are small and statistically indistinguishable from zero across all three lookback windows. Under the stricter DMA exclusion, the number of joint patents with old co-authors declines by 1.3–1.9 percent, while their citations remain flat or slightly increase. Thus, we find some evidence of a modest contraction in the quantity of collaboration with existing ties, but no deterioration in the quality of the output they produce.

Figure 4 reports the dynamic version of these estimates for the five-year lookback window. Under the county exclusion (top row), the coefficients for both joint patents and citations remain close to zero throughout the post-entry period, with no evidence of differential pre-trends. Under the DMA exclusion (bottom row), the patent-count estimates reproduce the small negative effect in Table 4: coefficients fall modestly below zero after Sinclair’s entry and remain negative through the end of the window. Citations, by contrast, remain at or slightly above zero. We therefore conclude that Sinclair’s entry leads at most to a modest reduction in joint patenting with existing co-authors outside the focal inventor’s media market, with no corresponding decline in the impact of their joint work.

7.2. New tie formation. The evidence presented so far points to the conclusion that SBG entry makes inventor networks more ideologically homogeneous and reduces innovation, with the largest effects concentrated among inventors whose collaborations initially spanned ideological boundaries. At the same time, we find little evidence that existing collaborations deteriorate following exposure to SBG. These findings suggest that the mechanism operates through a different margin: the formation of new collaborative relationships. To examine this possibility, we construct, at the inventor-year level, the number of new co-inventor ties formed each year, defining a new collaborator as one who appears on an inventor’s patent in year t but not on any of their patents in year $t - 1$ or earlier. We then classify each new collaboration according to the ideological distance between the focal inventor and the new collaborator, distinguishing collaborations formed within the same ideology (distance = 0) from those spanning ideological boundaries (distance > 0).

Figure ?? reports the dynamic version of these estimates for the five-year lookback window. Under the county exclusion (top row), the coefficients for both joint patents and citations remain close to zero throughout the post-entry period, with no evidence of differential pre-trends. Under the DMA exclusion (bottom row), the patent-count estimates reproduce the small negative effect in Table ??: coefficients fall modestly below zero after Sinclair’s entry and remain negative through the end of the window. On the other hand, citations remain at or slightly above zero. This dynamic pattern reinforces our main results that Sinclair’s entry leads at most to a modest reduction in joint patenting with existing co-authors outside

the focal inventor’s media market with no corresponding decline in the impact of their joint work.

Table 5 presents the main results. Column (1) shows that SBG entry significantly reduces the formation of new collaborative ties overall, with an estimated effect of -0.117 . Columns (2) and (3) reveal that this decline is almost entirely driven by collaborations that cross ideological boundaries. New collaborations between ideologically similar inventors decline only modestly (-0.026), whereas collaborations between ideologically distant inventors fall by -0.086 . Column (4) reports the difference between the two estimates, which is -0.061 and statistically significant at the 1% level. The difference between Columns (2) and (3) allows us to distinguish a general decline in new collaborations from one that is specific to cross-partisan ties. While overall collaboration may fall for many reasons, only collaborations spanning ideological boundaries experience an additional decline following SBG entry. This pattern provides direct evidence that partisan media disproportionately discourages the formation of new cross-partisan collaborations.

TABLE 5. Effect of SBG entry on new co-inventor ties by ideological distance

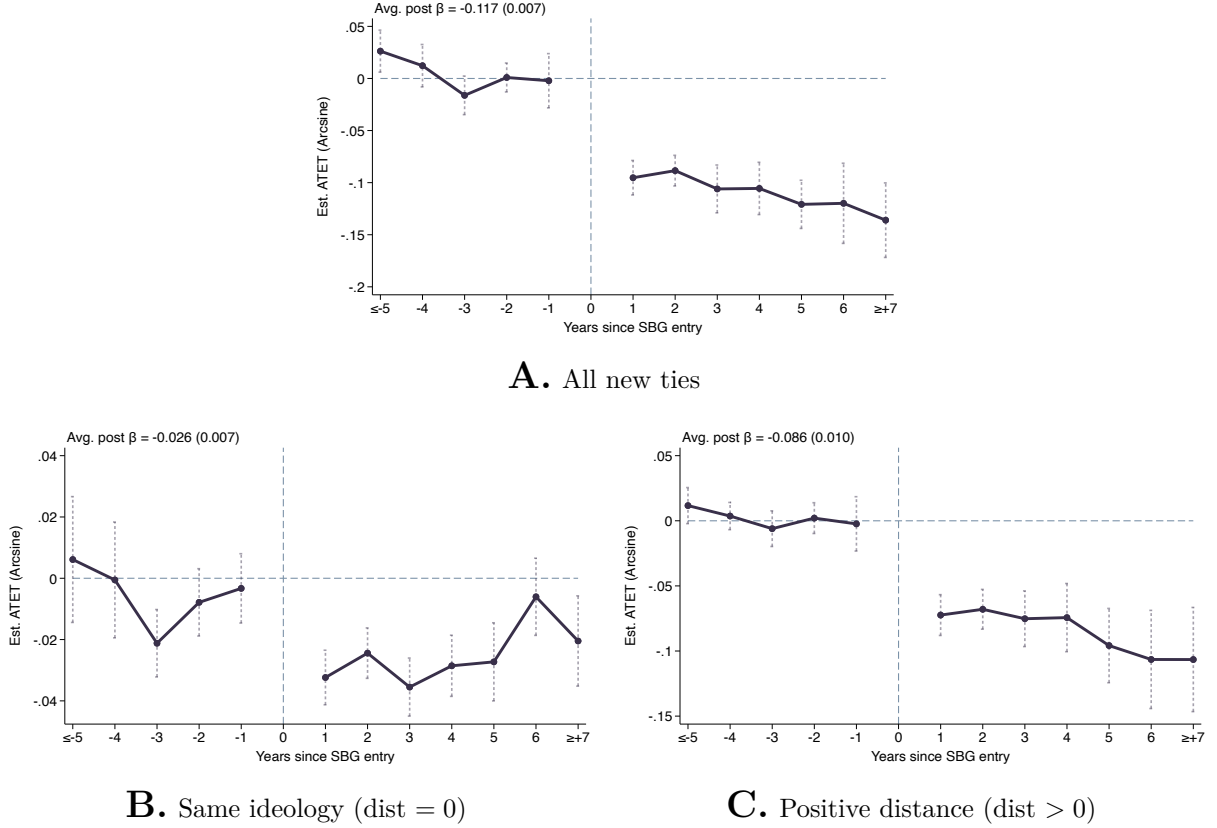
	(1) All new ties	(2) Same ideology (dist = 0)	(3) Positive distance (dist > 0)	(4) Differential (3) – (2)
SBG $\times$ After Entry	-0.117^{***} (0.007)	-0.026^{***} (0.007)	-0.086^{***} (0.010)	-0.061^{***} (0.015)
N	4,307,727	4,307,727	4,307,727	4,307,727
Inventor FE	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓

Notes: All outcomes transformed by IHS. All specifications use the pre-residualized outcome $\tilde{Y}_{it}$: state $\times$ year fixed effects are removed in a first step by regressing on state $\times$ year dummies using only never-treated inventors (Borusyak et al., 2024). The dependent variable is the count of new co-inventor ties formed in year t , defined as co-inventors on the focal inventor’s patents in t that did not appear on any of their patents in $t - 1$ or earlier. Column 1 uses all new ties; column 2 restricts to new ties at the same county-level ideology score (distance = 0); column 3 restricts to new ties at any strictly positive ideological distance. Column 4 reports the differential between columns 3 and 2. All specifications use the Abraham & Sun (2021) estimator; standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5 complements these findings by illustrating the dynamics of these effects. Panel A shows that the overall number of new collaborations remains stable prior to SBG entry and declines sharply afterward. Panel B shows little change in the formation of ideologically similar collaborations, whereas Panel C displays a large and persistent decline in new collaborations between ideologically distant inventors. Across all three panels, pre-treatment

coefficients remain close to zero, providing no evidence of differential pre-trends, while the post-treatment dynamics closely mirror the average treatment effects reported in Table 5.

FIGURE 5. Event study: new co-inventor ties by ideological distance



Notes: Event-study plots using the Abraham & Sun (2021) estimator. Outcome is the count of new co-inventors on the focal inventor's patents in year t that did not appear on any of their patents before t , transformed by IHS. Panel B restricts to new co-inventors at the same county-level ideology score (distance = 0). Panel C restricts to new co-inventors at any strictly positive ideological distance. $k = 0$ is the omitted base period; dashed lines are 95% confidence intervals with standard errors clustered at the DMA level.

Taken together, the evidence identifies the extensive margin as the mechanism through which partisan media affects innovation. Existing collaborations remain largely unaffected following SBG entry, but inventors become substantially less likely to establish new collaborations across ideological lines. The productivity losses documented in Section 5.2 therefore arise not because existing cross-partisan relationships deteriorate, but because the collaborations that would otherwise have formed never materialize.

8. NETWORK SPILLOVERS

Section 5.1 shows that SBG entry contracts inventors' collaborative networks and reduces their exposure to ideologically diverse collaborators. An important implication is that

these effects may extend beyond directly treated inventors through pre-existing collaboration networks. This section examines whether SBG generates productivity spillovers through existing collaboration networks and, if so, identifies the margin through which they arise. The evidence shows that these spillovers do not operate by weakening existing cross-partisan collaborations.

8.1. Network exposure and joint estimation. We define *network exposure* (NE_{it}) as the share of inventor i 's pre-2012 collaborators located in DMAs that have been entered by SBG by year t . We exploit its year-over-year change, ΔNE_{it} ,⁴ which becomes positive only when SBG enters an additional DMA containing one of the inventor's pre-2012 collaborators. This transformation isolates new exposure generated by SBG's staggered expansion rather than differences in the initial composition of inventors' collaboration networks. The identifying variation comes from the timing of SBG's acquisitions across the markets where an inventor's collaborators happened to reside before the expansion began. Because the collaboration network used to construct NE_{it} is fixed prior to 2012, subsequent changes in ΔNE_{it} are determined by SBG's acquisition decisions rather than by inventors' endogenous collaboration choices. Conditional on inventor, firm $\times$ year, and state $\times$ year fixed effects, this variation is plausibly exogenous.

Let $\tilde{Y}_{it}$ denote the transformed outcome residualized on state $\times$ year fixed effects using never-treated inventors, $G_i \in \mathcal{G}$ the treatment cohort, and $e_i \in \mathcal{E}$ the exposure cohort for never-treated inventors (the first year in which $NE_{it} > 0$). We estimate the following specifications using the exact saturated estimator of Wooldridge (2023), extended to accommodate continuous treatment intensity:⁵

$$(8.1) \quad \tilde{Y}_{it} = \sum_g \sum_{t \geq g} \delta_{gt} D_{igt} + \alpha_i + \psi_{ft} + \varepsilon_{it}$$

$$(8.2) \quad \tilde{Y}_{it} = \sum_e \sum_{t \geq e} \gamma_{et} E_{iet} \cdot \Delta NE_{it} + \alpha_i + \psi_{ft} + \varepsilon_{it}$$

$$(8.3) \quad \tilde{Y}_{it} = \sum_g \sum_{t \geq g} \delta_{gt} D_{igt} + \sum_e \sum_{t \geq e} \gamma_{et} E_{iet} \cdot \Delta NE_{it} + \sum_g \sum_{t \geq g} \phi_{gt} D_{igt} \cdot \Delta NE_{it} + \alpha_i + \psi_{ft} + \varepsilon_{it}$$

where $D_{igt} \equiv \mathbf{1}\{G_i = g\} \cdot \mathbf{1}\{\text{year} = t\}$ identifies observations belonging to treatment cohort g in calendar year t , and $E_{iet} \equiv \mathbf{1}\{e_i = e\} \cdot \mathbf{1}\{\text{year} = t\}$ identifies observations belonging to exposure cohort e , defined by the first year in which network exposure becomes positive, in

⁴Formally, $\Delta NE_{it} = NE_{it} - NE_{i,t-1}$.

⁵The three specifications are: (A) the binary direct-effect model with cohort $\times$ year dummies D_{igt} and ATT weights $w_{gt} = N_{gt}/N^+$; (B) the network-exposure slope for never-treated inventors, using exposure-cohort $\times$ year cells $E_{iet} \cdot \Delta NE_{it}$ with weights $w_{et}^e = N_{et}^{\text{ctrl}}/N^{\text{ctrl}+}$; and (C) the joint model combining both channels and their interaction $D_{igt} \cdot \Delta NE_{it}$ for directly treated inventors.

calendar year t ; α_i denotes inventor fixed effects, and ψ_{ft} denotes firm $\times$ year fixed effects. Equation (8.1) reproduces the baseline estimates using only direct treatment. Equation (8.2) isolates the network spillover channel by relating inventor productivity to changes in network exposure among never-treated inventors. Equation (8.3) estimates both channels jointly and allows the direct effect of SBG entry to vary with the degree of network exposure.

TABLE 6. Network Spillovers: Direct vs. Peer Effects on Inventor Productivity

	Inventor Productivity			
	All pat. (1)	Citations (2)	Wt. pat. (3)	Wt. cit. (4)
<i>Panel A: Direct SBG entry effect only</i>				
Direct Effect	-0.021*** (0.007)	-0.074*** (0.018)	-0.017*** (0.004)	-0.043*** (0.014)
N	4,307,727	4,307,727	4,307,727	4,307,727
<i>Panel B: Network exposure effect (Wooldridge)</i>				
Network Exposure (controls)	0.047** (0.019)	0.077* (0.042)	0.023** (0.010)	0.047* (0.027)
N	3,701,769	3,701,769	3,701,769	3,701,769
<i>Panel C: Full model (Wooldridge)</i>				
Direct Effect	-0.028*** (0.007)	-0.085*** (0.018)	-0.019*** (0.004)	-0.048*** (0.013)
Network Exposure (controls)	0.041** (0.019)	0.080** (0.040)	0.019* (0.010)	0.053** (0.025)
Direct $\times$ Network	-0.038 (0.072)	-0.209 (0.357)	0.039* (0.023)	-0.183 (0.272)
N	4,307,727	4,307,727	4,307,727	4,307,727
Inventor FE	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓

Notes: All outcomes transformed by IHS. All panels use the Wooldridge (2021) exact saturated estimator with cohort $\times$ year interaction cells aggregated to ATT via cell-count weights. State $\times$ All specifications use the pre-residualized outcome $\tilde{Y}_{it}$: state $\times$ year fixed effects are removed in a first step by regressing on state $\times$ year dummies using only never-treated inventors (Borusyak et al., 2024). Treatment intensity is $\Delta NE_{it} = NE_{it} - NE_{i,t-1}$ for network exposure. Standard errors clustered at the DMA level (210 markets).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 reports the corresponding estimates. Panel A reproduces the direct treatment effects reported in Section 5.2 and serves as a benchmark. Panel B estimates the effect of network exposure among never-treated inventors, while Panel C jointly estimates the direct treatment effect, the network exposure effect, and their interaction. The estimates in Panel B reveal that never-treated inventors whose pre-2012 collaborators become progressively exposed to SBG exhibit a small but statistically significant increase in measured productivity. We argue that, rather than contradicting the proposed mechanism, this positive average

reflects a mechanical reallocation of collaborative output. When one collaborator becomes less productive following SBG entry, a larger share of joint output is mechanically attributed to the untreated inventor, who may also redirect effort toward other projects. This reallocation effect is independent of ideology and therefore affects all inventors connected to treated collaborators.

Panel C separates this mechanical component from the ideological channel. The interaction between direct treatment and network exposure is small and statistically indistinguishable from zero, indicating that the productivity losses documented in earlier sections do not arise because existing cross-partisan collaborations deteriorate after SBG entry. Instead, the evidence suggests that the network mechanism operates primarily through the formation of new collaborative relationships rather than through the disruption of pre-existing ones.

TABLE 7. Inventor Productivity: Unaffected Focal Inventors Only, Split by Coauthor Ideology Similarity

	Inventor Productivity			
	All pat. (1)	Citations (2)	Wt. pat. (3)	Wt. cit. (4)
High homogeneity	0.042** (0.019)	0.092** (0.039)	0.021* (0.011)	0.061** (0.027)
Low homogeneity	0.024 (0.018)	0.011 (0.036)	0.011 (0.011)	0.006 (0.026)
Differential (Low – High)	–0.018 (0.019)	–0.082** (0.036)	–0.010 (0.012)	–0.055** (0.024)
N	929,404	929,404	929,404	929,404
Inventor FE	✓	✓	✓	✓
State × Year FE	✓	✓	✓	✓
Firm × Year FE	✓	✓	✓	✓

Notes: All outcomes transformed by IHS. All specifications use the pre-residualized outcome $\tilde{Y}_{it}$: state×year fixed effects are removed in a first step by regressing on state×year dummies using only never-treated inventors (Borusyak et al., 2024). Cells are (cohort×year)× Δ NE, split by subgroup; weights proportional to obs with Δ NE > 0 in each cell. Sample consist of all inventors are in markets never acquired by Sinclair. Inventors are split at the median pre-2012 ideological distance between the focal inventor and their co-inventor network. Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Two forces can explain the positive effect of network exposure: a mechanical reallocation of collaborative output that affects all inventors connected to treated collaborators, and the loss of cross-partisan knowledge, which should operate only for inventors whose pre-existing collaborations span ideological differences. To separate these two components, we partition never-treated inventors according to their pre-treatment ideological distance from the average ideology of their collaborators. We expect the positive effect to be concentrated among inventors whose collaborators are already ideologically similar, since there is relatively

little cross-partisan knowledge to lose. By contrast, for inventors whose collaborators are ideologically distant, the richer exchange of distinct perspectives is more likely to be disrupted as SBG homogenizes their collaborators’ local media environment.

Table 7 reports the corresponding estimates. Among inventors whose collaborators were already ideologically similar, network exposure is associated with a positive and statistically significant increase in productivity, particularly for citation-based outcomes. By contrast, inventors whose collaborators were ideologically distant exhibit effects that are small and statistically indistinguishable from zero. We argue that this pattern isolates the mechanical reallocation effect, indicating that the loss of cross-partisan knowledge largely offsets the mechanical productivity gain generated by reallocation.

The estimated differential is negative and statistically significant for the citation index (-0.082) and weighted citations (-0.055), while remaining statistically insignificant for patent counts (-0.018) and weighted patents (-0.010). This pattern mirrors the baseline results in Section 5.2, where SBG entry had a substantially larger effect on innovation quality than on innovation quantity.⁶ Consistent with those findings, the network spillover operates primarily along the quality margin, suggesting that the loss of cross-partisan knowledge reduces the novelty and influence of inventions rather than the number of inventions produced.

The inventor-level evidence above shows that exposure to SBG generates a positive spillover through existing collaboration networks. We next ask whether this spillover is also reflected in the collaboration itself. If the exposure of one inventor to SBG alters the productivity of an existing collaboration, the effect should be observable when the unit of observation is the inventor–collaborator pair. This dyad-level analysis therefore allows us to assess whether existing collaborative relationships are affected by a collaborator’s exposure to SBG or whether the mechanism instead operates elsewhere.

To explore this question, in Table 8 we change the unit of analysis from the inventor to the collaboration pair. We track inventor–co-inventor pairs that patented together before 2012, focusing on collaborations in which the focal inventor is never directly exposed to SBG. We then ask whether joint inventive output changes once the collaborator’s local media market is acquired. Because collaboration pairs remain in the sample even after they stop producing patents, the analysis captures both a gradual weakening of existing collaborations and their complete disappearance. Panel A reproduces the positive average spillover documented at the inventor level. SBG entry into the collaborator’s market is associated with a small but statistically significant increase in joint patenting and citations, consistent with the same mechanical reallocation of collaborative output identified above.

⁶The estimation sample is smaller than in the baseline because the analysis is restricted to never-treated focal inventors, requires identifying variation in network exposure, and conditions on observable pre-treatment ideological distance.

Panel B then partitions dyads according to their pre-treatment ideological distance. Contrary to what the intensive-margin mechanism would predict, neither ideologically similar nor ideologically distant collaborations exhibit a significant response, and the difference between the two groups is statistically indistinguishable from zero across all specifications, including those controlling for both three- and four-digit technology classes.

TABLE 8. Network Spillovers: Dyad-Level Collaboration and Ideological Heterogeneity

	Joint patents		Joint citations	
	3-digit IPC (1)	4-digit IPC (2)	3-digit IPC (3)	4-digit IPC (4)
<i>Panel A: Average treatment effect (Abraham & Sun 2021)</i>				
SBG Entry (co-inventor's market)	0.014** (0.007)	0.014* (0.007)	0.025* (0.014)	0.025* (0.014)
N	1,617,228	1,616,497	1,617,228	1,616,497
<i>Panel B: Heterogeneity by dyadic ideological distance (Wooldridge 2021)</i>				
SBG $\times$ After (Low distance — placebo)	0.000 (0.012)	−0.000 (0.013)	0.001 (0.029)	−0.002 (0.028)
SBG $\times$ After (High distance — cross-partisan)	−0.002 (0.012)	−0.003 (0.013)	0.006 (0.026)	0.002 (0.025)
Differential (High — Low)	−0.002 (0.002)	−0.003 (0.002)	0.005 (0.006)	0.004 (0.006)
N	1,617,228	1,616,497	1,617,228	1,616,497
Dyad FE	✓	✓	✓	✓
Focal County $\times$ Year FE	✓	✓	✓	✓
IPC class $\times$ Year FE	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓

Notes: All outcomes transformed by IHS. All specifications use the pre-residualized outcome $\tilde{Y}_{it}$: state $\times$ year fixed effects are removed in a first step by regressing on state $\times$ year dummies using only never-treated inventors (Borusyak et al., 2024). Unit of observation is a focal inventor–co-inventor–year triplet (2003–2023). Focal inventors are in markets never acquired by SBG; co-inventors are in treated or never-treated markets. The dyad universe is restricted to pairs with at least one joint patent before 2012 and focal-inventor activity on both sides of 2012. *Panel A* reports the overall average treatment effect via Abraham and Sun (2021), where the cohort is the year SBG entered the co-inventor's market. *Panel B* partitions dyads at the median pre-treatment ideological distance, defined as the absolute difference in county-level Democratic vote share between the focal inventor and the co-inventor. Ideologically close dyads (low distance) serve as a within-sample placebo; cross-partisan dyads (high distance) are most exposed to SBG's homogenising effect on local information environments. Columns 1 and 3 include 3-digit IPC class $\times$ year fixed effects; columns 2 and 4 use 4-digit IPC class $\times$ year fixed effects, where the IPC class is the modal technology class of the dyad's pre-2012 joint patents. Standard errors clustered at the co-inventor's DMA. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Taken together, these findings suggest that the deterioration of existing cross-partisan collaborations does not explain the productivity losses documented in our main results. If that were the case, ideologically distant collaboration pairs would experience a relative decline in joint output once one collaborator becomes exposed to SBG. Instead, existing collaborations appear largely unaffected.

9. CONCLUSION

This paper studies whether partisan media affects the production of new knowledge. We use the staggered expansion of the Sinclair Broadcast Group across U.S. television markets as a shock to local information environments and compare inventors at the same firm in the same year who live in different markets. After SBG entry, inventors' collaboration networks become more ideologically homogeneous, patent applications fall by 1.6%, and forward citations fall by 5.8%. The effects build over time, survive alternative staggered difference-in-differences estimators and bounded violations of parallel trends, and are larger in markets where the acquired station occupies a more prominent channel position.

The productivity losses are concentrated among inventors who collaborated across ideological lines before treatment. Inventors whose networks were already homogeneous are unaffected. Existing collaborations do not deteriorate when one partner's market is acquired, whether we look at focal inventors or at inventor-co-inventor dyads. What changes is the formation of new ties. Inventors form fewer new collaborations after SBG entry, and almost all of the decline comes from collaborations with ideologically distant partners. Partisan media does not dissolve the diverse relationships inventors already have. It prevents new ones from forming. Since the loss shows up in citations far more than in patent counts, the collaborations that fail to form appear to be the ones that would have produced the most influential work.

Debates over media ownership have focused on political outcomes such as vote shares, turnout, and the quality of local political coverage. Our results indicate that consolidation also affects the economy's ability to generate new ideas, and that it does so by changing whom people are willing to work with rather than only what they believe. The within-firm-year comparison is informative on this point. Colleagues at the same company, working on the same technologies, diverge in their collaborative behavior according to the media market in which they live, so firm-level incentives do not offset the effect.

Several limitations suggest directions for future work. Our ideology measure is based on county-level vote shares and therefore captures the political environment inventors live in rather than their individual views. We observe the change in tie formation but not the search and matching process behind it, so we cannot tell whether inventors become less willing to reach across partisan lines or simply have fewer opportunities to do so. Our estimates are also partial-equilibrium. They compare treated and control inventors but do not quantify the aggregate loss of innovation, which would require a model of network formation in which collaboration choices respond to the information environment. Examining whether the effects differ across industries, firm sizes, and technology classes would also help clarify where partisan media does the most damage. Taken together, our findings suggest

that the reach of partisan media is not confined to politics. It shapes the diversity of the knowledge flows on which innovation depends.

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ONLINE APPENDIX

APPENDIX A. APPENDIX

TABLE A.1. Robustness to estimator and functional form (Network Shrinkage)

	<i>Outcome: IHS transformation</i>		N
	Ideological Dispersion (1)	Ideological Distance (2)	
<i>Panel A: Linear estimators</i>			
TWFE, OLS	−0.002*** (0.000)	−0.002*** (0.001)	4,307,727
A & S (2021)	−0.002*** (0.001)	−0.002*** (0.001)	4,307,727
Wooldridge (2021)	−0.002*** (0.001)	−0.002*** (0.001)	4,307,727
Local Proj. DiD	−0.001*** (0.000)	−0.001 (0.001)	1,907,953
<i>Panel B: Raw levels (TWFE)</i>			
TWFE, Levels	−0.001*** (0.000)	−0.002*** (0.001)	4,307,727
Inventor FE	✓	✓	
State × Year FE	✓	✓	
Firm × Year FE	✓	✓	

Notes: Each cell reports the average post-entry treatment effect on the treated (ATT). Panel A: IHS outcomes; all estimators pre-residualise on state × year FE using never-treated observations. TWFE shown as benchmark. A&S: Abraham & Sun (2021) interaction-weighted estimator. Wooldridge (2021): exact saturated estimator with cohort × year interaction cells, aggregated to ATT via cell-count weights. Local Proj. DiD: Dubé et al. (2023) estimator using never-treated units; ATT averaged over post-entry horizons $h = 0, \dots, 6$. Panel B: raw outcome levels. Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.2. Robustness to estimator and functional form (Inventor Productivity)

	Outcome: IHS transformation				N
	All patents (1)	Citations (2)	Wt. patents (3)	Wt. citations (4)	
Panel A: Linear estimators					
TWFE, OLS	−0.021*** (0.007)	−0.073*** (0.017)	−0.016*** (0.005)	−0.043*** (0.015)	4,307,727
A & S (2021)	−0.020*** (0.006)	−0.073*** (0.017)	−0.016*** (0.004)	−0.042*** (0.013)	4,307,727
Wooldridge (2021)	−0.021*** (0.007)	−0.074*** (0.018)	−0.017*** (0.004)	−0.043*** (0.014)	4,307,727
Local Proj. DiD	−0.050*** (0.010)	−0.104*** (0.021)	−0.027*** (0.006)	−0.060*** (0.014)	1,907,953
Panel B: Level and Count variable outcomes					
TWFE, Levels	−0.090** (0.038)	0.094 (0.896)	−0.031*** (0.012)	0.240 (0.306)	4,307,727
TWFE, Poisson	−0.075*** (0.021)	−0.157*** (0.026)	—	—	3,800,431
Inventor FE	✓	✓	✓	✓	
State × Year FE	✓	✓	✓	✓	
Firm × Year FE	✓	✓	✓	✓	

Notes: Each cell reports the average post-entry treatment effect on the treated (ATT). Panel A: IHS outcomes; all estimators pre-residualise on state × year FE using never-treated observations. TWFE shown as benchmark. A&S: Abraham & Sun (2021) interaction-weighted estimator that accounts for heterogeneous treatment effects across cohorts. Wooldridge (2021): exact saturated estimator with cohort × year interaction cells, aggregated to ATT via cell-count weights. Local Proj. DiD: Dubé et al. (2023) local projection estimator using never-treated units as the control group; ATT is the simple average over post-entry horizons $k = 0, \dots, 6$. Panel B: raw outcome levels; Poisson uses raw counts (available only for All patents and Citations). Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.3. Robustness to Fixed Effects (Firm FE)

	Networks and Ideology		Inventor Productivity			
	Ideo. Disp. (1)	Ideo. Dist. (2)	All pat. (3)	Citations (4)	Wt. pat. (5)	Wt. cit. (6)
<i>Panel A: Abraham & Sun (2021)</i>						
SBG $\times$ After Entry	-0.003*** (0.000)	-0.001 (0.001)	-0.143*** (0.011)	-0.323*** (0.019)	-0.072*** (0.003)	-0.209*** (0.011)
N	4,839,346	4,839,345	4,839,346	4,839,346	4,839,346	4,839,346
<i>Panel B: TWFE</i>						
SBG $\times$ After Entry	-0.003*** (0.000)	-0.001 (0.001)	-0.143*** (0.013)	-0.322*** (0.022)	-0.072*** (0.004)	-0.208*** (0.011)
N	4,839,346	4,839,345	4,839,346	4,839,346	4,839,346	4,839,346
Inventor FE	✓	✓	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓	✓	✓
Firm	✓	✓	✓	✓	✓	✓

Notes: All outcomes transformed by IHS. This table replicates the baseline results using Firm Fixed Effects instead of Firm $\times$ Year Fixed Effects. Panel A: Abraham & Sun (2021) estimator. Panel B: TWFE. Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.4. Robustness: Full Sample (No Pre-treatment Restriction)

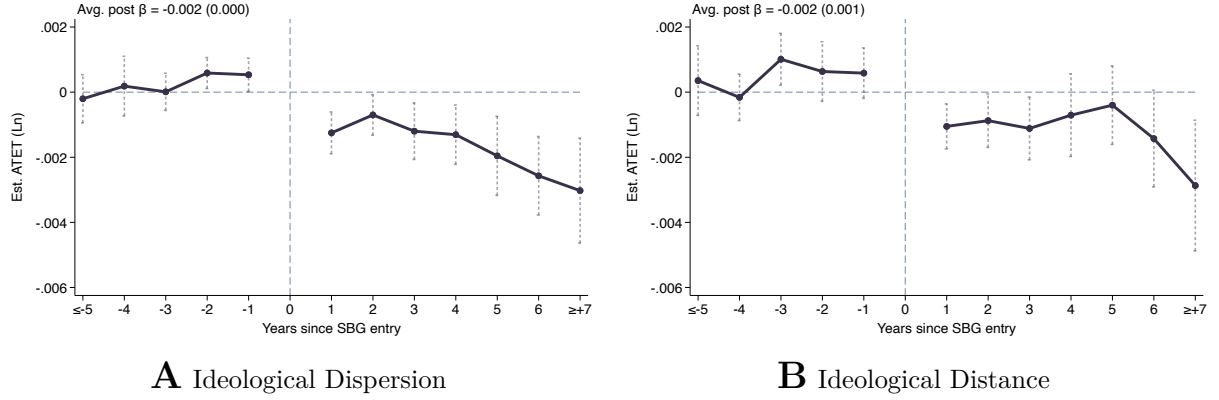
	Networks and Ideology		Inventor Productivity			
	Ideo. Disp. (1)	Ideo. Dist. (2)	All pat. (3)	Citations (4)	Wt. pat. (5)	Wt. cit. (6)
<i>Panel A: Abraham & Sun (2021)</i>						
SBG $\times$ After Entry	-0.002*** (0.001)	-0.002*** (0.001)	-0.015** (0.006)	-0.057*** (0.017)	-0.016*** (0.004)	-0.033** (0.013)
N	6,002,943	6,002,940	6,002,943	6,002,943	6,002,943	6,002,943
<i>Panel B: TWFE</i>						
SBG $\times$ After Entry	-0.002*** (0.000)	-0.002*** (0.001)	-0.015** (0.007)	-0.056*** (0.016)	-0.016*** (0.005)	-0.033** (0.014)
N	6,002,943	6,002,940	6,002,943	6,002,943	6,002,943	6,002,943
Inventor FE	✓	✓	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓	✓	✓

Notes: All outcomes transformed by IHS. This table replicates the baseline results of Tables 1 and 2 using the full sample of inventors, without requiring pre-treatment observations for treated inventors or a balanced window around 2012 for controls. Panel A: Abraham & Sun (2021) interaction-weighted estimator. Panel B: TWFE benchmark. All specifications include inventor, state $\times$ year, and firm $\times$ year fixed effects. Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

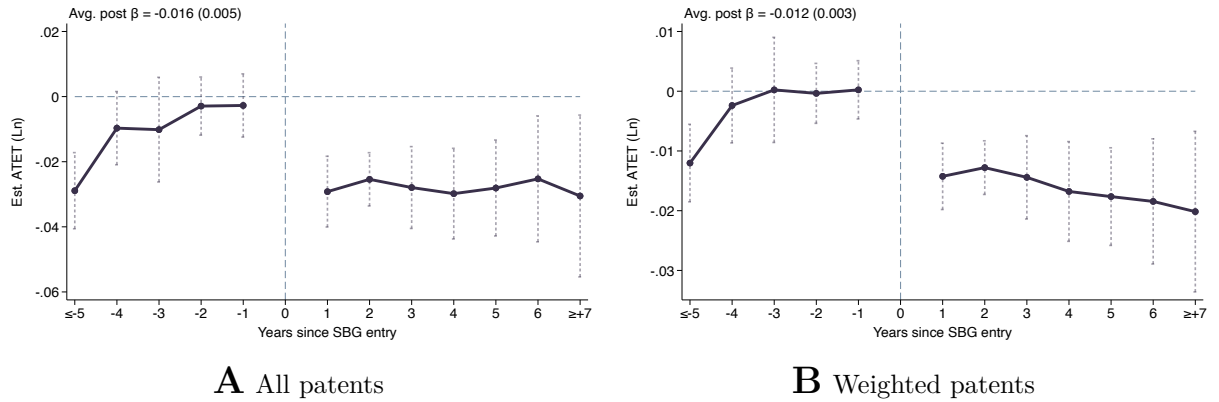
TABLE A.5. Intensity of treatment: channel position

	Networks and Ideology		Inventor Productivity			
	Ideo. Disp. (1)	Ideo. Dist. (2)	All pat. (3)	Citations (4)	Wt. pat. (5)	Wt. cit. (6)
<i>Panel A: Wooldridge (2021)</i>						
Rank SBG Chan. $\times$ After Entry	-0.002*** (0.001)	-0.003*** (0.001)	-0.025*** (0.009)	-0.094*** (0.027)	-0.019*** (0.006)	-0.056*** (0.020)
N	4,307,727	4,307,726	4,307,727	4,307,727	4,307,727	4,307,727
<i>Panel B: TWFE</i>						
Rank SBG Chan. $\times$ After Entry	0.005*** (0.001)	-0.002 (0.002)	0.081*** (0.018)	0.100*** (0.028)	0.046*** (0.012)	0.072*** (0.020)
N	4,307,727	4,307,726	4,307,727	4,307,727	4,307,727	4,307,727
Inventor FE	✓	✓	✓	✓	✓	✓
State $\times$ Year FE	✓	✓	✓	✓	✓	✓
Firm $\times$ Year FE	✓	✓	✓	✓	✓	✓

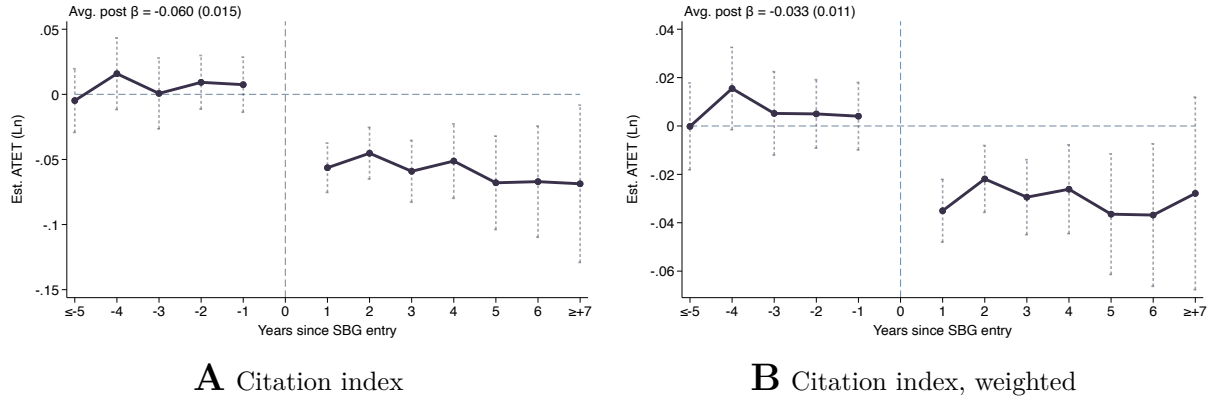
Notes: All outcomes transformed by IHS. The treatment is the product of a post-entry indicator and the channel rank dosage measure. Panel A: Wooldridge (2021) exact saturated estimator with cohort $\times$ year interactions with treatment intensity, aggregated via cohort-time cell weights. Panel B: TWFE. Standard errors clustered at the DMA level (210 markets). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE A.1. Event study: ideological diversity ($\ln(x + 1)$)

Notes: Event-study plots using the Abraham & Sun (2021) estimator. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Outcomes transformed by $\ln(x + 1)$.

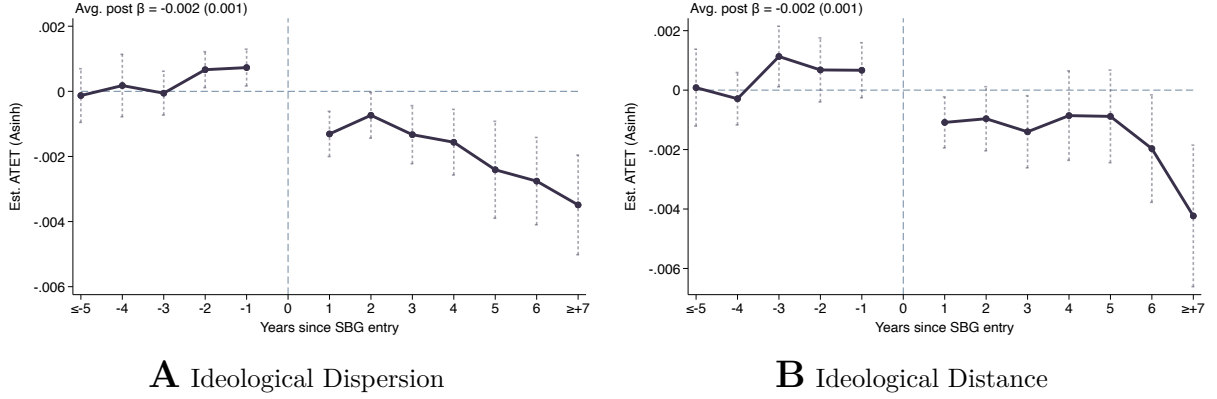
FIGURE A.2. Event study: effect of SBG entry on patent output ($\ln(x + 1)$)

Notes: Event-study plots using the Abraham & Sun (2021) estimator. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Outcomes transformed by $\ln(x + 1)$.

FIGURE A.3. Event study: effect of SBG entry on innovation quality ($\ln(x + 1)$)

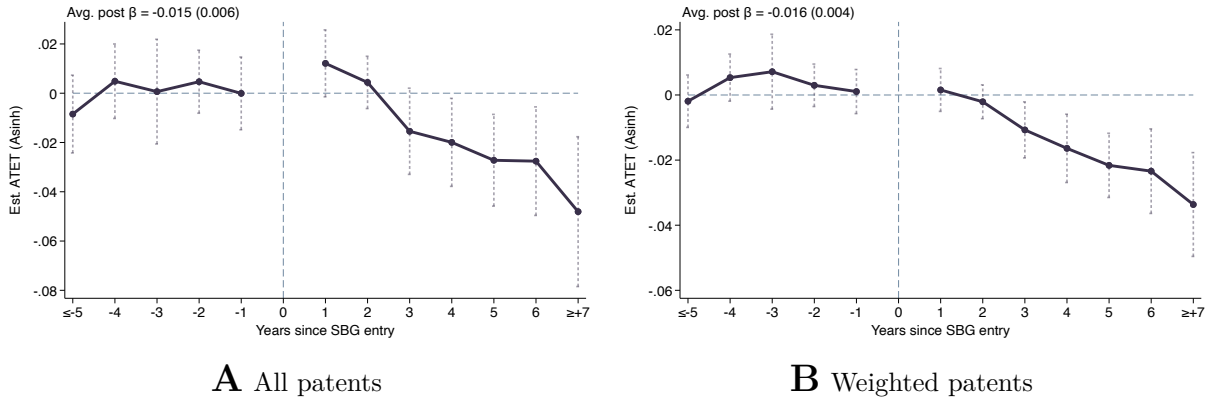
Notes: Event-study plots using the Abraham & Sun (2021) estimator for citation-based quality measures. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Outcomes transformed by $\ln(x + 1)$.

FIGURE A.4. Event study: effect of SBG entry on Ideological Diversity (Full Sample)



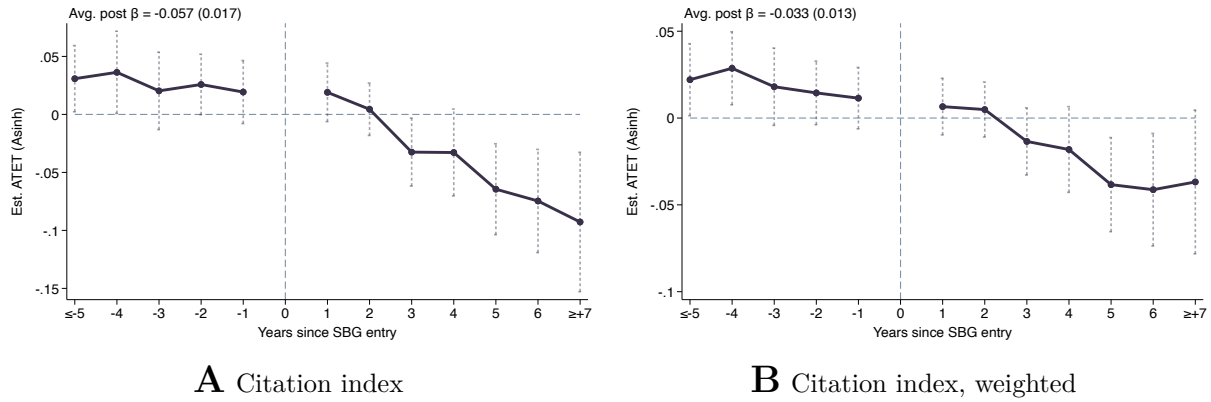
Notes: Event-study plots using the Abraham & Sun (2021) estimator. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Full sample estimation without pre-treatment observation restrictions.

FIGURE A.5. Event study: effect of SBG entry on Patent Output (Full Sample)



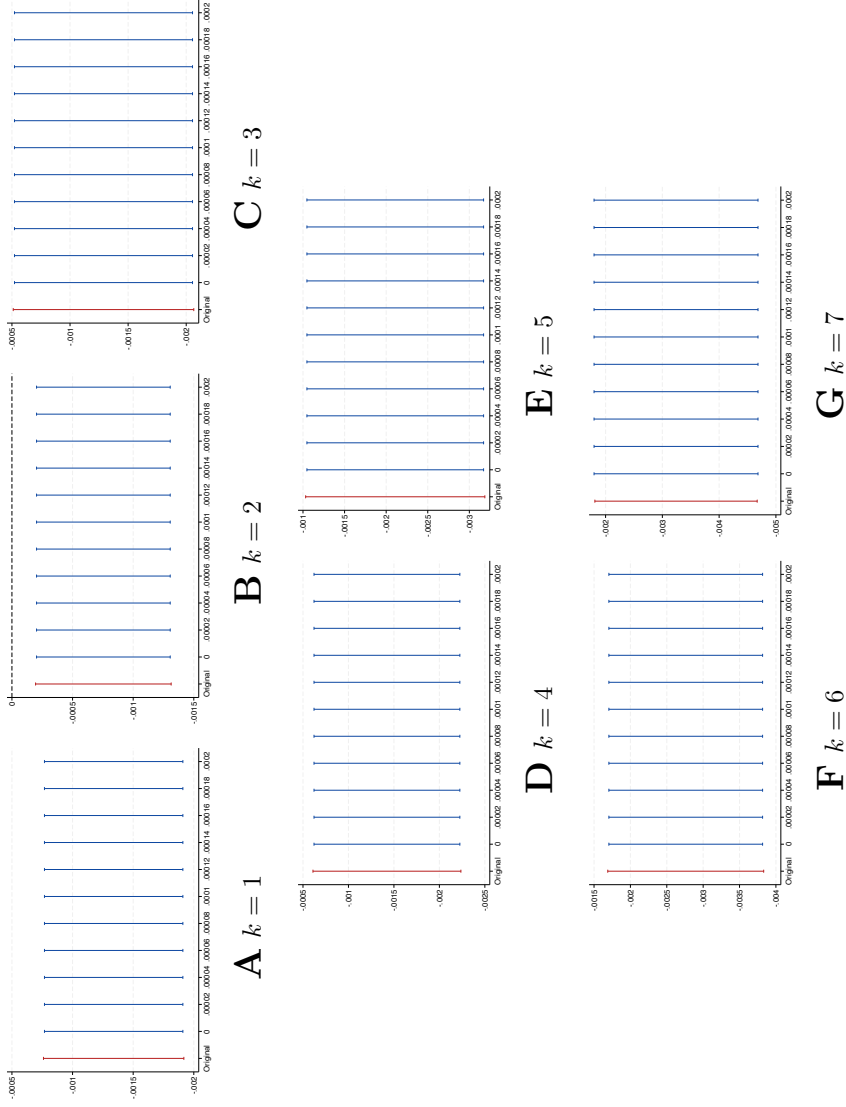
Notes: Event-study plots using the Abraham & Sun (2021) estimator. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Full sample estimation without pre-treatment observation restrictions.

FIGURE A.6. Event study: effect of SBG entry on Innovation Quality (Full Sample)



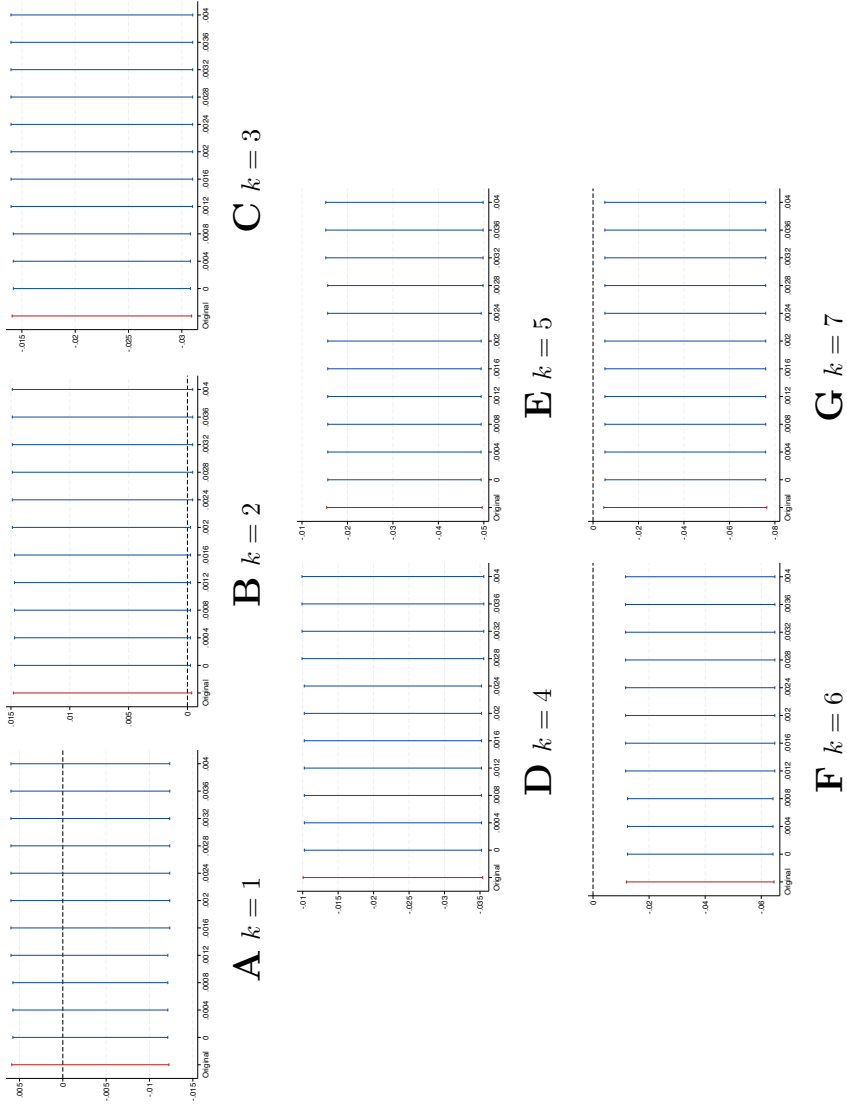
Notes: Event-study plots using the Abraham & Sun (2021) estimator for citation-based quality measures. The x -axis denotes years relative to SBG entry; $k = 0$ is the omitted base period. Dashed lines show 95% confidence intervals with standard errors clustered at the DMA level (210 markets). Full sample estimation without pre-treatment observation restrictions.

FIGURE A.7. Honest DiD: Ideological Dispersion



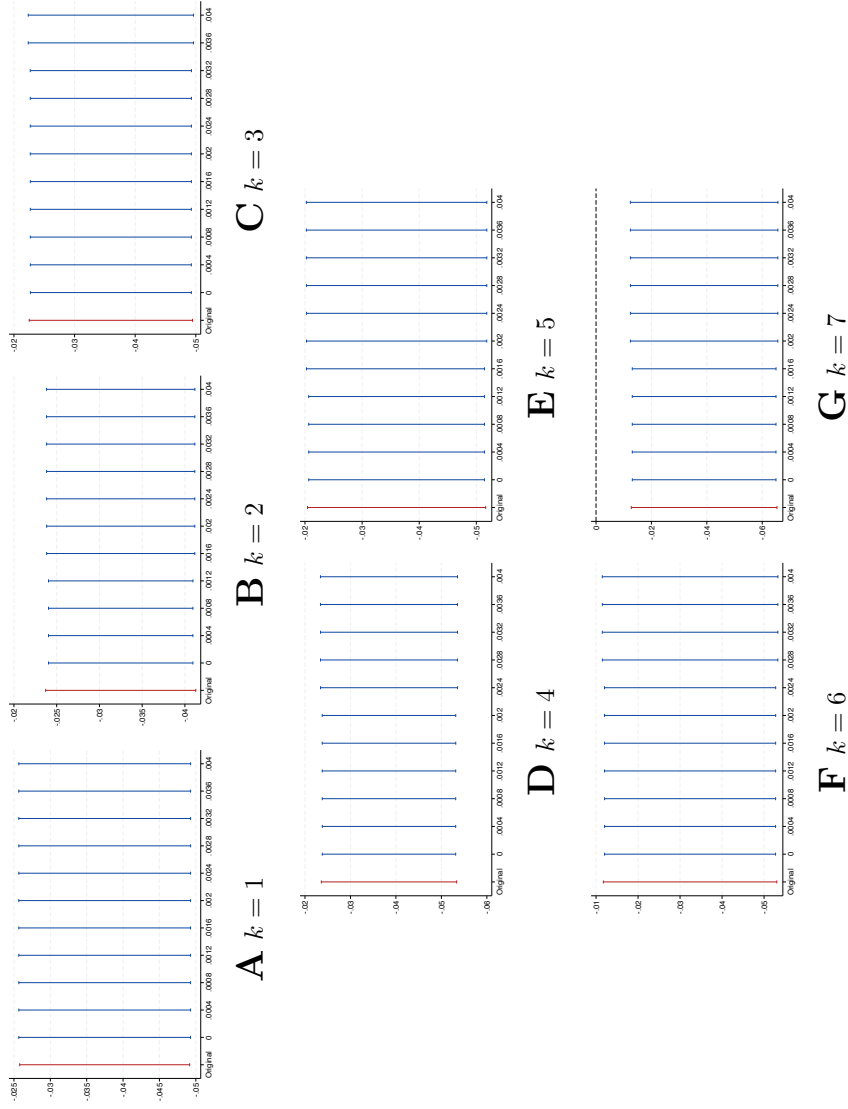
Notes: Honest DiD sensitivity analysis (Rambachan and Roth, 2023) for the effect of SBG entry on the ideological dispersion (IHS transformation). Each panel plots the 90% robust confidence set for the ATT at post-treatment period k , where $k = 1$ is the year of SBG entry and $k \geq 7$ corresponds to $k \geq 7$ years after entry. The x -axis shows $\bar{M}$, the maximum allowed change in the pre-trend slope between consecutive pre-treatment periods.

FIGURE A.8. Honest DiD: Number of Coauthors



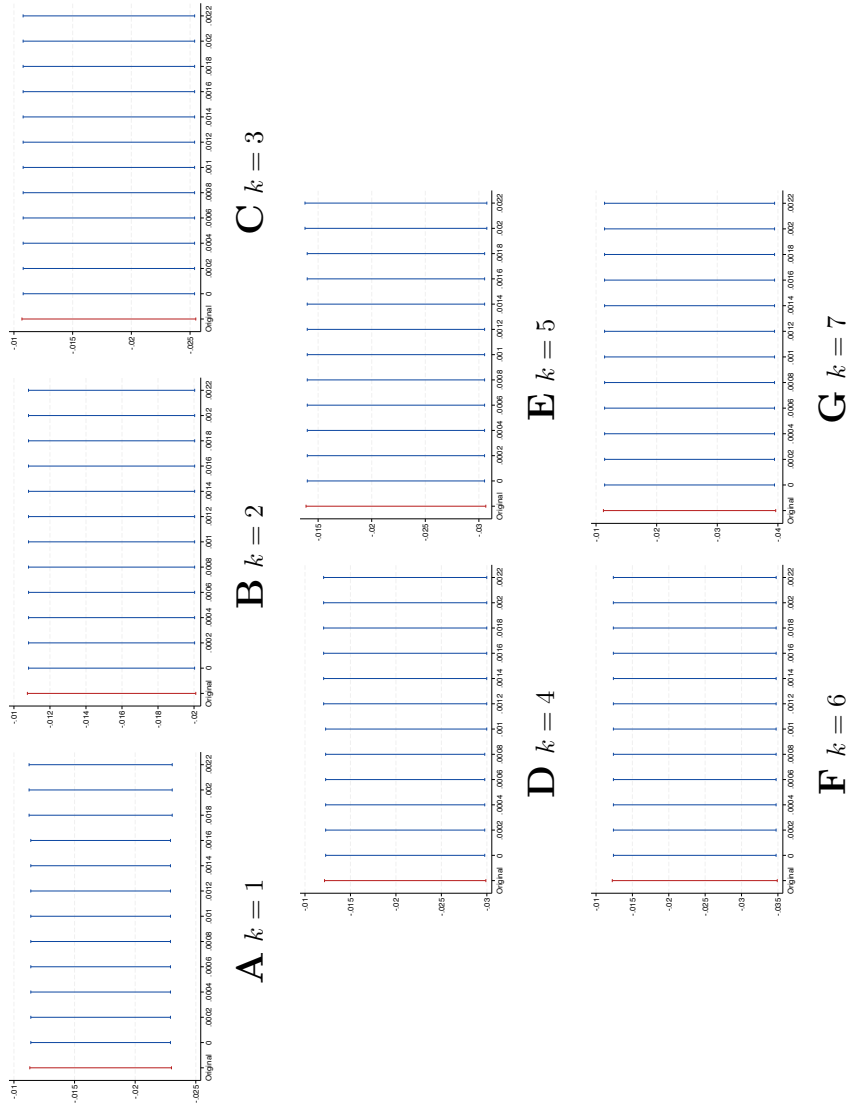
Notes: Honest DiD sensitivity analysis (Rambachan and Roth, 2023) for the effect of SBG entry on the number of unique coauthors (IHS transformation). See notes to Figure A.7.

FIGURE A.9. Honest DiD: All patents



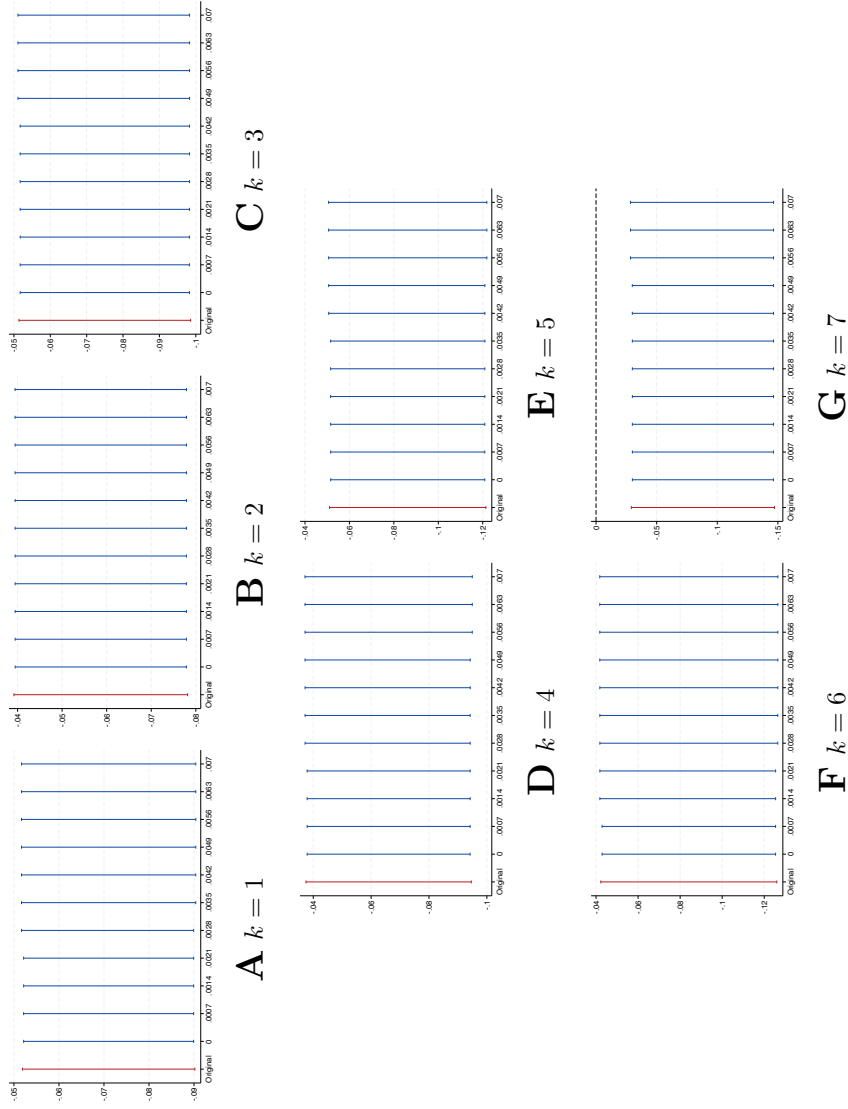
Notes: Honest DiD sensitivity analysis (Rambachan and Roth, 2023) for the effect of SBG entry on all patents (IHS transformation). See notes to Figure A.7.

FIGURE A.10. Honest DiD: Weighted patents



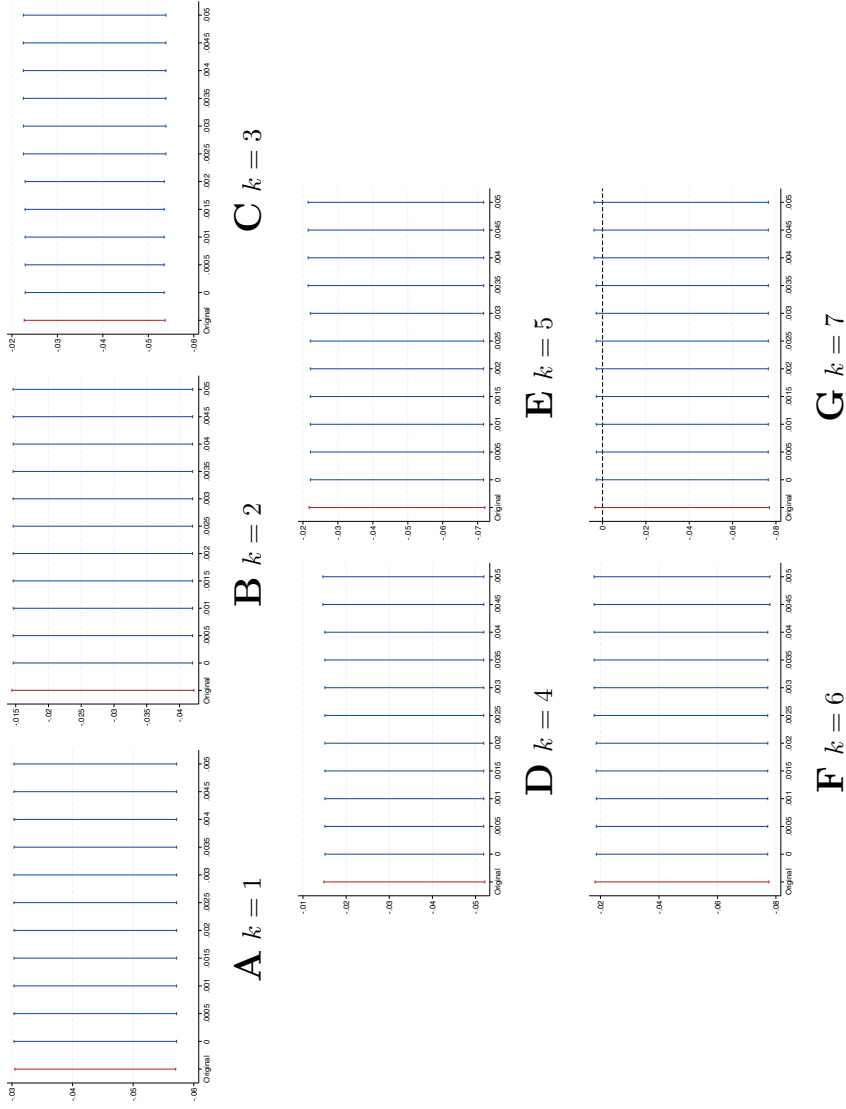
Notes: Honest DiD sensitivity analysis (Rambachan and Roth, 2023) for the effect of SBG entry on weighted patents (IHS transformation). See notes to Figure A.7.

FIGURE A.11. Honest DiD: Citations



Notes: Honest DiD sensitivity analysis (Rambachan and Roth, 2023) for the effect of SBG entry on the citation index (IHS transformation). See notes to Figure A.7.

FIGURE A.12. Honest DiD: Weighted Citations



Notes: Honest DiD sensitivity analysis (Rambachan and Roth, 2023) for the effect of SBG entry on the weighted citation index (IHS transformation). See notes to Figure A.7.