Political Distance, Talent Mobility, and the Diffusion of Ideas *

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Abstract

We study how political distance between places affects the mobility of skilled labor, the diffusion of ideas, and corporate innovation. Using a county-pair-by-year panel spanning over 20 years, we show that ideological mismatch significantly restricts the reallocation of highly skilled labor across spatial and organizational boundaries. Specifically, a one-standard-deviation increase in the difference in Republican presidential vote shares between origin and destination counties reduces bilateral inventor flows by 17%. The effect is concentrated among cross-party county pairs and longer-distance moves, and does not intensify during periods of heightened polarization. At the firm level, a one-standard-deviation increase in PAC-donation-based ideological distance implies a 62.5% decline in inter-firm inventor moves. A regression discontinuity design based on close presidential elections reveals a pull mechanism: destination counties narrowly electing Republicans attract fewer inventors, with no comparable origin-side effect. The same political distance also dampens the spatial diffusion of knowledge: a one-standard-deviation increase in county-pair political distance is associated with a 9.6% decline in bilateral patent citations. Political ideology is a friction in the reallocation of skilled human capital and the idea it carries. Furthermore, we document that this ideologically induced labor friction restricts firms from expanding into novel technological frontiers, resulting in significant declines in bilateral new technology class entries and a reduction in overall localized patenting output. Ultimately, political ideology acts as a structural friction in the reallocation of talent, imposing a real cost on the local economy.

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1 Introduction

The 2020 U.S. presidential election underscored a pronounced spatial polarization in American politics, characterized by a gap between the expansive geographic area carried by Donald Trump and the highly concentrated hubs of economic activities secured by Joe Biden. However, this geographic sorting along partisan lines extends well beyond electoral geography. Rather, it is indicative of a systemic trend of ideological homophily. While a growing body of evidence documents that partisan identity now shapes decisions well beyond the voting booth (e.g., Mian, Sufi, and Khoshkhou, 2023; Meeuwis, Parker, Schoar, and Simester, 2022; McCartney, Orellana-li, and Zhang, 2024), its role as a structural friction in the corporate market for the economy's most elite innovative talent remains an open and vital question.

Recent literature establishes that political sentiment affects incumbent innovation output (Engelberg et al., 2025) and that business owners exhibit profound homophily in their baseline employment matching (Colonnelli et al., 2025). Yet, we lack an understanding of whether political ideology impedes the geographic and organizational reallocation of skilled labor, which is the primary channel through which tacit knowledge diffuses across firms and regions (Singh and Agrawal, 2011; Akcigit et al., 2018; Hombert and Matray, 2017). If political polarization introduces dyadic matching frictions into this reallocation network, the consequences extend far beyond individual career trajectories and threaten the long-run efficiency of corporate talent allocation.

In this paper, we study whether political distance between locations impedes the flow of high-skilled labor, utilizing the mobility of inventors across U.S. counties as our empirical setting. We utilize a gravity model framework, combining dyadic county-pair and firm-pair network data from 2001 to 2023. We complement this geographic analysis with a firm-pair design using PAC-donation-based ideology scores (Bonica, 2024, 2014) to test whether these ideological frictions operate through organizational as well as spatial channels. We then extend the analysis beyond inventor mobility to capture the real economic losses of this friction, examining its impact on bilateral patent citations, the adoption of novel

technologies, and overall patenting output.

Our baseline results show a negative relationship between political distance and inventor mobility. We find that a one-standard-deviation increase in county-pair political distance reduces inventor moves by approximately 17% in a fully saturated specification. Transitioning the analysis to the firm level shows that a one-standard-deviation increase in PAC-donation-based CFscore distance implies a 62.5% decline in inter-firm inventor moves.

Second, we explore geographic proximity. When we interact political distance with indicators for neighboring-state and within-state county pairs, we find that geographical proximity partially neutralizes the political friction: the net effect of political distance is statistically zero among neighboring-state pairs, while it remains significant for longer-distance, cross-state moves. This pattern is consistent with political ideology mattering most when the baseline cost of relocation is nontrivial—precisely the margin at which place-based amenities and social environment are likely to weigh most heavily in the destination.

Third, we split the sample by the partisan alignment of county pairs. Among county pairs that share the same party, the coefficient on political distance is negative but insignificant. Among county pairs on opposite sides of the partisan divide, however, the effect is large and highly significant. This result is intuitive. When both counties lean toward the same party, marginal differences in vote share may carry limited social meaning. When the pair spans opposing partisan environments, larger political gaps likely capture a more salient mismatch in local norms, media climate, and expected social fit.

A natural concern with the baseline panel results is that unobserved time-varying factors may simultaneously drive both political distance and inventor mobility. County-pair fixed effects absorb all time-invariant bilateral confounders, but they cannot rule out time-varying omitted variables. To address this concern, we implement a regression discontinuity design (RDD) based on close county-level presidential elections from 2004 to 2020. The identifying assumption, formalized by Lee (2008), is that counties in which the Republican

candidate barely wins are comparable in expectation to counties in which the Republican candidate barely loses, so that any discrete change in inventor flows at the zero-margin cutoff can be attributed to the realized political shock. Covariate balance tests confirm that counties on either side of the cutoff are statistically indistinguishable. A McCrary (2008) density plot also confirms that the voting share margin has no manipulation of selection into either side of the cutoff.

The RDD results reveal an economically informative asymmetry. When we assign the close-election treatment to the destination county, we find that counties that narrowly elect the Republican candidate subsequently attract significantly fewer inventors, with the effect sharpening as the bandwidth narrows. In contrast, the origin-county design produces uniformly insignificant coefficients. This pattern—strong destination-side effects, null origin-side effects—suggests a pull mechanism in which inventors respond to the ideological environment of the place they would move into, rather than being pushed out of their current location. Political ideology thus appears to enter the relocation decision as a nonpecuniary cost of destination attractiveness.

Next, we extend the analysis to the diffusion of ideas themselves. Following Peri (2005), we construct a directed county-pair-by-technology-class-by-year panel of forward patent citations and ask whether politically distant counties exchange fewer ideas. The estimated effect is negative, statistically significant, and economically meaningful: a one-standard-deviation increase in county-pair political distance is associated with roughly a 9.6% decline in bilateral patent citations, a result that survives the inclusion of origin-county-by-technology, destination-county-by-technology, and technology-class-by-year fixed effects. Because inventor mobility is itself a primary carrier of tacit knowledge across regions (Singh and Agrawal, 2011; Akcigit et al., 2018), this citation result is the natural downstream counterpart of our mobility findings: political distance does not only impede the movement of the people who carry ideas, but it also impedes the movement of the ideas themselves. Furthermore, we document that this breakdown in knowledge diffusion is exacerbated when citations attempt to cross political party lines, capturing ideological

frictions at the technology-class level.

Finally, we show that this ideologically induced labor friction translates into real consequences for corporate innovation. First, we document a significant decline in bilateral new technology class entries, indicating that political distance starves locations of the cross-pollinating talent required to expand into novel technological frontiers. Second, we show that a destination's aggregate weighted political exposure directly reduces its overall patenting output. By demonstrating how political distances impact inventor flows and ultimately diminish technological adoption and patent production, we show that partisan polarization posts a real cost on the local economy.

This paper contributes to several strands of literature. Most directly, it extends the rapidly growing body of work on how political partisanship shapes economic outcomes. Existing research has documented partisan effects on household financial decisions (Meeuwis et al., 2022; McCartney et al., 2024; Pan et al., 2023), professional credit ratings (Kempf and Tsoutsoura, 2021), corporate political participation, leadership changes and broad hiring practices (Colonnelli et al., 2025; Hassan et al., 2019; Fos et al., 2022), innovation activity (Engelberg, Lu, Mullins, and Townsend, 2025), and within-firm inventor collaboration (Henriksson and Rice, 2024). While prior work demonstrates how politics affects incumbent productivity or general baseline employment, we show that ideological mismatch creates a matching friction in the cross-firm and cross-regional market for elite, innovative talent, which also shapes knowledge diffusion and corporate technology adoption.

Second, we contribute to the innovation geography literature that studies how knowledge flows across space. Since Jaffe et al. (1993), a substantial body of evidence has linked inventor mobility to knowledge spillovers and patent citation flows (Singh and Agrawal, 2011; Akcigit, Caicedo, Miguelez, Stantcheva, and Sterzi, 2018). Our findings identify a novel friction, political ideology, that impedes this mobility, complementing existing work on the roles of geographic distance, noncompete enforcement (Marx, Strumsky, and Fleming, 2009; Jeffers, 2024), and housing costs (Hsieh and Moretti, 2019) in shaping the

allocation of innovative labor. By documenting that political distance also dampens bilateral citation flows between counties, we further show that this friction reaches beyond the labor market for inventors into the spatial diffusion of the knowledge they produce. We find that this knowledge diffusion is particularly hindered when citations attempt to cross political party lines. Moreover, we show that this ideological friction translates into real technological deficits: firms and counties isolated by political distance experience significant declines in new technology class entries, effectively starving them of novel innovation.

Third, our paper speaks to the broader literature on political polarization and its real economic consequences. While much of this literature has focused on aggregate consumption, investment, and trade (Mian, Sufi, and Khoshkhou, 2023; Autor, Dorn, Hanson, and Majlesi, 2020), we document that polarization also affects the labor market for the economy's most specialized workers. The pull-side mechanism uncovered by our RDD, where destination political environment deters inventor inflows, suggests that polarization imposes a non-pecuniary tax on destination attractiveness, potentially reinforcing geographic clustering of talent along partisan lines. Ultimately, this spatial clustering carries severe aggregate consequences for local economies and corporate productivity. We document a substantial decline in overall patent output for counties exposed to higher weighted political distance.

2 Data

This section describes the construction of the main variables and the structure of the estimation sample. We organize the discussion around the two core measures—county-pair inventor flows and county-pair political distance—before turning to summary statistics and control variables.

2.1 County-Pair Inventor Flows

Our unit of observation is an ordered county pair by year. For every origin county o and destination county d, we record the number of inventors who relocate from o to d in year t. Using Patentsview pre-grant datasets, we identify an inventor's origin county in a given year as the county of the company where the inventor applies the largest number of patents in that year. We identify a county as the inventor's destination county if the county of the company changes in a certain year. Then, we pair the destination county with the origin county that is the last immediate county associated with the inventor. Because our interest lies in the bilateral flow between specific origin-destination pairs, we retain observations in which no inventor move occurs in a given year. The resulting sample is therefore a balanced county-pair-year panel spanning 2001 to 2023, containing 897,190 observations, with 1,629 unique origin counties and 1,675 unique destination counties.

The decision to preserve zero-flow observations is central to the empirical design. The economic question is not limited to the volume of inventor exchanges conditional on positive mobility; it also encompasses whether political distance deters movement from occurring at all. Dropping zeros would condition on positive matches and shift the estimand toward an intensive-margin effect, altering the economic interpretation of the coefficients. Retaining them ensures that the extensive margin—whether any inventor relocates between a given county pair in a given year—remains part of the identifying variation.[1]

The distributional properties of the dependent variable are important for the choice of estimator. County-pair inventor moves have a mean of 0.354 and a standard deviation of 6.102. The distribution is heavily right-skewed: the median and the 75th percentile are both zero, and even the 99th percentile is only five. These moments indicate that inventor mobility is sparse and concentrated in a small number of county pairs, with a large mass at zero and a long right tail. This feature of the data motivates our use of the Poisson pseudo-maximum likelihood (PPML) estimator throughout the paper (Cohn et al., 2022).

[1]Not retaining the zero-flow cells and exploring the intensive margin conditional on a already-happened move yields qualitatively similar results, though this is a substantially different research question.

Unlike log-linear alternatives, PPML naturally accommodates the count nature of the outcome without requiring arbitrary transformations of the dependent variable, preserves the balanced-panel structure, and yields estimates that are interpretable in proportional terms.

2.2 County-Pair Political Distance

We follow Pan, Pikulina, Siegel, and Wang (2023) to construct our main independent variable, county-pair political distance. It is defined as the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. The absolute-value construction is able to capture the *distance* between political environments that impedes mobility. We obtain presidential election voting data from MIT Election Lab. Formally, for county pair (o, d) observed in year t, we define its one-year lagged political distance as:

$$PoliticalDistance_{od,t-1} = |RepublicanVotingShare_{o,e} - RepublicanVotingShare_{d,e}| \quad (1)$$

where e denotes the last recent presidential election as of year $t-1$. This measure is bilateral by construction: it captures the ideological gap an inventor would face when considering a move from one county to another, rather than the partisan leaning of any single county in the pair. It is continuous, allowing us to exploit variation along the full spectrum of ideological mismatch rather than relying solely on discrete partisan categories. The measure updates every four years with each presidential election cycle and is lagged one year relative to the observed inventor flows, ensuring that the political environment is predetermined with respect to the mobility outcome.

We complement this continuous measure with two discrete political indicators to control for broader county political preferences. *Misaligned county* pair equals one when the origin and destination counties supported different parties in the most recent presidential election. *RtoR* equals one when both counties are Republican-leaning.

2.3 Samples for the Implication Tests

The implication analyses in Section 5 draw on three additional samples that share our political-distance measure and bilateral structure but differ in unit of observation. For knowledge flows, we build a directed county-pair-by-technology-class-by-year panel of forward citations among over two million U.S. utility patents (2001–2023), assigning each patent to its lead inventor's county and to the modal CPC class of the cited patent (Peri, 2005); we augment it with *class-pair political distance*, the absolute gap in net-Democratic inventor share between the citing and cited CPC three-digit classes (Engelberg et al., 2025). For technological diversification, a county-pair-by-year panel counts the distinct classes a destination county newly enters—no filing over a trailing three-year window—that the origin county already held. For aggregate output, we form a destination-county-by-year *weighted political exposure*, an inverse-distance- or headcount-weighted average of a county's political distance to every other inventor-producing county, with weights frozen at a pre-sample baseline so that only election-driven variation remains (Section 5.3). As in the mobility sample, we retain zero-flow cells throughout.

2.4 Firm-Level Ideological Distance

For the firm-level tests in Section 3.2, we measure ideological distance between the origin and destination firm of an inventor move using PAC-donation records from Bonica (2024, 2014). *cfscore-distance* is the absolute difference in the two firms' contribution-finance ideology scores on the liberal–conservative scale, while *Republican donation difference* is the absolute difference in the share of PAC contributions each firm directs to Republican candidates. The cfscore captures a firm's overall ideological position and is time-invariant, whereas the donation-share measure is a more direct, time-varying proxy for partisan giving. The firm-pair panel follows the same bilateral, zero-retaining structure as the county-pair sample.

2.5 Summary Statistics and Control Variables

Table 1 reports summary statistics for the estimation sample. Panel A describes the main variables at the county-pair-by-year level. County-pair inventor moves have a mean of 0.354, confirming the sparsity of bilateral inventor flows: the typical county pair records no inventor exchange in a given year. County-pair political distance has a mean of 0.147 and a standard deviation of 0.117, with the interquartile range spanning 0.053 to 0.216. This large variation provides meaningful statistical power for our identification. The mean of Misaligned county pair is 0.442, indicating that roughly 44% of county-pair-year observations connect counties on opposite sides of the partisan divide, while the mean of R to R is 0.144.

Panel A also reports the two auxiliary political-distance measures introduced in subsection 2.3. Class-pair political distance has a mean of 0.081 and a standard deviation of 0.116 across the citing–cited class pairs, and the two weighted political-exposure measures average 0.206 (raw) and 0.191 (geographic-distance-discounted) across the destination-county-year sample, with the discounted measure the tighter of the two.

Panel B reports the underlying county-level Republican vote shares. The mean Republican share is 0.572 in origin counties and 0.573 in destination counties, with very similar standard deviations. This symmetry is important: the explanatory variation does not arise mechanically from one side of the mobility market being systematically more Republican than the other, but from pairwise differences that shift across election cycles.

Panel C restricts attention to county-pair-year observations with positive inventor flows. Conditional on at least one inventor moving, the mean flow rises to 3.196 with a standard deviation of 18.091, confirming the lumpy, heavy-tailed nature of inventor mobility. The mean political distance among positive-flow observations is 0.134, slightly below the unconditional mean of 0.147—consistent with the hypothesis that politically closer county pairs exchange more inventors.

Panel D summarizes the firm-level sample used in Section 3.2. Firm-pair inventor moves are even sparser than county-pair moves, averaging 0.191 in the full sample and

2.849 conditional on positive flows. cfscore-distance has a mean of 0.247 (SD 0.331) and Republican donation difference a mean of 0.215 (SD 0.267); 27.1% of firm pairs are politically misaligned and 52.5% are R-to-R pairs. As in the county-pair data, political distance is lower among positive-flow observations (0.208 for cfscore-distance, 0.189 for donation difference), consistent with more inventor exchange between ideologically proximate firms.

The baseline regressions include a set of time-varying bilateral economic controls, each constructed as the absolute difference between the origin and destination county. Zillow House value index captures differences in housing costs, a first-order component of moving costs (Hsieh and Moretti, 2019). Unemployment rate proxies for differences in local labor-market slack. GDP growth captures short-run economic dynamism differentials. Economic Policy Uncertainty (EPU), measured at the state-by-month level (Baker et al., 2016), accounts for divergent policy environments. Geographic distance captures the invariant physical difference across counties. Together, these controls address the concern that county-pair political distance may be correlated with both time-invariant and time-varying economic divergence between counties.

3 Results

3.1 County-Level Results

To study how political distance affects inventor moves, we estimate the following county-pair-by-year regression:

$$E[Inventor\ Moves_{odt}] = \exp(\beta Political\ Distance_{od,t-1} + \Gamma' X_{od,t-1} + \alpha_{ot} + \gamma_{dt} + \epsilon_{odt}) \quad (2)$$

where o indexes origin counties, d indexes destination counties, and t indexes years. Our main dependent variable, $InventorMoves$, is the total number of inventors who move from origin county o to destination county d in year t. Since inventor moves are count data,

highly skewed, and contain zeros, we follow Cohn, Liu, and Wardlaw (2022) and estimate a Poisson model, which generates more consistent and efficient estimates than ordinary least squares.[2] The primary variable of interest, $PoliticalDistance$, measures the political similarity between the origin and destination counties in each county pair od in year $t-1$, based on the most recent presidential election vote shares. The vector $\Gamma' X_{odt}$ controls for the absolute differences in a set of time-varying and fixed characteristics between the two counties in the pair, including geographic distance, unemployment rates, state-level economic policy uncertainty index (EPU) as a proxy for economic conditions, GDP growth rate, and Zillow House Value Index (HVI) as a proxy for moving costs. We also control for whether the county pair is politically misaligned and whether both counties in the pair are both Republican leaning, based on the most recent presidential election results. Our analysis begins with origin-county, destination-county, and year fixed effect to control for invariant county characteristics and general time trends. To stress test the analysis, we also include origin-county-by-year fixed effects (α_{ot}) and destination-county-by-year fixed effects (γ_{dt}). The origin-by-year fixed effects absorb any time-varying determinant of an origin county's overall propensity to send inventors in a given year, including local labor-market conditions, economic shocks, and shifting amenities. The destination-by-year fixed effects provide the analogous absorption on the receiving side. This interactive fixed-effect structure also subsumes standard year fixed effects, so common macroeconomic and labor-allocation trends are netted out as well. The coefficient on political distance is therefore identified from variation across county pairs that share the same origin-year and destination-year cells. In other words, identification comes from comparing how a given origin's outflows and a given destination's inflows vary with political distance to the counties on the other side of the pair. Standard errors are double-clustered by origin county and destination county, allowing for arbitrary correlation in unobserved shocks among all county pairs that share a common origin and among all pairs that share a common destination.

[2]We report the estimation results using the Poisson pseudo-maximum likelihood regression model throughout the entire paper, unless otherwise noted.

Table 2 presents the baseline estimates of the relation between county-pair political distance and inventor mobility. In column 1, the univariate specification shows a strong negative association between political distance and inventor moves. This relation remains negative and highly significant after we add the full set of county-pair controls and cluster standard errors in columns 2 and 3. In column 4, the estimate remains significantly negative after controlling for general time trends and fixed origin- and destination-county characteristics. Column 5 presents our most demanding specification, where we include origin-county-by-year and destination-county-by-year fixed effects, which absorb any time-varying shock specific to an origin county or a destination county in a given year. The coefficient on political distance in column 5 remains significantly negative.

The effect of political distance on inventor moves is also economically meaningful. Based on the coefficient on political distance in column 5 of Table 2, a one-standard-deviation increase in county-pair political distance leads to a 17% decline in county-pair inventor moves.[3]

The other coefficients in Table 2 are informative as well. In the less demanding specifications, misaligned county pairs, R-to-R pairs, and several bilateral economic controls are strongly significant. As the fixed-effect structure becomes tighter in columns 4 and 5, the significance pattern of these controls changes. Some coefficients attenuate as the interactive fixed effects absorb the variation they previously captured, while others become sharper, and the R-to-R indicator drops out once origin-by-year and destination-by-year fixed effects are included. Across all specifications, however, county-pair political distance remains significantly negative. The fact that it survives even the saturated specification—which nets out all time-varying origin- and destination-specific conditions—suggests that ideological mismatch between specific county pairs predicts inventor mobility above and beyond economic factors operating at the level of a single county in a given year.

Finally, the clustering strategy is important. Inventor flows have a directed dyadic structure, in which each origin county and each destination county appears in many pairs.

[3] -17%=$\exp(-1.59 \times 0.117) - 1$, where 0.117 is the standard deviation of political distance from Table 1, and -1.59 is the coefficient in column 5 of Table 2

A shock to an origin county—a plant closure or a change in state policy, for example—can correlate the error terms of all pairs that share that origin. The same logic applies to shocks to a destination county. Double clustering by origin county and destination county allows for arbitrary correlation along both of these margins.[4]

Overall, Table 2 provides the core evidence of the paper: inventors move less across politically distant county pairs, and this conclusion survives increasingly demanding controls for economic differences, saturated origin- and destination-by-year fixed effects, and conservative two-way clustered inference.

3.2 Firm-Level Results

Table 3 moves the analysis from geography to patenting firms. The motivation is straightforward. If the mechanism truly reflects ideological mismatch, then the effect should not disappear when political distance is measured at the firm level rather than at the county level. To test this idea, we construct two firm-pair measures of political distance using firms' PAC-donation records. The first measure, *cfscore-distance*, is the absolute difference between the origin and destination firm's PAC-donation-based contribution finance ideology scores (*cfscore*) from Bonica (2024).[5] The second measure, Republican donation difference, is the absolute difference between the origin and destination firm's fraction of PAC contributions to Republican candidates. The *cfscore*-based measure captures overall ideological distance on a continuous liberal-conservative scale, while the donation-share measure provides a more direct proxy for partisan distance in observed political giving.

Panel D of Table 1 shows that the firm-pair outcome is also sparse. The mean number of firm-pair inventor moves is 0.191 in the full sample and 2.849 conditional on positive flows. The mean *cfscore-distance* is 0.247 in the full sample and 0.208 among positive-flow observations. The mean Republican donation difference is 0.215 in the full sample

[4]The sharp drop in the t-statistic on political distance between columns 2 and 3, where clustering is introduced, illustrates why two-way clustering matters in our setting.

[5]*cfscore* is a political ideology score that measures the targets' ideological leaning on the liberal-conservative scale estimated using their entire political donation records. Readers interested in the detailed construction of this measure are referred to Bonica (2014).

and 0.189 among positive-flow observations.[6] The panel also shows that 27.1% of firm pairs are politically misaligned, while 52.5% are classified as R-to-R pairs. The sample period spans from 2001 to 2023 and follows the same bilateral sample structure as the county-pair tests.

Table 3 reports the regression results. Columns 1 and 2 use Republican donation difference as the main independent variable. Column 1 includes origin-firm, destination-firm, and year fixed effects. The coefficient is -1.959 and statistically significant at 1% level. Column 2 replaces these additive fixed effects with origin-firm-by-year and destination-firm-by-year fixed effects, which absorb time-varying shocks specific to each sending and receiving firm. The coefficient becomes -2.721 and remains highly significant. Columns 3 and 4 repeat the exercise using *cfscore-distance*. The coefficient is -3.153 in Column 3 with origin-firm, destination-firm, and year fixed effects, and -2.964 in Column 4 with origin-firm-by-year and destination-firm-by-year fixed effects. Both estimates are statistically significant at 1% level. Standard errors are double-clustered by origin firm and destination firm.

The fixed-effect structure in Columns 2 and 4 is especially demanding. It absorbs not only persistent differences across origin and destination firms, but also time-varying firm-level shocks—such as changes in patenting intensity, R&D activity, or hiring scale—that could simultaneously affect inventor flows and the firm's political environment. The estimates are therefore identified from bilateral variation across firm pairs after netting out time-varying origin- and destination-firm heterogeneity, substantially reducing concerns that the result merely reflects stable differences in firm type or contemporaneous shocks at either end of the firm pair.

The economic magnitudes are meaningful. Using the standard deviation of Republican donation difference from Panel D of Table 1, the Column 2 estimate implies that a one-standard-deviation increase in Republican donation difference is associated with roughly

[6] One weakness of *cfscore* to proxy for a firm's political stance is that it does not vary over time, since it is calculated using each firm's entire contribution records.

a 51.6% decline in inventor moves between the firm pair.[7] Using the standard deviation of *cfscore-distance*, the Column 4 estimate implies that a one-standard-deviation increase in firm-pair ideological distance is associated with roughly a 62.5% decline in inventor moves.[8] These magnitudes are sizeable and substantially larger than the county-pair estimate. One plausible interpretation is that firm-level political leaning is a more direct and relevant measure of the ideological environment an inventor would face in the workplace. Counties capture the broader social and political context of place, whereas firms' political giving and *cfscore* are more closely tied to the organization's own political identity.

This firm-level exercise is important for the paper's contribution because it shows that the political-distance effect is not solely a story about counties. Across two distinct measures of firm-pair political distance, inventors move less between politically distant firms even after absorbing time-varying origin- and destination-firm heterogeneity. This result strengthens the argument that ideology affects the mobility of innovative labor through both place-based and firm-based channels.

4 Identification Strategy and Economic Mechanism

4.1 Identification via the Within-State Moves

Our baseline estimation documents a robust negative association between political distance and bilateral inventor flows, but two plausible alternative interpretations remain. First, political distance may proxy for unobserved geographic, cultural, or economic distance: counties that drift apart politically may also diverge along other dimensions—climate, demographics, or industrial composition—that independently reduce mobility between them. Second, state-level institutional frictions known to shape inventor mobility and yet hard to be controlled for, including non-compete enforceability (Marx et al., 2009),

[7] $\exp(-2.721 \times 0.267) - 1 \approx -51.6\%$, where 0.267 is the standard deviation of Republican donation difference and -2.721 is the coefficient from Column 2 of Table 3.

[8] $\exp(-2.964 \times 0.331) - 1 \approx -62.5\%$, where 0.331 is the standard deviation of firm-pair *cfscore-distance* and -2.964 is the coefficient from Column 4 of Table 3.

state tax regimes, professional licensure, and state employment law, may vary jointly with political environments and could therefore drive the apparent friction we attribute to political distance itself. We address both concerns through two complementary identification strategies. This subsection decomposes the friction by the geographic structure of the move, isolating an estimate identified entirely from within-state variation that holds state-level institutional environments fixed. subsection 4.2 complements this analysis with a regression discontinuity design around close Presidential county-level elections.

We partition directed county pairs into three mutually exclusive groups based on the geographic character of the move: pairs within the same state ($Within_{od} = 1$), pairs in different but neighboring states ($Neighbor_{od} = 1$ & $Within_{od} = 0$), and pairs in non-neighboring states, which form the omitted base group, $Far = (Neighbor_{od} = 0$ & $Within_{od} = 0)$. We then estimate a single PPML specification that fully saturates the political-distance slope across these three groups:[9]

$$E[InventorMoves_{odt}] = \exp\Big(\beta_1 Within_{od} + \beta_2 Neighbor_{od} + \beta_3 ABScountyPolDist_{odt-1} + \beta_4\big(Within_{od} \times ABScountyPolDist_{odt-1}\big) + \beta_5\big(Neighbor_{od} \times ABScountyPolDist_{odt-1}\big) + \Gamma' X_{odt-1} + \alpha_o + \gamma_d + \delta_t + \epsilon_{odt}\Big) \quad (3)$$

where X_{odt-1} is the same vector of controls used in our baseline specification, and α_o, γ_d, and δ_t are origin-county, destination-county, and year fixed effects. Standard errors are double clustered by origin and destination county. The three group-specific semi-elasticities of inventor flows with respect to political distance are recovered as $\beta_{\text{far}} = \beta_3$ for non-neighboring pairs, $\beta_{\text{neighbor}} = \beta_3 + \beta_5$ for neighboring pairs, and $\beta_{\text{within}} = \beta_3 + \beta_4$ for within-state pairs.[10]

Table 4 reports the results. The pattern is sharp. For non-neighboring out-of-state pairs,

[9] This saturated model makes sense as the omitted interaction term $\beta\big(Within_{od} \times Neighbor_{od} \times ABScountyPolDist_{odt}\big)$ is mechanically dropped as there are no observations for $Neighbor_{od} = 1$ & $Within_{od} = 1$.

[10] We conduct the linear combination of parameter test with the same standard error clustering level to confirm the statistical power below.

the coefficient is negative and highly significant at the 1% level. The economic magnitude is also nontrivial. A one-standard-deviation increase in political distance reduces bilateral inventor flows by approximately 12.5%.[11] For pairs in neighboring states, the friction is statistically and economically indistinguishable from zero ($\hat{\beta}_{\text{neighbor}} = +0.223$, $t = 0.61$). For within-state cross-county pairs, the friction is stronger in both statistical and economic terms: the coefficient $\hat{\beta}_{\text{within}}$ is -4.98 and significant at the 1% level, and a one-standard-deviation increase in political distance reduces flows by approximately 44%. This effect is much larger than the corresponding effect for moves between non-neighboring out-of-state pairs.[12]

This decomposition serves two distinct identification purposes. First, the economic magnitude of three subgroups of moves mitigates the omitted variable concern. Under a confounding interpretation in which political distance proxies for unobserved geographic, cultural, or economic distance, the estimated friction should scale *with* distance: it should be small for proximate moves and large for distant moves. The results deliver the opposite. The within-state estimate—where geographic distance is smallest and the state-level institutional environment is held constant—delivers the largest impact, while the neighboring-state estimate is statistically zero. This pattern rules out a broad class of confounding stories in which political distance proxies for the geographic, cultural, demographic, or economic differences.

Second, the within-state estimate provides a coefficient on political distance that is purged of state-level institutional confounds. Within-state moves hold constant non-compete enforceability, state tax regimes, state employment law, professional licensure, federal jurisdictional boundaries, and state-level political institutions—the full set of state-level frictions documented in the labor-mobility literature to affect inventor relocation. Variation in political distance across same-state county pairs therefore reflects fine-grained local cul-

[11] The coefficient of $\hat{\beta}_{\text{far}}$ is -1.14. The standard deviation of county-pair political distance is 0.117 from Table 1. $12.5\% = exp(-1.14 \times 0.117) - 1$

[12] The coefficient of $\hat{\beta}_{\text{within}}$ is -4.98. The standard deviation of county-pair political distance is 0.117 from Table 1. $44\% = exp(-4.98 \times 0.117) - 1$

tural and political differences rather than institutional differences between states. The within-state coefficient of $\hat{\beta}_{\text{within}} = -4.98$ is therefore the cleanest estimate of the political channel in our data, identified entirely from variation that no existing institutional mobility friction can explain. We view it as the central identification result of this paper: the political-distance friction survives—and indeed intensifies—precisely when every state-level alternative explanation is shut down by construction.

The proximity decomposition addresses time-invariant institutional and geographic confounders, but it cannot rule out time-varying unobserved heterogeneity that may correlate with political distance trajectories. We therefore complement this evidence with a regression discontinuity design that exploits plausibly random local political shocks from close county-level presidential elections.

4.2 Regression Discontinuity Design

Our baseline county-pair regressions document a robust negative association between political distance and inventor mobility, but a natural concern is that unobserved time-varying county-pair variables may simultaneously affect both political distance and bilateral inventor flows. For example, places that become politically more distant may also diverge along social, cultural, or economic dimensions that independently reduce bilateral mobility. While county-pair fixed effects absorb all time-invariant sources of such heterogeneity, they cannot rule out time-varying omitted factors that move jointly with political distance and inventor flows.

The ideal experiment for establishing causality would randomly assign political environments to counties and observe the resulting changes in inventor mobility. Because political outcomes are endogenous in practice, we complement our panel analysis with a regression discontinuity design (RDD) based on close county-level presidential elections from 2004 to 2020, covering five elections. The basic idea, formalized by Lee (2008), is that in elections decided by a narrow margin, the electoral outcome contains a meaningful component of randomness. Counties in which the Republican candidate barely wins

should be comparable in expectation to counties in which the Republican candidate barely loses, so that any discrete change in inventor mobility at the zero-margin cutoff can be attributed to the realized political shock rather than to preexisting differences between counties.

The identifying assumption—standard continuity of potential outcomes through the zero-margin cutoff (Lee, 2008; Lee and Lemieux, 2010)—is most plausible when the comparison is restricted to counties with nearly indistinguishable election outcomes. As Akey (2015) notes in the context of close congressional elections, as long as agents cannot precisely determine the outcome in advance, the RDD captures a local average treatment effect that is plausibly free of omitted-variable confounds. In our setting, this means that counties barely electing Republicans and counties barely electing Democrats should not differ discontinuously in other determinants of inventor flows at the cutoff. Eggers, Fowler, Hainmueller, Hall, and Snyder (2015) examine the validity of close-election RDDs across more than 40,000 races and find no systematic evidence of sorting or covariate imbalance around electoral thresholds, further supporting this assumption.

To formally verify the absence of sorting in our sample, we apply McCrary (2008)'s density test for manipulation of the voting share margin, the running variable, at the cutoff. We also plot the voting share margin against its density in Figure 1 to examine whether the density is smooth through the cutoff. The test yields a p-value of 0.166, suggesting that there is no manipulated selection into either side of the threshold. Visual inspection of the density plot in Figure 1 confirms this statistical finding, showing a smooth distribution across the cutoff.

Our implementation proceeds as follows. The running variable is the county-level presidential election margin, defined as the Republican candidate's vote share minus the Democratic candidate's vote share, with the cutoff equal to zero. The treatment indicator, $CloseRWin_{d,e}$, equals one when the Republican candidate wins election e in county d and zero otherwise. Consistent with our baseline specification, the close-election treatment is assigned based on the most recently completed election as of year $t-1$, ensuring that the

political shock is predetermined relative to the year in which inventor moves are observed. Following Akey (2015), we estimate the RDD across alternative narrow bandwidths, 0.05 and 0.02, around the zero-margin cutoff, where the identifying assumption is most plausible. Panel A of Table 5 reports the distribution of election events by winning margin and confirms that, within each bandwidth, the sample is roughly balanced between Republican and Democratic wins—a pattern consistent with quasi-random assignment near the cutoff.

This RDD design is especially useful in our setting because it allows us to separate two economically distinct channels. When we assign the close-election treatment to the *destination* county, we test whether a county that narrowly becomes more Republican attracts fewer inventors from elsewhere—a pull-side mechanism in which the political environment of the destination becomes less attractive to potential movers. When we assign the treatment to the *origin* county, we test whether inventors are pushed out of counties that barely elect one party rather than the other—a push-side mechanism operating through the political environment the inventor leaves behind. If the mobility friction operates primarily through destination attractiveness, we should observe stronger effects in the destination-county RDD than in the origin-county RDD.

For the destination-county design, we estimate:

$$E[InventorMoves_{ode}] = \exp(\ \beta Close\ R\ Win_{d,e} + f(Margin_{d,e}) + Close\ R\ Win_{d,e} \times g(Margin_{d,e}) + \Gamma' X_{ode} + \delta_e + \epsilon_{ode}\ ) \quad (4)$$

where o indexes origin counties, d indexes destination counties, and e indexes election years. $Margin_{d,e}$ is the running variable for destination county d in election e, and $f(\cdot)$ is a flexible control function of the margin.[13] δ_e denotes election year fixed effects, since our test involves multiple election events. To accommodate the count nature of the dependent variable, the model is estimated using a Poisson regression model. Following Bertrand, Duflo, and Mullainathan (2004), who argue that clustering should be done by the unit of

[13] In Table 5, we use first order linear control function. Results are similar if using a quadratic control function.

observation of the main explanatory variable, we cluster the standard errors at the origin/destination county level. For the origin-county design, the specification is analogous, replacing destination-county variables with origin-county variables.

Panel A of Table 5 presents summary statistics of election events across different bandwidth choices. While the full sample contains significantly more Republican-winning counties than Democratic-winning counties, narrowing the bandwidth around the zero cutoff yields a roughly even distribution of outcomes, supporting the comparability of the local sample.[14]

As formalized by Lee (2008), the causal interpretation of an RDD requires that there be no observable differences between treated and control units around the discontinuity. We test this assumption in Panels B and C of Table 5, which compare key economic conditions between counties where the Republican candidate narrowly won and lost within a 5% winning-margin bandwidth. Panel B focuses on destination counties. Across all four covariates—EPU, unemployment rate, GDP growth, and house value index—the differences between winning and losing counties are small in magnitude, and none of the robust t-statistics exceed conventional significance thresholds. Panel C repeats this exercise for origin counties and produces a similarly reassuring pattern: the differences are economically negligible and statistically insignificant across all four variables. While failing to reject the null hypothesis of no difference is not conclusive, these results suggest that counties on either side of the election cutoff are highly comparable along the observable economic dimensions most likely to independently affect inventor mobility, validating the close-election RDD as a source of plausibly exogenous variation in local political environments.

Panel D of Table 5 reports the estimation results using Equation 4. In the destination-county design, columns 1–4, the coefficient on $Close\ R\ Win$ is small and insignificant in the full sample of all elections, but becomes sharply negative and statistically signifi-

[14] This link talks about how the Democratic Party dominates much less but much more densely populated counties. For example, in 2020, Donald Trump won 2,548 of the roughly 2,960 smaller, less-populated counties, while Joe Biden won only 126 of the top 151 most populous "vote-rich" counties.

cant when the sample is restricted to narrow bandwidths around the cutoff. Across bandwidths from 0.05 down to 0.02, the treatment coefficients remain consistently negative and significant, indicating that a close Republican victory deters inventor inflows into the destination county. In contrast, the origin-county design, columns 5–8, yields uniformly insignificant coefficients across all bandwidths. This pattern—strong destination-side effects coupled with null origin-side effects—is consistent with a pull mechanism rather than a push mechanism. On the one hand, when a destination county narrowly elects a Republican candidate, potential movers become less willing to relocate there, indicating a response to the ideological environment of the place they would move into. On the other hand, the absence of a comparable origin-side discontinuity suggests that close election outcomes do not appear to push inventors out of their current counties.

Overall, the RDD results complement our baseline findings by exploiting plausibly quasi-random variation from close elections, alleviating the concern that the negative association between political distance and inventor mobility is driven by time-varying omitted factors. Furthermore, the RDD uncovers an economically informative asymmetry: the effect operates primarily through the destination side, with inventors becoming less willing to move into counties that narrowly elect Republican candidates. The absence of a comparable origin-side effect suggests that political ideology enters the relocation decision as a friction on destination attractiveness rather than as a force pushing inventors out of their current locations. This pull-dominated pattern is consistent with ideology acting as a non-pecuniary cost in the relocation decision of high-skilled labor.

5 Implications of Political Distance

5.1 Knowledge Flows

The preceding sections establish that political distance acts as a friction in the bilateral reallocation of inventive talent across counties and firms. The economic importance of this friction ultimately depends on how inventor mobility contributes to the diffusion of

knowledge. A long tradition in the economics of innovation, beginning with Jaffe, Trajtenberg, and Henderson (1993), treats the movement of skilled human capital as a primary channel through which tacit knowledge diffuses across regions. Subsequent work has formalized the role of inventor mobility in transmitting ideas across firms and places (Singh and Agrawal, 2011; Akcigit et al., 2018). Knowledge diffusion, however, is not confined to physical relocation alone. Patent citations capture broader channels of idea transmission, such as professional networks, cross-regional collaboration, and informal learning, that can operate even in the absence of inventor mobility (Agrawal et al., 2011; Singh, 2005).

If political distance hinders these interactions in addition to migration decisions, politically distant counties should exchange fewer ideas than would be predicted by reduced mobility alone. We bring this prediction to the data using patent citation flows, a standard empirical proxy for cross-region knowledge spillovers (Jaffe et al., 1993; Peri, 2005).

We construct a directed county-pair-by-technology-class-by-year panel of citation flows, consisting of over 2 million U.S. utility patents from 2001 to 2023, covering over 3,000 counties, including both origin and destination counties, and over 120 technology classes, defined at the CPC class level.[15] The unit of observation is (i, j, K, t), where i is the origin county, j is the destination county, K is a technology class, and t is a year. Following Peri (2005), the dependent variable $\textit{Citations}_{i,j,K,t}$ counts the forward citations made by patents filed in destination county j in year t to prior patents originating in origin county i within technology class K. The directional convention mirrors our mobility design: county i is the source of the knowledge being absorbed, and county j is the absorber. The citation panel therefore asks whether the same political mismatch that deters inventors from moving from i to j also dampens j's absorption of i's ideas. We assign K as the modal CPC class of the cited, or origin, patent and identify each patent's location with the county of its lead

[15] Of 2 million patents, over 1.6 million are at least cited once in our sample period.

inventor.[16] As before, we retain zero-flow cells, since the substantive question is whether political distance deters citations from occurring at all rather than the intensity of citation flows conditional on citations having already occurred.[17]

We estimate the following Poisson pseudo-maximum likelihood regression specification:

$$E[\textit{Citations}_{i,j,K,t}] = exp(\beta, \textit{Political Distance}_{i,j,t-1} + \Gamma' X_{i,j,t-1} + \alpha_{i,K} + \delta_{j,K} + \tau_t + \varepsilon_{i,j,K,t}) \quad (5)$$

where *Political Distance*$_{i,j,t-1}$ is constructed as in section 2, $\alpha_{i,K}$ is an origin-county-by-technology-class fixed effect, $\delta_{j,K}$ is a destination-county-by-technology-class fixed effect, and τ_t is a year fixed effect. The vector $X_{i,j,t}$ includes county-level absolute differences in GDP growth, the politically misaligned county-pair indicator, the $R\text{-}to\text{-}R$ indicator, and a within-state indicator, together with bilateral geographic distance and the origin-county and destination-county patent stocks within technology class K. Geographic distance has been the standard control in citation regressions since Jaffe et al. (1993). The two patent-stock terms scale the size of the citable pool in i and the citing capacity of j in technology class K, both of which mechanically affect the count of citations and would otherwise be correlated with persistent local economic conditions.

The fixed-effect structure absorbs the most plausible sources of non-political heterogeneity. The origin-by-technology fixed effects $\alpha_{i,K}$ hold constant the productive endowment of each origin county in each technology, ensuring that we do not confuse a place's knowledge-output capacity with its political environment. The destination-by-technology fixed effects $\delta_{j,K}$ provide the analogous absorption on the absorber side, removing persistent differences in j's tendency to cite within technology class K. Year fixed effects absorb

[16] Using the modal class of the cited patent is consistent with the interpretation of K as the technology field of the knowledge being drawn upon. Inventor location is preferred to assignee location because inventor addresses capture where the knowledge is actually produced and absorbed, whereas assignee addresses often reflect a firm's headquarters location rather than the locus of inventive activity (Singh and Agrawal, 2011). In the case of a tied modal CPC class, we use the first CPC class listed on the cited patent.

[17] Like in the baseline inventor move results, the knowledge flow test also yields qualitatively similar results if we do not retain zero-flow cells and only explore the intensive margin conditional on the already-happened flows. Nevertheless, this is a substantially different research question.

common shocks to aggregate citation activity, including the well-documented secular rise in citations made per patent and the strong cohort effects that arise because forward citations accumulate over many years following a patent's grant (Hall et al., 2001; Jaffe and de Rassenfosse, 2016).[18]

Table 6 reports the estimates. The coefficient on county-pair political distance is negative and statistically significant at the one-percent level across all three specifications, and its magnitude is stable as the fixed-effect structure tightens. In Column 1, which includes year, origin-county, and destination-county fixed effects together with the bilateral controls and patent-stock measures, the estimated coefficient is -0.811. Replacing year fixed effects with technology-class-by-year fixed effects in Column 2 leaves the coefficient essentially unchanged at -0.874. Column 3 is our preferred and most stringent specification, with origin-county-by-technology-class, destination-county-by-technology-class, and technology-class-by-year fixed effects. The coefficient in this column is -0.553 and remains highly significant, indicating that the deterrent effect of political distance on citation flows is not an artifact of unobserved differences in county-level production capacity, technology mix, or differential aggregate trends across fields.

The economic magnitude is meaningful. Using the standard deviation of county-pair political distance from Panel A of Table 1 (0.117) and the coefficient in Column 3, a one-standard-deviation increase in political distance implies a 6.3% decline in bilateral patent citations.[19] The control coefficients are also informative. Geographic distance loads negatively and significantly across all columns, replicating the spatial decay of citations documented in Jaffe et al. (1993). Both patent-stock terms are significantly positive, confirming

[18] This combination of origin-by-technology, destination-by-technology, and year fixed effects is our preferred specification because patenting activity is highly concentrated in a small number of county-by-technology cells—Silicon Valley counties in computing and communications, San Diego and Boston in biotechnology, Detroit in automotive technology—and these specialized hubs tend to occupy distinctive positions on the political spectrum. Without origin-by-tech and destination-by-tech fixed effects, the political-distance coefficient could mechanically reflect cross-county differences in technological specialization rather than the ideological friction we aim to identify. The estimated effect nonetheless survives under both less-saturated specifications and more demanding ones that interact technology class with year to absorb field-specific citation trends in columns 1 and 2 of Table 6.

[19] $\exp(-0.553 \times 0.117) - 1 \approx -6.3\%$.

that the model captures the production- and absorption-side scaling of the knowledge pool rather than residual political variation. The within-state indicator is significantly positive, consistent with the findings in Jaffe et al. (1993).

We interpret these results as the natural downstream counterpart of our mobility findings. Because political distance suppresses inventor mobility, and because inventor mobility is a primary mechanism through which tacit knowledge diffuses across places (Singh and Agrawal, 2011; Akcigit et al., 2018), the reduced-form citation coefficient nests the mobility channel by construction. We do not attempt to decompose the share of the citation effect operating strictly through inventor relocation from the share operating through related interpersonal channels, such as cross-region collaboration networks, professional conferences, or co-authorship ties. Both classes of friction are economically meaningful, and both are plausibly shaped by ideological mismatch between places. The point of this section is more modest but, in our view, more substantive: political distance not only impedes the movement of the people who carry ideas, it also impedes the flow of the ideas themselves. Together with the mobility results in section 3 and section 4, this finding supports the broader claim that political polarization imposes real costs on the diffusion of innovative human capital and the productive knowledge it transmits.

5.1.1 Knowledge Flows – Crossing Party Lines

The preceding citation results treat political distance as a property of *places*: the ideological gap between the county that produces an idea and the county that absorbs it. But ideology is also embedded in the *technological fields* themselves. A growing body of evidence documents that inventive activity is partisan-sorted across technology classes, with Democratic-leaning inventors concentrated in fields such as clean energy and biotechnology and Republican-leaning inventors over-represented in fields such as fossil-fuel extraction and defense-related technologies (Engelberg et al., 2025). If political identity attaches to technology classes as well as to counties, then the diffusion of an idea may encounter friction not only when it crosses a politically distant place but also when it crosses a polit-

ically distant *field*—when a patent rooted in an ideologically coded technology cites prior art rooted in a technology of the opposite ideological complexion.

We test this conjecture by augmenting the citation panel of subsection 5.1 with a measure of *class-pair* political distance. Using the partisan leaning data in Engelberg et al. (2025), we define CPC 3-digit class-pair political distance as the absolute difference in this net-Democratic share between the citing patent's class and the cited patent's class.[20] A larger class-pair distance indicates that the citing and cited technologies sit on opposite sides of the inventor-partisan spectrum. We estimate

$$E[\text{Citations}_{i,j,a,b,t}] = \exp\Big(\beta_1 \,\text{ClassPolDist}_{a,b} + \beta_2 \,\text{PoliticalDistance}_{i,j,t-1} + \beta_3 \,\text{DiffClass}_{a,b} + \Gamma' X_{i,j,t-1} + \phi + \varepsilon_{i,j,a,b,t}\Big). \quad (6)$$

where i is the origin, or cited, county; j is the destination, or citing, county; a is the cited patent's technology class; b is the citing patent's technology class; and t is the year. $\text{ClassPolDist}_{a,b}$ is the class-pair political distance, $\text{PoliticalDistance}_{i,j,t-1}$ is the county-pair political distance from Section 2, and $\text{DiffClass}_{a,b}$ is an indicator equal to one when the citing and cited patents belong to different CPC three-digit classes, which controls for the mechanically lower frequency of cross-class citations. The term ϕ denotes the fixed effects, which tighten across columns. We enter county-pair and class-pair political distance as separate regressors rather than as an interaction so that each is estimated net of the other: the coefficient on $\text{ClassPolDist}_{a,b}$ isolates the ideological friction operating across *fields*, holding fixed the ideological friction operating across *places*, and vice versa. Standard errors are clustered at the cited-class by citing-class level, the level at which the field-based regressor varies.

Table 7 reports the estimates. Column 1 controls only for county-pair political distance; column 2 adds origin-county, destination-county, cited-class, citing-class, and year fixed

[20] Because the measure is built from the partisan composition of the inventors who patent within a class, it captures the ideological variation of a technological field rather than of any individual patent. It is time-invariant by construction and absorbed by the class fixed effects in the saturated specifications, so it is identified from the political gap *between* the citing and cited fields.

effects, together with the full set of county-pair controls used in the previous tests; and column 3, our preferred specification, adds origin-county-by-cited-class and destination-county-by-citing-class fixed effects, which absorb each county's field-specific propensity to supply and to absorb citations. Even after controlling for whether the citing and cited patents fall in different technology classes and for the origin- and destination-county patent stocks, the coefficient on class-pair political distance remains negative and statistically significant. This result indicates that its effect on citations is not a mechanical artifact of the citation-counting process. Crucially, county-pair political distance also remains negative and significant throughout, confirming that the place-based friction documented in Table 6 is not an artifact of omitted field-level ideology. The two frictions are distinct and additive: citations are deterred both when they must travel between politically distant counties and when they must bridge politically distant technologies.

The economic magnitude of the field-based measure is also meaningful. A one-standard-deviation increase in class-pair political distance implies roughly a 14.5% decline in citations.[21]

We read these results as sharpening the diffusion story of subsection 5.1. Political distance does not merely slow the movement of ideas across the map; it also slows their recombination across the ideologically coded boundaries of the idea space itself. The breakdown in knowledge diffusion is most acute precisely when a citation attempts to cross party lines—both the partisan lines that separate places and the partisan lines that separate fields.

5.2 Enter the New Technology Class

The mobility and citation results establish that political distance impedes both the movement of inventors and the flow of the ideas they carry. We now ask whether this friction has a tangible consequence for the technological development of places: does political

[21] 14.5%=$\exp(-1.335 * 0.116) - 1$, where -1.335 is the coefficient of class-pair political distance in column 3 and 0.116 is the standard deviation of class-pair political distance in the testing sample.

distance slow the rate at which a county and its resident firms expand into *new* areas of invention? Inventor mobility is a primary channel through which a region acquires the tacit capabilities required to operate in an unfamiliar technological domain (Singh and Agrawal, 2011; Akcigit et al., 2018), and a long literature on absorptive capacity and technological diversification holds that places enter new fields by drawing on the know-how embodied in the people and ideas that arrive from elsewhere (Cohen and Levinthal, 1990; Hidalgo, Klinger, Barabási, and Hausmann, 2007). If political distance starves a county of cross-pollinating talent from politically distant origins, it should also slow that location's entry into the technologies those origins already command, preventing firms from efficiently crossing the technological frontier.

We construct a directed county-pair-by-year panel of new-technology-class entries. For an ordered pair of counties (i, j), the dependent variable counts the distinct CPC three-digit classes that destination county j *newly* enters in year t—classes in which j filed no patent over the trailing window $t-3$ to $t-1$ but files in year t—and that origin county i *already held* in its three-year stock as of $t-1$.[22] The variable therefore captures a directed flow of *technological capability*: the extent to which j moves into fields that i has already established. We estimate

$$E\big[\text{NewTechEntry}_{i,j,t}\big] = \exp\Big(\beta\,\text{PoliticalDistance}_{i,j,t-1} + \Gamma' X_{i,j,t} + \phi + \varepsilon_{i,j,t}\Big) \tag{7}$$

where ϕ denotes different fixed effects. The control vector $X_{i,j,t}$ includes the technological-proximity measure of Bloom et al. (2013) and Jaffe (1986) aggregated to the county level, the origin-county and destination-county technology-class stocks, and indicators for whether the two counties share a state and a commuting zone. Column 1 clusters standard errors only; column 2 adds additive origin-county, destination-county, and year fixed effects; and column 3, our preferred specification, replaces these with origin-county-by-

[22]The trailing-window construction defines a class as part of a county's capability stock if the county filed at least one patent in that class over the preceding three years, and as a new entry if the county had no such filing over that window but files in the current year. County is assigned by lead-inventor location and year by application year, consistent with the rest of the paper.

year and destination-county-by-year fixed effects, absorbing any time-varying shock to a county's overall capacity to supply or to enter technologies.

Table 8 reports the results. The coefficient on county-pair political distance is negative and highly significant across all three columns—-0.374, -0.331, and -0.343—and is notably stable as the fixed-effect structure tightens. In the preferred column 3, the coefficient is -0.343 ($z = -15.14$). The effect is economically meaningful: a one-standard-deviation increase in county-pair political distance implies roughly a 3.9% decline in bilateral new-technology entries, and moving from the 25th to the 75th percentile of political distance implies roughly a 5.4% decline.[23]

These estimates push the friction one step further down the causal chain. Political distance not only deters inventors from relocating and ideas from being cited; it also blunts the receiving county's ability to expand into novel technological frontiers, depriving it of the specialized talent through which unfamiliar capabilities are acquired. Ideological separation between places thus translates into a narrower, more slowly diversifying technological base.

5.3 Patenting Output – Using Weighted Political Distance

The analysis so far is dyadic: it characterizes how the political distance between two specific places shapes the flows between them. We close the section by aggregating these bilateral frictions to the level of the receiving place and asking whether they leave a footprint on its overall innovative output. If a county is, on average, ideologically far from the places that produce the nation's inventive talent, then the cumulative friction it faces in attracting inventors and absorbing ideas should depress the level of patenting it is able to sustain.

To capture a county's aggregate ideological isolation, we construct a destination-level *weighted political exposure*. For destination county d in year t, the measure is a weighted av-

[23] $-3.9\% = \exp(-0.343 \times 0.117) - 1$ and $-5.4\% = \exp(-0.343 \times 0.163) - 1$, using the standard deviation (0.117) and interquartile range ($0.216 - 0.053 = 0.163$) of county-pair political distance from Panel A of Table 1.

erage of the political distances between d and every other county in the inventor-producing universe:

$$\text{PolExp}^{\text{raw}}_{d,t} = \sum_{o \neq d} \omega^{\text{raw}}_{o} \left|\text{Rep}_{o,e} - \text{Rep}_{d,e}\right|, \qquad \omega^{\text{raw}}_{o} = \frac{N^0_o}{\sum_{o' \neq d} N^0_{o'}}, \tag{8}$$

$$\text{PolExp}^{\text{geo}}_{d,t} = \sum_{o \neq d} \omega^{\text{geo}}_{o,d} \left|\text{Rep}_{o,e} - \text{Rep}_{d,e}\right|, \qquad \omega^{\text{geo}}_{o,d} = \frac{N^0_o / \text{dist}_{o,d}}{\sum_{o' \neq d} N^0_{o'} / \text{dist}_{o',d}}, \tag{9}$$

where $\text{Rep}_{o,e}$ is origin county o's Republican vote share in the most recent presidential election e as of year $t-1$, N^0_o is origin o's inventor headcount frozen at a pre-sample baseline, and $\text{dist}_{o,d}$ is the geographic distance between o and d. The raw measure in equation (8) weights each origin by its national share of inventive talent; the geographic distance-discounted measure in equation (9) additionally down-weights distant origins by inverse distance. Two features of the construction are essential. First, the weights are built from the *full* universe of origin counties rather than from realized inventor flows, so the measure does not condition on the politically sorted mobility network whose determinants we are studying. Second, fixing the headcount weights at a pre-sample baseline renders the exposure variation predetermined with respect to contemporaneous patenting, similar to a shift-share instrument where identification rests on the exogeneity of the baseline shares (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). The only time variation in $\text{PolExp}_{d,t}$ comes from the political-distance shifters, which update with each election cycle.

We relate this exposure to destination-county patenting via

$$E[\text{Patents}_{d,t}] = \exp\Big(\beta\, \text{PolExp}_{d,t} + \Gamma' X_{d,t} + \alpha_d + \delta_t + \varepsilon_{d,t}\Big), \tag{10}$$

where the dependent variable is the raw count of patents filed by destination county d in year t, α_d and δ_t are county and year fixed effects, and standard errors are clustered at the destination-county level. The control vector $X_{d,t}$ includes GDP growth, the unemployment rate, the house value index, the county's patent stock, and its technology-class stock. Crit-

ically, $X_{d,t}$ also includes the destination county's *own* Republican vote share, so that β is identified from the county's ideological *distance* from the talent-producing universe rather than from its own partisan leaning.

Table 9 reports the estimates. Both exposure measures enter negatively. The gravity-discounted measure is the more powerful: its coefficient is -1.693 ($z = -3.45$) in the sparse specification of column 1 and remains negative and significant at -1.193 ($z = -3.11$) in the fully controlled column 3. The raw measure is also negative and significant, at -0.645 ($z = -1.68$) in column 2 and -0.687 ($z = -2.17$) in column 4. A A-standard device increase in geographic distance-discounted political exposure implies roughly a 9.6% decline in destination patenting.[24] namely that the geographic distance-discounted measure dominates the raw measure: ideological distance from *nearby* talent-producing counties matters more than distance from the national pool, consistent with the well-documented localization of knowledge spillovers (Jaffe et al., 1993). The destination's own Republican vote share is economically small and statistically insignificant in both full specifications (0.159 and 0.037), which establishes that the output penalty is not a story about Republican-leaning counties patenting less, but about *politically isolated* counties patenting less, regardless of which direction their own politics lean.

This node-level evidence completes the chain. The dyadic frictions we document do not net out in the aggregate; they accumulate into a measurable drag on the innovative output of the places most ideologically removed from the nation's inventive talent. Political polarization, by isolating places along partisan lines, imposes a real and quantifiable cost on local innovation.

6 Heterogeneity Tests

In this section, we examine when the political-distance effect is stronger and where it is concentrated by interacting county-pair political distance with measures that capture

[24] $-9.6\% = \exp(-1.193 \times 0.085) - 1$, using the column 3 coefficient and the standard deviation of the distance-discounted exposure measure,

national polarization and county-pair partisan alignment.

6.0.1 Political Polarization

We begin with Table 10, which examines whether the effect of county-pair political distance becomes stronger during periods of heightened national political polarization. We use two measures of polarization. The first is the continuous partisan conflict index from Azzimonti (2018). The second is a binary variable, *Post Trump*, that equals one for years from 2017 to 2019 and zero for years from 2013 to 2015.

Table 10 reports the regression results. Column 1 interacts county-pair political distance with the continuous polarization measure. The baseline effect of political distance remains negative and highly significant, with a coefficient of -1.831. The interaction term is also negative, at -0.008, and is weakly significant at the ten-percent level. Column 2 replaces the continuous polarization measure with the *Post Trump* indicator. In this specification, the baseline effect of political distance remains negative and significant, but the interaction between *Post Trump* and political distance is negative and statistically insignificant (-0.227, $t = -0.398$). All columns include controls, origin-county fixed effects, destination-county fixed effects, and year fixed effects, with standard errors double-clustered at the county-pair and year level.

Taken together, the evidence provides at most limited support for the idea that political-distance frictions intensify during periods of heightened national polarization. The continuous polarization measure points in the predicted direction, but the effect is only weakly significant. The discrete post-2016 comparison, by contrast, shows no statistically significant strengthening. We therefore interpret this pattern cautiously. Unlike outcomes such as media consumption, household spending, or portfolio choice, inventor mobility is a high-friction decision shaped by long-term employment relationships, firm-specific human capital, team-based production, and contractual restrictions such as non-disclosure obligations and intellectual property protections (e.g., Liu, Mao, and Tian, 2023; Ma, Wang, and Wu, 2025). As a result, inventor mobility may not respond sharply to short-run increases

in national political salience. Instead, the evidence is more consistent with county-pair political distance operating as a persistent baseline friction in the allocation of innovative talent, rather than as a channel that becomes materially stronger only during periods of peak national polarization.

6.0.2 Politically Aligned County-pairs

One might suspect that when both counties in a pair lean toward the same party, marginal differences in vote share carry limited social meaning and the political-distance effect should collapse to zero. We test this possibility directly in Table 11. We construct an indicator variable, *Aligned*, equal to one if the origin and destination counties support the same presidential party in the most recent presidential election and zero otherwise. We then estimate the political-distance effect in a pooled specification that interacts *Aligned* with political distance in Column (1), and separately within the same-party and different-party subsamples in Columns (2) and (3).

The data reject the conjecture that political distance matters only across party lines. In Column (1), the level coefficient on *Aligned* is positive and statistically significant (0.373, $t = 3.744$), implying that same-party county pairs have higher expected inventor flows than different-party pairs when political distance is zero. At the same time, the political-distance slope for different-party pairs, the omitted baseline group, is negative and significant (-0.935). The interaction between *Aligned* and political distance is also negative and significant (-1.596, $t = -4.255$), implying an even steeper political-distance slope among same-party pairs. The implied slope for same-party pairs in the pooled specification is therefore -2.531.

Columns (2) and (3) confirm this pattern in split samples. The coefficient on county-pair political distance is -2.408 among same-party pairs and -1.649 among different-party pairs, both significant at the one-percent level. Using the baseline standard deviation of political distance, these estimates imply roughly a 24.5% decline in expected inventor moves for a one-standard-deviation increase in political distance among same-party pairs

and roughly a 17.5% decline among different-party pairs.[25] The marginal penalty from ideological divergence is therefore present in both regimes, but it is more pronounced among same-party county pairs.

These results point to a two-part friction. Moving from same-party to different-party county pairs is associated with a lower level of expected flows, consistent with a discrete partisan-boundary effect. Conditional on being within the same partisan regime, however, political distance still matters, and the slope is even steeper among same-party pairs. The economic intuition is that among aligned pairs, vote-share differences capture fine-grained variation in ideological intensity, such as the difference between a deep-red rural county and a moderately red suburb. Inventors who are already considering politically compatible destinations may still be sensitive to these subtler gradations of local norms and social fit. Among different-party pairs, by contrast, the dyad is already in a lower-flow regime because the partisan boundary itself captures part of the mismatch. Taken together, the positive level effect for aligned pairs and the steeper within-alignment gradient suggest that political identity operates through both a discrete partisan boundary and a continuous intensity margin in the geographic reallocation of inventive talent.

7 Conclusion

This paper documents that political ideology acts as a significant friction in the geographic reallocation of high-skilled labor. Using a county-pair-by-year panel spanning 2001 to 2023, we show that inventors move less between politically distant counties. In our most demanding county-pair specification, a one-standard-deviation increase in political distance reduces bilateral inventor flows by approximately 17%. This effect survives saturated origin-county-by-year and destination-county-by-year fixed effects and conservative two-way clustered inference, suggesting that political distance predicts inventor mobility beyond time-varying conditions specific to either the sending or receiving county.

[25] $-24.5\% = \exp(-2.408 \times 0.117) - 1$ and $-17.5\% = \exp(-1.649 \times 0.117) - 1$, where 0.117 is the standard deviation of county-pair political distance from Table 1.

We support this interpretation with two complementary identification strategies. First, the geographic decomposition shows that the effect is strongest within state borders and remains economically meaningful among non-neighboring out-of-state pairs, while it is statistically indistinguishable from zero among neighboring-state pairs. This pattern is difficult to reconcile with a simple story in which political distance merely proxies for broad geographic or institutional separation. Second, a regression discontinuity design based on close presidential elections reveals a pull-side mechanism: destination counties that narrowly elect a Republican candidate attract significantly fewer inventors, while we find no comparable origin-side effect.This establishes political ideology as a non-pecuniary tax on destination attractiveness that distorts the efficient matching of talent to firms.

The consequences extend beyond mobility. Politically distant counties exchange fewer ideas, as measured by bilateral patent citations, indicating that the same political mismatch that slows inventor movement also dampens the spatial diffusion of the knowledge they carry. This diffusion friction also appears inside the idea space itself: citations are less likely when they must bridge politically distant technology classes, even after accounting for the political distance between the counties involved. Political distance therefore slows knowledge diffusion along both geographic and technological margins.

These frictions carry real implications for corporate strategy and diversification. Politically distant county pairs exhibit fewer bilateral entries into new technology classes, suggesting that ideological separation limits the cross-pollinating talent needed for firms to expand into novel technological frontiers. At the aggregate level, places more ideologically distant from the national pool of inventive talent also produce fewer patents. In sum, these results trace a coherent chain from reduced inventor mobility to weaker knowledge diffusion, to slower corporate technological diversification, and ultimately to lower overall innovative output and competitive advantage.

The firm-level analysis reinforces the interpretation that ideology affects inventive labor mobility through more than local political environments. Using firms' PAC-donation records, we find that politically distant firms exchange fewer inventors under both a

Republican-donation-share measure and a *cfscore*-based ideological-distance measure. In the most demanding specifications, a one-standard-deviation increase in Republican donation difference implies roughly a 51.6% decline in inter-firm inventor moves, while a one-standard-deviation increase in *cfscore-distance* implies roughly a 62.5% decline. The heterogeneity tests further clarify the nature of the county-level friction. We find only limited evidence that the effect intensifies during periods of heightened national polarization, suggesting that political distance operates as a persistent baseline friction rather than only as a short-run response to partisan salience. We also find that political distance reduces inventor mobility among both same-party and different-party county pairs, consistent with political identity operating through both a discrete partisan boundary and a continuous intensity margin.

By establishing political ideology as a spatial and organizational barrier, alongside traditional determinants such as geographic distance, housing costs, and non-compete agreements, our findings carry implications for innovation policy and corporate strategy. If inventive labor is less willing or less able to move across politically distant environments, polarization can distort the allocation of elite talent and slow the diffusion of ideas. For firms, ideological sorting may act as an implicit recruitment friction that restricts talent acquisition. For the broader economy, these frictions may reinforce the geographic clustering of innovative activity and widen regional disparities in technological capacity.

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Figures and Tables

Figure 1: **Discontinuity Cutoff Manipulation Test**

This figure presents the McCrary (2008) density test for manipulation of the running variable at the RD cutoff. The running variable is the voting share margin in county-level, where positive values indicate a Republican win and negative values indicate a Democratic win. The histogram and local polynomial density estimates are shown separately on each side of the cutoff (marked by the vertical dashed line at zero). The absence of a discontinuous jump in the density at the cutoff suggests that precise manipulation of election outcomes is unlikely, supporting the validity of the RD design.

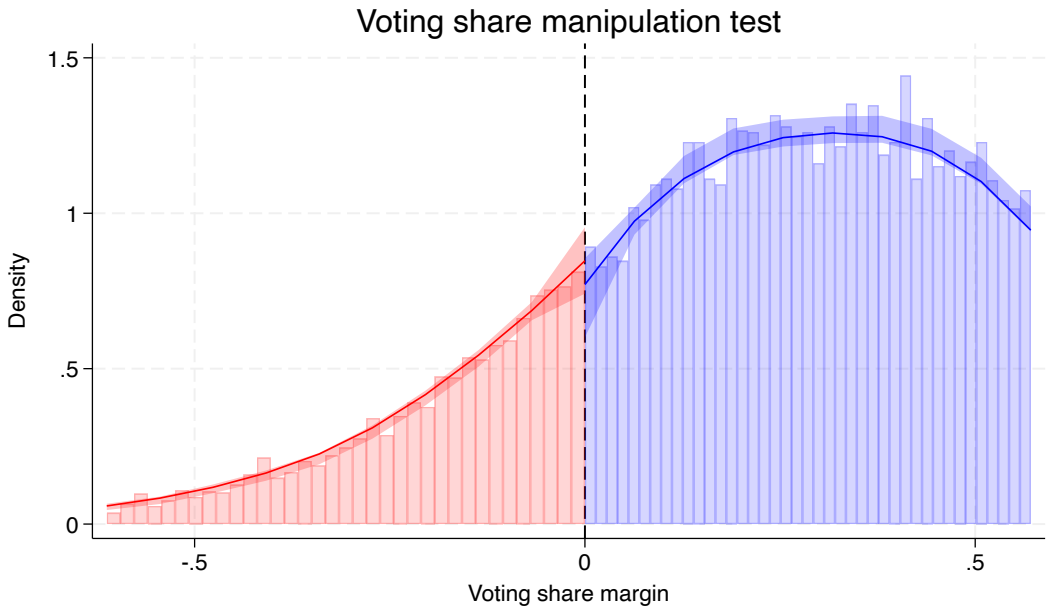


Table 1: **Summary Statistics**

Panel A reports summary statistics for the main variables in the county-pair by year over the period 2001-2023. County-pair inventor moves is the number of inventor moves from an origin county to a destination county in a given year. County-pair political distance is the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. Misaligned county pair takes value of one if the origin and destination counties are politically misaligned and zero otherwise. R to R is an indicator variable of value one if both counties are Republican-leaning. Geo distance (log transformed), House value index (log transformed), unemployment rate (log transformed), GDP growth (in percentage), and EPU (divided by 100 for better coefficient display) are county-level controls measured as the absolute value of county-pair differences. Panel B presents summary statistics for the Republican vote share of origin and destination counties. Panel C reports summary statistics for county-pair inventor moves and county-pair political distance in the subsample excluding county-pair-year observations with zero inventor moves. Panel D reports summary statistics for the main variables in the firm-level test in Table 3. Definitions for all variables are provided in Appendix A.

Panel A: Main Variables

Variable	N	Mean	SD	p1	p25	p50	p75	p99
County-pair inventor moves	897,190	0.354	6.102	0	0	0	0	5
County-pair political distance	897,190	0.147	0.117	0	0.053	0.121	0.216	0.488
Class-pair political distance	7,019,273	0.081	0.116	0	0	0.015	0.123	0.469
Weighted PolExp - Geo Dist	64,258	0.191	0.085	0.078	0.119	0.170	0.249	0.416
Weighted PolExp - Raw	64,258	0.206	0.093	0.083	0.124	0.184	0.273	0.440
Misaligned county pair	897,190	0.442	0.497	0	0	0	1	1
R to R	897,190	0.144	0.351	0	0	0	0	1
Distance	897,190	6.745	1.523	0	6.257	7.117	7.771	8.343
House value index	807,893	0.592	0.476	0	0.212	0.486	0.869	2.010
Unemployment rate	864,392	0.256	0.208	0	0.093	0.210	0.371	0.896
GDP growth	833,161	0.869	0.882	0.005	0.280	0.640	1.183	4.054
EPU	889,460	0.519	0.573	0	0.110	0.350	0.730	2.530

Panel B: Origin (Destination) County Political Leaning

Variable	N	Mean	SD	p1	p25	p50	p75	p99
Orig county Republican share	37,187	0.572	0.130	0.225	0.495	0.571	0.664	0.841
Dest county Republican share	38,176	0.573	0.131	0.222	0.495	0.572	0.665	0.846

Panel C: County-pair Moves and Political Distance, Excluding Zero Moves

Variable	N	Mean	SD	p1	p25	p50	p75	p99
County-pair inventor moves	99,331	3.196	18.091	1	1	1	2	33
County-pair political distance	99,331	0.134	0.109	0	0.045	0.112	0.199	0.454

Table 1: **Summary Statistics (Cont'd)**

Panel D: Summary Statistics (Firm-level)

Full Sample								
Variable	N	Mean	SD	p1	p25	p50	p75	p99
Firm-pair inventor moves	175,214	0.191	4.896	0	0	0	0	3
cfscore-distance	175,214	0.247	0.331	0	0	0.103	0.383	1.330
Republican donation diff	175,214	0.215	0.267	0	0	0.090	0.399	1
Misaligned firm pair	175,214	0.271	0.444	0	0	0	1	1
R to R	175,214	0.525	0.499	0	0	1	1	1
House value index	162,731	0.493	0.497	0	0.032	0.366	0.795	1.919
Unemployment rate	160,022	0.185	0.191	0	0.013	0.137	0.293	0.777
GDP growth	149,934	0.721	0.802	0.003	0.062	0.489	1.092	3.457
Distance	175,214	5.630	2.802	0	3.542	6.829	7.929	9.056
Origin (Destination) Firms Political Leaning								
Variable	N	Mean	SD	p1	p25	p50	p75	p99
Orig firm cfscore	63,733	0.345	0.452	−0.765	0.158	0.321	0.621	1.306
Orig firm Rep donation share	63,733	0.568	0.356	0	0.363	0.580	0.932	1
Dest firm cfscore	64,906	0.348	0.456	−0.810	0.158	0.321	0.621	1.325
Dest firm Rep donation share	64,906	0.573	0.355	0	0.368	0.592	0.952	1
Firm-pair Moves and Political Distance, Excluding Zero Moves								
Variable	N	Mean	SD	p1	p25	p50	p75	p99
Firm-pair inventor moves	11,727	2.849	18.723	1	1	1	2	26
cfscore-distance	11,727	0.208	0.303	0	0	0.060	0.327	1.269
Republican donation diff	11,727	0.189	0.255	0	0	0.052	0.339	1

Table 2: **Inventor Mobility and Political Distance: County-pair Baseline Results**

This table presents the effect of county-pair political distance on inventor moves over the 2001 to 2023 sample period. The dependent variable in all columns is county-pair inventor moves, measured as the number of inventor moves from an origin county to a destination county in a given year. The main independent variable is county-pair political distance, defined as the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. All variables are defined in Appendix A. The columns progressively add control variables, fixed effects, and clustered standard errors. Column 1 reports the univariate regression. Column 2 and 3 add the full set of control variables and standard error clustering. Column 4, as our preferred specification, includes origin-county, destination-county, and year fixed effects. Column 5 stress tests by including origin-county by year and destination-county by year fixed effects. t-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are double clustered by origin-county and destination-county level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	County-pair inventor flows				
	(1)	(2)	(3)	(4)	(5)
County-pair political distance	-6.152***	-1.772***	-1.772***	-1.879***	-1.590***
	(-25.940)	(-17.651)	(-3.295)	(-6.281)	(-5.059)
Distance		-0.387***	-0.387***	-0.431***	-0.461***
		(-46.387)	(-19.359)	(-15.004)	(-17.368)
Misaligned county pair		-0.874***	-0.874***	-0.128*	-0.201***
		(-47.421)	(-7.185)	(-1.645)	(-3.638)
R to R		-1.720***	-1.720***	0.056	
		(-27.920)	(-6.401)	(0.449)	
House value index		-0.002	-0.002	-0.276***	-0.216***
		(-0.076)	(-0.017)	(-3.743)	(-2.726)
Unemployment rate		-1.218***	-1.218***	-0.781***	-0.757***
		(-17.953)	(-5.336)	(-7.676)	(-7.080)
GDP growth		-0.008	-0.008	-0.098***	-0.139***
		(-0.558)	(-0.139)	(-6.406)	(-5.336)
EPU		-0.176***	-0.176***	-0.050	-0.019
		(-8.042)	(-4.682)	(-1.306)	(-0.403)
Observations	897,190	691,203	691,203	684,370	539,989
Orig county FE	No	No	No	Yes	No
Dest county FE	No	No	No	Yes	No
Year FE	No	No	No	Yes	No
Orig county by year FE	No	No	No	No	Yes
Dest county by year FE	No	No	No	No	Yes
Clustered SE	No	No	Yes	Yes	Yes
Pseudo R-squared	0.0409	0.212	0.212	0.616	0.648

Table 3: **Firm-Level Ideological Distance and Cross-Firm Inventor Mobility**

This table presents the effect of firm-level firm-pair political distance on inventor moves over the sample period 2001 to 2023, using firms' PAC donations (Republican Donation) and contribution finance ideology scores (cfscore) to proxy for firms' political leaning.Two main independent variable-Cfscore-distance is the absolute difference in cfscore between the origin and destination firm; and Republican donation diff is the absolute difference in donations made to Republican candidates between the origin and destination firm. The dependent variable in all columns is firm-pair inventor moves. All variables are defined in Appendix A. z-statistics are reported in parentheses. The standard errors are double-clustered by origin and destination firm level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	Firm-pair Inventor Moves			
	(1)	(2)	(3)	(4)
Republican Donation Diff	-1.959***	-2.721***		
	(-2.946)	(-6.727)		
cfscore-distance			-3.153***	-2.964***
			(-5.031)	(-4.262)
Distance	-0.411***	-0.378***	-0.402***	-0.361***
	(-6.462)	(-5.781)	(-5.932)	(-5.139)
House value index	0.091	0.039	0.129	0.116
	(0.253)	(0.112)	(0.368)	(0.358)
Unemployment rate	-0.272	-1.183***	-0.294	-1.152***
	(-0.635)	(-3.687)	(-0.692)	(-3.443)
GDP growth	-0.174**	-0.183*	-0.189***	-0.238**
	(-2.565)	(-1.771)	(-2.778)	(-2.186)
Misaligned firm pair	-1.071***	-0.299	-1.305***	-0.699***
	(-3.102)	(-1.484)	(-4.361)	(-4.136)
R to R	-0.824***	-0.259	-0.859***	-0.311*
	(-2.919)	(-1.535)	(-2.976)	(-1.930)
Observations	137,943	20,065	137,943	20,065
Orig & Dest firm FE	Yes		Yes	
Year FE	Yes		Yes	
Orig firm by Year FE		Yes		Yes
Dest firm by Year FE		Yes		Yes
Pseudo R-squared	0.438	0.716	0.444	0.718
Clustered SE	Yes	Yes	Yes	Yes

Table 4: **Identification Strategy Using Within-state Moves**

This table presents the effect of county-pair political distance on inventor moves over the 2001 to 2023 sample period, decomposed by the geographic character of the move. The dependent variable is county-pair inventor moves, measured as the number of inventor moves from an origin county to a destination county in a given year. The main independent variable is county-pair political distance, defined as the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. Each directed county-pair is classified into one of three mutually exclusive groups based on the geographic relationship between origin and destination: within-state cross-county pairs ($Within = 1$), pairs in different but bordering states ($Neighbor = 1$), and pairs in non-neighboring states ($Within = 0$ AND $Neighbor = 0$), which serves as the omitted base group. Column 1 reports estimates from a fully saturated specification that interacts county-pair political distance with both the $Within$ and $Neighbor$ indicators. Column 2 reports linear combination test results that recover the three group-specific semi-elasticities of inventor moves with respect to county-pair political distance from the column 1 coefficients: $\beta_{far} = \beta_3$ for non-neighboring out-of-state pairs, $\beta_{within} = \beta_3 + \beta_4$ for within-state cross-county pairs, and $\beta_{neighbor} = \beta_3 + \beta_5$ for pairs in neighboring states. All variables are defined in Appendix A. z-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are double clustered at the origin and destination county level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	County-pair inventor moves	
	(1)	Linear combination test
County-pair political distance ($\beta_3 \equiv \beta_{far}$)	-1.139***	$\hat{\beta}_{far} = -1.139$***
	(-2.908)	(-2.908)
Within	1.330***	
	(15.457)	
Within × County-pair political distance (β_4)	-3.836***	$\hat{\beta}_{within} = \beta_4 + \beta_3 = -4.975$***
	(-10.847)	(-18.650)
Neighbor	-0.543***	
	(-6.554)	
Neighbor × County-pair political distance (β_5)	1.362***	$\hat{\beta}_{neighbor} = \beta_5 + \beta_3 = 0.223$
	(2.969)	(0.610)
County-pair Controls	Yes	
Observations	684,370	
Orig county FE	Yes	
Dest county FE	Yes	
Year FE	Yes	
Clustered SE	Yes	Yes
Pseudo R-squared	0.625	

Table 5: **Regression Discontinuity Design – Close Elections**

This table presents the effect of close elections on inventor moves over the 2001 to 2023 sample period using a regression discontinuity design. The dependent variable in all columns is county-pair inventor moves, measured as the number of inventor moves from an origin county to a destination county in a given year. Panel A reports summary statistics for the election events (2004-2020) used in the analysis, including the total number of elections in the full sample and the number of close elections with different bandwidth surround the zero cutoff. Panel B and C present the difference test of key economic conditions between destination (origin) winning and losing counties using a 5% winning margin. Panel D reports the regression discontinuity results. Columns 1 to 3 focus on destination-county elections, and Columns 4 to 6 focus on origin-county elections. The main independent variable is Close R win, an indicator variable equal to one if the winner of the election is Republican and zero if the winner of the election is Democratic. Columns 1 and 4 report results using the full sample of close elections. Columns 2 to 3 and Columns 5 to 6 restrict the sample using different bandwidths around the election cutoff, as indicated in the column headings. All variables are defined in Appendix A. t-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are clustered at the destination county level for Columns 1 to 3 and at the origin county level for Columns 4 to 6. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

Panel A: Summary Statistics of Election Events

		Number of elections by winning margin			
	Full sample	1%	2%	3%	5%
All elections	15,770	265	529	790	1,291
Republican winning	12,530	134	278	410	673
Democrat winning	3,240	131	251	380	618

Panel B: Differences of Destination Counties around the Discontinuity

	Winning County	Losing County	Difference	t-statistics
EPU	0.808	0.841	-0.034	-0.92
Unemployment rate (%)	6.539	6.627	-0.088	-0.56
GDP growth (%)	-0.248	-0.304	0.056	0.57
House value index	172,661	178,934	-6273	-1.02

Panel C: Differences of Origin Counties around the Discontinuity

	Winning County	Losing County	Difference	t-statistics
EPU	0.815	0.822	-0.008	-0.21
Unemployment rate (%)	6.440	6.548	-0.108	-0.70
GDP growth (%)	-0.256%	-0.261%	0.005	0.05
House value index	172,969	179,350	-6380	-1.02

Table 5: **Regression Discontinuity Design – Close Elections (Cont.)**

Panel D: Regression Discontinuity Design

	County-pair inventor moves					
	Destination County Elections			Origin County Elections		
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Small bandwidth		Full sample	Small bandwidth	
		0.02	0.05		0.02	0.05
Close R win	-0.135	-1.148**	-0.991**	-0.156	-0.814	-0.726
	(-0.593)	(-2.183)	(-2.024)	(-0.650)	(-1.553)	(-1.495)
Observations	165,159	8,227	20,422	165,171	8,144	20,192
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Election Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.183	0.205	0.153	0.178	0.202	0.131

Table 6: **Ideological Frictions and Knowledge Spillovers: Evidence from Patent Citations**

This table presents the effect of county-pair political distance on bilateral patent citation flows over the 2001 to 2023 sample period. The dependent variable in all columns is county-pair-by-tech-class citations, measured as the number of forward citations made by patents filed in the destination county in a given year to prior patents originating in the origin county within the same technology class. The main independent variable is county-pair political distance, defined as the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. The columns progressively tighten the fixed-effect structure. Column 1 includes year, origin-county, and destination-county fixed effects. Column 2 replaces year fixed effects with technology-class-by-year fixed effects. Column 3 reports the preferred specification with origin-county-by-technology-class, destination-county-by-technology-class, and technology-class-by-year fixed effects. All variables are defined in Appendix A. t-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are double clustered by the origin county and destination county level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	County-pair-by-Tech-class Citations		
	(1)	(2)	(3)
County-pair political distance	-0.811***	-0.874***	-0.553**
	(-3.964)	(-5.013)	(-2.341)
Dest county-Tech class patent stock	0.744***	0.778***	0.527***
	(26.999)	(30.928)	(5.673)
Orig county-Tech class patent stock	0.671***	0.711***	0.158***
	(34.150)	(34.441)	(3.412)
Same state	0.581***	0.580***	0.513***
	(3.996)	(4.027)	(3.956)
County-pair controls	Yes	Yes	Yes
Observations	32,938,406	32,936,372	32,792,823
Year FE	Yes		Yes
Orig Pat Cty FE	Yes	Yes	
Dest Pat Cty FE	Yes	Yes	
Tech Class FE	Yes		
Tech Class by year FE		Yes	
Orig Pat Cty by Tech Class FE			Yes
Dest Pat Cty by Tech Class FE			Yes
Pseudo R-squared	0.648	0.655	0.703
Clustered SE	Yes	Yes	Yes

Table 7: **Ideological Frictions and Knowledge Spillovers: Evidence from Citations Crossing Party Lines**

This table presents the effect of technology class-pair political distance on bilateral patent citations over the 2001 to 2023 sample period. The dependent variable in all columns is county-pair by class-pair citations, measured as the number of forward citations made by patents filed in the destination county in a given year to prior patents originating in the origin county across different technology class pairs. The main independent variable is the class-pair political distance, defined as the absolute difference in the net fraction of Democratic inventors between the citing patent technology class and the cited patent technology class. We progressively include controls and fixed effects from columns 1 to 3. Column 1 only controls for the county-pair political distance and clusters standard errors. Column 2 adds origin, destination county, citing and cited patent's technology class and year fixed effects. Column 3 adds two-way fixed effects – origin county by cited patent's technology class and destination county by citing patent's technology class fixed effects. All variables are defined in Appendix A. z-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are clustered at the cited patent technology class by citing patent technology class. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	County-pair by class-pair Citations		
	(1)	(2)	(3)
Class-pair political distance	-4.509***	-1.157**	-1.335***
	(-5.790)	(-2.574)	(-2.796)
County-pair political distance	-1.171***	-0.525*	-0.583***
	(-2.629)	(-1.896)	(-3.314)
Different classes		-1.089***	-1.177***
		(-6.843)	(-8.029)
Destination county patent stock		0.596***	0.769***
		(6.680)	(5.569)
Origin county patent stock		0.459***	0.186***
		(7.434)	(3.393)
County-pair Controls	No	Yes	Yes
Observations	7,019,194	6,181,349	6,167,956
Year FE	Yes	Yes	Yes
Orig Cty FE	Yes	Yes	
Dest Cty FE	Yes	Yes	
Cited Pat Tech FE	Yes	Yes	
Citing Pat Tech FE	Yes	Yes	
Orig Cty by Cited Tech FE			Yes
Dest Cty by Citing Tech FE			Yes
Pseudo R-squared	0.426	0.530	0.614
Clustered SE	Yes	Yes	Yes

Table 8: **Ideological Frictions and Entry of New Technology**

This table presents the effect of county-pair political distance on bilateral new technology class entries over the 2001 to 2023 sample period. The dependent variable in all columns is county-pair number of new technology classes entry, measured as the number of distinct technology classes the destination county newly enters in a given year that the origin county held in the prior year. The technology class stock of a given county is determined using a three year trailing window, and a class counts as a new entry if the destination had no patents in it during the preceding three years. The main independent variable is county-pair political distance, defined as the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. We progressive add controls and fixed effects from column 1 to 3. Column 1 only clusters standard errors. Column 2 adds origin, destination county and year fixed effects. Column 3 includes two-way fixed effects – origin county by year and destination county by year fixed effects. All variables are defined in Appendix A. z-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are double clustered by the origin county and destination county level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	County-pair New Tech Entry		
	(1)	(2)	(3)
County-pair political distance	-0.374***	-0.331***	-0.343***
	(-2.586)	(-11.215)	(-15.143)
Tech Similarity		-0.144***	-0.084***
		(-7.205)	(-4.571)
Orig cty tech class stock		1.205***	
		(133.128)	
dest cty tech class stock		-0.453***	
		(-12.906)	
Same state		0.011***	0.010***
		(3.741)	(4.236)
Same CZ		0.037***	0.031***
		(5.030)	(4.508)
County Controls	No	Yes	Yes
Observations	210,273,848	89,695,974	49,822,619
Pseudo R-squared	0.000	0.397	0.399
Fixed effect	No	Additive	Multiplicative
Clustered SE	Yes	Yes	Yes

Table 9: **Ideological Frictions and Patent Output**

This table presents the effect of destination county weighted political exposure on its patent output over the 2001 to 2023 sample period. The dependent variable in all columns is the raw count of granted patents filed by the destination county in each year. The main independent variables are the raw weighted destination county political exposure and geographic distance discounted weighted destination county political exposure. Details on the construction of the weighted political distance is in subsection 5.3. We progressively add control variables from column 1 to 4. Column 1 and 2 only includes main independent variables, fixed effects and standard error clustering. Column 3 and 4 are full specifications. All variables are defined in Appendix A. z-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are clustered by the destination county level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	# of Patents			
	(1)	(2)	(3)	(4)
Weighted PolExp - Geo Dist	-1.693***		-1.193***	
	(-3.445)		(-3.111)	
Weighted PolExp - Raw		-0.645*		-0.687**
		(-1.676)		(-2.171)
GDP Growth			0.027***	0.027***
			(3.075)	(3.056)
Unemployment rate			0.015	0.010
			(0.345)	(0.217)
House value index			0.063	0.073
			(1.085)	(1.261)
Republican vote share			0.159	0.037
			(0.916)	(0.207)
Patent stock			0.532***	0.547***
			(5.416)	(5.261)
County Tech Class stock			0.404***	0.401***
			(11.534)	(11.269)
Observations	63,315	63,315	39,654	39,654
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes
Pseudo R-squared	0.976	0.976	0.981	0.980

Table 10: **Inventor Mobility and Political Distance: By Political Polarization**

This table presents the effect of county-pair political distance on inventor moves over the 2001 to 2023 sample period, conditional on the level of national political polarization. The dependent variable in all columns is county-pair inventor moves, measured as the number of inventor moves from an origin county to a destination county in a given year. The main independent variable is county-pair political distance, defined as the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. Column 1 interacts county-pair political distance with polarization measure in Azzimonti (2018). Column 2 interacts county-pair political distance with an indicator variable taking value of one for years from 2017 to 2019 and zero for years from 2013 to 2015 otherwise. All variables are defined in Appendix A. t-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are double clustered at the county-pair and year level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	County-pair inventor flows	
	(1)	(2)
County-pair political distance	-1.831***	-1.456***
	(-6.012)	(-4.050)
Polarization × County-pair political distance	-0.008*	
	(-1.707)	
Post Trump × County-pair political distance		-0.227
		(-0.398)
Observations	684,370	204,404
Controls	Yes	Yes
Orig county FE	Yes	Yes
Dest county FE	Yes	Yes
Year FE	Yes	Yes
Clustered SE	Yes	Yes
Pseudo R-squared	0.616	0.620

Table 11: **Inventor Mobility and Political Distance: Same-Party versus Cross-Party Moves**

This table presents the effect of county-pair political distance on inventor moves over the 2001 to 2023 sample period, conditional on whether the origin and destination counties are politically aligned. The dependent variable in all columns is county-pair inventor moves, measured as the number of inventor moves from an origin county to a destination county in a given year. The main independent variable is county-pair political distance, defined as the absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election. Column 1 interacts county-pair political distance with an indicator variable taking the value of one if the origin and destination counties are politically aligned from the most recent presidential election and zero otherwise. Column 2 restricts the sample to county pairs in which the origin and destination counties are politically aligned, i.e., sharing the same party affiliation. Column 3 restricts the sample to county pairs in which the origin and destination counties are politically misaligned, i.e., sharing a different party affiliation. All variables are defined in Appendix A. t-statistics are reported in parentheses. The standard errors are heteroskedasticity consistent and are double clustered at the county-pair and year level. *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

	County-pair inventor moves		
	(1) Full sample	(2) Same party	(3) Different party
County-pair political distance	-0.935***	-2.408***	-1.649***
	(-3.386)	(-5.468)	(-3.484)
Aligned × County-pair political distance	-1.596***		
	(-4.255)		
Aligned	0.373***		
	(3.744)		
Observations	684,370	384,809	293,630
Controls	Yes	Yes	Yes
Orig county FE	Yes	Yes	Yes
Dest county FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Pseudo R-squared	0.616	0.674	0.303

Appendix

A Variable Description

Main dependent variable

County-pair inventor moves: The number of inventor moves from an origin county to a destination county in a given year. The sample is constructed as a balanced county-pair-year panel, so county-pair-year observations with no inventor move remain in the sample and take the value of zero.

County-pair by Tech-class citations: The number of forward citations made by patents filed in destination county to prior patents originating in origin county within the technology class (CPC Class) in a given year. As before, zero-flow cells are retained. County of the patent is determined by its lead inventor county and year uses patent application year.

County-pair by Tech-class-pair citations: The number of forward citations made by patents in a technology class filed in destination county to prior patents in another technology class originating in origin county in a given year. Citing and cited patents can belong to either the same or different technology class. County of the patent is determined by its lead inventor county and year uses patent application year.

County-pair new tech entry: The number of distinct CPC-3 technology classes that destination county newly enters in a given year (no filing in the class over a trailing three-year window from $t-3$ to $t-1$, then a filing in year t) and that origin county held in its 3-year stock at $t-1$ (a filing in the class over $t-3$ to $t-1$). County of the patent is determined by its lead inventor county and year uses patent application year.

Main independent variable

County-pair political distance: The absolute difference in Republican vote shares between the origin and destination counties in the most recent presidential election.

Class-pair political distance: The absolute difference in the net fraction of Democratic inventors (i.e., % of Democratic inventors minus % of Republican inventors) between the

citing patent technology class (CPC 3-digit class) and cited patent technology class (CPC 3-digit class) using the partisan leaning data as in Engelberg et al. (2025).

Aligned: An indicator variable equal to one if the origin and destination counties are aligned with the same political party in the most recent presidential election, and zero otherwise.

cfscore-distance: The absolute value of the difference between the origin firm's contribution finance ideology score (cfscore) and the destination firm's contribution finance ideology score.

Close R win: An indicator variable equal to one if the winner of the relevant close election is Republican and zero if the winner is Democratic.

Destination county patent stock: Log of all filed patents in years before a given year of citing county in citing technology class.

Dest county Republican share: The Republican vote share of the destination county in the most recent presidential election.

Dest county-Tech class patent stock: The log transformation of the raw count of patents that belongs to the same CPC Class as the cited patent in the destination county.

Dest cty tech class stock: Log of one plus total distinct technology class (CPC 3-digit class) in the destination county in the previous year.

Dest firm cfscore: The contribution finance ideology score (cfscore) of the destination firm, constructed from the firm's PAC donation-based political ideology.

Different class: An indicator variable being 1 if the cited and citing patents belong to the different CPC 3-digit class.

Distance: The logarithm of the geographic distance between the origin and destination county (firm) plus one.

EPU: The absolute value of the difference in economic policy uncertainty between the origin and destination counties as in Baker et al. (2016).

Firm-pair inventor moves: The number of inventor moves from an origin firm to a destination firm in a given year.

GDP growth: The absolute value of the difference in GDP growth between the origin and destination counties, in percentage.

House value index: The absolute value of the difference in house value index between the origin and destination counties.

Misaligned county pair: An indicator variable equal to one if the origin and destination counties are politically misaligned in the most recent presidential election, and zero otherwise.

Misaligned firm pair: An indicator variable equal to one if the origin and destination firms are politically misaligned based on their most recent year's PAC donation, and zero otherwise.

Neighbor: An indicator variable equal to one if the origin and destination counties are located in neighboring states, and zero otherwise.

Origin county patent stock: Log of all filed patents in years before a given year of cited county in cited technology class.

Orig county Republican share: The Republican vote share of the origin county in the most recent presidential election.

Orig county-Tech class patent stock: The log transformation of the raw count of patents that belongs to the same CPC Class as the cited patent in the origin county.

Orig cty tech class stock: Log of one plus total distinct technology class (CPC 3-digit class) in the origin county in the previous year.

Orig firm cfscore: The contribution finance ideology score (cfscore) of the origin firm, constructed from the firm's PAC donation-based political ideology.

Polarization: The national political polarization measure as in Azzimonti (2018), centered around zero.

Post Trump: An indicator variable equal to one for years after 2016 and zero otherwise.

R to R: An indicator variable equal to one if both the origin and destination counties are Republican-leaning in the most recent presidential election, and zero otherwise.

Republican donation diff: The absolute value of the difference between the origin firm's

and destination firm's PAC contributions to Republican candidates. Winsorized at 1% and 99%.

Same CZ: An indicator variable equal to one if both origin and destination county are in the same commuting zone.

Same state: An indicator variable equal to one if both origin and destination county are in the same state.

Tech similarity: Technological-proximity measure as in Bloom et al. (2013) and Jaffe (1986), aggregated to county level.

Unemployment rate: The absolute value of the difference in unemployment rate between the origin and destination counties.

Within : An indicator variable equal to one if the origin and destination counties are located within the same state.