

Local Networks and Technology Adoption during Industry-Wide Technological Change

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Abstract

I study how firms' adoption responses to local network information change during the U.S. hydraulic-fracturing transition. I combine spatial panel models that characterize local network signals with a bunching estimator that isolates peer drilling as a plausibly exogenous source of new information. At the same local-development stage, the adoption response to peer activity is negative in markets that develop when the technology is young industry-wide and positive in markets that develop later. The cross-vintage difference is statistically significant. In later markets, the response weakens as local development accumulates. Early in the transition, the adoption response is negative but the investment response among investing firms is positive. A calibrated model uses this difference to distinguish returns to local evidence from starting costs as channels through which industry development affects firms' use of local network information. The benchmark combines an early starting-cost response that declines with industry and local development with diminishing returns to local evidence.

JEL Classification: O33, D83, G31, L71, Q35, R12.

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Firms placed near one another observe each other’s choices and their results, transact repeatedly, and share workers who carry knowledge from one operation to the next. A large literature studies these local networks as an important source of productivity growth and technological change.¹ Yet a local network rarely grows in isolation. It forms while the broader industry is still learning the technology, adoption is spreading across markets, and performance is improving. The effect of a firm’s local network may depend on when that local evidence arrives relative to the industry-wide transition.

New technologies contribute to growth only as firms adopt them and adoption is uneven. Some technologies sweep an industry while others stall or diffuse slowly. Others never spread at all. Patent holders capture the productivity gains or innovative firms displace their competitors. The diffusion process is less well understood than innovation or creative destruction yet accounts for a large share of the link between technological change and growth. Local networks are a candidate piece of that process but this paper suggests it may be a conditional one. What firms have learned outside of the local context, the increasing competition for inputs, and what the general adoption trend says about the demand for the new technology can all impact how firms process shared information in a local network.

I study this question in the U.S. oil and gas hydraulic-fracturing (“fracking”) revolution where a consequential technology spread gradually through incumbent firms as well as entry by new firms. Horizontal drilling and hydraulic fracturing made it possible to extract tight oil from shale and sandstone formations at large scale, with effects on global energy markets.² In early 2010, the new technology accounted for about 10% of U.S. oil output. By 2023, almost 70% of output came from fracked wells. Over the same period, U.S. crude oil output rose from 5.5 million barrels per day in 2010 to 12.9 million in 2023.³

¹Knowledge flows are geographically localized (Jaffe, Trajtenberg and Henderson, 1993; Audretsch and Feldman, 1996), they raise the productivity of nearby plants (Moretti, 2004; Greenstone, Hornbeck and Moretti, 2010), and knowledge sharing is part of why firms cluster in the first place (Ellison, Glaeser and Kerr, 2010).

²See Kilian (2017).

³The historical hydraulically fractured share is from EIA, “Hydraulic fracturing accounts for about half of current U.S. crude oil production” (March 15, 2016), <https://www.eia.gov/todayinenergy/detail.php?id=25372>, which is based on EIA, IHS Global Insight, and DrillingInfo well-completion and production data. The post-2015 extension uses EIA’s Short-Term Energy Outlook Data Browser, Table 10b, tight-oil production by play, <https://www.eia.gov/outlooks/steo/data/browser/>, aggregating tight-oil plays and dividing by total U.S. crude oil production. The total crude-oil output figures are annual averages from EIA Petroleum and Other Liquids, “U.S. Field Production of Crude Oil,” series MCRFPUS2, annual frequency, 5.48 million barrels per day in 2010 and 12.93 million barrels per day in 2023.

The transition occurred in waves across oil-producing regions of the country as new formations were discovered and this staggered development makes it possible to compare the effect of a firm’s local network across stages of the industry-wide transition. Drilling records clearly identify when and where investments are made. Those same permitting records identify the technological nature of the investment while mandatory production reports track monthly output.⁴ I use these records to construct measures of the information a local network carries about productivity. These data also allow me to construct firms’ nationwide portfolios of technology choices. Adoption measures the shift in a firm’s technology mix toward horizontal drilling relative to its previous mix. Investment activity creates observable signals, ranging from implementation choices to the decision to invest itself. I combine these measures with plausibly exogenous variation in peer investment to estimate how adoption responses vary with the strength of the local network signal.

The empirical strategy combines local network signals constructed from previously completed development blocks with contractually timed variation in peer activity. I estimate spatial models formation by formation on consecutive 2,000-well blocks and classify each local peer environment using four signals from earlier wells. These signals capture local performance clustering (“peer performance”), the joint explanatory power of peers’ observed techniques (“technique intensity”), the number of informative technique attributes (“peer-technique breadth”), and the skill of nearby operators (“peer skill”). For each firm-quarter observation, I use the network measures estimated from the most recently completed block. The variation in peer activity comes from lease expirations. An oil and gas lease typically lasts three to five years and the right to drill expires unless a well is drilled, so expirations concentrate peer drilling at dates set years earlier.⁵ I use a bunching estimator, motivated by the bunching of drilling at lease expiration documented in Herrnstadt, Kellogg and Lewis (2024), to isolate the expiration-induced component of peer activity. The estimator assigns each unique well to one nearby lease and estimates the excess number of wells drilled near expiration. I exclude firm-county-quarters in which the firm’s own leases expire. The estimating equation interacts expiration-driven peer activity with the local network signal and compares responses across signal types, calendar eras, and formation development stages, on both the decision to adopt and the scale of investment.

The pooled adoption responses are positive for peer performance and technique intensity. The

⁴Physical output is rarely observable in firm data. Productivity measures in the literature are typically backed out of sales, so prices and demand movements confound physical efficiency (Foster, Haltiwanger and Syverson, 2008). Here productivity is measured directly from quantities produced.

⁵See Herrnstadt, Kellogg and Lewis (2024).

mean peer-performance and technique-intensity signals in Table 1 are 0.0285 and 0.0320. Positive expiration-driven peer activity averages approximately 0.50 excess wells. At these values, the pooled estimates imply adoption responses of about 0.22 percentage points under peer performance and 0.43 percentage points under technique intensity. These magnitudes are about 18 and 35 percent of the mean extensive-adoption rate of 1.21 percent.

I find that the result changes over time. Before 2015, the adoption response to peer performance and technique intensity is weak or negative. Both signals become positive from 2015 through 2017. After 2017, the responses no longer increase and in some cases decline. The adoption response to local network information depends on both the stage of the industry-wide transition and accumulated local development. Table 3 compares formations whose first 2,000-well block was completed before 2012Q4, when fracking was expanding but still developing industry-wide, with formations whose first block was completed in 2014Q1 or later. At this common stage of local development, the late-minus-early adoption difference is 0.38*** for peer performance and 1.29** for technique intensity.⁶ The later-block estimates show that local development also shapes the response. By 2019, after both vintage groups have reached later blocks, the initial first-block difference between late- and early-vintage formations no longer remains.

The conceptual framework gives economic content to the industry-wide transition. National adoption and productivity rise over the episode as well design and completion times converge toward national practice. Together, these trends describe a broader change in the industry’s production and implementation environment. The model connects that change to firms’ use of local evidence. Broader industry development can change the return value of local evidence, the fixed cost of starting and the cost of scaling investment. These objects capture changes in firms’ ability to interpret local evidence, the expansion of specialized suppliers, the standardization of implementation and competition for scarce inputs. I calibrate the model to the vintage-block adoption and investment estimates. Counterfactuals then show which combinations of channels reproduce those comparisons and the untargeted calendar reversal. The vintage-block comparisons distinguish industry timing from local information accumulation. The adoption-investment difference helps distinguish changes in returns from changes in costs. The benchmark combines an early cost of starting that falls as industry and local implementation mature with diminishing returns to additional local evidence. Across the mechanisms considered, the broader industry environment has the same substantive

⁶The late-vintage technique-intensity estimate is imprecise on its own. The directly estimated cross-vintage difference is significant because the early-vintage estimate is negative and precise.

role. At a given stage of local development, industry maturity alters the effect of local network activity on adoption and investment by changing the return value of the information it conveys and the cost of acting on that information.

The mechanism connects two literatures that usually hold different forces fixed. Aggregate diffusion models emphasize industry-wide learning and declining adoption costs but abstract from local information. Research on local learning studies information transmitted through nearby peers while holding the broader technology environment fixed. Agglomeration research allows local clusters to advance the aggregate frontier, as in Silicon Valley. The direction studied here is different. Industry-wide development alters the economic value of information propagated through local networks. The evidence concerns how an industry-wide transition conditions local network effects. The reverse direction from local clusters to the aggregate transition lies outside the analysis.

The paper proceeds as follows. After the literature review, Section 2 describes the setting and the data. Section 3 presents the empirical strategy. Section 4 reports the reduced-form results and what distinguishes the signals. Section 5 reports robustness. Section 6 develops the framework and takes it to the data. Section 7 concludes.

Related Literature

Growth theory gives knowledge a central role because one firm's discovery can raise the productivity of other firms without being used up (Romer, 1990; Jones, 2022; Aghion and Howitt, 1998). For new technologies, those gains arrive only when other firms learn enough to adopt and use the technology. I study how information propagated through local networks contributes to that diffusion process during an industry-wide technology transition. Aggregate diffusion and growth research models how better technologies spread across firms and countries over the long run (Perla and Tonetti, 2014; Buera and Oberfield, 2020; Stokey, 2021; Comin and Mestieri, 2014) and how hard new ideas are to produce (Bloom et al., 2020). The local-learning literature instead studies bounded peer information, where peer experience affects choices when it is informative for the decision-maker's own production problem (Foster and Rosenzweig, 1995; Conley and Udry, 2010). The paper studies a new mechanism through which industry-wide development and advances in the technology frontier alter the value of information propagated through local networks and the costs firms face when acting on it. The block-vintage design separates a formation's own development from the timing of that transition. First blocks compare markets at the same local stage but at different points in the industry transition, while later blocks trace how the adoption response

changes as local evidence accumulates.

A broader spillover literature documents how knowledge spills across geographic and technological distance and shapes innovation, productivity and industry location (Jaffe, Trajtenberg and Henderson, 1993; Greenstone, Hornbeck and Moretti, 2010; Ellison, Glaeser and Kerr, 2010; Bloom, Schankerman and Reenen, 2013; Myers and Lanahan, 2022), and a growing disclosure literature observes the inputs firms reveal (Covert, 2015; Fetter et al., 2018; Hodgson, 2024; Steck, 2018). The paper distinguishes the breadth of disclosed technique information from the joint explanatory content of those disclosures. Spatial panel models classify local networks by whether peer productivity predicts later productivity, whether observed implementation choices jointly explain productivity, and how many disclosed attributes are individually informative. The distinction matters because more disclosure is not necessarily better guidance. Peer-technique breadth has no positive adoption effect, even though technique intensity does. The paper also separates adoption from investment because the two decisions discipline different mechanisms. In the conceptual framework, adoption responds to the return value of local evidence and the cost of starting, while investment levels conditional on positive investment respond to the return value and scaling costs. The adoption-investment split helps distinguish which economic channels can rationalize the timing pattern.

The design draws on spatial peer-effects methods but assigns the spatial estimate a different role. Spatial econometric models estimate relationships across nearby units (Anselin, 2001). Peer-effects models show why those relationships are difficult to separate from correlated environments (Manski, 1993) and how network structure can help (Bramoullé, Djebbari and Fortin, 2009). Applications to technology learning find that peer experience can affect production choices and adoption (Conley and Udry, 2010; Bandiera and Rasul, 2006). Here, the spatial coefficients characterize the strength and content of the local network rather than causal peer effects. Signal strength alone does not identify firms' response to local information because firms may endogenously invest in locations with stronger signals. Lease-expiration timing isolates changes in peer activity at a given signal strength. This variation changes the amount of information flowing through the network. Interacting peer activity with signal strength estimates how firms' adoption responds to that additional information.

The oil and gas setting links these questions to a literature on learning, option timing, and disclosure in drilling. Kellogg (2011) finds that learning is strong inside producer-contractor relationships but finds little transfer between neighboring producers drilling side by side. Decaire, Gilje and Taillard (2020) find that real-option exercise responds to peer exercise behavior, and Decaire and Wittry (2024) find that firms delay drilling while waiting for peer wells to reveal in-

formation. Related work studies fracking inputs, disclosure, local drilling signals, drilling timing under price uncertainty, and lease-deadline investment (Covert, 2015; Fetter et al., 2018; Hodgson, 2024; Steck, 2018; Kellogg, 2014; Herrnstadt, Kellogg and Lewis, 2024). Against this work, the paper makes the technology mix an outcome, separates it from drilling investment, and studies when expiration-induced peer activity changes adoption during the industry-wide transition.

2 Setting and Data

Horizontal drilling with multi-stage hydraulic fracturing is a distinct technology, not simply a more intensive version of conventional drilling. It uses a lateral wellbore and staged fracturing to produce shale and tight-sand resources that vertical wells cannot profitably reach. The well design is fixed when the well is drilled, and each permit records this irreversible technology choice. I use those records to classify the type of well investment and track firm-level adoption. The Supplemental Appendix illustrates the two designs.

Oil and gas leases grant firms the right, but not the obligation, to drill specified acreage for a fixed primary term. If no well is drilled before the term expires, the lessee loses those rights. Drilling concentrates immediately after signing and again near contractual expiration (Figure 1). Panel A reports that 35.3 percent of first linked wells occur within the first year after signing, after which drilling generally declines as the lease ages. In Panel B, this decline reverses as expiration approaches. First-well activity rises within four quarters of expiration, and 21.6 percent of first linked wells occur between four quarters before expiration and one quarter after it.

Oil and gas is unusually well suited to measuring how local information affects technology adoption. Mandatory state filings reveal each well’s location, timing, technology, and design, so they identify both the firm’s adoption decision and the techniques disclosed by nearby peers. Production is reported in common physical units, which makes peer performance observable without relying on sales or prices. The resulting project-level data contain adoption, disclosed implementation choices, and subsequent productivity.

The data come from Enverus, formerly DrillingInfo, a widely used industry data provider that compiles the production, permit, and lease records that states require operators to file.⁷ I link each well’s monthly output to its permit and lease information through its API number and identify firms by operator. The sample covers onshore wells in the lower-48 states spudded in 2005 or later

⁷These are the same well-completion and production records that underlie EIA’s official U.S. production statistics.

First linked wells bunch at lease signing and lease expiration

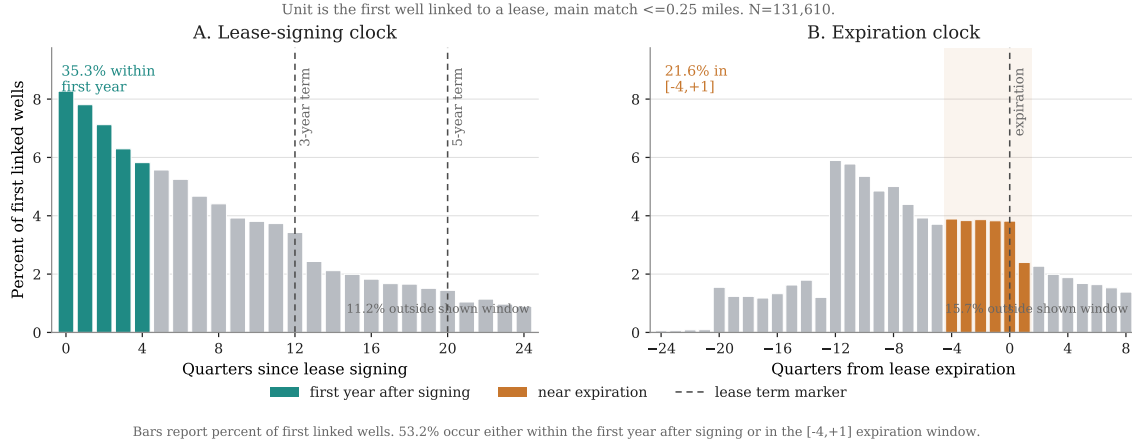


Figure 1: First linked wells around lease signing and expiration

Notes. The unit is the first well linked to a lease under the spatial well–lease match. The main sample uses wells linked to leases within 0.25 miles. Panel A plots event time in quarters since lease signing. Panel B plots event time in quarters relative to lease expiration. Highlighted bars mark the first year after signing and the expiration window $\tau = -4, \dots, 1$, which is the window used to construct excess peer activity.

by firms drilling at least ten wells. A formation is the named geological target recorded for the well, such as the Bakken or Eagle Ford. I use formation in the panel because horizontal productivity and completion choices are comparable within these geological targets but need not be comparable across them. The response panel is at the firm–county–formation–quarter level and spans 2008 through 2022. A county can contain more than one active formation, so county-level peer activity and county controls are measured once at the county–quarter level and attached to each active county–formation row. I also exclude firm–county–quarters in which the operator has same-county leases expiring, so that a firm’s response is not confounded with its own drilling deadline. Peer activity is measured at the county level because lease records locate acreage but do not identify the target formation. The county measure also captures nearby drilling outside the 15 formations for which network signals can be estimated. These wells account for about half of expiration-driven peer activity and capture local drilling even when they target smaller, often vertical formations in the same basin. This distinction matters because 105 of the 249 counties contain multiple formations and account for 67 percent of the response panel.

The monthly production records allow me to measure productivity from physical quantities without inferring it from sales, which also reflects prices and demand. Because well output declines steeply with age, productivity is the residual from a standard Arps decline curve. Firm skill is the firm–quarter component of this measure net of location, estimated using the firm’s wells across all formations in which it operates. Appendix B gives both constructions.

Table 1: Descriptive statistics, response panel

Variable	Mean	SD	<i>N</i>
Adoption, extensive	0.0121	0.1093	1,002,519
Investment, extensive	0.0144	0.1190	1,002,519
Adoption, intensive	0.0137	0.9983	1,002,519
Investment, intensive	0.0869	1.2364	1,002,519
Expiration-driven peer activity (lag 1)	0.0490	0.2595	1,002,519
Peer performance	0.0285	0.0295	968,821
Peer skill	0.0122	0.0937	968,821
Technique intensity	0.0320	0.0165	788,111
Peer-technique breadth	3.5359	4.3393	1,002,519

Notes. The unit is a firm–county–formation–quarter, restricted to quarters in which the operator has no same-county leases expiring, covering 15 formations over 2008–2022. Extensive adoption is an indicator that the firm’s drilling in the county shifts its horizontal share upward, and extensive investment is an indicator that the firm drills any horizontal well. In the response regressions, intensive adoption is the horizontal-share change conditional on positive adoption and intensive investment is the horizontal well count conditional on positive horizontal investment. The intensive-outcome means shown here are unconditional over the displayed sample, with zero values retained when the firm has no positive activity. Expiration-driven peer activity is the bunching-weighted measure used in the response regressions, lagged one quarter, constructed at the 0.25-mile lease match radius and excluding the responding firm’s own wells. Signal rows have smaller counts where the signal is missing.

The constructed response panel, after excluding firm–county–quarters in which the operator has same-county leases expiring, contains 1,002,519 firm–county–formation–quarter observations, 795 unique firms, 249 unique counties and 15 formations. Table 1 reports descriptive statistics. Adoption and investment are rare at the firm–county–formation–quarter level, so both are zero for most observations.⁸ The positive adoption and investment samples used in the intensive specifications contain 12,116 and 14,410 observations, respectively. The all-distance lagged ex-firm horizontal well count averages 22.24, while the lagged expiration-driven peer-activity measure at the baseline 0.25-mile match radius averages 0.049.

I define adoption as an increase in a firm’s horizontal share to capture the transition within incumbent operators from vertical to horizontal drilling. The shift toward horizontal drilling has substantial output consequences. The estimated relative-output coefficient for horizontal wells rises from about 1.3 in 2008 to nearly 2.0 by 2020 (Figure 2), so the technology choice affects expected physical output as well as well design. Horizontal wells also rise from about 30 percent of new wells in 2008 to more than 90 percent by 2022 (Figure 3). The same shift occurs among operators active by 2010Q4, not only through entry by new horizontal operators (Figure 4).

Later-developing formations also appear to enter a more standardized engineering environment.

⁸Adoption is also bounded from above by the construction in equation (1). In the panel, 120,425 rows have a lagged horizontal share of one and none of them records adoption. The share of rows in that position is not monotone over the episode, at 12.9, 9.8, 11.0 and 14.8 percent across the four periods, while the adoption rate falls throughout, at 2.21, 0.98, 1.32 and 0.74 percent. The time path of adoption is not a mechanical consequence of the bound.

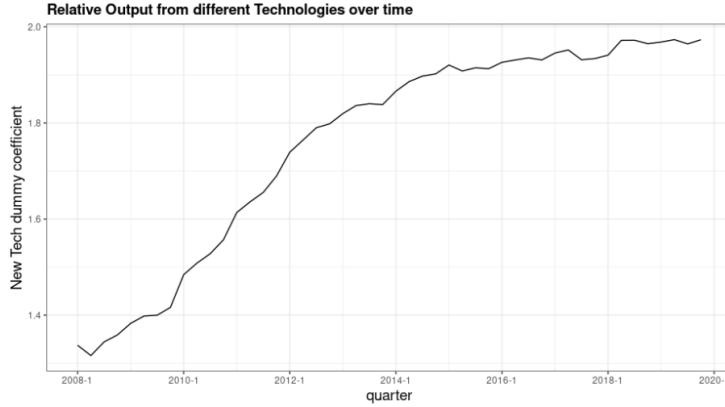


Figure 2: Productivity of horizontal versus vertical wells over time

Notes. The sample contains horizontal and vertical wells drilled in the lower 48 states. Each point reports γ from a separate quarterly well-month regression, $\log(O_{wt}) = \alpha + \beta \log(Age_{wt}) + \gamma Horizontal_w + \varepsilon_{wt}$. O_{wt} is well w 's physical output in month t , Age_{wt} is the number of months since production began, and $Horizontal_w$ indicates a horizontal well. The age control accounts for the decline in output as a well matures. Larger values of γ indicate a greater output advantage for horizontal wells.

Perforated interval length captures well design and project scale, while spud-to-completion time captures execution speed. Among wells in the peer-performance and technique-intensity response samples drilled after 2017, both measures are less dispersed around contemporaneous national practice in later-vintage formations than in early-vintage formations. Supplemental Appendix Table OA.1 reports these comparisons. This convergence is consistent with industry-wide learning and standardization in how the technology is implemented. The paper studies how information propagated through local networks affects adoption as this broader industry environment evolves.

The joint adoption and productivity trends define the industry-wide transition used throughout the paper. The transition appears in the joint increase in horizontal adoption and relative productivity and in the displacement of vertical drilling from firms' technology mixes. The reduced-form analysis leaves these changes as separate empirical features instead of collapsing them into a single observed state variable. Calendar periods locate adoption and investment responses within the industry-wide transition, while formation-vintage comparisons separate that timing from a formation's own development. The comparisons reveal whether firms' responses to local peer activity depend on the stage of the broader transition without assigning that transition to a single mechanism.

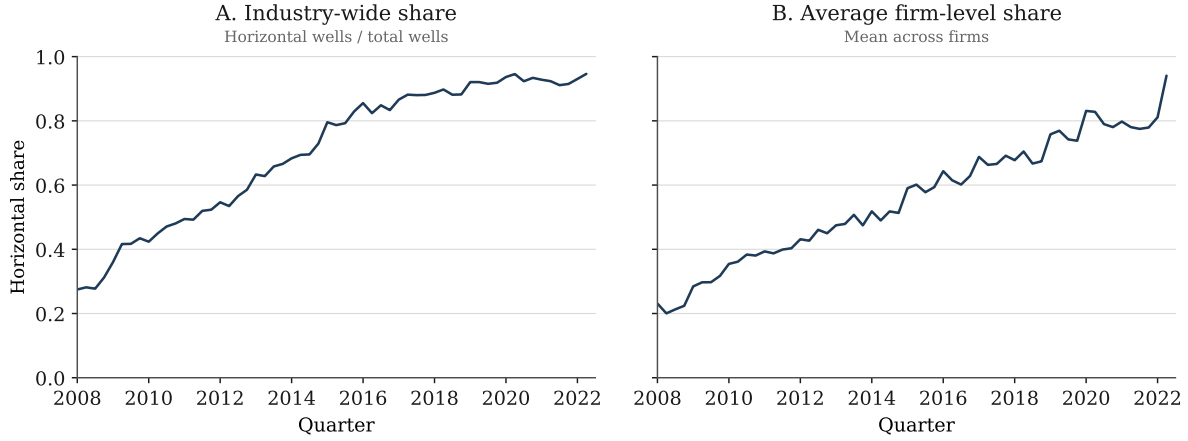


Figure 3: Diffusion of horizontal fracking, 2008Q1 to 2022Q2

Notes. The sample contains wells in the response panel from 2008Q1 through 2022Q2. The top panel divides the total number of horizontal wells drilled in each quarter by the total number of horizontal and vertical wells. The bottom panel first computes this horizontal share separately for every operator that drills in the quarter, then reports the unweighted average across those operators. The top panel weights operators by drilling activity, while the bottom panel gives each active operator equal weight.

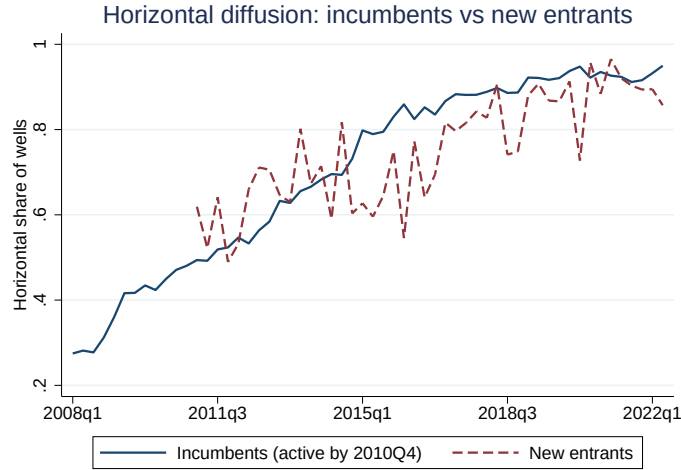


Figure 4: Horizontal diffusion among incumbents versus new entrants

Notes. The sample contains wells in the response panel from 2008Q1 through 2022Q2. Incumbents are operators whose first active quarter was 2010Q4 or earlier. Later entrants are operators whose first active quarter occurred after 2010Q4. For each group and quarter, the horizontal share equals the group's total horizontal wells divided by its total horizontal and vertical wells. The series are group-level shares, not averages of firm-level shares.

3 Empirical Strategy

The empirical strategy estimates whether expiration-driven peer activity changes adoption and investment differently across local network signals constructed from previously completed development blocks. This section defines the peer-activity measure, the local network signals, the outcomes, the response equation, and the identifying assumptions.

3.1 Expiration-driven peer activity

Nearby peer drilling is endogenous to the same local returns that shape the firm’s own adoption decision. If peers drill when a formation becomes more attractive, a raw peer-activity measure combines local evidence with the common shock moving all firms in the area. The design uses lease expirations to isolate peer drilling whose timing is shifted by a contractual deadline set years earlier. Oil and gas leases typically expire unless the lessee drills before the end of the primary term. A well drilled near expiration is more likely to reflect the lease deadline than contemporaneous local returns.

The construction begins by assigning each unique well to one candidate lease. Eligible leases must be signed before the well is spudded and lie within 0.25 miles of the well. I assign the nearest lease and use the earliest expiration to break ties among leases at nearly the same distance. The spatial assignment is inferred, not an observed legal link between a well and a lease. It permits the well operator and leaseholder to have different standardized names. Section 5.4 rebuilds the measure using operator–lessee name agreement and reports the corresponding response estimates.

I then measure event time as the number of quarters from the assigned lease’s expiration to the well’s spud date. Assigned wells bunch near lease expiration under the baseline spatial match (Figure 5). I fit a smooth fifth-order event-time profile over quarters -12 through 4 , with separate indicators for quarters -4 through 1 . Setting those indicators to zero gives the counterfactual count in Figure 5. In both the quarter before expiration and the expiration quarter, about 32 percent of observed assigned wells lie above the fitted counterfactual. Each assigned well receives the estimated excess share at its event time as a fractional weight, with zero weight outside the expiration window. Appendix A gives the estimator and the excess-share calculation.

The peer-activity measure sums these weights within a county-quarter. I remove the responding firm’s own operated and leased wells, then lag the resulting measure one quarter.⁹ I also exclude

⁹Section 5.4 reports additional lags.

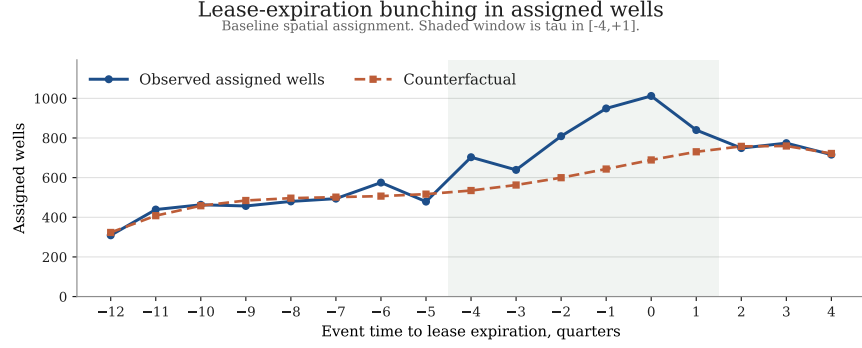


Figure 5: Lease-expiration bunching in assigned wells

Notes. The unit is a unique well assigned to the nearest eligible lease signed before the well was drilled and located within 0.25 miles. Event time is the number of quarters between the well’s drilling date and the assigned lease’s expiration. The figure plots the observed number of wells at each event time and the fitted counterfactual from $C_\tau = \alpha + \sum_{p=1}^5 \eta_p \tau^p + \sum_{k=-4}^1 \lambda_k \mathbf{1}\{\tau = k\} + u_\tau$, estimated over quarters -12 through 4 . The counterfactual sets the expiration-window indicators to zero. The share of observed wells above that counterfactual at each event time, bounded between zero and one and set to zero outside quarters -4 through 1 , is the fractional weight assigned to each well when constructing expiration-driven peer activity.

firm-county-quarter observations in which the firm has its own same-county lease expiring in the response quarter. Section 5.1 widens this exclusion to the full bunching window. The restriction prevents the measure from substituting the firm’s own lease deadline for prior peer activity.¹⁰ Supplemental Appendix Figure OA.2 reports the distribution of the resulting measure across response samples and formations.

3.2 Measuring local network signals

Local network signals classify the network environment represented by earlier peer wells. I estimate them separately within the geological formations that define the response panel in Section 2.¹¹ To make the signals dynamic, I sort horizontal wells in each formation by first production month, split them into consecutive 2,000-well blocks, and assign each firm-county-formation-quarter the signal from the most recently completed block in that formation.

The block precedes the response quarter, but its productivity measure uses the full subsequent production record of the wells in that block. The signals are ex post classifications of the network environment, not literal measures of the information available to firms when the block closed.

The signal construction uses formation-block spatial regressions. The baseline model relates well productivity to weighted productivity and operator skill from other firms’ wells that began producing earlier. Additional specifications replace operator skill with exposure to peers’ disclosed

¹⁰Section 5.1 reports the sample loss from this exclusion and a broader version of it.

¹¹Formation labels are simplifications. Some named formations contain multiple subformations. Finer geological units would be more precise in principle but would often leave too few wells to estimate the network measures reliably.

drilling and completion attributes. The spatial specifications produce the four local network signals described below. The weight matrix W determines which earlier peer wells enter each measure. I estimate the signals under alternative weights that emphasize geographic proximity, recency, a common development episode, or relative operator skill. Appendix C gives the full specifications and weight definitions.

Peer-performance networks capture local performance clustering. In each formation-block, the spatial regression relates a well’s productivity to weighted productivity from other firms’ wells that began producing earlier. The resulting coefficient measures the strength of local productivity co-movement. The source of that clustering remains open. Shared geology, service markets, operating constraints, copying, skill transfer, or a portable operating recipe can all contribute. The same regression includes the weighted skill of nearby peer operators. The peer-skill coefficient measures whether nearby operator skill has an additional association with productivity after accounting for peer performance. Because skilled operators are also likely to drill productive wells, I use peer skill as a diagnostic, not a separate network channel.

The two peer-technique signals use disclosed drilling and completion attributes, including fracking inputs and pressure readings. For each attribute, I estimate whether a well’s productivity is associated with exposure to earlier peers whose records report that attribute, conditional on peer performance and the spatial-model controls. The resulting coefficient compares wells with greater and lesser exposure to peers for whom that information is available. Because disclosure rules, reporting systems, and compliance vary across states and over time, the measure cannot separate information availability from the usefulness of the information disclosed. Peer-technique breadth counts the attributes with positive and statistically precise productivity loadings. Technique intensity is the additional explanatory power from including all peer-technique exposure terms in the spatial model. The four local network signals enter the response regressions in their original units. Coefficients can be compared over time for the same signal and outcome, but not across signals. Appendix D lists the attributes and gives the peer-technique regressions.

3.3 Outcomes and samples

I distinguish adoption from investment using four outcomes. Adoption records whether drilling in a county-formation-quarter shifts the firm’s overall technology mix toward horizontal wells. Investment records whether and how many horizontal wells the firm drills in that market. Let H_{iq} and V_{iq} denote firm i ’s accumulated horizontal and vertical wells at the start of quarter q , across all

markets in which it operates. Let h_{icgq} and v_{icgq} denote its horizontal and vertical wells in county c , formation g , and quarter q . The percentage-point change in the firm's horizontal share is

$$A_{icgq} = 100 \left(\frac{H_{iq} + h_{icgq}}{H_{iq} + V_{iq} + h_{icgq} + v_{icgq}} - \frac{H_{iq}}{H_{iq} + V_{iq}} \right). \quad (1)$$

I define extensive adoption as an indicator that $A_{icgq} > 0$. Conditional on a positive shift, A_{icgq} measures intensive adoption. Firms can shift their technology mix toward horizontal drilling over multiple quarters. The adoption measure records each increase in horizontal share, not only a firm's first horizontal well. Section 5.3 examines whether the estimated effects vary with prior horizontal experience. Extensive investment indicates that $h_{icgq} > 0$. Conditional on positive horizontal investment, h_{icgq} measures the intensive investment level. Because each intensive sample conditions on the corresponding extensive outcome, comparisons between extensive and intensive coefficients are suggestive and do not compare a common sample directly.

Equation (1) separates adoption from investment, which is why horizontal drilling alone is insufficient as an outcome. A firm that already drills only horizontal wells can drill a great many more without changing its technology mix at all and it registers zero adoption however large its investment. A firm that drills one horizontal well while half its stock is vertical registers a positive shift. The measure asks whether this market's drilling moved the firm toward the new technology, not how much drilling occurred, and it is a firm-level object that county drilling counts cannot deliver.

3.4 Main empirical framework

I estimate the response in the firm-county-formation-quarter panel from 2008 through 2022:

$$Y_{icgq} = \beta (\hat{E}_{c,q-1}^{-i} \cdot S_{gq}) + \theta_E \hat{E}_{c,q-1}^{-i} + \theta_S S_{gq} + \mu_i + \kappa_c + \alpha_{ic} + \lambda_q + X'_{c,q-1} \Gamma + X_{iq}^{f'} \Phi + u_{icgq}. \quad (2)$$

Here Y_{icgq} is one of the four outcomes defined above. The variable $\hat{E}_{c,q-1}^{-i}$ is the estimated number of expiration-driven peer wells in county c during the previous quarter after removing wells operated or leased by firm i . Each assigned well contributes the excess-share weight for its event time shown in Figure 5, and these weights are summed within the county-quarter. The variable S_{gq} is the local network signal from the most recently completed block in formation g . The coefficient β measures how the response to one additional estimated excess peer well changes when the local signal increases by one unit. The coefficients θ_E and θ_S include the corresponding lower-order

terms.

The regressions absorb operator fixed effects μ_i , county fixed effects κ_c , operator-by-county fixed effects α_{ic} , and calendar-quarter fixed effects λ_q . Firm-county fixed effects compare a firm’s outcomes within the same county over time and remove time-invariant differences across its local operations. Calendar-quarter fixed effects remove shocks common to all counties in a quarter, including oil prices and aggregate drilling conditions. Lagged county controls account for changes in local drilling activity and other county-level conditions. They are the county horizontal-production share and annual county size. The firm-quarter controls X_{iq}^f are the firm’s horizontal-production share, its horizontal and total well stocks, its county-level horizontal well stock, and a firm-quarter productivity index. Standard errors are clustered by formation-block. Unless otherwise noted, Section 4 uses this specification.

3.5 Specification across eras

I allow the coefficients on the controls to vary across eras. The firms and formations active early differ from those active later, so imposing a common relationship between the controls and outcomes across the full period can distort changes in the estimated peer-activity response. The preferred specification estimates equation (2) separately within each era. An alternative specification holds the control coefficients constant across eras. The two approaches differ most clearly for the early technique-intensity estimate, while their later estimates are similar. Supplemental Appendix Table OA.12 reports both specifications. All differences across eras are tested directly.

3.6 Identification and threats

Identification requires expiration-driven peer activity to be unrelated to unobserved changes in the responding firm’s outcome after conditioning on the lower-order terms, fixed effects and controls in equation (2). The conditional-mean assumption applies to the variation in peer activity used to estimate adoption and investment effects within each measured network state. The network signals need not be exogenous to local development because the specification targets heterogeneity in the effect of peer activity, not the causal effect of changing a signal. They identify where the adoption or investment response to expiration-driven peer activity is stronger or weaker. Their construction and timing still create separate threats discussed below.

The first threat is the responding firm’s own expiration pressure. The peer-activity measure removes wells operated or leased by the responding firm. The baseline sample also excludes firm-

county-quarters in which the firm has a lease expiring in the same county. An expiration elsewhere in the firm’s portfolio could still cause it to mobilize drilling across several markets. Section 5.1 applies a stricter exclusion to every firm-quarter in which the firm has a matched lease expiration anywhere in its portfolio. The main sign pattern remains under this restriction.

The second threat is that the bunching estimator may classify drilling driven by local conditions as expiration-driven. Drilling declines after lease signing and then increases again as expiration approaches (Figure 1). The reversal is difficult to reconcile with a smooth local development trajectory alone. The estimator defines excess drilling relative to the event-time profile outside the expiration window and assigns each well only the estimated excess share at its event time. The expiration spike remains when the bunching specification conditions on county-quarter drilling and when wells are linked to leases using operator-lessee name matches. The name-matched response estimates also retain the main pooled sign pattern. Supplemental Appendix Tables OA.2–OA.3 report these analyses. Supplemental Appendix Table OA.4 addresses uncertainty from the estimated peer-activity measure. The county bootstrap re-estimates the bunching curve, reconstructs peer activity and re-estimates the response equation in each draw while holding the network signals fixed. The bootstrap percentile intervals preserve the central pooled results for extensive adoption and exclude zero for technique intensity on intensive investment. The bootstrap standard errors exceed the formation-block-clustered standard errors in seven of the eight reported specifications. The exception is technique intensity on intensive investment. The breadth estimate for intensive investment loses precision. Expiration-driven drilling also reflects a leaseholder’s choice to drill instead of letting the lease lapse. Section 5.1 finds no sign that this choice selects on favorable local conditions. New leasing fails to rise with expiration-driven drilling. Wells drilled in the expiration window have no productivity advantage where more expiring leases are drilled. Among county-quarters with scheduled expirations, positive recent productivity innovations are associated with slightly less expiration-driven drilling.

The network signals raise separate measurement and interpretation concerns. They are estimated relationships among earlier wells, not measures of productivity levels. Peer performance is the coefficient on weighted prior peer productivity, while breadth and intensity summarize how disclosed peer techniques relate to productivity. Because the outcomes are adoption and investment, the dependent variable does not enter the signal construction mechanically. The signals may still proxy for geology, local productivity or development maturity. Formations with declining peer-performance coefficients continue to experience strong productivity growth after accounting

for the lower-order signal term in the response equation. The corresponding trajectory analysis is reported in the Supplemental Appendix. A declining network coefficient is not equivalent to declining productivity. Web Appendix Table W.1 reports the four preferred network measures for every completed formation block. Supplemental Appendix Table OA.5 compares alternative spatial weights on the same blocks. The comparison separates sensitivity to spatial weights from differences in the stage of local development. The analyses clarify the variation used by the interaction without making the signals causal.

Signal timing creates an additional concern. Each signal is estimated from a completed 2,000-well formation block and remains fixed until the next block closes. A timing analysis drops the first response quarter after every block closure, removing the quarter in which wells used to complete the block could also enter lagged peer activity. The headline pooled signs remain in Supplemental Appendix Table OA.6. Equal-sized blocks hold the number of wells used to estimate each network state approximately constant across updates. Appendix C gives the block construction. The reported standard errors nevertheless treat the estimated network signals as fixed.

A remaining threat is that formation discovery produces a wave of lease signing, followed by clustered expirations several years later. The locations of those expirations are not random. Their timing is less likely to reflect current information about the formation. Among first linked wells, 35.3 percent are drilled within the first year after signing. First-well activity then declines before increasing again among leases that remain as expiration approaches (Figure 1). An earlier discovery may explain why many leases were signed in the same place, but it is less likely to explain why drilling on the remaining leases increases in the expiration quarter instead of during the intervening years. The bunching estimator assigns only this incremental expiration-related share to peer activity. Removing the responding firm’s wells and expiration exposure then isolates its response to drilling shifted by its peers’ deadlines. Calendar-quarter effects absorb the common oil-price level and other industry-wide conditions. Oil prices could still change firms’ sensitivity to peer activity or network signals, so Section 5.2 interacts prices with both. The main adoption estimates remain similar and the price interactions are imprecise. To distinguish a response specific to horizontal technology from a general increase in local drilling, I re-estimate equation (2) with vertical drilling as the outcome. A general local drilling boom should produce a parallel positive vertical response. No such pattern appears in the estimates. Section 5.4 varies the lag and lease-matching distance to determine whether peer-activity effects are concentrated at the temporal and spatial ranges used in the baseline design. An unobserved local shock could still coincide with clustered expirations

and affect firms differently across network states. I interpret the estimates as net responses to expiration-driven peer activity, not as pure information effects.

4 Local Network Responses to Expiration-Driven Peer Activity

This section presents results from the baseline specification in equation (2). The coefficient of interest is the interaction between expiration-driven peer activity, $\widehat{E}_{c,q-1}^{-i}$, and a formation-level network signal measured before the response quarter, S_{gg} . The peer-activity measure is excess peer drilling induced by lease expirations in the prior quarter, excluding the responding firm’s own expiration exposure. I estimate the specification separately across peer performance, peer skill, peer-technique breadth and technique intensity, and compare how the adoption and investment effects of the same expiration-driven increase in peer activity vary across network states.¹² The outcomes separate adoption and investment, each on the extensive and intensive margin.

4.1 Pooled network responses

Table 2 reports the baseline response pooled across the whole sample period. The four columns separate adoption from investment, each on the extensive and intensive margin. Peer performance is positive for extensive adoption, extensive investment and intensive adoption, while technique intensity is positive on all four margins. Peer-technique breadth has the opposite effect, with negative interactions where it is precise. Peer skill is imprecise for both extensive outcomes and intensive adoption. Its negative intensive-investment estimate is not robust to the county bootstrap in Supplemental Appendix Table OA.4. Because the signal measures use different units, I do not compare raw coefficient magnitudes across signals. Web Appendix Table W.3 reports descriptive statistics for the peer-performance and technique-intensity response samples used in the magnitude comparisons below.

To interpret the magnitudes, consider Haynesville as a concrete example. Haynesville has local network estimates close to the average for both peer performance and technique intensity. Its peer-performance signal is 0.044, and positive expiration-driven peer activity averages 0.50 excess wells. Applying the pooled extensive-adoption coefficient of 0.153** implies a 0.33 percentage point larger probability that the firm’s drilling shifts its horizontal share upward. The implied change is about 27 percent of the average extensive-adoption rate of 1.21 percent in Table 1. The intensive-adoption

¹²The main display uses distance-time weights for peer performance, peer skill and technique intensity, and equidistant weights for peer-technique breadth.

Table 2: Pooled response to peer activity by signal

	Adopt (ext)	Invest (ext)	Adopt (int)	Invest (int)
<i>Peer performance (WY) [distance-time]</i>				
$\widehat{E}_{c,q-1}^{-i} \times \text{signal}$	0.1531** (0.0649)	0.1835** (0.0756)	9.4487*** (2.6951)	5.6188 (6.6970)
N	582,531	582,531	7,234	8,565
R^2	0.381	0.402	0.911	0.641
<i>Peer skill (WZ) [distance-time]</i>				
$\widehat{E}_{c,q-1}^{-i} \times \text{signal}$	0.0404 (0.1688)	0.0272 (0.1014)	-1.7864 (2.3706)	-37.4633** (15.5702)
N	152,297	152,297	912	1,080
R^2	0.536	0.541	0.980	0.866
<i>Peer-technique breadth [equidistant]</i>				
$\widehat{E}_{c,q-1}^{-i} \times \text{signal}$	-0.0020*** (0.0006)	-0.0025*** (0.0007)	-0.0222 (0.0367)	-0.3267* (0.1741)
N	683,440	683,440	7,058	8,420
R^2	0.354	0.370	0.957	0.579
<i>Technique intensity [distance-time]</i>				
$\widehat{E}_{c,q-1}^{-i} \times \text{signal}$	0.2661*** (0.0955)	0.2988** (0.1249)	8.8524 (7.3287)	37.6117 (27.1502)
N	778,002	778,002	8,704	10,348
R^2	0.358	0.378	0.862	0.615
Firm-quarter controls	Yes	Yes	Yes	Yes
County-quarter controls	Yes	Yes	Yes	Yes
Firm / county / firm-county / quarter FE	Yes	Yes	Yes	Yes
Standard errors	formation-block	formation-block	formation-block	formation-block

Notes. The unit is a firm–county–formation–quarter. Each entry reports the coefficient on one-quarter-lagged expiration-driven peer activity, $\widehat{E}_{c,q-1}^{-i}$, interacted with the listed network signal, S_{gq} , from a separate regression for the indicated outcome. Every regression includes the lower-order peer-activity and signal terms. Controls include firm and county horizontal-production shares, firm horizontal and total well stocks, the firm’s county-level horizontal well stock, a firm-quarter productivity index and annual county size. The regressions absorb operator, county, operator-by-county and calendar-quarter fixed effects. Each signal-specific sample contains observations for which that signal is positive and statistically different from zero under its preferred weight. The intensive-outcome samples also require a positive value of the corresponding outcome. Peer performance, peer skill and technique intensity use distance-time weights. Peer-technique breadth uses equidistant weights. Standard errors are clustered by formation-block and reported in parentheses. N and R^2 are reported for each regression. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

coefficient of 9.45*** implies a 0.20 percentage point larger horizontal-share shift, about 17 percent of a typical positive adoption change.¹³ The extensive-investment response is also positive, while the intensive-investment estimate is positive but imprecise. The pooled pattern indicates a clearer effect on whether firms drill horizontally than on how much they drill once active.

At the Haynesville benchmark, the technique-intensity signal is 0.047. The pooled coefficients imply a 0.63 percentage point increase in the probability of adoption. The intensive-investment point estimate implies 0.88 additional horizontal wells conditional on positive horizontal investment, but it is imprecise under formation-block clustering. Peer performance likewise has a clear adoption

¹³Supplemental Appendix Table OA.7 reports standardized estimates where peer activity and network signals are scaled by one standard deviation.

effect but no precise intensive-investment response.¹⁴ The pooled results provide stronger evidence about whether firms adopt than about how much they invest conditional on positive horizontal investment. They are consistent with local productivity comovement helping firms assess whether the technology is viable under shared local conditions and with observed peer techniques informing implementation, but they do not distinguish learning from shared geology, services, or other local complements.

Technique intensity is the partial R^2 from jointly adding the peer-technique terms, so greater attribute availability can mechanically increase its explanatory power. The measure remains informative because firms can use only techniques they observe. Reporting volume produces no detectable heterogeneity in the peer-activity effect across the full panel (Supplemental Appendix Table OA.8). Within formation blocks where technique intensity is positive and precisely estimated, reporting volume and intensity move together, so the two cannot be separated empirically. Technique intensity is best read as combining the availability of peer data with the extent to which those data jointly explain productivity. It does not isolate informativeness holding availability fixed.

Peer-technique breadth presents a sharp contrast. Supplemental Appendix Table OA.9 groups formations according to whether breadth increases or remains flat across successive 2,000-well development blocks. Formations with increasing breadth add more attributes with positive productivity loadings but those attributes overlap more in what they explain. Greater breadth may characterize formations where productive drilling requires a larger or more complex set of techniques instead of providing a clearer guide to adoption. If breadth reflects a more demanding implementation problem, additional attributes may attenuate the adoption response to peer activity instead of strengthening it. I examine the design of firms' own wells to assess whether breadth matters after adoption. Perforated interval measures the length of the completed horizontal section and provides a proxy for project scale and complexity, while drill time provides a measure of execution speed and, less directly, cost. Breadth is associated with longer perforated intervals at lags two and three in Supplemental Appendix Table OA.10 but has no consistent relationship with drill time. The additional technique information may help firms already using the technology configure more complex wells while revealing a higher implementation threshold for firms deciding whether to adopt. The combined evidence suggests that peer activity affects different decisions depending on what the local network reveals. Performance comovement bears on local viability, jointly informative techniques bear on implementation and scale, and a broad but overlapping set of techniques bears

¹⁴The estimates use signal-specific samples, and I do not test their difference.

on project design while potentially increasing the threshold for adoption.

4.2 The adoption response over time

The pooled estimates combine periods in which horizontal adoption, productivity, and supporting industry capacity differ substantially. The adoption response changes across calendar periods (Figure 6). Before 2015, the adoption effect is not positive even where the measured local signal is positive and statistically precise. The interaction is -0.046 and imprecise for peer performance and -0.174^{***} for technique intensity. It becomes positive for both signals in 2015 to 2017, at 0.282^{***} and 0.357^* , respectively. After 2017, the peer-performance response falls while the technique-intensity response remains positive.¹⁵

Direct tests confirm the reversal. Between the first two periods, the peer-performance response rises by 0.328^{***} and the technique-intensity response rises by 0.531^{**} . After 2017 the two estimates follow different paths. The peer-performance response falls by 0.610^{***} , while the technique-intensity change is small and imprecise.¹⁶

Adoption and investment can also move in opposite directions (Figure 6). From 2008 through 2014, the technique-intensity interaction is -0.174^{***} for adoption and 29.3 for investment levels conditional on positive horizontal investment, although the investment estimate is imprecise. The early negative adoption response is absent from the intensive investment level. Section 6 uses this difference and the later divergence between peer performance and technique intensity to distinguish among possible mechanisms. Before turning to those mechanisms, the next subsection separates calendar timing from accumulated local development.

4.3 Formation vintage and local development

The reversal in Figure 6 could reflect accumulated local development, when that development occurs within the industry-wide transition, or both. Table 3 separates these dimensions using the quarter in which a formation completes its first 2,000-well block. Early-vintage formations complete that block by 2012Q3. Late-vintage formations complete it in 2014Q1 or later. No formation completes its first block between these dates. The first-block estimates are not restricted to a single calendar period. They compare formations according to when the first local-development state was established. The

¹⁵Supplemental Appendix Table OA.11 enters lags one through four jointly. The added terms indicate some persistence but leave the one-quarter lag interpretation unchanged.

¹⁶The signals use different estimation samples, so I do not test whether these changes differ. Supplemental Appendix Table OA.13 tabulates intensive investment for all three signals, the two margins not plotted and the peer-technique-breadth estimates. Web Appendix Table W.5 reports the complete four-margin table.

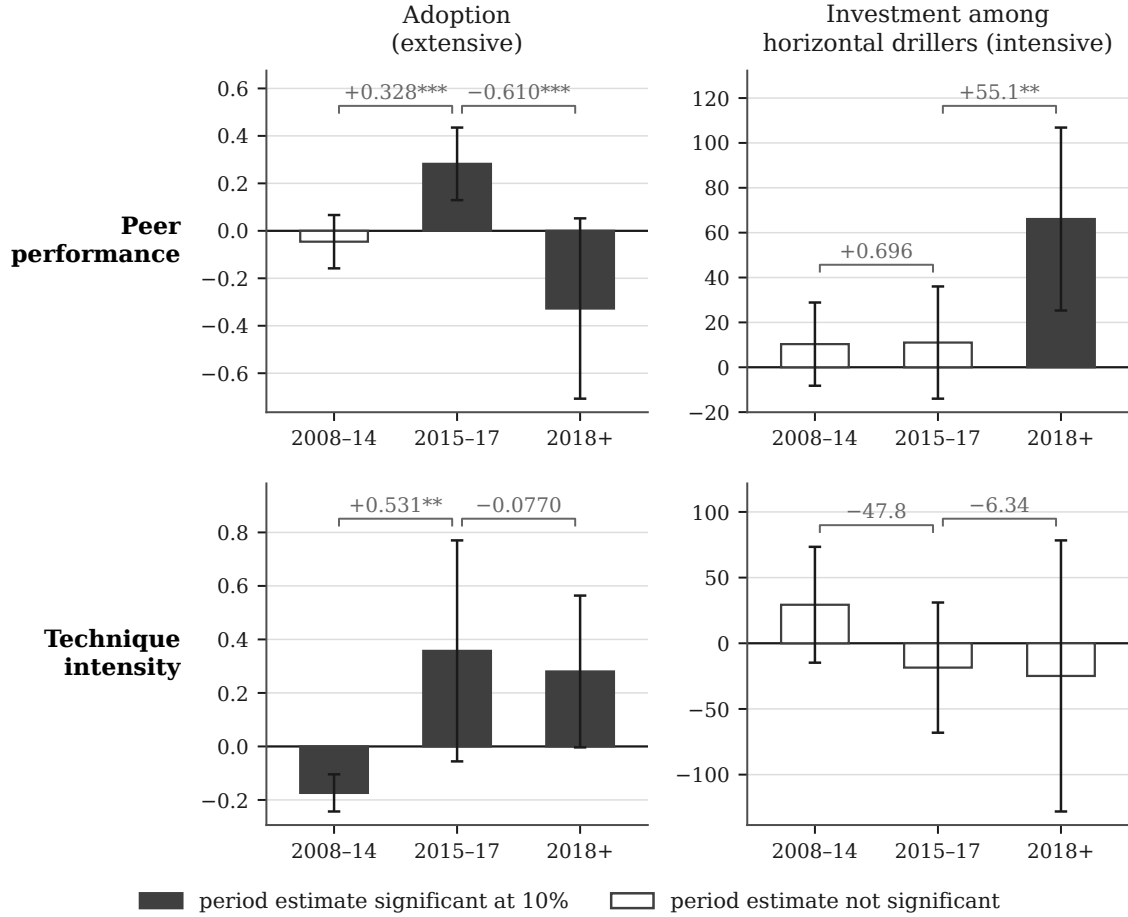


Figure 6: Adoption and intensive-investment responses by period

Notes. The unit is a firm-county-formation-quarter. Each bar reports the coefficient on one-quarter-lagged expiration-driven peer activity interacted with peer performance (top row) or technique intensity (bottom row). The left column uses extensive adoption. The right column uses horizontal well counts among firms with positive horizontal investment. Each regression is estimated separately for 2008–14, 2015–17 or 2018 onward. It includes the lower-order peer-activity and signal terms. Controls include firm and county horizontal-production shares, firm horizontal and total well stocks, the firm’s county-level horizontal well stock, a firm-quarter productivity index and annual county size. The regressions absorb operator, county, operator-by-county and calendar-quarter fixed effects. Control coefficients are allowed to differ across periods. Both signals use distance-time weights. Each signal-specific sample contains observations for which that signal is positive and statistically different from zero. The brackets report directly estimated contrasts between adjacent periods. Whiskers are 95 percent confidence intervals based on formation-block-clustered standard errors. Filled bars are significant at the 10 percent level. Supplemental Appendix Table OA.13 tabulates intensive investment for all three signals and reports the additional margins and peer-technique-breadth estimates. Web Appendix Table W.5 reports all three signals and all four outcomes.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Response by formation vintage, block position, and calendar timing

Era and local-development state	Early vintage	Late vintage	Late minus early
<i>Panel A. Peer performance (WY), extensive adoption</i>			
First-block state	−0.144* (0.077)	0.234** (0.093)	0.378*** (0.120)
Later blocks, through 2014	−0.069 (0.065)	—	—
Later blocks, 2015–16	−0.133 (0.232)	—	—
Later blocks, 2017+	0.227 (0.207)	−0.677* (0.348)	−0.904** (0.405)
Later blocks, 2019+	0.284 (0.316)	−0.782** (0.306)	−1.066** (0.440)
<i>Panel B. Technique intensity, extensive adoption</i>			
First-block state	−0.460** (0.228)	0.826 (0.591)	1.286** (0.634)
Later blocks, through 2014	−0.184** (0.073)	—	—
Later blocks, 2015–16	0.188*** (0.060)	—	—
2015–16 minus through 2014	0.372*** (0.081)	—	—
Later blocks, 2017+	0.157 (0.195)	0.267* (0.145)	0.110 (0.243)
Later blocks, 2019+	0.183 (0.241)	0.032 (0.360)	−0.150 (0.434)
Firm-quarter controls	Yes	Yes	Yes
County-quarter controls	Yes	Yes	Yes
Firm / county / firm-county / quarter FE	Yes	Yes	Yes
Standard errors		formation-block	

Notes. The unit is a firm–county–formation–quarter. Each entry is the coefficient on one-quarter-lagged expiration-driven peer activity interacted with the listed signal in an extensive-adoption regression. Early- vintage formations complete their first 2,000-well development block by 2012Q3. Late-vintage formations complete it in 2014Q1 or later. First-block estimates have no response-period restriction. Later blocks contain blocks two and above. The 2019+ row is nested within the 2017+ row. Dashes indicate that late-vintage formations have no later-block observations before 2017. The first-block through 2017+ rows come from a saturated specification that jointly estimates the listed vintage-period responses. The 2019+ row re-estimates the aligned later-block comparison over 2019–21. The last column reports directly estimated late-minus-early differences. The additional technique-intensity row reports the directly estimated change within early-vintage formations from later blocks through 2014 to later blocks in 2015–16. Every regression includes the lower- order peer-activity and signal terms. Controls include firm and county horizontal-production shares, firm horizontal and total well stocks, the firm’s county-level horizontal well stock, a firm-quarter productivity index and annual county size. The regressions absorb operator, county, operator-by-county and calendar-quarter fixed effects. Both signals use distance-time weights. Each signal-specific sample contains observations for which that signal is positive and statistically different from zero. Standard errors are clustered by formation-block and reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

later-block estimates are divided by response period. The saturated specification estimates each vintage-period response jointly and reports direct cross-vintage differences where both groups are observed. Web Appendix Table W.6 reports the aligned intensive-investment counterpart, including the common 2019–21 comparison.

Both signals differ across vintages in the first-block state. For peer performance, the adoption response is -0.14^* in early-vintage formations and 0.23^{**} in late-vintage formations. The late-minus-early difference is 0.38^{***} . For technique intensity, the corresponding estimates are -0.46^{**}

and 0.83. Although the late-vintage coefficient is imprecise, the directly estimated difference is 1.29**. The evidence lies in the change across formation vintages, not a separately precise positive technique-intensity response in late-vintage first blocks.

The subsequent technique-intensity estimates trace how that initial difference changes as local development accumulates. Among early-vintage formations in later blocks, the adoption response moves from -0.18^{**} through 2014 to 0.19^{***} in 2015–16. The difference is 0.37^{***} . The estimate is 0.16 from 2017 onward and 0.18 from 2019 onward. Late-vintage formations do not reach later blocks until 2017. Their technique-intensity response is 0.27^* from 2017 onward and 0.03 from 2019 onward. Over the common 2019–21 period, the late-minus-early difference is -0.15 and imprecise. The initial cross-vintage difference in technique intensity dissipates once both groups have accumulated local development.

Peer performance follows a different later path. From 2019 onward, its adoption response is 0.28 in early-vintage later blocks and -0.78^{**} in late-vintage later blocks. The late-minus-early difference is -1.07^{**} . The negative difference cannot be attributed to greater accumulated development in the late-vintage group. Early-vintage observations are further along on average, at approximately block 4.6 compared with block 3.5 for late-vintage observations. Local information saturation alone would predict the opposite ordering.

The adoption and investment estimates provide additional evidence on how to interpret the vintage patterns. In early-vintage later blocks through 2014, the technique-intensity response is -0.18^{**} for adoption but 34.4^{***} for horizontal-well investment conditional on positive investment. Peer performance is imprecise for adoption in the same group but has an intensive-investment response of 35.4^{**} . In late-vintage later blocks from 2017 onward, the peer-performance response is -0.68^* for adoption and 114.3^* for intensive investment. From 2019 onward, the technique-intensity response is close to zero for adoption but 203.2^{***} for intensive investment. Local signals can affect investment levels conditional on positive investment after their adoption response has faded or become negative.

The first-block and later-block comparisons reveal how industry timing and local development interact. A purely local account would predict the same first-block response across formation vintages, contrary to the first-block differences for both signals. One interpretation is that local development has two offsetting effects early in the transition. Additional local information becomes less valuable but accumulated development also reduces the cost of acting on that information. When local development begins later, those starting costs may already be lower, leaving information

saturation as the dominant force. Section 6 formalizes this interaction.

The two signals point to different economic mechanisms. The technique-intensity pattern is consistent with industry-wide development making local technique information easier or less costly to use when a formation first develops, followed by diminishing informational value as local experience accumulates. Peer performance need not follow the same path because realized outcomes can convey both local opportunities and the competitive consequences of successful nearby activity. Its negative adoption response in late-vintage later blocks, combined with positive intensive-investment responses, could reflect competition deterring remaining nonadopters, higher investment levels among firms with positive horizontal investment, or selection in the firms that remain at risk of adoption. I leave distinguishing among these explanations to future research.

5 Robustness

The robustness analysis addresses four threats to the interpretation. Subsection 5.1 examines the identifying assumption that expiration timing shifts peer drilling independently of the responding firm’s own incentives to adopt or invest. Subsection 5.2 considers whether oil prices or fixed differences across formations explain the calendar and block-vintage patterns. Subsection 5.3 evaluates alternative explanations for adoption and investment, including general drilling booms, responses without measured network signals, competition and changes in firm composition. Subsection 5.4 examines whether the results depend on how peer activity and network signals are constructed and timed.

5.1 Endogeneity of Expiration-Driven Drilling

The design uses expiration timing as a source of variation in peer drilling. The identifying assumption is that this timing is unrelated to unobserved changes in the responding firm’s incentives to adopt or invest. The responding firm’s own leases may expire alongside its peers’ leases, so the baseline sample excludes firm-county-quarters in which the responding firm has a same-county lease expiration. An expiration elsewhere could induce drilling across the firm’s portfolio, including in counties where it has no lease expiring. Supplemental Appendix Table OA.14 accordingly excludes every firm-quarter in which the firm has a matched expiration anywhere in its portfolio and also excludes observations with an own same-county expiration anywhere in the full six-quarter bunching window. The pooled and block-vintage patterns remain similar under both restrictions. Web

Appendix Table W.4 gives the complete sample accounting.

Expiration creates a deadline, but peers still decide whether to exercise their leases. Favorable local information could both increase peers’ exercise of expiring leases and affect nearby firms’ adoption or investment. If recent information drives exercise, expiration-driven drilling should coincide with new leasing, wells drilled near expiration should be more productive where more expiring leases are exercised, or recent local productivity growth should precede more expiration-driven drilling. Supplemental Appendix Table OA.15 tests each implication. Expiration-driven drilling is uncorrelated with new leasing. Wells drilled in the expiration window show no productivity advantage where a larger share of expiring leases are exercised. Among counties with scheduled expirations, a one-standard-deviation increase in recent productivity predicts 0.007 fewer excess wells and a 0.9 percentage point lower probability of any expiration-driven drilling. The analyses cannot establish that lease exercise is random, but they provide no evidence that favorable contemporaneous information generates the expiration-related variation in peer activity.

5.2 Robustness of the Calendar and Vintage Patterns

The dynamic evidence makes two comparisons. The calendar results compare responses at different dates, so changes in oil prices or other aggregate conditions may explain the reversal. The block-vintage results compare formations that reach the same local-development stage at different dates, so fixed differences between early- and late-vintage formations may explain that contrast. I examine each possibility in turn.

Calendar-quarter fixed effects absorb the common oil-price level, but prices could still change firms’ sensitivity to peer activity or network signals. Supplemental Appendix Table OA.16 adds oil-price controls and interacts prices with peer activity and each signal. The main extensive-adoption interactions remain close to the pooled estimates, while the triple interactions with oil prices are imprecise. Because the same formation can produce both oil and gas, exposure to oil-price movements varies with its production mix. Supplemental Appendix Table OA.17 compares formations’ pre-2014 gas shares with peer performance and technique intensity across periods. Both signals are more strongly associated with oil-heavy formations in 2008–14 and 2015–17, even though the adoption response changes sign between those periods. The correlations are near zero after 2018. No result links oil-price exposure to the calendar reversal.

The block-vintage comparison could instead reflect fixed differences between formations that develop early and late. Supplemental Appendix Table OA.18 compares their first blocks. Late-

vintage first blocks have lower average technique intensity, lower peer performance and lower well productivity than early-vintage first blocks. Their stronger adoption response is not accompanied by stronger measured signals or greater average productivity.

Fixed differences across vintages cannot explain changes within a vintage. Among early-vintage formations, the technique-intensity response in later blocks rises from -0.18^{**} through 2014 to 0.19^{***} in 2015–16. A direct test estimates the increase at 0.37^{***} . The estimate remains positive at 0.16 from 2017 onward. Local development also advances over these periods, so the comparison cannot isolate calendar timing. The within-vintage estimates make fixed differences across formation vintages an incomplete explanation for the dynamic pattern.

5.3 Alternative Explanations and Placebos

A general local productivity or demand boom could increase drilling without operating through the horizontal network signals. Supplemental Appendix Table OA.19 replaces the horizontal outcomes with vertical drilling. A general drilling boom should produce a parallel positive response in vertical activity. No parallel pattern appears. Peer performance is negatively associated with positive vertical drilling and vertical well counts, while technique intensity and breadth produce no consistent positive response. Negative vertical estimates could reflect substitution toward horizontal drilling, so the placebo weighs against a general drilling boom without identifying the mechanism behind the horizontal response.

The interaction estimates alone provide an incomplete account of how firms respond to peer activity and network signals. Supplemental Appendix Table OA.20 reports the lower-order peer-activity and signal coefficients from the baseline specifications. For extensive adoption, the peer-performance and technique-intensity interactions are positive and precise, while their lower-order signal coefficients are smaller and imprecise. The peer-activity coefficient evaluates the marginal response at a signal value of zero, which lies outside these positive-signal estimation samples. It is not an estimate of the peer-activity response where no signal is measurable.

Supplemental Appendix Table OA.21 estimates that comparison directly using observations where none of the four network signals is distinguishable from zero. Peer activity has positive extensive responses of 0.0113^{***} for adoption and 0.0108^{**} for investment. The intensive-adoption response is also positive at the 10 percent level, while the intensive-investment response is imprecise. The same table shows that the no-signal group contains 2.7 percent of the panel and about 6 percent of observed adoption and investment. Network signals are not the only reason firms respond to

peer activity, but most aggregate activity occurs where at least one signal is measurable. The small size of the no-signal group is itself informative about the prevalence of measured network structure.

Competition may also contribute to the estimated response. Peer drilling can provide information while increasing demand for rigs, crews, acreage and other local inputs. The estimates capture the net effect of these forces. A competition-only explanation would also need to account for the calendar reversal, the first-block difference across formation vintages and the opposing responses associated with technique intensity and breadth. Competition remains consistent with these patterns only if its effect varies systematically with timing and measured network content.

Changes in the firms responding provide another explanation for the dynamic pattern. The high-minus-low response gaps are negative early and positive later for both peer performance and technique intensity. The composition of responsive firms changes over the episode, although the evidence cannot determine whether that change explains the aggregate reversal or accompanies it (Supplemental Appendix Figure OA.4).

Supplemental Appendix Table OA.22 further separates firms with no prior horizontal experience, experience in another local market and experience in the current market. In early-vintage first blocks, the technique-intensity response is negative for firms that have never drilled horizontally, -0.189^{**} , and for firms already drilling in the market, -3.072^{**} . In late-vintage first blocks, firms with experience elsewhere have a positive but imprecise estimate of 0.298. No single ordering by prior experience emerges. The types of firms responding can change over the episode, a source of heterogeneity from which the conceptual framework abstracts.

5.4 Measurement of Peer Activity and Network Signals

The main sign patterns remain robust to alternative variable constructions and data choices. The expiration spike remains when the bunching specification accounts for county-quarter drilling conditions, as reported in Supplemental Appendix Table OA.2. Separately, I vary how wells are assigned to leases. The baseline assigns each well to the nearest eligible lease within 0.25 miles. The alternative instead links wells to leases using standardized operator and lessee names, supplemented by a manual bridge between related entities. Supplemental Appendix Table OA.3 reports both the sharper expiration spike and the pooled response estimates under this construction. Other specifications vary which wells enter peer activity and when their effects appear. Restricting the measure to the first well on each lease removes 58 percent of bunching-weighted activity but preserves the pooled signs, OA.23. The estimates are strongest under tighter well-to-lease links, as shown in Web

Appendix Table W.2. Jointly including four quarterly lags places the technique-intensity response in the baseline one-quarter lag, while peer performance is more persistent, OA.11. Web Appendix Table W.7 reports the full four-signal grid, including the persistent breadth estimates. Dating peer activity at completion instead of spud preserves the signs but reduces precision, OA.24.

6 Conceptual Framework

The reduced-form results show that the adoption response to local network information depends on industry timing and accumulated local development. Adoption and investment also respond differently early in the transition, suggesting that local information may affect the cost of starting separately from the return to investment. I use a simple firm problem to organize these channels and a calibrated counterfactual to evaluate which combinations can reproduce the empirical patterns. The exercise is diagnostic rather than a structural estimate.

6.1 Model and Calibration

A firm chooses whether to adopt a new technology in a local market and, conditional on adoption, how much to invest. I normalize peer activity to one and write the firm's payoff from adoption as

$$M(S, n, N)d - \frac{\eta}{2}d^2 - F(S, n, N), \quad (3)$$

where S is the local signal, n is local development, and N is industry maturity. The function M is the operating return from the technology, F is the fixed cost of adoption, and η governs how quickly marginal investment costs rise. Firms differ in an adoption hurdle with distribution Ψ and density ψ . Optimal investment is $d^* = M/\eta$, adoption surplus is $\Pi = M^2/(2\eta) - F$, and the adoption share is $p = \Psi(\Pi)$. The responses to the local signal are

$$R^d(n, N) = \frac{M_S(n, N)}{\eta}, \quad R^p(n, N) = \psi(\Pi) \left[\frac{M}{\eta} M_S(n, N) - F_S(n, N) \right]. \quad (4)$$

The return response M_S affects both decisions, while the starting-cost response F_S affects adoption without directly changing optimal investment. For the quantitative exercise, I impose $M_S(n, N) = (m_0 + m_1 N)e^{-bn}$ and $F_S(n, N) = f(1 - N)e^{-dn}$. In this exercise, N is measured by the industry-wide horizontal share, while $n = 0$ denotes a first block and $n = 1$ denotes a later block. After

rescaling the investment estimates, I normalize η , M/η , and $\psi(\Pi)$ to one. The responses become

$$r^d(n, N) = (m_0 + m_1 N)e^{-bn}, \quad r^p(n, N) = (m_0 + m_1 N)e^{-bn} - f(1 - N)e^{-dn}. \quad (5)$$

I fit the five parameters to ten technique-intensity estimates for adoption and investment levels conditional on positive investment across five mutually exclusive vintage-block groups. Appendix E derives the responses and Appendix E.3 reports the calibration.

6.2 Counterfactual Results

The first comparison holds local development fixed and changes industry maturity. Empirically, the technique-intensity adoption response is higher in late- than early-vintage first blocks. It also increases across periods among early-vintage formations that have already reached later blocks. In the model, the slope of the first-block response with respect to N is $m_1 + f$, while the corresponding later-block slope is $m_1 e^{-b} + f e^{-d}$. Holding $n = 0$, the fitted response rises from -0.42 at early-vintage industry maturity to 0.40 at late-vintage industry maturity. The fitted later-block response also rises over the transition. Since the fitted m_1 is negative, these increases come from the decline in the starting-cost response rather than a rising return response. Local attenuation alone cannot account for differences across industry maturity at the same local stage.

The block comparisons show that the effect of local development also depends on industry maturity. Early in the transition, the adoption response becomes less negative after a formation moves beyond its first block. In late-vintage formations, the technique-intensity response instead declines from first to later blocks. At a fixed value of N , the model comparison is

$$r^p(1, N) - r^p(0, N) = (m_0 + m_1 N)(e^{-b} - 1) + f(1 - N)(1 - e^{-d}). \quad (6)$$

The first term is negative when the return value of additional local information attenuates, $b > 0$. The second is positive when local development reduces the starting-cost response, $d > 0$. At early-vintage industry maturity, moving from $n = 0$ to $n = 1$ raises the fitted response from -0.42 to -0.07 . At late-vintage industry maturity, the same change lowers it from 0.40 to 0.12 . Local cost relief dominates early, while return attenuation dominates after industry maturity has already reduced the starting-cost response. Either mechanism alone would move the response in the same direction at both points in the transition.

The adoption-investment comparison helps distinguish between the remaining mechanisms. In

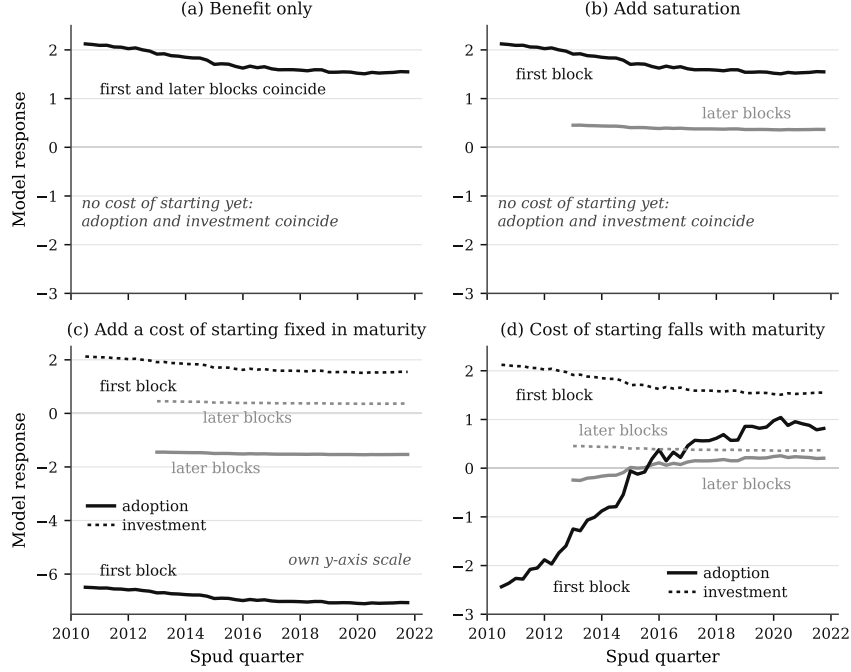


Figure 7: Building up the model's responses

Notes. Each panel evaluates the model at the industry-wide horizontal share observed each quarter. Black curves hold $n = 0$, while gray curves hold $n = 1$. Solid and dotted lines report normalized adoption and investment responses. Panels (a)–(d) sequentially add the return response, local attenuation, the starting-cost response, and its decline with industry maturity using the same fitted parameters.

early-vintage later blocks through 2014, technique intensity is associated with lower adoption and higher investment levels conditional on positive investment. Under the normalization in equation (5), the model difference is

$$r^d(n, N) - r^p(n, N) = f(1 - N)e^{-dn}. \quad (7)$$

A return-only explanation moves adoption and investment in the same direction and cannot produce this difference. With $f > 0$, the starting-cost response can outweigh the return response for adoption while the model investment response remains positive. The difference narrows as N or n increases.

Figure 7 summarizes the same logic by adding the mechanisms sequentially without recalibrating. Panel (a) includes only the fitted return response, which cannot separate adoption from investment or local stages. Panel (b) adds local return attenuation. It lowers later-block responses but misses the vintage comparison and adoption-investment difference. Panel (c) adds a starting-cost response that declines with local development. It separates the decisions but misses the increase across vintages while that response remains fixed across industry maturity. Panel (d) allows it to decline with industry maturity and produces the full fitted pattern.

The calendar estimates are not calibration targets. The model predicts adoption responses of -0.70 , 0.20 , and 0.24 , reproducing the reversal but not the exact post-2017 flattening. Within the benchmark, declining starting costs generate the increase with industry maturity and diminishing returns generate the decline with local development. The cost decline may reflect standardization or supplier capacity. Appendix E.3.3 presents a scaling-cost alternative.

7 Conclusion

The relationship between information propagated through local networks and technology adoption changes over an industry-wide transition. I establish this result by combining local network signals measured from earlier wells with lease-expiration-induced peer drilling. Peer drilling makes new local activity observable, although the estimates capture its net informational and competitive effects, not a pure information channel. The vintage-block estimates provide the clearest evidence. In first blocks, the late-minus-early adoption difference is 0.38^{***} for peer performance and 1.29^{**} for technique intensity. Because these comparisons describe the same stage of local development, accumulated local experience cannot fully explain them. After both vintages reach later blocks, technique-intensity responses converge toward zero while peer performance develops a significant negative late-minus-early difference. Local development and industry timing both contribute to the adoption response, but the two signals also contain different economic information.

The difference between adoption and investment narrows the economic mechanisms consistent with this pattern. Early in the transition, technique intensity has a negative adoption response, while its intensive-investment estimate is positive but imprecise. A lower return value of local evidence would push both model responses downward. The absence of a corresponding negative investment-level response instead favors a cost that affects whether a firm starts using the technology without directly reducing optimal investment in the model. Under the benchmark with constant scaling costs, the starting-cost response accounts for negative adoption early and declines as the industry and local market develop. Diminishing returns to local evidence account for the decline across later local blocks. Together, these forces reproduce the calendar reversal and the vintage-block comparisons. The framework identifies no unique structural mechanism, but it explains why the corresponding single-channel explanations fail to reproduce the full set of results.

The findings imply that local network effects cannot be evaluated independently of the broader technology transition. Industry-wide development changes the value or cost of acting on local evi-

dence, while accumulated local development determines how much an additional signal contributes. The results also caution against equating more disclosure with more useful information. Peer-technique breadth has no positive adoption response even though technique intensity, constructed from the same disclosed attributes, does. Policies that expand information may have limited effects when firms lack the capacity, specialized inputs, or standardized practices needed to act on it. The evidence cannot determine which constraint dominates, so it supports this complementarity without selecting a particular intervention.

The firm-heterogeneity results suggest an important direction for future research. Relative responsiveness shifts from smaller and less experienced firms early in the transition toward larger and more experienced firms later. The shift in responsive firm types could contribute to the aggregate timing pattern or accompany changes in the value of local evidence. Further analysis could examine firm type and adoption capacity as well as the reverse relationship through which successful local clusters contribute to industry-wide development. The analysis here establishes that the stage of the broader transition conditions what local networks contribute to firm adoption and investment.

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Conflict of Interest

None declared.

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A Peer-Activity and Lease-Link Construction

Section 3.1 describes the baseline spatial assignment. Within each county, I match a well to leases signed before its spud date and located within 0.25 miles. I assign the nearest lease. When multiple leases lie within 0.01 miles of the nearest lease, I choose the earliest expiration date, then the earliest signing date, then the smallest lease identifier. The spatial assignment does not require the standardized operator and lessee names to agree. A first linked well is the earliest well assigned to a lease and is used only in Figure 1. The bunching estimator uses all uniquely assigned wells.

The alternative construction requires the standardized operator name to match the leaseholder name after applying the manual name bridge. I join operator wells to leases held by the matched lessee within the same county, retaining leases signed before the well was spudded. When a well matches multiple leases, I assign the earliest expiration date, then the earliest signing date, then the smallest lease identifier. The event-time estimator is otherwise unchanged. Supplemental Appendix Table OA.3 reports the resulting response estimates.

For each assigned well w , event time is $\tau_w = q_w^{spud} - q_w^{expire}$, where q_w^{spud} is the spud quarter and q_w^{expire} is the expiration quarter of the assigned lease. Let C_τ be the national count of assigned wells at event time τ , using the main spatial match. I estimate the bunching regression

$$C_\tau = \alpha + \sum_{p=1}^5 \eta_p \tau^p + \sum_{k \in \mathcal{B}} \lambda_k \mathbf{1}\{\tau = k\} + u_\tau, \quad (\text{A.1})$$

where $\mathcal{B} = \{-4, -3, -2, -1, 0, 1\}$ is the prespecified expiration window. The fifth-order polynomial is estimated over $\tau \in [-12, 4]$. Setting the bunching-window indicators to zero gives the smooth counterfactual count $\hat{C}_\tau^0$. The estimated excess share at each event time is

$$\hat{\pi}_\tau = \mathbf{1}\{\tau \in \mathcal{B}\} \max \left\{ 0, \min \left\{ 1, \frac{C_\tau - \hat{C}_\tau^0}{C_\tau} \right\} \right\}, \quad (\text{A.2})$$

with the share set to zero when $C_\tau = 0$. An assigned well drilled near expiration receives fractional weight $\hat{\pi}_{\tau_w}$ from equation (A.2), the estimated share of wells at that event time above the smooth counterfactual.

The excess mass remains positive under third-, fifth-, and seventh-order polynomials. The seventh-order estimates are larger, while the ninth-order specification leaves only one residual degree of freedom and is uninformative. I retain the fifth-order specification as the baseline. The Supplemental Appendix Section OA.2.1 reports the estimates and standard errors.

The county-quarter excess peer-activity measure sums these fractional weights among wells spudded in county c during quarter q , $\hat{E}_{cq} = \sum_{w \in (c,q)} \hat{\pi}_{\tau_w}$. For firm i , I remove the firm's own operated and leased wells from this county-quarter total. With operated and leased components denoted by $\hat{E}_{icq}^{op}$ and $\hat{E}_{icq}^{les}$, and with $\hat{E}_{icq}^{both}$ restoring wells for which the firm is both operator and lessee, the firm-excluded measure is $\hat{E}_{cq}^{-i} = \hat{E}_{cq} - \hat{E}_{icq}^{op} - \hat{E}_{icq}^{les} + \hat{E}_{icq}^{both}$. The baseline response specifications use $\hat{E}_{c,q-1}^{-i}$, the one-quarter lag. Supplemental Appendix Table OA.11 reports the corresponding specification with lags one through four entered jointly.

B Productivity and Skill Measurement

I construct the productivity and skill inputs to the network regressions using a modified decline-curve approach built around the classic Arps production model. Because well output is highly age-dependent, raw monthly production conflates underlying productivity with well age. Arps-style decline curves impose a parsimonious parametric shape on the production path as a function of well age. In its common hyperbolic form,

$$q(t) = \frac{q_0}{(1 + bD_0t)^{1/b}},$$

where q_0 is an initial production level, D_0 is a decline parameter, and b governs curvature.

First, I estimate a common hyperbolic decline curve $\hat{q}(\cdot)$ as a function of age and form an age-adjusted production residual, $\log(q_{it}/\hat{q}(age_{it}))$. From this residual I construct a standardized productivity index, comparable across wells, that serves as the dependent variable Y in the spatial regressions. The decline curve is fitted once on all well-months in the production data, for wells that began producing in 2005 or later, through the end of the data in 2022. A well's productivity is its average residual over every month in which it reports production. For a well in a given block, that average includes production reported after the block closes. The network signals classify each block using the full subsequent production record. They are not limited to information available when the block closed.

Second, I use the same decline adjustment to construct a time-varying firm skill proxy. Using the pooled sample, I regress decline-adjusted production on location controls and absorb firm-quarter fixed effects. The estimated firm-quarter component captures systematic differences in performance across firms within a quarter, net of the common decline structure and observed location. I use this component as the firm-quarter skill proxy Z that enters the spatial regressions through WZ .

Because this proxy is estimated from the firm’s broader operated portfolio across formations, not only wells in the firm’s own formation, it captures firm-level performance differences beyond purely local outcomes.

C Spatial Network Model, Weights, and Dynamic Blocks

The baseline spatial model links a well’s productivity to the performance and skill of earlier wells drilled by other firms in the same formation. All models are estimated separately by formation and, in the dynamic construction, separately within each completed 2,000-well block. For well i in formation g , the model is $Y_i = \gamma_1^g \sum_{j \neq i} w_{ij} Y_j + X_i' \gamma_2^g + \beta^g \sum_{j \neq i} w_{ij} Z_j + \nu_i$, or in matrix notation, $\mathbf{Y} = \gamma_1^g \mathbf{WY} + \mathbf{X} \gamma_2^g + \beta^g \mathbf{WZ} + \nu$. Here $\mathbf{Y}$ is well productivity, $\mathbf{Z}$ is firm skill and $\mathbf{W}$ defines peer exposure. The element w_{ij} is nonzero only when peer well j was drilled earlier by a different firm in the same formation and lies inside the relevant local neighborhood. The products $\mathbf{WY}$ and $\mathbf{WZ}$ are weighted peer performance and weighted peer skill. The coefficient γ_1^g is the peer-performance signal, WY , and β^g is the peer-skill signal, WZ . The control vector X_i contains five firm controls and the same five measures for the well’s county. They are the horizontal share of production, the horizontal well count, the total well count, the standard deviation of perforated-interval length among wells that began producing in the same year, and the mean first-year output of those wells.

I estimate each network object under four weighting schemes. Let t_i be well i ’s first production month, d_{ij} the great-circle distance in miles between wells i and j , $o(i)$ the operating firm and z_i the skill proxy for the operator of well i . The weights are directional. A peer well can enter row i only if it is in the same formation, began producing earlier and was drilled by another firm. Peers are ordered by first production month, not by drilling date. For the distance-based, distance-time and relative-skill weights, the eligible peer set is $\mathcal{J}_i = \{j : g_j = g_i, o(j) \neq o(i), 0 < t_i - t_j \leq 36, d_{ij} \leq 50\}$. The unnormalized inverse-distance entries are $\tilde{w}_{ij}^{ID} = \mathbf{1}\{j \in \mathcal{J}_i\}/d_{ij}$. Distance-time entries are $\tilde{w}_{ij}^{DT} = \mathbf{1}\{j \in \mathcal{J}_i\}/[d_{ij}(t_i - t_j)]$. Equidistant common-period entries are $\tilde{w}_{ij}^{EQ} = \mathbf{1}\{j \in \mathcal{J}_i\}\mathbf{1}\{t_i - t_j \leq 4\}$. Relative-skill entries are $\tilde{w}_{ij}^{RS} = \mathbf{1}\{j \in \mathcal{J}_i\} \max\{z_j - z_i, 0\}$. The estimation uses these entries without row normalization. Inverse-distance weights place more weight on nearby prior wells. Distance-time weights multiply inverse distance by inverse elapsed time, so the most influential peers are both nearby and recent. Equidistant common-period weights give equal weight to prior peer wells in a short local development episode. Relative-skill weights place weight on earlier wells drilled by more-skilled firms, with weight increasing in the skill gap

Table D.1: Peer-technique attributes used to construct breadth and intensity

Category	Attribute
Hydraulic-fracturing input	Proppant
Hydraulic-fracturing input	Biocide
Hydraulic-fracturing input	Breaker
Hydraulic-fracturing input	Buffer
Hydraulic-fracturing input	Clay control
Hydraulic-fracturing input	Crosslinker
Hydraulic-fracturing input	Friction reducer
Hydraulic-fracturing input	Gelling agent
Hydraulic-fracturing input	Iron control
Hydraulic-fracturing input	Scale inhibitor
Hydraulic-fracturing input	Surfactant
Hydraulic-fracturing input	Energizer
Hydraulic-fracturing input	Diverter
Pressure reading	Casing pressure
Pressure reading	Flowing tubing pressure
Pressure reading	Shut-in pressure

Notes. Each listed attribute is converted to an availability indicator equal to one when the underlying well record reports that field. The peer-technique models use weighted peer exposure to these availability indicators, not the reported quantities themselves.

between the peer firm and the operator of the current well.

Within each formation, I sort horizontal wells by first production month and divide them into consecutive, non-overlapping blocks of 2,000 wells. I drop the final incomplete block and estimate each completed block separately. A block's regressions use only wells within that block, so its peer set does not include wells from earlier blocks. I date each block by its first and last production quarters. A response observation receives the signal from the most recently completed block in its formation.

D Peer-Technique Measurement

Let $k \in \mathcal{K}$ index one of the $K = 16$ reported design and operating attributes listed in Table D.1.

For each attribute, I estimate a separate spatial regression that replaces the peer-skill term in the baseline spatial model with exposure to peers whose well records report attribute k :

$$\mathbf{Y} = \gamma_1^g \mathbf{W}\mathbf{Y} + \mathbf{X}\gamma_2^g + \beta_k^g \mathbf{W}\mathbf{A}^k + \nu. \quad (\text{D.1})$$

$\mathbf{A}^k$ is an $N \times 1$ indicator vector, where $A_i^k = 1$ if attribute k is reported for well i . The coefficient β_k^g

measures the association between productivity and exposure to peers whose records report attribute k , conditional on the baseline spatial lag WY and controls.

Breadth is the count of attributes whose peer-exposure coefficient is positive and whose 95% confidence interval excludes zero. To construct technique intensity, I include all K peer-technique exposure terms jointly in the same model. Intensity is the partial R^2 from adding those terms to the baseline model with WY and controls. The corresponding Wald test evaluates whether the peer-technique terms are jointly significant.

E Derivations and Calibration for the Conceptual Framework

E.1 Firm Problem

Peer activity is normalized to one. Conditional on adoption, the firm solves the problem below. The parameter $\eta > 0$ is independent of the local signal.

$$\max_{d \geq 0} \left\{ M(S, n, N)d - \frac{\eta}{2}d^2 - F(S, n, N) \right\}.$$

For an interior solution, optimal investment conditional on adoption and the surplus from adoption are

$$d^*(S, n, N) = \frac{M(S, n, N)}{\eta},$$

$$\Pi(S, n, N) = \frac{M(S, n, N)^2}{2\eta} - F(S, n, N).$$

Firm i adopts when $\Pi(S, n, N) \geq \xi_i$. If Ψ is the distribution of ξ_i , the adoption share is $p(S, n, N) = \Psi(\Pi(S, n, N))$. The investment response to the local signal is

$$\frac{\partial d^*}{\partial S} = \frac{1}{\eta} M_S. \tag{E.1}$$

The corresponding adoption response is

$$\frac{\partial p}{\partial S} = \psi(\Pi) \left[\frac{M}{\eta} M_S - F_S \right]. \tag{E.2}$$

E.2 Parameter Restrictions

Under the benchmark normalizations, the predicted investment and adoption responses are

$$r^d(n, N) = (m_0 + m_1 N)e^{-bn}, \quad r^p(n, N) = (m_0 + m_1 N)e^{-bn} - f(1 - N)e^{-dn}.$$

Let N_{EF} , N_{EL} , N_{LF} , and N_{LL} denote industry maturity in the early-vintage first block, early-vintage later blocks through 2014, late-vintage first block and late-vintage later blocks from 2017. Their measured values are 0.745, 0.678, 0.858 and 0.913.

In the early-vintage first block, the adoption estimate is negative and the intensive-investment point estimate is positive. The model counterpart is

$$r^d(0, N_{\text{EF}}) = m_0 + m_1 N_{\text{EF}} > 0, \quad r^p(0, N_{\text{EF}}) = m_0 + m_1 N_{\text{EF}} - f(1 - N_{\text{EF}}) < 0.$$

Together these imply $f(1 - N_{\text{EF}}) > m_0 + m_1 N_{\text{EF}} > 0$. Because $N_{\text{EF}} < 1$, the adoption-investment contrast requires $f > 0$.

The first-block vintage comparison subtracts two responses at $n = 0$. Thus

$$r^p(0, N_{\text{LF}}) - r^p(0, N_{\text{EF}}) = (m_1 + f)(N_{\text{LF}} - N_{\text{EF}}).$$

Because $N_{\text{LF}} > N_{\text{EF}}$, a higher late-vintage first-block response requires $m_1 + f > 0$.

For late-vintage blocks, the observed comparison is

$$(m_0 + m_1 N_{\text{LL}})e^{-b} - f(1 - N_{\text{LL}})e^{-d} < m_0 + m_1 N_{\text{LF}} - f(1 - N_{\text{LF}}).$$

Given $N_{\text{LL}} > N_{\text{LF}}$, $m_1 + f > 0$ and $d \geq 0$, this inequality cannot hold when $b = 0$. Matching the point-estimate ordering requires enough saturation, $b > 0$, to offset the increase in industry maturity. The direct first-to-later difference is imprecise, so the ordering does not identify b separately.

For early-vintage blocks, the comparison is

$$r^p(1, N_{\text{EL}}) - r^p(0, N_{\text{EF}}) = \left[(m_0 + m_1 N_{\text{EL}})e^{-b} - (m_0 + m_1 N_{\text{EF}}) \right] - f \left[(1 - N_{\text{EL}})e^{-d} - (1 - N_{\text{EF}}) \right].$$

If $d = 0$, $b \geq 0$ and $m_1 \geq 0$, the first bracket is not positive and the second equals $N_{\text{EF}} - N_{\text{EL}} > 0$. The later-block response would be lower. Under these sign restrictions, matching the observed

ordering requires $d > 0$. This is a sufficient result rather than general identification of d . The unrestricted calibration permits $m_1 < 0$. Its $d = 0$ fit preserves the early-vintage ordering only by setting $b < 0$, which conflicts with the late-vintage decline and calendar trajectory.

The calendar response in period t averages the model response over that period’s estimation sample $\mathcal{S}_t$:

$$\bar{p}_t = \frac{1}{|\mathcal{S}_t|} \sum_{i \in \mathcal{S}_t} r^p(n_i, N_{q(i)}).$$

Because this expression depends on each period’s mix of first and later blocks, the calendar pattern is evaluated numerically rather than imposed as a separate parameter restriction.

E.3 Calibration Details

Table E.1 reports the extensive-adoption and intensive-investment targets for five mutually exclusive technique-intensity groups. Let $\hat{r}_k^p$ and $\hat{r}_k^d$ denote the two responses for group k . I set $n_k = 0$ for first blocks and $n_k = 1$ for later blocks. I measure N_k with the industry-wide horizontal share averaged over the observations in each group’s estimation sample, which weights quarters as in the regression.

Target	n_k	N_k	Adoption	Investment	Scaled investment
Early vintage, first block	0	0.7455	−0.4597**	59.64	1.1086
Early vintage, later blocks through 2014	1	0.6777	−0.1836**	34.41***	0.6396
Early vintage, later blocks from 2015	1	0.8936	0.2221*	−38.61**	−0.7177
Late vintage, first block	0	0.8585	0.8261	45.09	0.8381
Late vintage, later blocks from 2017	1	0.9125	0.2668*	2.44	0.0453

Table E.1: Calibration targets

Notes. The targets are technique-intensity extensive-adoption and intensive-investment estimates for five mutually exclusive formation-vintage, local-block, and calendar-period groups. The early-vintage later-block target from 2015 combines the finer calendar groups reported in Table 3. Local development is normalized to $n_k = 0$ for first blocks and $n_k = 1$ for later blocks. Industry maturity N_k is the industry-wide horizontal share averaged over the adoption estimation sample for target k . Scaled investment multiplies the intensive-investment estimate and its standard error by 0.018588. The calibration weights each target by the inverse of its reported formation-block-clustered sampling variance.

I impose the scale normalizations $\psi(\Pi) = 1$, $M/\eta = 1$ and $\eta = 1$. The resulting responses are given in equation (5). The parameter vector $\theta = (m_0, m_1, b, f, d)$ minimizes

$$\mathcal{L}(\theta) = \sum_{k=1}^5 \left[\frac{(r_k^p(\theta) - \hat{r}_k^p)^2}{(\text{se}_k^p)^2} + \frac{(r_k^d(\theta) - \hat{r}_k^d)^2}{(\text{se}_k^d)^2} \right]. \quad (\text{E.3})$$

Investment estimates and standard errors are multiplied by 0.018588, the slope from a regression through the origin of the two late-vintage adoption estimates on the corresponding intensive-

investment estimates. The factor is fixed and each target is weighted by its inverse sampling variance. These choices set the relative scale of the two outcomes but do not change their signs.

The minimization places no sign restrictions on the parameters. Conditional on b and d , the responses are linear in m_0 , m_1 and f , which are obtained by weighted least squares. I profile the loss over a two-dimensional grid for b and d , then polish the best grid points. Because n takes only two values, the targets identify first-to-later-block ratios rather than the exponential shape between them.

The fitted values are $m_0 = 2.73$, $m_1 = -1.29$, $b = 1.44$, $f = 8.62$, and $d = 1.51$. They are also reported in Supplemental Appendix Table OA.25. The loss is 11.9094. Table E.2 compares the fitted responses with the ten targets. The fit is closer for adoption than for investment. The model predicts a positive investment response for early-vintage later blocks from 2015, while the estimate is negative.

Target	Adoption		Scaled investment	
	Estimate	Fitted	Estimate	Fitted
Early vintage, first block	-0.460	-0.425	1.109	1.768
Early vintage, later blocks through 2014	-0.184	-0.173	0.640	0.440
Early vintage, later blocks from 2015	0.222	0.171	-0.718	0.373
Late vintage, first block	0.826	0.403	0.838	1.622
Late vintage, later blocks from 2017	0.267	0.201	0.045	0.368

Table E.2: Full five-parameter fit

Notes. The table compares the model’s fitted responses with the ten technique-intensity targets in Table E.1. Adoption is the extensive-adoption response. Scaled investment is the intensive-investment response multiplied by 0.018588 so that the two outcomes enter the calibration on a common scale. The fitted values use the five parameters reported in Supplemental Appendix Table OA.25.

Supplemental Appendix Figure OA.5 recalibrates the model after setting $f = 0$, $b = 0$, or $d = 0$. Removing f forces adoption and investment to coincide, while removing b or d reverses the fitted ordering of late-vintage first and subsequent blocks. Unlike Figure 7, each restricted model is recalibrated to the same ten targets.

E.3.1 Calendar Prediction

The calendar responses in Figure 6 are not calibration targets. I calculate them by evaluating equation (5) for each observation in the corresponding period regression, using its block position and its quarter’s industry-wide horizontal share, then averaging over the estimation sample. The predicted responses are -0.702 , 0.202 , and 0.236 . The model reproduces the reversal from the first period to the second but not the subsequent flattening. Its predicted response rises slightly after

2017.

E.3.2 Why the Cost Depends on Local Development

Setting $d = 0$ fixes the starting-cost response across local development. The best fit has a loss of 14.2385 and sets $b = -0.6970$, so the benefit rises rather than saturates with local development. It predicts -0.11 for the late-vintage first block and 0.18 for its later blocks, with calendar responses of -0.35 , -0.04 and 0.18 . The restricted model preserves the early-vintage ordering only by reversing benefit saturation. It misses the positive late-vintage first-block response and the subsequent decline.

E.3.3 Relaxing the Constant- η Assumption

Section 6.1 assumes that η is constant. The alternative sets $F_S = 0$ and allows peer activity to change both the return to investment and the cost of scaling as a function of the local signal. Under the same normalizations,

$$r_k^d = M_{S,k} - \eta_{S,k}, \quad r_k^p = M_{S,k} - \frac{1}{2}\eta_{S,k}.$$

I use

$$M_S(n, N) = (\alpha + \gamma N)e^{-\beta n}, \quad \eta_S(n, N) = -q(1 - N)e^{-\delta n}, \quad (\text{E.4})$$

with $\gamma, \beta, q, \delta > 0$. Early in the episode, $M_S < 0$ reduces adoption while $\eta_S < 0$ lowers the cost of scaling and raises optimal investment conditional on positive investment. The condition $M_{SN} > 0$ makes the return response less negative as industry maturity increases. Local development attenuates the return response toward zero. Consequently, $M_{Sn} > 0$ while $M_S < 0$ and $M_{Sn} < 0$ after the return response becomes positive.

The fitted values are $\alpha = -14.30$, $\gamma = 15.87$, $\beta = 1.51$, $q = 15.79$, and $\delta = 1.42$. A stronger signal lowers the return to investment early in the episode, $M_S < 0$, while industry maturity raises that return. The negative scaling-cost response produces positive investment, and the alternative reproduces the block trends. The drill-time evidence in Supplemental Appendix Table OA.10 cannot distinguish the two versions because drill time per well is not the curvature of cost in the number of wells. The technique-intensity estimate is positive at lag three but imprecise at the other lags, and the sample starts in 2014Q4. Setting $\gamma = 0$ also sets $M_{SN} = 0$ and removes the reversal.