An empirical and theoretical approach to Network Effects in Technology Diffusion: *Lessons from the Energy Sector*

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Abstract

This paper develops a new empirical and theoretical approach to studying network effects in the diffusion, or internal firm adoption, of new technology. The empirical model devises a two step method which first categorizes geographies based on a spatial panel or network model. Then, it compares firm behavior across these categories when there is an exogenous change in information flow that affects all areas. The case study in the American oil & gas fracking revolution documents novel results that firm adoption of new technology is more sensitive to an increase in usable knowledge in highly networked areas. I then propose a theoretical framework for understanding diffusion as a dynamic transition process which can explain these empirical trends. I take a classic model of firm investments and incorporate a technology adjustment dimension. The model predicts different rates of aggregate technology diffusion depending on whether the firm confronts the technology problem holistically or as separate business lines. I show that true technology transition where old technology is endogenously retired are not always possible.[1] Spillovers in productivity efficiency are more likely to result in higher diffusion levels as opposed to spillovers in lowering adjustment costs. I show empirically testable implications using the heterogeneous response across firm size and specialization.

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[1] Which is of particular concern in industries that are important for the clean energy transition.

The introduction of new technology, or innovation, is a key process in economic growth. Yet, these new technologies also need to be adopted by agents in the economy, or diffuse, to be effective. This latter process is not as well studied as the former. For example, it is not clear why some technologies seem to organically spread throughout an industry while others never take off.[2] As with many economic applications, network effects is a natural hypothesis to consider. It has already been studied in firm productivity (Giroud et al. (2021)) and the closely related R&D process (Myers and Lanahan (2022)). However, from both an empirical and theoretical perspective, studying networks in a dynamic process like diffusion is difficult. This paper develops a new empirical approach to understanding the impact of shared learning on the adoption process of newly discovered technologies. I employ the method to provide novel evidence of networks effects on diffusion in a recent technology revolution that had a meaningful impact on the global economy, the fracking revolution in American oil & gas.[3] Then, I illustrate the implications of this network effect in a classic model of firm investments incorporating the technology adoption dimension. It provides a framework for analyzing how firm behavior interacts with the macro technology process. It also studies aggregate dynamics such as the rate of transition between technologies which is of particular policy interest in industries like renewable energy.

Results from a standard network estimation method can be interpreted as evidence that outcomes in an economy are correlated with each other. In the technology setup, this could show that it's beneficial to adopt the same technology simply because there is a common supplier or the technology is well suited to an area. I augment this procedure to show that elasticity to information flows such as data leakage is directly related to network strength. The two-stage "stress test" procedure first establishes a county-level categorization using a spatial panel model. At this stage, I introduce an innovative method for capturing true knowledge effects. Rather than estimate correlations in outcomes, I design a specification around a simple thought experiment. If there's no knowledge sharing, productive wells should cluster together regardless of the skill of the firms nearby. I exploit

[2] Stokey (2020) noted in a recent working paper examining the literature on this topic that "... the importance of most new technologies derives from the fact that they spread across many different users and uses, as well as different geographic regions. Thus, the diffusion of technological improvements, across producers within a country and across international borders, is arguably as critical as innovation for long run growth."

[3] The institutional details section below provides an example of diffusion in this setting and an additional discussion of why this case study is well-suited for analysis.

this to measure the spatial network effect from "indirect effects" like proximity to skilled firms. Then, I compare the sensitivity of adoption decisions to plausibly exogenous influxes of useful information. If there is useful, shareable information produced when firms invest then changes in investment levels are a useful proxy for information flow. Importantly, the method does not compare network strengths across groups directly. It doesn't even require interpretation of the network estimates which is only used for sorting. Rather, the coefficient of interest captures the response *within a network group* to exogenous information changes.

I use a standard term in drilling leases to get exogenous variation in investment. Most leases include an initial three-year term at the end of which lessees must have shown investment activity in order to retain the rights in the lease.[4] The two-stage-least-squares ("2SLS") baseline specification shows that firm-level adoption rates in strong network areas are more sensitive to higher investment activity than weaker network areas. This new measure, adoption rate, captures how investments in each area contribute to the rate at which firms are changing the new technology ration of their capital stock. In response to one additional well drilled by other firms in the area during the preceding quarter, the adoption rate is 1.3% higher in higher network counties. The same number in the lowest network area is 0.01%. The results are complemented by a productivity benefit from investing in strong network areas. Using a typical functional form for oil production, monthly output from wells in high network areas is 7.6% higher in response to a one unit investment increase. By contrast, the same number in low network areas is 0.05%. In back of the envelop calculations, this amounts to 1.4 million more barrels of oil (equivalent) over five years. On the other hand, when the experiment is replicated with the older, conventional technology, the coefficients on investment are negative in most network categories. Intuitively, the old technology is more established and less amenable to productivity gains since it's already at the productivity frontier. With nothing to learn, there are no productivity or investment responses to shocks in the network.

Networks can appear due to a number of things such as shared supply lines or human

[4] Prior work has shown that this results in bunching of investment activity around expiration dates. See Herrnstadt et al. (2020).

capital exchange. The method can also be used to test these different network sources by varying the spatial weighting assumptions in the first stage. In the main exercise, the first stage weighting approximation uses inverse-distances to approximate knowledge sharing which is motivated by a natural propagation structure. In the oil extraction setting, wells drilled nearby present more useful information than those drilled far away as they are exploiting the same underlying geological structure.[5] Further, heterogeneity in complexity *across* geologies provide cross-sectional differences which makes the estimation effective. In some areas, all wells drilled within a thirty mile radius are similar in depth and design while others contain meaningful differences even for wells drilled close to each other.[6] I replicate the experiment with an equidistant network which is the broadest test of other sources of contagion. Here, the result is completely reversed. The elasticity of adoption to investment activity is highest in *weaker* network areas and negative in the *stronger* network areas.

Motivated by these results, I propose a new model of technology adoption which can endogenously lead to diffusion in a dynamic model with heterogeneous firms. The model uses a generic AK model so it can be applied broadly. Firms face the classic investment problem while incorporating a technology adjustment dimension. I use MIT shocks to general productivity between steady states of the economy to study aggregate transition paths. I show that if firms mimic conglomerations where deploying each type of technology is treated like an individual business line, then the economy is much less susceptible to a true technology transition. Old technology is not disposed of even as new technology investment increases. On the other hand, smaller firms with shared resources across technology types are more sensitive to tipping into full diffusion. I also study the difference between productivity-based knowledge spillovers and cost-based knowledge spillovers. Cost savings have to be very high to have an impact on new technology investment levels. Their impact on the adoption rates of new technology is also inelastic because they don't affect old technology as directly. Finally, I take advantage of the heterogeneous model to derive testable implications for empirical work. In particular, adoption rates are higher for small firms when firms don't act like conglomerates. On the other hand, adoption rates

[5] Note that this does not mean general purpose knowledge does not exist. Rather, the method is designed to exploit additional benefits from proximity.

[6] Figure 2 illustrates this with an example.

are strongly impacted by firm sizes when they look more like conglomerates because the marginal value of additional capital (by type) effect dominates. I test the model results using the oil & gas case as a test case.

The paper proceeds as follows. After a literature review, section I reviews the empirical framework including the empirical strategy, the network model, the institutional details, and the data. Section II presents the main adoption and productivity results using the baseline network specification along with robustness tests around alternative explanations. Section III presents the new model of diffusion and the results. Section IV concludes.

Related Literature

This paper contributes to a body of literature that has sought to endogenize the technological change necessary for broader economic growth. Romer (1990) observed that the non-rivalry of ideas can be useful in reconciling observed exponential growth rates in output despite more linear physical capital investment levels. Since then, the literature has sought to explain the conditions under which these ideas are created, usually in the context of profit-maximizing firms. For example, Jones (2021), Jones (2005), Aghion and Howitt (1997), Aghion and Howitt (1992), Akcigit et al. (2021), Bloom et al. (2020) are all versions of this question. Many of these focus on the trade-offs between investing in capital that produces output as compared to ideas which improve production, potentially with risk. Others such as Akcigit et al. (2021) study the creation of new ideas measured through patents on the under different tax schemes.[7] Imitation has emerged as a mechanism of interest in the innovation debate. Important theoretical contributions to the question of imitation include Perla and Tonetti (2014) and Benhabib et al. (2021). Other theories of diffusion focused on specific mechanisms such as firm heterogeneity including Akcigit and Kerr (2018) and Comin (2014), Hall and Khan (2003), and Akcigit et al. (2020a). Other important empirical work on the idea of R&D spillovers include Bloom

[7]At the same time, a number of papers have returned to the macroeconomic roots of the endogenous growth literature to study the implications of endogenous technological change which these papers examined. These questions broadly studied how the process of endogenous technological growth interacts with economic growth, business cycles, and labor-capital shares. For example, Acemoglu (2002), Comin and Gertler (2006), Anzoategui et al. (2019), Akcigit and Ates (2021), Eberly and Wang (2009), Acemoglu and Guerrieri (2008). Interestingly Acemoglu et al. (2012) takes this approach to analyze the implications for the environment.

et al. (2021), Lucking et al. (2019), and Akcigit et al. (2020b).[8] Finally, work in international economics such as Comin (2014) have made significant strides in understanding this issue of diffusion and spillovers.

Despite this large literature on innovation, diffusion is a different story. Stokey (2020) summarizes the existing empirical literature on diffusion and notes their empirical limitations. The earliest works on this begins with Griliches (1957) who studied the adoption of hybrid corn. Recently, Bloom et al. (2013) proposed a method to allow econometricians to disentangle the effects of technology spillovers and product competition. While this approach is different from the network sorting method used in this paper, I relied on this concept in building this method.

The paper draws on ideas in the agglomeration and productivity literature such as, Giroud et al. (2021), Audretsch (1998), Matray (2021), Kline and Moretti (2014), Davis et al. (2014) which examine spillovers across a variety of mechanisms. Jaffe et al. (2006) in particular studies knowledge spillovers in a localization context. The literature on intangible capital and the data economy is critical to understanding how knowledge enters the firm investment problem. Some recent examples include Farboodi et al. (2019), Abis and Veldkamp (2020), Farboodi and Veldkamp (2021), and Peters and Taylor (2017).

Finally, this paper relates to the growing literature on energy and the environment. There have been a number of papers studying technological growth in the context of climate change. Nordhaus (2014) and Jaffe et al. (2010) are two prominent examples. On the other hand, this topic has also come up for researchers trying to understand the energy sector itself. For example, Kellogg (2011) and Covert (2015). In particular, Decaire et al. (2019) and Decaire and Wittry (2022) study peer effects in real options exercise which is closely related to this paper. The baseline productivity analysis in this paper lends support to their contention that the information from peers is valuable which aligns with their result that firms do indeed wait to gain access to it.

[8] Thompson (2001) and Mishra et al. (2021) analyze diffusion and adoption in specific industries.

I. Empirical Framework

When firms make physical capital investments in a network, shared knowledge is created as an externality. In areas where the network is able to transfuse that information in a useful manner, firms should react more strongly to any change in investments because wells can take advantage of this new information. The main empirical framework is designed to mimic this logical framework. Figure 3 illustrates this thought experiment. This section begins with a description of the institutional details and data. Then, the empirical strategy section discusses the econometric specification and how it is implemented in the oil & gas setting. It relies on two important aspects. First, the spatial panel model used to assign initial network strengths to each county. Then, I discuss the strategy for constructing "indirect effect" explanatory variables which help disentangle contagion and knowledge sharing. These variables include the skill level of the influencing firms and a measure of the amount of auxiliary data available from the influencing wells.

A. Institutional Details & Data Description

The discovery that horizontally drilled wells can be combined with the hydraulic fracturing technique known as "fracking" unlocked vast resources in the continental United States and revolutionized American oil and gas.[9] This innovation is a completely new well design. Often, the geographic area will dictate the type of well you use. While additions and changes can be made after a well has been completed, it is not possible to change from horizontal to a vertical well. In fact, drilling permits require you to specify which type of well you will be drilling. This information is used in this project to identify the technology type in the data.

Before firms can apply for a permit from municipal and state regulators giving them permission to drill, firms must retain a lease from either the government or private landowners[10] giving them the option but not the obligation to drill. These leases con-

[9] One absurd early attempt to recover these fuels by the US Army in the fifties involved a nuclear bomb https://www.cpr.org/2019/09/06/remember-the-first-time-colorado-tried-fracking-with-a-nuclear-bomb/.

[10] While the government fixes the prices and terms for leases on their lands, private leases can vary significantly.

tain an initial or primary term which last three years in most of the United States. If no well is drilled on that land prior to lease expiration, the lessee loses the rights. Herrnstadt et al. (2020) showed that there is significant drilling activity clustered around expiration dates. I use the number of leases that are due to expire that quarter as an instrument for investments by other firms which will be referred to as ex-firm investment activity in the sequel.[11] Once firms have a lease they will apply for a permit which includes information about the well including the direction (horizontal vs vertical), the geo-coordinates of the well, and other design features. These data are useful indicators of the well design even though they are not the full specification. In addition to using this information in this paper, it motivates the data leakage that leads to knowledge sharing beftween firms. A classic production function for oil wells is known as the Arp's model[12],:

$$\begin{aligned} O_{w,t} &= Q_w Age_{w,t}^{\beta} \\ log(O_{w,t}) &= \alpha_w + \beta log(Age_{w,t}) \end{aligned} \tag{1}$$

For well w, month t output $O_{w,t}$ is modeled as a function of a well's age $Age_{w,t}$. β, which is referred to as the "decline rate" is usually less than zero and governs the rate at which well output declines over time. Q_w is sometimes called the "baseline productivity rate". This variable captures overall well-level quality.

Figure 1 motivates the main idea in the paper. The first panel shows the relative productivity of horizontally drilled wells as compared to its traditional vertical counterparts. The measure is derived from amending log form of production function 1 with a fixed effect for conventional or horizontal well type. The model is re-estimated each quarter using the full sample and the plot shows the coefficients β_q. In addition to being more productive at discovery, the new technology has continued to grow relative to the old technology. Over the same time period as the productivity rise, the intensive margin adoption rate in the second panel is also increasing. This variable is the average firm-level new technology investment ratio, $\frac{Horizontal\ wells\ drilled_i}{Total\ wells\ drilled_i}$, for all firms in the sample. As aggregate investment levels rise (fall) in the second panel, more (less) information is accumulated

[11]For a firm in consideration, any investments made within the quarter of its own lease expiration is not counted in the dependent variable.

[12]There are more complex versions of this decline model but I choose the simple one because it lends itself well to linearization and more complex models aren't needed for this analysis.

and made available to all firms in the industry. As a result, the productivity of wells rise (fall) in kind. The picture motivates the use of adoption rate as a key dependent variable of interest. While prior studies have discussed creative destruction as a method for technology diffusion, figure 1 shows an example where the diffusion of the new technology is not propelled by specialized firms driving conventional firms out of the industry. Instead, firms are gradually changing the technological makeup of their capital stock through their investment decisions.

A.1. Discussion of the Data

State regulators require operators to report their monthly production which includes total barrels of oil produced or oil equivalent amount of gas. All of these data are made publicly available. The data used in this paper is provided by Enverus[13] who collects this filing information. The company's analytical data is widely used in the industry.[14] The data include the well-month production information linked to their corresponding, static permit and lease information through their API number. Each well is associated with an operator who may or may not be the only firm actively operating the well. I use this variable to identify firms. Investments are measured by the number of wells drilled and they are recorded for this project in the month that the well is completed.

To be included in the data sample, wells must be drilled after 2005 even though I start the analysis in 2008. A well has to appear in the dataset for at least 30 months. This allows me to estimate lifetime production rates with more accuracy and removes wells that may have prematurely stopped production. Counties that have produced fewer than 100 wells in its history are not included. The summary statistics reported in section **??** shows the average well count within the geographies that are included. No offshore or Alaskan wells are included.

[13] Prevoiusly DrillingInfo

[14] Even the federal energy information administration (EIA) uses the data from Enervus in its reports and assessments of the American oil industry.

B. Empirical Strategy

Unlike existing models, this empirical test considers both the existence of a network effect and quantifying how that network alters the elasticity of firm decisions to changes like information flow. Intuitively, the procedure can be thought of as a stress test. The first step is to estimate the network strength in each oil producing geography using a spatial panel model. Then, I examine differences between networks in how firms react when there's an influx of useful information. Knowledge sharing in this case is motivated by data leakage when firms drill wells so changes in investment should proxy for information flow. I use lease expirations as an exogenous shock to investment levels which is uncorrelated with network strengths. If there is a strong sharing effect then exogenously altering the investment levels should disproportionately affect the stronger network areas. I also explore two explanatory variables constructed to disentangle the shared knowledge effect from general contagion. They are referred to as "indirect variables" because they exemplify an indirect estimate of networks as opposed to a direct method such as using the performance of nearby investments.

B.1. Estimating Networks: Spatial Panel Model

The spatial panel (or autoregressive) model is a weighted linear regression model which allows the explanatory variable realizations of "nearby" observations to influence the dependent variable. The specification for the spatial lag model is,

$$\begin{aligned} \mathbf{Y}^g &= \gamma_1^g \mathbf{W}\mathbf{Y}^g + \mathbf{X}_t^g \gamma_2^g + \beta^g \mathbf{W}\mathbf{S}^g + \nu \\ \nu &= \lambda \mathbf{W}\nu + \epsilon \end{aligned} \tag{2}$$

The appendix[15] contains a discussion of the econometrics in this specification but I proceed with an intuitive description here. The analysis is conducted at the well-level and the regression is run separately for each oil producing county in the United States.[16] Let N denote the total number of wells that have ever been drilled in county g over the sample period. $\mathbf{Y}$ is a $N \times 1$ vector containing a measure of an investment's lifetime performance.[17] $\mathbf{W}$ is a $N \times N$ weighting matrix which governs how nearby "influence" wells can

[15] available at nverachau.com/research

[16] Restrictions to eliminate smaller counties are described in the appendix.

[17] Generally, Q_w, the baseline productivity rate is used.

be related to the "reference" well contained in row $n \in N$. In the baseline specification, this matrix $\mathbf{W}$ contains the inverse-distance and inverse-time difference between reference well n and influence well m. This is calculated as, $\frac{1}{|d_{n,m}|} \times \frac{1}{|t_{n,m}|}$ as long as well m was drilled before well n. $d_{n,m}$ is the physical distance between rows n, m. $t_{n,m}$ measures the time in months between when well n and well m were drilled. All other wells are given zero weight in matrix $\mathbf{W}$ as well as any well , m, that is drilled by the same firm. The inverse distance and time weights capture a structure where wells that are drilled farther away are less useful because the underlying geology will be less similar. Additionally, wells that were drilled a long time ago will not be as helpful as recent ones since information is likely cumulative.

γ_1^g absorbs contagion effects to assuage concerns that the network model is only capturing clustering around successful geographies. The two variables used for the indirect effect variable, $\mathbf{S}$, are firm skill and data availability which are detailed next. They are designed so that coefficient β^g is unlikely to capture a direct contagion effect. Also included in each measure are geography and firm level controls for inherent quality or size effects in matrix $\mathbf{X}_t$. These controls are contemporaneous and there is no spatial effect but each observation n has a set of these controls.[18] Eligible counties are sorted according to point estimates of β^g. Limiting the sample to counties where β^g yield a significant estimate would tighten the results. However, it is unclear how meaningful the standard errors are in this case. Because the goal is simply to sort counties based on the perceived evidence of network strength and then further stress- test that strength, I use the more inclusive point estimate.

B.2. Indirect Effect Variables: Skills and data availability

To better capture the specific knowledge-based spillover in this paper, I introduce two new variables which are referred to as "indirect effect variables". Unlike γ_1 in equation 2 which could result from many spillover sources, these variables address an additional question, "From whom are you learning and what are you learning?". Firm skill is not geography specific. Intuitively, if there is no learning from other firms then drilling near a skilled firm should be no different than drilling near an unskilled one. Figure 4 captures this idea

[18] The full list with descriptions are included in the appendix.

with an illustrated example. Note that this coefficient will capture the additional benefit of drilling near a skilled firm *conditional on there being any effect in the first place.* It does not capture the unconditional effect of the network so it is a more restrictive measure. The data availability measure is constructed using additional information regarding a well's fracking program. These data are only available in some areas due to regulatory differences in disclosure rules. It's also not uniformly useful everywhere.[19]

Skill Vector The skill vector $\mathbf{S}_{i,t}$ is estimated using a firm's entire nation-wide portfolio of wells. For each firm, a "horizontal" and "conventional" skill is measured separately. I amend the Arp's[20] production function in 1 to estimate a version of baseline production rate Q_w that is firm-specific as opposed to well-specific. Using the full dataset with every horizontal well drilled across all geographies I estimate,

$$\begin{aligned} log(O_{w,t}) &= \alpha_w + \beta log(Age_{w,t}) \implies \\ log(O_{w,t}) &= \beta log(Age_{w,t}) + \eta_{i,q} \mathbf{1}_{\{Firm\ i\}} \times \mathbf{1}_{\{q\}} + \epsilon_{w,t} \end{aligned}$$

Rather than α_w capturing the baseline production rate of well w, this model has $\hat{\eta}_{i,q}$ which captures the firm-quarter baseline production rate. This coefficient is then used to index the firm-quarter skill level.[21] Vector S_t then contains this estimate, $\hat{\eta}_{i,q}$ if firm i drilled a well in the quarter that contains month t. Substituting these specific variables into the specification described in equation 2 for each well in county g,

$$\begin{aligned} \mathbf{Y}_t^g &= \gamma_1^g \mathbf{W} \mathbf{Y}_t^g + \mathbf{X}_t^g \gamma_2^g + \beta^g \mathbf{W} \mathbf{S}_t^g + \nu_t \\ \mathbf{Y}_t^g &= \begin{bmatrix} \hat{\alpha}_{w_1,t} \\ \vdots \\ \hat{\alpha}_{w_N,t} \end{bmatrix}, \quad \mathbf{S}_t^g = \begin{bmatrix} \hat{\eta}_{i_1,q} \\ \vdots \\ \hat{\eta}_{i_N,q} \end{bmatrix} \end{aligned} \tag{3}$$

where $w \neq w'$.

[19] Not all states and municipalities require the same amount of disclosure regarding supplemental data. This introduces variation in the availability of these data. Even when municipalities require certain data, the implementation of the policy varies.

[20] There are more complex versions of this decline model but I choose the simple one because it lends itself well to linearization and more complex models aren't needed for this analysis.

[21] A similar exercise is done to obtain the geography-quarter level "skill" or production controls but with $\mathbf{1}_{\{Geo\ g\}} \times \mathbf{1}_{\{q\}}$ instead of the firm-quarter fixed effect

Data Availability There are a number of details related to the fracking program which some municipalities require in regular filings. For example, "proppant" measures the amount of sand (mixed with chemicals and water) used to hold fissures open during the fracking process. The appendix details each of these variables. For each variable in this set, z, let vector A^z contain a 1 if the information is available for the well in row w and 0 otherwise.[22] The estimate then proceeds as in equation 3 but with the vector of $\beta_z^g \mathbf{W} A_t^z$ instead of $\beta^g \mathbf{W}\mathbf{S}_t^g$ for each individual z in the supplementary set. Then, the mean of the recorded β_z^g is used to sort the counties in the data availability network sort. As with the skill based β^g, the sorting is done using the average of the *point estimates* of $\hat{\beta}_z^g$.

B.3. Baseline Specification

$\hat{\beta}^g$, the coefficient from the spatial panel model is used to sort counties into quartiles. I focus on the counties where $\hat{\beta}^g > 0$.[23] To avoid confounding the network sort with the main effect, the spatial panel model is estimated using the data from 2008Q1 to 2014Q3 only.[24] I use lease expirations as an instrument for investment activity so the final specification is a 2SLS conducted separately for each treatment (high network bucket) and control (low network bucket) group. [25] The specification for each bucket, net_n for $n \in \{1, 2, 3, 4\}$, is given by,

[22]Note that I use the empirical observation for data availability instead of a likelihood estimate given state or municipal policy. There are some areas where the information is technically required but enforcement is more lax so the data is not in fact available. It's possible to use a likelihood estimate and use the result to measure data availability. However, because the goal is to study the impact of the data availability on productivity and firm behavior, I chose the more direct path of simply using the data that would be available to firms.

[23]Note that the cuts are made at the county level and not weighted by the production activity in each county.

[24]Figure 5 depicts the West Texas Intermediate "WTI" spot price for oil over the sample period. The lines in red shows the results of a Markov switching model estimated using the oil price. The "pre-sorting" period used to get the network estimates corresponds with the introduction and initial growth of the horizontal drilling technique. Compared with the second panel of figure **??**, aggregate investment levels tend to move with the oil price. Thus, I avoid using the full sample to estimate the network strength because periods of investment drop overall will impact firm behavior and the network measures. Further, by choosing an early period for the spatial estimates, I avoid incorporating effects that I am estimating into the network sort. For example, firms might invest more over time in high network areas.

[25]I follow Herrnstadt et al. (2020) who uses lease expirations as an instrument for investment activity. The standard lease format gives lessees a fixed number of years ("primary term") to show activity. If no well is drilled (Note this can be an exploratory well, it does not usually need to be a producing well. However, empirically, both types of well appear) within that time period, the lease is terminated. If a well is drilled before the primary term expires, the firm retains the right to the lease indefinitely and can drill as many additional wells as they want.

$$
\begin{aligned}
I^H_{i,g,q-1} &= \eta + \beta^{net_n}\mathbf{L}_{g,q-1} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \nu_{g,t} \quad (first\ stage) \\
A_{i,g,t} &= \alpha + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \epsilon_{w,t} \quad (second\ stage) \\
log(O_{w,t}) &= \omega + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \epsilon_{w,t} \quad (second\ stage')
\end{aligned}
\tag{4}
$$

$I^H_{g,q-1}$ is the ex-firm investment activity in county g during the preceding quarter $q-1$. The H superscript indicates that this specification only includes investments made in *horizontally fracked wells*, the new technology in this analysis. To construct this, I first aggregate all horizontal wells drilled in the county that quarter, then subtract the wells that were drilled by the firm i. $\mathbf{L}_{g,q-1}$ denotes the number of leases whose primary term was set to expire in the preceding quarter. In the second stage, the dependent variable, $A_{i,g,t}$ denotes the adoption rate for firm i in geography g during quarter q while $O_{w,t}$ denotes output in barrels of oil equivalent ("BOE") for well w in month t. The adoption rate is defined as

$$
A_{i,g,t} = \frac{O^H_{i,t}}{O_{i,t}} - \frac{O^H_{i,t} - O^H_{i,g,t}}{O_{i,t} - O_{i,g,t}} \tag{5}
$$

Let $O_{i,t} = \sum_i O_{w,t}$ where $O_{w,t}$ is the monthly output from well w and is drilled by firm i. Also, let $O_{i,g,t} = \sum_{w \in g} O_{w,t}$ which denotes the total amount of output drilled by firm i in geography g. H denotes horizontal output. The first term of the adoption rate is the technological sophistication of firm i output at month t. The second term denotes the hypothetical technological sophistication of firm i without the contribution from all of firm i's capital in geography g. The variable captures the contribution of geography g in changing firm i's technological sophistication. The adoption result does not rely on productivity gains from using shared information. Firms can believe the information is useful but fail in executing on it. A supplementary productivity analysis, *second stage*$'$ uses $log(O_{w,t})$ in the second stage to study this relationship. This version is the log version of the Arp's production model with the inclusion of the ex-firm investment level estimated in the first stage.

Adoption is measured using output to capture both the extensive and intensive margin effects. The shared information is likely most useful on the extensive margin when well design occurs. However, I don't want to exclude improvements such as workovers of completed wells. Because oil output declines at such a steep rate over time, spillover effects on completed wells will naturally contribute less to adoption. I also include a control for age to account for the fact that networks are unlikely to have the same impact on older wells.[26]

$\mathbf{X}_{g,t}$ and $\mathbf{X}_{i,t}$ are a full set of geographic controls detailed in the appendix. The controls $\mathbf{X}_{g,t}, \mathbf{X}_{i,t}$ are measured at time t for both stages even though the first stage dependent variable is the ex-investment level over the previous quarter. I do not change the controls in the first stage because the 2SLS specification should use the same controls over both stages. However, there is significant persistence in the firm and geography characteristics so the controls are unlikely to be different between the current and lagged sets.

II. Main Adoption & Productivity Result

In the appendix, I include a discussion of the network estimates that come from the first stage. In this main specification, those results only appear in the sorting. The summary statistics are also included in the appendix. The baseline results test the main specification in equation 4 given by

$$\begin{aligned}
I^H_{i,g,q-1} &= \eta + \beta^{net_n}\mathbf{L}_{g,q-1} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \nu_{g,t} \quad (first\ stage) \\
A_{i,g,t} &= \alpha + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \epsilon_{w,t} \quad (second\ stage) \\
log(O_{w,t}) &= \omega + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \epsilon_{w,t} \quad (second\ stage')
\end{aligned}$$

There are two different second stage specifications considered. The first studies adoption rates and the second considers productivity. Table I reports the results from the network estimated using well-level baseline productivity $\mathbf{Y} = Q_w$ as the dependent variable and the firm skill vector $\mathbf{S}$ as the indirect effect.[27] I will refer to this as the Q-skill sort in the sequel. The first panel shows the inverse-distance-time weight matrix and the second panel shows equidistant networks. In the second row of the first panel, the second

[26]The appendix includes analyses done using firm-month-investment level instead of output based adoption specifications for robustness.

[27]The appendix contains these results with a Wald test between each network quartile to consider the statistical significance of the differences.

stage coefficient of adoption rates on ex-firm investment, $\hat{\nu}^{net_n}$m is largest for $n = 3, 4$ although the results are not monotonically increasing in networks. Estimated ν^{net_n} is 0.00016 and -0.000046 in the two weaker network areas. In the two stronger network areas, the coefficients are 0.013 and 0.00022 respectively. All the studies are conducted at the well-month level with a control for $log(Age)$.[28] To interpret the results, recall the construction of adoption rate,

$$A_{i,g,t} = \underbrace{\frac{O^H_{i,t}}{O_{i,t}}}_{\text{New Technology Ratio}} - \underbrace{\frac{O^H_{i,t} - O^H_{i,g,t}}{O_{i,t} - O_{i,g,t}}}_{\text{New Technology Ratio w/out county g}}$$

The first term, new technology ratio, is bounded by $\{0, 1\}$ where 1 denotes firms who produces 100% of its output from new technology. Suppose this same firm has county g adoption rate of 0.05. Then, without firm i's output from county g, its technology ratio would have been 5% lower at 95%. Now, consider the coefficients in networks 3 and 4. The contribution of area g to firm i's technology ratio is 0.02% to 1.3% higher in response to each additional well (as instrumented in the first stage) drilled by other firms in the county. On average, the ex-firm investment levels in buckets three and four 40 so the actual effect is likely to be much higher than 0.02%.[29] Using a conservative estimate of 20 ex-firm investments, the predicted adoption rate impact from network effect is $0.4\%, 2.6\%$ in buckets four and three respectively. Relative to the sample average of $A_{i,g,t} = 4.1\%$, these effects in network buckets 3 and 4 represent a meaningful increase.

The results from the first stage are reported in the first row of the panel. The directions of the coefficients are consistent with the hypothesis, investment levels are higher in quarters when there are more leases due to expire. Across the network buckets, there is no correlation between the first stage results and second stage results. The most sensitive investment levels are in buckets 1 and 2 even though the second stage coefficients are lowest there. This assuages concerns that the impact of ex-firm investment on the adoption rate in the second stage is due to the magnitude of the first stage estimates.

[28] The results contain the same set of firm and geography level monthly controls in both stages and all the results are clustered at the well-level.

[29] Of course, the effect is unlikely to be linear so we should not interpret the real average effect as $40 \times \hat{\nu}$.

The second panel of table I shows the results on productivity. The specification is the log version of Arp's production function with the instrumented ex-firm investment, $\hat{I}^H_{i,g,t}$, added in. The results are increasing in networks. The coefficient in network bucket 1 and 2 are 0.00071 and 0.00068 respectively while the corresponding number in buckets 3 and 4 are 0.076 and 0.011 . Productivity does not need to be higher to drive firm adoption decisions, firms may simply take advantage of networks because it is less costly to drill in high network areas. These results show that there is a productivity rationale for the adoption results in the first panel for this network sort. This log form of the production function lends itself to simple interpretation by incorporating this effect into the functional form. Figure 6 plots the production function

$$Y_t = exp(\hat{Q}_w + \hat{\beta}log(Age_{w,t}) + \hat{\nu}^{net_n}\hat{I}^H_{i,g,t})$$

The plots show outputs for an average well drilled in a high vs. low spillover area. $\hat{Q}_w, \hat{\beta}$ is set to the average overall wells in the sample. $\hat{\nu}^{net_3} = 0.076$, the estimated result from the top panel of table I. Similarly, $\hat{\nu}^{net_1} = 0.00051$. I set $\hat{I}^H_{i,g,t} = 30$ which is the average number of ex-firm investments per quarter in the sample. The third panel of the figure shows the difference in cumulative output between the two hypothetical wells. At 60 months which is towards the end of a well's life, an average well in a lower network area will have produced 148,530 barrels of oil . By contrast, the average well in a high network area will have produced 1.2 million barrels. The difference throughout the wells' production life is almost 1 million barrels of oil. This is a simplified version of the production function so the estimated difference should be viewed skeptically. However, it illustrates the impact of the network effect. Because the functional form sets up the network effect as a multiplier on lifetime production, even with the decline rate, the effect is for *every month of a well's producing life*. Cumulatively, the effect can be large and persistent.[30]

[30] Replicating the same experiment with the coefficient from network 4, the lifetime difference in production is 54,934 barrels of oil which is significantly smaller.

A. *Alternative Explanations*

The weight matrices in the spatial panel model are not just a statistical detail, they reflect economic assumptions about the nature of the spillover. The second panel in table I uses an equidistant weight matrix in the spatial panel estimate. It looks for evidence that clustered investments are more productive without any additional knowledge based structure. In the specific oil and gas example, a simple version of this contagion could just be that the underlying geology is naturally more productive. The weight assigned to all influence wells is $\frac{1}{F}$ where F denotes the number of influence wells drilled in the county within three quarters of well w.[31] In this set of results, the coefficients in increasing network order are $-0.0011, 0.00015, -0.0030, -0.0018$. Network buckets 3 and 4 have the lowest sensitivity to ex-firm investments and is lower in magnitude than Network bucket 1. The first stage of this test are similar with the baseline so that cannot account for the differences in the second stage.

Concern that the adoption reaction is driven by contagion does not seem to be the case as the trend doesn't replicate in the equidistant sort. The last results row of panel 2 shows the productivity results from the equidistant network sort. The second stage coefficients here are strongly increasing in network sorts. As other firms invest more, wells in high contagion areas are more productive. Despite that, there is no corresponding drive to adopt as a result. The productivity result reiterates that there are many ways in which productivity is improved by spillovers. However, the nature of the spillovers, exemplified by the network weighting assumption, matters. In the knowledge-based networks of the main result, the externality is directly beneficial to firms who are considering new technology adoption. When the network type does not clearly emit this benefit as in the equidistant case, there's no diffusion impact even though the investments are more productive. Table IV shows a version of this specification for the strongest network areas, bucket four, only. It compares inverse-distance-time and equidistant networks and includes an indicator for the inverse-distance-time network interacted with the continuous skill variable of the operating firm. In columns 1 and 2 which studies output and efficiency, the interaction term shows a negative coefficient for knowledge based networks as compared to equidistant

[31] I limit the time to three quarters because I can't discount older wells here. Geographies with a long history and more investments may also be more productive and I don't want that confound.

ones. Individual firm skill is more important to productivity in the equidistant network areas. The results suggest that the contagion (equidistant) networks are at least partially attributable to skilled firms clustering together around favorable geographies. The opposite is true for the knowledge (inverse-distance-time) networks because firms can efficiently learn from other firms regardless of their own skill.

Table II shows results for the baseline productivity specification using the older, conventional wells instead of horizontal wells. As before, the matrix in the spatial panel model is inverse-distance-time weighted. The methods and skills around the older technology should be better established. Therefore, there is little to learn from other firms and there should be little knowledge-based reasons for investing when other firms do. This test using older technology does not preclude other spillover benefits such as cost savings. The first panel shows the results for productivity. The second panel shows the results on firm-county investment levels measured in total firm-month-county drilling activity.[32] First, there is no trend in productivity. Increasing investment by other firms generally has a negative effect on well output. In the second panel, the investment level results are noisy and not significant. Even taking just the coefficient magnitudes into consideration, there is no trend across network quartiles.

B. *Data Availability*

Table III presents the baseline results using the data availability matrices $\mathbf{A}_z$ in the network analysis. The spatial panel model for data availability is amended as such,

$$\begin{aligned}\mathbf{Y}^g &= \gamma_1^g \mathbf{W}\mathbf{Y}^g + \mathbf{X}_t^g \gamma_2^g + \beta_1^g \mathbf{W}\mathbf{A}_{z_1} + \nu \\ &\vdots \\ \mathbf{Y}^g &= \gamma_1^g \mathbf{W}\mathbf{Y}^g + \mathbf{X}_t^g \gamma_2^g + \beta_k^g \mathbf{W}\mathbf{A}_{z_k} + \nu\end{aligned}$$

where k denotes the total number of auxiliary well design details available. The vector$\mathbf{A}_{z_j|}$ contains a "1" if that variable is available and "0" otherwise. The analysis is done separately for each of the k variables and then an average of $\hat{\beta}^g_{z_j}$ is taken as the

[32] This is used in place of adoption rates as the concept makes less sense in the old technology context.

network indicator for county g. As with the skill variable, this analysis uses the point estimate, retaining $\hat{\beta}$'s even if they are not statistically significant. The first panel shows the adoption results. Each of the second stage coefficients are negative and statistically significant except for the results from network bucket 4 which is positive and significant at 0.0037. The reason for this higher adoption sensitivity in network bucket 4 and none of the others is more complex than the trend in the skill-based measures. The second panel shows the productivity results for the availability networks. Unlike the skill-based network studies reported in table I, the largest second stage coefficient is in the second and third network buckets as opposed to the third and fourth. There is not a strong case to be made that there is a productivity rationale for the result in the strongest availability-based networks. Intuitively, it is unsurprising that firms react to an increase in available data even if the effective deployment of that data can be noisy.

C. Mechanism and network formation

The appendix shows results exploring the mechanism and network formation. I use proxies for well complexity and drilling costs to study how firms execute on the network effect. In particular, I show that the productivity gains tend to achieved through less complex but slightly more expensive wells. Despite that, a carefully measured, per capital unit measure of output efficiency is shown to improve significantly across the network sorts. I also explore how networks which manifest in more productive wells , the Q-skill sorts, are related to networks formed by design imitation. In other words, are areas where drilling near skilled firms result in more productive wells also areas where people tend to drill more complex wells when skilled firms are nearby?

III. A new Model of Technology Diffusion

The empirical results using this network sorting method new method provides evidence that shared knowledge affects firm adoption decisions. To understand diffusion as a mechanism for technology change and economic growth which can help explain trends like the fracking revolution, a new model of firm investments which incorporates this adoption dimension is needed. In this section, I develop a continuous-time, dynamic model of heterogeneous firms who face both the classic investment with convex adjustment costs problem and a technology decision. The production function is a generic "Ak" model so that the results can be applied and tested broadly in future work.

There are several goals for this theoretical discussion. First, shared information can be useful in a number of ways. It can improve the efficiency so that each unit of capital produces more output or it can lower the adjustment cost of installing new capital. The empirical setup remains agnostic about the specific mechanism partly because the data cannot perfectly measure all of these.[33] In the model, I carefully consider these differences. The model also revisits the idea of internal capital allocation explored in papers such as Bakke and Gu (2017). I show two different ways of modeling the technology problem within firms and illustrate the different implications for technology change. Finally, I compare the transition dynamics for both investment levels and adoption rates between these varying assumptions. In particular, I show how the old technology fares in these scenarios which is of interest in applications like the transition to clean energy.

A. Model Set Up

This section describes the two main models studied. The first is referred to as the "separate capital" model. This version views different types of capital like business lines within a corporation. Firms make decisions regarding each individual capital type investment based on the marginal value of adding one unit of that capital while keeping in mind a firm-level adjustment cost which reflects overhead applied when shifting a firm's resources. The second is called the "technology adjustment" model. Here, firms are defined by their technological sophistication which directly impacts their productivity and adjustment costs. They make an overall investment level decision for the firm, then allocate that investment based on their chosen technological sophistication.

Separate Capital Model Firms are faced with two different types of capital which produce a single, homogeneous output. The two types differ in their productivity and are

[33] There are estimates where the first stage network assumptions are changed. For example, one set considers network effects in drill times.

indexed by $\{o, n\}$ for "old" and "new". The firm problem is,

$$
\begin{aligned}
max_{\{xo,xn\}}\ zz_n k_n^{\alpha} + zk_o^{\alpha} - xo - xn - \frac{\theta}{2}\left(\frac{x_o}{k_o}\right)^2 k_o - \frac{\theta c_k}{2}\left(\frac{x_n}{k_n}\right)^2 k_n - \frac{\theta c_k}{2}\left(2\gamma'\right)^2 k \\
z_n = K^{\nu}, \quad c_k = K^t, K = \int k_n g dk_n\ dk_o\ dz \\
dz = \mu(z)dt + \sigma(z)dW_t
\end{aligned}
\tag{Model 1}
$$

I've suppressed the time subscript in this notation for simplicity. K is the aggregate amount of new capital stock in the economy, g denotes the distribution over capital stocks. z is the general productivity process which applies to both types of capital. It is Ornstein-uhlenbeck in levels. $z_n \equiv z. * K^{\nu}$ is an additional productivity parameter which applies only to the new technology. x_o, x_n are the investments in levels. These are subject to convex adjustment costs where θ is the adjustment cost for both types of capital but new types have an additional cost parameter, c_k. The additional cost is a function of aggregate new type capital. The model also features a firm-level adjustment cost over γ' which denotes the change in the technology ratio $\frac{k_n}{k_n+k_o}$ as a result of investments x_n, x_o. I consider two scenarios. When spillovers have a positive "cost" effect because one can learn from other firms, it lowers the adjustment cost for firms who want to install the new type of capital and $t < 0$. Investing can also be more costly when there are more firms competing for suppliers or land. In this case, $t > 0$.

The individual state variables in this model are (kn, ko, z) where z includes an idiosyncratic productivity shock in the process. The aggregate state variables are $K, g()$ where $K =_n gdk$ is the aggregate new type capital stock installed in the economy and g is the distribution over firm types.

Technology Adjustment Model A second formulation of the problem is given by,

$$
\begin{aligned}
&max_{\{x,\gamma'\}}\ z_n k^{\alpha} - x - \frac{\theta c_k}{2}\left(\frac{x}{k}\right)^2 k - \frac{\theta c_k}{2}\left(2\gamma'\right)^2 k \\
&z_n = K^{\nu\gamma}, \quad c_k = K^{t\gamma} \\
&K = \int\int\int k_n g dk\ dg\ dz, \quad \gamma = \frac{k_n}{k_o + k_n} \\
&dz = \mu(z)dt + \sigma(z)dW_t
\end{aligned}
\tag{Model 2}
$$

Firms decided their total investment level, x, over the entire firm. They then separately make a decision regarding how to allocate their resources between the old and new technology. $\gamma \in (0,1)$ determines the firm's technology ratio. Productivity gains and cost benefits from the new technology, z_n, c_k, are both scaled by the firm's technological sophistication. In other words, firms are more productive if they are more technologically sophisticated. The adjustment cost of investment is also scaled by c_k. However, there's an additional adjustment cost given by, $\frac{\theta c_k}{2}\left(2\gamma'\right)^2 k$. To understand this, consider a firm at time t who has chosen to change their technological sophistication by γ'. They would have to increase (decrease) their new technology stock by $k\gamma'$ and increase (decrease) old technology stock by $k(1-(\gamma+\gamma')) - k(1-\gamma) = -k\gamma'$. Scaling the adjustment cost by the total capital stock, $\frac{\theta c_k}{2}\left(\frac{2\gamma' k}{k}\right)^2 k$ gives the equation in model 2. The intuition behind these two models are discussed with the results below.

Solution Overview: I reserve the full HJB and the discussion of the solution method for the appendix. Here, I give an overview of the results depicted in the paper. To solve the problem, I use finite-difference to solve for the steady state solution. The equilibrium K for the steady state is given by the fixed point $K = f(K)$ where f is firm maximization problem solved over the entire distribution of firm types. I follow the method described in Achdou et al. (forthcoming) when solving for the steady state g. Intuitively, the steady state g solution is found when the kolmogorov-forward equation implies no more movement in the distribution given the solution to the firm problem f. To study dynamic transition paths, I consider an "MIT shock" to the long run mean of z or the standard deviation σ.

In the sequel, I'll refer to this as the "productivity shock". In math terms,

$$dz_t = \kappa(\mu - z_t)dt + \sigma z_t dW_t$$

I solve for the steady state given μ_0, then I solve for the steady state given a shock to μ_1. I then iterate through possible transition paths using the time-dependent value function iteration and kolmogorov-forward equation to find solutions $V_t(k_n, k_o, z), K_t, g_t$ until the transition path converges.[34].In the solutions below, I show comparative statics between the separate capital and technology adjustment models. I also vary the parameters of ν and t to analyze each individual mechanism.

B. Internal Capital Allocation & Mechanisms

Figure 7 shows adoption rates for the separate capital and technology adjustment models. The plot shows the transition paths after ashock to the long-term mean of the productivity process, μ. The results are for the productivity only model with $\nu = 0.05, t = 0$. Both economies settle into a long-term adoption rate of zero. Technology ratios, γ_i stop moving around and firms continue to make investments based on a new ratio. The mechanism for reaching the new steady state differs between these two models. The second and third panel plotting capital paths for new and old types illustrates this.[35] In the separate capital model, the productivity shock results in higher investment levels in both types. However, the rate of increase for new type capital is initially faster due to $z_n = K^\nu$. Therefore, adoption rates are positive but declining because the the marginal benefit from z_n declines as K increases. The technology adjustment model is different. Firms benefit from the spillover captured in $z_n = K^\nu$ by shifting their technology ratio. The entire firm is more productive if it gets rid of its old technology. Thus, the path to the new adoption rate of zero is driven by a true technology transition, the aggregate shift away from old technology and into the new. Note that disinvestment is allowed in both cases so firms could also shift away from old technology in the separate capital case. But there's no benefit because the opportunity cost of not investing in the new technology does not exceed the benefit of an old technology which is still productive.

[34]The method is proposed by Achdou et al. (forthcoming)

[35]Note that I'm showing the capital stock and not investments but the trend looks similar

While the results are intuitive mathematically, it's worth discussing the real world motivation behind these assumptions. The separate capital case is more likely to reflect large conglomerates who operate each business line like an independent business. Smaller firms where different business lines share resources are more likely to look like the technology adjustment case. For example, consider an energy firm that can only afford to hire one set of engineers to work on all wells as opposed to British Petroleum who can hire different engineers for different types of wells. Continuing to operate the old technology is costly for the smaller firm as the new technology becomes more productive.

For internal diffusion (as opposed to a Schumpeterian, creative destruction model) to lead to a technology transition, the industry needs more small firms which look like the technology adjustment model. Thus, industries which are not dominated by large multi-business conglomerates are more susceptible to aggregate energy transitions through diffusion. This does not mean that the new technology does not grow with larger, separate capital firms. Rather, the growth in new technology complements industry growth overall. This has particular implications for the clean energy transition. One view of this trend is to look at how energy is produced and compare fossil-fuel companies with renewable energy producers like solar and wind. In that case, the adoption is unlikely to be internal as most firms do not produce both fossil fuel and renewable energy. However, the clean energy transition also relies on firms in many industries changing the way that they produce. One thought is that cleaner manufacturing processes will become more productive and firms will retire older, browner methods. For example, the utility sector which provides energy for households is one area that could face such an internal adoption problem. The results from this model suggest that sectors with more concentrated, larger firms will be unlikely to make this transition on their own, even with the benefits of shared knowledge networks in the new technology. Regulatory action is needed whereas it is not as important in industries dominated by smaller firms.

This difference between the models does not hold in the case with cost spillover, $t < 0$. Figure 8 shows the transition paths for these models. In both cases, there is an increase in both new and old type capital shown in panels two and three. Old type capital increases due to the productivity shock in the long-run mean of z. The spillover benefit to adjustment costs does lead to small increases in the new type capital investment but it is extremely small. The aggregate new technology ratio never reaches a rate above 5% in this model. The spillover cost effect for the separate capital case is even smaller to the point that aggregate adoption actually decreases. The productivity shock to both capital types far outweighs the cost benefit of lower adjustment cost to new technology. As a result, firms do not shift their investments in that direction and average adoption rates decline.

C. Investment effect on Diffusion

Because the model does not emit analytical solutions, it's difficult to analyze the $\frac{\partial \gamma'}{\partial K}$, the rate at which adoption (and other aggregates) change when investment levels shift. In this section, I re-solve the partial equilibrium of each model, taking the aggregate K as given rather than endogenous. The results for both the technology adjustment and separate capital model is shown in figure 9. The plots show the technology ratios for both the old steady state with $\mu = 0$ and the one after the productivity shock. The technology adjustment model is much more sensitive to tipping into the new technology regime where most of the capital stock is in k_n. Because spillover is modeled as K^{ν}, it is unsurprising that any $K > 1$ will tip the model. In the productivity only case, any tipping into a slight advantage for technological sophistication, tends to end up in full diffusion. Endogenously, the economy does not always end up at the tipping point, even with the productivity shock. Figure 10 shows the transition path for diffusion levels (average technology rates in the economy) for the technology adjustment model. The top panel shows the productivity only version. At the old steady state, the economy had not tipped yet so aggregate diffusion is only at 10%. With the shock, the economy eventually reaches the tipping point. For the cost spillover ($t < 0$) model, the economy does not ever tip into full diffusion even with the productivity shock.

The separate capital model is much more sensitive to aggregate investment activity. With the same set of K's as the technology adjustment model, diffusion never exceeds 70% and it is clearly increasing in K. Additionally, the old steady state version with $\mu = 0$ exhibits lower diffusion levels than the new steady state after the productivity shock. In other words, the diffusion level for the separate capital model is elastic to both aggregate investment activity and the general productivity process. This complements the policy discussion above. Suppose the government wants to subsidize new technology investments with the hope that it creates knowledge spillovers which will tip firms into adopting the new technology. The comparisons here suggest that a small subsidy will have a large effect for smaller firms that mimic the technology adjustment model. On the other hand, diffusion amongst multi-business firms do react to higher aggregate investment activity but it will not reach full diffusion as quickly or easily.

D. Firm Heterogeneity

In addition to the impact of aggregate investment levels on diffusion, one other important partial equilibrium outcome from this model is heterogeneity in adoption. Figure 11 shows adoption rates over the distribution of firm types. The technology adjustment model is over the (firm size, technology ratio) state space while the separate capital model is shown over the (new capital, old capital) space. The results are for one realization of productivity z at one time period in the transition $t = 30$ between steady states. Figure 12 plots the corresponding new investment levels. The results are helpful for developing empirical tests of the models as they show drastically different patterns over the state space. Further, firm size and technology ratios can be observed empirically in many cases.

The technology adjustment model shows a smooth pattern. Adoption rates are highest for small firms. As expected, the effect declines for more technologically sophisticated firms since the marginal benefit adopting decreases. In the separate capital model, adoption rates also tends to be higher for low specialization forms. However, the result interacts differently with firm size. First, a 45-degree line over the x-y or (new technology, old technology) dimension marks the firms who are evenly split in their technology ratio. To the right are those with technology ratios < 0.5 and to the left are those with ratios > 0.5. As you move to the right where firms are less technologically sophisticated, the adoption rates are increasing. As you move to the left, they tend to be lower. However, the adoption rates are not decreasing in firm size as it is in the technology adoption case. As a clear example, return to the 45 degree line. All firms on this line have the same technology ratio, 50%. However, as you move up the line towards the far corner with $k_n = 100, k_o = 100$, the adoption rates are increasing as firms get larger. Holding k_n constant at any given k_n level, the adoption rates are increasing in k_o. The same is generally true holding k_o constant.

It's worth carefully considering what is driving the shape of these adoption surfaces by studying the corresponding investment behavior. In addition to being informative, they provide another layer of testable empirical predictions. Figure 12 shows the investment levels for both capital types in the separate capital model. The solution is not as smooth for small firms or firms with very low old technology ratios. However, an intuitive trend appears. Firm investments in new and old technology are driven by their size. Old technology investment is decreasing in k_o and vice versa for k_n. The derivation for the investment policy function used in the finite-difference problem is given in the appendix. Intuitively, in the separate capital case, the investment decision is largely driven by the marginal value of new and old type capital individually which leads to this result. The slope of the individual curve, $(\frac{\partial x_n}{\partial k_n}|_{k_o}, \frac{\partial x_o}{\partial k_o}|_{k_n})$, is driven by the productivity of new type capital and slightly impacted by the firm-level adjustment cost over γ'. Because z appears in the productivity of both types, the slopes look similar. In the top panel depicting new type investment, the spillover impact is visible. As k_n increases, the spread over the no spillover benchmark is wider and the slope is less steep. By contrast, the old type investment in the bottom panel is virtually indistinguishable from the no-spillover benchmark. One supplementary empirical test of the two models is to examine adoption rates within firms of similar old or new type capital.

IV. Concluding Remarks

Network effects are a natural mechanism to consider when studying endogenous technology diffusion. However, the dynamic nature of the problem makes it difficult both empirically and theoretically. Using a recent, salient example of technology diffusion in the American oil & gas fracking revolution, this paper develops an empirical framework for quantifying the impact of shared knowledge on adoption decisions made by firms. A spatial panel model is used to categorize counties based on their network strengths. Then, I compare firm behavior across these networks there is an exogenous change in information flow.

When data leakage occurs as a result of investments, exogenous variation in investment levels is shown to disproportionately impact adoption decisions when networks are strong. I then move to consider what this effects means for aggregate technology diffusion. I introduce a model where firms face the classic investment problem while incorporating a technology adjustment dimension. I show that how we model the firm internal capital allocation problem has important implications for aggregate technology change. Additionally, the mechanism for knowledge spillovers also matters for aggregate technology transition. Increasing productivity which disproportionately impacts new technology does not necessarily lead to a transition away from the old technology.

One shortcoming of the approach in this paper is that the opportunity costs of investing in old technology when new technology is improving ins not captured well. I include firm-level adjustment costs over the adoption rate but this is imperfect. Future work should consider a budget constraint on the firm. By limiting the resources for investment, the opportunity cost would be better incorporated and the energy transition may become more pronounced.

Further research could also expand the empirical methodology and apply it to other innovative sector. For example, I take a literal view of networks in the spatial panel model. A deeper consideration of network formats in other sectors could produce more interesting views on what is a "knowledge-based" network and how it differs from other forms of spillovers. Where the energy sector is concerned, spillovers in renewable energy and sectors like electric utilities where firms face these internal adoption decisions would be of interest to environmental economics and policy makers. The method could also be applied to study effects other than information flow. For example, one could look at regulatory changes applied to high and low network areas.

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V. Figures & Tables

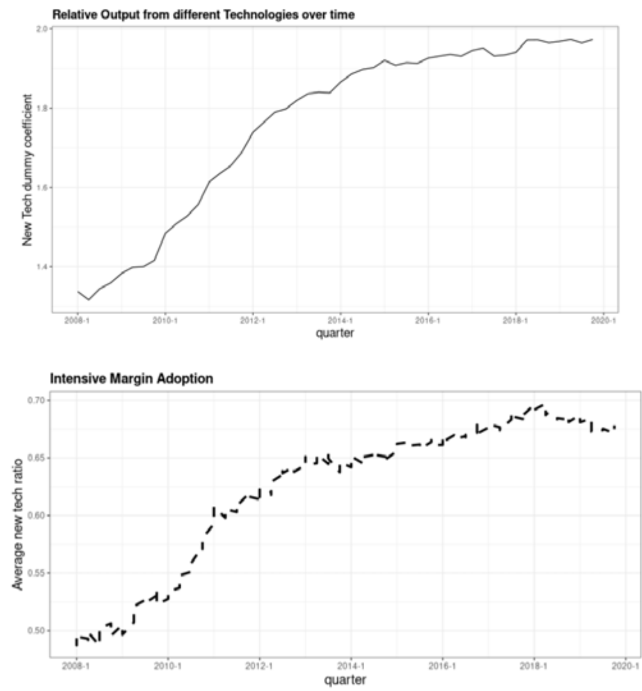


Figure 1: Productivity and Adoption trends over time

The two figures are derived using the full sample of horizontal and vertical wells drilled and operated in the lower 48 states. The top panel plots the coefficient γ from quarterly regressions of the following form for well w and month t,

$$log(O_{w,t}) = \alpha + \beta log(Age_{w,t}) + \gamma \mathbf{1}_{\{horizontal\}} + \epsilon$$

The regressions are conducted each quarter at the well-month level. $\mathbf{1}_{\{horizontal\}}$ is an indicator variable equal to one when the well is drilled using the new, horizontally fracked technology. The specification is a simplified version of the Arp's production function, a typical formula used by geologists to model oil output.

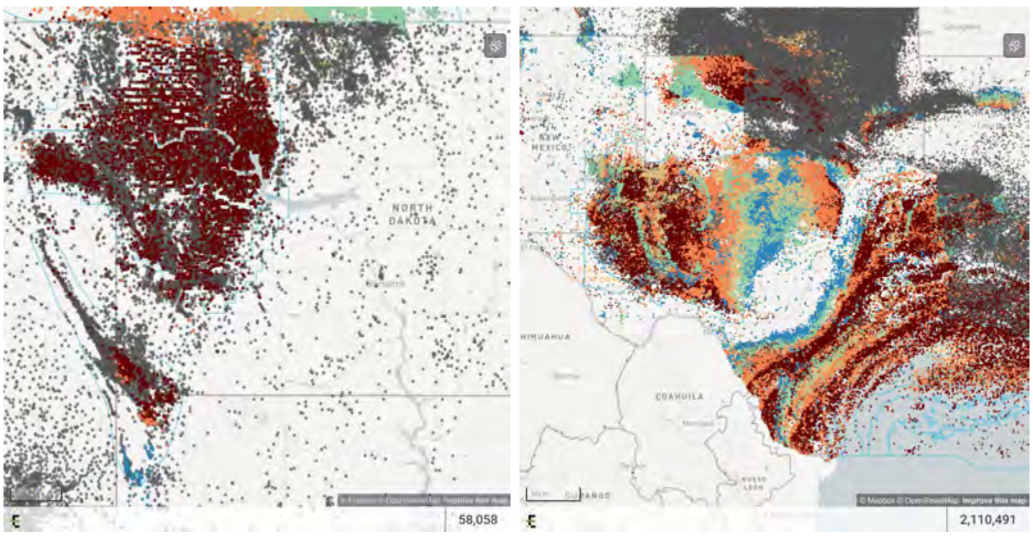


Figure 2: Geography heterogeneity in knowledge sharing propensity

The figure is pulled from Enverus analytics. It depicts the surface location of wells drilled in the Bakken shale of North Dakota and the Barnett and surrounding shale in Texas. The colors depict the depths of the wells drilled. There are significant geographic differences in both the variance of depths as well as the spacing of wells across the two regions. North Dakota in the top panel features well-lined wells with homogeneous depths. Texas in the bottom panel features more differences in depths as well as the surface locations of wells.

Note that this is not meant to suggest that one region is easier to drill or more productive. Rather, areas differ in the usefulness of other firms nearby. In North Dakota, it is likely more predictable on average. However, in Texas, there will be more information which can be used by other firms.

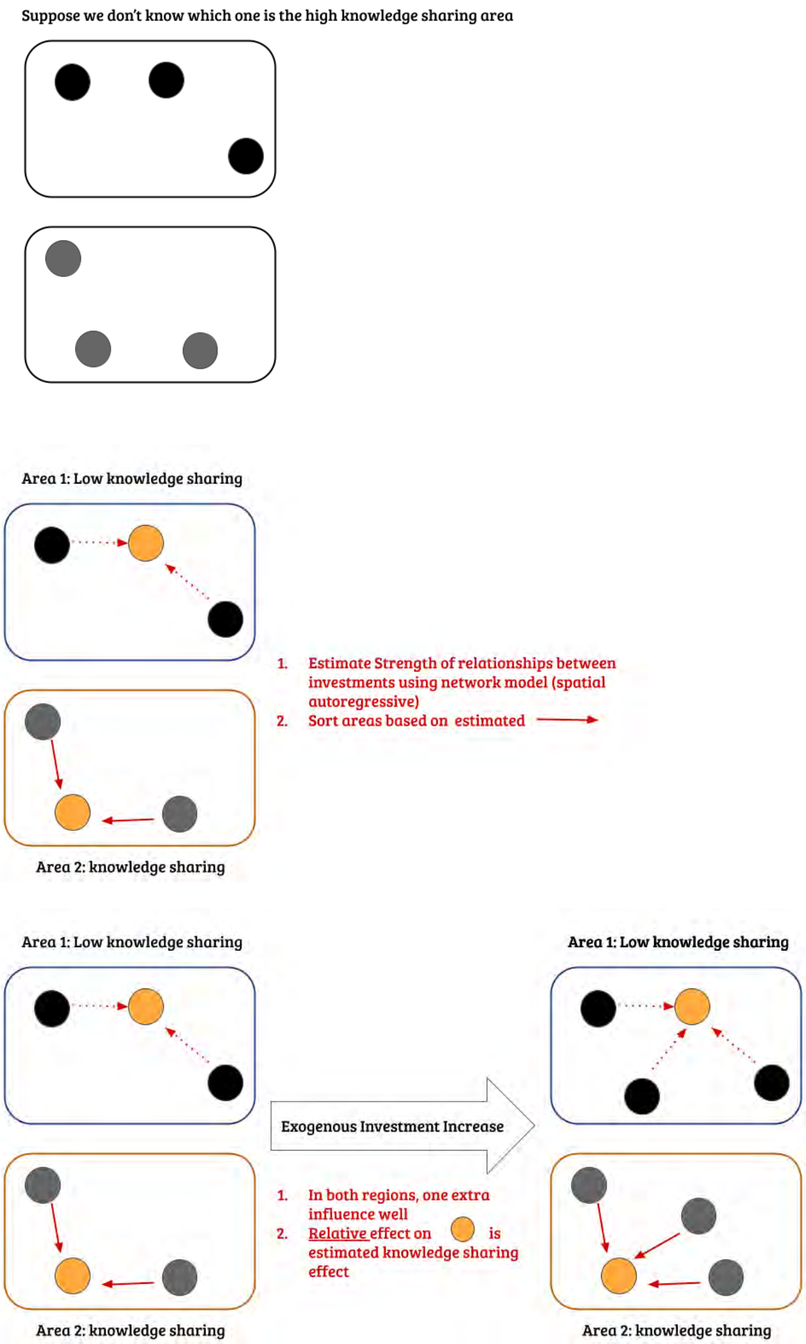


Figure 3: Thought Experiment for two-stage empirical setup

The picture is a graphical representation of the thought experiment underpinning the main empirical specification. Despite the motivation for cross-sectional differences in network strengths, the econometrician does not know which is the higher knowledge sharing area. The first task is to estimate that network strength. Then, when investments decline, a node is essentially detracted from each network. The area with the stronger network should be disproportionately impacted by that decline.

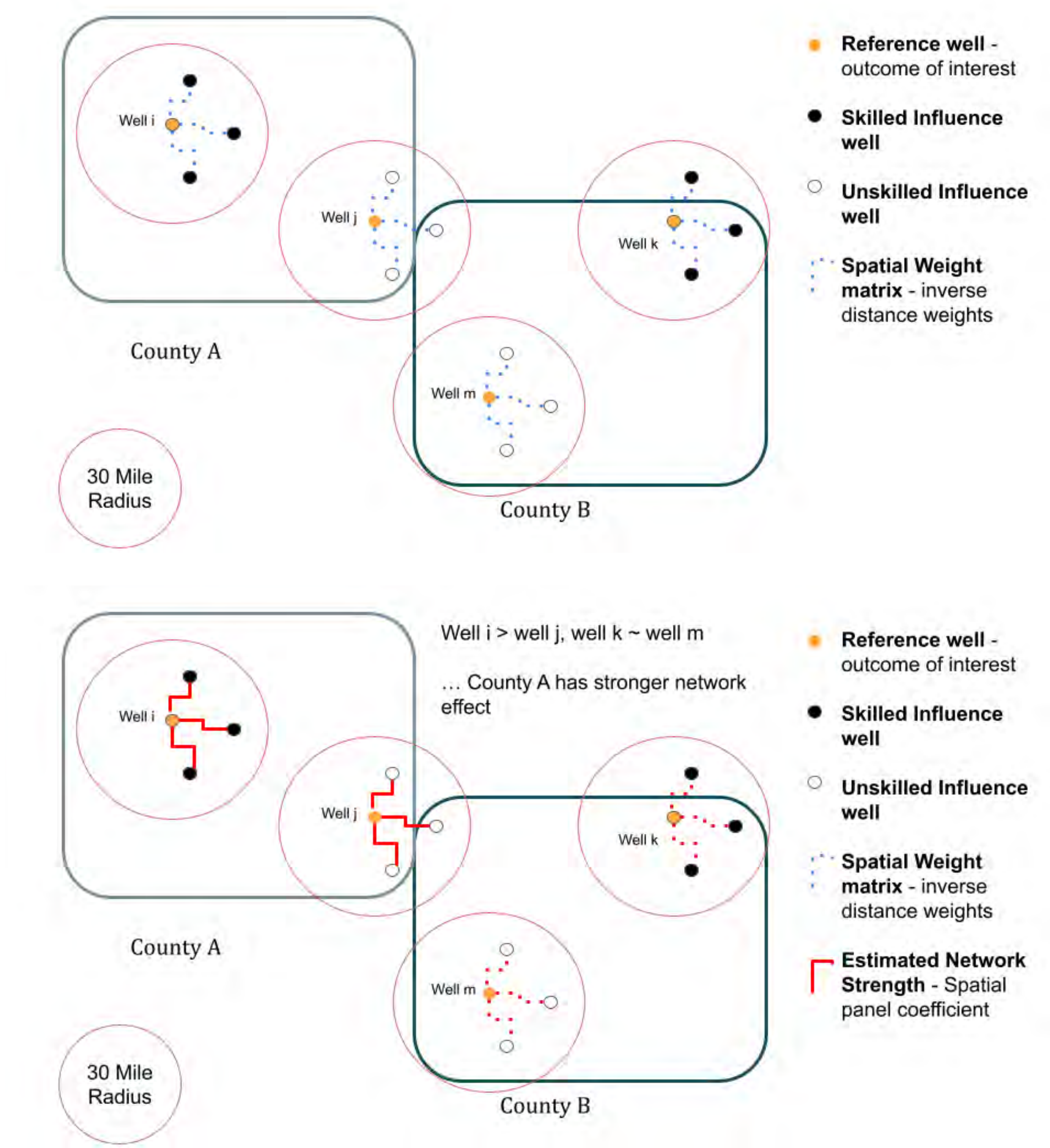


Figure 4: Spatial lag model illustrated

The picture is a graphical representation of what the spatial panel model using skill as an indirect variable estimates. It describes intuitively how to think about why β^A would be different than β^B. The econometric details are available in the section on the spatial lag model in the main paper.

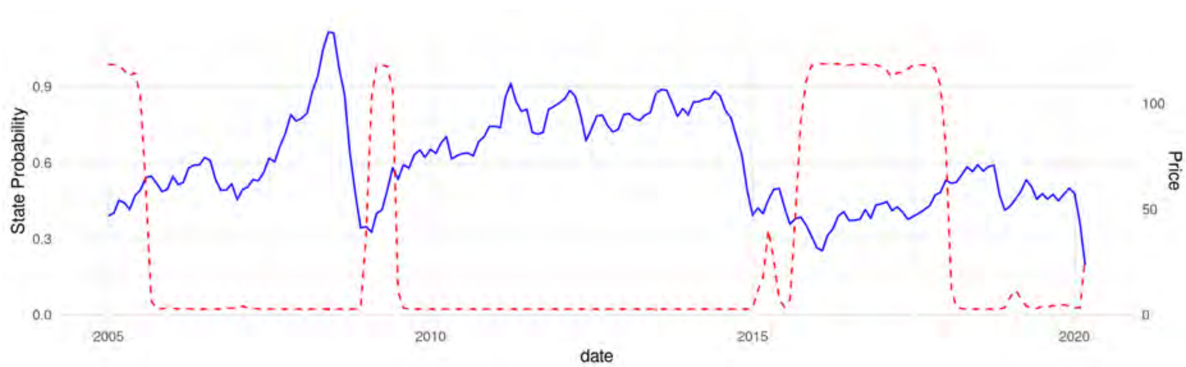


Figure 5: Long term oil price trends with Markov Switching

The figure shows the WTI oil spot price in blue. Its corresponding y-axis is on the right. In red are the estimated probabilities from fitting a two stage Markov switching process to the data. Two large structural breaks can be seen. Between 2010-2015, the model estimates a low consistently low probability of being in the low state. The period from 2015 to 2018 shows consistently high probability of being in the low state. The two regimes depicted will be used to instrument for investment levels over those two, long time periods.

Table I: Main results: Network effects on adoption and productivity

Horizontally Drilled Wells: 2014Q4 - 2020Q1

Inverse-distance-time network	Network Bucket 1		Network Bucket 2		Network Bucket 3		Network Bucket 4	
	Stage 1: Ex-firm Investment	Stage 2:	Stage 1: Ex-firm Investment	Stage 2:	Stage 1: Ex-firm Investment	Stage 2:	Stage 1: Ex-firm Investment	Stage 2:
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inverse-distance-time network: first stage							
Lease Expirations #	0.011*** (0.00045)		0.038*** (0.00025)		0.0020*** (0.00014)		0.0012*** (0.000025)	
	Adoption Results							
Ex-firm Investment		0.00016*** (0.000015)		-0.000046*** (0.000013)		0.013*** (0.00088)		0.00022*** (0.000030)
	Productivity Results							
Ex-firm Investment		0.0051*** (0.0013)		0.0068*** (0.00023)		0.076*** (0.0058)		0.011*** (0.00069)

Equidistant network	Network Bucket 1		Network Bucket 2		Network Bucket 3		Network Bucket 4	
	Stage 1: Ex-firm Investment	Stage 2:	Stage 1: Ex-firm Investment	Stage 2:	Stage 1: Ex-firm Investment	Stage 2:	Stage 1: Ex-firm Investment	Stage 2:
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Equidistant network: first stage							
Lease Expirations #	0.015*** (0.00025)		0.033*** (0.00046)		0.028*** (0.00021)		0.00084*** (0.000025)	
	Adoption Results							
Ex-firm Investment		-0.0011*** (0.000050)		0.00015*** (0.000011)		-0.00030*** (0.000020)		-0.0018*** (0.00010)
	Productivity Results							
Ex-firm Investment		0.00071 (0.0012)		0.0085*** (0.00033)		0.012*** (0.00029)		0.015** * (0.0011)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Cluster	Well-level	Well-level	Well-level	Well-level	Well-level	Well-level	Well-level	Well-level

Notes: The table shows results from the 2sls specification:

$$I^H_{i,g,q-1} = \eta + \beta^{net_n}\mathbf{L}_{g,q-1} + \Gamma\,[\mathbf{X}_{g,t}\ \ \mathbf{X}_{i,t}]' + \nu_{g,t} \quad (first\ stage)$$

$$A_{i,g,t} = \alpha + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\,[\mathbf{X}_{g,t}\ \ \mathbf{X}_{i,t}]' + \epsilon_{w,t} \quad (second\ stage)$$

$$log(O_{w,t}) = \omega + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\,[\mathbf{X}_{g,t}\ \ \mathbf{X}_{i,t}]' + \epsilon_{w,t} \quad (second\ stage')$$

continued below

Table I: Main results: Network effects on adoption and productivity (cont'd)

Notes: The first row of each panel shows the first stage results of ex-firm investment levels on the number of leases expiring in the county that quarter. The second rows shows second stage results of adoption on instrumented ex-firm investments while the third row shows productivity as the main variable of interest. The regressions are conducted at the individual well-month level, sorted into four network buckets based on the county where they are located.

The first panel sorts counties based on inverse-distance-time weight networks which captures the depreciation of useful knowledge as distances and time increase. The second panel shows results when networks are sorted based on equidistant weights. This network is used as a comparison to test the results. Unlike knowledge-based networks, this is more likely to capture general contagion or other spillovers which are distance-neutral. All regressions contain the same set of firm and county level controls which are detailed in the appendix. The standard errors are clustered at the well-level. The results do not include the early time period when oil prices were increasing as the technology was just beginning to develop, they start in 2014Q4.

Adoption rates are measured at the firm-month-county level.[a] The equation for adoption rates is,

$$A_{i,g,t} = \underbrace{\frac{O^H_{i,t}}{O_{i,t}}}_{\text{New Technology Ratio}} - \underbrace{\frac{O^H_{i,t} - O^H_{i,g,t}}{O_{i,t} - O_{i,g,t}}}_{\text{New Technology Ratio w/out county g}}$$

[a] The main paper discusses why I use these firm-level results with a well-level specification.

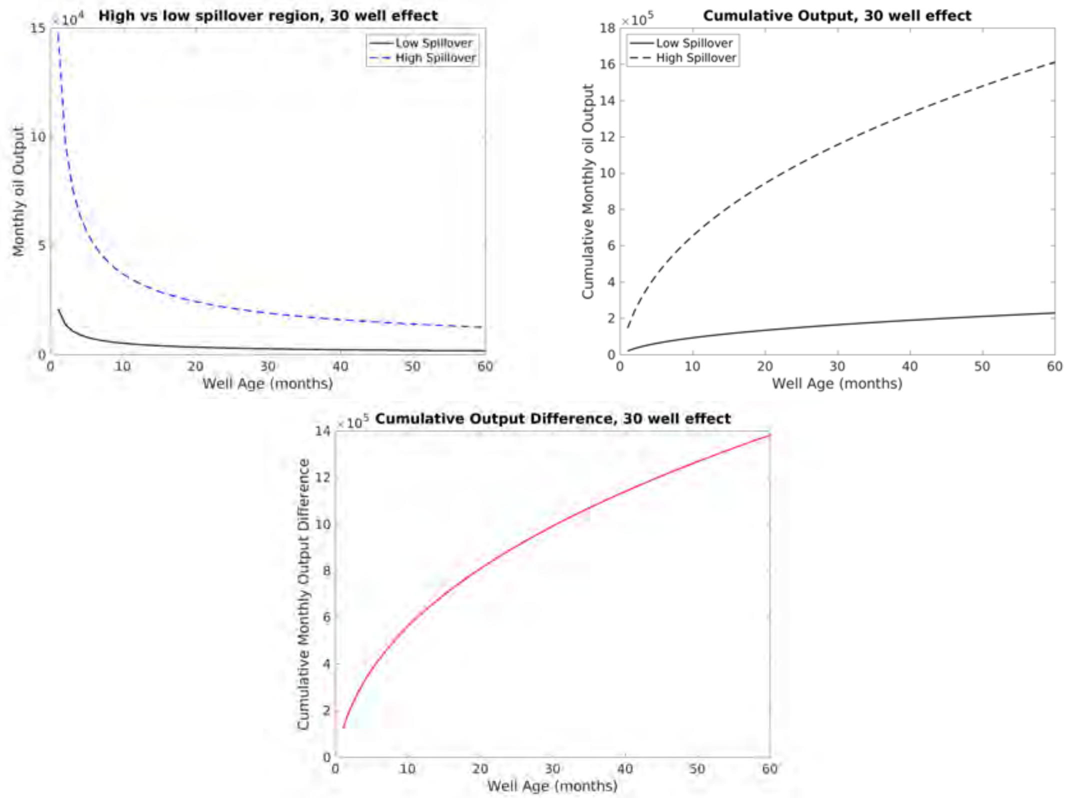


Figure 6: Simulated output with network effects

The three figures show simulations of the economic impact from network effects. The top panel shows simulated monthly output using the Arp's production model which was estimated in logs based on the following specification,

$$O_{w,t} = Q_w Age_{w,t}^{\beta}$$
$$log(O_{w,t}) = log(\hat{Q}_w) + \hat{\beta} log(Age_{w,t}) + \epsilon_{w,t}$$

Each line shows the same baseline productivity rate Q_w for a hypothetical well. All wells share the same $log(Q) = 9.5$ which is the average in the data sample and $\beta = -0.6$. I then plot,

$$O_{w,t} = exp(log(\hat{Q}) + \hat{\gamma}^{ks_n} \times I_t + \hat{\beta} * log(Age_{w,t}))$$

with $I_t = 30$ which is the average ex-firm investment level in the sample. The high spillover measure is has $\hat{\gamma} = 0.011$ and the low spillover has $\hat{\gamma} = 0.00051$ coefficients. The second panel shows the cumulative outputs to simulate the total effect over time. The third panel shows the cumulative output difference.

Table II: Comparison of Network effects in Old Technology

Vertically Drilled Wells: 2008Q1 - 2018Q1

Productivity Results

	Network Bucket 1		Network Bucket 2		Network Bucket 3		Network Bucket 4	
Conventional Wells (Old Technology)	Stage 1: Ex-firm Investment	Stage 2: log(BOE)	Stage 1: Ex-firm Investment	Stage 2: log(BOE)	Stage 1: Ex-firm Investment	Stage 2: log(BOE)	Stage 1: Ex-firm Investment	Stage 2: log(BOE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lease Expirations #	0.0029		0.11***		-0.0064***		0.011***	
	(0.0032)		(0.0048)		(0.00054)		(0.0020)	
Ex-firm Investment		0.37		-0.035***		-0.055***		-0.020**
		(0.36)		(0.0031)		(0.012)		(0.0065)
N	22690	22690	561281	561281	243452	243452	602758	602758
Underidentification		0.82		278.0		95.7		27.7
Weak identification		0.86		554.7		140.9		34.4

Investment Level Results

	Network Bucket 1		Network Bucket 2		Network Bucket 3		Network Bucket 4	
Conventional Wells (Old Technology)	Stage 1: Ex-firm Investment	Stage 2: Investment levels	Stage 1: Ex-firm Investment	Stage 2: Investment levels	Stage 1: Ex-firm Investment	Stage 2: Investment levels	Stage 1: Ex-firm Investment	Stage 2: Investment levels
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lease Expirations #	0.011**		0.13***		-0.0048***		0.033***	
	(0.0035)		(0.013)		(0.00047)		(0.0043)	
Ex-firm Investment		-0.0073		0.00075		0.012***		-0.00029
		(0.0046)		(0.0010)		(0.0033)		(0.00062)
N	1008	1008	4401	4401	2852	2852	4841	4841
Underidentification		9.55		102.0		74.4		43.2
Weak identification		9.88		100.6		103.4		61.5
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geography Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates the 2sls specification using the old technology, vertically drilled wells.

$$I^H_{i,g,q-1} = \eta + \beta^{net_n}\mathbf{L}_{g,q-1} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \nu_{g,t} \quad (first\ stage)$$

$$log(O_{w,t}) = \omega + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \epsilon_{w,t} \quad (second\ stage')$$

Because adoption is not a well-defined concepts for the old technology, the second panel shows investment levels. This is defined as the total wells drilled by firm i in county g during month t the investment level results are conducted at the firm-month-county level and standard errors are clustered at the firm level. The productivity results are at the well-month level and standard errors are clustered at the well-level. Both results use the same inverse-distance-weighted network sorts from the baseline. However, the spatial panel model was estimated using only the vertically drilled wells.

Table III: Data Availability Measure: Network effects on adoption and productivity

Horizontally Drilled Wells: 2014Q4 - 2020Q1

Adoption Results

Horizontal Wells (New Technology)	Network Bucket 1		Network Bucket 2		Network Bucket 3		Network Bucket 4	
	Stage 1: Ex-firm Investment	Stage 2: Adoption Rate	Stage 1: Ex-firm Investment	Stage 2: Adoption Rate	Stage 1: Ex-firm Investment	Stage 2: Adoption Rate	Stage 1: Ex-firm Investment	Stage 2: Adoption Rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument: Lease Expiration	0.024***		0.030***		0.0028***		0.0074***	
	(0.00052)		(0.00072)		(0.00032)		(0.00013)	
Ex-firm Investment (prev qtr)		-0.00061***		-0.00015**		-0.0012***		0.0037***
		(0.000029)		(0.000052)		(0.00030)		(0.000094)
N	444461	444461	823175	823175	1395977	1395977	2053541	2053541
Underidentification		2415.7		1627.3		93.5		2841.4
Weak identification		2187.8		1700.2		80.1		3024.1

Productivity Results

Horizontal Wells (New Technology)	Network Bucket 1		Network Bucket 2		Network Bucket 3		Network Bucket 4	
	Stage 1: Ex-firm Investment	Stage 2: log(boe)	Stage 1: Ex-firm Investment	Stage 2: log(boe)	Stage 1: Ex-firm Investment	Stage 2: log(boe)	Stage 1: Ex-firm Investment	Stage 2: log(boe)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrument: Lease Expiration	0.024***		0.030***		0.0028***		0.0074***	
	(0.00052)		(0.00072)		(0.00032)		(0.00013)	
Ex-firm Investment (prev qtr)		0.011***		0.018***		0.12***		0.014***
		(0.00060)		(0.00098)		(0.014)		(0.0010)
N	444127	444127	822603	822603	1394652	1394652	2052986	2052986
Underidentification		2416.4		1625.9		93.1		2849.3
Weak identification		2188.6		1699.3		79.8		3033.3

Notes: The two panels replicate the baseline 2sls specification:

$$I^H_{i,g,q-1} = \eta + \beta^{net_n}\mathbf{L}_{g,q-1} + \Gamma\,[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}]' + \nu_{g,t} \quad (first\ stage)$$
$$A_{i,g,t} = \alpha + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\,[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}]' + \epsilon_{w,t} \quad (second\ stage)$$
$$log(O_{w,t}) = \omega + \beta log(Age_{w,t}) + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\,[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}]' + \epsilon_{w,t} \quad (second\ stage')$$

The spatial panel model used to sort the networks regresses baseline productivity Q on the auxiliary data availability measure instead of the skills of firms drilling nearby. The first row of each panel shows the first stage results of ex-firm investment levels on the number of leases expiring in the county that quarter. The second rows shows second stage results of adoption on instrumented ex-firm investments in the first panel and productivity in the second. The regressions are conducted at the individual well-month level, sorted into four network buckets based on the county where they are located. Both sets of results use the inverse-distance-time weighting matrix to sort networks.

Adoption rates are measured at the firm-month-county level[a] using

$$A_{i,g,t} = \underbrace{\frac{O^H_{i,t}}{O_{i,t}}}_{\text{New Technology Ratio}} - \underbrace{\frac{O^H_{i,t} - O^H_{i,g,t}}{O_{i,t} - O_{i,g,t}}}_{\text{New Technology Ratio w/out county g}}$$

[a]The main paper discusses why I use these firm-level results with a well-level specification.

Table IV: Skill Coefficient comparison between knowledge and equidistant networks

Horizontally Drilled Wells: 2014Q3 - 2020Q1

	BOE-per-ft	log(boe)	interval (ft)	drill time
	Q-Skill			
	(1)	(2)	(3)	(4)
Ex-firm Investment	0.018***	0.014***	-139.8***	3.23***
	(0.00083)	(0.00087)	(15.7)	(0.73)
$\mathbf{1}_{\{knowledge-based\}}$	0.61	1.41***	-54971.7***	1659.9***
	(0.40)	(0.40)	(6377.6)	(288.9)
$\mathbf{1}_{\{knowledge-based\}} \times Skill$	-0.083*	-0.14***	5190.5***	-160.7***
	(0.038)	(0.038)	(595.5)	(27.0)
N	6442066	6474411	61536	62035

Notes: The three panels show results from the following,

$$I^H_{i,g,q-1} = \eta + \beta^{net_n}\mathbf{L}_{g,q-1} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \nu_{g,t} \quad (first\ stage)$$

$$Y_{w,t} = \alpha + \beta\mathbf{1}_{\{Skill\ based\}} \times Skill + \nu^{net_n}\hat{I}^H_{i,g,t} + \Gamma\left[\mathbf{X}_{g,t}\ \mathbf{X}_{i,t}\right]' + \epsilon_{w,t}$$

The specification is similar to the baseline. The analysis is limited to counties in network bucket 4. The variable $\mathbf{1}_{\{skill\ net\}}$ is an indicator variable which is one for counties in bucket 4 of the inverse-distance-time weighted networks and zero for those in equidistant networks. *Skill* is the operating firm's quarter level ability measured by applying the Arp's production function to the full data sample,

$$log(O_{w,t}) = \beta log(Age_{w,t}) + \eta_{i,q}\mathbf{1}_{\{Firm\ i\}} \times \mathbf{1}_{\{q\}} + \epsilon_{w,t}$$

The four dependent variables of interest include production efficiency, output, well complexity, and drilling costs. The first two are conducted at the well-month level while the latter two are at the well level. The first panel shows bucket 4 comparisons for the baseline productivity-skill (Q-skill) networks, the second shows interval-skill, and the third shows drill time-skill networks. The test considers the importance of firm-skill in knowledge based networks as compared to general contagion. The Q-skill networks are the baseline sorts in the main analyses. The second two study alternative network formations where well designs are influenced by the skill of those drilling nearby.

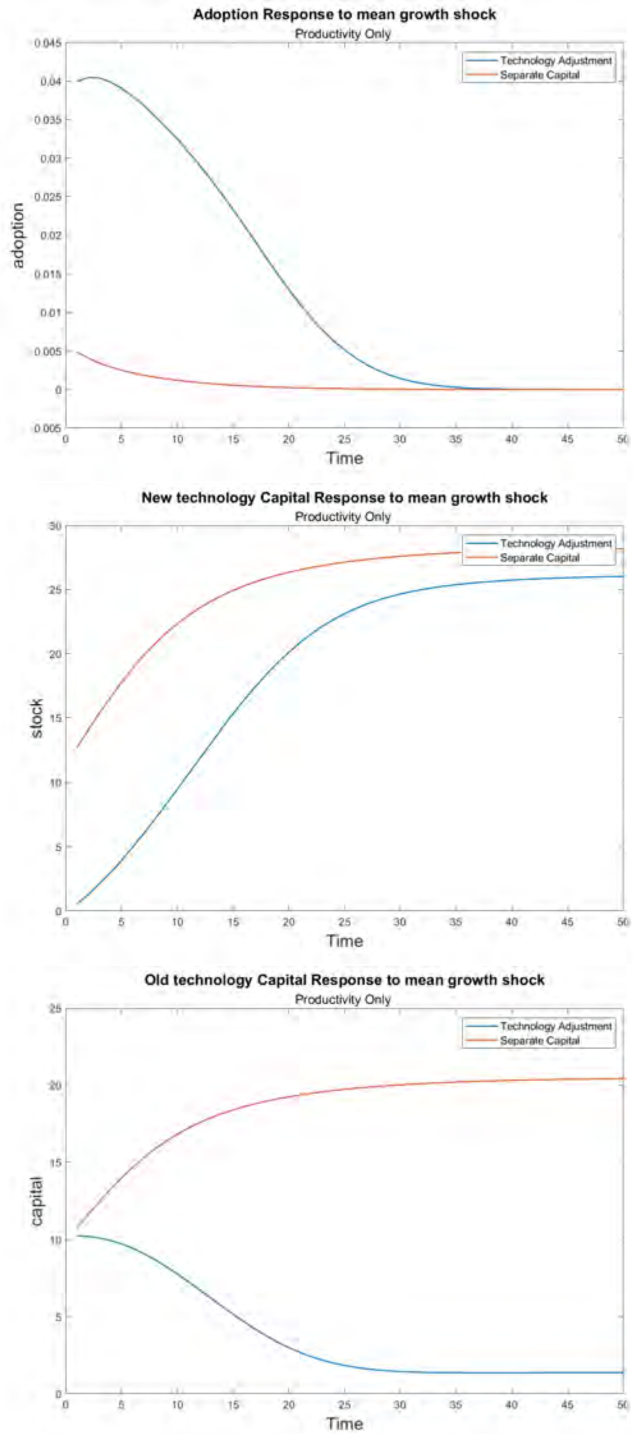


Figure 7: Transition dynamics for Productivity Only Model

The panel plots transition dynamics for the model where $\nu = 0.5, t = 0$. The first panel shows adoption rates which is measured by the new technology ratio as a result of investments in that time period minus the firm's previous technology ratio, $\frac{k_n}{k_n+k_o}$. The second panel shows average new technology capital stock and the third shows old technology capital. Time period 0 reflects the old steady where $\mu = 0$ in the productivity process z. The dynamic transitions follow an MIT shock to $\mu > 0$, the long-term mean of the mean-reverting O-U process, z.Results are shown for the technology adjustment model and the separate capital model.

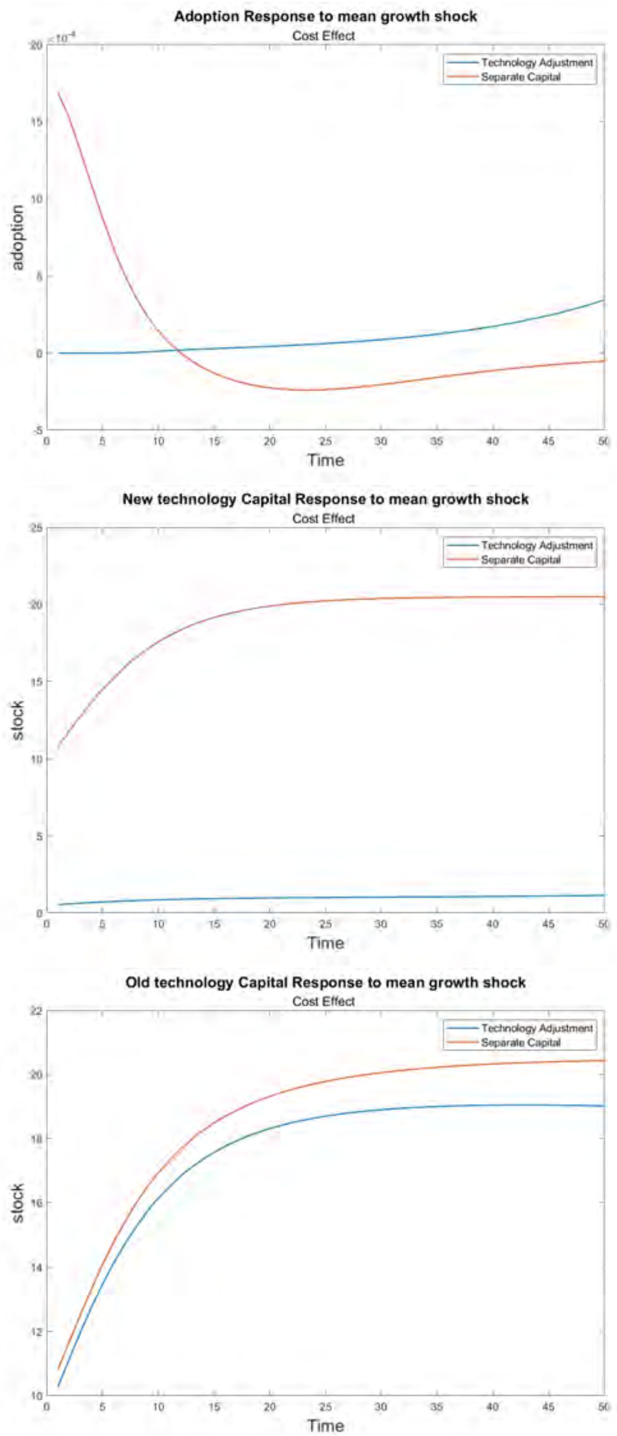


Figure 8: Transition dynamics for Cost Effect Model

The panel plots transition dynamics for the model where $\nu = 0, t < 0$. The first panel shows adoption rates which is measured by the new technology ratio as a result of investments in that time period minus the firm's previous technology ratio, $\frac{k_n}{k_n+k_o}$. The second panel shows average new technology capital stock and the third shows old technology capital. Time period 0 reflects the old steady where $\mu = 0$ in the productivity process z. The dynamic transitions follow an MIT shock to $\mu > 0$, the long-term mean of the mean-reverting O-U process, z.Results are shown for the technology adjustment model and the separate capital model.

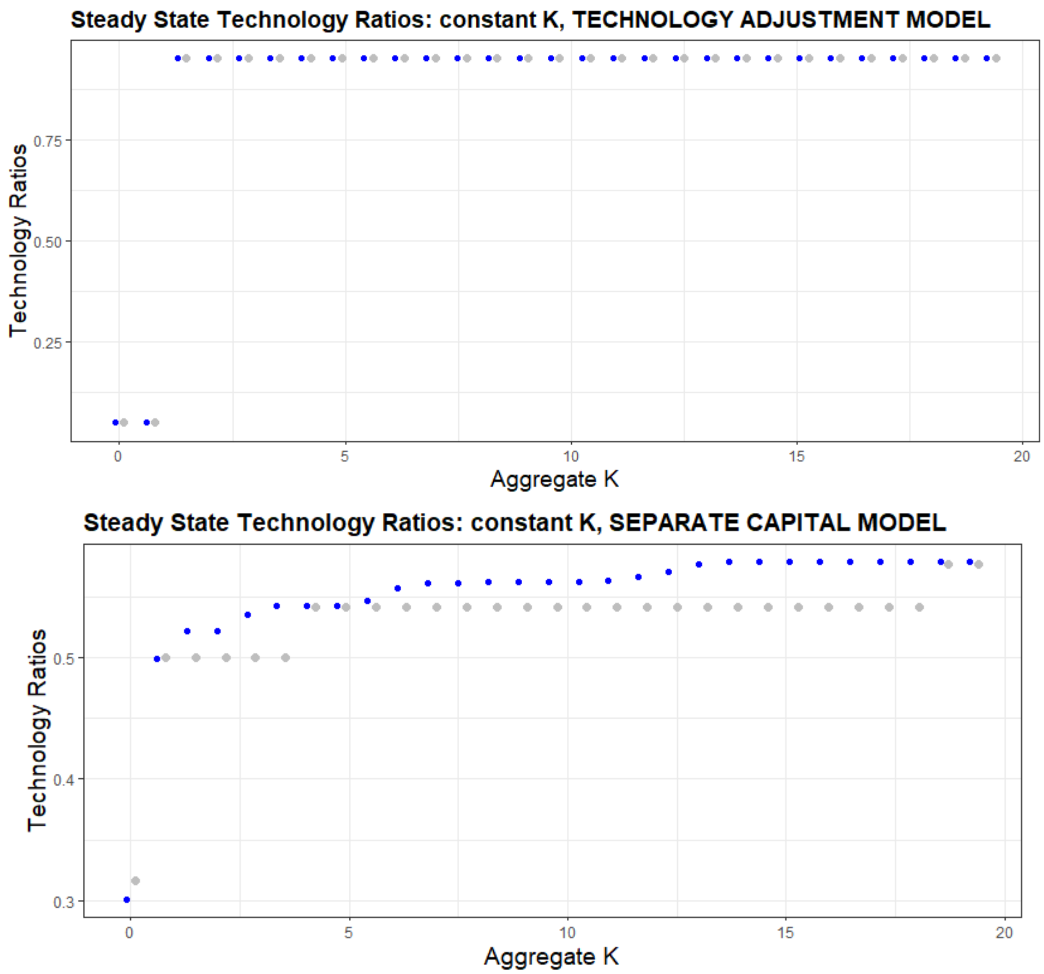


Figure 9: Average Adoption Rate response to K, productivity only model

The two plots show diffusion level or average $\frac{k_n+x_n}{k_n+k_o+x_n+x_o}$ over all firms in the economy. The partial equilibrium results take aggregate K as given. The results are shown for the productivity only model with $\nu = 0.05, t = 0$. The points in blue show the steady state technology ratio for the economy following the MIT shock with $\mu > 0$ and the gray shows the case with $\mu = 0$ in productivity process z.

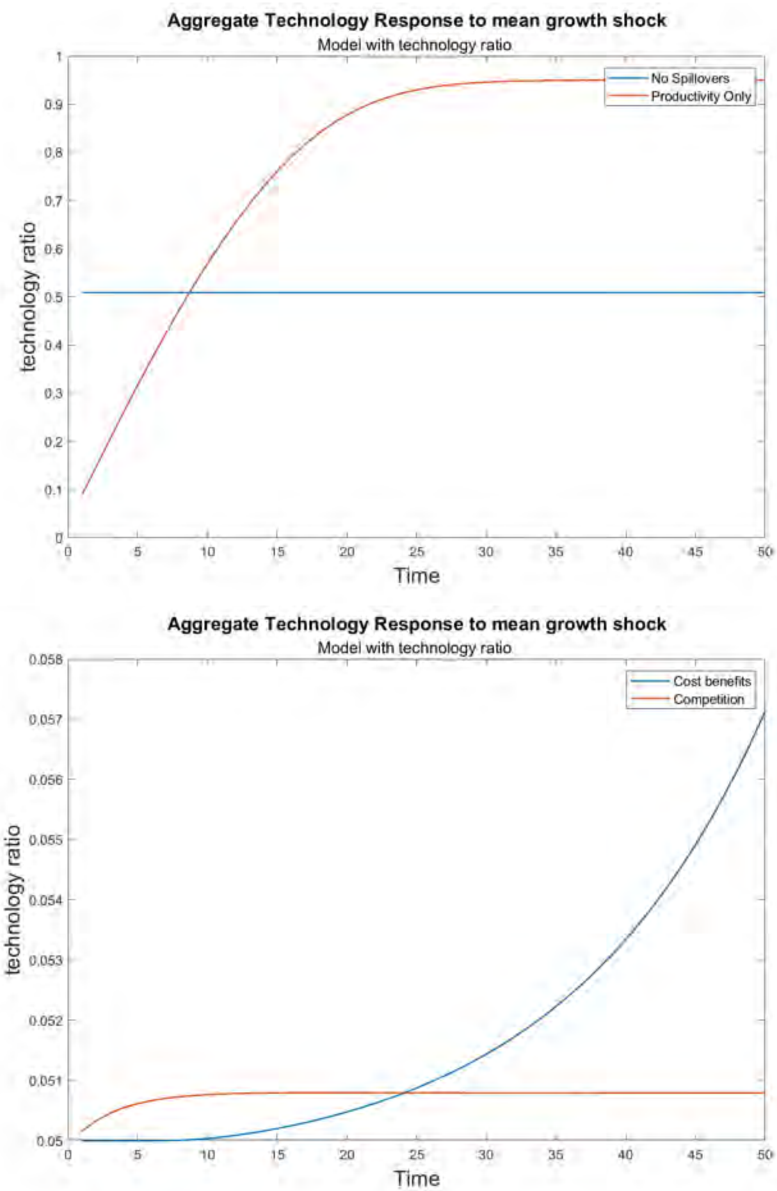


Figure 10: Transition dynamics of diffusion for Technology Adjustment Economy

The Figures show transition dynamics for the technology adjustment model. The top panel compares the productivity only model, $\nu = 0.05, t = 0$ with the no spillovers benchmark. The bottom panel shows the cost benefit model with $t < 0$ to the competition model with $t > 0$. The y-axes show diffusion level or average $\frac{k_n+x_n}{k_n+k_o+x_n+x_o}$ over all firms in the economy.

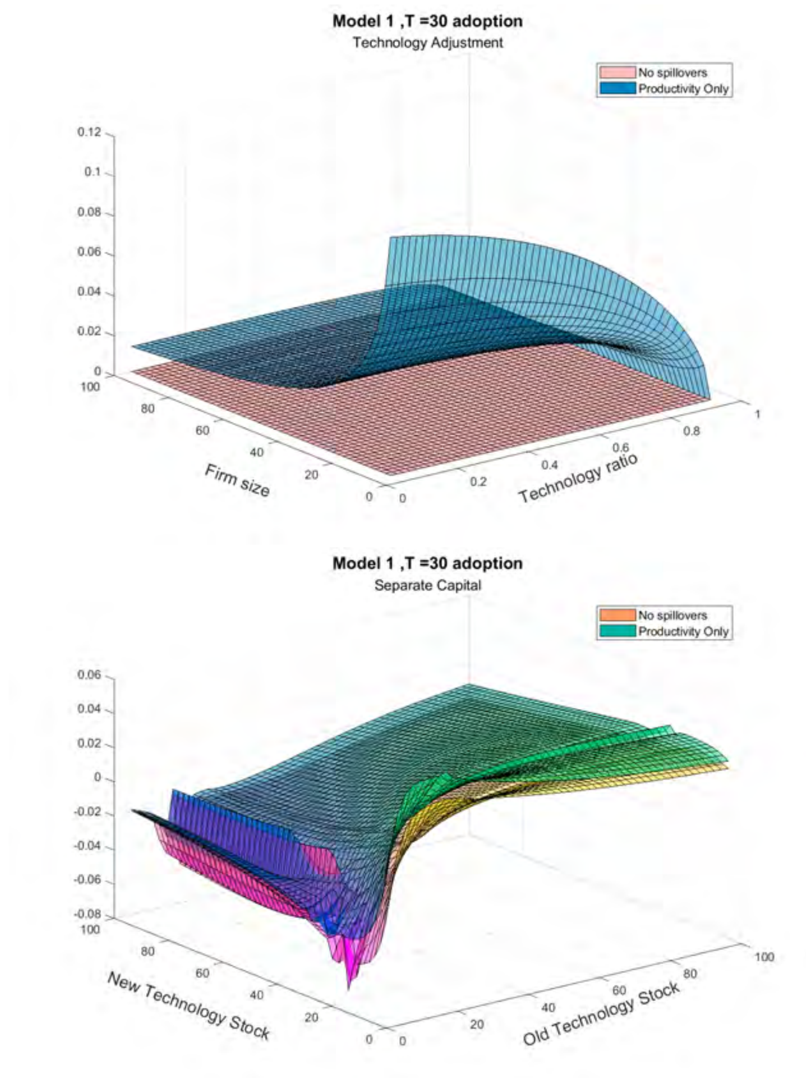
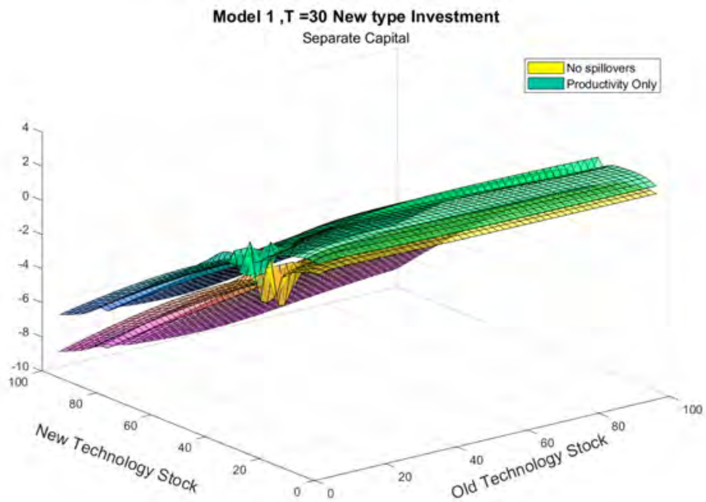


Figure 11: Heterogeneity in Adoption Decisions

The two plots show snapshots of adoption decisions, $\gamma' = \frac{k_n+x_n}{k_n+k_o+x_n+x_o} - \frac{k_n}{k_n+k_o}$, over the entire firm state space. The technology adjustment model in the top panel is shown over the (firm size, technology ratio) space while the separate capital in the bottom panel is shown over the (k_n, k_o) space. The surfaces compare the productivity only model with $\nu + 0.05, t = 0$ to the no spillover benchmark. The result is shown for one realization of z and one point, $T = 30$ in the transition between steady states.



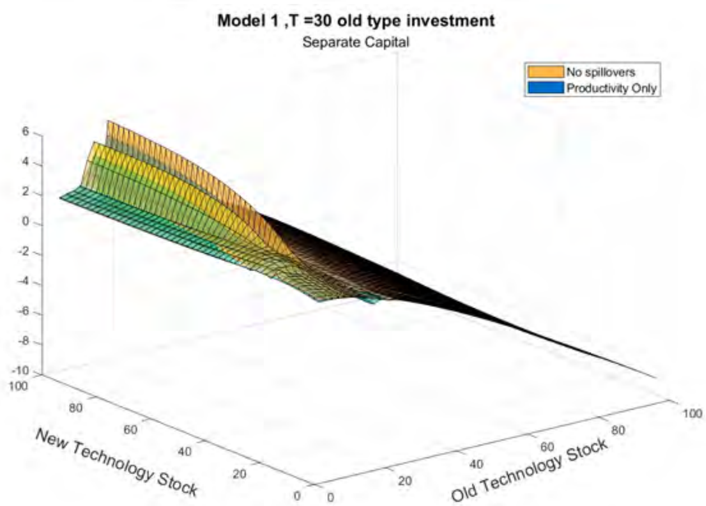


Figure 12: Heterogeneity in Investment Decisions

The two plots show snapshots of new type investment, x_n, over the entire firm state space. The technology adjustment model in the top panel is shown over the (firm size, technology ratio) space while the separate capital in the bottom panel is shown over the (k_n, k_o) space. The surfaces compare the productivity only model with $\nu + 0.05, t = 0$ to the no spillover benchmark. The result is shown for one realization of z and one point, $T = 30$ in the transition between steady states.