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Geography, Geology, and Regional Economic Development☆

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ABSTRACT

We examine how large and localized resource discoveries affect long-run population growth in the United States, and examine how these shocks interact with pre-existing geographic properties of the discovery site. Using a dynamic event study analysis and developing novel, geographically delineated measures of both amenity value and geographic isolation, we find that resource discoveries cause population to grow both in the short and long-run (e.g., fifty years). However, this effect is largely driven by discoveries in unfavorable locations that might struggle to grow in the absence of a resource discovery. More generally, this paper highlights the importance of considering heterogeneous effects of resource shocks and yields insights into the observed spatial distribution of people in the United States.

"*New roads, agriculture, employment, education, these are just a few of the things we can offer you, and I assure you ladies and gentlemen, that if we do find oil here, and I think there's a very good chance that we will, this community of yours will not only survive, it will flourish*" — Daniel Plainview, There Will Be Blood.

1. Introduction

What determines where people choose to live? At the sub-national level with minimal labor migration frictions, people "vote with their feet" to consume optimal bundles of private and public goods (Tiebout, 1956).[1] All else equal, people prefer to live in places with low crime (Tita et al., 2006), good schools (Kane et al., 2006), and environmental amenities like warm temperature (Roback, 1982), mountain viewsheds (Groothuis et al., 2007), clean air (Chay and Greenstone, 2005; Banzhaf, 2008), and rainfall

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[1] Testing Tiebout's theory, Banzhaf (2008) finds that people move to places that experience an exogenous increase in public goods (an improvement in air quality in particular). Albouy and Stuart (2014) also find that quality of life is more important in determining where people live than employment opportunities and show that changing quality of life can "massively" redistribute populations within the U.S.

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(Englin, 1996). But private consumption and real wages are also important; positive labor demand shocks attract people from near and far away. This feature of human behavior is well documented in the economics literature and is especially salient in the resource-based development literature, which affirms a robust relationship between natural-resource shocks, labor demand, and inward migration (Jacobsen and Parker, 2016; Allcott and Keniston, 2017; Feyrer et al., 2017; Richter and James, 2018; James and Smith, 2020). But this literature has overlooked the joint role of economic shocks and environmental amenity. Just as a high school degree is more important for people with low cognitive ability (Murnane et al., 2000), a boost to labor productivity might be especially important for population growth in otherwise less desirable locations.

We examine how large and localized productivity shocks—in the form of major oil and mineral discoveries—affect long-run population growth, and examine how these shocks interact with pre-existing geographic properties of the discovery site. Estimating long-run, truly posterior effects of economic shocks requires an analysis of events that happened long ago. However, doing so is often frustrated by the lack of available data; causal inference typically requires observing initial conditions. While census records provide historical subnational population estimates, county borders change over time and additional counties are added as new territories are acquired. To account for these issues, we make use of novel geospatial population count estimates measured at a 1-km^2 resolution for decades between 1790 and 2010 constructed by Fang and Jawitz (2018). These data, along with our identification strategy, allow us to measure both short, medium and long-run effects (e.g., 50 years) of natural-resource discoveries.[2]

We uniquely explore important heterogeneities in the effect of resource shocks along two dimensions: environmental-amenity value and geographic isolation. Rather than relying on existing estimates of county-level environmental amenity, which may reflect endogenous factors such as school quality (Bieri et al., 2014), or may not reflect historical preferences for environmental amenities, we use the idea that population density reflects, among other things, people's preferences for natural amenities and construct a data-driven estimate of amenity value that is a function of purely exogenous, naturally-occurring characteristics like weather and topography. Our constructed measure of amenity value averages historical and modern preferences to reflect changes in the value of different amenities over time, and examines a much longer time span than existing indices which are surveyed in Waltert and Schläpfer (2010). We measure geographic isolation as the cost of traveling from a county to the nearest major market, defined as either an existing city, railroad, or marine highway. Instead of relying on an "as the crow flies" measure of distance, we develop a novel measure of geographic isolation that incorporates information about terrain ruggedness and water coverage between locations. In constructing these estimates, we add to the literature on economic geography by providing novel estimates of local, naturally-occurring amenity value and geographic isolation that complement the work of Blomquist et al. (1988), Allen and Arkolakis (2014), Henderson et al. (2017), among others.

The event-study analysis indicates that, fifty years after discovering oil, population density in the average treatment county is roughly 65% greater than it otherwise would have been. However, this average effect conceals important heterogeneities. When limiting our sample according to environmental and geographic favorability, we find that for relatively unfavorable counties (those with low amenity value or high transportation cost) the long-run treatment effect on population increases to roughly 170%. While the results for moderate-favorability places are similar to the overall average treatment effect, effects for high-favorability places are qualitatively small and statistically insignificant. Examining the effects of mineral discoveries reveals similar heterogeneities, although the effects tend to be short lived, partially reflecting the relatively short life of a typical mine.

We carry out several robustness checks designed to test for endogeneity bias and reverse causality, and explore the sensitivity of the results to various modeling assumptions. Our results prove to be quite robust and do not appear to be driven by endogenous natural-resource discoveries (whereby economic development leads to discovery). In particular, while discovery is potentially endogenous, the size of discovery is left to chance and we find that discoveries of large oil fields generate significantly larger effects than discoveries of small fields. We also reject the idea that our heterogeneous results are mechanical, whereby low-favorability places are less populated to begin with, and so experience larger percent increases in population following the discovery of a resource. Our analysis also addresses recent methodological scrutiny of the two-way fixed effects estimator in difference-in-differences approaches (e.g. Goodman-Bacon, 2018; Sun and Abraham, 2020), by re-estimating our main results using the interaction-weighted estimator developed by Sun and Abraham (2020).

Most directly, we contribute to a large literature that examines the economic and social effects of resource booms in the United States.[3] To our knowledge, we offer the first event-study analysis of historical oil and mineral discoveries in the United States, allowing for more robust causal inference. Because many major resource deposits were discovered in the late 1800s, researchers often rely on the use of cross sections of data which are not well suited to identify pre-trends in development. Because we observe many (e.g., fifty years) of pre-discovery population data, we can better isolate and identify the causal effect of discoveries. This alone constitutes a significant contribution to the existing literature. But in addition to this, the existing literature almost exclusively estimates average treatment effects. We demonstrate that important heterogeneities exist, raising questions about the external validity of any region-specific analysis.

[2] It is important to note that our population analysis only applies to non-indigenous peoples. Our population data from Fang and Jawitz (2018) reconstructs spatial population distributions that do not consider Native Americans, because the US Census did not begin counting Native Americans until 1900. Therefore, we stress that when we refer to uninhabited frontier locations, we mean uninhabited by non-indigenous peoples. Exploring how the population dynamics studied in this paper interacted with the pre-existing presence of Native Americans is beyond the scope of this paper but would be an interesting avenue for future study.

[3] This literature includes (Michaels, 2011; Weber, 2012, 2014; Jacobsen and Parker, 2016; Muehlenbachs et al., 2015; James and Aadland, 2011; Matheis, 2016; Allcott and Keniston, 2017; Bartik et al. 2019; Feyrer et al., 2017; Marchand and Weber, 2018; James and Smith, 2020).

Existing estimates of the medium and long-run effects of American resource booms are mixed, with some finding benefits (Michaels, 2011; Allcott and Keniston, 2017) and others finding no or negative effects (James and Aadland, 2011; Jacobsen and Parker, 2016). From the perspective of a Tiebout sorting model where people "vote with their feet", our results suggest that, on average, long-run effects of oil discoveries on the desirability of a place is strongly positive. Whether driven by marketed (e.g., labor market opportunities) or non-marketed amenities (e.g., public parks, schools, roads), people have flocked to the location of historical U.S. oil discoveries and the effect has been persistent.

This paper is organized as follows: Section 2 describes the discovery process of historical resource discoveries in the U.S., and provides a theory of how geographic properties interact with resource shocks to bring about long-run population growth. Section 3 discusses the two main identification strategies. The various data sources are discussed in Section 4 and Section 5 describes the estimation of both amenity value and transportation cost. The results are given in Section 6. Section 7 presents a series of robustness checks and Section 8 concludes.

2. Resource-discovery process & theoretical motivation

2.1. Resource-discovery process

As discussed in detail by Yergin (2011), the process of discovering oil can broadly be broken down into two periods: pre and post 1920. Prior to the early 1920s, oil fields were typically discovered by observing surface seeps and broader "surface geology" characteristics. However, limiting exploration to geology associated with surface seeps was not suitable for the vast majority of fields hidden below the ground. Based on this rudimentary technology, prominent geologists predicted that the U.S. had already reached peak oil production by the early 1900s. But the 1920s also marked the start of a technological revolution in U.S. oil exploration that relied on geophysics. The emergence of the technology was not random; much of it was developed and deployed during World War 1 and included the torsion balance, magnetometer, aerial surface plotting, micropaleontology, and the seismograph which was used by the German military to locate enemy artillery placements (Yergin, 2011).

While this more sophisticated technology proved quite useful, luck continued to play a significant role in the oil-discovery process and great uncertainty remained about how much oil remained in the United States. In fact, in 1923, the Federal Trade Commission warned that "The supply of crude petroleum in this country is being rapidly depleted". This point is highlighted by Yergin's description of the 1920s discovery of oil on Signal Hill just south of Los Angeles, California. The discovery came as a surprise, setting off a stampede of oil companies to an area that was in the process of being developed into residential lots.

Anecdotally, "surprise" is a common feature of major historical oil discoveries in the United States. Consider, for example, how the Yates oil field in Texas was discovered in 1926. The property was originally purchased for the purpose of ranching. The land owners, Ira and Ann Yates, reportedly had no idea their land was home to one of the largest oil fields in North America. It was not until they experienced financial difficulties that they, on a hunch, hired Transcontinental to drill an exploratory well. "The well turned into an uncontrolled gusher, producing so much oil that they had nowhere to store it. So much oil was produced and with no nearby infrastructure, the only way to contain it was to dam a nearby canyon to create a large holding pond".[4] The discovery of the East Texas oil field was similarly surprising. According to the Texas State Historical Society,[5] when the East Texas oil field was discovered in 1930, "no one appeared more surprised than Joiner [the owner of the well]". Further to the north, the discovery of oil in North Dakota "climaxed years of exploration, drilling, and hoping". Prior to discovery in 1951, oil "was not easy to find, and many people scoffed at the idea of finding it in North Dakota... There was definite reason for their pessimism. All attempts to find oil in the state prior to 1951 had ended in failure".[6] The early discovery process in Colorado followed a similar trend. The first (failed) oil wells were drilled in Rangely Colorado in 1901. It took three decades until a major discovery was made in 1931. By 1933, the producing well would be named "the most productive oil well of all time".[7]

Discoveries of minerals followed a related process. Whereas prospectors did not randomly search for valuable deposits, there was great uncertainty about where and when discoveries would be made. Over half of the mineral discoveries in our data cite ore mineral outcropping as the primary discovery method. In other words, prospectors might have found mineralization in a stream bed, and looked upstream until the orebody outcropping was spotted. Geochemical, magnetic, and aerial survey techniques are not identified as discovery methods for any deposits in our dataset (though many observations have unknown or missing discovery methods). For gold, prospecting may start with familiar panning techniques. Iron ore can be observed through oxidation. Many discoveries, like that of the Climax molybdenum deposit, are likely to be the inadvertent result of prospecting for gold.

Anecdotally, some of the largest mines operating in the United States today were initially discovered by unexpectedly spotting anomalous features in a landscape. For example, the largest zinc mine in the world, Red Dog, was discovered when Alaska bush pilot Bob Baker noticed discoloration in a creek (Kelley and Jennings, 2004). The deepest open pit mine in the world, the Bingham Canyon Mine, was discovered when two ranchers and loggers were prospecting for minerals in their spare time (Richardson, 1993). The largest copper mine in North America, the Morenci Mine, was discovered when California patrols pursuing Apache Indians spotted colorful outcroppings.[8]

[4] See https://www.landmanblog.com/yates-oil-field/.
[5] See https://www.tshaonline.org/handbook/entries/east-texas-oilfield.
[6] See https://commons.und.edu/cgi/viewcontent.cgi?article=2047&context=theses.
[7] See https://townofrangely.colorado.gov/history.
[8] https://www.co.greenlee.az.us/history/morenci-mining-district/

In reviewing the discovery process of historical oil and mineral discoveries, we conclude that, while exploration was traditionally guided by observed geography and surface geology, there was great uncertainty about where and when a natural resource would ultimately be discovered. Anecdotally, discovery was very much driven by chance, often the result of happenstance or luck. Further, in the case of oil, the surge of discoveries in the early 1900s (see Appendix Fig. A.2) was largely driven by exogenous shocks in exploration technology. We rely on these features of the discovery process in our identification strategy, discussed in detail in Section 3.

2.2. Theoretical motivation

According to Corden and Neary (1982), large natural-resource discoveries—and booming resource sectors more generally—increase local demand for labor. By offering relatively high wages, a resource sector has the potential to pull labor from other sectors (e.g., service and manufacturing), and wages in all sectors rise as a result. The subsequent rise in wages can also create a demand shock for non-resource goods and services. This causes the price of services to rise (because service prices are determined locally), but leaves the manufacturing price unchanged as this price is assumed to be determined by national or international markets. Rising service prices incentivize additional services production and employment. With sufficiently high labor migration costs, the theory predicts that resource-boom towns are characterized by high wages, large resource and service sectors, and small (traded) manufacturing sectors. Further, if the traded sector benefits from learning-by-doing (or some other positive production externality), a one time resource shock (that depresses the amount of learning-by-doing taking place) can reduce wages and economic growth in the long run (Matsuyama, 1992). Whether or not resource discoveries cause long run economic growth (and hence population growth) is therefore theoretically ambiguous.

The existing empirical evidence strongly supports the idea that booming natural-resource sectors cause local wages to rise (see for example (Weber, 2012, 2014; Jacobsen and Parker, 2016; Allcott and Keniston, 2017; Feyrer et al., 2017; Richter and James, 2018; James and Smith, 2020)). Further, there is little evidence that manufacturing employment shrinks in response to booming resource sectors (Allcott and Keniston, 2018) To the contrary, local non-resource sectors tend to be pro-cyclical to resource shocks (Maniloff and Mastromonaco, 2017). One possible explanation is that significant inward migration offsets some of the Dutch Disease effects (Beine et al., 2015) and it is well established that resource booms—and energy booms in particular—attract labor from near and far away (Richter and James, 2018; Wilson, 2020).

In the event that the extraction process is long lasting, a resource discovery has the clear potential to create long run population growth. However, even a short-lived labor demand shock can have persistent effects due to agglomeration. Existing studies examine how historical events that concentrate populations in certain areas lead to agglomeration effects and persistent development, or "path-dependence". Bleakley and Lin (2012) show that portage locations in the South and Mid-Atlantic United States, made obsolete by more modern transportation modes, have maintained their outsized role as economic hubs. Some portage sights have even grown into major metropolitan centers such as Philadelphia and Chicago. Michaels and Rauch (2017) provide additional evidence of path dependence by studying the collapse of the Roman Empire, which they argue allowed Britain to reset its urban network achieving more favorable coastal access for long run growth. See also Jedwab et al. (2017) who study colonial rail networks in Kenya and Davis and Weinstein (2002) who examine the dynamic effect of negative shocks to city sizes from the allied bombing of Japanese cities during World War 2. Central to the idea of path dependence is the idea that established communities offer economic advantages over less populated areas. These advantages might come in the form of reduced transportation costs of goods (Krugman, 1991) or of labor (Glaeser, 2010). Others argue that agglomeration benefits come from knowledge spillovers and learning by doing. A related theory posits that firms in urban areas share public goods that are inputs to production—such as access to deep labor markets, transportation infrastructure, schools, and other services (Eberts and McMillen, 1999). The per capita cost of building and maintaining an airport, for example, decreases as population rises and is prohibitively expensive for sparsely populated areas. It is worth noting too that positive resource shocks tend to generate additional public revenue that state and local governments can use to finance public goods such as education and transportation infrastructure (James, 2015).

In this context, a key determinant of the long run effect of a resource discovery is whether the resulting shock is both necessary and sufficient for agglomeration to develop. A small discovery might not attract a sufficiently large number of people to finance the fixed costs of building a town. In this case, when the resource is exhausted, people simply move away. In the event a resource discovery is not "necessary", the discovery site would have been developed even in the absence of the discovery. Southern California, for example, is rich with natural amenities and sea ports and also happens to be home to some of the largest oil fields in North America. Even today, southern California produces roughly the same amount of crude oil as Alaska. And yet, it is difficult to imagine that the oil-rich counties of Orange, San Luis Obispo, Kern, Los Angeles, Monterey, Santa Barbara, and Ventura would not be heavily populated in the absence of major oil discoveries occurring in the late 1800s and early 1900s. And of course neighboring counties that did not experience large oil discoveries—such as San Diego, Santa Clara, and San Mateo are similarly populated. This observation is consistent with asymmetry in the medium and long run population effects of historical resource discoveries. Whereas highly desirable locations, such as southern California, might develop even in the absence of major resource discoveries, other, less desirable locations, may not.

Based off of these observations and the existing literature, we predict that major resource discoveries attract labor and increase the local population. Whether this effect is persistent and long-lasting depends on the pre-existing desirability of the discovery site. People are likely to move to high-amenity locations even in the absence of discovery. As such, we expect to find minimal long run effects of discoveries in such places. Less desirable locations—with rugged terrain, cold weather, and geographic isolation—are less likely to populate without the lure of high wages resulting from a natural-resource discovery. As such, we expect to find relatively large effects of discoveries in these places.

3. Identification strategy

Our main analysis is an event-study framework that estimates the dynamics of population around the time that a resource discovery is made. Our analysis separately considers two varieties of high-value non-renewable resources: oil fields and metallic mineral deposits.[9] Oil fields and mineral resources provide complementary evidence of the effect of non-renewable resource discovery on long-run economic development. Generally speaking, oil fields in the United States are geographically larger, economically more valuable, and have longer periods of utilization relative to mineral deposits. We therefore anticipate finding more significant and persistent treatment effects for oil. The unique geographic and temporal distribution of oil and mineral discoveries also lends to somewhat distinct empirical strategies. The complementary nature of these strategies show the robustness of our findings, while also providing insight into the underlying mechanisms. Since America has been thoroughly prospected and only a few discoveries have been made since the 1950s, our treatment sample should closely correspond to the true distribution of resources within the United States.

Our analysis considers heterogeneity across two dimensions: local amenity value and transportation cost to national and international markets. Local amenities are utility-improving exogenous characteristics relating to weather, proximity to mountains and coasts, and soil quality. Transportation cost is based on the distance from—and topographic features between—a particular location and the nearest market. We create a discrete three-point scale of locations based on their favorability in these two dimensions. The most favorable locations have high amenity values and/or low transportation cost. Unfavorable locations have low amenity values and/or high transportation costs. Moderate locations fall in between. We assign locations into low, medium or high bins according to 20th/80th percentile cutoffs of our numerical amenity and transportation cost values (the construction of these measures is described in Section 5). To evaluate heterogeneous effects of resource discovery, we separately estimate effects within each amenity and transportation cost bin.

The event study examining effects of resource discoveries on local population density is specified below:

$$\ln(\text{Pop})_{i,s,t} = \alpha + \sum_{u \neq -10} \beta_u E_{i,t+u} + \sum_{t=1870}^{2000} \gamma_t X_i + \phi_i + \delta_{s,t} + \epsilon_{i,t} \tag{1}$$

where $\ln(\text{Pop})_{i,s,t}$ is the natural log of population density for county i in state s in census year t,[10] $E_{i,t+u}$ is a set of indicators equal to one if county i experienced a major discovery,[11] u years ago, with $u = -10$ as the omitted category. A set of year indicators is given by γ_t and X_i is a set of fixed properties of county i. These properties include dummies for whether the county is in the low, medium, or high amenity bin, whether the county is in the low, medium, or high transportation cost bin, and the population density as of 1870 to control for convergence effects. County fixed effects are given by ϕ_i and $\delta_{s,t}$ is state-year fixed effects. The coefficient of interest, β_u, represents the effect of discovering oil u years ago. We observe population every 10 years (corresponding to national censuses) from 1870 to 2000 (excluding 1960, which is missing from our population data. See Section 4.3), using 1870 as a cutoff because that is before the first major oil discovery and also when the vast majority of counties have non-zero population and thus are not dropped from our natural-log specification. We assign the event year (u=0) as the first census year after a county makes its first discovery. Standard errors are clustered at the county level.

We first estimate Eq. (1) for the full nationwide sample of counties to find an overall average effect of oil discoveries. We then estimate it separately for each transportation cost and amenity bin to study heterogeneous effects by location favorability. When analyzing a certain amenity bin, we retain our transportation cost-by-year interactions as controls (and vice versa), which is important since amenity value and transportation cost are correlated. For the full sample, we expect β_u to be positive in the periods after discovery. We also expect the population effects in favorable locations to be smaller than in unfavorable locations.

We conduct an analogous exercise for mineral discoveries, with several key differences. Whereas our data on oil fields is given at the county level,[12] we know the precise spatial coordinates of mineral deposits (e.g., the mine shaft entrance or center of the ore-body). We leverage this property along with our geospatial data providing decennial population estimates at a 1-km^2 cell resolution to analyze cell-level population effects in close proximity to mines. A cell-level analysis offers some advantages over a county-level one. First, mineral deposits are more geographically confined than oil fields, and cell-level analysis allows us to more accurately define treatments based on mine proximity. Second, since mineral deposits are more common in mountainous areas, they tend to appear in less densely populated and geographically larger counties with a mix of rugged and flat terrain. (Even within the western US, counties with a mine discovery are roughly twice as large on average as those without.) Cell-level analysis allows us to more precisely control for local terrain ruggedness.

[9] Metallic minerals include the precious metals (e.g. gold, silver, platinum group metals), major metals, (e.g. iron, copper, lead, zinc, tin, aluminum), alloying metals (e.g. nickel, molybdenum, cobalt), rare and specialized metals (e.g. the lanthanides, gallium, lithium, uranium, beryllium). However, we exclude nearly all non-metallic mineral resources (e.g. sand/gravel, clay, stone, phosphate, pot ash). We also exclude coal resources (despite their regional significance) because the discovery of major bituminous coal basins in the United States pre-dates the country's independence, let alone our population data. Carrying out an event study of the effects of discovering coal deposits is not feasible.

[10] To account for shifting county borders over time, for each census year we find the population within present-day county borders using our spatial population dataset. See Section 4.3 for further detail.

[11] As detailed in Section 4, a major oil discovery is of a field known to contain at least 100 million barrels. A major mineral deposit is one described as "world class" in the USGS Mineral Resources Data System.

[12] As discussed in Section 4, we know the counties in which major oil fields were discovered, but we do not know the precise locations of fields.

Another key difference for our mineral analysis is that the vast majority of major mineral discoveries occurred in the western U.S. at a time when it was extremely sparsely populated by non-indigenous peoples. (The first gold rush in northern California occurred in 1848, the same year most of the western U.S. was annexed from Mexico.) We therefore limit our mining sample to western states.[13] We also use the sample period of 1850–1950, which covers the period from when most of the West became U.S. territory to at least a few decades after the vast majority of mineral discoveries.

For our baseline mineral specification, a cell is considered treated if it is within 30 miles of a major deposit that has been exploited.[14] Deposits tend to be in especially rugged mountain areas and the associated mining towns sometimes locate fairly far away in the nearest flat land (Durango, Colorado for example). There is a tradeoff between choosing a treatment distance that is large enough to capture this phenomenon but small enough that any effects are not washed out over large distances. We choose 30 miles as a baseline, as the resulting footprint of a circle with radius 30 miles (2,827 square miles) is roughly equal to the average size of counties in our Western US sample (2,866 square miles), so treatment areas are commensurate with our county-level oil analysis. But we also estimate effects using 5, 10, and 50 miles in Appendix B.

Because the vast majority of cells are uninhabited by non-indigenous peoples at the beginning of our sample period, we also modify our outcome variable in Eq. (1) to be a binary indicator variable that equals 1 if the cell contains a population of at least one and zero otherwise. We therefore consider this an analysis of extensive margin population effects in the American West. Fig. A.7 shows how this cell-level population dummy evolves over space and time within our sample. The fact that the Western U.S. is so sparsely populated during the mineral-discovery period makes this setting particularly relevant for testing the theory outlined in Section 2.2.

Finally, we also modify our control variables for the mineral analysis. First, we re-bin the amenity index and transportation cost measures for the Western U.S. cell-level sample, again using 20th/80th percentile cutoffs.[15] Second, we do not control for convergence effects since the outcome is an indicator dummy and the initial population is zero for the vast majority of the sample. Third, we create cell-level ruggedness bins (again using 20th and 80th percentile cutoffs) and additionally control for ruggedness[16] interacted by year; although average cell ruggedness is a component of our county-level amenity value that is applied to cells (see Section 5.1), we can measure local ruggedness much more precisely at the cell level, and this is plausibly a major factor in determining cell-level population growth. Finally, for the mineral analysis standard errors are clustered at the zip code level.[17]

4. Data

In this section we describe the data sources used in the estimation of Eq. (1). We collected additional data from a variety of sources for the estimation of county-level amenity value and transportation cost. That data is discussed in detail in the corresponding amenity and transportation cost estimation in Section 5 below.

4.1. Oil-discovery data

Data on large, historical oil field discoveries were collected from the Oil & Gas Journal Data Book (2000). The book identifies, by year and field name, all U.S. discoveries of oil fields containing at least 100 million barrels of oil up to the year 1999, of which there were 263. Oil fields were matched by name to U.S. counties using the Energy Information Administration (EIA) Oil and Gas Field Code Master List, 2015. Matching oil field discoveries to U.S. counties decreases the number of observed discoveries to 231.

We confirm using historical references that the discovery year reported in the Oil and Gas Journal Data Book corresponds to the date of first production. During the historical period of greatest interest, initial production from a well was often required to determine if a field had the potential to produce hundreds of millions of barrels, or to produce any oil at all. From the standpoint of identification, this suggests a limited ability for a population to anticipate a discovery of a large field (eg. $>$ 100 million barrels) in the time period before first production.

Panel (a) of Fig. A.1 shows the spatial distribution of major oil-field discoveries. The majority of discoveries took place in a handful of states: Texas, California, Wyoming, Montana, Utah, Oklahoma, Louisiana, and New Mexico, though a number of discoveries were also made in North Dakota, Mississippi, Kansas, Colorado, Arkansas, Alabama, and Illinois. Fig. A.1(b) describes the temporal distribution of the discoveries. The earliest discovery was made in 1880, and the latest in 1988. The large majority of the discoveries were made early in the 20th century. For example, roughly 85% occurred prior to 1950 and 45% occurred prior to 1930. Only 9 discoveries (3.4%) occurred post 1970.

For context, we estimate the gross in-situ value of oil fields at the time of their discovery. Using price data from BP's Statistical Review of World Energy, we estimate that the median discovery has a value of $2.6B in 1998 USD. The 5th percentile field is $1.2B and the 95th percentile is $18B.

[13] These states are: New Mexico, Colorado, Wyoming, Montana, Arizona, Utah, Nevada, Idaho, California, Oregon, Washington.

[14] The USGS mineral deposit data indicates present-day development status. We only use mines with status "Producer" or "Past Producer" and do not use those with status "Occurrence" or "Prospect". This eliminates 15 of the 194 world-class deposits in the Western US.

[15] Our amenity index is constructed at the county level, so we assign each cell within a county the same index score. See Section 5.

[16] See Section 5.2 for information about our ruggedness measure.

[17] An alternative would be county-level clusters, but for the regressions that restrict the sample to certain amenity or transportation cost bins this results in more parameters than clusters.

4.2. Mineral-discovery data

Data on the location (geographic coordinates), date, and significance of metallic mineral discoveries comes from the USGS's Mineral Resources Data System (MRDS). MRDS characterizes the size of mineral discoveries as being of "world class significance" or not. This is a qualitative designation by the USGS, but is based on the total endowment of contained commodity, which includes all past production and reserves. Each commodity is considered separately for this designation. In other words, the tonnage required for world class significance is different for gold than for iron.

We define the event year for a mineral discovery as the first census year after the mine is discovered, though for several mines this date of discovery is not available. For these cases, we use the first production date instead. If both the discovery year and first production year are unavailable, we do not include the mine in our analysis. This eliminates an additional 39 world-class deposits from our sample (after dropping non-producing deposits). Cells near multiple mines are assigned the earliest event year. We do not include cells with an event census year before 1860 or after 1950, so that we have at least one observation before and after treatment for each treated cell, and those are compared only to cells that are untreated. This leaves us with 129 world-class deposits with which to identify effects of mineral discovery.

As shown in Fig. A.1, mineral resources exist primarily in the western United States. While the eastern United States contains a significant number of individual coal mines and non-metallic mineral quarries, we do not consider these resources in our analysis. Fig. A.1(b) describes the temporal distribution of the world-class discoveries within the western US. The earliest discovery was made in 1800 (though the next one was not until 1848), and the latest in 1981. The majority of the discoveries were made late in the 19th century. Roughly 74% occurred prior to 1900, and 43% occurred prior to 1880. A little over one third of the deposits produce gold as the primary commodity, but the sample contains a number of copper, zinc, iron and molybdenum deposits as well. As with oil, we estimate the gross in-situ value of world class mineral deposits at the time of their discovery, with mineral price data assembled from USGS Series 140. For the 65 deposits with sufficient data on grade and tonnage, we estimate that the median discovery has a value of $302 m in 1998 USD. Relative to oil fields, mineral deposits have a much larger range of values. The 5th percentile deposit is $0.6 m and the 95th percentile is $31.5B.

4.3. Population data

Various data limitations restrict our analysis to population dynamics, but this is also an important outcome variable to consider. In a subnational setting with minimal labor-migration frictions, population density can be a more revealing statistic than, say, average income which may reflect significant inequality, regional price differences, or serve as a compensating differential.[18] It is worth mentioning too that existing literature has used population density as a proxy for historical levels of economic development (Acemoglu, Johnson, and Robinson, 2002) or to test for path dependence (Bleakley and Lin, 2012, 2015).[19]

Our population data comes from Fang and Jawitz (2018), which provides geospatial population count estimates at a 1-km^2 resolution for every decade from 1790–2010 except for 1960, for which digital urban population data are missing. Estimates are based on county-level census counts, which are then down-scaled to the 1-km^2 level using five models of increasing complexity. We use the most complex model "M5", which is demonstrated to be the most accurate. This specification utilizes the spatial extent of urbanization and non-inhabitable areas (e.g., water bodies and mountains), topographical features and the distance to city centers to disaggregate county census counts. Some of the inputs to the Fang and Jawitz (2018) model are similar to variables we use in constructing our amenity index, such as topographical data (see Section 5.1). This does not confound our analysis of amenity impacts because our amenity scores are constructed at the county level, and the Fang and Jawitz (2018) model is only used to distribute census population counts within counties.

For our county-level analysis of oil-resource discoveries, we aggregate the 1-km^2 resolution population maps up to modern county boundaries. In this way, we have a consistent spatial unit for analysis over time. For our analysis of mineral discoveries, we use the 1-km^2 data directly. A potential adverse consequence of using estimated population data is that it may attenuate our mineral-discovery results (oil-discovery results will be unaffected as they are estimated at the county level). Population growth nearby a mine that is not large enough to be defined by Fang and Jawitz (2018) as an urban area (defined as population >2,500) can be partially diffused throughout the rural portions of a county, underestimating population in the treatment nearby the mine and overestimating population further away in the control areas.

The unconditional means of population outcomes, as well as the amenity and transportation cost estimates, are presented for oil rich and oil poor U.S. counties in Table A.1. Cell-level population statistics for mineral-rich and mineral-poor cells are given in Table A.2. It is worth noting that, prior to discovery, oil-discovery counties are significantly less populated than those in the control

[18] Because people move in order to maximize their utility (and not their income), relatively high wages may be demanded in less desirable locations, and vice-versa. This makes interpreting income as a quality of life indicator challenging; a long run increase in income suggests that other (perhaps non-marketed) features of a place have degraded. In the context of resource booms, Tsvetkova and Partridge (2016) argue that, "In mining boomtowns with socioeconomic, congestion, remoteness, and environmental concerns, high income is to a large extent a compensating differential, while during the bust, some of the income decline reflects less of a need for such compensating differentials".

[19] Our population analysis only applies to non-indigenous peoples. Our population data from Fang and Jawitz (2018) reconstructs spatial population distributions that do not consider Native Americans, because the US Census did not begin counting Native Americans until 1900. Therefore, we stress that when we refer to uninhabited frontier locations, we mean uninhabited by non-indigenous peoples. Exploring how the population dynamics studied in this paper interacted with the pre-existing presence of Native Americans is beyond the scope of this paper but would be an interesting avenue for future study.

group. Conversely, counties that discovered "Large" oil fields were slightly more populated than those that discovered "Small" fields. It is also interesting to note that the dispersion in population across the various groups widens significantly by the year 2000, with population in oil discovery counties increasing by a relatively large amount. The opposite pattern exists in the mining data. Prior to discovery, cells within thirty miles of a mine are significantly more likely to be populated than those further away from mines. Taken together, while populations vary across treatment and control units prior to resource discoveries, the variation does not appear to be systematic. We also carry out a series of robustness checks to limit the degree of pre-existing heterogeneity (see Section 7).

5. Amenity value & transportation cost

Our analysis considers heterogeneity across two dimensions of location favorability: local natural amenity value and transportation cost to the nearest market. In this section we describe the construction of each. Local amenities are utility-improving characteristics such as temperature, humidity, soil productivity, and sunlight hours. Transportation cost is based on the distance from—and topographic features in between—a particular location and the nearest market.

5.1. Estimation of amenity value

We construct an index of amenity value that reflects a large variety of strictly exogenous, naturally-occurring environmental characteristics. We focus on exogenous features to avoid problems associated with reverse causality (historical resource discoveries potentially influence the contemporary distribution of public goods). These characteristics are theoretically utility improving for residents, and as we describe in Section 2.2, higher levels of amenity should, all else equal, result in larger population levels. We leverage this intuition in constructing our index. Namely, we regress the total population living in a county on a vector of county-level amenity characteristics and state fixed effects. The resulting regression coefficients (excluding state fixed effects) are then used to construct a county-level amenity index, as described below.[20]

For a given census year, we flexibly model amenity-driven population using the following specification:

$$ln(Pop)_{i,t} = \sum_{k} f(a_{k,i}) + s_i + \epsilon_i, \quad \text{for} \quad t \in [1870, 2000], \tag{2}$$

where $Pop_{i,t}$ is the natural log of population density in county i in decade t, s_i are state fixed effects, and $a_{k,i}$ refers to a particular amenity k for county i. Recognizing that the effect of continuously measured amenities (such as temperature) may be highly non-linear, we flexibly model the effects of such amenities with a set of decile bins for each amenity. These amenities are average January temperature, average July temperature, average January sunlight, average annual humidity, average annual rainfall, soil quality, and terrain ruggedness. We also include dummy variables that identify counties on the coast, near (within 50 miles of) a mountain range, and within a mountain range. Finally, we control for a location's transportation cost using the estimates described in Section 5.2.

To calculate the index value for a given county, we multiply the coefficient values from Eq. (2) by the county's amenity variables, but exclude transportation cost (so the index is conditional on transportation cost) and state fixed effects. Therefore we are identifying amenity values using within-state variation, but then applying these values across the country without including state averages, which are impacted by many other unobservable factors.[21]

Finally, we allow for the effect of these amenities to change in value over time by estimating Eq. (2) separately for each decade, and likewise construct the index separately by decade. The index is then averaged over time to provide a single value of amenity that reflects both contemporary and historical preferences for various amenities over our sample period. For our cell-level mineral analysis, cells are assigned the amenity index value of the county they lie within. We use this information in our analysis of resource discoveries by assigning counties (or cells) to either high, medium or low amenity groups based on 20th and 80th percentile cutoffs.

One concern with using population as an outcome measure to construct an amenity index is that it is circularly related to our main outcome variable: population density. This would be true if the effects of interest were the main effects of amenity value on population. But we are specifically interested in the marginal effect of a resource discovery given a certain level of amenity. This is somewhat analogous to the intuition of a quantile-style regression model, but instead of dividing the range of the outcome variable by quantiles of its distribution, we divide estimates by the distribution of the outcome according to the amenity index.

[20] Our estimation of amenity value fits into a large literature that estimates the value of non-marketed amenities. Following Rosen (1974, 1979)), hedonic price models assume that environmental amenities are capitalized into local prices. Examining wages and housing prices in the United States, Albouy et al. (2016) estimate willingness to pay (WTP) for a variety of exogenous environmental amenities including sunshine and temperature. Population density is also strongly correlated with exogenous, non-marketed environmental amenities such as temperature, sunshine, and precipitation (Albouy and Stuart, 2014). Because we are interested in estimating historical non-marketed amenity value, and lacking detailed historical data on wages and land prices, we use predicted population density as a proxy for amenity value. We construct a novel index because of the geographic and temporal limitations of existing indices (Waltert and Schlaäpfer 2010).

[21] Suppose we did not include state fixed effects in Eq. (2). Then this analysis would be vulnerable to over-fitting. For example, the Eastern U.S. is much more densely populated than the west, which may be for many reasons unrelated to amenities. Without state fixed effects the model would simply weight amenity traits that are common in the east. Because we are using many amenity traits, the within-sample predictions would likely be very good even if all predictors were in fact irrelevant. But by conditioning on state fixed effects, we eliminate correlations based on broad regional patterns of population density, and identify amenity value based only on within-state variation. Then, excluding state fixed effects from the amenity index calculation ensures that we only base the index on observable amenity traits that apply equally to all counties.

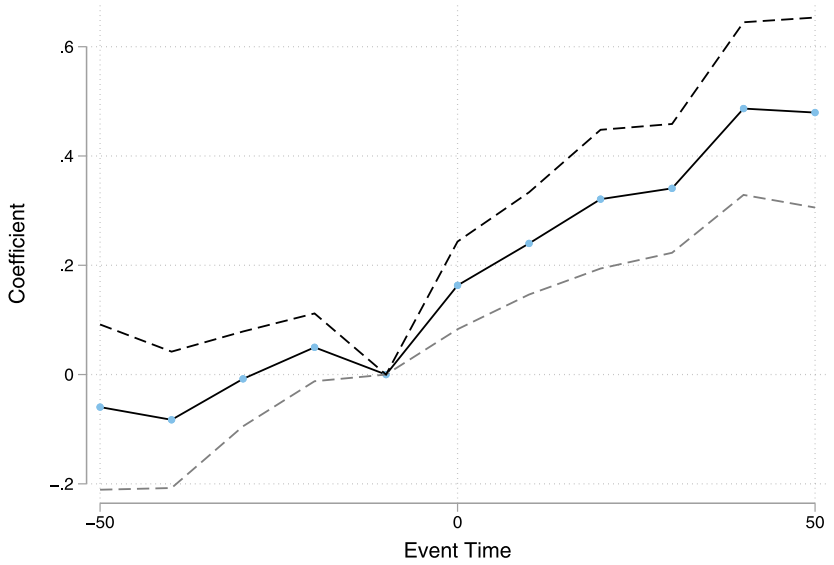


Fig. 1. Log population density effect of oil discovery.
The graph plots the average effects of oil discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. In the pooled dataset, population density is 20% (65%) larger in oil rich counties one (five) decades after discovery relative to counties without a discovery.

Panel (a) of Fig. A.4 describes environmental amenity value by county. For comparison, panel (b) maps population density in 2000. Several notable features emerge. First, the correlation between our amenity index and observed population density in 2000 is quite strong. Our model predicts that coastal counties should be more heavily populated, as well as mid-western counties east of the Rocky Mountain range. The model also predicts that the Salt Lake Valley and Denver county (which are relatively flat places, but near mountains) should be more heavily populated relative to nearby counties, which we also observe. We also predict that the northern part of the U.S. should be less populated due largely to below-average temperatures. There is also some error in the model. For example, whereas we predict southeastern Arizona should be sparsely populated due to its very arid and hot climate, it is actually densely populated. We similarly predict that parts of northern California and southern Oregon should be more heavily populated than they are. For the year 2000, the correlation between our predicted log of population density and actual log density is 0.57.

Several sources of data are utilized to construct the amenity index. Data on temperature were collected from the USDA Natural Amenities Scale. Total January sunlight hours is measured as an average from 1941–1970.[22] Data on annual rainfall (averaged over 1961–1990) by county comes from the USGS.[23] County-level soil quality data come from Schaetzl et al. (2012) and measure exogenous "natural native soil productivity", which reflects soil characteristics such as soil tilth, clay mineralogy, organic carbon content, and the presence of root-impeding layers. Our spatial mountain range shapefile comes from "Landforms of the World", from ArcGIS online. The measure of terrain ruggedness for 1-km^2 cells is described in the following subsection. For the county-level amenity index, we use the average ruggedness measure for cells within a county.

5.2. Estimation of transportation cost

This subsection describes the construction of the transport-cost variable used in our main analysis. We first describe the nature of the transportation cost problem and then discuss a discrete formulation of the problem and how it is parameterized.

Broadly, we are interested in the variable cost $C_{f,m}$ of moving goods between a frontier location f and the nearest market m. One approach would be to proxy for $C_{f,m}$ using "as-the-crow-flies" distance between f and m, as in Redding and Venables (2004), for example. However, this distance ignores potentially important topographic features (mountains, marshland, large lakes and rivers), which may exist between the frontier and markets. In a practical U.S. context, Denver, Colorado is approximately as close to the port of San Francisco as it is to the port of Houston (approximately 1,500 kilometers). However, between Colorado and San Francisco are the Rocky Mountains, Great Basin Ranges, and Sierra Nevada Mountains, which pose significantly higher transportation costs than the relatively flat Denver–Houston route.

A second option might be to refine the distance proxy by calculating the cost along realized modern transportation networks (as in Donaldson and Hornbeck (2016)). This method acknowledges topography between f and m via the realization of the network;

[22] See Fig. A.3 for a spatial description of each of these USDA inputs to the amenity value index.
[23] The data is available at: https://catalog.data.gov/dataset/united-states-average-annual-precipitation-1961-1990-direct-download.

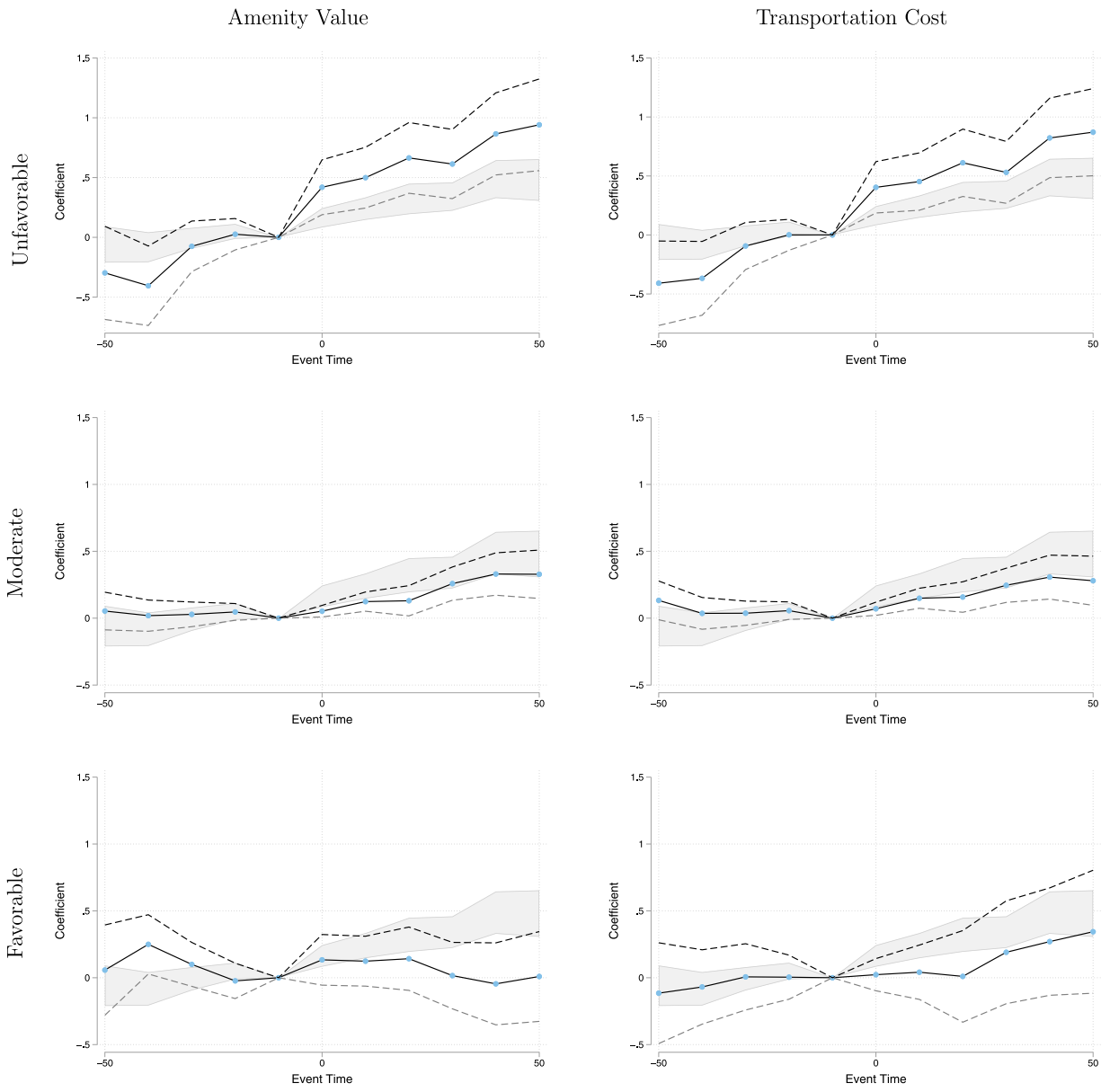


Fig. 2. Heterogeneity in population dynamics of oil-discovery counties.
The graphs plot the average effects of oil discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. The data is partitioned based on the 20th and 80th percentile cutoffs into high, medium, or low amenity and transportation groups, and separate regressions are run for each of the six groups. For reference, the shaded region is the confidence interval of the average treatment effect.

engineers incorporate the cost of building transportation networks in rugged terrain. A problem with this method in our setting is that the spatial pattern of the contemporary transportation network is potentially endogenous to historical resource discoveries, as intermittent cities develop nearby.

Given the shortcomings of these alternatives, we construct an exogenous measure of transportation cost that exploits important topographic features between places. Our estimate is based on a transportation cost framework common in linear and network programming. The transportation-cost problem conceptualizes the United States as a grid of 1-km x 1-km cells, with each cell i having associated cost c_i, which is incurred to pass through it. Transportation cost is a function of the distance across the cell (which in our case is fixed at 1-km), and the topography of the cell. Each frontier location f seeks the least-cost path to any market location m across this grid. Because the actual cost of transportation within any given cell is unobserved, we develop an approximation of the transportation model's cost parameters inferred by the structure of the modern rail network. From the solution to the transportation cost problem, the likelihood of the presence of modern rail in a given cell is a decreasing function of the cost

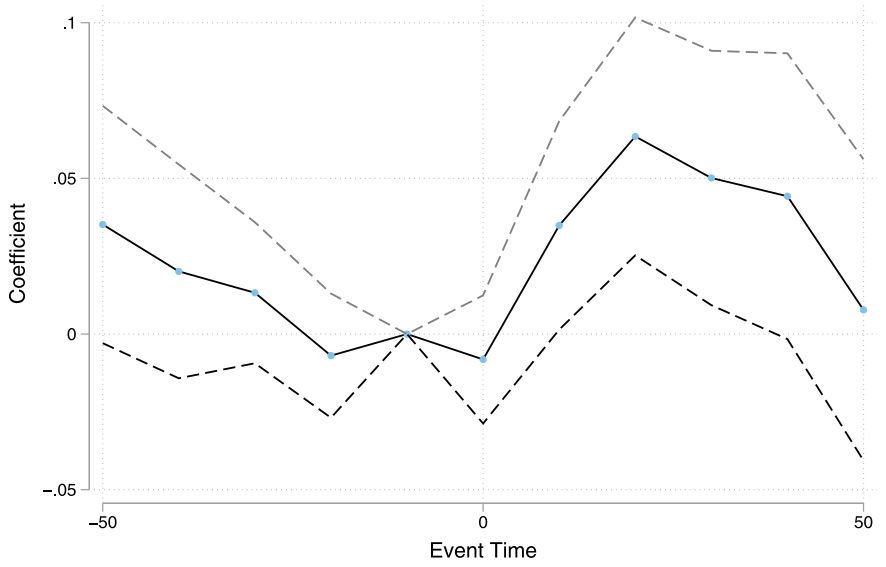


Fig. 3. Population effect of mineral discovery, 5 decades before and after.
The graph plots the average effects of a "world class" mineral discovery on the probability that a 1-km^2 cell within 30 miles of the discovery is populated. Effects are estimated using Eq. (1). 95% confidence intervals are included.

associated with traveling through that cell. We estimate this relationship using a logistic regression model of the form:

$$\text{rail}_{i,2017} = f(\text{terrain}_i) + \epsilon_i, \tag{3}$$

where the binary variable $\text{rail}_{i,2017} = 1$ if cell i contains rail as of 2017 and 0 otherwise and $f(\text{terrain}_i)$ is a function of the ruggedness of the terrain within the cell and the percentage of the cell containing water. Intuitively, both uneven terrain and bodies of water such as lakes and rivers pose significant and expensive challenges for the construction of a railroad. To measure ruggedness, we use the National Elevation Dataset (NED), which provides elevation measures at a 30 × 30 meter resolution. We define ruggedness as the standard deviation of elevation within each 1-km^2 cell in the grid. To avoid making assumptions about linearity, we include indicator variables for every percentile of ruggedness within the sample. The percentage of water within a cell is measured by decile-bin indicators for having no water, between 0%–10% water, 10%–20% water, and so on.

We use the estimated model to predict fitted probability values of observing rail in a given cell, i.e. $\text{P}(rail|terrain) = \hat{rail}$ for the entire grid. Next, we transform the model's fitted values into an approximation of cost, using the inverse of rail probability: $\hat{c}_i = 1/\hat{rail}$. This transformation is somewhat arbitrary, but makes the reasonable assumption that a cell with half the probability of containing a rail line is twice as costly to traverse (and for our purposes only relative cell costs are important, since we ultimately evaluate heterogeneous treatment effects by relative differences in total transportation costs). Intuitively it makes sense that the relationship between the probability of rail and rail construction cost is non-linear. When construction cost is very high, increasing construction cost arguably has little effect on the probability of rail. But when cost is low, increasing cost is more likely to make alternative routes more appealing from a cost-minimization standpoint.

Fig. A.8 presents the estimates from Eq. (3) of the change in rail probability associated with values of terrain ruggedness and water. We generally find a consistent negative relationship between rail probability and ruggedness, with an especially steep drop in probability at more extreme values. However, we do oddly find a steeply increasing rail probability for the first few percentiles (i.e., the most flat ones).[24] The percentage of water coverage is also generally negatively associated with rail probability.

With the transportation cost problem parameterized, we populate our U.S. grid with our estimated cost values and solve for the lowest-cost path between every cell and the lowest-cost market destination.[25] We define market destinations as rail lines existing as of 1870, marine highways, and pre-existing cities of at least 5000 people.[26] In this way, our transportation cost measure captures the difficulty of constructing a new rail line to access the existing rail or waterway network (which then allow goods to be transported

[24] This is at least partially explained by the fact that many relatively flat cells lie very near the coast, and rail lines are rarely so close to the ocean. Many other flat cells are observed in the remote salt flat region of Utah and Nevada, and also the upper reaches of the Northern Midwest where glaciers carved the landscape. Because few people live in these largely remote, and yet relatively flat terrains, there are few rail lines present. However, the overall relationships shown in Fig. A.8 are robust to state fixed effects, further suggesting that near perfectly flat terrain tends to be indicative of somewhat inhospitable land (aside from coastal cells).

[25] This is done with the "Cost Distance" tool in ArcGIS.

[26] For the analysis of oil discoveries we use cities of at least 5000 as of 1900, since this is shortly before the vast majority of oil discoveries. For the analysis of mineral discoveries, we use cities as of 1850, reflecting the timing of most mineral discoveries.

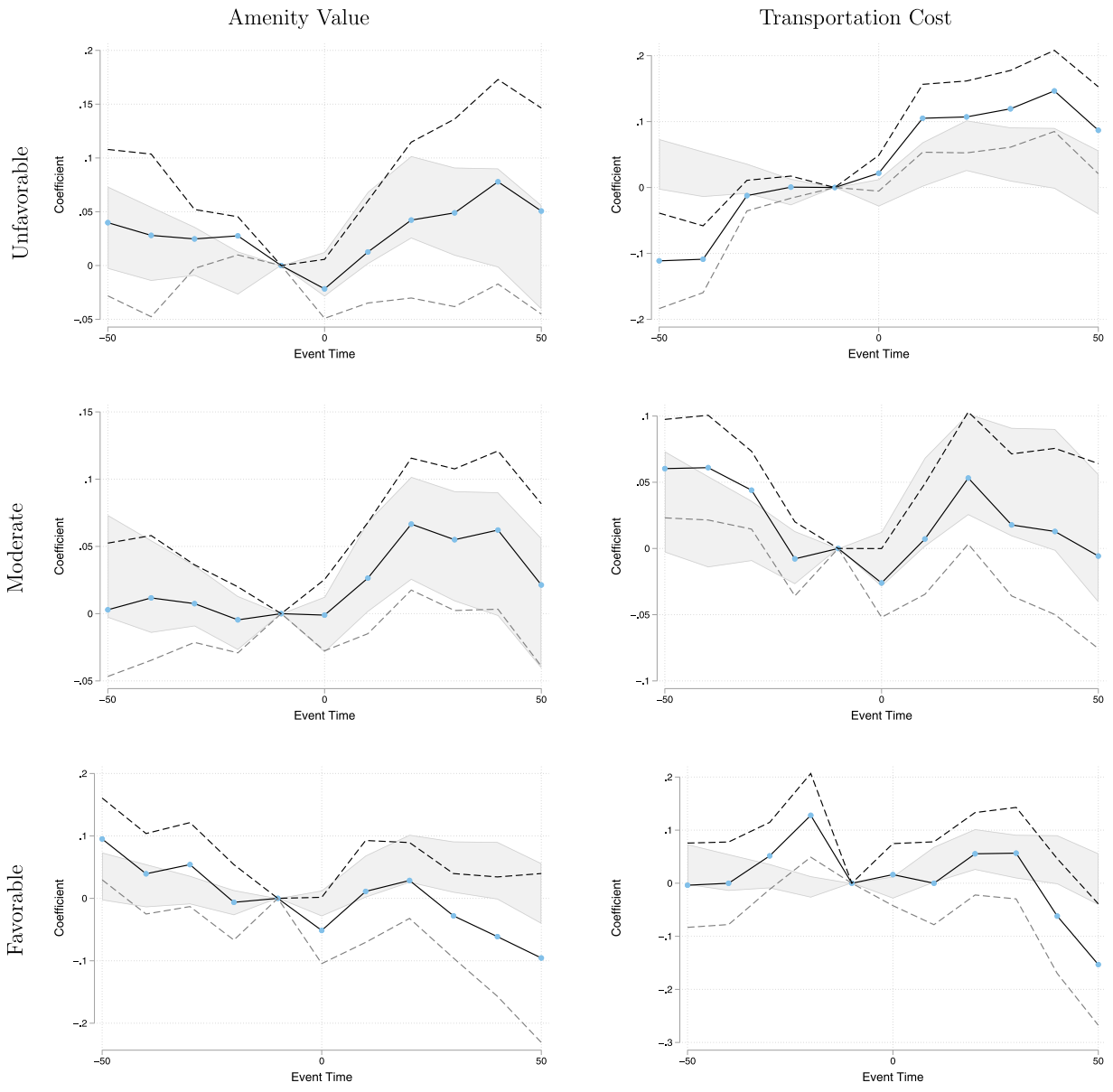


Fig. 4. Population dynamics of 30 mile mineral-discovery buffer, 5 decades before and after.
The graph plots the average effects of a "world class" mineral discovery on the probability that a 1-km^2 cell within 30 miles is populated over time and is estimated by Eq. (1). 95% confidence intervals are included. The data is partitioned based on the 20th and 80th percentile cutoffs into high, medium or low amenity and transportation groups, and separate regressions are run for each of the six groups. For reference, the shaded region is the confidence interval of the average treatment effect.

to any market destination at relatively low cost) or to a city plausibly large enough in size to serve as a market in its own right. The cost of traversing this lowest-cost path is then our cell-level transportation cost measure. Finally, we average cell-level transportation cost estimates to the county level.

We evaluate the accuracy and soundness of our transportation cost measure by comparing the predicted lowest-cost paths between cities to the actual rail network in four separate case studies. We do not expect to find that predicted paths perfectly match actual ones; by design our prediction is based purely off of exogenously determined geographic features of the landscape, and in reality, transportation infrastructure reflects a number of endogenous factors including the location of pre-existing markets. We nonetheless use these case studies to shed some light on the predictive power of our estimates, and to test whether our model simply predicts linear least-cost paths. Fig. A.5 shows these four instructive examples in the western US, where the prevalence of mountains will often make the lowest-cost path indirect. The first example, Santa Fe to Salt Lake City, shows that the modern rail network is endogenous to regional economic development. We estimate the lowest-cost path as a relatively straight line through

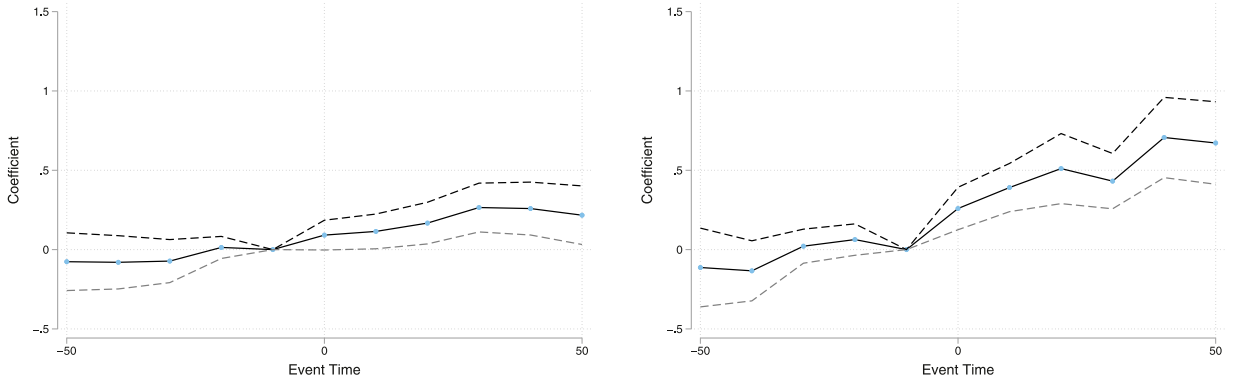


Fig. 5. Population dynamics for high and low oil endowments.
Estimated average effects on log population density and 95% confidence intervals disaggregated by high and low endowments. "Low" endowments are those below the median of the treatment group and "High" endowments are above median.

mostly flat terrain. In reality, the rail network heads north out of Santa Fe to Denver, Colorado, or west to Los Angeles, before heading to Salt Lake City, Utah. The Santa Fe, New Mexico to Salt Lake City, Utah connection is likely not important enough to build an additional, more direct route. A similar argument likely holds for the Boise–Sacramento connection. However, our predicted path aligns very well with the actual rail lines between Denver, Colorado and Las Vegas, Nevada, which avoid a route that is much more direct but covers more rugged terrain. Finally, the Boise–Helena route offers perhaps the most straightforward test of our cost parameterization: both cities are important enough to be rail hubs, there are few or no other major cities in the area that might divert rail lines, and there are mountains blocking the most direct path. In this case both our predicted path and the actual rail network go around the mountains and through the valley to the south in a very similar way, demonstrating that our procedure is at least in some cases applying an appropriately high penalty of mountain terrain in finding the lowest-cost path.

Fig. A.6 shows cell-level transportation costs, along with 1870 rail lines, marine highways, and cities of at least 5000 (green dots). The results in panel (a) limit the cities that serve as markets to those that had populations greater than 5,000 by 1850 (used for the mineral deposit results), while for panel (b) cities with populations greater than 5,000 by 1900 also serve as markets (used for the oil results). Note how costs increase rapidly as one moves east from the headwaters of the Columbia River in Washington State into Idaho and Montana, while costs rise more gradually as one moves west from Minnesota into the Dakotas. These figures show the locations with the highest transportation costs are Montana, Wyoming, North Dakota, the Four-corners area (New Mexico, Utah, Colorado, and Arizona) and Western Texas. Population expansion between 1850 and 1900 reduced the isolation of these locations to some degree, but many areas in the Western United States still remained highly isolated.

6. Results

6.1. Oil discoveries

Fig. 1 plots the estimated effects of oil discovery on logged population density by event-time for the 50 years before and after a discovery (with the first census decade prior to discovery as the reference period), along with 95% confidence intervals. Prior to discovering the resource, both oil-rich and oil poor counties conditionally grow at similar rates. Population density in oil-rich counties is 20% larger than the counterfactual in the decade a discovery is made, and 65% larger after five decades.[27] Fig. 2 plots the population dynamics associated with oil discovery when estimating Eq. (1) with the sample limited to each of the six amenity and transportation-cost groups. To aid comparison we also include the 95% confidence interval from the full-sample result from Fig. 1 (shaded in gray). Unfavorable locations are those with low amenity values or high transportation costs, favorable locations have the reverse characteristics, and moderate locations fall in between. Unfavorable locations experience by far the largest population effects from oil discoveries, while moderate locations also see significant, albeit relatively smaller, effects. Favorable locations experience no significant effects. These findings persist through the end of the sampled post-discovery period with no indication of attenuating effects 50 years after discovery. While there is some pre-existing trend for unfavorable locations 30–50 years before discovery, trend is negligible for the twenty years prior to discovery for all favorability bins.[28]

Fig. 2 shows similar effects for the low-amenity and high-transport-cost bins. This is due to similar treatment groups for both bins. Although they are constructed independently, there is correlation in favorability between amenity and transportation cost

[27] Note that the dependent variable is the natural log of population density. As such, β implies a $e^{\beta} - 1$ percent change in population density.

[28] In the robustness section we discuss the results from an alternative model specification in which the event indicator is interacted with the z-score of favorability and we separately control for the interaction of initial population and event time. This effectively reduces pre-existing trends 30–50 years before discovery that is present in the "unfavorable" panels of Fig. 2.

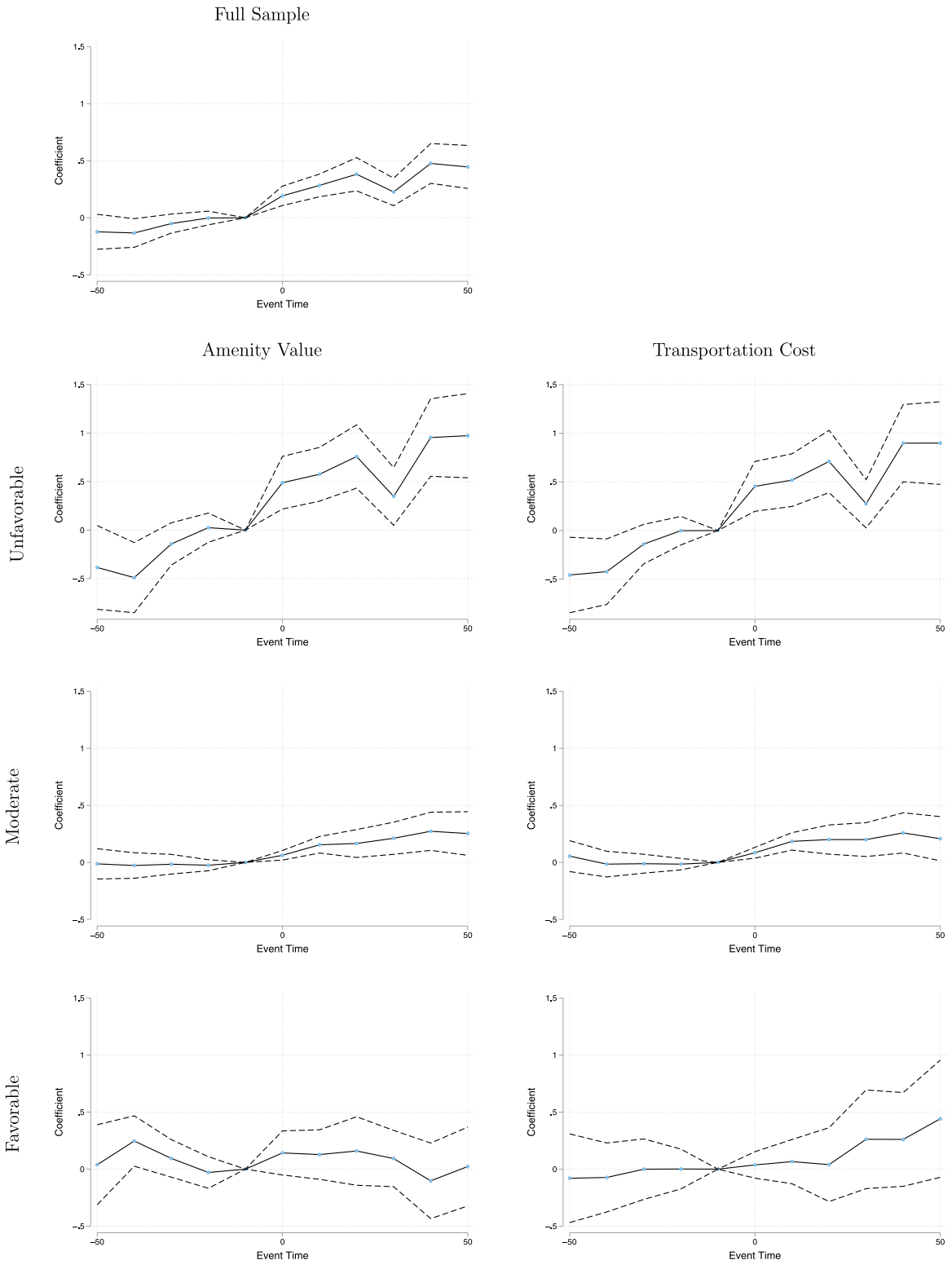


Fig. 6. Oil discoveries: interaction-weighted event studies.
The graph plots the average effects of oil discovery on log population density over time using an interaction-weighted estimator. 95% confidence intervals are included.

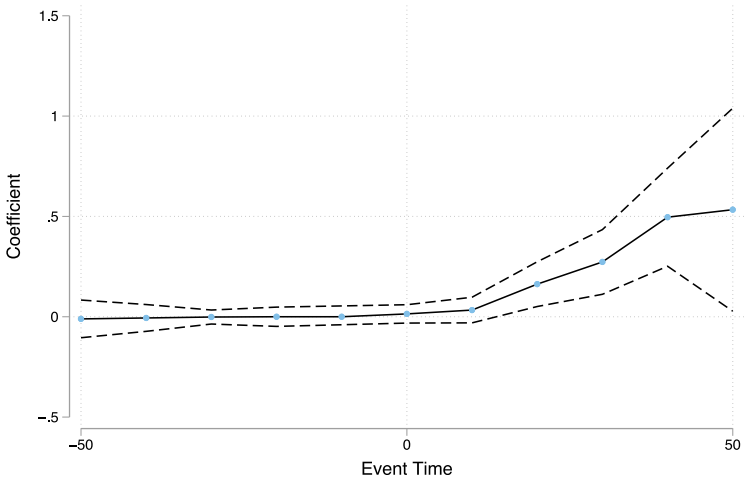
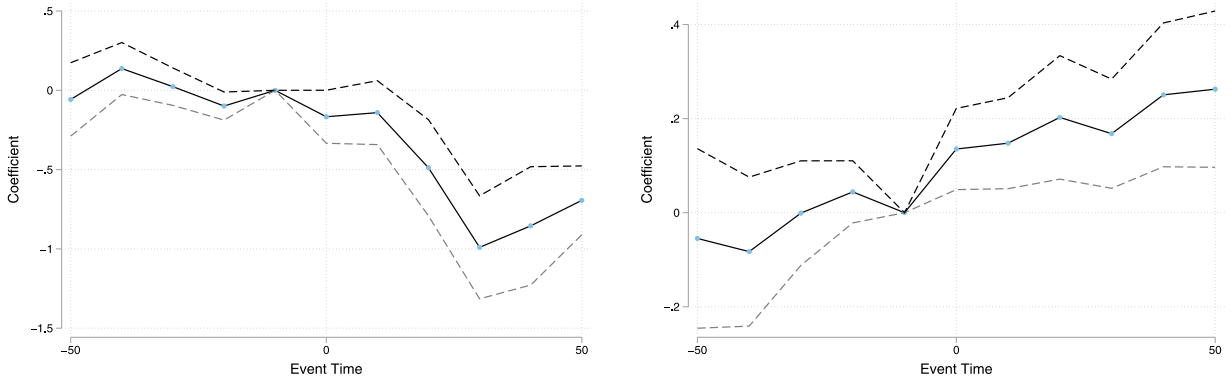


Fig. 7. Oil discoveries: only treated event study.
The graph plots the average effects of oil discovery on log population density over time using an interaction-weighted estimator. Only treated units are included in the estimation. 95% confidence intervals are included.



(a) Amenity Value (b) Transportation Cost

Fig. 8. Interaction of event year and z-score of favorability.
The graphs show the coefficients for event-time interacted with the z-scores for amenity index and transportation cost, conditional on the interaction of event-time and population density in the year 1870 and the non-interacted event-time indicators. Because amenity value and transportation cost have been transformed to z-scores, these estimates are interpreted as the additional effect of discovery given a one standard deviation increase in amenity index or transportation cost.

measures. For the full sample, there are still many counties that are counted as unfavorable by one measure but not by the other. But within the treatment group, 90% of low-amenity counties are also high transportation cost, largely due to a disproportionate number of counties in western Texas. Therefore, for the oil-discovery analysis we cannot strongly separately identify effects for low-amenity vs. high-transportation-cost bins. This is less of an issue for the mineral-discovery analysis that follows, as less than half of the low-amenity treatment cells are also high transportation cost. In any case, here the conclusion remains that effects are largest for low-favorability counties.

6.2. Mineral discoveries

We next turn to population effects of mineral discoveries estimated from Eq. (1) at the cell level and with the modifications discussed in Section 3. Fig. 3 plots the estimated effects of mineral discoveries for the five decades before and after discovery. Specifically, it plots the effect on the probability that a given cell will be populated by at least one person of a mineral-resource discovery within 30 miles. A potential concern with identification of the effect of discovery on population is that population growth in particular places may lead to resource discovery (rather than the reverse). Fig. 3 alleviates this concern by showing that prior to discovery, conditional population for mineral-discovery areas is actually trending down relative to non-discovery areas (though it is roughly flat in the two decades prior). Two decades after discovery, treated cells are over 5% more likely to be populated. However, this effect declines and is statistically insignificant after five decades.

Table 1
Heterogeneous effects of mineral discovery on present-day infrastructure.

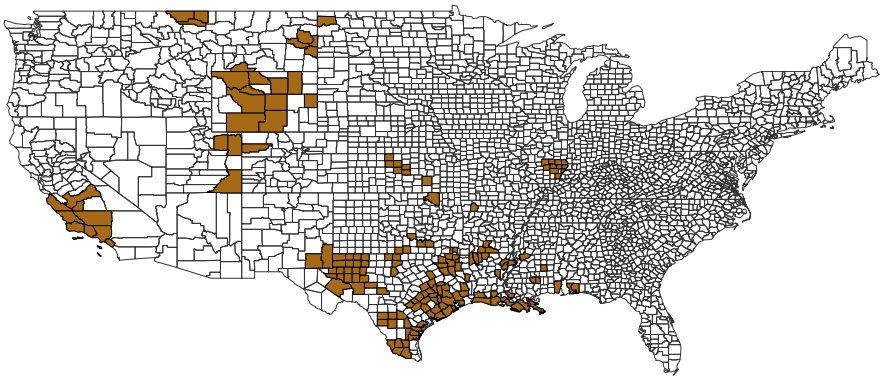
	Total	Low Trans.	Med. Trans.	High Trans.
Roads 2017> 0 (30 Mile Radii)				
Coef.	.0002	.018	.018	−.016
(Std. Err.)	(.009)	(.016)	(.012)	(.014)
Roads 2017> 0 (10 Mile Radii)				
Coef.	.042***	.034*	.056***	.038**
(Std. Err.)	(.011)	(.018)	(.016)	(.017)
Roads 2017> 0 (5 Mile Radii)				
Coef.	.093***	.031	.114***	.093***
(Std. Err.)	(.015)	(.024)	(.022)	(.019)
Road Density 2017 (30 Mile Radii)				
Coef.	−8.79	−121.29	3.09	28.54
(Std. Err.)	(26.515)	(93.71)	(33.64)	(39.43)
Road Density 2017 (10 Mile Radii)				
Coef.	71.29*	−218.30	85.95*	103.97**
(Std. Err.)	(38.66)	(155.00)	(51.04)	(50.89)
Road Density 2017 (5 Mile Radii)				
Coef.	214.36***	−263.91	286.50***	205.46**
(Std. Err.)	(58.22)	(194.38)	(85.80)	(63.80)
Rail 2017> 0 (30 Mile Radii)				
Coef.	.003*	−.007	.0004	.011***
(Std. Err.)	(.001)	(.005)	(.001)	(.002)
Rail 2017> 0 (10 Mile Radii)				
Coef.	.008***	.003	.0004	.012***
(Std. Err.)	(.003)	(.015)	(.003)	(.004)
Rail 2017> 0 (5 Mile Radii)				
Coef.	.0125***	.028	.008	.009*
(Std. Err.)	(.005)	(.025)	(.006)	(.006)
N	2,752,848	550,508	1,651,756	550,584

Note: Each entry in the table is the estimated effect of being a treated 1-km^2 cell. Standard errors clustered by zip code are provided in parentheses below each estimate. Column headings (Total, Low Trans., etc.) describe which cells are being used in the estimation. For example, "Low Trans." gives the treatment effect when limiting the sample to cells in the low transportation cost bin. The "Total" column gives the results using all cells in the sample. Results are conditioned on amenity bin dummies, transportation cost dummies, inverse rail probability dummies (see the discussion on transportation cost estimation), and state fixed effects. *Statistically significant at 10% level; ** at 5% level; *** at 1% level.

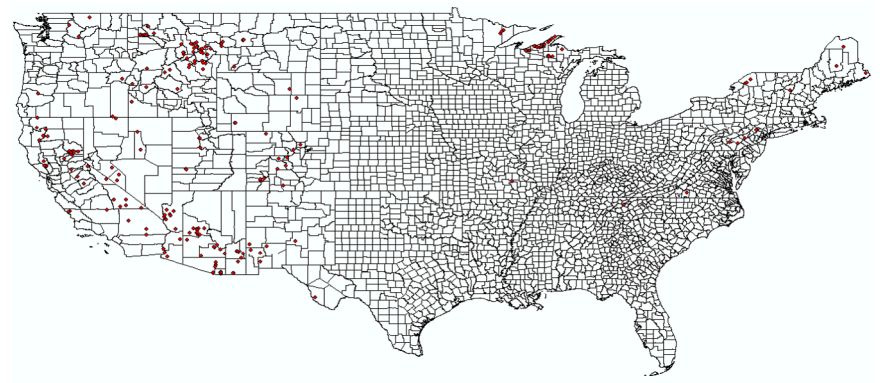
Fig. 4 plots the estimated effects of mineral discovery when limiting the sample to each of the six amenity and transportation cost groups. Unfavorable locations experience positive population effects after mineral discovery, particularly those with high transportation costs. After five decades, low amenity cells within 30 miles of a mineral discovery are approximately 7% more likely to be populated while high transportation cost cells within 30 miles are 15% more likely to be populated. For moderately favorable locations, treated cells are approximately 5% more likely to be populated two to four decades after mineral discovery, with the effect disappearing after five decades. We observe similarly transient effects for moderate transportation cost cells. Finally, in favorable locations, there is no evident population boom after discovery, but there is some evidence of a negative effect four to five decades after discovery. The negative results for these more favorable locations is likely a driver of the boom-and-bust pattern we observe in the full-sample effects in Fig. 3.

Overall, the pattern of geographic heterogeneity for minerals is broadly consistent with the evidence provided from the oil discoveries; locations with less favorable geography tend to experience larger gains from economic booms than locations with more favorable geography. However, the primary difference is that the positive population effects are not persistent out to 50 years for mineral discoveries. There are several possible reasons for this. First, our definitions of "significant" oil and mineral discoveries are not evaluated based on the same measures of their importance. We classify significant oil discoveries as those with more than 100 million barrels of reserves, while we adopt the USGS's qualitative definition of whether a particular discovery is "world class". The difference in average value of these resources at the time of their discovery is an order of magnitude. As discussed in Section 4, the median oil discovery has an in-situ value of $2.6B compared to $300 m for minerals. Consistent with the idea that more valuable resources generate larger population shocks, we illustrate in Fig. 5 that larger oil discoveries (those above the median number of in-situ barrels discovered) generate larger population effects.

There are also differences in the longevity of resource extraction. All oil discoveries in our sample were still producing at some level in the year 2000 (70 years after initial average discovery), while the median world-class mineral deposit in our sample had a 48-year mine life. It could be the case that the larger and more persistent oil-discovery effect is being driven by the fact that these



(a) Oil Discoveries



(b) Mineral Discoveries

Fig. A.1. Mineral and oil discoveries.
Note:Oil discoveries are recorded at the county level whereas mineral discoveries are recorded by the latitude and longitude of the discovery site. Oil-discovery locations come from the EIA. Mineral discoveries data come from USGS Mineral Resource Data System.

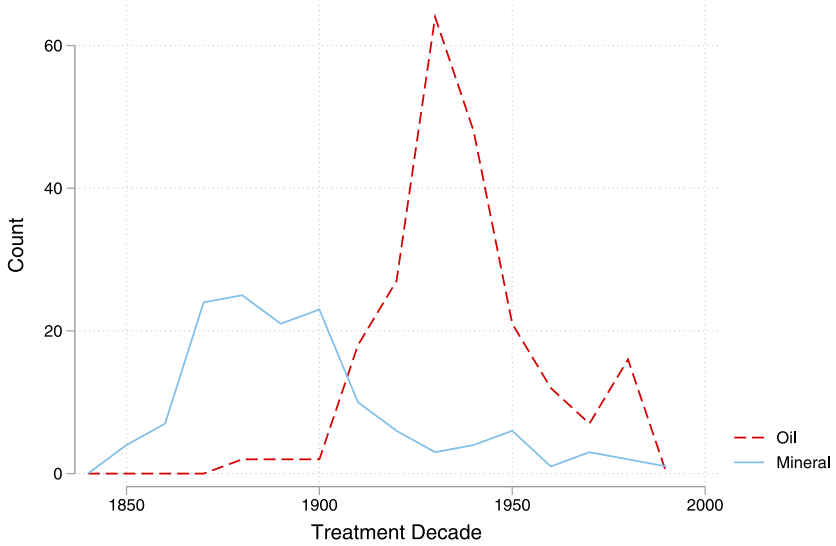
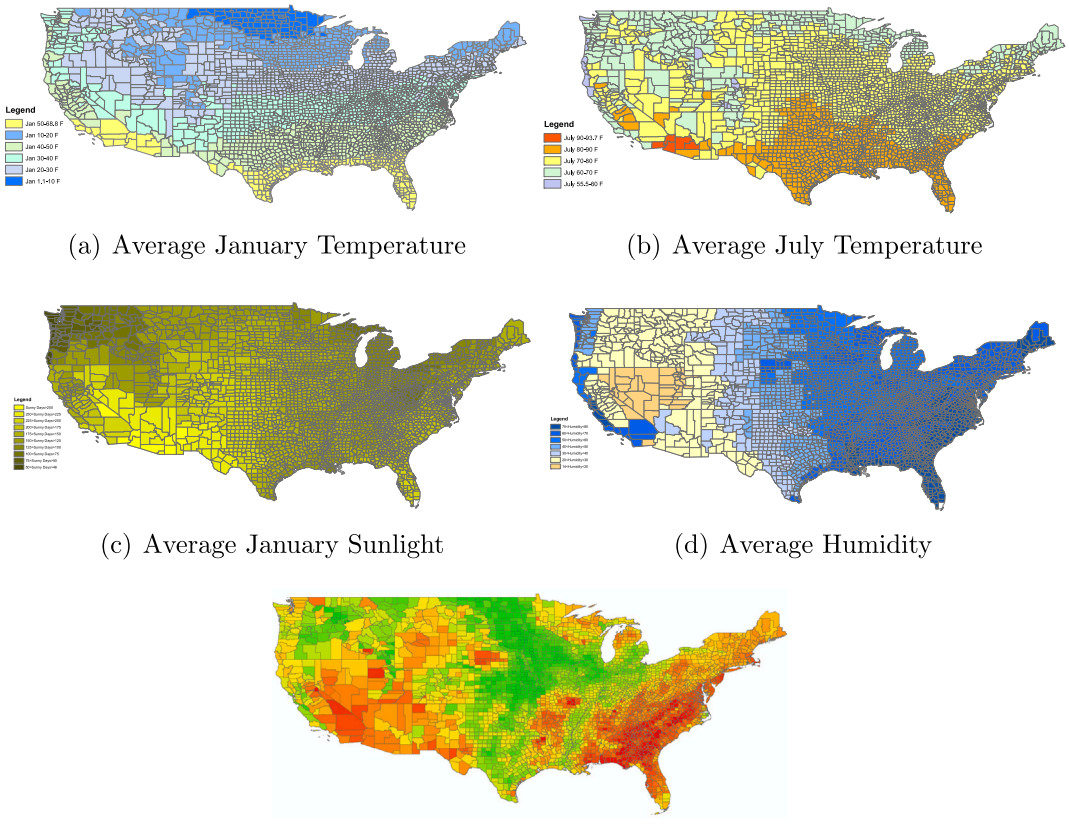


Fig. A.2. Timing of major oil field and mineral deposit discoveries.
Note: Oil fields are major if they are larger than 100 million barrels. Mineral discoveries are major if they were qualitatively determined by the US Geological Survey to be of "world class significance". For mineral discoveries, if discovery date was missing, year of first production was used. Oil-discovery dates come from the Oil and Gas Journal. Mineral discoveries data come from USGS Mineral Resource Data System.



(a) Average January Temperature

(b) Average July Temperature

(c) Average January Sunlight

(d) Average Humidity

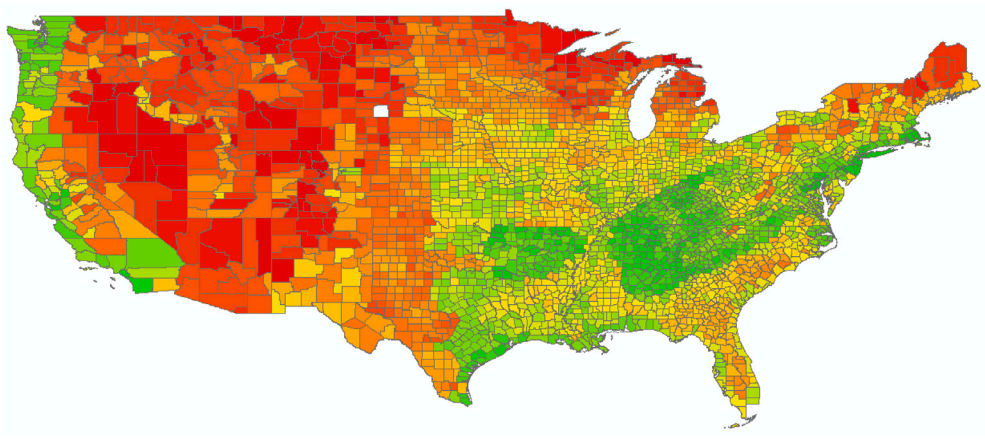
(e) Soil Productivity

Fig. A.3. Temperature, sunshine, humidity & soil productivity. *Source:* Figure from authors compiled from data from various sources. Data on temperature, humidity, and sunlight come from the USDA Natural Amenities Scale. Total January sunlight hours is measured as an average from 1941–1970. County-level soil quality data come from Schaetzl et al. (2012).

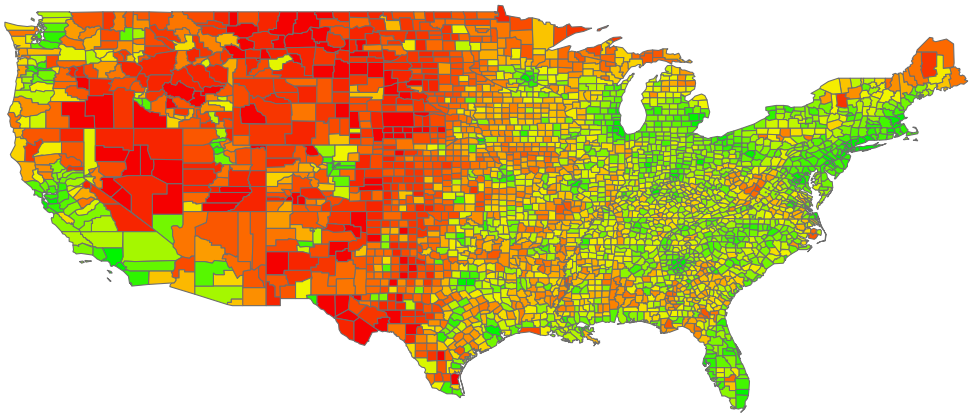
locations are still actively producing after 50 years, while the mineral resources are, on average, depleted around this time. These results are nonetheless consistent with the idea that there may be more intrinsic differences between oil and mineral resources in terms of their effects on development. In addition to oil and mineral deposits differing in terms of value and importance, there are differences in the labor requirements of the start-up and operating periods of resource extraction, creating differences in the timing and intensity of labor demand. There are also differences in the transportation infrastructure needed to move the commodities to export markets.

It is also important to note that, whereas most oil discoveries are made in relatively flat places, minerals like gold and silver are often found in rugged terrain (such as the Rockies and Sierra Nevada mountain range—see the bottom panel of Fig. A.1). An interesting aspect of our heterogeneous analysis is that we document persistent effects of mineral discoveries for high transportation cost locations only. One somewhat speculative interpretation of this finding is that mineral discoveries finance the construction of transportation infrastructure such as roads, bridges, and railways. Such investments might be prohibitively expensive in the absence of mineral discoveries, and so these places tend to remain vacant. The construction of transportation infrastructure related to resource extraction might be especially important for the long run development of such places. Anecdotally, note that many ski towns and resorts are located in or near historical silver or gold mines such as Alta and Snow Bird in Utah, and Palisades Tahoe in California. Another popular ski town in Colorado (Telluride) was even named after the telluride ores (gold and silver) that were previously extracted there. We provide supporting evidence of this theory by estimating the effect of mineral discoveries on present-day transportation infrastructure.

To estimate the effect of mineral discoveries on transportation infrastructure, we again evaluate treatment effects at the 1-km^2 cell level, and limit the sample to cells in western states. We present average and heterogeneous treatment effects based off of transportation cost separately. For completeness, we consider three different outcome variables: (1) an indicator for the presence of



(a) Amenity Index (2000)



(b) Population Density (2000)

Fig. A.4. Predicted population (amenity index).
Note: Panel (a) gives predicted populated levels for each county, which serves as the proxy for exogenous environmental amenity. Panel (b) gives actual population density for the year 2000. For both figures, green indicates a high population density, yellow indicates medium population density, and red indicates low population density. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a road measured in the year 2017,[29] (2) road density (meters of road within a cell) in 2017, and (3) an indicator for the presence of a railroad in 2017. For robustness, treatment cells are defined as those within five, ten, and thirty kilometers from the point of discovery. We condition on indicators for medium and high transportation cost and amenity bins, and for medium and high "inverse rail probability" bins which parsimoniously and flexibly account for cell-level ruggedness and water coverage (i.e., the fitted values from Eq. (3), which are discretized into three bins separated by the 20th and 80th percentiles). We again cluster standard errors at the zip code level.

Across all three measures of transportation infrastructure, we see that the effect of mineral discoveries in high transportation cost counties tend to be more pronounced than those in low transportation cost counties, especially when treated cells are defined locally (e.g., using a five or ten-kilometer-radius threshold rather than the thirty kilometer threshold). For example, from Table 1 in 2017, high transportation cost cells within five kilometers of a mineral discovery were roughly 9% more likely to have a road intersecting them than high transportation cost cells that were not in proximity to a historical discovery. Similar results are documented for road density, and the presence of rail.

7. Robustness checks

We carry out a battery of tests that highlight the overall robustness of the main findings. Starting with the results for oil discoveries, we first consider the possibility that oil discoveries generated significant spatial spillovers (as documented by Feyrer

[29] Geospatial road density data provided at the 1-km^2 cell level comes from the NOAA National Geophysical Data Center, and is found on ArcGIS Online.

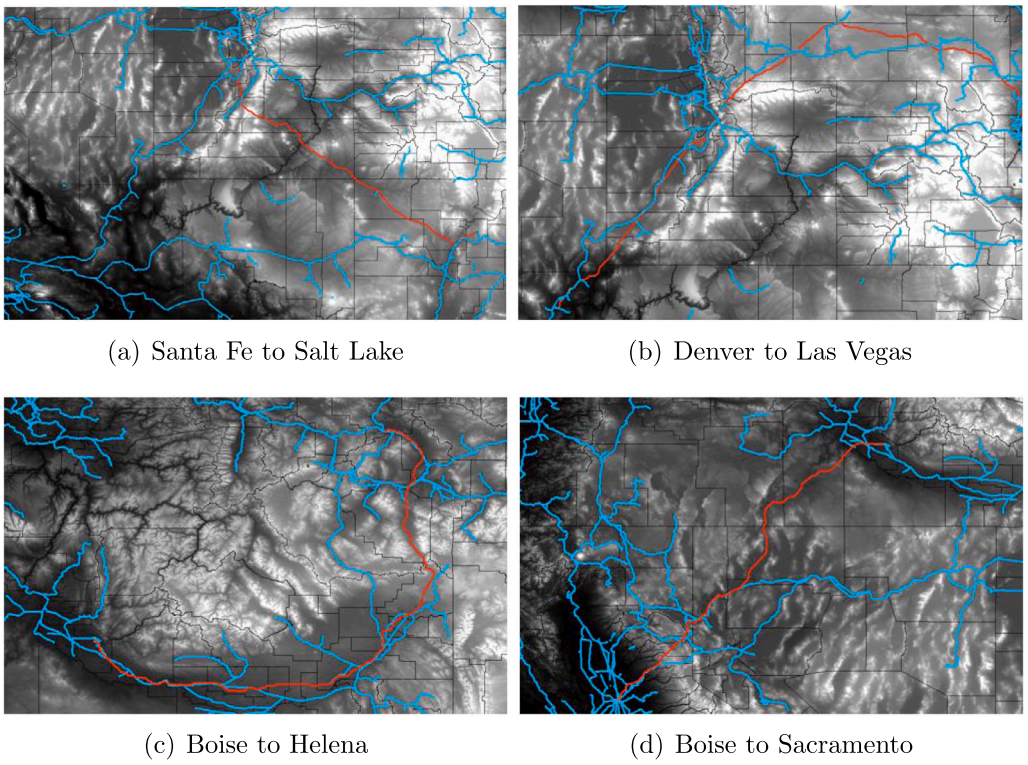


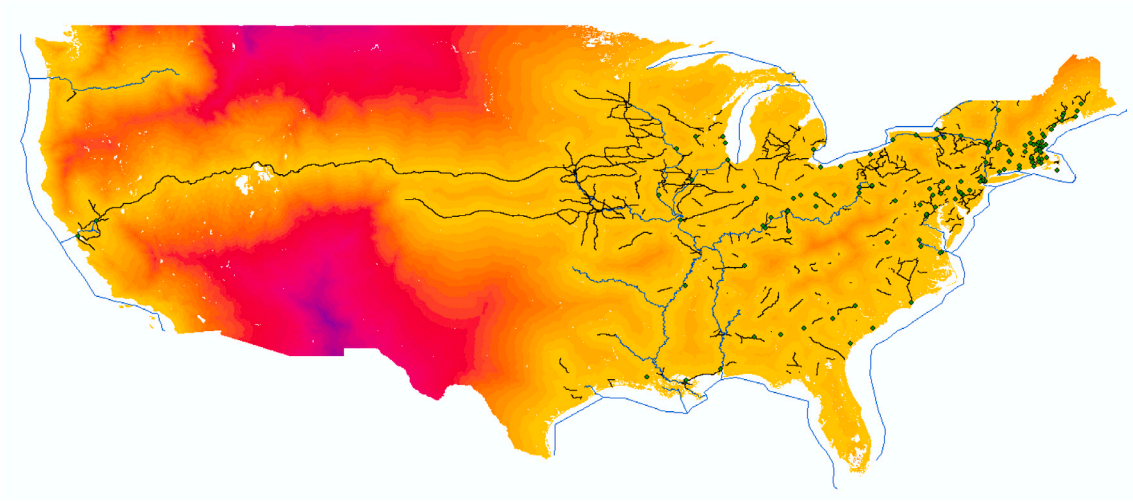
Fig. A.5. Predicted v. actual rail network in four case studies.
Note: The current actual rail network is depicted in blue. The predicted paths based on cell-level measures of terrain ruggedness and water coverage are given in red. These are overlaid on a topographical map. These cases show a high-fidelity to the actual rail network from our method in panels (b) and (c), but our method also rightly ignores the endogenous city development and predicts more direct routes in panels (a) and (c). See Section 5.2 for details.

et al. (2017), James and Smith (2020)) which would cause treatment effects to be biased downward. We address this concern by dropping all counties that are contiguous to treatments and re-estimate our baseline set of equations. These results are given in Fig. B.1. For the full sample, fifty years after discovery, the average treatment effect is estimated to be 0.5, which is nearly identical to that found using the full set of counties. The effects by favorability are also very similar to before, suggesting the baseline results are not biased due to spatial spillovers.

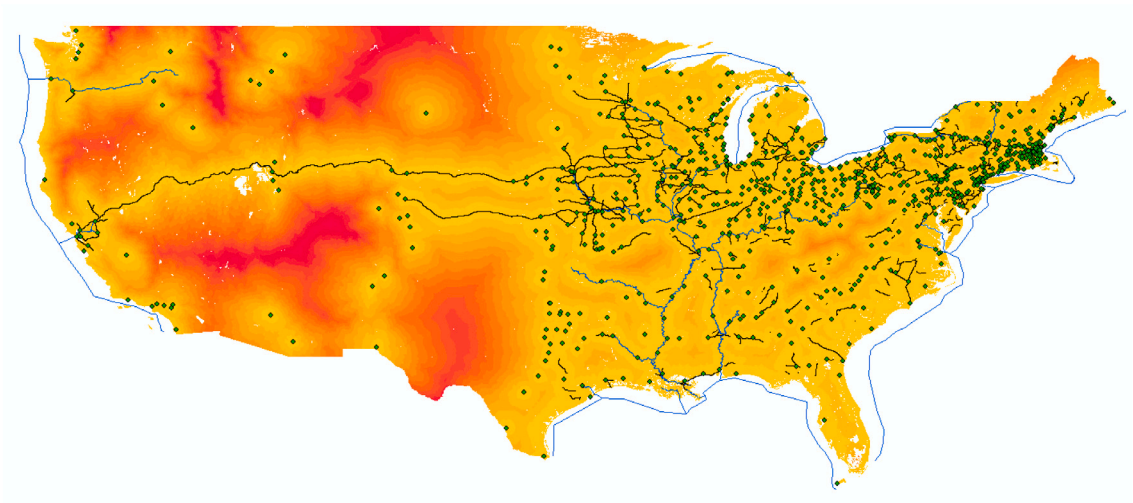
Of clear concern is the idea that the timing of a discovery is endogenous to economic development within the region. If oil fields are discovered as a result of population growth, our results are potentially explained by reverse causality. We argue that this is unlikely affecting our results, noting that pre-existing trends in the baseline event-study analyses are largely insignificant. Nonetheless, it is possible that contemporaneous population growth led to discovery. To address this concern, we examine whether estimated treatment effects are sensitive to the size of the fields being discovered. More specifically, we re-estimate baseline estimation Eq. (1) for both "high" and "low" oil endowments, defined as being above or below the treatment group median, respectively.[30] While exploration and search effort are potentially endogenous variables, conditional on discovering oil, whether a field is above or below median size is determined by chance. The results are given in Fig. 5 below.

Note that for both subsets of the treatment group, pre-existing trends are minimal. While short and long-run treatment effects are positive for both groups, fifty years after discovery population density is estimated to be roughly 90% greater in counties with above-median endowments and just 30% greater in counties with below-median endowments. Even if one attributed the estimated effect of small discoveries purely to endogeneity, the "additional" effect of large discoveries is significant (90%-30%=60%) and should be considered a lower bound on the effect of discovering an above-median sized oil field. Figs. B.2 and B.3 give the heterogeneous effects by favorability for above and below median sized endowments and largely reinforce the idea that effects are larger for low amenity, high transportation cost places. For example, fifty years after discovering an above-median size oil field, population density in low-amenity counties is 350% greater than the pre-discovery counterfactual (this number is closer to 64% for below-median discoveries). There is no long-run effect of large or small discoveries in high-amenity places.

[30] Field size is estimated by summing cumulative production and estimated remaining reserves for fields from the Oil and Gas Journal Data book. Total endowments are then calculated by summing together fields within a county. When the same field is assigned to multiple counties, it is assumed that endowments are divided proportionally by county area.



(a) Transportation Cost by Cell (1850 cities)



(b) Transportation Cost by Cell (1900 cities)

Fig. A.6. Estimated transportation cost.
Note: Estimated transportation cost from each 1-km^2 cell to the nearest national or international market location. Warmer colors indicate higher costs to reach markets. Markets are defined by either a pre-existing city of 5000 or more population, a railroad built by 1870, or a navigable waterway. Cities which reached 5000 people by 1850 or 1900 are denoted by points. Railroads in 1870 and marine highways (major, navigable waterways) are given by black and blue lines, respectively.

Recently it has been shown that a two-way fixed effects difference-in-differences specification in which there is variation in the timing of treatment recovers the average treatment effect only when treatment effects are homogeneous (Goodman-Bacon, 2018; Sun and Abraham, 2020; de Chaisemartin and d'Haultfoeuille, 2020; Borusyak and Jaravel, 2017); Athey and Imbens, 2018). These studies show that the traditional difference-in-differences estimator is a weighted combination of all possible 2 × 2 difference-in-difference estimators in which a cohort with a certain treatment timing is compared to either a never-treated group or a treated cohort with different timing. Unless treatment effects are homogeneous over time, then comparisons with "already treated" cohorts become problematic and can cause biased estimates. That said, this issue is unlikely to create significant bias in our estimates because the majority of the control group in our event study is never treated (recall that there are roughly 3,100 counties and only 231 discovered a major oil field), so the weights on the potentially problematic 2 × 2 comparisons are inevitably small. Nonetheless, as a robustness check we use the "interaction-weighted" estimator developed by Sun and Abraham (2020) to re-estimate our baseline set of results for oil discoveries (STATA estimation command *eventstudyinteract*. These results are provided in Fig. 6 and, as expected, are similar to our baseline estimates.

To better account for relevant unobserved heterogeneity between treated and control units, we also estimate baseline effects for oil using only treated units. Here, comparison units for counties treated in year t are those counties that were treated either before

Table A.1
Summary statistics for oil-rich and poor counties.

	N	Population (000s)	
		1890	2000
All Counties	2961	21	91
Discovery			
No	2789	20.8	90.9
Yes	172	10.9	157.5
Difference		10.5***	−70.7
Discovery Size			
Large	86	12.8	270.7
Small	86	8.8	44.4
Difference		3.9**	226.2*
No Discovery with Amenity:			
High	580	30.6	118.7
Medium	1668	22.9	88.2
Low	541	6.9	48.4
No Discovery with Transp. Cost:			
High	482	4.8	38.9
Medium	1705	18.7	72.7
Low	602	42.3	165.0
Discovery with Amenity:			
High	10	15.5	25.6
Medium	111	14.7	220.7
Low	51	1.8	45.9
Discovery with Transp. Cost:			
High	55	2.4	43.6
Medium	102	14.8	222.4
Low	15	15.0	134.4

Note: Summary statistics for population in 2000 and 1890 are presented for all counties, counties with and without oil discoveries, and counties with and without oil discoveries by amenity and transportation cost favorability. Counties with zero population in 1870 are excluded. N is the number of counties that fall into a particular category. Population is the average population in 1000s of persons. Stars indicate the significance levels from mean comparison tests assuming unequal variance. *Statistically significant at 10% level; ** at 5% level; *** at 1% level.

Table A.2
Summary statistics for cells near mineral discoveries.

	N (1850)	underlinePopulation	
		1850	1950
Discovery			
Yes	291,471	.025	.339
No	2,388,223	.009	.332
Difference		.013***	−.007***
No Discovery with Amenity:			
High	484,715	.020	.531
Medium	1,419,191	.006	.316
Low	484,317	.011	.178
No Discovery with Transp. Cost:			
High	435,772	.005	.282
Medium	1,439,652	.008	.294
Low	512,799	.017	.483
Discovery with Amenity:			
High	55,298	.079	.438
Medium	171,661	.016	.357
Low	64,512	0	.206
Discovery with Transp. Cost:			
High	81,943	0	.337
Medium	177,498	.014	.310
Low	32,030	.146	.510

Note: N is the number of cells that fall into a particular category. Population is the percent of cells within a category with a population greater than zero. Mineral rich cells are those within thirty miles of a mineral discovery. Stars indicate the significance levels from mean comparison tests assuming unequal variance. *Statistically significant at 10% level; ** at 5% level; *** at 1% level.

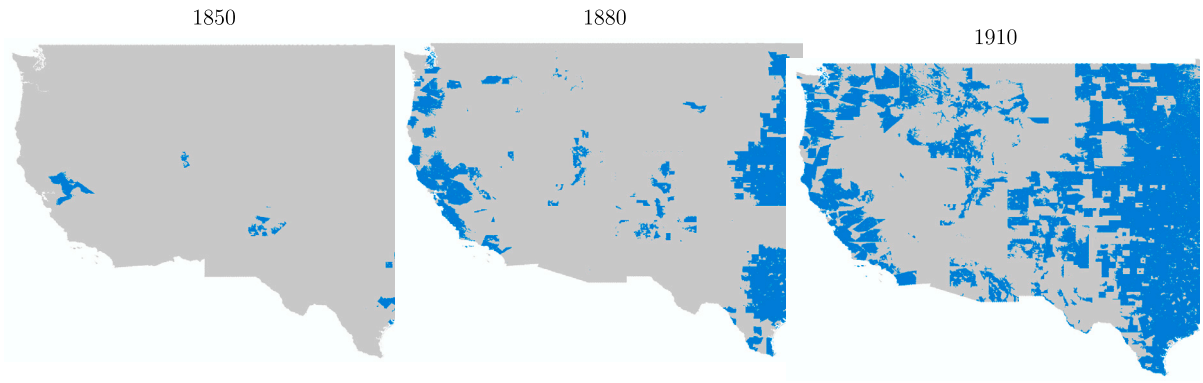
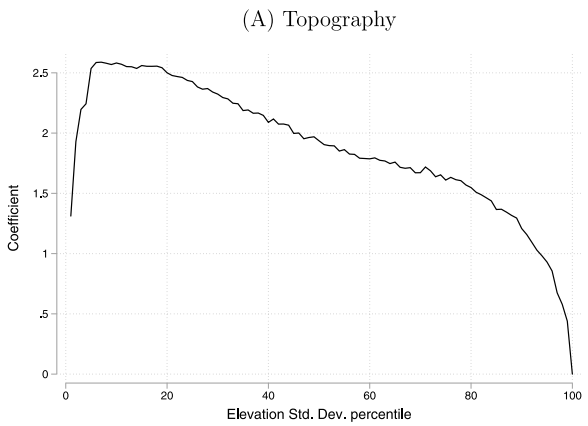
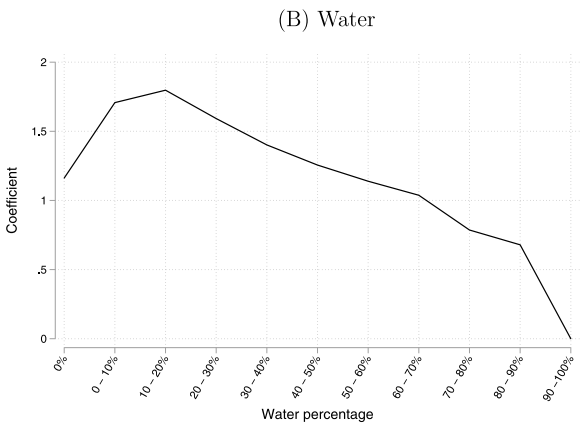


Fig. A.7. Population dummy by cell over time in western US.
Note: 1-km^2 cells are populated (blue) if they have more than one person living in them, according to the estimates by Fang and Jawitz (2018).



(A) Rail Probability Effect by Elevation SD Percentile.



(B) Rail Probability Effect by Water Percentage.

Fig. A.8. Effects of terrain on rail probability.

or after t. In this case, the concerns outlined by Goodman-Bacon (2018) and Sun and Abraham (2020) discussed above are much more relevant[31] and so we again use the interaction-weighted estimator developed by Sun and Abraham (2020). These results are provided in Fig. 7 and are qualitatively similar to the full-sample results.

Another possible concern with our finding that less favorable locations see larger effects is the possibility that oil discoveries have similar population effects in terms of raw numbers of people in all locations, but that low-favorability places have smaller initial populations, and so experience larger percentage increases following discovery. While this scenario would not change the overall conclusion that low-favorability places see larger relative impacts, it would imply that this is a result of low starting population rather than amenities or transportation costs directly (note that this is less of a concern when examining mineral discoveries, because the West was largely unpopulated with non-indigenous peoples prior to the first mineral discoveries in the mid-1800s).

For such a mechanical explanation to be driving our results, favorable locations that discover resources must have relatively large populations not just in the present, but at the time of resource discovery. Grouping oil-discovery counties by amenity value, these counties had average populations at the time of discovery of 13,000 for low amenity, 30,000 for medium amenity, and 26,000 for high amenity. For perspective, these averages correspond to the 28th, 62nd and 57th percentiles of county populations at discovery time.[32] In other words, these locations on average do not represent extreme cases on either side of the distribution, nor do they represent particularly large or small populations in levels terms. Particularly, medium and high amenity locations had quite similar populations in the discovery decade.

[31] This is because the "problematic" two-way comparisons between two already treated units make up a much higher share of comparisons and thus receive much more weight in the estimators.

[32] More precisely, for a given discovery, we find the percentile of the county's population compared to all counties at the time of discovery, then average these percentiles over all treatment counties.

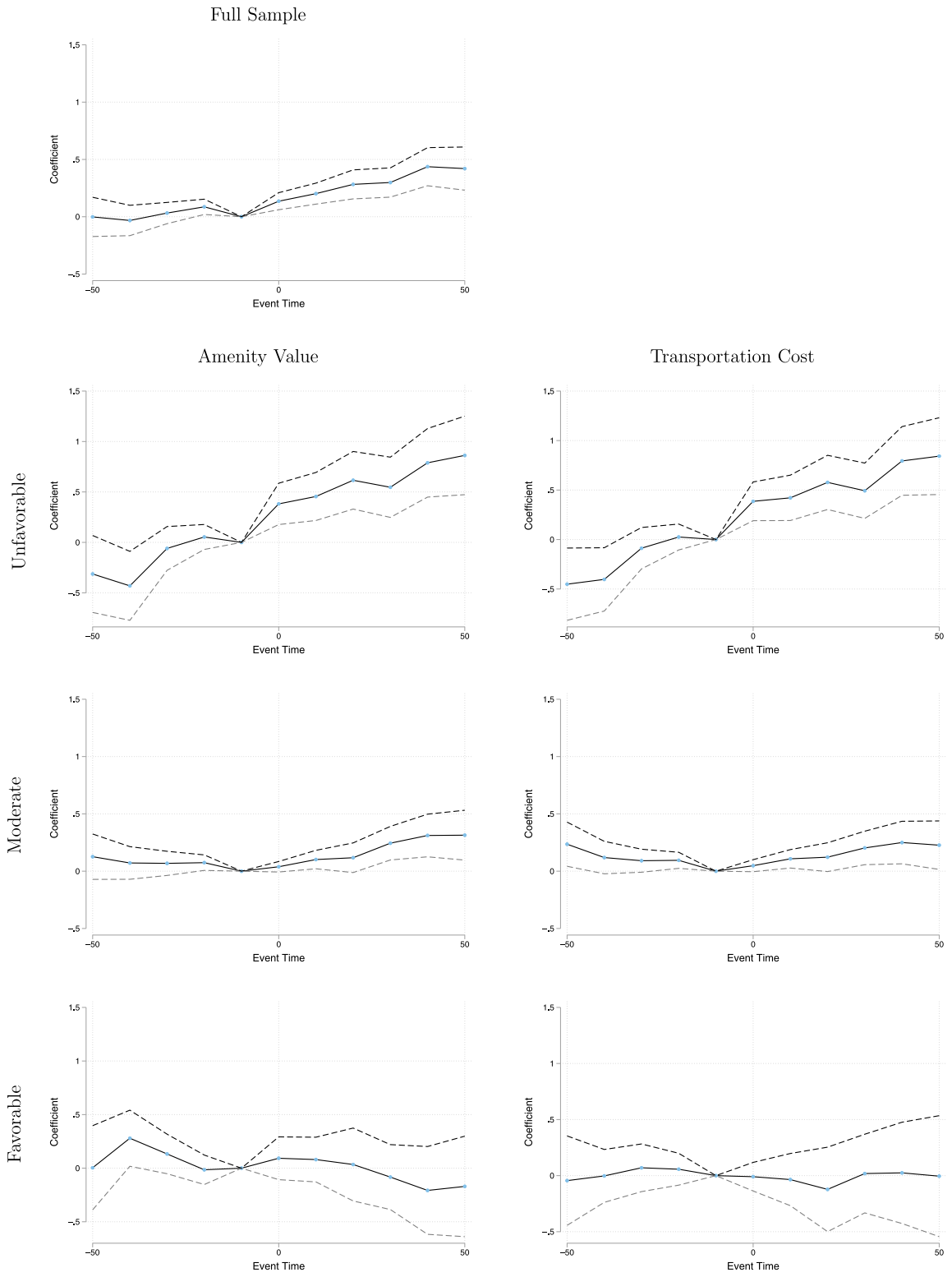


Fig. B.1. Oil-discovery results, bordering counties excluded.
The graphs plot the average effects of oil discovery on log population density over time estimated from Eq. (1), with control counties bordering treatment counties excluded from the sample. 95% confidence intervals are included.

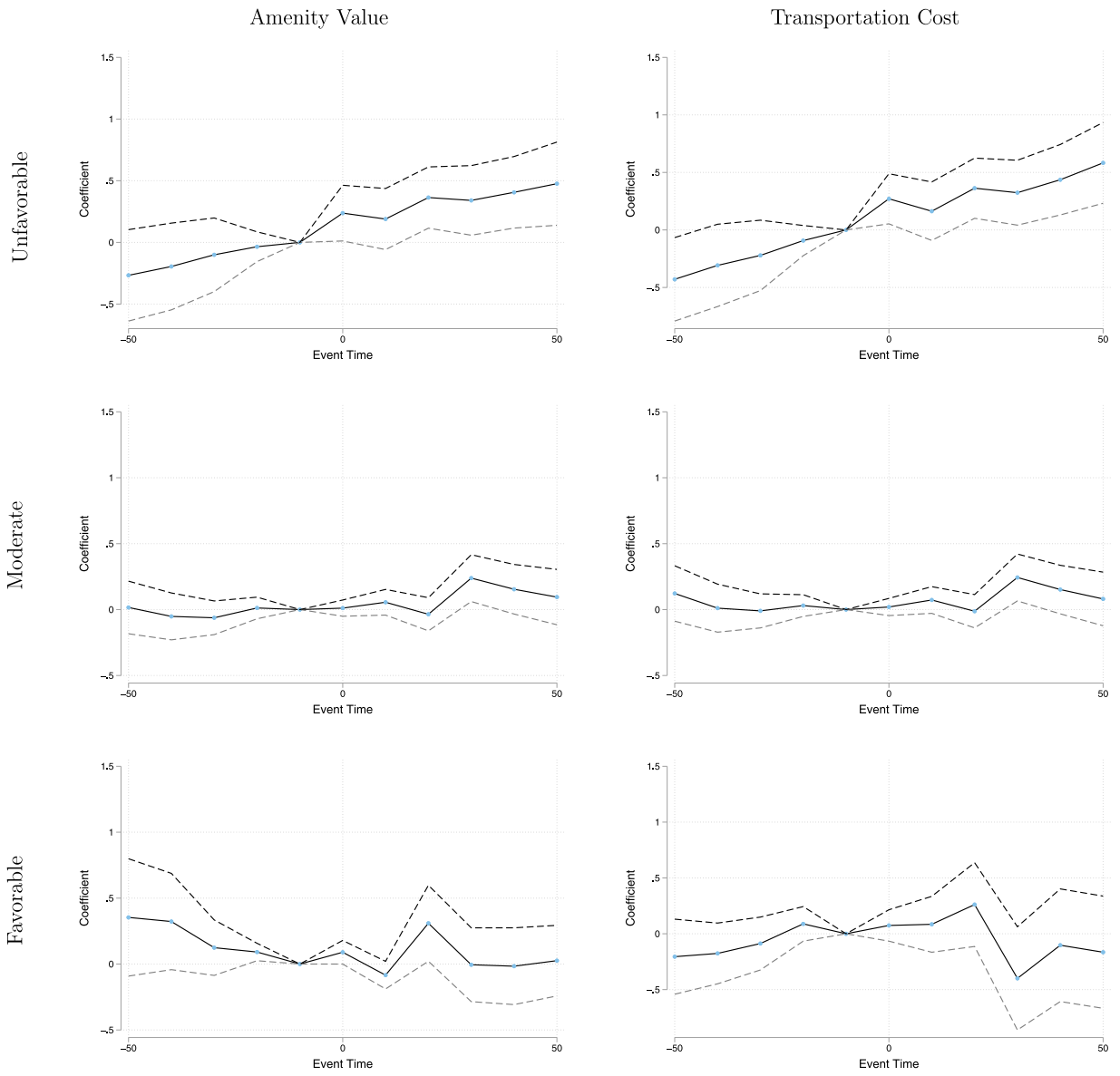


Fig. B.2. Oil-discovery results, low reserves treatments.
The graphs plot the average effects of oil discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. Only below median oil deposits are used in the estimation. The data is partitioned based on the 20th and 80th percentile cutoffs into high, medium or low amenity and transportation groups.

More formally, we also consider a specification of our model that controls for the interactions of event-time indicators and log population density in 1870. For parsimony, in these regressions, rather than separating by bins, we include interactions of event-time indicators by the Z-scores of our amenity index or transportation cost measures (along with non-interacted event-time indicators). These heterogeneous effects are given in Fig. 8 and show that counties with above-average amenity value (or below-average transportation cost) experience smaller population gains resulting from oil discoveries, even after controlling for treatment interacted with starting population. These results again reinforce our baseline conclusions and quell concerns that our results simply reflect variation in initial population density across high and low amenity places.

To the extent that regional resource discoveries generate state-wide economic growth and development, one can argue that including state-by-year fixed effects is too restrictive, as it exploits only within-state variation in outcomes. We therefore estimate an additional model that substitutes state-by-year fixed effects with year fixed effects. These results are nearly identical to before and are provided in Fig. B.4.

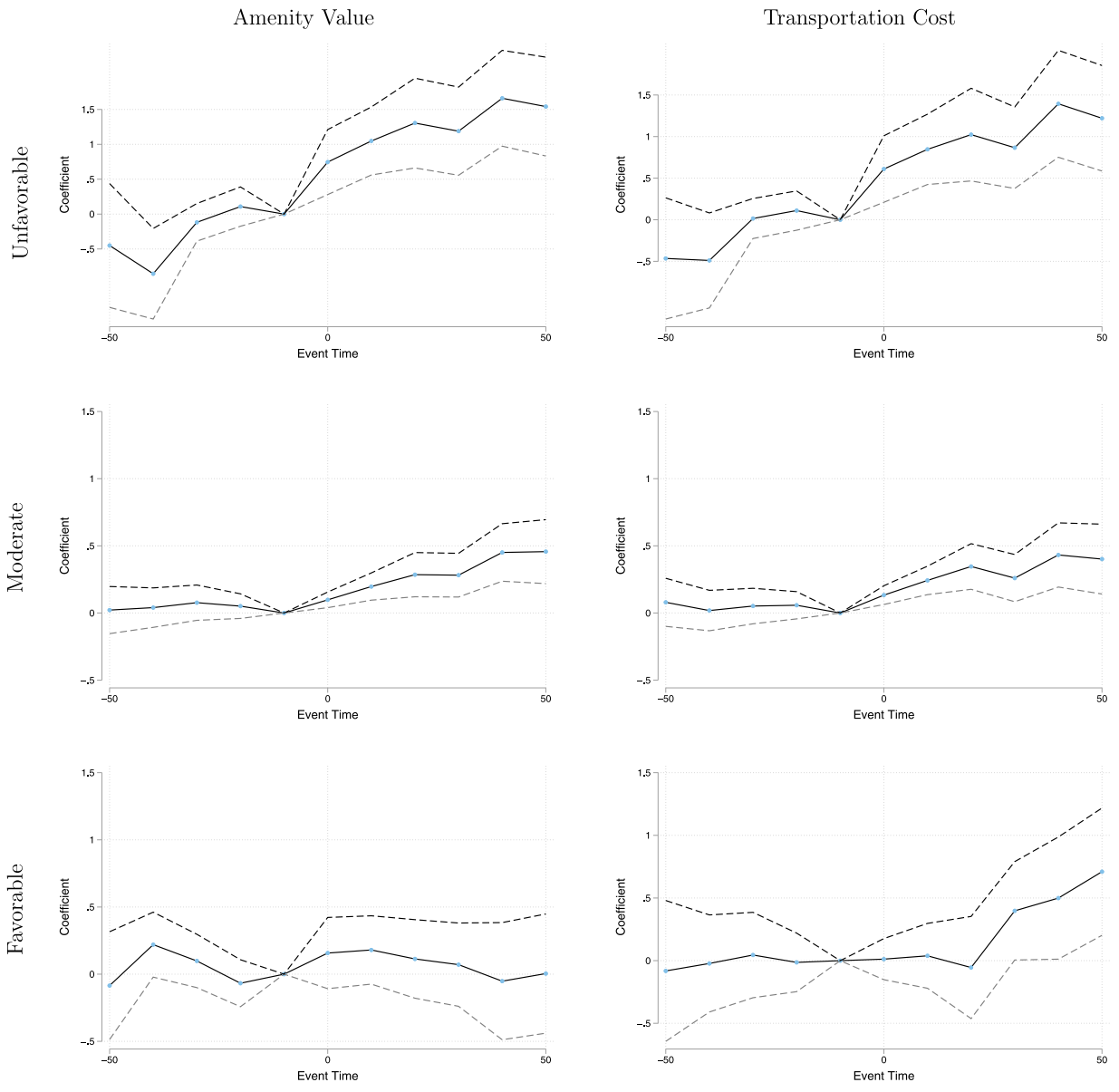


Fig. B.3. Oil-discovery results, high reserves treatments.
The graphs plot the average effects of oil discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. Only above median oil deposits are used in the estimation. The data is partitioned based on the 20th and 80th percentile cutoffs into high, medium or low amenity and transportation groups.

We further examine the robustness of the heterogeneous effects by favorability by alternatively defining "high" and "low" favorability using 90% and 10% thresholds rather than 80% and 20% as in the baseline specification. These results are given in B.5 and are quite similar to our baseline results. We again document large treatment effects for low-amenity places, smaller effects for moderate-favorability places, and no effect for high favorability places.

Turning to the results for mineral discoveries, recall that for the baseline specification treatment, cells are chosen as those within thirty miles of a mineral discovery. Here, we let this radius vary from five, to ten, to fifty miles. Using a five-mile radius and the full sample, Fig. B.6 shows that the average treatment effect is greater than in the baseline specification, which uses a 30-mile radius. This makes some intuitive sense—if mineral discoveries attract populations, and populations are more heavily concentrated near the mine, one would expect larger treatment effects for smaller radii, though there are examples of boomtowns locating farther away in the nearest flat land. However, in this particular case, note that the estimated treatment effects for favorable locations, while somewhat erratic and imprecisely estimated, are actually larger than those for unfavorable locations. Similar results are found using a ten-mile radius (see Fig. B.7). The results using a fifty-mile radius are more in line with the baseline specification (see Fig. B.8).

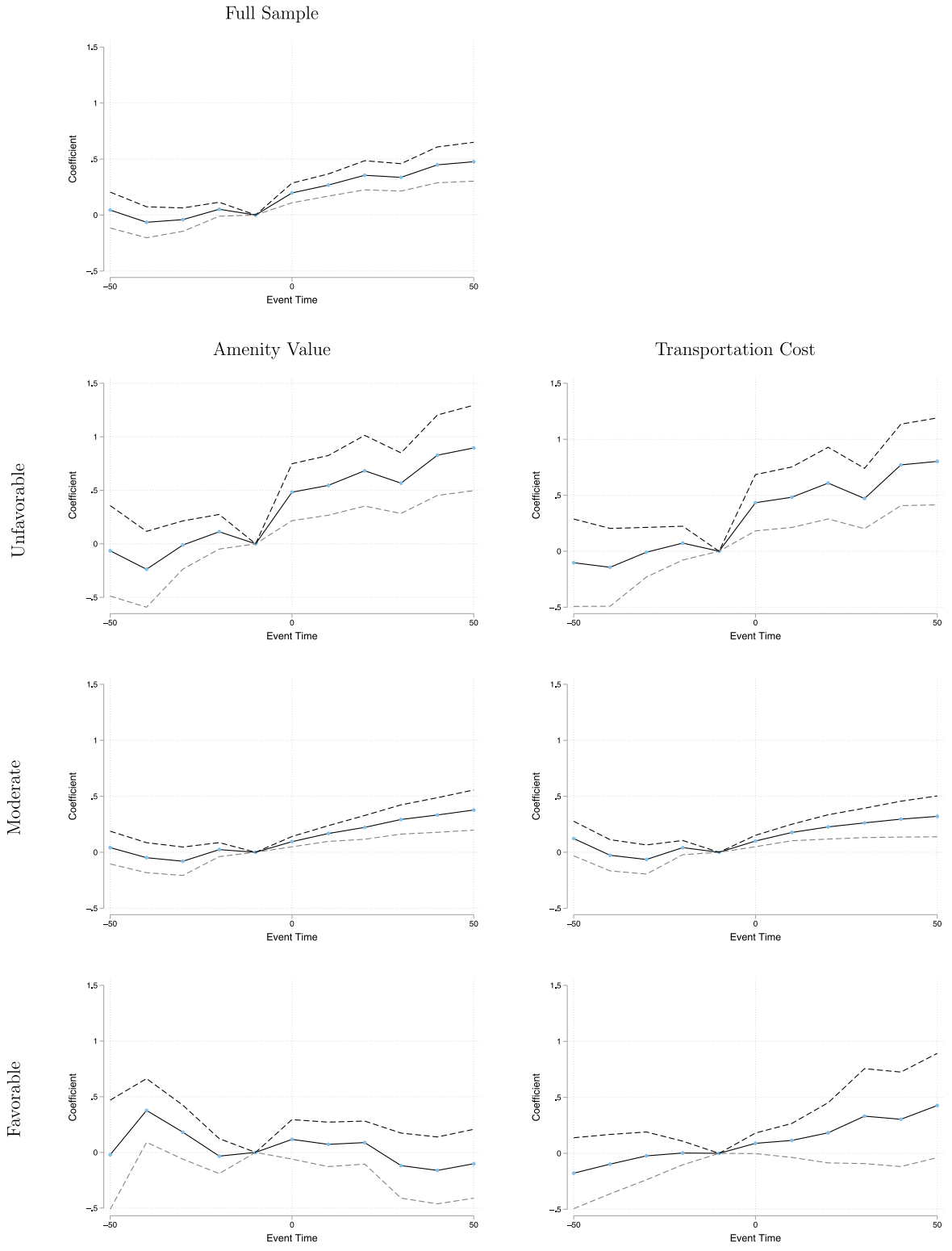


Fig. B.4. Oil-discovery results, year FEs.
The graphs plot the average effects of oil discovery on log population density over time estimated from Eq. (1), with year fixed effects included instead of state-by-year fixed effects. 95% confidence intervals are included.

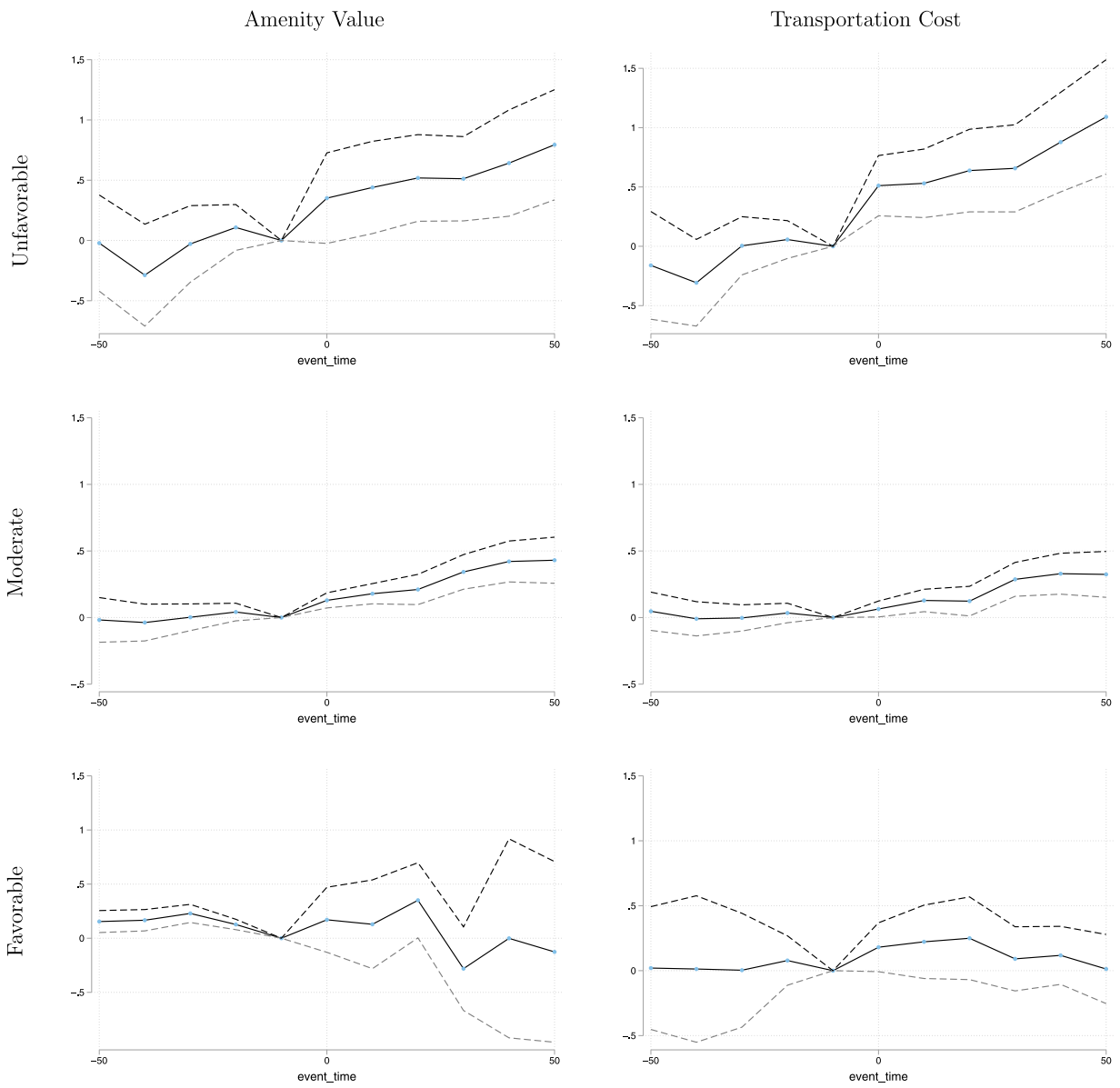


Fig. B.5. Oil-discovery results, alternate bins.
The graphs plot the average effects of oil discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. The data is partitioned based on the 10th and 90th percentile cutoffs into high, medium or low amenity and transportation groups, rather than 20th and 80th percentile cutoffs.

8. Conclusion

A growing literature estimates the short and long run effects of natural-resource production, dependence, and discoveries (Michaels, 2011; Jacobsen and Parker, 2016; Muehlenbachs et al., 2015; Berman et al., 2017; Allcott and Keniston, 2017; Feyrer et al., 2017; Matheis, 2016). While estimating short run effects is (relatively) straight forward, identifying longer run, posterior effects of natural resources is more challenging and is often frustrated by various data limitations.

We exploit a novel population dataset that allows us to estimate the long run (eg., 50 years) effect of such historical resource discoveries using a series of event studies. We also explore heterogeneous effects based on the environmental amenities and extent of geographic isolation of the discovery site, constructing novel measures of both. We theorize that a major resource discovery plays a more important role in permanently populating an area if that place is otherwise undesirable and unlikely to develop on its own. Conversely, highly desirable places, such as those with moderate climate that are centrally located near major markets, are likely to populate even in the absence of a major resource discovery.

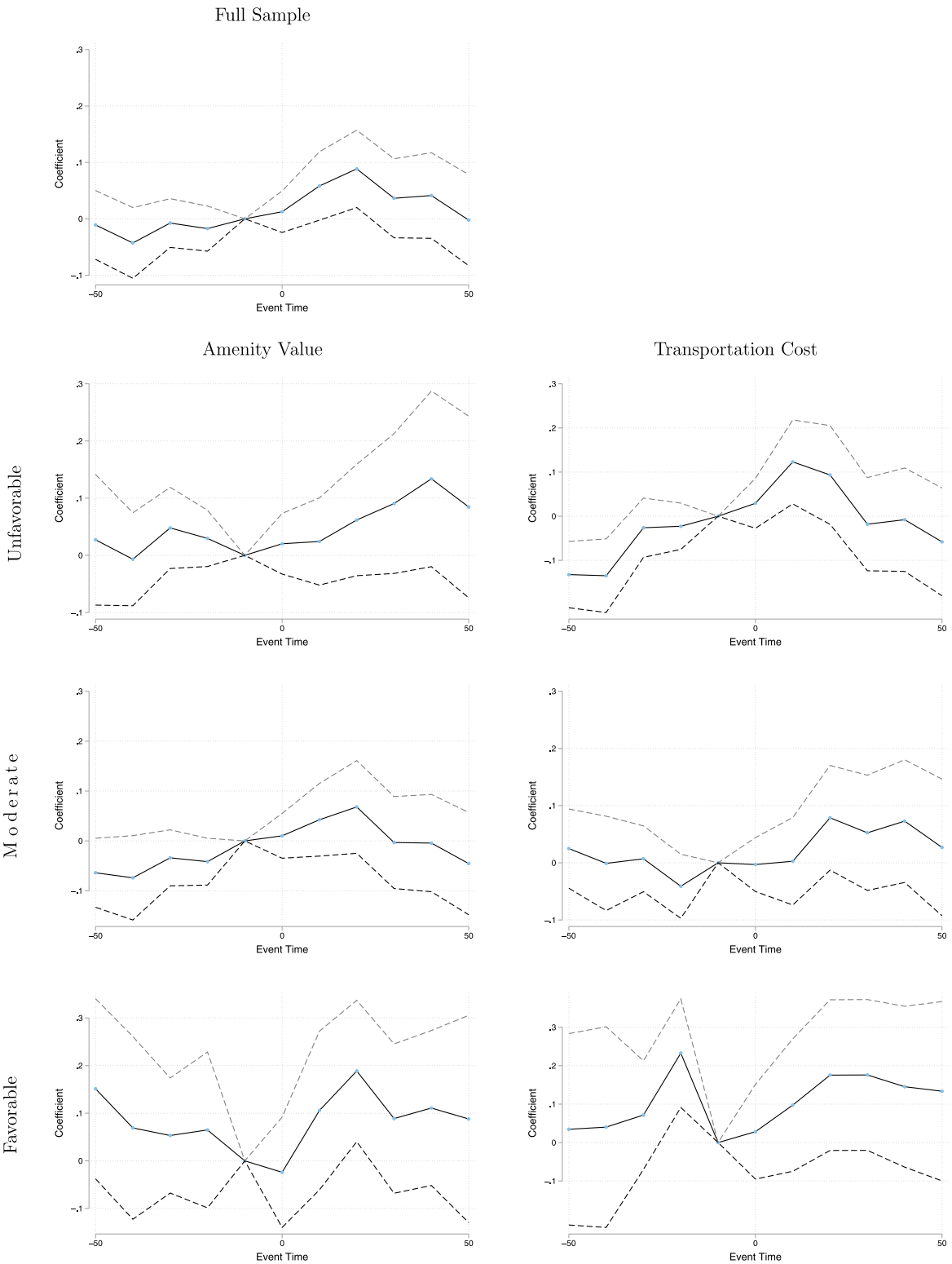


Fig. B.6. Mine discovery results, using a 5-mile treatment threshold.
The graphs plot the average effects of mineral discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. The data is partitioned based on the 20th and 80th percentile cutoffs into high, medium or low amenity and transportation groups. Treatment cells are those within 5 miles of a discovery rather than 30 miles as in the baseline specification.

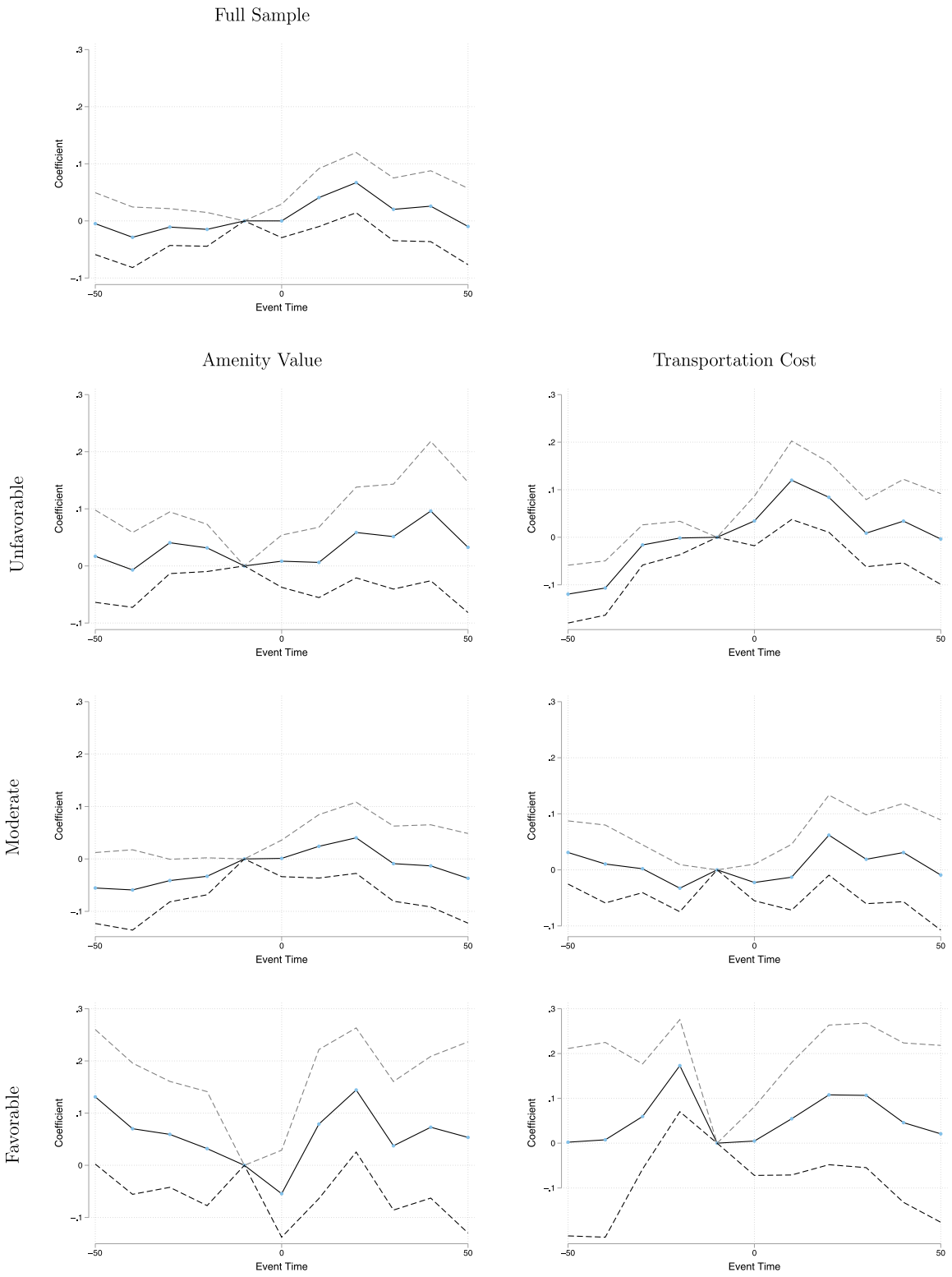


Fig. B.7. Mine discovery results, using a 10-mile treatment threshold.
The graphs plot the average effects of mineral discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. The data is partitioned based on the 20th and 80th percentile cutoffs into high, medium or low amenity and transportation groups. Treatment cells are those within 10 miles of a discovery rather than 30 miles as in the baseline specification.

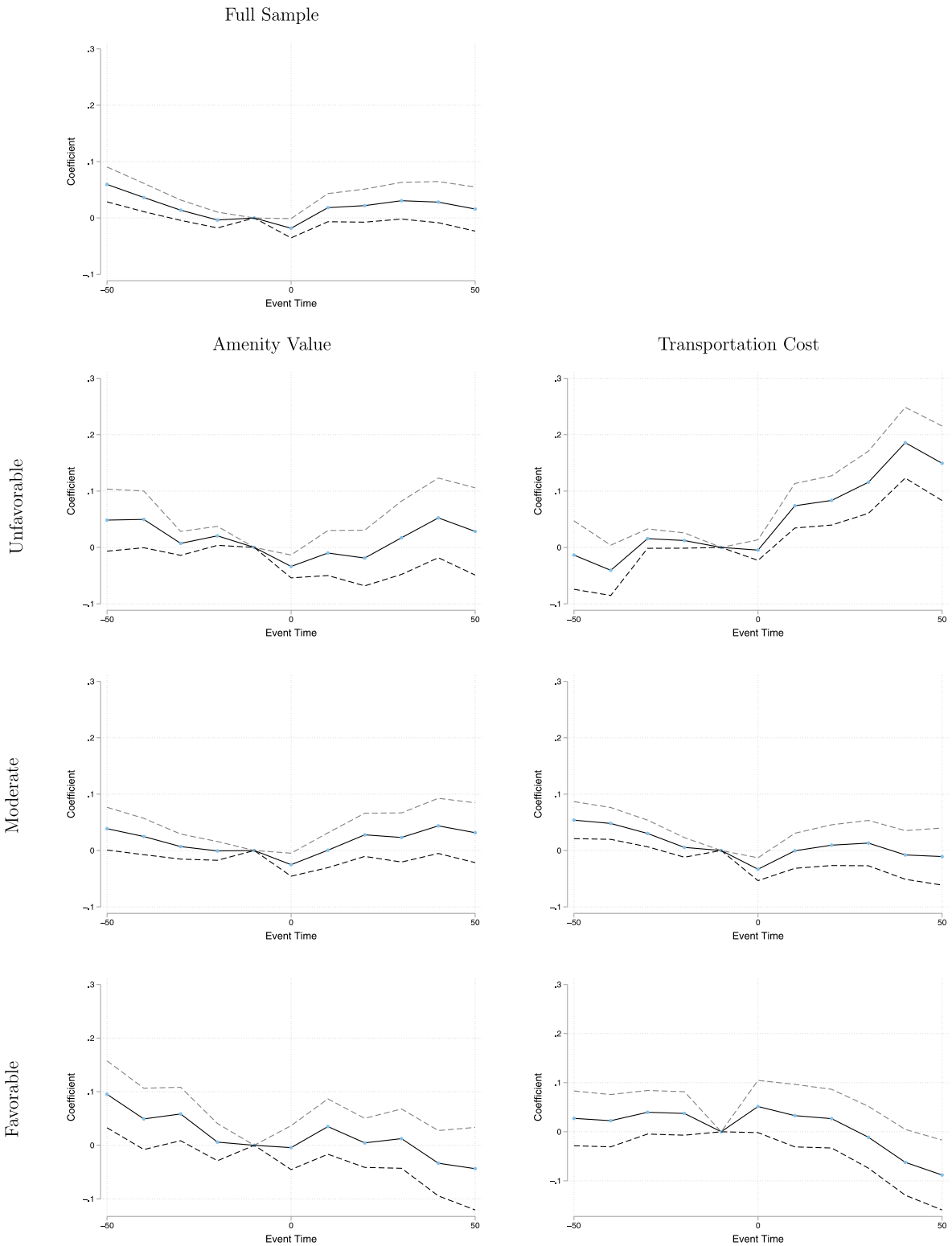


Fig. B.8. Mine discovery results, using a 50-mile treatment threshold.
The graphs plot the average effects of mineral discovery on log population density over time estimated from Eq. (1). 95% confidence intervals are included. The data is partitioned based on the 20th and 80th percentile cutoffs into high, medium or low amenity and transportation groups. Treatment cells are those within 50 miles of a discovery rather than 30 miles as in the baseline specification.

Empirically, we find that resource discoveries immediately, and in some cases permanently elevate local populations. The effects are statistically and economically significant. Averaged across treated counties, fifty years after discovering oil, population density is roughly 65% greater than it otherwise would have been. In a sub-national setting with minimal migration frictions, this implies that discovering oil makes a place more attractive to live in. After all, people "vote with their feet" to consume optimal bundles of public and private goods (Tiebout, 1956). This result runs counter to the hypotheses that countries—and even U.S. counties (James and Aadland, 2011)—are "cursed" by endowments of natural resources. The contrasting conclusions are explained by differences in empirical strategy. To the best of our knowledge, we are the first to carry out an event study of the long run effect of historical resource discoveries in the United States. In doing so, we are able to condition our estimates on pre-discovery heterogeneity and test for parallel trends.

We also demonstrate that long run average treatment effects mask significant and important heterogeneities. Among highly desirable counties with warm temperatures and access to national and/or international markets, the effect of discovery is negligent. For the most undesirable counties the effect of discovery increases to 170%. These results are enhanced when evaluating the effects of especially large fields. For example, fifty years after discovering a field of above median size, population density in low-amenity counties is 350% greater than it would have been in the absence of discovery. These results are corroborated by analyses of mineral discoveries which often occur in relatively rugged and geographically isolated terrains.

We focus our attention on heterogeneities arising from environmental and geographic characteristics, but other sources of heterogeneity likely exist. For example, limited work has been done on the joint role of historic shocks and tax rates, environmental regulation, and public policy more generally. Understanding these possible sources of heterogeneity is important for designing policies to capture resource rents and transform temporary shocks into long run economic gains. We hope that our paper helps to motivate this line of research.

Appendix A. Additional tables & figures

See Tables A.1 and A.2 and Figs. A.1–A.8.

Appendix B. Robustness

See Figs. B.1–B.8.

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