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ESTIMATING PATH DEPENDENCE IN ENERGY TRANSITIONS

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Estimating Path Dependence in Energy Transitions
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ABSTRACT

How can an economy transition from dirty to clean inputs? When transitional dynamics exhibit strong path dependence, a temporary shock to input composition can trigger permanent structural change. This paper examines whether such dynamics characterize the U.S. energy sector's use of coal - the most climate-damaging energy input - over the 20th century. Exploiting local coal transport distance shocks driven by the changing regional accessibility of subsurface coal resources, I find increasing imbalance in the coal composition of electricity capital lasting ten decades following a shock. Additional tests detect increasing returns to scale as the underlying mechanism. To inform energy transitions more broadly, I develop a model of scale-driven structural change to map reduced-form estimates onto a key parameter found across a class of structural change models. Calibrated model simulations further characterize conditions under which a temporary climate policy can trigger a permanent future transition towards clean energy.

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1 Introduction

Economies tend to consume more abundant resources first, turning to alternatives only after sufficient depletion has set in (Herfindahl, 1967). However, if use of an abundant resource generates substantial social costs, it may be efficient for the transition to occur earlier. How can a sustained transition to alternative resources be induced? The answer depends on the degree of path dependence in underlying transitional dynamics. In the traditional view that path dependence is limited, a *permanent* intervention altering the composition of resource use is required. In contrast, recent theoretical work (e.g., Acemoglu et al. (2012, 2016)) emphasizes that when transitional dynamics exhibit strong path dependence, even a *temporary* intervention can trigger a permanent transition. Which of these dynamics actually govern resource transitions, however, remains an open empirical question.

This paper examines the transitional dynamics of the U.S. energy sector over the 20th century and finds evidence of strong path dependence. I focus on coal, a prime example of an abundant but dirty resource. Coal contains over half of energy stored in global fossil fuel deposits (BP, 2017). Its local pollution has long captivated economists, inspiring early papers on external costs (Pigou, 1920; Coase, 1960), and continues to motivate an extensive valuation literature.[1] Coal is also the most carbon-intensive fossil fuel, responsible for over half of emitted anthropogenic carbon dioxide since the pre-industrial era (Boden and Andres, 2013). As a consequence, it is widely recognized today that any effective climate policy must somehow transition global energy production permanently away from using coal.

How a climate policy achieves this energy transition is critically linked to the strength of path dependence. When path dependence is weak, carbon emissions are determined primarily by relative fuel supply. To offset coal's supply advantage, a permanent policy that lowers coal use - such as a Pigouvian tax - is needed. If the policy were ever removed, the forces of relative supply would return, enabling coal consumption and carbon emissions to resume upward trajectories. Unfortunately, governments have difficulty committing to long-term policies. Indeed, the short history of climate policies to date is filled with examples of policy revisions, reversals, and withdrawals.[2] On the other hand, when path dependence is strong, a sufficiently large, but temporary, climate policy can permanently overcome coal's

[1] Recent empirical studies have shown that local pollution from coal burning leads to increased health risks and reduced property values (Chay and Greenstone, 2003, 2005; Barreca, Clay and Tarr, 2014; Clay, Lewis and Severnini, 2016; Beach and Hanlon, 2018; Hanlon, 2016).

[2] For example, the U.S. recently withdrew from the U.N. Paris Agreement and announced plans to review the Clean Power Plan, its domestic climate policy. In 2011, Canada withdrew from the Kyoto Protocol, the preceding U.N. climate agreement, several years after the Protocol entered into force. Key details of the E.U. and California carbon trading markets have been revised since their inceptions. See Acemoglu and Rafey (2018) for other examples.

abundant supply. Under such circumstances, carbon emissions will continue to decline even after the policy is lifted.[3]

While strong path dependence in energy transitions can arise from various mechanisms, in a reduced-form sense, it occurs whenever an exogenous and temporary shock to fuel composition triggers diverging fuel imbalance over time, as detailed in Section 3. To meet these statistical requirements, Section 4 constructs shocks to local coal transport distance driven by the changing regional accessibility of subsurface coal. The introduction of mechanized mining around the early 20th century allowed extraction over previously inaccessible coal held in deep underground deposits. Mechanized mining, together with the location and subsurface depth of coal resources, altered coal transport distances and thus the spatial distribution of delivered coal prices. As such, these *local* coal transport distance shocks are driven primarily by two remote *regional* factors - the time-invariant spatial structure of subsurface coal geology and time-varying mining technology - and thus plausibly uncorrelated with unobserved local determinants of fuel composition. In Section 5, I examine the consequences of these shocks on the U.S. electricity sector with an event study design using panel data covering mid-western counties across the 20th century.

I find that shocks to local coal transport distance before the switch to deep coal have increasing influence on the fuel composition of electricity capital, with lagged effects detected up to ten decades later. Notably, these lagged effects display discrete jumps at two and seven decades after the switching event, corresponding to the expected timing of two subsequent vintages of electricity capital. In support of my parallel trends assumption, I do not find pre-trends in key covariates or in the outcome variable. A series of robustness checks addresses further identification, data construction, sample restriction, and statistical modeling concerns.

Without knowing the relevant mechanism, reduced-form evidence of strong path dependence in energy transitions alone can not directly inform climate policy design. Path dependence emerges from a combination of "push" and "pull" forces. Prior literature highlights two mechanisms that can amplify energy transitions: increasing returns to scale in electricity production (Nerlove, 1963; Christensen and Greene, 1976) and the accumulation of fuel-specific productivity (Acemoglu et al., 2012, 2016). The literature also suggests a dampening force against runaway transitions: imperfect long-run substitutability between electricity from different fuels (Acemoglu et al., 2012). In Section 6, I incorporate these elements into a model of structural change for the electricity sector with vintaged capital. I

[3] A related literature from the economics of technological change discusses how path dependence can differentially lock-in certain technologies over time (Schumpeter, 1942; Schmookler, 1966; David, 1985; Aghion and Howitt, 1992; Arthur, 1994; Fouquet, 2016).

then use the structure of the model to test whether increasing returns to scale or productivity accumulation is the relevant mechanism behind my reduced-form results, finding empirical support for the scale channel. Additional tests fail to detect alternative explanations related to cost-of-service electricity regulation, the U.S. Clean Air Act, coal procurement contracts, increasing returns in coal transportation, and residential household sorting.

Having isolated the relevant mechanism, Section 7 proceeds with interpreting reduced-form estimates through the lens of my model. A formal definition of strong path dependence in energy transitions enables a mapping between my reduced-form estimates and the long-run elasticity of substitution across fuels, a key parameter found across a broad class of structural change models driven by supply-side forces, first posited by Baumol (1967).[4] Recovery of this parameter enables my findings to externally inform other settings whereby energy transition is driven by alternative mechanisms. For example, in the context of Acemoglu et al. (2012)'s model of optimal climate policy with directed technical change, my recovered elasticity of 3.6 implies that a temporary policy intervention could prevent the climate from deteriorating to a point beyond recovery.

Finally, I calibrate my model using reduced-form estimates to draw lessons for future clean energy transitions. Strong path dependence implies it is possible for a temporary intervention to induce permanent fuel switching. But under what conditions can this occur for the U.S. electricity sector which faces low baseline relative coal prices? To answer this question, I use my calibrated model to simulate future U.S. electricity sector carbon emissions triggered by temporary relative coal price shocks of varying magnitude and duration. Simulations show that for a better than 50% chance of achieving a permanent switch away from coal and thus weakly declining carbon emissions, a temporary shock equal in magnitude to recent high relative coal prices (due to natural gas hydraulic fracturing) must last at least four decades. Alternatively, if the shock can only last one decade, it must then be six times higher than that of recent prices to trigger sustained fuel switching. Further simulations explore how requirements for sustained clean energy transitions change with technological advances in scale economies and fuel substitutability. Altogether, these simulations conclude that, absent government interventions to fuel prices or technology, current economic conditions are insufficient for sustaining a permanent U.S. energy transition away from coal.

Two related papers examine how fuel price shocks at higher temporal frequencies affect the composition of inputs in the energy sector. Aghion et al. (2016) study firm-level path dependence in clean and dirty patenting activity for the automobile sector across 80 countries

[4]Prominent models in this class consider structural change driven by intermediate sector-level differences in total factor productivity (Ngai and Pissarides, 2007), factor proportions and capital deepening (Acemoglu and Guerrieri, 2008), and directed technical change (Acemoglu, 2002; Acemoglu et al., 2012; Lemoine, 2016).

in response to annual oil prices during 1986-2005. Knittel, Metaxoglou and Trindade (2015) examine U.S. electricity fuel-switching due to monthly variation in natural gas prices during 2003-2012. My study has the advantage of exploring transitional dynamics over a long time horizon sufficient for detecting capital investments. Recovery of a long-run elasticity of substitution is important given that adequate future reductions in carbon emissions is unlikely to occur with existing electricity capital stock.

This paper's identification strategy relates to a growing empirical literature examining dynamic effects following some change in the productivity of a natural resource. This literature is generally classified by whether a new technology "turns on" or "turns off" the productive use of some resource. The adjustment literature estimates lagged effects after a resource becomes productive (Feyrer, 2009; Nunn and Qian, 2011; Hornbeck and Keskin, 2014). The path dependence literature, which this paper follows, explores the lagged effects of a previously productive or accessible resource (Bleakley and Lin, 2012; Dell, 2012; Hornbeck, 2012; Severnini, 2014; Hornbeck and Naidu, 2014; Glaeser, Kerr and Kerr, 2015). Finally, this paper also belongs to a growing literature using shocks to transport distances as identifying variation (Feyrer, 2009; Atkin and Donaldson, 2015; Donaldson, 2018).

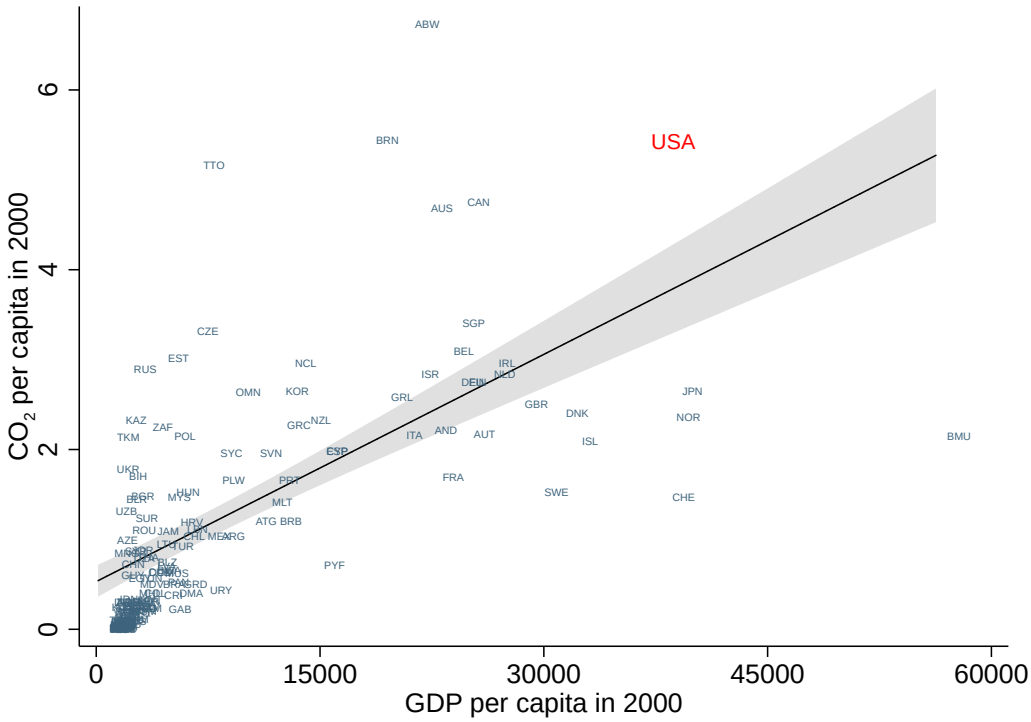
2 Prima facie: Why is the U.S. so dependent on coal?

The United States has one of the most carbon-intensive economies in the world. Figure 1 plots carbon dioxide (CO_2) emissions per capita against GDP per capita for non-OPEC countries in 2000 using data from Boden and Andres (2013) and World Bank (2014). U.S. emissions per capita is nearly 2 standard deviations higher than what income would predict. This reflects the U.S. electricity sector's heavy reliance on coal, the most carbon-intensive of energy fuels.[5] Since the 1960s, roughly 40% of U.S. electricity has been produced from coal (Energy Information Administration, 2012). Why is the U.S. electricity sector so dependent on coal? Many observers point to its world-leading coal resources. However, a casual exploration of historical patterns of local coal use suggests that a supply-based explanation may be incomplete.

Before turning to these patterns, it is useful to first introduce how coal composition is measured throughout this paper. In the electricity sector, capital size is usually denoted by the capacity of a generating unit, or the maximum electricity it can produce in an hour. Thus, a natural measure of coal composition is the ratio of the capacity of coal-fired generating

[5] Bituminous coal, the most common type of coal for electricity, produces 206 lbs of CO_2 per million British Thermal Units (BTU). By contrast, oil and natural gas produces 157 and 117 lbs of CO_2 per million BTU, respectively.

Figure 1: CO_2 emissions intensity and income in 2000



NOTES: Plot shows carbon dioxide emissions (in tons of carbon) per capita against GDP (in nominal USD) per capita in 2000. Linear regression fit shown with 95% confidence interval. OPEC countries excluded. Data from Boden and Andres (2013) and World Bank (2014).

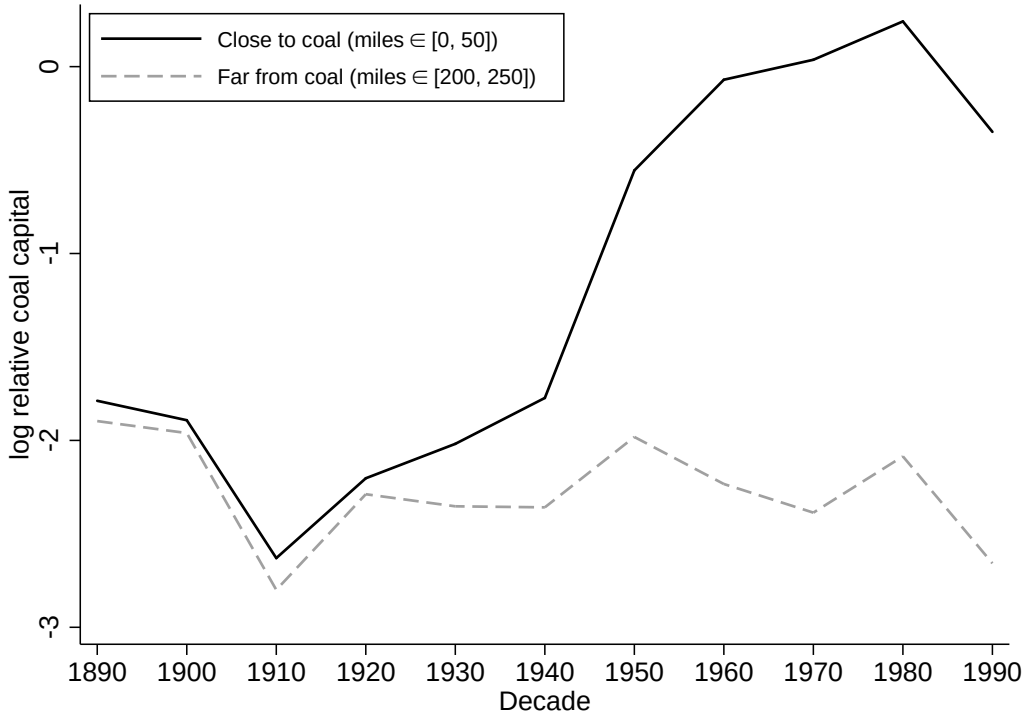
units to the capacity of generating units using other fuels. I call this relative coal capital.[6]

Figure 2 examines U.S. relative coal capital at the county-by-decade level (see Section 4.2 for data construction details).[7] It plots average log relative coal capital over 1890-1990 separately for counties that are close to (between 0 and 50 miles) and further away (between 200 and 250 miles) from coal resources in the Illinois Coal Basin, the basin studied in this paper (for reasons discussed in Section 4.1). Consistent with a coal supply argument, counties closer to coal resources exhibit higher relative coal capital throughout the 20th century. However, the gap between these two sets of counties widens dramatically over this period. Such a pattern cannot be explained by coal supply alone, which predicts relative coal capital convergence, not divergence, over time as locations closer to coal deplete their supplies more rapidly. Instead, these divergent dynamics hint at the presence of path dependence, which occurs when past relative coal capital has a causal effect on future relative coal capital.

[6] Relative coal capital is preferred over coal capital share as my main outcome variable. This is largely because predictions from standard models of structural change (discussed further in Sections 6 and 7) are typically expressed as factor input ratios. Note further that it is important to examine an outcome variable that is a function of both coal and non-coal electricity capital. Because coal and non-coal capital are jointly determined, simply examining each in isolation would not be informative of structural change.

[7] Because electricity capital last multiple decades, I use a decade as the time-step for all empirical analyses.

Figure 2: Relative coal capital for counties close to and far from Illinois Coal Basin



NOTES: Plot shows log relative coal capital averaged across counties with centroids that are less than 50 miles (solid black) and between 200 and 250 miles (dashed gray) from the nearest coal resource in the Illinois Coal Basin for each decade from 1890 to 1990.

Unfortunately, Figure 2 does not provide causal evidence of path dependence in energy transitions. Among other concerns, the dynamics displayed in Figure 2 may reflect the role of unobserved time-invariant characteristics with ongoing influence on relative coal capital, rather than the direct influence of past relative coal capital. The next section details this and other statistical considerations.

3 Empirical framework

This section begins by describing the empirical challenges to identifying path dependence in relative coal capital. I then discuss how shocks to local coal transport distance driven by the changing regional accessibility of subsurface coal may overcome these challenges. To focus for now on empirical issues, this section defines path dependence and its strength within a reduced-form setting. Section 7 will offer formal definitions through the lens of a structural change model.

3.1 Challenges to identifying path dependence

Statistically, path dependence is present when past outcomes have a causal effect on future outcomes. Path dependence in structural change occurs when the outcome exhibiting such dynamics is an economy's composition of inputs. I begin with a simple empirical framework to illustrate the challenges with estimating path dependence in energy transitions. There are two decades, $t \in \{1, 2\}$, and two fuel-specific intermediate sectors of electricity production, $j \in \{c, n\}$. Sector c produces electricity using coal; sector n produces electricity using other fuels. The outcome of interest is relative coal capital in county i, $\widetilde{K}_{it} = \frac{K_{cit}}{K_{nit}}$. w_{cit} is the delivered coal price. Demand for relative coal capital for each period is

$$\ln \widetilde{K}_{i1} = \pi \ln w_{ci1} + \xi_{i1} \tag{1a}$$

$$\ln \widetilde{K}_{i2} = \rho \ln \widetilde{K}_{i1} + \pi \ln w_{ci2} + \xi_{i2} \tag{1b}$$

where π is the contemporaneous price effect. ρ is my reduced-form parameter for path dependence. The error term ξ_{it} contains unobserved time-varying and -invariant determinants of relative coal capacity. The presence of the latter, in particular, implies that a component of ξ_{i2} also appears in $\widetilde{K}_{i1}$ such that the autoregressive coefficient obtained by directly estimating equation (1b) may not distinguish path dependence following a transitory shock from the persistent effects of time-invariant determinants.[8] To formalize this concern, insert equation (1a) into (1b)

$$\ln \widetilde{K}_{i2} = \rho\pi \ln w_{ci1} + \pi \ln w_{ci2} + \varepsilon_{i2} \tag{1c}$$

where $\varepsilon_{i2} = \rho\xi_{i1} + \xi_{i2}$. Two statistical assumptions are needed for the ratio of lagged to contemporaneous effects, $\frac{\partial ln\widetilde{K}_{i2}/\partial lnw_{ci1}}{\partial ln\widetilde{K}_{i2}/\partial lnw_{ci2}}$, to identify ρ. The first is $E[w_{ci2}\varepsilon_{i2}|w_{ci1}] = 0$, which states that contemporaneous coal prices must be exogenous. This exogeneity assumption would be violated if, for example, relative coal capital and prices were simultaneously determined. The second identifying assumption is $E[w_{ci1}\varepsilon_{i2}|w_{ci2}] = 0$, which requires that past coal prices be uncorrelated with unobserved contemporaneous determinants of relative coal capital. If this "exclusion restriction" assumption is satisfied, past prices affect current relative capital only through past relative capital. When both assumptions are satisfied, effects that grow over time, $\frac{\partial ln\widetilde{K}_{i2}/\partial lnw_{ci1}}{\partial ln\widetilde{K}_{i2}/\partial lnw_{ci2}} > 1$, imply strong path dependence in energy transitions. Conversely, dissipating effects, $\frac{\partial ln\widetilde{K}_{i2}/\partial lnw_{ci1}}{\partial ln\widetilde{K}_{i2}/\partial lnw_{ci2}} < 1$, imply weak path dependence.

In practice, another complication arises when estimating equation (1c), which implicitly assumes that lagged effects can be detected within a single decade. Electricity capital decays

[8] See a related discussion in Bleakley and Lin (2012).

slowly over multiple decades. To detect effects on subsequent new capital investments (and not just on depreciated existing capital), one needs county-level coal prices across much of the 20th century. Unfortunately, to the best of my knowledge, such historical data were either never collected or, if collected, are no longer available today (see Appendix B for a summary of historical data collection and availability).

3.2 Solution: regionally-driven local coal transport distances

To address these empirical challenges, I construct shocks to local coal transport distance that rely on plausibly weaker identifying assumptions and span a 110-year period. The basic idea is to construct *local* shocks using the changing *regional* accessibility of subsurface coal.

Mechanized mining and access to deep coal resources Prior to the 20th century, most coal in the U.S. was manually mined which generally limited extraction to coal resources less than 200 feet from the surface (Fisher, 1910; Speight, 1994). Mechanized mining was introduced around the turn of the century and eventually came to dominate coal extraction. As shown in Figure A.1, nearly the entire production increase in bituminous coal - the variety most used for electricity - between 1890-1930 came from mechanized extraction (U.S. Census Bureau, 1975). The main benefit of mechanization was the introduction of mechanized drills that allowed for the excavation of previously inaccessible deep coal resources. The interaction between this aggregate technology shock and the spatial distribution of deep coal resources altered local delivered coal prices.

Using local coal transport distances To illustrate how changing regional coal accessibility from the introduction of mechanized mining can be exploited, I return to the empirical framework in Section 3.1. Suppose only shallow coal resources below 200 ft could be extracted in the first decade. In the second decade, technology enables deep coal mining. Denote the set of operating mines in each period as M_t.

To construct local coal transport distance shocks in this setting, I enlist the Herfindahl Principle (Herfindahl, 1967), a common result in models of spatial competition. The Herfindahl Principle states that when a homogeneous resource is costly to transport across space, and homogeneous suppliers are perfectly competitive, a consumer buys from the physically nearest supplier at a price that is set, in part, by distance to that supplier.[9] For county i in

[9] More specifically, the Herfindahl Principle states that under perfect competition, a consumer will buy resources from the producer with the lowest cost of supplying to that consumer. When producers have homogeneous resource endowments and extraction costs, and transport costs scale with distance, the lowest cost producer for a consumer is its physically nearest producer. See Gaudet, Moreaux and Salant (2001) for a generalized setting with multiple, spatially differentiated, consumers. Robustness checks in Section 5.3

decade t, distance to the nearest mine is

$$d_{it} = \min_{m_t \in M_t} \{||i - m_t||\}$$

where $||i - m_t||$ is the Euclidean distance between county i and coal mine $m_t \in M_t$. Delivered coal price can then be decomposed into

$$\ln w_{cit} = \ln d_{it} + \zeta_{it} \tag{2}$$

where ζ_{it} includes other supply-side factors. Inserting equation (2) into equation (1c)

$$\ln \widetilde{K}_{i2} = \rho\pi \ln d_{i1} + \pi \ln d_{i2} + \mu_{i2} \tag{3}$$

where $\mu_{i2} = \rho\pi\zeta_{i1} + \pi\zeta_{i2} + \varepsilon_{i2}$. $\ln d_{i2}$ is log distance to the nearest mine when mechanized mining is available. $\ln d_{i1}$ is log distance to the nearest mine before mechanized mining.[10] To ensure $\frac{\partial ln\widetilde{K}_{i2}/\partial lnd_{i1}}{\partial ln\widetilde{K}_{i2}/\partial lnd_{i2}}$ has a path dependence interpretation, the updated exogeneity and exclusion restriction assumptions for equation (3) are $E[\ln d_{i2}\mu_{i2}|\ln d_{i1}] = 0$ and $E[\ln d_{i1}\mu_{i2}|\ln d_{i2}] = 0$, respectively.[11]

Compared with directly using coal prices in equation (1c), use of $\ln d_{it}$ has two distinct advantages. First, construction of $\ln d_{it}$ requires only historical data on the location, coal depth, and operating years of coal mines, which, unlike historical coal prices, is available across the 20th century. Second, observe that outside of county i's location (addressed below), $\ln d_{it}$ is driven primarily by two *regional* determinants: (i) the time-invariant spatial distribution of the depth of subsurface coal resources and (ii) the time-varying introduction of mechanized mining which made deep coal accessible. As a consequence, use of $\ln d_{it}$ is more likely to satisfying my identifying assumptions.

3.3 Regression specification

Equation (3) from Section 3.1's simple empirical framework is a cross-sectional regression. In practice, I use a county-by-decade panel dataset to estimate an event study specification

considers potential complications that arise when coal resources have heterogeneous quality and when coal mines have market power.

[10] In this setting, it need not be the case that $\ln d_{i1} \neq \ln d_{i2}$ for all counties. The introduction of mechanized mining may not lead to the opening of a deep coal mine that is closer to a given county than an existing shallow coal mine.

[11] Observe that the coefficient on distance in equation (2) need not be one. As long as this coefficient is time-invariant and the identifying assumptions for equation (3) are satisfied, $\frac{\partial ln\widetilde{K}_{i2}/\partial lnd_{i1}}{\partial ln\widetilde{K}_{i2}/\partial lnd_{i2}}$ would cancel out this coefficient and identify ρ. That is, to estimate path dependence, I only require that the identifying variation - in this case local coal transport distances - drive relative coal capital. This variation need not directly capture coal prices, per se.

that generalizes equation (3). This approach allows several additional advantages. First, identifying assumptions are now in terms of parallel trends. Namely, in the absence of shocks to local coal transport distance, relative coal capital would have followed the same trends in all sample counties. Second, because each county experiences the event of first switching to deep coal at different moments in time, lagged effects of distance to the nearest shallow mine can be estimated in "event time" and are distinct from secular time trends over the 20th century. Third, the presence of multiple decades of data for each county enables estimation of lead effects and lagged effects over a long time horizon. Lead effects provide an indirect test of parallel trends. Lagged effects across multiple decades allow sufficient time for capturing new electricity capital decisions.

Denote $h = -2, \ldots, 10$ as the event-time index. For each county, there are three distinct periods, each occurring when the distance to its nearest coal mine changes. The focal event occurs when a county's nearest mine switches from a shallow to a deep coal mine for the first time. $h > 0$ denotes the period after that switch. $h = 0$ marks the period before the switch during which a county was closest to a shallow coal mine.[12] $\ln d_i^0$ is distance to that shallow coal mine and represents my local coal transport distance shock. $h < 0$ indicates an earlier period when a county's coal supplier was yet a different shallow coal mine. Using this event study setting, I estimate for county i, in state s, during decade t

$$\ln \widetilde{K}_{it} = \sum_{\substack{-2 \leq \tau \leq 10 \\ \tau \neq 0}} \beta^\tau [\ln d_i^0 \times \mathbf{1}(\tau = h)] + \pi \ln d_{it} + \sum_{\substack{-2 \leq \tau \leq 10 \\ \tau \neq 0}} \gamma^\tau \mathbf{1}(\tau = h) + \varpi_i + \phi_{st} + \mu_{ist} \quad (4)$$

where γ^τ captures common event-time effects and μ_{ist} is an error term. County fixed effects, ϖ_i, removes concerns that local coal transport distance shocks may be correlated with a county's time-invariant characteristics such as its geography. State-by-decade fixed effects, ϕ_{st}, removes the presence of regional economic conditions that may jointly influence deep coal mine openings and relative coal capital. In Section 5.1, I show pre-trend tests for key covariates that support the inclusion of these controls. π is the contemporaneous effect of local coal transport distance. β^τ indicate lead and lagged effects. When $\tau > 0$, β^τ are lagged effects, with $\frac{\beta^\tau}{\pi} > 1$ and $\frac{\beta^\tau}{\pi} < 1$ implying strong and weak path dependence, respectively. When $\tau < 0$, β^τ are lead effects and test for the presence of differential pre-trends in relative coal capital. Equation (4) is my baseline specification. In Section 5.3, I also estimate variants of equation (4) to address remaining identification concerns.

[12] Note that $h = 0$ can span multiple decades if the shallow coal mine is a county's nearest supplier for some time.

4 Data

This section first details how spatial data on coal resources and mines are used to construct shocks to local coal transport distance. I then describe the construction of relative coal capital, my main outcome variable. For both variables, I present several tests to verify assumptions used in each construction procedure.

4.1 Local coal transport distance

The USGS National Coal Resource Assessment (NCRA) recently amassed and digitized spatial data on coal resources and mining that was previously held separately in the archives of state geological agencies (East, 2012). As shown in Figure A.2, the NCRA provides GIS shape files for coal resources of depths greater than and less than 200 ft from the surface for each of the major U.S. coal basins.[13] This paper makes several sample restrictions for data availability and estimation reasons.

I focus on coal resources found in the Illinois coal basin.[14] Of the major basins assessed by the NCRA, only for the Illinois Basin there is data on the location, area, and opening and closing years of coal mines.[15] This data goes back to 1890. The Illinois Basin is also advantageous for its geological properties. As Figure 3 shows, it has a dish-like shape with shallow coal resources in the outer regions and deeper resources near the center.[16] Coal across a single large deposit is less likely to be heterogeneous in quality. Indeed, data from the FERC-423 coal procurement forms displayed in Table A.1 show that of the five major coal basins, the Illinois Basin contains coal with the second lowest standard deviation in heat and ash content. Other coal basins also exhibit more complicated subsurface structures with overlapping coal layers situated under the same location. In such cases, shallow coal mining could lead directly to deep coal extraction.

Within the Illinois Basin, I consider only coal mines whose spatial area exceeds the 95% percentile for that basin. This is done for identification reasons. First, larger coal resources are more likely to be mined in response to regional, rather than local coal demand. Second,

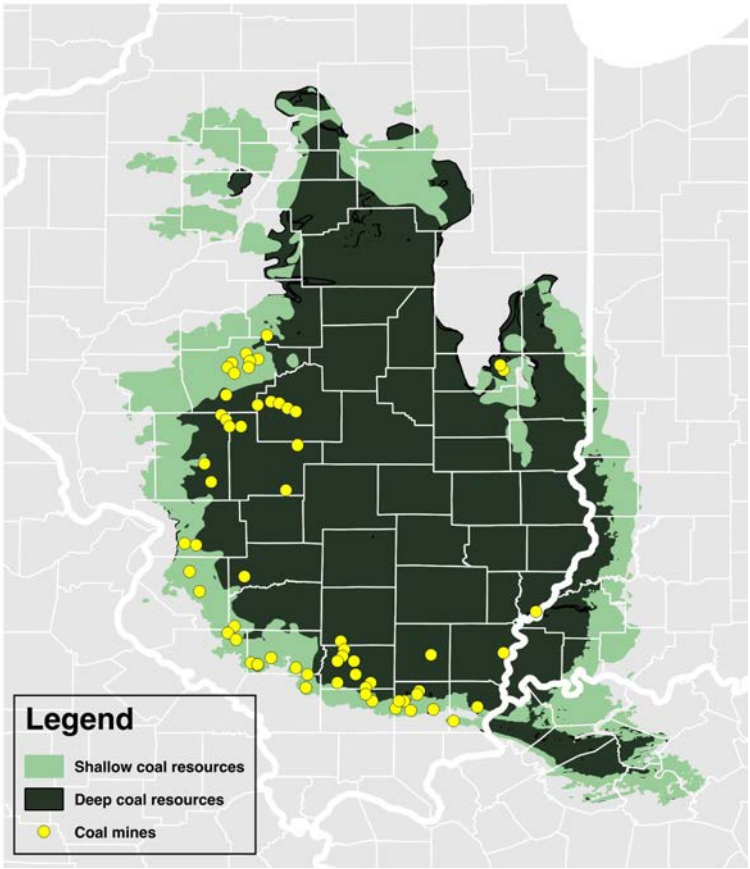
[13] The NCRA does not provide shape files with finer intervals of coal depth. Fortunately, Fisher (1910) notes 200 ft from the surface as generally the depth limit for manual coal mining prior to the 20th century.

[14] In the 1990s, the Illinois Coal Basin provided 20% of bituminous coal in the U.S. (Energy Information Administration, 1994) That share is likely to have been higher earlier in the 20th century before the large scale extraction of western U.S. coal.

[15] Historical coal mine data for other basins are still held by state-level natural resource agencies. These agencies typically possess a coal mine "final map" which dates a mine's closing, but not opening year.

[16] While the NCRA provides shape files of modern coal resources, much of the Illinois Basin has been characterized since the start of the 20th century such that one can interpret Figure 3 as indicating the location of coal resources known across much of the 20th century. For example, the shape of the Illinois Basin shown in Figure 3 matches closely with that found in Campbell (1908).

Figure 3: Location of Illinois Basin coal resources and mines



NOTES: Green (lighter) shaded area indicates shallow coal resources (<200 ft. underground). Black (darker) shaded area indicates deep coal resources (>200 ft. underground). Yellow dots show all large coal mines that operated at any point after 1890. County and state boundaries also shown.

larger coal resources have lower Hotelling, or scarcity rents, which may be an endogenous component of the delivered coal price (Hotelling, 1931). Figure 3 shows the location of these mines over the Illinois Basin. On the demand side, I restrict my county sample to those whose distance from centroid to nearest Illinois coal resource is (i) less than the distance to the nearest Appalachian coal resource and (ii) less than 250 miles. The first restriction reduces the influence of coal from nearby Appalachian Basin on delivered coal prices. The second restriction reduces the influence from other coal basins. The resulting sample of counties is shown in Figure A.3. These particular sample restrictions will be subjected to robustness checks.

Using the NCRA spatial data, I identify a county's distance to its nearest coal mine for each decade from 1890 to 1990 (see Appendix A for data construction details). Figure A.4 maps county distance to nearest mine from 1890-1950, showing how its spatial distribution has changed over the 20th century. From this data, I can also determine the decade in which a county's nearest mine switches from a shallow to a deep coal mine for the first time. Figure

A.5 shows the timing of this switch for each sample county, stacked according to the decade when it occurs. Observe that the timing of the switching event differs across counties.

I turn to three pieces of auxiliary evidence to verify my construction of coal transport distances. First, the use of transport distance assumes that transport costs are an important component of delivered coal prices. Figure A.6 shows that transport costs were between 40-60% of national U.S. delivered coal prices over the first half of the 20th century. This is consistent with previous research emphasizing the high costs of transporting coal, the heaviest fossil fuel by heat content (Joskow, 1987; Busse and Keohane, 2007; McNerney, Farmer and Trancik, 2011; Preonas, 2018).

Second, my construction procedure relies on the Herfindahl Principle, in which power plants buy coal from its nearest mine. Using coal procurement data from 1990-1999 FERC-423 forms, Figure A.7 shows how the share of coal purchased by a county varies according to the rank in the transport distance to coal-supplying counties.[17] Nearly 50% of purchased coal came from the nearest coal supplying county. There is a steep and sustained drop in the share of coal purchased from other counties.

As a final check, I regress observed county-level delivered coal prices obtained from the FERC-423 forms during the 1970s, 1980s, and 1990s against local coal transport distance for sample counties. A perfect statistical fit is not expected nor desired as observed prices may contain endogenous components in addition to transport costs. The correlations shown in Table A.2 are statistically significant at the 5% level across all three decades and thus provide confidence that my transport distance shocks is capturing variation in delivered coal prices.

4.2 Electricity capital

Fuel-specific electricity capital, or capacity, at or below the county level throughout the 20th century is also not directly available (see Appendix B for details). Instead, I turn to modern EIA-860 forms to construct a county-by-decade panel of relative coal capital from 1890 to 1990. Importantly, this construction of historical data is made possible because EIA-860 collects data on capacity, operating years, and primary fuel input for both active and retired generating units at power plants that were operating at the time of reporting. The availability of retired generating units, in particular, enables one to observe historical electricity capital that is no longer active today (see Appendix A for construction details).

Three assumptions must be satisfied for my constructed relative coal capital to match

[17] Unfortunately, FERC-423 forms provide the county of origin for delivered coal, and not mine. Because I am unable to directly link power plants with coal mines, Figure A.7 provides a noisy test of the Herfindahl Principle.

historical values. First, all power plants since 1890 must continue to have at least one active generating unit today. If an entire power plant retires, their generating units would not appear in modern EIA-860 forms. To test the degree in which my constructed data may be missing retired power plants, I turn to available national historical data since 1920 (U.S. Census Bureau, 1975). Panel A of Figure A.8 compares U.S. electricity capacity (in gigawatt, GW) summed across generating units burning fossil fuels (i.e., coal, oil, and natural gas) constructed from EIA-860 forms against observed values from the U.S. Historical Census for the 1920-1970 period. Panel B of Figure A.8 provides a similar comparison but for annual capacity changes. While my constructed data under reports fossil fuel capacity levels prior to 1955, the two national data series track closely in terms of annual changes throughout the 1920-1970 period. This suggests that my constructed data may be missing power plants that began operation prior to 1920 but less likely those operating after 1920. Panels C and D of Figure A.8 draw a similar conclusion for electricity capital using hydro power.

My second and third assumptions are that a generating unit must not change its capacity and primary fuel during its lifetime. Section 6.1 discusses engineering reasons for why these features are likely to be stable over time. Nonetheless, such changes may occur. Table A.3 examines the consistency of key generating unit characteristics across the 1990-2012 EIA-860 forms. For each characteristic across columns of Table A.3, row values indicate the percentage of 1990-2011 EIA-860 forms with values that differed from that reported in the 2012 EIA-860 form. 75%, 94%, 97% and 80% of generating units consistently reported using the same capacity, primary fuel, opening year, and retirement year in 1990-2011 as was reported in 2012.

To examine the consistency of generating unit characteristics over a longer time horizon, I digitized the 1980 EIA "Inventory of Power Plants in the United States," the earliest available comprehensive generating-unit dataset, with data collected during the late 1970s. Figure A.9 plots generating unit capacity reported in 2012 against the capacity reported in the late 1970s, showing a nearly one-for-one relationship. Table A.4 shows the distribution of reported primary fuel in 2012 conditional on primary fuel reported in the late 1970s. There has been little fuel switching since the late 1970s.

Imputing missing small power plants The EIA-860 forms have one additional limitation: they exclude generating units on power plants with less than 1 megawatt (MW) of combined electricity capacity. This omission can be consequential for relative coal capital and how it is modeled. Suppose a county's non-coal electricity only comes from less than 1 MW power plants. Then my data would erroneously assigned a zero value to non-coal capital, leading to a missing value for relative coal capital. Such data censuring would result

in a smaller sample and a lower sample mean for relative coal capital. Similarly, if a county's coal-fired electricity is produced only with missing small power plants, then both coal capital and relative coal capital would be incorrectly assigned zero values. This form of censuring increases the skewness of relative coal capital.

In the absence of historical data, one can try to predict the frequency of power plants below the 1MW threshold using the observed power plant size distribution. Figure A.10 plots the size distribution for all U.S. power plants appearing in the EIA-860 forms that were built during the 1910s and 1950s.[18] The solid and dashed lines show the fitted and predicted frequency of power plants between 1 and 30 MW capacity using a flexible polynomial specification. Because of the skewness of the size distribution, Figure A.10 predicts there are more power plants below 1 MW built each decade across the U.S. than power plants of any other size. In Appendix C, I introduce an imputation procedure which takes the predicted national frequency of new missing power plants for each decade, splits it by fuel according to the national coal share, and assigns new power plant capital uniformly across electricity-producing counties.

Column 1 of Table A.5 shows summary statistics for raw relative coal capital. Columns 2-4 provide summary statistics for relative coal capital following this imputation procedure with the national power plant size distribution for each decade is fitted using 3rd, 4th, and 5th order polynomial functions, respectively. As expected, my imputation procedure increases the sample size, raises the mean, and reduces the skewness of relative coal capital. Column 5 displays summary statistics for relative coal capital using an alternative imputation approach which simply adds 1 MW to new coal and non-coal capital investment in each county-by-decade observation. Robustness checks will examine all five measures of relative coal capital in Table A.5.

Finally, regardless of my imputation procedure, relative coal capital, remains right-skewed. This skewness in my outcome variable can be mitigated by the log transformation applied in equation (4). However, a log transformation is also sensitive to small values of the untransformed variable, which may depend on my imputation procedure. To produce estimates that are less sensitive to my imputation method, I estimate equation (4) using a Poisson model.[19] I also consider other models as robustness checks.

[18] Size distributions for plants built during other decades have similar shapes.

[19] Specifically, the Poisson version of equation (4) is

$$\widetilde{K}_{it} = exp\left(\sum_{\substack{-2\leq\tau\leq 10\\ \tau\neq 0}} \beta^{\tau}[\ln d_i^0 \times \mathbf{1}(\tau = h)] + \pi \ln d_{it} + \sum_{\substack{-2\leq\tau\leq 10\\ \tau\neq 0}} \gamma^{\tau}\mathbf{1}(\tau = h) + \varpi_i + \phi_{st}\right) + \mu_{ist} \qquad (4')$$

The Poisson model has the additional benefit of being a member of the linear exponential family such that even if the density is misspecified, one can still obtain consistent point estimates through quasi-MLE provided

5 Reduced-form results

This section presents reduced-form evidence of path dependence in energy transitions. To guide the specification of my baseline model, I first test for pre-trends in key county covariates across models with different controls. I then present baseline reduced-form estimates and various robustness checks.

5.1 Examining pre-trends in county covariates

The baseline specification in equation (4) includes county and state-by-decade fixed effects. Table 1 verifies the importance of these controls by examining whether a county's distance to its nearest shallow mine before its switch to deep coal (i.e., $\ln d_i^0$), correlates with contemporaneous county characteristics that broadly capture coal demand. These covariates were obtained from Haines (2010) and shown down the rows of Table 1. Total and urban population proxy for residential coal demand. The number of establishments, employment, capital value, and output value for the manufacturing sector are indicative of that sector's coal demand.[20]

Each column of Table 1 estimates a model with different identifying assumptions. Column 1 shows the effect of $\ln d_i^0$ on log covariates in levels. Column 2 examines the effect of $\ln d_i^0$ on log covariates in first-differences, analogous to a panel estimator with county fixed effects. Column 3 augments column 2 by further including state fixed effects, akin to a panel estimator with county and state-by-decade fixed effects. Only in column 3 are pre-trends in these covariates systematically unrelated to $\ln d_i^0$.

5.2 Baseline estimates of path dependence

The thick solid red line in Figure 4 shows my baseline point estimates of β^τ from equation (4) estimated using a Poisson model with relative coal capital, $\tilde{K}_{it} = \frac{K_{cit}}{K_{nit}}$, as the outcome. These estimates are also printed in column 1 of Table 2.

Standard Poisson models impose that the first and second moments of the outcome be equal. Table A.5 shows that the variance of relative coal capital exceeds its mean. To address this overdispersion issue, my baseline model has standard errors clustered at the county level. This adjustment relaxes the assumption of equal first and second moments

that the conditional mean function is correctly specified.

[20] A more precise test of pre-trends in manufacturing activity would isolate subsectors that are coal or electricity intensive. Historically, such data would have been collected by the U.S. Census of Manufacturers (COM). For our sample counties, pre-trend tests require data during 1880-1960. Unfortunately, as noted by Vickers and Ziebarth (2018), most COM data from this period has either since been lost or was never collected.

Table 1: Pre-trends in county covariates

Outcome	(1) Levels	(2) Changes	(3)
Log population (1890-1990)	-0.13	-0.014	-0.016
	(0.086)	(0.0090)	(0.013)
Number of counties	261	261	261
Log urban population (1890-1980)	-0.085	-0.013	0.019
	(0.17)	(0.017)	(0.022)
Number of counties	183	171	171
log mgf establishments (1890-1990)	-0.20**	-0.052	0.046
	(0.098)	(0.056)	(0.064)
Number of counties	260	260	260
log mgf employment (1890-1990)	-0.16	0.11**	0.00096
	(0.20)	(0.052)	(0.068)
Number of counties	258	255	255
log mfg capital (1890-1900)	0.071	0.17**	0.093
	(0.24)	(0.085)	(0.15)
Number of counties	106	105	105
log mfg output (1890-1940)	-0.44	0.17**	0.044
	(0.35)	(0.075)	(0.16)
Number of counties	114	113	113
State fixed effects	No	No	Yes

NOTES: Each coefficient comes from a separate regression of $\ln d_i^0$ on a contemporaneous county covariate as outcome. Time coverage for covariates indicated. County sample shown in Figure A.3. Covariates in column 1 in log levels. Covariates in columns 2 and 3 in first log differences. Column 3 augments column 2 by including state fixed effects. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

by allowing arbitrary forms of within-county heteroskedasticity and serial correlation in the error term. The darker shaded area of Figure 4 shows baseline 95% point confidence intervals for β^τ using county-level clustered standard errors. It is possible that error terms are spatially correlated across counties. To address this, the lighter shaded area shows the 95% point confidence interval when errors are clustered at the state-by-decade level, which allows arbitrary heteroskedasticity and spatial correlation across counties in the same state and decade. These two confidence intervals cover similar ranges.

Table 2: Baseline reduced-form estimates of path dependence

	(1) relative coal capital	(2) relative coal capital investment
$\ln d_i^0$ (β^τ)		
2 decades lead	-1.38	0.60
	(1.02)	(2.00)
1 decade lead	-0.66	-0.33
	(0.67)	(2.32)
	–	–
1 decade lag	-0.68	-4.47**
	(1.25)	(1.89)
2 decades lag	-4.11***	-3.46
	(1.15)	(2.17)
3 decades lag	-3.75***	-7.75**
	(0.66)	(3.61)
4 decades lag	-3.51***	-5.68
	(0.71)	(5.21)
5 decades lag	-4.58***	-4.46
	(0.98)	(3.59)
6 decades lag	-3.71***	-2.93
	(0.75)	(3.89)
7 decades lag	-6.20***	-10.1**
	(1.37)	(4.20)
8 decades lag	-7.30***	-6.42
	(1.59)	(4.27)
9 decades lag	-7.30***	-3.83
	(1.56)	(4.55)
10 decades lag	-7.01***	-2.77
	(1.56)	(5.82)
$\ln d_{it}$ (π)	-1.53***	-3.48***
	(0.53)	(0.88)
Observations	2,371	2,371
Counties	261	261

NOTES: Estimates of β^τ and π from equation (4) using Poisson model. Outcomes variables are at the county-by-decade level. Each model includes event time, county, and state-by-decade fixed effects. County sample shown in Figure A.3. Time period is 1890-1990. Outcome in column 1 is relative coal capital. Outcome in column 2 is relative coal capital investment. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

I do not detect lead effects (i.e., $\beta^\tau : \tau < 0$). The absence of differential pre-trends in my outcome variable is consistent with the lack of pre-trends in county covariates shown in column 3 of Table 1 and provides even stronger support for a parallel trends assumption.

Next, consistent with a reduced-form definition of strong path dependence, I detect statistically significant lagged effects (i.e, $\beta^\tau : \tau > 0$) that become more negative over time. Several observations suggest that past local coal distance shocks are leading to fuel imbalance in subsequent electricity capital investments. First, lagged effects that grow in magnitude cannot be attributed solely to capital in existence prior to the event as depreciation over time should generate dissipating, not strengthening, lagged effects. Second, as Figure 4 shows, lagged effects display two distinct jumps after the switching event: a 1% increase in transport distance discretely lowers relative coal capital by 4.11% and 6.20% two and seven decades later, respectively. These jumps coincide roughly with the expected construction of two subsequent vintages of electricity capital.[21] Third, column 2 of Table 2 shows estimates of β^τ when the outcome is relative coal capital investment, $\tilde{X}_{it} = \frac{X_{cit}}{X_{nit}}$, the ratio of new coal to non-coal electricity capital built in each county i and decade t. Shocks to local coal transport distance alter relative coal capital investment over many subsequent decades.

5.3 Robustness checks

I turn now to a series of robustness checks designed to address further identification, data construction, sample restriction, and statistical modeling concerns. Point estimates for all robustness checks are shown as thin non-solid blue lines in Figure 4.

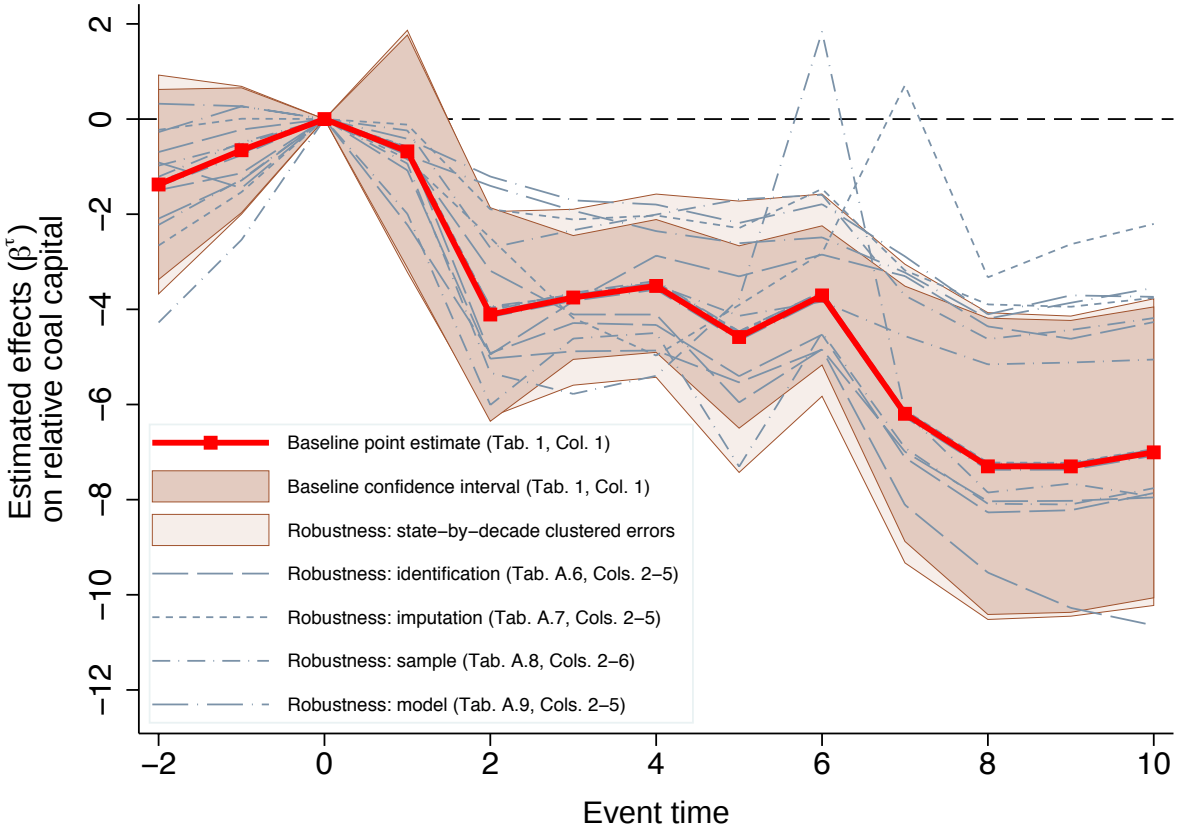
Remaining identification concerns Table A.6 explores remaining identification concerns, with column 1 replicating my baseline estimates.

Other components of the delivered coal price may be correlated with distance to the nearest coal mine. One such component is the mill price set by the nearest mine which reflects its marginal cost of coal extraction (Hotelling, 1929; C. d'Aspremont, 1979; Salop, 1979; Vogel, 2008) and the Hotelling rent associated with the size of its coal resource (Hotelling, 1931; Gaudet, Moreaux and Salant, 2001). The mill price may also capture dimensions of heterogeneity in coal quality, such as heat, ash, and sulfur content, that can alter the amount of coal needed to produce a unit of electricity. To control for mine-specific heterogeneity, column 1 augments my baseline model with a fixed effect for the nearest shallow mine right before switching event.[22] I find similar lagged effects up to five decades. Longer lags are

[21] The average generating unit in my sample lasts 4.7 decades.

[22] There are 52 mines that served as the nearest supplier to sample counties right before the switching event.

Figure 4: Reduced-form estimates of path dependence in relative coal capital



NOTES: Thick solid red line and darker shaded area show baseline point estimates and 95% confidence intervals for β^τ from equation (4) with county-level clustered standard errors. Outcome is relative coal capital at the county-by-decade level. County sample shown in Figure A.3. Time period is 1890-1990. Estimates also shown in column 2 of Table 2. Lighter shaded area shows the 95% confidence interval when estimating equation (4) with state-by-decade clustered standard errors. Thinner non-solid blue lines show point estimates from various robustness tests displayed in columns 2-5 of Table A.6, columns 2-5 of Table A.7, columns 2-6 of Table A.8, and columns 2-5 of Table A.9.

smaller in magnitude but within the 95% confidence of my baseline model.

It is possible that distance to the nearest shallow mine continues to directly influence relative coal capital after the switching event. While this implies that lagged effects would not have a clean path dependence interpretation, the resulting bias is likely towards zero, with lagged coefficients understating the true strength of path dependence. This is because, on its own, increasing mill prices from the ongoing depletion of the shallow mine would predict weakening, not strengthening, lagged effects over time.

A particular channel through which a shallow mine may exert direct influence on relative coal capital after the switching event is if the mine could price discriminate. For example, if mine A as initially the nearest supplier to a county but becomes the second nearest supplier following the opening of mine B, mine B could price-discriminate by setting a buyer's coal

price equal to its distance to mine A (MacLeod, Norman and Thisse, 1988; Vogel, 2011). Under this form of market power, distance to mine A would directly determine a county's subsequent coal price even if it were no longer supplying coal.[23] To remove the possibility of price discrimination from affecting my results, column 3 estimates my baseline model without the counties for which the earlier supplying shallow mine becomes the second nearest mine at any point after the switching event. My results are little affected.

Finally, I examine the possibility that distance to the shallow mine may be correlated with trends in other determinants of relative coal capital. In column 4, I augment the baseline model with three county-by-decade covariates available throughout the 20th century that proxy for residential and manufacturing demand: population, number of manufacturing establishments, and manufacturing employment, all in logs. Similarly, column 5 accounts for trends in transport costs by adding interaction terms between a linear time trend and two geographical features that affect transport costs: a county's distance to the nearest navigable waterway and its ruggedness, as approximated by its variance in slope, both in logs (see Appendix A for data details). Coefficients in columns 4 and 5 are similar to those of baseline results.

Imputing missing small power plants Table A.7 examines alternative imputations for missing power plants with less than 1 MW capacity. Column 1 replicates my baseline result which uses a 4th order flexible polynomial function to fit the national size distribution of new power plants built each decade. Columns 2 and 3 employ the same imputation procedure but uses 3rd and 5th order polynomial functions, respectively. Point estimates and standard errors are little affected. In column 4, I use a simpler, though less informed, imputation procedure by adding 1 MW capacity to coal and non-coal capital investment. The overall shape and precision of lagged effects are unchanged. While the magnitude of all coefficients are smaller, the ratio of lagged to contemporaneous effects is unaffected. Finally, column 5 estimates equation (4) using unadjusted relative coal capital. Despite the much smaller sample, lagged effects up to six decades have similar magnitudes to baseline results, with 3 to 5 decade lags statistically significant at the 10% level. Longer lagged effects are noisier.

Sample restrictions Table A.8 considers different sample restrictions, with column 1 reproducing my baseline results. On the coal supply side, recall that in order to isolate local coal transport distance shocks driven by regional conditions, I focused on large mines with areas above the 95th percentile of Illinois Basin mines. Estimates in columns 2 and 3 use

[23] There is evidence from recent years showing price discriminating behavior by railroad companies that sell coal to power plants (Busse and Keohane, 2007; Preonas, 2018). Little is known, however, about whether such mark-ups existed across the longer time period considered in this study.

transport distances constructed from mines with area above the 90th and 97.5th percentiles, respectively. While the inclusion of smaller mines result in statistically significant lead coefficients, these coefficients trend in the opposite direction of lagged effects.

On the coal demand side, to lessen the competing effects of other coal basins, my benchmark sample restricted counties to those within 250 miles of the nearest Illinois Basin coal resource and are situated closer to the Illinois Basin than to the Appalachian Basin. In column 4, I further weaken the influence of other coal basins by restricting the sample to counties within 200 miles of the nearest Illinois Basin coal resource. I find similar point estimates and standard errors. In column 5, I allow more counties into the sample by increasing the distance threshold to 300 miles. In column 6, I allow counties that are situated closer to the Appalachian Basin into the sample. For both larger samples, effect sizes are smaller, possibly due to the influence of other coal resources. However, point estimates are within the confidence intervals of baseline results.

Modeling choices The log-log functional form of equation (4) implicitly assumes that the relationship between relative coal capital and coal transport distance is an isoelastic function. While this will be appealing for the theory in Section 6, this functional form may not be empirically supported. Figure A.11 examines whether the data supports linearity by estimating a variant of equation (4) that breaks log distance to the nearest mine into discrete bins, allowing a flexible relationship between distance and relative capital for each event-time period. Figure A.11 shows log relative coal capital predicted by log distance to the contemporaneous nearest mine, and by log distance to the earlier shallow mine two and seven decades after the switching event. These three relationships are approximately linear.

The baseline model in equation (4) includes 10 lag and 2 lead terms. More lag terms allow effects on new capital investments to be detected and 10 is the largest number of lags permitted by my 11 decade-long dataset. I vary the number of lead terms in Table A.9. Column 1 replicates the baseline model, column 2 includes 1 lead term, and column 3 includes 3 lead terms. I do not detect statistically significant lead terms across these models, nor very different lagged effects.

Finally, I consider two alternatives to the baseline Poisson model. The first alternative is a log-log linear model. The downside to such an approach is that a log transformation is sensitive to small values of an outcome variable, which may arise from how missing small power plants are imputed. A second alternative is to employ a negative binomial model. In contrast to a Poisson model which semi-parametrically addresses overdispersion via clustered standard errors, a negative binomial model parametrically models overdispersion as a function of the expected outcome.

Column 4 of Table A.9 estimates equation (4) using a log-log linear model, while column 5 uses a negative binomial model. Both alternative models produce statistically significant lagged effects, mostly at the 5% level. The overall shape of lagged effects from these two models, including the jumps at two and seven decades later, mirrors baseline results. While these coefficients are smaller in magnitude, the ratio of lagged to contemporaneous effects actually imply stronger path dependence.

6 Mechanisms

Section 5's reduced-form evidence of strong path dependence in energy transition suggests it is possible for a permanent energy transition to be induced by a temporary intervention. However, from a climate policy perspective, this statistical result may be unsatisfactory for two reasons. First, it is unclear how these historical reduced-form estimates can inform future energy transitions in the U.S. or elsewhere. Second, even if estimates are externally valid, it is unclear under what conditions can future climate policies sustain a transition towards clean energy.

Addressing these concerns requires additional theory and empirics in order to isolate the relevant mechanism behind my reduced-form results. To that end, this section first develops a model of structural change model for the electricity sector which incorporates two possible mechanisms previously highlighted in the energy economics literature: increasing returns to scale and the accumulation of fuel-specific productivity. Informed by the structure of this model, I then conduct a series of empirical tests designed to isolate the relevant mechanism. For completeness, I also test for mechanisms not considered by the model. While these tests by no means exhaust all possible explanations, their results lend confidence for the particular structural interpretation of my reduced-form results considered in Section 7.

6.1 A model of structural change for the electricity sector

Electricity production exhibits several distinct features that have long been recognized in the literature. I first summarize these features before building them into a model.

F1 **"Putty-clay" capital** In a power plant, a generating unit consists of a boiler which produces steam from fuel and a generator which produces electricity from the boiler's steam. Boilers are typically designed to consume a particular fuel at a particular quantity. Sustained use of other fuels or use of the intended fuel in other quantities can result in large efficiency losses (Avallone, Baumeister and Sadegh (2006), p.871). Because of this feature, prior literature has modeled electricity capital as "putty-clay"

with capital, once built, becoming fully utilized (Joskow, 1985, 1987; Atkeson and Kehoe, 1999).

F2 **Fuel and capital as perfect complements** Fuel is essential for producing electricity and cannot be substituted with other inputs. As such, the combination of fuel and capital in a generating unit is typically modeled using a Leontief function (Komiya, 1962; Atkeson and Kehoe, 1999; Fabrizio, Rose and Wolfram, 2007).

F3 **Returns to scale** At the power plant-level, boilers can be linked to multiple generators. Thus, when a new boiler is installed, it can serve both new and existing generators, providing efficiency gains for generating units across multiple vintages of capital. This spillover effect, together with newer boilers typically being more efficient, provides a physical basis for increasing returns to scale. Nerlove (1963) and Christensen and Greene (1976) provide seminal early estimates of scale economies in the electricity sector.

F4 **Imperfect substitutability across fuel-specific electricity** Electricity properties differ across input fuels. For example, electricity from coal provides "base load" supply that cannot be easily ramped up or down in response to variable demand, unlike electricity from natural gas. Similarly, electricity from solar and wind is less reliable than fossil-fuel based electricity due to the intermittent availability of these renewable resources. This imperfect substitutability across fuels is a crucial element of the directed technical change model developed by Acemoglu et al. (2012).

I incorporate these features into a model of the electricity sector with vintaged capital. The index t denotes the time increment between each capital vintage. At the top tier, the final good, electricity, Y_t, is produced using two intermediate goods, Y_{ct} and Y_{nt}, representing electricity from coal and all other fuels respectively. Specifically, it takes the following Constant Elasticity of Substitution form

$$Y_t = \left(Y_{ct}^{(\epsilon-1)/\epsilon} + Y_{nt}^{(\epsilon-1)/\epsilon} \right)^{\epsilon/(\epsilon-1)} \tag{5}$$

where ϵ is the long-run elasticity of substitution between electricity produced from the two intermediate sectors.[24] To allow for imperfect substitutability between electricity from different fuels (i.e., F4), I assume $\epsilon \in (1, +\infty)$. Final good price is normalized to 1.

Fuel-specific electricity, the intermediate good, is produced via middle and lower tiers of

[24] This parameter is long-run in the sense that it reflects changes in capital.

the production structure. These two tiers combine to form the following expression

$$Y_{jt} = (\min[A_{Xjt}X_{jt}, A_{Ejt}E_{jt}])^{\alpha}(\min[A_{Xjt-1}(1-\delta)X_{jt-1}, A_{Ejt-1}E_{jt-1}])^{\alpha} \quad \text{for} \quad \text{j}\in\{\text{c,n}\} \quad (6)$$

where $\delta \in (0,1)$ is the capital depreciation rate and $\alpha \in (0,1)$ is the fuel-specific electricity elasticity of input. Returns to scale (i.e., F3) is reflected in the middle tier where fuel-specific electricity comes from combining generating units across two vintages with scale parameter $\psi = 2\alpha$.[25] At the lowest tier, generating units combine fuel, E_{jt}, and t-vintaged capital, X_{jt} as perfect complements in a Leontief function (i.e., F2). $A_{Xjt} > 0$ and $A_{Ejt} > 0$ indicate capital and fuel productivities, respectively.

To explore how scale and productivity effects could generate path dependence for otherwise similar intermediate sectors, suppose capital and fuel productivities were the same across the two intermediate sectors in period $t-1$, such that $A_{Xct-1} = A_{Xnt-1}$ and $A_{Ect-1} = A_{Ent-1}$. Next, observe that when fuel and capital are perfect complements, efficient allocation in the lower production tier imply $A_{Xjt}X_{jt} = A_{Ejt}E_{jt}$ for each intermediate sector j. Furthermore, "clay" past-vintage capital (i.e., F1) with large efficiency losses implies that it is fully utilized, set at $A_{Xjt-1}(1-\delta)X_{jt-1} = A_{Ejt-1}E_{jt-1}$ for each intermediate sector j.[26] Rewriting the first order conditions in terms of current-vintage relative coal capital investment, $\widetilde{X}_t = \frac{X_{ct}}{X_{nt}}$, yields (see Appendix D.1 for full derivation)

$$\widetilde{X}_t = \widetilde{w}_t^{\frac{\epsilon}{\varphi-1}} \widetilde{X}_{t-1}^{\frac{\alpha(1-\epsilon)}{\varphi-1}} \widetilde{A}_{Xt}^{\frac{\alpha(1-\epsilon)}{\varphi-1}} \quad (7)$$

where $\widetilde{w}_t = \frac{w_{ct}}{w_{nt}}$ is the relative input price index and $\widetilde{A}_{Xt} = \frac{A_{Xct}}{A_{Xnt}}$ is the ratio of capital productivity for coal and non-coal generating units of vintage t. $\varphi = (1-\alpha)(1-\epsilon) < 0$, from earlier assumptions. Equation (7) provides two channels through which past relative input prices, $\widetilde{w}_{t-1}$, affect current-vintage relative coal capital investment, $\widetilde{X}_t$. First, after applying equation (7) recursively, it can shown that past relative input prices affect past-vintage relative coal capital investment, $\widetilde{X}_{t-1}$. This occurs through the scale channel. Second, while not explicitly modeled here, in the presence of sector-biased technical change, past relative input prices could also affect current-vintage relative capital productivities, $\widetilde{A}_{Xt}$. This productivity channel would occur if there was accumulation over time in fuel-specific capital productivity such as via learning-by-doing or if relative input prices direct research towards fuel-biased technological change.

[25] This allows for diminishing marginal product under varying returns to scale. Otherwise, the relative input demand curve becomes upward sloping. The assumption that returns to scale is constant for coal and non-coal electricity production is examined in Table 3.

[26] Appendix D.2 shows how large efficiency losses when using electricity capital below its designed capacity lead to full utilization of past-vintage capital.

To empirically isolate which of these two channels are relevant for the estimates in Section 5, I turn next to a series of nested empirical tests informed by the tiered structure of the model. First, I conduct power plant-level cost regressions for plants that only use coal to recover the plant-level scale parameter. Because such estimates may be biased in the presence of productivity effects, I then turn to generating unit-level regressions to test for productivity effects.

6.2 Testing for scale effects at the power plant level

To recover the scale parameter, ψ, I follow the approach developed initially by Nerlove (1963) and implemented by Christensen and Greene (1976) to estimate returns to scale in the electricity sector. Following Fabrizio, Rose and Wolfram (2007), I use power plant-level cost data from the Utility Data Institute (UDI) from 1981-1999. To remove the influence of the elasticity of substitution parameter, ϵ, I restrict my sample to power plants p in county i and state s that exclusively use coal. Cost minimization of equation 6 implies the following regression of non-fuel cost (see Appendix D.3 for full derivation)

$$\ln \overline{\text{non_fuel_cost}}_{pis} = \frac{1}{\psi} \ln \overline{Y}_{pis} + \theta' \overline{\boldsymbol{Z}}_{pis} + \eta_{pis} \tag{8}$$

where the bar indicates time-averaged variables over 1981-1999. My parameter of interest is the scale parameter ψ. $\overline{Y}_{pis}$ is electricity output in megawatt-hours (MWh). $\overline{\boldsymbol{Z}}_{pis}$ is a vector of cross-sectional controls. They include observed log power plant-level delivered coal price from UDI, state fixed effects, and the latitude and longitude of the county centroid. I also control for differences across transmission grids by including NERC region fixed effects. Standard errors, η_{pis}, are clustered at the county level. Table 3 displays estimates of ψ for coal-only power plants in my baseline county sample. I estimate a scale parameter of $\hat{\psi} = 1.8$ that is statistically significant at the 1% level.

Potential simultaneity bias in equation (8) has been noted as early as Nerlove (1963). In particular, electricity prices for electric utilities are historically regulated to cover a plant's average costs. As a consequence, electricity output may be correlated with unobserved determinants of non-fuel costs. To address this endogeneity concern, I use past delivered coal prices as an instrument for current electricity output via an instrumental variables (IV) approach. Specifically, my instrument is the interaction between county distance to the nearest shallow mine before the switch to deep coal and the number of decades since that switching event. For identification to be valid, shocks to local coal transport must affect

current non-fuel costs only through current output. Specifically, my first stage regression is

$$\ln \overline{Y}_{pis} = \kappa_1 \ln d_i^o * sinceEvent_i + \kappa_2 \ln d_i^o + \kappa_3 sinceEvent_i + \vartheta' \overline{\boldsymbol{Z}}_{pis} + \nu_{pis} \tag{9}$$

s Equation (9) estimates the event time-varying effects of past transport distance shocks and is the cross-sectional analog to my panel estimator in equation (4). In particular, κ_1 captures the event time-varying effect of past shocks, or the slope of the lagged effects shown in Figure 4. Column 2 of Table 3 shows an IV estimate that is statistically significant at the 1% level and similar in magnitude to my OLS estimate. Furthermore, this IV estimate is robust to the potential presence of a weak instrument. The p-value and confidence interval from a conditional likelihood ratio test strongly reject a null hypothesis that the coefficient on electricity output in equation (8) is zero (Moreira, 2003), assuaging concerns over a seemingly low Kleibergen-Paap first-stage F-statistic. Henceforth, my preferred scale parameter estimate is $\hat{\psi} = 1.66$ from column 2.

The production function presented in Section 6.1 assumes that coal and non-coal electricity exhibit the same returns to scale. To examine this assumption, I estimate equation (8) for power plants that consume natural gas and oil in columns 3 and 4 of Table 3. Because the UDI database has few plants that only consume natural gas and oil in my county sample, for adequate statistical power, I expand the sample to the entire U.S. and to plants UDI designates as consuming natural gas and oil as primary fuels.[27] I estimate scale parameters for gas and oil-fired power plants that are statistically indistinguishable from that of coal-fired power plants.

Finally, despite differences in sample time periods, it is noteworthy that the scale parameter estimates from 1981-1999 in Table 3 are similar to estimates from the prior literature. Nerlove (1963)'s study of electricity sector firms in 1955 recovers a scale parameter of 1.39. For the same sample of firms, Christensen and Greene (1976) estimate an analogous scale parameter of 1.26.

6.3 Testing for productivity effects at the generating unit level

Past shocks to local coal transport distance could also directly affect the accumulative of coal-specific productivity. If so, the IV estimator in Section 6.2 would not satisfy the exclusion restriction needed for identifying the scale parameter. To detect productivity effects, I turn to generating unit-level regressions where productivity effects can be most cleanly iso-

[27] Federal forms used in compiling the UDI data do not explicitly designate a power plant's primary or secondary fuel. For multi-fuel plants, UDI establishes primary fuel by calculating the energy input of each fuel consumed and then assigning primary fuel to the fuel with the highest energy input.

Table 3: Returns to scale regressions at the power plant-level

	(1)	(2)	(3)	(4)
		Outcome is ln non-fuel cost		
$\ln \overline{Y}_{pis}$ $(1/\psi)$	0.56***	0.60***	0.57***	0.51***
	(0.028)	(0.087)	(0.052)	(0.054)
Kleibergen-Paap F-stat		3.250		
CLR p-value		0.0081		
CLR confidence int (90%)		[.54, .89]		
Implied scale parameter, ψ	1.78***	1.66***	1.75***	1.96***
	(0.090)	(0.24)	(0.16)	(0.21)
Model	OLS	IV	OLS	OLS
County sample	Baseline	Baseline	All U.S.	All U.S.
Fuel input	Only coal	Only coal	Primary gas	Primary oil
Power plants	103	96	32	73

NOTES: Estimates of ψ from equation (8) using power plant-level log non-fuel cost as outcome. All models include observed power plant-level log fuel price, state and NERC region fixed effects, and county centroid longitude and latitude. Non-fuel cost and fuel price are 1981-1999 averages. Columns 1 and 2 include coal-only power plants in baseline county sample shown in Figure A.3. Columns 3 and 4 include all U.S. power plants using natural gas and oil as primary fuels, respectively. Columns 1, 3, and 4 show results from OLS regressions. Column 2 shows the result from an IV regression with equation (9) as the first stage. Column 2 shows the Kleibergen-Paap F-statistic (Kleibergen, 2004) as well as the p-value and confidence interval (in brackets) from a conditional likelihood ratio test against a null hypothesis that $1/\psi$ is zero (Moreira, 2003). Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

lated. I employ two standard measures of generating-unit productivity. Following Davis and Wolfram (2012), my measure of capital productivity, A_{Xct}, is the ratio of electricity output to generating unit capacity on an annualized basis. My second measure is thermal efficiency, or the ratio of heat from electricity produced to heat from fuel consumed. This measure corresponds to fuel productivity, A_{Ect}. To obtain both measures, I combine the previously mentioned generating unit capacity data from EIA-860 forms with generating-unit electricity production and boiler-level fuel consumption from EIA-923 forms (see Appendix A for data details). Averaging generating unit-level data across 2009-2012,[28] I estimate the following regression for generating unit g, in power plant p, located in county i and state s using both productivity measures as outcomes

$$\ln \overline{A}_{gpis} = \omega_1 \ln d_i^o \times sinceEvent_i + \omega_2 \ln d_i^o + \omega_3 sinceEvent_i + \lambda' \overline{\boldsymbol{Z}}_{gpis} + \upsilon_{gpis} \tag{10}$$

[28] Because productivity presumably accumulates over time, any lagged effects of past shocks to local coal transport distance should be stronger and more detectable with more recent productivity data.

where the set of controls $\overline{\boldsymbol{Z}}_{gpis}$ includes state and NERC region fixed effects, and the latitude and longitude of the county centroid. The standard error, υ_{gpis}, is clustered at the county level. As with equation 9, ω_1 in equation 10 captures the event time-varying effects of past coal transport distance shocks on generating unit productivity.

Table 4: Productivity regressions at the generating unit-level

	(1)	(2)	(3)	(4)
	Outcome is ln			
	capital productivity		fuel productivity	
$\ln d_i^o \times sinceEvent_i$ (ω_1)	-0.052	-0.032	0.015	0.034
	(0.032)	(0.031)	(0.047)	(0.047)
$\ln d_i^o$ (ω_2)	0.12	0.078	-0.33	-0.37
	(0.17)	(0.18)	(0.26)	(0.27)
$sinceEvent_i$ (ω_3)	0.14	0.034	-0.12	-0.22
	(0.12)	(0.11)	(0.18)	(0.16)
age		-0.012**		-0.011
		(0.0048)		(0.0072)
Generating units	224	224	224	224

NOTES: Estimates from equation 10 using generating unit-level outcomes. All models includes state and NERC region fixed effects, and county centroid longitude and latitude. Sample includes generating units in coal-only power plants located in baseline county sample shown in Figure A.3. Outcome in columns 1 and 2 is the 2009-2012 average ratio of electricity generation to generating unit capital, which approximates capital productivity, A_{Xct}. Outcome in columns 3 and 4 is the 2009-2012 average thermal efficiency, which approximates fuel productivity, A_{Ect}. Models in columns 2 and 4 additionally include generating unit age. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results are shown in Table 4 for generating units in coal-only power plants located in my baseline county sample. Columns 1 and 2 examine log capital productivity. I do not detect statistically significant effects of past coal prices. Imprecise effects become smaller when I additionally control for the age of the generating unit in column 2. Columns 3 and 4 replicate columns 1 and 2 but with log thermal efficiency as the outcome. Again, I do not find that past shocks affect subsequent fuel productivity.

It is perhaps unsurprising that local productivity is unresponsive to past local transport distance shocks at the county level. Most determinants of productivity operate at broader scales. For example, innovation responds to incentives in the research sector, which are rarely confined to individual counties. Similarly, if productivity improvements occur through human capital accumulation, such effects are unlikely to be restricted to a single county when firms with multiple power plants can distribute human capital across several counties.

6.4 Alternative mechanisms

The model in Section 6.1 necessarily omits other potential mechanisms. While the presence of other mechanisms would not invalidate Section 5's reduced-form estimates of strong path dependence in energy transitions, they would complicate how these results are structurally interpreted. This subsection tests for the presence of several alternative mechanisms.

Electricity sector regulation Capital investment responds to regulation. In particular, two regulations may be pertinent for electricity capital decisions. For much of the 20th century, electricity producers faced cost-of-service regulation by state Public Utility Commissions (PUC) which set output prices to ensure producers recover "prudently incurred" variable costs plus a regulated rate of return on capital investments. As noted first by Averch and Johnson (1962), when the allowed rate of return exceeds the cost of capital, electricity producers have an incentive to inefficiently over invest in capital relative to other inputs.[29] Conceptually, the Averch-Johnson effect is unlikely to drive my reduced-form results in Section 5. Structural change pertains to the composition of capital across different fuels and not the overall level of capital. Because cost-of-service regulations for electricity producers do not specify different rates of return for electricity capital using different fuels, such regulations are unlikely to alter the relative marginal product of capital across fuels. This is supported empirically by column 2 of Table A.10 which estimates my baseline model in equation (4) but uses only the subset of observations during which there was no state PUC regulation of electric utilities (see Appendix A for details). Despite the smaller sample size, I still detect statistically significant lagged effects with magnitudes that are similar to my baseline estimates in column 1 of Table A.10.

A second important regulation is the U.S. Clean Air Act. Beginning with the 1970 U.S. Clean Air Act Amendments, counties with concentrations of criteria air pollution exceeding national ambient air quality standards were labeled as being in "nonattainment". Both existing and new polluting facilities in nonattainment counties were required to invest in pollution abatement equipment. Because coal is dirtier than other fuels, it is possible that the 1970 and later Clean Air Act Amendments altered the fuel composition of electricity capital. Table A.10 provides two empirical tests. In column 3, I restrict the sample to observations during 1890-1960, the period before the introduction of the 1970 Clean Air Act Amendments. I find lagged effects that are similar in magnitude to my baseline results. Column 3 also suggests that my path dependence estimates do not differ across the 20th

[29] The literature has found some empirical support for the Averch-Johnson effect in the U.S. energy sector. Joskow and Rose (1989) reviews evidence from the 1960-1980 period. Cicala (2015) finds this effect using more recent data.

century. To provide a more direct test, column 4 restricts my sample to the subset of counties that never received a nonattainment designation during the 20th century. Again, I do not find lagged effects that differ much from my baseline estimates. In summary, Table A.10 suggests that these two regulations are not driving my path dependence results.

Upstream and downstream sectors The electricity sector consumes fuel from upstream extraction and transport sectors and produces electricity for downstream manufacturing and residential sectors. Features of these up- and down-stream sectors could generate the strong path dependence detected in Section 5.

Power plants typically procure coal through long-term contracts with mines (Joskow, 1987). As a consequence, plants may continue buying coal from certain producers even as contemporaneous circumstances change. Joskow (1987) showed that the average coal contract length in 1979 lasted 12.8 years. More recent work by Kozhevnikova and Lange (2009) and Jha (2015) find this duration has since decreased to 4.4 years in the 1980s and 1990s. Coal contracts of such duration are unlikely to generate lagged effects over multiple decades, as detected in Section 5. Furthermore, even if coal contracts were of longer duration, it is unclear why they would cause lagged effects to strengthen over time.

Rail and highway networks serve as complementary capital for delivering coal to power plants. Increasing returns along with sunk costs in the transport sector can also generate path dependence in the fuel composition of the electricity sector.[30] To examine whether past coal transport distance shocks affect the coal transport sector itself, I turn to a county-level version of the specification in equation (10). Column 1 of Table A.11 examines whether there are event time-varying effects of past transport distance shocks on log railroad density in 2010 (in miles per square mile). I do not find such effects which is unsurprising given that most modern U.S. railroads lines were already established by the end of the 19th century (Atack, 2013). Column 2 of Table A.11 also fails to detect effects of past transport distance shocks on log highway density in 2010 (in miles per square mile).

Finally, I consider downstream effects. Previous literature detects long-term effects of historical access to hydropower electricity on local manufacturing sector employment (Kline and Moretti, 2014) and population density (Severnini, 2014). Indeed, one alternative explanation for my results involves downstream manufacturing sectors also exhibit increasing returns to scale and somehow preferring electricity produced from coal over that from other fuels. If so, one would expect my lagged effects to be altered when I control for local manufacturing sector demand. Column 3 of Table A.6 shows that is not the case.

[30] Sunk costs alone, however, would not generate path dependence in the long-run as initial capital would eventually depreciate. See discussion in Bleakley and Lin (2012).

Preference sorting by residential households provides another potential downstream mechanism (Tiebout, 1956). If households with low valuation for environmental amenities sort into historically coal-dependent locations, these residents may support more lenient local environmental policies that enable the expansion of coal-fired electricity even as economic circumstances that initially favored coal disappear. Using the same specification from columns 1 and 2, columns 3 and 4 explore this sorting mechanism by estimating event time-varying effects of past coal transport distance shocks on the share of a county's population belonging to one of three major environmental NGOs in 1996 and the county share of eligible voters that voted for the 2000 Republican Presidential candidate (see Appendix A for data details). Neither proxy for environmental preferences responds to past transport distance shocks.

7 Structural interpretation

Having isolated returns to scale as the relevant mechanism, this section employs the structure of the model in Section 6.1 to interpret my reduced-form estimates. First, I formally define path dependence in energy transitions as a function of two parameters: returns to scale, ψ, and the long-run elasticity of substitution between electricity produced from coal and other fuels, ϵ. I then use this definition to recover ϵ implied by my reduced-form estimates of path dependence in Section 5 and my estimates of the scale parameter in Section 6.2. Because this parameter appears across a broad class of structural change models, this exercise enables external validity for my reduced-form results. Finally, I explore through calibrated model simulations the conditions under which temporary interventions to fuel composition can induce sustained future transitions towards clean energy.

7.1 Formal definitions of path dependence

I formally defined scale-driven path dependence within the model in Section 6.1. To do this, I first apply a log transformation to equation (7) and rewrite it recursively. Current-vintage relative coal capital investment becomes

$$\begin{aligned}
\ln \widetilde{X}_t &= \frac{\epsilon}{(\varphi-1)} \ln \widetilde{w}_t + \frac{\alpha(1-\epsilon)\epsilon}{(\varphi-1)^2} \ln \widetilde{w}_{t-1} + \frac{\alpha^2(1-\epsilon)^2\epsilon}{(\varphi-1)^3} \ln \widetilde{w}_{t-2} + ... \\
&\quad + \frac{\alpha(1-\epsilon)}{(\varphi-1)} \ln \widetilde{A}_{Xt} + \frac{\alpha^2(1-\epsilon)^2}{(\varphi-1)^2} \ln \widetilde{A}_{Xt-1} + \frac{\alpha^3(1-\epsilon)^3}{(\varphi-1)^3} \ln \widetilde{A}_{Xt-2} + ... \\
&= \sum_{s=0}^{t} \frac{\epsilon}{(\varphi-1)} \left[\frac{\alpha(1-\epsilon)}{(\varphi-1)}\right]^s \ln \widetilde{w}_{t-s} + \sum_{s=0}^{t} \left[\frac{\alpha(1-\epsilon)}{(\varphi-1)}\right]^{s+1} \ln \widetilde{A}_{Xt-s} \qquad (11)
\end{aligned}$$

where s is a lagged time index. An increase in relative coal price lowers contemporaneous relative coal capital investment, $\frac{\partial \ln \widetilde{X}_t}{\partial \ln \widetilde{w}_t} < 0$, and also lowers future relative coal capital investment, $\frac{\partial \ln \widetilde{X}_t}{\partial \ln \widetilde{w}_{t-s}} < 0$. The relative magnitude of these two effects dictate the strength of path dependence in energy transitions. Formally,

PROPOSITION 1 ***Weak path dependence:*** *The effect of past relative coal prices weakens over time,* $\frac{\partial \ln(\widetilde{X}_t)}{\partial \ln(\widetilde{w}_{t-1})} / \frac{\partial \ln(\widetilde{X}_t)}{\partial \ln(\widetilde{w}_t)} = \frac{\alpha(1-\epsilon)\epsilon}{(\varphi-1)^2} / \frac{\epsilon}{(\varphi-1)} < 1$*, or when* $\psi < \frac{-\epsilon}{1-\epsilon}$.

PROPOSITION 2 ***Strong path dependence:*** *The effect of past relative coal prices strengthens over time,* $\frac{\partial \ln(\widetilde{X}_t)}{\partial \ln(\widetilde{w}_{t-1})} / \frac{\partial \ln(\widetilde{X}_t)}{\partial \ln(\widetilde{w}_t)} = \frac{\alpha(1-\epsilon)\epsilon}{(\varphi-1)^2} / \frac{\epsilon}{(\varphi-1)} > 1$*, or when* $\psi > \frac{-\epsilon}{1-\epsilon}$.

Strong path dependence occurs whenever an increase in the relative coal price triggers a downward shift in the relative marginal product of capital investment in subsequent periods. This shift is the net result of two countervailing forces. To illustrate these two forces, I consider each first in isolation.

The first force is increasing returns to scale, captured by ψ. Suppose there is only one intermediate sector which uses coal for electricity. When $\psi > 1$, the cross partial derivative of Y_{ct} with respect to past and current capital investment exceeds the second partial derivative of Y_{ct} with respect to current capital investment.[31] This "push" enables relative coal prices to have a stronger effect on future coal capital investment than on current coal capital investment.

However, when there is more than one sector, $\psi > 1$ alone does not dictate the strength of path dependence. A countervailing "pull" force comes from the imperfect substitutability between electricity produced from coal and other fuels, $\epsilon \in (1, +\infty)$. Suppose there is no increasing returns to scale. An increase in the relative coal price induces a contemporaneous decrease in relative coal capital investment. This capital imbalance does not persist in subsequent periods. When electricity from coal and other fuels are imperfect substitutes, subsequent periods experience a relative increase in demand for electricity from coal which induces relatively more investment in coal-specific capital. As a consequence, the capital imbalance across the two fuels eventually dissipates.

When both forces are at play, Proposition 2 states that strong path dependence can only be achieved when increasing returns to scale provides a large enough push to overcome the

[31] This comes directly from applying Euler's theorem. Formally, the cross partial derivative of a function $Y(X_{ct}, X_{ct-1})$ of homogeneous degree ψ can be written as

$$\frac{\partial^2 Y_{ct}}{\partial X_{ct} \partial X_{ct-1}} = \left(\frac{\psi - 1}{X_{ct-1}}\right) \frac{\partial Y_{ct}}{\partial X_{ct}} - \left(\frac{X_{ct}}{X_{ct-1}}\right) \frac{\partial^2 Y_{ct}}{\partial^2 X_{ct}^2}$$

Setting $X_{ct} = X_{ct-1}$ so that one can compare the effects of lagged capital investment against current capital investment, $\frac{\partial^2 Y_{ct}}{\partial X_{ct} \partial X_{ct-1}} > -\frac{\partial^2 Y_{ct}}{\partial^2 X_{ct}^2}$ only when $\psi > 1$.

pull from imperfect substitutability, or when $\psi > \frac{-\epsilon}{1-\epsilon}$.[32] In the context of the electricity sector, this occurs whenever the amplifying force of increasing returns to scale in electricity production offsets the dampening force due to differences in the properties of electricity from different fuels.

7.2 Recovering the long-run elasticity of substitution

The long-run elasticity of substitution between intermediate sectors, ϵ, appears across a broad class of structural change models (Baumol, 1967; Ngai and Pissarides, 2007; Acemoglu, 2002; Acemoglu and Guerrieri, 2008; Acemoglu et al., 2012; Lemoine, 2016). Because these models exhibit different mechanisms for generating path dependence, recovering ϵ enables this paper to inform settings in which a different mechanism drives path dependence in energy transitions. Specifically, I recover ϵ using the mapping between the structural expression in equation (11) and reduced-form coefficients in equations (4) and (8).

To start, observe that the time index in equation (11) is in terms of capital vintages. The time index in my empirical results is in decades relative to the switching event. Noting that the average lifespan of generating units in my sample is 4.7 decades, I convert from event time to vintage time by taking the average reduced-form lagged effect across 5 decades. Specifically, using $\hat{\beta}^{\tau}$ and $\hat{\pi}$ from column 2 of Table 2, the ratio of reduced-form lagged to contemporaneous effect is $\widehat{\rho} = \frac{\frac{1}{5}\sum_{\tau=1}^{5}\hat{\beta}^{\tau}}{\hat{\pi}} = 1.49$, with a standard error of 0.85. Mapping this ratio to its structural analog $\frac{\partial \ln(\widetilde{X}_t)}{\partial \ln(\widetilde{w}_{t-1})} / \frac{\partial \ln(\widetilde{X}_t)}{\partial \ln(\widetilde{w}_t)} = \frac{\alpha(1-\epsilon)\epsilon}{(\varphi-1)^2} / \frac{\epsilon}{(\varphi-1)}$ and taking the estimated scale parameter $\hat{\psi} = 1.66$ from column 2 of Table 3, one can express the long-run elasticity of substitution entirely in terms of estimated statistical parameters

$$\epsilon = 1 + \frac{\widehat{\rho}}{\frac{\hat{\psi}}{2} - \widehat{\rho}(1 - \frac{\hat{\psi}}{2})} = 3.6$$

As an example of how this elasticity value can inform other structural change models, in Acemoglu et al. (2012)'s model of optimal climate policy under directed technical change, $\epsilon = 3.6$ falls within the parameter space for which a temporary policy intervention is sufficient to avoid long-term climate disaster, defined as the state of the climate beyond which recovery is impossible.

[32] Notice the similarities here with the "market" and "price" effects found in models of directed technical change (Acemoglu, 2002; Acemoglu et al., 2012).

7.3 Simulating future clean energy transitions

Evidence of strong path dependence implies it is possible for a temporary shock to fuel composition to induce permanent fuel switching. In the context of climate change policy, it suggests that a temporary policy can induce a long-term decline in carbon emissions. But under what conditions can this occur? In particular, given the abundance of coal resources in the U.S., what is the required magnitude and/or duration of an intervention that can trigger a sustained clean energy transition? And how can changes in underlying structural parameters alter these requirements?

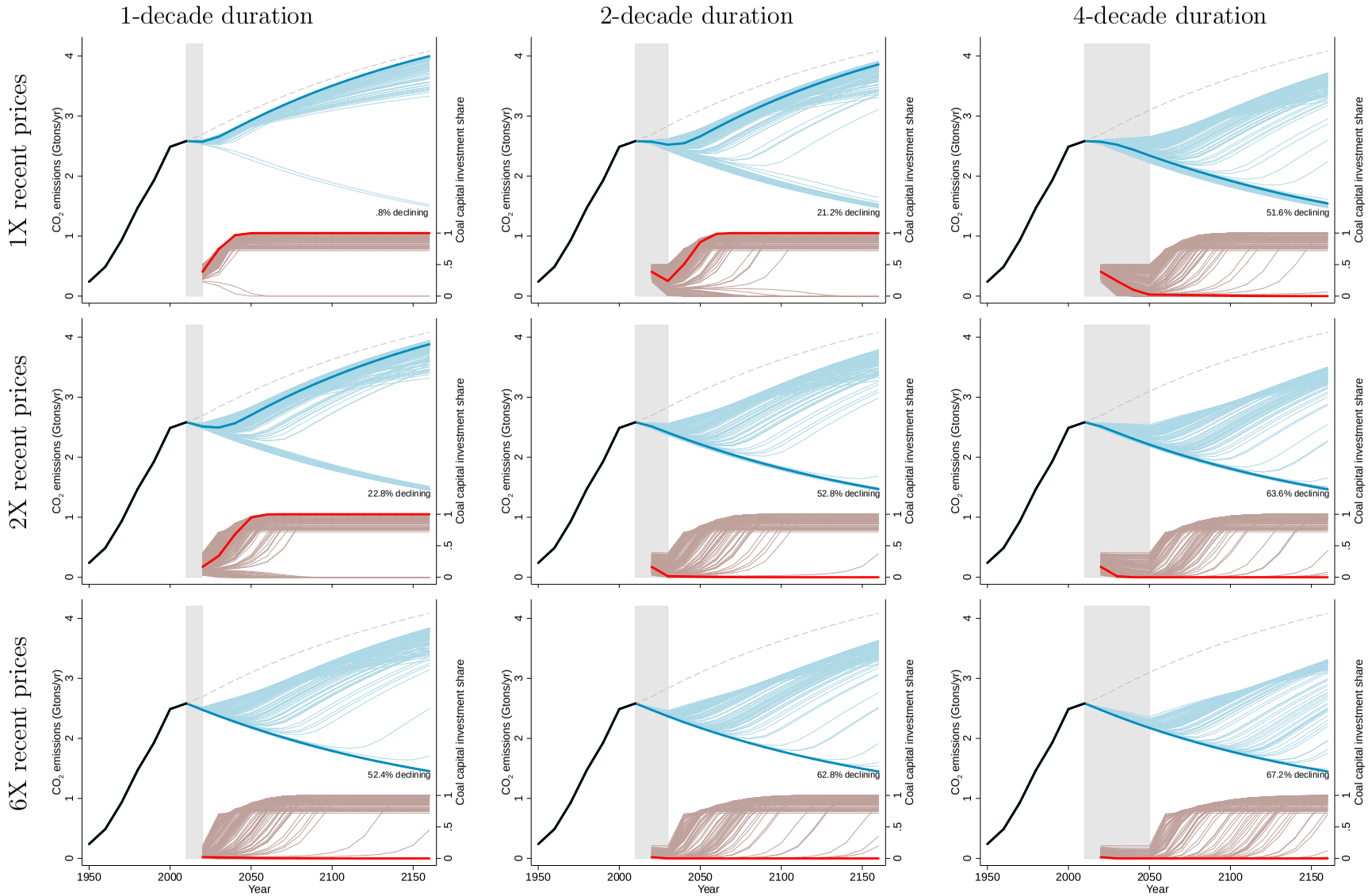
To shed light on these questions, I calibrate my structural model with reduced-form parameters to simulate future U.S. electricity sector CO_2 emissions following relative coal price shocks of varying magnitude and duration. To ground my simulations in recent economic conditions, the magnitude of the shocks considered are benchmarked to recent high relative coal prices following the introduction of natural gas hydraulic fracturing. As shown in Figure A.12, as a consequence of hydraulic fracturing, relative coal prices in 2009 and 2010 was 143% higher than what a quadratic trend estimated over 1985-2008 would have predicted.

My simulations employ several simplifying assumptions (see Appendix E for details). First, only electricity from coal and natural gas are considered.[33] Second, to avoid forecasting trends in productivity, electricity demand, and other economic conditions, I assume that future productivity, total U.S. coal and natural gas capital, capital depreciation, and baseline relative coal prices in the absence of the shock are held constant at recent values. Third, I assume that the scale and elasticity of substitution parameters are constant throughout the simulation period. With these assumptions, one should not interpret these simulations as forecasts of U.S. electricity sector CO_2 emissions but instead as exercises in understanding the conditions for triggering a sustained future clean energy transition.

Figure 5 shows how CO_2 emissions are altered when one varies the magnitude and duration of the temporary relative coal price shock. Top, middle, and bottom panels use price shocks that are 1, 2, and 6 times that of recent relative coal prices. Left, middle, and right panels use price shocks that last 1, 2, and 4 decades. Business-as-usual emissions in the absence of the shock are shown as dashed gray lines. When shocks are introduced, the thick solid blue and red lines show CO_2 emissions and the coal share of capital investment under mean values of ψ and ϵ, respectively. The thin solid blue and red lines show CO_2 emissions and coal capital investment share, respectively, from Monte Carlo draws using the estimated uncertainty for each structural parameter. Each panel also indicates the percentage of draws

[33] In 2009, coal- and natural gas-fired generating units constituted 92% of total U.S. electricity capital using fossil fuels.

Figure 5: Simulating future U.S. CO_2 emissions following temporary relative coal price shocks

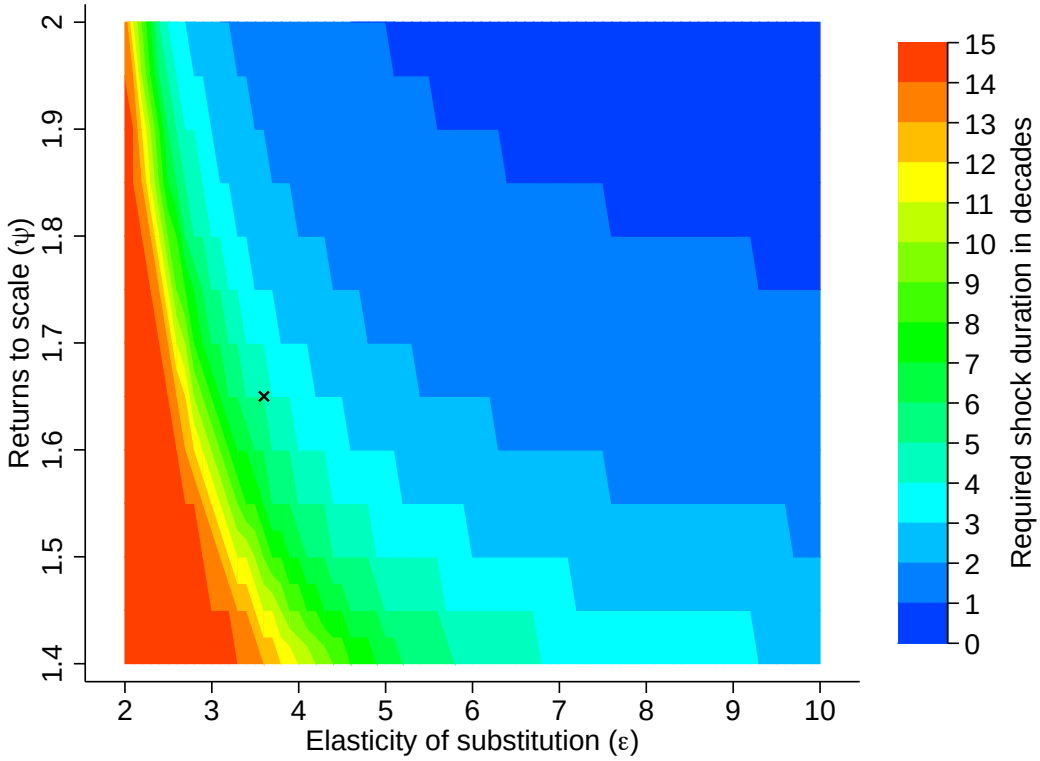


NOTES: Simulations of U.S. CO_2 electricity sector emissions following temporary relative coal price shocks of varying magnitudes and durations. Top, middle, and bottom panels use price shocks 1, 2, and 6 times that of recent relative coal prices (see Figure A.12). Left, middle, and right panels use price shocks that last 1, 2, and 4 decades (shown as shaded gray areas). Solid black lines show historical emissions. Dashed gray lines show future business-as-usual emissions without the shock. Thick solid blue and red lines show future projected annual CO_2 emissions (in Gton/yr) and coal capital investment share under the shock, respectively, using mean estimated values of ψ and ϵ. Thin solid blue and red lines show future projected annual CO_2 emissions and coal capital investment share under the shock, respectively, from 250 Monte Carlo draws of the estimated uncertainty for ψ and ϵ. Percentage of draws with weakly declining long-term CO_2 emissions are also shown. See Appendix E for details.

in which CO_2 emissions are weakly declining in the long-term.[34]

In general, the likelihood of achieving weakly declining CO_2 emissions in the long-term increases with larger shocks and/or shocks of longer duration. Examining the top row of Figure 5, if recent relative coal prices were to last up to 2 decades, CO_2 would still rise in the long-term on average. For a better than 50% chance of weakly declining emissions and a sustained switch away from new investments in coal-fired electricity capital, recent relative coal prices must last at least 4 decades. Going down the first column of Figure 5, if an intervention can only last for 1 decade, it must be at least 6 times that of recent relative coal prices for a greater than 50% chance of achieving weakly declining long-term emissions.

Figure 6: Required duration of temporary shock under different structural parameter values



NOTES: Vertical axis shows values for the returns to scale parameter, ψ. Horizontal axis shows values for the elasticity of substitution parameter, ϵ. Heat map shows the minimum number of decades that a shock equal in magnitude to that of recent relative coal prices must last in order for long-term CO_2 emissions to be weakly declining. X indicates parameter values estimated in this paper. See Appendix E for details.

Figure 5 suggests that given current parameters, a sustained clean energy transition would require either a very large and/or long duration intervention. However, my structural model also suggests certain electricity sector technological advances that can alleviate

[34] Because natural gas still contains carbon, in none of the simulations do CO_2 emissions reach zero in the long term. Instead, emissions converge asymptotically to a steady-state level where all electricity is produced from natural gas. Thus, these simulations focus on whether temporary policies achieve weakly declining CO_2 emissions in the long-term.

this requirement by altering the elasticity of substitution and returns to scale parameters. Storage technology may reduce the intermittency of solar and wind-based electricity, making renewable energy sources stronger substitutes for coal. Similarly, new technologies may increase the returns to scale of electricity production. Figure 6 examines future energy transitions under different values of ϵ and ψ. For each pair of parameter values, the heat map in Figure 6 shows the minimum number of decades a shock equal in magnitude to that of recent relative coal prices must last in order to achieve weakly declining long-term CO_2 emissions. The require length of the intervention falls when values of ϵ and ψ are higher than those estimated in this paper.

8 Conclusion

This paper estimates path dependence in energy transitions for the U.S. electricity sector over the 20th century. Exploiting shocks to local coal transport distance driven by the changing regional accessibility of subsurface coal, I find increasing imbalance in the coal composition of electricity capital lasting ten decades following a shock. This suggests that it is possible for temporary shocks of sufficient magnitude and/or duration to induce permanent fuel switching in the electricity sector. Additional evidence detects increasing returns to scale in electricity production as the underlying mechanism. To interpret these results, I develop a model of scale-driven structural change for the electricity sector which allows for a formal definition of strong path dependence and a mapping between my reduced-form estimates and a key structural parameter found across a class of structural change models.

This historical evidence is particularly timely given recent developments in the U.S. electricity sector and increasing concerns over climate change impacts. The current spike in relative coal prices following breakthroughs in natural gas extraction is contributing to a slow-down in the construction of new coal-fired power plants. However, these circumstances may not be enough to trigger a sustained transition away from coal in the U.S. electricity sector. Simulations of future energy transitions using this paper's calibrated structural model demonstrate that a sustained U.S. energy transition away from coal would require either a larger and/or longer lasting shock to fuel composition. These simulations also show that a sustained clean energy transition can be more easily achieved if investments were made to either increase scale economies in electricity production or towards stronger substitutability between electricity from coal and alternative fuels.

The presence of strong path dependence in energy transitions also provides a new argument in favor of Pigouvian interventions that directly price an externality over second-best policies that favor specific technologies or resources. It is widely argued that technology- and

resource-specific policies are inefficient because they may fail to target cost-effective mitigation strategies. The presence of path dependence amplifies this cost. Suppose a natural gas-specific subsidy induces a transition from coal to natural gas but large climate damages ultimately requires a switch to even cleaner fuels. The ensuing path dependence in natural gas would make the later switch to cleaner fuels even more costly. A Pigouvian intervention would avoid this detour.

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Appendix to

Estimating Path Dependence in Energy Transitions

FOR ONLINE PUBLICATION

A Data Sources

This section details data used in the paper.

A.1 Coal resources, mining, and delivered prices

USGS National Coal Resource Assessment (NCRA) I use two spatial datasets from the NCRA (East, 2012). The first dataset contains shape files of Illinois and Appalachian Basin coal resources that are situated less than and greater than 200 feet below the surface. These shape files are used to generate Figure A.3 which maps coal resources for the two basins by depth. The second dataset contains characteristics of all coal mines in the Illinois Basin that has operated since 1890. Variables include mine location, opening year, closing year, and area.

Construction of local coal transport distances requires several steps. First, I spatially overlay all large mines in the Illinois Basin that ever existed since 1890 onto shape files of the basin's shallow and deep coal resources, as shown in Figure 3. Using the opening and closing years of each mine, I construct a mine-by-depth-by-decade panel indicating when each shallow or deep coal mine was in operation.[35] Next, for each county and decade, I search for the nearest mine according to the Euclidean distance between that county's spatial centroid and the mine, noting whether it is from a shallow or deep coal resource. This distance is d_{it} in equation (4). Finally, for each county, I find the first decade in which a county's nearest mine first switches from shallow coal to deep coal. Distance to the nearest shallow mine right before the switching event is denoted d_i^0 in equation (4).

FERC-423 forms FERC-423 provides annual data on the quantity, price, heat content, sulfur content, and ash content of purchased coal for each pair of purchasing power plant and county of coal origin. This paper uses FERC-423 data in three ways. First, for the 1990-1999 period where the county of coal origin is more reliable,[36] FERC-423 data on coal heat, sulfur, and heat content is aggregated to the county of origin and averaged across years to produce Table A.1 which documents the heterogeneity in coal quality across the five major U.S. coal basins. Second, data from the 1990-1999 FERC-423 forms are used to test the Herfindahl Principle, as shown in Figure A.7. Third, I use observed delivered coal prices from the entire set of 1972-1999 FERC-423 forms to verify my local coal transport distances in Table A.2.

[35] Specifically, if the mine was in operation for any year in a decade, I note that it was in operation during that decade.

[36] According to the EIA, "The instructions for the FERC Form-423 require the respondent to report the county in which the coal was mined. However, this data is not always known or reported correctly... It is very difficult to verify county level data. Users of the data should be aware of this and use the data accordingly."

A.2 Electricity capital and production

EIA-860 forms The EIA-860 forms records the capacity (or capital size), opening and closing years, and primary fuel input at the generating unit level.[37] This paper uses data on generating units from the EIA-860 forms to construct my main outcome variable, relative coal capital at the county-by-decade level covering decades from 1890 to 1990. There are several steps to this construction.

First, I create a cross-sectional dataset of operating and retired generating units, taking the most recent data for each generating unit across the 1990-2012 EIA-860 forms. I then expand this cross-sectional dataset along the time dimension using the opening and closing years of each generating unit to create a generating unit-by-year panel dataset. Next, I sum all generating units that use coal and all generating units that use other fuels to the county-by-decade level. Relative coal capital is defined as the ratio of total capital across generating units that use coal to total capital across generating units that use other fuels. Besides serving as my main outcome variable, relative coal capital is also used to generate Figure 2.

Underlying assumptions behind this data construction procedure are examined in Figures A.8, A.9 and Tables A.3 and A.4, using data from the 1990-2012 EIA-860 forms as well as from the 1980 EIA-860 form, which was digitized for this paper.

Knowing when generating units were built, I can also construct a county-by-decade dataset of relative coal capital investment. I sum new generating units that use coal and that use other fuels to the county-by-decade level. Relative coal capital investment is then defined as the ratio of total capital across newly-built generating units that use coal to total capital across newly-built generating units that use other fuels.

A.3 Control variables

Residential and manufacturing sector covariates County-by-decade residential and manufacturing covariates from 1890 to 1990 come from historical U.S. censuses, collected by Haines (2010).[38] These variables include total population, urban population, number of manufacturing establishments, manufacturing employment, manufacturing capital value, and manufacturing output value. To account for changing U.S. county boundaries from 1890 to 1930, I redraw pre-1930 counties to their 1930 spatial definitions to produce a county-by-decade panel of covariates that are spatially consistent over the 20th century. This procedure uses historical GIS county shape files from the U.S. National Historical Geographical Information System (N.H.G.I.S.)[39] and is a modification of the method used by Hornbeck (2012). The resulting data serve as outcome variables in the pre-trend tests shown in Table 1 and as control variables in column 3 of Table A.6.

[37] I only include generating units owned by public utility companies because units owned by non-utilities are inconsistently reported across EIA-860 forms during the 1990-2012 period.

[38] Available: http://doi.org/10.3886/ICPSR02896.v3

[39] Available: https://www.nhgis.org{}/documentation/gis-data

Geographical covariates County-level variance in slope is constructed using the USGS National Elevation Dataset. County-level distance to nearest navigable river or canal at the start of the 20th century combines GIS shape files from Atack (2015) and Atack (2017).[40] Both variables are used as controls in column 4 of Table A.6.

A.4 Testing mechanisms

PLATTS/UDI Power plant-level cost data for 1981-1999 was obtained from PLATTS/UDI. It provides non-fuel cost, or the difference between total production costs and fuel costs, which serves as the outcome variable for the return to scale parameter estimates in Table 3.

EIA-923 forms Generating unit-level electricity output and boiler-level coal input data comes from the 2009-2012 EIA-923 forms. Table 4 uses two generating unit-level productivity measures. Following Davis and Wolfram (2012), my capital productivity measure is capital operating performance, or the ratio of a generating unit's electricity output to its capacity. For generating unit g, in power plant p, county i, and state s, 2009-2012 averaged annual capital operating performance is

$$\overline{A}_{Xgpis} = \frac{Y_{gpis}}{X_{gpis} * 8760}$$

where Y_{gpis} is annual electricity output (in MWh, from EIA-923 forms), X_{gpis} is capacity (in MW, from EIA-860 forms), and 8760 is the number of hours in a year. My fuel productivity measure is thermal efficiency. For generating unit g, in power plant p, county i, and state s, 2009-2012 averaged annual thermal efficiency is

$$\overline{A}_{Egpis} = \frac{Y_{gpis} * 1000 * 3412}{E_{gpis}}$$

where E_{gpis} is generating unit-level fuel input (in BTU) and 3412 is the equivalent BTU heat content of one KWh of electricity.[41] Generating unit-level E_{gpis} is not directly observed. Instead, the EIA-923 forms provide a boiler-to-generator correspondence, which can have many-to-many matches. To obtain generating unit-level fuel input, I assume that a boiler uniformly divides fuel input across linked generators. EIA-923 forms prior to 2009 did not include boiler-to-generator correspondences and therefore are excluded from the analysis.

Public Utility Commissions Column 2 of Table A.10 includes only counties in state and decades where there was no Public Utility Commission regulation of electric utilities. The following table summarizes when Public Utility Commission regulation electric utilities was introduced for states in my baseline sample and the data source

[40] Available: https://my.vanderbilt.edu/jeremyatack/data-downloads/

[41] See https://www.eia.gov/tools/faqs/faq.cfm?id=107&t=3 for details.

State	First decade of PUC regulation	Data source
Alabama	1920	Troesken (2006)
Arkansas	1920	State PUC website[42]
Iowa	1970	State PUC website[43]
Illinois	1920	Troesken (2006)
Indiana	1920	Troesken (2006)
Kentucky	1940	State PUC website[44]
Minnesota	1980	State PUC website[45]
Missouri	1920	Troesken (2006)
Mississippi	1960	State PUC website[46]
Tennessee	1920	Troesken (2006)
Wisconsin	1910	Troesken (2006)

U.S. Clean Air Act nonattainment status County-by-year nonattainment status during 1978-1999 under the Clean Air Act comes from the U.S. Environmental Protection Agency. A county-by-decade observation is labeled nonattainment if the county is designated wholly or partially in nonattainment for any of the six criteria pollutant during any year in that decade.[47] This data is used for the estimates in column 4 of Table A.10.

Transportation density County-level data on highway and railroad network density in 2010 come from the U.S. Department of Transportation's National Transportation Atlas Database.[48] These variables are used as outcomes in the regressions shown in columns 1 and 2 of Table A.11.

Environmental NGO membership and vote share County-level membership for the Natural Resources Defense Council, The Nature Conservancy, and The National Wildlife Federation in 1996 comes from Anderson (2011). County membership share divides membership by 2000 county population from Haines (2010). County-level Republican Presidential vote share in 2000 comes from Fujiwara, Meng and Vogl (2016). These variables are used as outcomes in the regressions shown in columns 3 and 4 of Table A.11.

[42] Available: http://www.apscservices.info/commission-history.asp
[43] Available: https://iub.iowa.gov/history
[44] Available: https://psc.ky.gov/Home/About#AbtComm
[45] Available: https://mn.gov/puc/about-us/
[46] Available: https://www.psc.state.ms.us/executive/pdfs/2010/2010%20ANNUAL%20REPORT.pdf
[47] The six regulated criteria pollutants are sulfur dioxide, particulates, nitrogen dioxide, carbon monoxide, ozone, and lead.
[48] Available: http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_atlas_database/2012/index.html

A.5 Other

Cross-country data Figure 1 uses country-level CO_2 emissions per capita and GDP per capita in 2000 from Boden and Andres (2013) and World Bank (2014), respectively.

U.S. time series data U.S. Census Bureau (1975) provides total and mechanically produced U.S. bituminous coal production during 1890-1950 (shown in Figure A.1) and total electricity capacity, from fossil fuel and hydropower during 1920-1970 (shown in Figure A.8).[49] Figure A.6 plots the transport cost share of national delivered coal prices during 1902-2007 obtained from McNerney, Farmer and Trancik (2011). Figure A.12 shows national coal and natural gas sales prices during 1985-2011 obtained from the Energy Information Administration (2012).

B Collection and availability of historical data

Sections 4.1 and 4.2 note that the required historical data were either never collected or, if collected, may no longer exist. This section summarizes the data that was historically collected, its relevance for this study, and its known availability today.

B.1 Coal prices

1882-1970

County-level producer coal prices were recorded by the U.S. Geological Survey Bureau of Mine in "Mineral Resources of the United States 1882-1931" and "Mineral Yearbook 1932-1970." This data source, however, does not provide the county-level delivered coal prices needed for this study.

Availability Online.[50]

B.2 Electricity capital

1902-1917:

The U.S. federal government first collected power plant-level data in 1902 in the inaugural "Central Electric Light and Power Station Census," administered at the time by the Department of Commerce and Labor. This survey was repeated in 1907, 1912, and 1917. Unfortunately, this survey classified power plants by prime-mover (i.e. steam, hydro, internal combustion) and not by input fuel, which this paper needs to calculate the fuel composition of electricity capital.

[49] Electricity capital data from the U.S. Census Bureau (1975) is broken by steam and hydropower. Steam power typically uses coal, oil, and natural gas as fuel.

[50] Available: hathitrust.org

Availability Summaries of these censuses at aggregate data levels are available online.[51] However, power plant-level data could not be located following extensive private conversations with archivists at the National Archives and Records Administration.[52]

1920-1970:

The Federal Power Commission (FPC), created in 1920, administered annual surveys to document electricity production and fuel consumption. The most important of these were the Annual Financial and Statistical Reports (Form 1) and the Power System Statements (Form 12). Form 1 collects fuel usage at the power-plant level but has two limitations. First, in order to recover fuel-specific capital, fuel-specific capacity factors are needed for each generating unit and are not available. Second, power plant coverage is incomplete. For example, data from the 1948 Form 1 accounts for only 67% of total U.S. steam-powered electricity capital.

Availability Annual state-level statistics for electricity capital by prime-mover and fuel consumption are available in "Production of Energy and Capacity of Plants and Fuel Consumption of Electric Power Plants" as well as in "Electric Power Statistics, 1920-1940".[53] The report titled "Steam-Electric Plant Construction Cost and Annual Production Expenses" has plant-level values from Form 1 and Form 12 for 1948-1974.[54]

1977-1989:

In 1977, the Federal Energy Regulatory Commission (FERC) began publishing the "Inventory of Power Plants in the United States," which combines data on generating units from the Monthly Power Plant Report (Form 4), Annual Power System Statement (Form 12), and the Supplemental Power Statement (Form 12E). This annual inventory includes includes capacity, input fuel, and built year for all operating generating units and those retired each year. Because data on previously retired generating units was not collected, this data cannot be used for reconstructing historical electricity capital.

Availability The 1980 "Inventory of Power Plants in the United States" is available online[55]. It was digitized for the data validation exercises discussed in Section 4.2. Reports from other years are available in microfiche in many research libraries.

[51] Available: http://hdl.handle.net/2027/mdp.39015028113663

[52] Typically, only 3% of historical government documents are deemed valuable and retained in NARA's permanent collection.

[53] Available: http://hdl.handle.net/2027/mdp.39015023906806

[54] Available: http://catalog.hathitrust.org/Record/000904499

[55] Available: http://hdl.handle.net/2027/umn.31951d02987924n

1990-:

In 1990, the Energy Information Agency (EIA) began collecting "The Annual Electric Generator Report," (Form EIA-860) which replaced earlier FERC Forms 4, 12, and 12E. EIA notes

> "The Form EIA-860 is a mandatory annual census of all existing and planned electric generating facilities in the United States with a total generator nameplate capacity of 1 or more megawatts. The survey is used to collect data on existing power plants and 10 year plans for constructing new plants, as well as generator additions, modifications, and retirements in existing plants. Data on the survey are collected at the individual generator level."

Availability Online.[56]

C Imputing missing small power plants

Power plants with less than 1 MW of combined capacity (or capital) across generating units do not appear in EIA-860 forms. This section explains how missing small power plants are imputed when constructing county-by-decade relative coal capital, $\widetilde{K}_{it} = \frac{K_{cit}}{K_{nit}}$.

For fuel j, county i, decade t, a new power plant indexed by p_{jit} has capacity $X_{p_{jit}}$. Because power plants with $X_{p_{jit}} < 1$ are missing from the EIA-860 data, county total fuel-specific capital investment can be decomposed as

$$\begin{aligned} X_{jit} &= \sum_{p_{jit}:X_{p_{jit}}<1} X_{p_{jit}} + \sum_{p_{jit}:X_{p_{jit}}\geq 1} X_{p_{jit}} \\ &= \underbrace{X^M_{jit}}_{\text{Missing}} + \underbrace{X^O_{jit}}_{\text{Observed from EIA-860}} \end{aligned}$$

Next, I discretize the support of power plant capacities into 1 MW-wide bins starting at 0.5 MW. Denote f^b_{jit} as the number of power plants with capacity $X_{p_{jit}} \in [b-.5, b+.5)$. The missing county total fuel-specific capital investment is then $X^M_{jit} = 0.5 * f^{0.5}_{jit}$. My imputation procedure predicts $f^{0.5}_{jit}$. Specifically, to obtain county total fuel-specific capital, K_{jit}, I implement the following procedure for each decade t

1. Estimate $f^b_t = g_t(b) + \text{error}\ \forall b \in \{1.5, \ldots, \bar{b}\}$, where $g_t()$ is a flexible polynomial function
2. Predict $\widehat{f}^{0.5}_t = \widehat{g}_t(0.5)$
3. Downscale national to local capital by using $\widehat{f}^{0.5}_{cit} = \frac{\widehat{f}^{0.5}_t s_t}{N_t}$, where N_t is the number of counties with any operating power plants in decade t and s_t is the national share of electricity capital

[56] Available: http://www.eia.gov/electricity/data/eia860/

using coal, aggregated from observed power plants. Likewise, $\widehat{f}^{0.5}_{nit} = \frac{\widehat{f}^{0.5}_{t}(1-s_t)}{N_t}$. This implies $\widehat{X}^{M}_{jit} = 0.5 * \widehat{f}^{0.5}_{jit}$.

4. Calculate county total fuel-specific capital using $K_{jit} = K^{O}_{jit} + \sum_{\tau=0}(1-\delta)^{\tau}\widehat{X}^{M}_{ji,t-\tau}$, where K^{O}_{jit} is the observed county total fuel-specific capital, $\delta = 0.06$ is the decadal depreciation rate set at 2000s values, and τ is the lagged time index.

Figure A.10 shows the fitted 4th order polynomial function, $\widehat{g}_t()$, estimated for new power plants built in the 1910s (left panel) and in the 1950s (right panel) using observed power plants. The dotted line shows the predicted national frequency of power plants smaller than 1 MW built each decade, or $\widehat{g}_t(0.5)$. Table A.5 shows summary statistics for raw relative coal capital in column 1 and imputed relative coal capital when using a 3rd, 4th, and 5th order polynomial function to fit $g_t()$ in columns 2-4, respectively. Finally, column 5 shows summary statistics for relative coal capital using an alternative, less-informed, imputation for missing small power plants. Specifically, I add 1 MW of coal and non-coal capital investment to each county-by-decade observation. This implicitly assumes that there was a new 1 MW coal-fired power plant and a new 1MW non-coal power plant built in each county-by-decade observation. I then calculate fuel-specific capital using the capital accumulation expression in step 4 above.

D Theory appendix

D.1 Model

This section solves the model presented in Section 6.1. In period t for each intermediate sector $j \in \{c, n\}$, the myopic electricity producer chooses capital, X_{jt}, and fuel, E_{jt}, for current-vintage generating units and fuel, E_{jt-1}, for past-vintage generating units. "Clay"-like capital for past-vintage generating units, X_{jt-1}, is fixed. The producer's problem is

$$\max_{X_{ct},X_{nt},E_{ct},E_{nt},E_{ct-1},E_{nt-1}} Y_t - z_{ct}(E_{ct} + E_{ct-1}) - z_{nt}(E_{nt} + E_{nt-1}) - r_t(X_{ct} + X_{nt}) \tag{A.1}$$

where z_{jt} is the fuel price and r_t is the price of capital. Final good Y_t is given by equation (5) and intermediate good Y_{jt} is given by equation (6). To explore how scale and productivity channels could generate path dependence for otherwise similar intermediate sectors, suppose productivities are the same across intermediate goods during period $t-1$, $A_{Xct-1} = A_{Xnt-1}$ and $A_{Ect-1} = A_{Ent-1}$.

Because fuel and capital are perfect complements, efficiency for current-vintage generating units implies that the producer need only to choose capital, and not fuel, set at $A_{Xjt}X_{jt} = A_{Ejt}E_{jt}$ for $j \in \{c, n\}$. Clay-like past-vintage capital further implies $A_{Ejt-1}E_{jt-1} = A_{Xjt-1}(1-\delta)X_{jt-1}$. The

resulting constrained optimization problem is

$$\max_{X_{ct},X_{nt}} \Big([A_{Xct}X_{ct}A_{Xct-1}(1-\delta)X_{ct-1}]^{\alpha(\epsilon-1)/\epsilon} + [A_{Xnt}X_{nt}A_{Xnt-1}(1-\delta)X_{nt-1}]^{\alpha(\epsilon-1)/\epsilon}\Big)^{\epsilon/(\epsilon-1)}$$
$$- z_{ct}(\frac{A_{Xct}}{A_{Ect}}X_{ct} + \frac{A_{Xct-1}}{A_{Ect-1}}(1-\delta)X_{ct-1}) - z_{nt}(\frac{A_{Xnt}}{A_{Ent}}X_{nt} + \frac{A_{Xnt-1}}{A_{Ent-1}}(1-\delta)X_{nt-1}) - r_t(X_{ct}+X_{nt})$$

with optimality condition

$$\alpha Y_t^{1/\epsilon}(A_{Xjt}A_{Xjt-1}X_{jt-1})^{\frac{\alpha(\epsilon-1)}{\epsilon}} X_{jt}^{\frac{\varphi-1}{\epsilon}} = \frac{A_{Xjt}}{A_{Ejt}}z_{jt} + r_t \quad for \quad j \in \{c,n\} \tag{A.2}$$

where $\varphi = (1-\alpha)(1-\epsilon)$. Taking the ratio of equation (A.4) for coal and non-coal subsectors, and rewriting in terms of current-vintage relative coal capital investment, $\widetilde{X}_t = \frac{X_{ct}}{X_{nt}}$, yields

$$\widetilde{X}_t = \widetilde{w}_t^{\frac{\epsilon}{\varphi-1}} \widetilde{X}_{t-1}^{\frac{\alpha(1-\epsilon)}{\varphi-1}} \widetilde{A}_{Xt}^{\frac{\alpha(1-\epsilon)}{\varphi-1}} \tag{A.3}$$

where $w_{jt} = \frac{A_{Xjt}}{A_{Ejt}}z_{jt} + r_t$ is the productivity-weighted input price index, $\widetilde{w} = \frac{w_{ct}}{w_{nt}}$ is relative input price, and $\widetilde{A}_{Xt} = \frac{A_{Xct}}{A_{Xnt}}$ is relative capital productivity for generating units of vintage t. Equation (A.3) is equation (7) in the main text.

D.2 Extension: productivity losses and capital under-utilization

Appendix D.1 assumes that past-vintage capital is fully utilized in the current period. This assumption has previously been used in the putty-clay literature to avoid a well-known curse of dimensionality problem in vintaged capital models (Atkeson and Kehoe, 1999). This section shows how this assumption is justified when there are large efficiency losses associated with using electricity capital below its designed capacity, as discussed in F1 of Section 6.1.

Suppose a generating unit could operate past-vintage capital below its designed capacity. Because $A_{Ejt-1}E_{jt-1} > A_{Xjt-1}(1-\delta)X_{jt-1}$ would lead to wasted inputs, the producer now faces the constraint $A_{Ejt-1}E_{jt-1} \leq A_{Xjt-1}(1-\delta)X_{jt-1}$ for $j \in \{c,n\}$. The resulting constrained optimization problem is

$$\max_{X_{ct},X_{nt},E_{ct-1},E_{nt-1}} \Big([A_{Xct}X_{ct}A_{Ect-1}E_{ct-1}]^{\alpha(\epsilon-1)/\epsilon} + [A_{Xnt}X_{nt}A_{Ent-1}E_{nt-1}]^{\alpha(\epsilon-1)/\epsilon}\Big)^{\epsilon/(\epsilon-1)}$$
$$- z_{ct}(\frac{A_{Xct}}{A_{Ect}}X_{ct} + E_{ct-1}) - z_{nt}(\frac{A_{Xnt}}{A_{Ent}}X_{nt} + E_{nt-1}) - r_t(X_{ct}+X_{nt})$$
$$s.t. \quad A_{Ejt-1}E_{jt-1} \leq A_{Xjt-1}(1-\delta)X_{jt-1} \quad \text{for} \quad j \in \{c,n\}$$

with optimality conditions

$$\alpha Y_t^{1/\epsilon}(A_{Xjt}A_{Ejt-1}E_{jt-1})^{\frac{\alpha(\epsilon-1)}{\epsilon}}X_{jt}^{\frac{\varphi-1}{\epsilon}} = \frac{A_{Xjt}}{A_{Ejt}}z_{jt} + r_t \quad for \quad j \in \{c,n\} \tag{A.4}$$

$$\alpha Y_t^{1/\epsilon}(A_{Xjt}A_{Ejt-1}X_{jt})^{\frac{\alpha(\epsilon-1)}{\epsilon}}E_{jt-1}^{\frac{\varphi-1}{\epsilon}} = z_{jt} + \lambda_j A_{Ejt-1} \quad for \quad j \in \{c,n\} \tag{A.5}$$

$$\lambda_j[A_{Ejt-1}E_{jt-1} - A_{Xjt-1}(1-\delta)X_{jt-1}] = 0 \quad for \quad j \in \{c,n\} \tag{A.6}$$

$$\lambda_j \geq 0 \quad for \quad j \in \{c,n\} \tag{A.7}$$

$$A_{Ejt-1}E_{jt-1} \leq A_{Xjt-1}(1-\delta)X_{jt-1} \quad for \quad j \in \{c,n\} \tag{A.8}$$

where λ_j is the Lagrange multiplier on each constraint.

Under what conditions would past-vintage capital be underutilized? To answer this, consider each sector j in isolation and take the ratio of equation (A.4) over (A.5). When the constraint binds (i.e., $\lambda_j > 0$) and past-vintage capital is fully utilized, the ratio can be rewritten as

$$\frac{z_{jt}}{w_{jt}} = \frac{X_{jt}}{E_{jt-1}} - \lambda_j \frac{A_{Ejt-1}}{w_{jt}} \tag{A.9}$$

When the constraint does not bind (i.e., $\lambda_j = 0$), this expression becomes

$$\frac{z_{jt}}{w_{jt}} = \frac{X_{jt}^*}{E_{jt-1}^*} \tag{A.10}$$

where the asterisk indicates the non-binding equilibrium. Setting equation (A.9) to equation (A.10) and substituting in the Leontief equality $E_{jt-1}^* = \frac{A_{X^*jt-1}}{A_{E^*jt-1}}(1-\delta)X_{jt-1}^*$ yields

$$A_{xjt-1}\frac{\lambda_j}{w_{jt}} = \frac{1}{1-\delta}\left(\frac{X_{jt}}{X_{jt-1}} - \frac{X_{jt}^*}{X_{jt-1}^*}\frac{A_{E^*jt-1}/A_{X^*jt-1}}{A_{Ejt-1}/A_{Xjt-1}}\right) \tag{A.11}$$

Next, define the fraction of under-utilization of past-vintage capital in the non-binding base as $\varrho_j = \frac{X_{jt-1}^*}{X_{jt-1}} \in [0,1]$. Further, denote the ratio of current-vintage capital for the non-binding over the binding case as $\varsigma_j = \frac{X_{jt}^*}{X_{jt}} > 0$. Inserting into equation (A.11)

$$A_{xjt-1}\frac{\lambda_j}{w_{jt}} = \frac{1}{1-\delta}\left(\frac{X_{jt}}{X_{jt-1}}\right)\left(1 - \frac{\varsigma_j}{\varrho_j}\frac{A_{E^*jt-1}/A_{X^*jt-1}}{A_{Ejt-1}/A_{Xjt-1}}\right) \tag{A.12}$$

which implies $\lambda_j > 0$ if and only if

$$\frac{\varrho_j}{\varsigma_j} > \frac{A_{E^*jt-1}/A_{X^*jt-1}}{A_{Ejt-1}/A_{Xjt-1}} > 0 \tag{A.13}$$

The right hand side of Equation (A.13) captures the lost in fuel productivity when past-vintage capital operates below its designed capacity. Vintage capital is more likely to be fully utilized when fuel productivity losses are large.

D.3 Recovering the scale parameter

Consider a power plant p that contains only coal-fired generating units. This allows one to ignore the upper tier of electricity production, drop the fuel index j, and only consider intermediate good production captured by equation (6). Applying efficient allocation for each generating unit, $A_{Xpt}X_{jt} = A_{Ept}E_{pt}$ and $A_{Xpt-1}(1-\delta)X_{pt-1} = A_{Ept-1}E_{pt-1}$, the constrained cost minimization problem can be written in terms of fuel inputs

$$\begin{aligned} C(z_{pt}, r_{pt}, Y_{pt}) = \min_{E_{pt}} \quad & z_{pt}\left(E_{pt} + E_{pt-1}\right) + r_t(\frac{A_{Ept}}{A_{Xpt}}E_{pt}) \\ s.t. \quad & Y_{pt} = (A_{Ept}E_{pt}A_{Ept-1}E_{pt-1})^{\alpha} \end{aligned}$$

Rewriting the production function as $E_{pt-1} = Y_{pt}^{1/\alpha}(A_{Ept}A_{Ept-1}E_{pt})^{-1}$, one obtains the following equivalent unconstrained minimization problem

$$\min_{E_{pt}} \quad (z_{pt} + \frac{A_{Ept}}{A_{Xpt}}r_t)E_{pt} + z_{pt}Y_{pt}^{1/\alpha}(A_{Ept}A_{Ept-1}E_{pt})^{-1} \tag{A.14}$$

Taking the first order condition of equation (A.14) yields a conditional demand function

$$E_{pt}^{*} = (Y_{pt})^{1/2\alpha}(\frac{z_{pt}}{z_{pt} + \frac{A_{Ept}}{A_{Xpt}}r_t})^{1/2}(A_{Ept}A_{Ept-1})^{-1/2} \tag{A.15}$$

Inserting equation (A.15) into non-fuel cost at the cost-minimizing input level, non_fuel_cost$_{pt}$ $= C(z_{pt}, r_{pt}, Y_{pt}) - z_{pt}(E_{pt}^{*} + E_{pt-1}) = r_t(\frac{A_{Ept}}{A_{Xpt}}E_{pt}^{*})$, and applying a log transformation

$$\ln \text{non_fuel_cost}_{pt} = \frac{1}{\psi}\ln Y_{pt} + \frac{1}{2}\ln(\frac{z_{pt}}{z_{pt} + \frac{A_{Ept}}{A_{Xpt}}r_t}) + \ln r_t + \ln(A_{Ept}^{1/2}A_{Ept-1}^{-1/2}A_{Xpt}^{-1}) \tag{A.16}$$

where $\psi = 2\alpha$. Equation (A.16) is the structural analog to the OLS specification in equation (8) from the main text with one exception. For ease of exposition, labor is omitted as a factor of production in equation (6) and hence missing from equation (A.16). In practice, the UDI measure of non-fuel cost modeled in regression equation (8) includes labor costs.

E Simulating future emissions

This section details the procedure for simulating future CO_2 emissions following a relative coal price shock, as shown in Figure 5.

E.1 Parameters

- Reduced-form path dependence parameter: $\widehat{\rho} = \frac{\frac{1}{5}\sum_{\tau=1}^{5}\hat{\beta}^{\tau}}{\hat{\pi}} = 1.49$, with standard error $\widehat{\sigma}_{\rho} = 0.85$ (from column 2 of Table 2)
- Returns to scale: $\widehat{\psi} = 1.66$, with standard error $\widehat{\sigma}_{\psi} = 0.24$ (from column 2 of Table 3)
- Baseline relative coal prices: $\widetilde{w}_t^o = 0.4$ (based on value in 2000s)
- Relative coal price shock: $\Delta = 1.43$ (based on Figure A.12)
- Relative productivity: $\widetilde{A}_{Xt} = 0.7$ (based on value in 2000s)
- Capital depreciation rate: $\delta = 0.06$ (based on value in 2000s)
- Carbon content of coal: $C_c = 4931.3$ lb CO_2/short ton coal[57]
- Carbon content of natural gas: $C_n = 119.9$ lb CO_2/thousand cubic feet[58]

E.2 Historical emissions

For each decade $t \in [1950, 2000]$, U.S. electricity sector CO_2 emissions is

$$M_t = E_{ct}C_c + E_{nt}C_n$$

where E_{ct} and E_{nt} is coal (in short tons) and natural gas (in thousand cubic feet) consumed respectively by the U.S. electricity sector in decade t.[59]

E.3 Simulating future emissions

For each combination of shock duration, $d \in \{10, 20, 40\}$, and shock multiplier, $M \in \{1, 2, 6\}$, define the time series of relative coal prices as

$$\widetilde{w}_t = \widetilde{w}_t^o + \Delta * M * \mathbf{1}(t \leq 2000 + d)$$

Conduct the following Monte Carlo procedure with $b = 1...250$ draws

- Draw $\psi(b) \sim N(\widehat{\psi}, \widehat{\sigma_{\psi}})$ and $\rho(b) \sim N(\widehat{\rho}, \widehat{\sigma}_{\rho})$. Define $\alpha(b) = \frac{\psi(b)}{2}$
- Obtain $\epsilon(b) = 1 + \frac{\rho(b)}{\frac{\psi(b)}{2} - \rho(b)\left(1 - \frac{\psi(b)}{2}\right)}$ and define $\varphi(b) = (1 - \alpha(b))(1 - \epsilon(b))$
- For each future decade $t \in [2010, 2150]$

[57] Available here: https://www.eia.gov/environment/emissions/co2_vol_mass.cfm
[58] Available here: https://www.eia.gov/environment/emissions/co2_vol_mass.cfm
[59] E_{ct} and E_{nt} obtained from the Energy Information Administration (2012).

1. Apply equation 11 to obtain relative coal capital investment:

$$\widetilde{X}(b)_t = exp\left(\sum_{s=0}^{\infty}\left(\frac{\epsilon(b)}{(\psi(b)-1)}\left[\frac{\alpha(b)(1-\epsilon(b))}{(\varphi(b)-1)}\right]^{s}\ln\widetilde{w}_{t-s} + \left[\frac{\alpha(b)(1-\epsilon(b))}{(\varphi(b)-1)}\right]^{s+1}\ln\widetilde{A}_{t-s}\right)\right)$$

2. Obtain coal capital investment while holding total capital fixed

$$X(b)_{ct} = \left(\frac{1}{\frac{1}{\widetilde{X}(b)_t}+1}\right)(K(b)_{ct-1}+K(b)_{nt-1})\,\delta$$

3. Obtain natural gas capital investment while holding total capital fixed

$$X(b)_{nt} = \left(1-\frac{1}{\frac{1}{\widetilde{X}(b)_t}+1}\right)(K(b)_{ct-1}+K(b)_{nt-1})\,\delta$$

4. Obtain coal capital

$$K(b)_{ct} = K(b)_{ct-1}(1-\delta) + X(b)_{ct}$$

5. Obtain natural gas capital

$$K(b)_{nt} = K(b)_{nt-1}(1-\delta) + X(b)_{nt}$$

6. Obtain total CO_2 emissions using 2000 emissions intensity

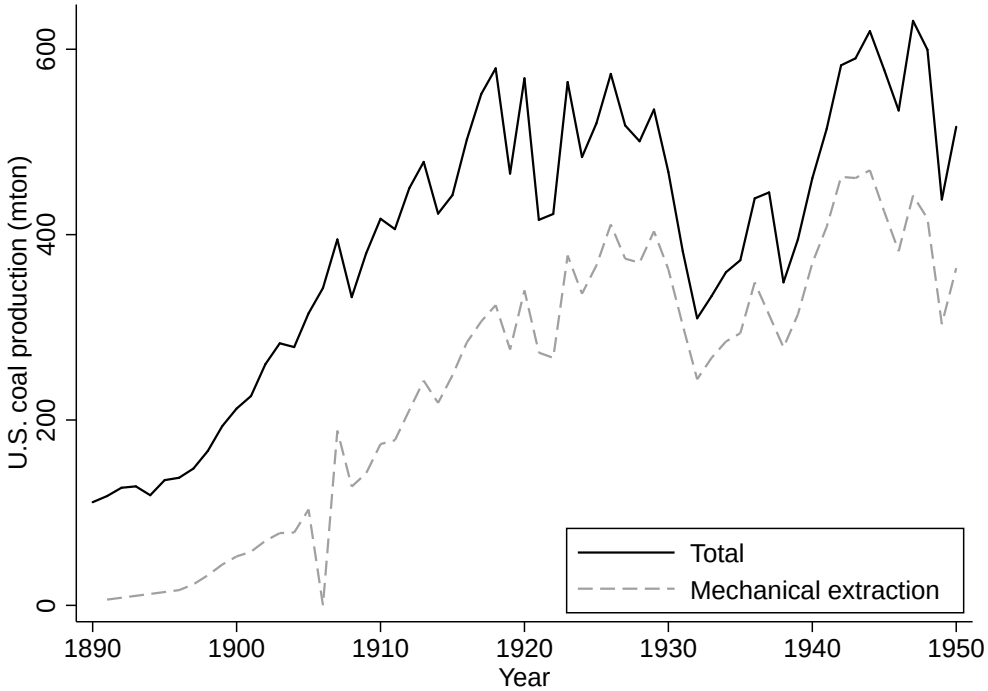
$$M(b)_t = K(b)_{ct}\frac{E_{c2000}}{K_{c2000}}C_c + = K(b)_{nt}\frac{E_{n2000}}{K_{n2000}}C_n$$

Figure 5 plots CO_2 emissions, $M(b)_t$, and the coal capital investment share, $\frac{X(b)_{ct}}{X(b)_{ct}+X(b)_{nt}}$, for the 250 Monte Carlo draws across each combination of shock duration, $d \in \{10, 20, 40\}$, and shock multiplier, $M \in \{1, 2, 6\}$. It also shows the percentage of Monte Carlo draws for which long-term CO_2 emissions are weakly declining.

To explore the consequences of different structural parameter values, Figure 6 replicates the above simulation procedure for different values of ϵ and ψ with the shock multiplier set at $M = 1$. The heat map plotted in Figure 6 shows the minimum shock duration d needed for long-term CO_2 emissions to be weakly declining.

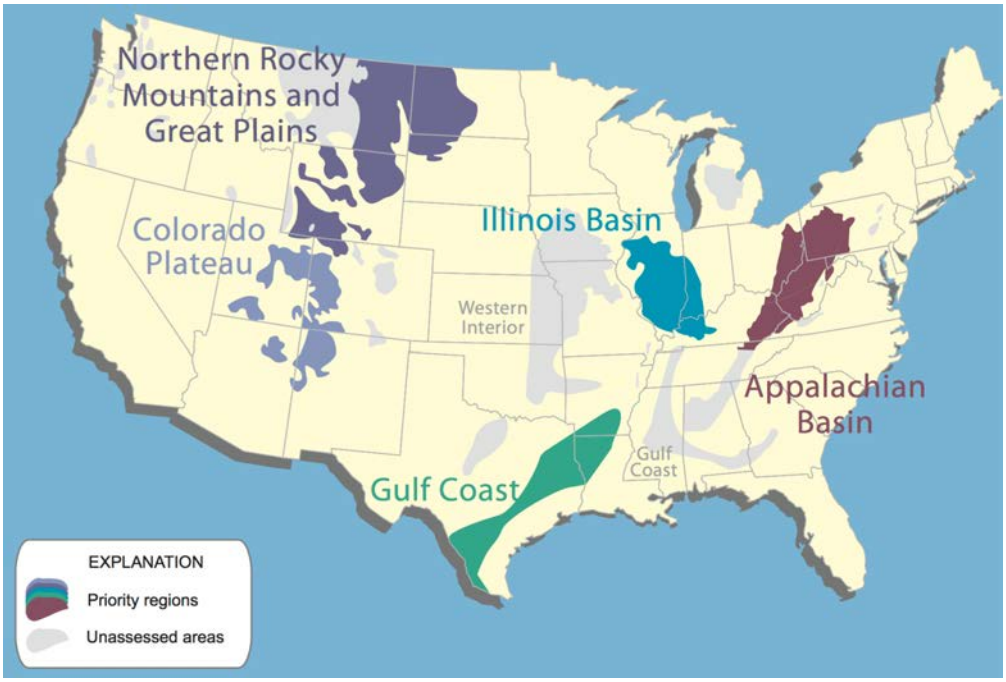
Appendix Figures

Figure A.1: U.S. bituminous coal production and mechanization



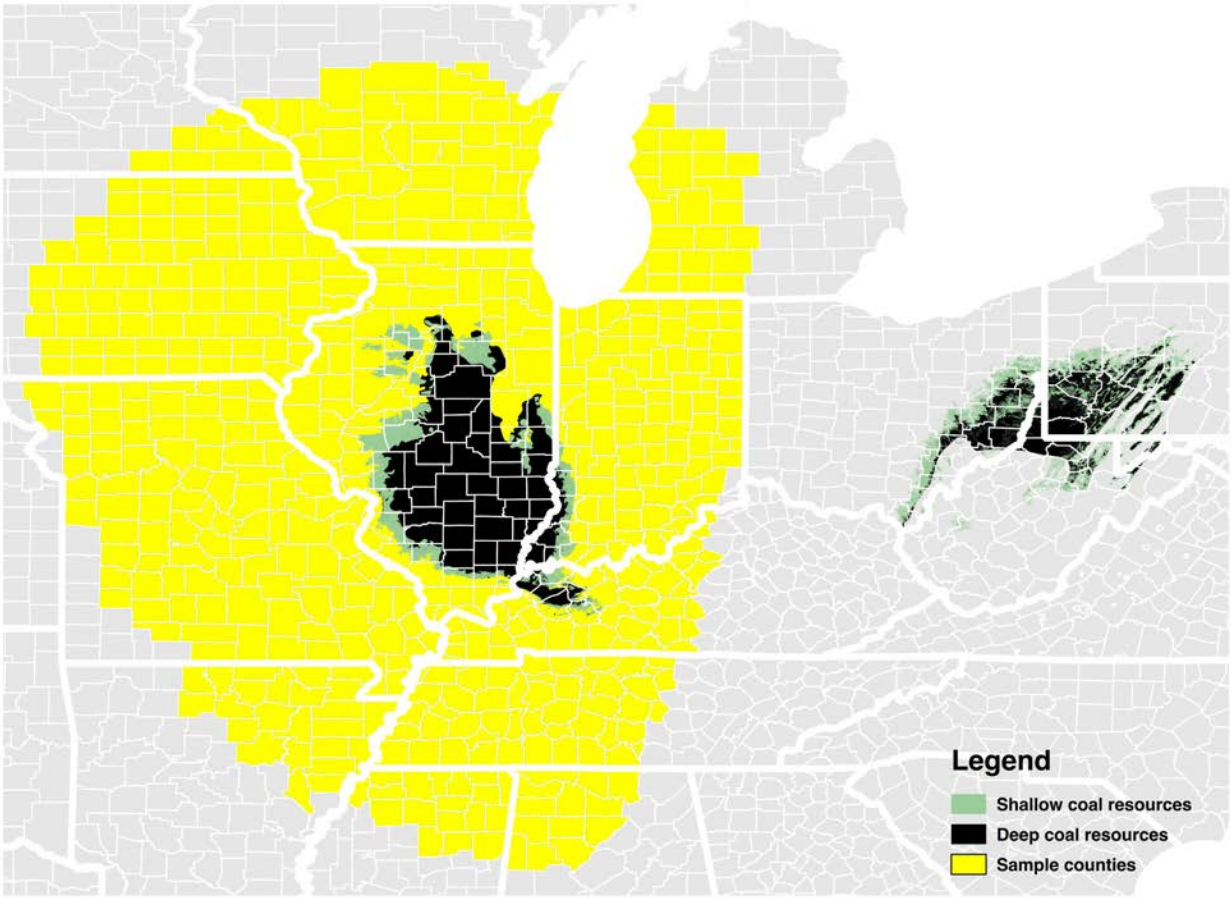
NOTES: Annual U.S. bituminous coal production (in mega short tons). Solid black line shows total coal production. Dashed gray line shows coal production from mechanical extraction. Data from U.S. Census Bureau (1975).

Figure A.2: U.S. coal basins



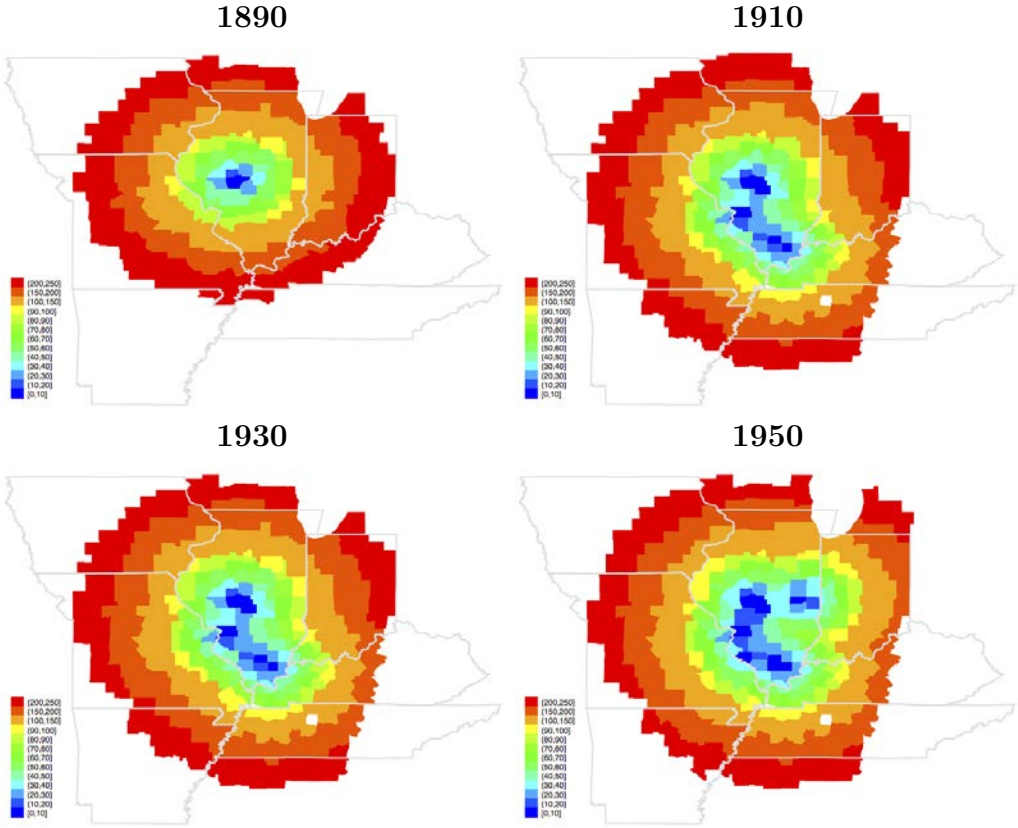
NOTES: Map of major U.S. coal basins. Reproduced from East (2012).

Figure A.3: Location of sample counties and coal basins



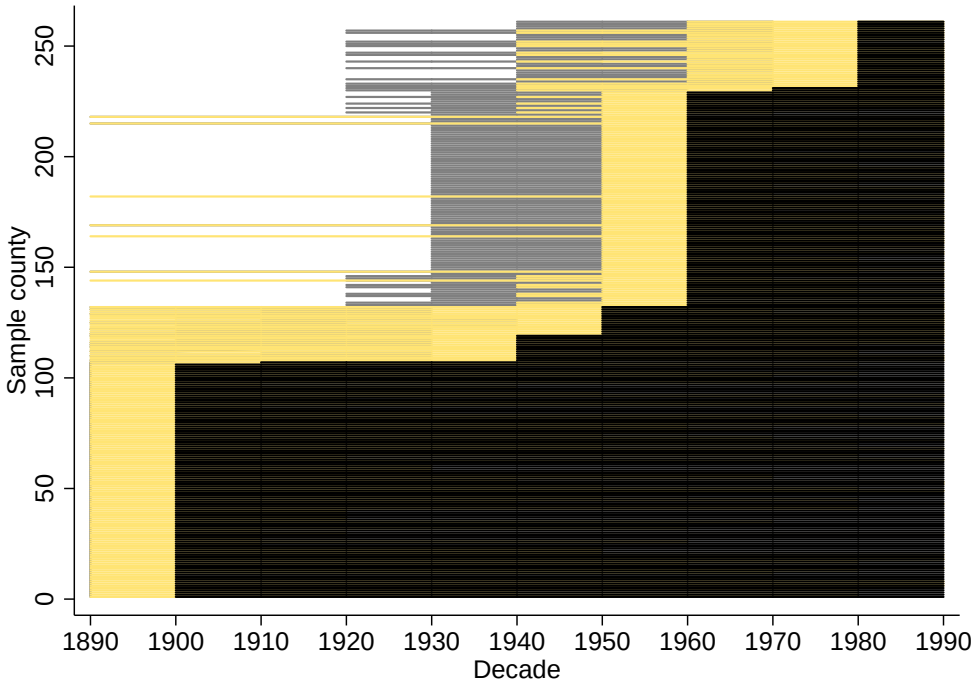
NOTES: A county is included in the baseline sample (in yellow shading) if its spatial centroid is (i) closer to coal resources in the Illinois Basin than in the Appalachian Basin and (ii) less than 250 miles from nearest Illinois coal resource. Shallow (< 200 ft. underground) and deep (> 200 ft. underground) Illinois and Appalachian Basin coal resources also shown in green and black shading, respectively.

Figure A.4: County distance to nearest mine by decade



NOTES: County distance to nearest coal mine during 1890-1950 over sample counties.

Figure A.5: Timing of shallow to deep coal switching for each sample county

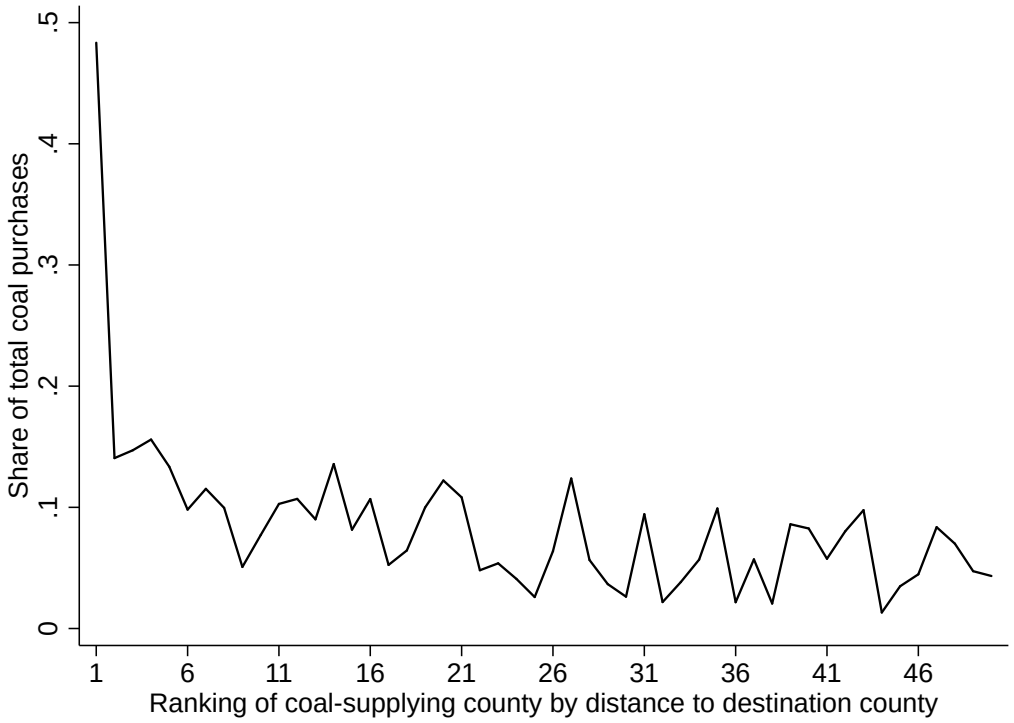


NOTES: The timing of when a sample county's nearest mine switches from a shallow to coal mine for the first time. Counties are stacked according to the decade when the switching event occurs. The gray, yellow, and black shaded areas correspond to event-time periods $h < 0$, $h = 0$, and $h > 0$, respectively.

Figure A.6: Share of delivered coal price due to transport costs at the national level

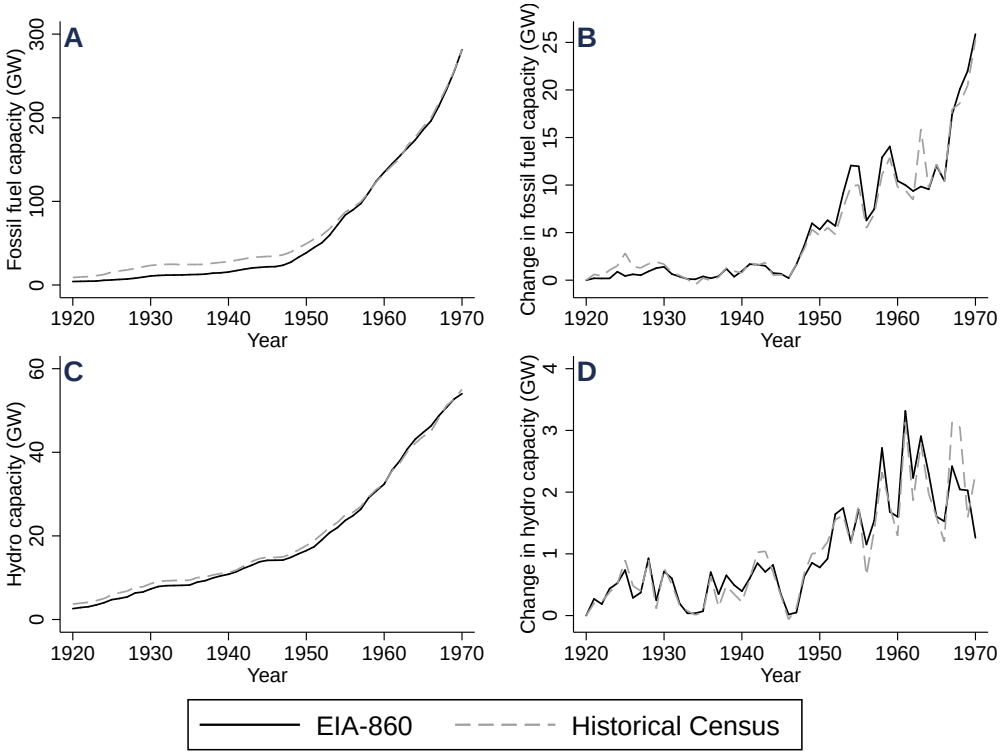
NOTES: Share of transport cost (nominal USD per short ton) in delivered coal price (nominal USD per short ton) for the U.S. during 1902-2007. Data from McNerney, Farmer and Trancik (2011).

Figure A.7: Testing the Herfindahl Principle



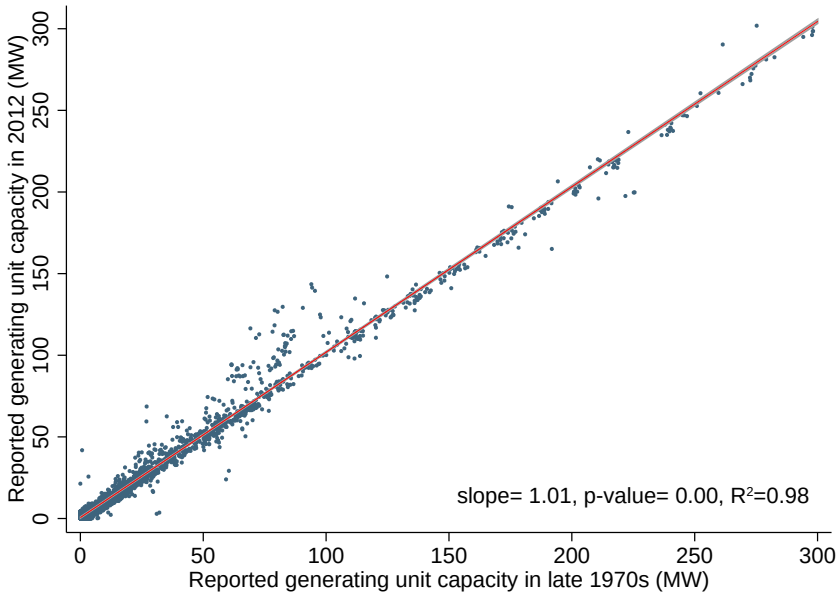
NOTES: Vertical axis shows share of total coal purchase from destination county. Horizontal axis shows the ranking of bilateral distance between spatial centroids of origin and destination counties. Data averaged over 1990-1999 and all U.S. counties that purchase coal for electricity.

Figure A.8: Comparing U.S. electricity capacity from EIA-860 vs. historical census



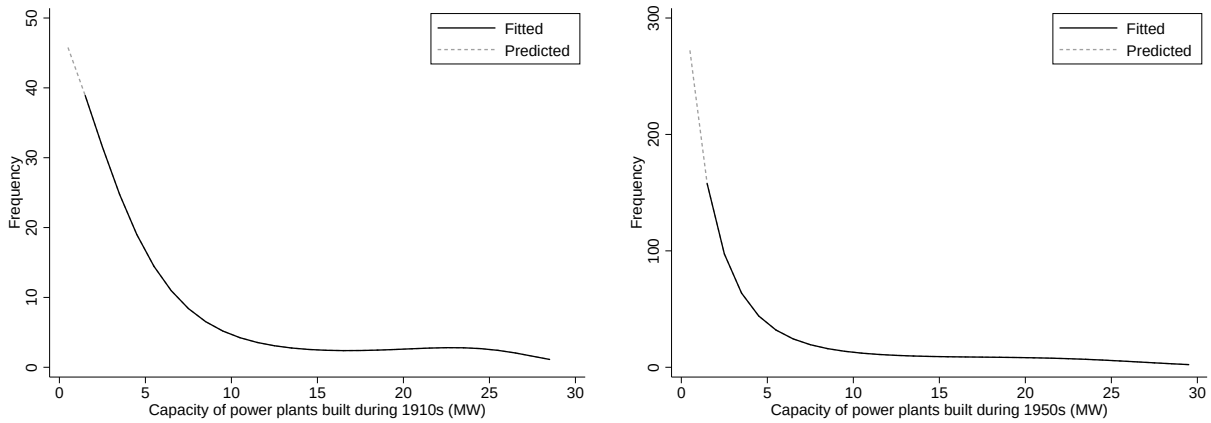
NOTES: Panel (A) compares annual aggregate U.S. electricity capacity (in GW) using fossil fuels constructed from EIA-860 forms (solid black lines) against values from the U.S. Historical Census (dashed gray lines) over 1920-1970. Panel (B) plots capacity changes. Panels (C) and (D) show the same information as in panels (A) and (B) but for aggregate U.S. hydropower capacity.

Figure A.9: Comparing generating unit capacity in late 1970s and 2012



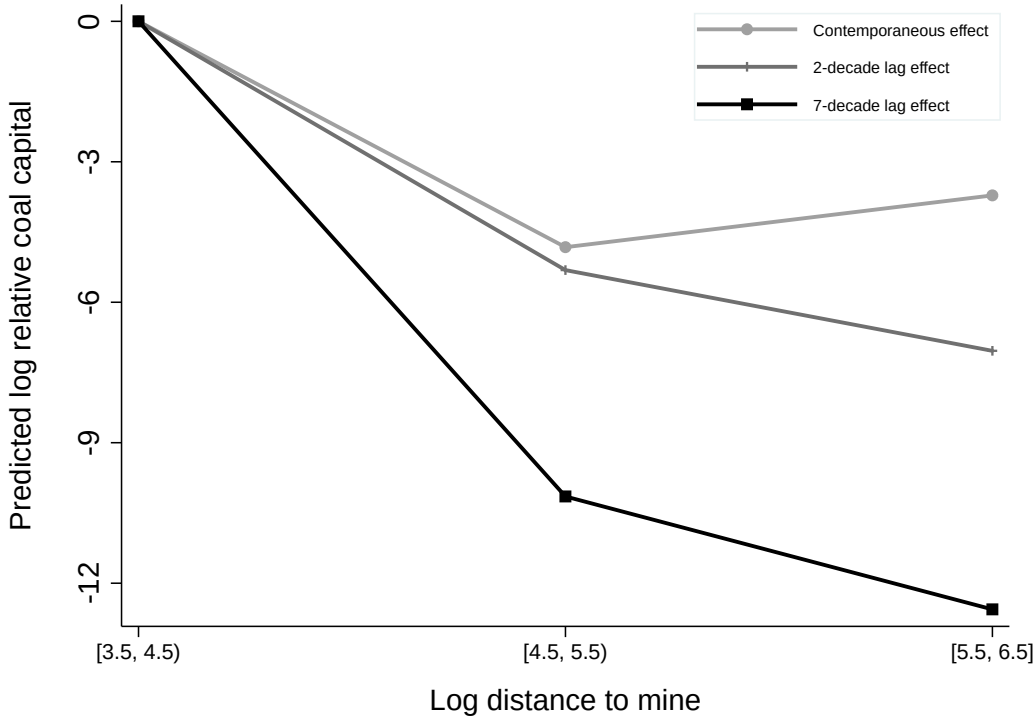
NOTES: Scatter shows reported generating unit capacity (in MW) in the 2012 EIA-860 form against reported generating unit capacity in the late 1970s (in MW). Both axes are truncated at 300 MW. Linear fit in red with 95% confidence interval shown in gray. Coefficient, p-value, and R^2 shown from a linear regression using all matched generating units.

Figure A.10: Fitted and predicted capacity distribution of power plants by built decade



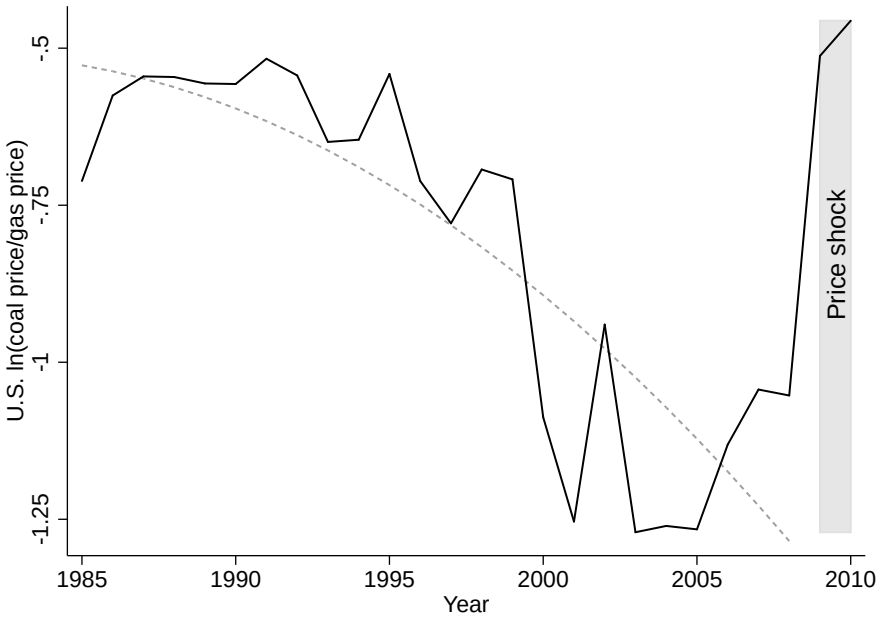
Notes: Solid line shows fitted capital frequency distribution of all power plants built during 1910s (left panel) and 1950s (right panel). Fitted relationship uses a 4th order polynomial function for power plants with capacity less than 30 MW and greater than 1 MW. Dashed line shows predicted capacity frequency for power plants with capacity less than 1 MW. See Appendix C for details.

Figure A.11: Testing for nonlinearity in the relative coal capital-distance relationship



NOTES: Plot examines whether log relative coal capital is linear in log distance to the nearest mine using a version of equation (4) with discretized log distance bins. Log relative coal capital is predicted using log distance to contemporaneous nearest mine, and log distance to shallow mine two and seven decades after the switching event. Each log distance variable is broken into 1 log distance wide bins. For each period, the predicted log relative coal capital is normalized to the value of the omitted log distance bin, defined as log distances between 0 and 3.5.

Figure A.12: Ratio of U.S. coal to natural gas sales price



NOTES: Solid black line shows log ratio of U.S. coal sales price to U.S. natural gas sales price (both in nominal USD per million BTUs) during 1985-2010. Dashed gray line shows quadratic time trend estimated over 1985-2008.

Appendix Tables

Table A.1: Coal quality heterogeneity by basin

Coal basin	No. of counties	heat content	Std. dev. in ash content	sulfur content
Appalachian	187	657.24 (1)	2.96 (3)	0.93 (5)
Colorado	79	1159.77 (3)	4.47 (5)	0.15 (1)
Gulf	56	1370.36 (5)	3.71 (4)	0.29 (3)
Illinois	279	807.30 (2)	2.52 (2)	0.84 (4)
Northern Rockies	65	1270.79 (4)	1.79 (1)	0.22 (2)

NOTES: Standard deviation in coal heat, ash, and sulfur content across counties that produce coal in each coal basin. Basin ranking for each characteristic in parentheses (1=least heterogeneous). County-level values calculated using 1990-1999 averages.

Table A.2: Observed delivered coal prices vs. constructed distance-based measure

	(1)	(2)	(3)
	Outcome is log delivered coal price		
$\ln d_{it}$	0.381**	0.582***	0.342***
	(0.150)	(0.153)	(0.113)
Decade	1970s	1980s	1990s
Counties	153	153	133

NOTES: Each column is a separate cross-sectional regression of observed log delivered coal price (in nominal USD per ton) averaged within each decade on log distance to nearest mine and state fixed effects. County sample shown in Figure A.3. Columns (1), (2), and (3) use data from the 1970s, 1980s, and 1990s, respectively. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Comparing generating unit characteristics across 1990-2012 EIA-860 forms

	Percentage of generating units with different reported values			
Number of different values	Capacity	Primary fuel	Opening year	Retirement year
0	74.78	94.25	96.88	80.01
1	2.62	1.49	0.52	1.98
2	1.81	0.57	0.44	2.92
3	1.07	0.23	0.08	0.87
4	1.26	0.2	0.08	0.87
5	0.85	0.51	0.19	1.5
6	0.69	0.46	0.24	0.67
7	0.95	0.29	0.29	0.72
8	0.53	0.27	0.22	1.08
9	0.79	0.2	0.14	1.74
10	0.72	0.25	0.24	1.04

NOTES: Row indicates the number of values from 1990-2011 EIA-860 forms that was different from the 2012 EIA-860 form. Column shows generator unit-level characteristics. Each cell shows the percentage of 1990-2011 EIA-860 forms with a reported value that is different from that reported in the 2012 EIA-860 form. For example, row 1, column 1 indicates that 76.78% of generating units reported the same capacity in 1990-2011 as was reported in 2012.

Table A.4: Comparing generating unit primary fuel in late 1970s and 2012

	Primary fuel in 2012				
Primary fuel in 1970s	Coal	Hydro	Nat. gas	Nuclear	Oil
Coal	92.2	0.0	5.9	0.0	1.1
Hydro	0.0	100.0	0.0	0.0	0.0
Nat. gas	0.8	0.0	77.2	0.0	21.9
Nuclear	0.0	0.0	0.0	100.0	0.0
Oil	1.0	0.0	24.4	0.0	74.6

NOTES: Each row shows the distribution of reported primary fuel in the 2012 EIA-860 forms conditional on the primary fuel reported in the 1970s. For example, 92.2% of generating units which reported coal as the primary fuel in the 1970s also reported coal in 2012.

Table A.5: Summary statistics for raw and imputed relative coal capital

	(1) Raw	(2) Imputed 3rd order poly.	(3) Imputed 4th order poly.	(4) Imputed 5th order poly.	(5) Imputed add 1 MW
			Number of observations		
Total	2,371	2,371	2,371	2,371	2,371
Missing	1,248	0	0	0	0
Zero	825	0	0	0	0
Other	298	2,371	2,371	2,371	2,371
			Summary statistics		
Obs	1,123	2,371	2,371	2,371	2,371
Mean	9.71	64.95	75.42	65.08	8.53
Median	0	.15	.16	.14	1
SD	53.44	355.17	416.33	356.31	37.28
Skewness	11.51	7.39	7.48	7.41	6.76

NOTES: Top panel shows the number of total, missing, zero-value, and other observations for the baseline county-by-decade sample shown in Figure A.3. Bottom panel shows various summary statistics. Column 1 shows unadjusted relative coal capital. Columns 2-4 adds imputed missing power plants with capacity less than 1 MW using 3rd, 4th, and 5th order polynomial functions for $g_t()$, respectively. Column 5 adjusts relative coal capital by adding 1 MW to both coal and non-coal capital investment. See Appendix C for details.

Table A.6: Robustness: additional identification concerns

	(1)	(2)	(3)	(4)	(5)
	Outcome is relative coal capital				
$\ln d_i^0$ (β^τ)					
2 decades lead	-1.38	-0.91	-1.49	-0.69	-2.09
	(1.02)	(1.07)	(0.96)	(1.61)	(1.90)
1 decade lead	-0.66	-1.45	-1.14	-0.22	-1.29
	(0.67)	(0.95)	(0.71)	(0.85)	(0.82)
	–	–	–	–	–
1 decade lag	-0.68	-0.60	-2.22**	-0.72	-1.08
	(1.25)	(1.29)	(1.01)	(1.05)	(1.40)
2 decades lag	-4.11***	-4.95***	-4.92***	-3.19***	-5.04***
	(1.15)	(1.25)	(1.39)	(1.07)	(1.20)
3 decades lag	-3.75***	-3.83***	-4.29***	-4.11***	-4.88***
	(0.66)	(0.76)	(0.62)	(1.39)	(1.10)
4 decades lag	-3.51***	-2.87***	-4.33***	-4.11***	-4.87***
	(0.71)	(0.88)	(0.67)	(1.53)	(1.22)
5 decades lag	-4.58***	-3.31***	-5.40***	-5.96***	-5.54***
	(0.98)	(0.98)	(1.09)	(1.68)	(1.15)
6 decades lag	-3.71***	-2.85***	-4.53***	-4.84***	-4.84***
	(0.75)	(0.91)	(0.67)	(1.43)	(1.15)
7 decades lag	-6.20***	-3.30**	-7.12***	-6.99***	-8.11***
	(1.37)	(1.67)	(1.45)	(1.81)	(1.52)
8 decades lag	-7.30***	-4.36**	-8.27***	-8.04***	-9.53***
	(1.59)	(1.77)	(1.71)	(1.93)	(1.68)
9 decades lag	-7.30***	-4.62**	-8.22***	-8.02***	-10.3***
	(1.56)	(1.96)	(1.69)	(2.05)	(1.69)
10 decades lag	-7.01***	-4.27**	-7.86***	-7.95***	-10.6***
	(1.56)	(1.89)	(1.68)	(2.05)	(1.83)
$\ln d_{it}$ (π)	-1.53***	-2.20**	-1.69***	-1.56**	-1.86***
	(0.53)	(0.86)	(0.55)	(0.61)	(0.50)
Mine fixed effect	No	Yes	No	No	No
Dropped if mine becomes 2nd closest	No	No	Yes	No	No
Demand covariates	No	No	No	Yes	No
Geography covariates	No	No	No	No	Yes
Observations	2,371	2,371	2,035	2,108	2,371
Counties	261	261	219	261	261

NOTES: Estimates of β^τ and π from equation (4) using a Poisson model. Outcome variable is relative coal capital at the county-by-decade level. County sample shown in Figure A.3. Time period is 1890-1990. Each model includes event time, county, and state-by-decade fixed effects. Column 1 replicates baseline estimates. Column 2 adds shallow mine fixed effects. Column 3 estimates baseline model but drops counties for which the shallow mine becomes the second nearest mine in any decade after the switching event. Column 4 adds county-by-decade population, number of manufacturing establishments, and manufacturing employment, all in logs. Column 5 adds log county distance to nearest navigable waterway and log variance in slope, both interacted with a linear time trend. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Robustness: imputing missing small power plants

	(1)	(2)	(3)	(4)	(5)
	Outcome is relative coal capital				
$\ln d_i^0$ (β^τ)					
2 decades lead	-1.38	-1.31	-1.32	-0.23	-2.66
	(1.02)	(1.01)	(1.00)	(0.46)	(2.22)
1 decade lead	-0.66	-0.70	-0.69	0.0069	-1.53
	(0.67)	(0.67)	(0.67)	(0.31)	(0.94)
	–	–	–	–	–
1 decade lag	-0.68	-0.58	-0.59	-0.12	-0.84
	(1.25)	(1.19)	(1.19)	(0.33)	(0.58)
2 decades lag	-4.11***	-3.97***	-3.97***	-1.90***	-2.49
	(1.15)	(1.07)	(1.08)	(0.44)	(2.02)
3 decades lag	-3.75***	-3.70***	-3.68***	-2.11***	-4.18**
	(0.66)	(0.66)	(0.66)	(0.41)	(2.03)
4 decades lag	-3.51***	-3.44***	-3.43***	-2.03***	-4.97**
	(0.71)	(0.71)	(0.71)	(0.37)	(1.94)
5 decades lag	-4.58***	-4.49***	-4.46***	-2.29***	-3.91*
	(0.98)	(0.91)	(0.91)	(0.37)	(2.08)
6 decades lag	-3.71***	-3.65***	-3.63***	-1.47***	-2.82
	(0.75)	(0.75)	(0.74)	(0.48)	(2.20)
7 decades lag	-6.20***	-6.15***	-6.12***	-3.18***	0.71
	(1.37)	(1.36)	(1.36)	(0.80)	(2.96)
8 decades lag	-7.30***	-7.24***	-7.22***	-3.90***	-3.33
	(1.59)	(1.58)	(1.57)	(0.80)	(2.64)
9 decades lag	-7.30***	-7.25***	-7.22***	-3.95***	-2.63
	(1.56)	(1.56)	(1.55)	(0.78)	(2.45)
10 decades lag	-7.01***	-6.96***	-6.94***	-3.76***	-2.20
	(1.56)	(1.55)	(1.54)	(0.75)	(2.83)
$\ln d_{it}$ (π)	-1.53***	-1.54***	-1.54***	-0.86**	-2.41***
	(0.53)	(0.53)	(0.53)	(0.40)	(0.75)
Small plant imputation	4th ord. poly	3rd ord. poly	5th ord. poly	add 1MW	none
Observations	2,371	2,371	2,371	2,371	382
Counties	261	261	261	261	66

NOTES: Estimates of β^τ and π from equation (4) using a Poisson model. Outcome variable is relative coal capital at the county-by-decade level. County sample shown in Figure A.3. Time period is 1890-1990. Each model includes event time, county, and state-by-decade fixed effects. Column 1 replicates baseline estimates which imputes missing small power plants with a 4th order polynomial function for $g_t()$ to construct relative coal capital (see Appendix C). Column 2 uses a 3rd order polynomial function for $g_t()$. Column 3 uses a 5th order polynomial function for $g_t()$. Outcome in column 4 adds 1 MW to both unadjusted coal and non-coal capital investment to construct relative coal capital. Outcome in column 5 is unadjusted relative coal capital. Of the 1,123 observations with non-missing unadjusted relative coal capital, column 5 drops 724 observations from counties where the outcome variable is always zero and 17 observations from counties with only one non-missing variable per county in order to estimate a Poisson model with fixed effects. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Robustness: sample restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome is relative coal capital					
$\ln d_i^0$ (β^τ)						
2 decades lead	-1.38	-4.28**	-0.98	-2.22*	-1.21	-1.41
	(1.02)	(1.68)	(1.07)	(1.27)	(1.02)	(1.05)
1 decade lead	-0.66	-2.54**	-0.53	-1.27	-0.49	-0.76
	(0.67)	(1.04)	(0.66)	(0.82)	(0.75)	(0.66)
	–	–	–	–	–	–
1 decade lag	-0.68	-0.94	-0.61	-1.99	-0.24	-0.71
	(1.25)	(1.40)	(1.22)	(1.23)	(1.17)	(1.05)
2 decades lag	-4.11***	-5.33***	-4.02***	-6.01***	-2.71***	-3.94***
	(1.15)	(1.02)	(1.12)	(1.16)	(1.03)	(1.03)
3 decades lag	-3.75***	-5.78***	-3.65***	-4.61***	-2.34***	-3.70***
	(0.66)	(1.14)	(0.65)	(0.83)	(0.90)	(0.65)
4 decades lag	-3.51***	-5.40***	-3.40***	-4.50***	-2.01**	-3.49***
	(0.71)	(1.39)	(0.71)	(0.93)	(0.96)	(0.69)
5 decades lag	-4.58***	-3.79**	-4.46***	-7.31***	-1.69	-4.14***
	(0.98)	(1.64)	(0.95)	(2.07)	(1.12)	(0.77)
6 decades lag	-3.71***	1.84	-3.63***	-4.49***	-1.59	-3.84***
	(0.75)	(3.80)	(0.74)	(0.98)	(1.16)	(0.73)
7 decades lag	-6.20***	-6.16**	-6.17***	-6.91***	-3.71**	-4.56***
	(1.37)	(3.07)	(1.37)	(1.36)	(1.50)	(0.97)
8 decades lag	-7.30***	-7.85**	-7.27***	-8.09***	-4.62***	-5.16***
	(1.59)	(3.11)	(1.58)	(1.54)	(1.69)	(1.21)
9 decades lag	-7.30***	-7.66**	-7.28***	-8.10***	-4.43***	-5.12***
	(1.56)	(3.10)	(1.56)	(1.48)	(1.66)	(1.23)
10 decades lag	-7.01***	-7.94**	-6.98***	-7.76***	-4.18**	-5.06***
	(1.56)	(3.23)	(1.55)	(1.48)	(1.67)	(1.23)
$\ln d_{it}$ (π)	-1.53***	1.89	-1.56***	-1.53***	-1.33**	-0.74
	(0.53)	(1.37)	(0.53)	(0.52)	(0.52)	(0.59)
Sample	Benchmark	>90th pct mines	>97.5th pct mines	<200 miles from Ill. coal	<300 miles from Ill. coal	Incl. closer to App. coal
Observations	2,371	1,922	2,403	1,938	2,881	3,218
Counties	261	223	261	208	320	338

NOTES: Estimates of β^τ and π from equation (4) using a Poisson model. Outcome variable is relative coal capital at the county-by-decade level. Time period is 1890-1990. Each model includes event time, county, and state-by-decade fixed effects. Column 1 uses baseline county sample shown in Figure A.3. Column 2 uses transport distance constructed from mines with area above the 90th percentile. Column 2 uses transport distance constructed from mines with area above the 97.5th percentile. Columns 3 and 4 restricts sample to counties within 200 and 300 miles from the nearest Illinois Basin coal resource and are closer to Illinois Basin coal than to Appalachian Basin coal. Column 5 restricts sample to counties within 250 from the nearest Illinois Basin coal resource but include counties that are closer to Appalachian Basin coal than to Illinois Basin coal. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Robustness: alternative modeling choices

	(1)	(2)	(3)	(4)	(5)
$\ln d_i^0$ (β^τ)					
3 decades lead			0.87		
			(1.49)		
2 decades lead	-1.38		-1.35	-0.27	0.32
	(1.02)		(1.00)	(0.42)	(1.04)
1 decade lead	-0.66	-0.72	-0.64	0.27	0.27
	(0.67)	(0.69)	(0.67)	(0.40)	(0.64)
	–	–	–		
1 decade lag	-0.68	-0.65	-0.71	-0.42	-0.76*
	(1.25)	(1.23)	(1.28)	(0.26)	(0.39)
2 decades lag	-4.11***	-4.06***	-4.16***	-1.21***	-1.40**
	(1.15)	(1.14)	(1.15)	(0.31)	(0.60)
3 decades lag	-3.75***	-3.70***	-3.82***	-1.71***	-1.93**
	(0.66)	(0.66)	(0.67)	(0.49)	(0.87)
4 decades lag	-3.51***	-3.44***	-3.58***	-1.80***	-2.36**
	(0.71)	(0.72)	(0.72)	(0.55)	(1.04)
5 decades lag	-4.58***	-4.53***	-4.65***	-2.18***	-2.61**
	(0.98)	(0.97)	(0.99)	(0.66)	(1.06)
6 decades lag	-3.71***	-3.65***	-3.78***	-1.79**	-2.49**
	(0.75)	(0.75)	(0.75)	(0.85)	(1.12)
7 decades lag	-6.20***	-6.14***	-6.27***	-2.89**	-3.23
	(1.37)	(1.37)	(1.37)	(1.29)	(2.04)
8 decades lag	-7.30***	-7.24***	-7.37***	-4.10***	-4.20**
	(1.59)	(1.59)	(1.59)	(1.37)	(2.02)
9 decades lag	-7.30***	-7.24***	-7.37***	-3.71**	-3.86*
	(1.56)	(1.56)	(1.57)	(1.51)	(2.04)
10 decades lag	-7.01***	-6.95***	-7.08***	-3.74**	-3.55*
	(1.56)	(1.56)	(1.57)	(1.71)	(2.08)
$\ln d_{it}$ (π)	-1.53***	-1.53***	-1.53***	-0.18	-0.66
	(0.53)	(0.53)	(0.53)	(0.62)	(0.90)
Model	Poisson	Poisson	Poisson	Linear	Neg. bin.
Observations	2,371	2,242	2,500	2,371	2,371
Counties	261	261	261	261	261

NOTES: Estimates of β^τ and π from equation (4). Outcome variable is at the county-by-decade level. County sample shown in Figure A.3. Time period is 1890-1990. Each model includes event time, county, and state-by-decade fixed effects. Column 1 replicates baseline model using a Poisson model with relative coal capital as the outcome and includes 2 lead terms. Column 2 is identical to column 1 except for having 1 lead term. Column 3 is identical to column 1 except for having 3 lead terms. Column 4 uses a log-log linear model with log relative coal capital as the outcome and includes 2 lead terms. Column 5 uses a negative binomial model with dispersion parameter that is a function of expected relative coal capital and includes 2 lead terms. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: Other mechanisms: cost-of-service and Clean Air Act regulations

	(1)	(2)	(3)	(4)
	Outcome is relative coal capital			
$\ln d_i^0$ (β^τ)				
2 decades lead	-1.38	-0.75	-1.61	0.093
	(1.02)	(0.91)	(1.00)	(1.39)
1 decade lead	-0.66	-0.71	-1.46	0.53
	(0.67)	(0.56)	(1.00)	(1.12)
	–	–	–	–
1 decade lag	-0.68	-2.80**	-1.91**	-3.09**
	(1.25)	(1.09)	(0.83)	(1.39)
2 decades lag	-4.11***	-2.93***	0.032	-3.26**
	(1.15)	(1.11)	(0.87)	(1.29)
3 decades lag	-3.75***	-2.93*	-3.12***	-4.14***
	(0.66)	(1.55)	(1.07)	(0.80)
4 decades lag	-3.51***	-6.99*	-2.46	-3.70***
	(0.71)	(3.92)	(2.02)	(1.13)
5 decades lag	-4.58***	-3.11***	-5.56*	-2.24*
	(0.98)	(1.13)	(2.91)	(1.26)
6 decades lag	-3.71***	-3.12***	-4.50	2.11
	(0.75)	(1.14)	(2.95)	(2.19)
7 decades lag	-6.20***		-4.85*	-4.30*
	(1.37)		(2.57)	(2.25)
8 decades lag	-7.30***			-5.75**
	(1.59)			(2.42)
9 decades lag	-7.30***			-5.94***
	(1.56)			(2.14)
10 decades lag	-7.01***			-5.31**
	(1.56)			(2.10)
$\ln d_{it}$ (π)	-1.53***	0.36	0.75	-1.76***
	(0.53)	(1.11)	(1.13)	(0.67)
Drop PUC	No	Yes	No	No
Drop ever in nonattainment	No	No	No	Yes
Sample period	1890-1990	1890-1970	1890-1960	1890-1990
Observations	2,371	746	1,588	1,685
Counties	261	201	261	185

NOTES: Estimates of β^τ and π from equation (4) using a Poisson model. Outcome variable is relative coal capital at the county-by-decade level. County sample shown in Figure A.3. Each model includes event time, county, and state-by-decade fixed effects. Column 1 replicates baseline estimates. Column 2 drop county-decade observations when there is a state Public Utility Commission regulating electric utilities. Column 3 includes only observations during 1890-1960. Column 4 drops counties that were ever designated as nonattainment under the U.S. Clean Air Act. Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.11: Other mechanisms: upstream and downstream sectors

	(1)	(2)	(3)	(4)
			Outcome is	
	ln railroad density	ln highway density	env. NGO share	republican vote share
$\ln d_i^o \times sinceEvent_i$ (ω_1)	-0.048	-0.022	-0.000022	0.0033
	(0.031)	(0.018)	(0.000078)	(0.0034)
$\ln d_i^o$ (ω_2)	-0.0019	0.013	-0.00057	-0.0022
	(0.17)	(0.11)	(0.00046)	(0.021)
$sinceEvent_i$ (ω_3)	0.23*	0.051	-0.000095	-0.011
	(0.14)	(0.072)	(0.00031)	(0.014)
Counties	458	458	458	458

NOTES: Estimates from equation 10 using county-level outcomes. All models includes state and NERC region fixed effects, and county centroid longitude and latitude. County sample shown in Figure A.3. Outcome in column 1 is log railroad density in 2010 (in miles per square mile). Outcome in column 2 is log highway density in 2010 (in miles per square mile). Outcome in column 3 is the population share of individuals who are members of three major environmental NGOs in 1996 (in %). Outcome in column 4 is the share of eligible voters who voted for the Republican Presidential candidate in 2000 (in %). Robust standard errors clustered at the county level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.