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Highlights

- We present a theoretical model showing that deregulation downstream leads to more rigid procurement contracts upstream;
- These contracts provide higher-powered incentives to mines, which should lead to an increase in productivity;
- The theoretical predictions of this model are tested using a difference-in-difference identification strategy based on the history of deregulation in the US;
- The empirical results provide clear support for our theoretical priors;
- Our analysis is important as it illustrates that existing analyses may be missing an important part of the picture.

A Look Upstream: Market Restructuring, Risk, Procurement Contracts and Efficiency*

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Abstract

We study how market deregulation affects the upstream industry both theoretically and empirically. Our theory predicts that firms respond to increases in uncertainty due to deregulation by writing more rigid contracts with their suppliers. Using the restructuring of the U.S. electricity market as our case study, we find support for our theoretical predictions. Our findings imply a greater emphasis on efficiency at coal mines contracting with restructured plants. The evidence suggests a 17% improvement in productivity at these mines, relative to those contracting with regulated plants. We find, on the other hand, that transaction costs may have increased. We conclude that deregulation has significant impacts upstream from deregulated markets.

JEL Classification: Q31, Q35, Q48, L14, L51

***Keywords**:* Coal Use, Energy, Electricity Market Restructuring, Procurement Contracts, Efficiency, Transaction Costs.

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1 Introduction

Attempts to liberalize previously regulated natural monopolies such as telecommunications, rail and air transportation, water provision, and energy generation and distribution have been commonplace in OECD countries since at least the late 1970s. A large literature has emerged that assesses the effects of deregulation (Olley and Pakes, 1996; Ng and Seabright, 2001; Syverson, 2004; Davis and Kilian, 2011, among others). Most contributions to date, however, have taken a rather narrow view of the issues and discussed the consequences of the policy exclusively from the point of view of firms operating directly in the deregulated market. Such analyses, while informative, provide at best a partial picture of the overall consequences of deregulation, as they neglect its impacts on the supply chain upstream from the deregulated market. This omission is certainly relevant from a theoretical standpoint, as the aim of the policy is to eliminate all types of inefficiencies and transfer the associated rents to the final consumers. It is, however, also likely to be empirically significant in situations where input costs represent a large share of the total costs of production.

In this paper we take a first step into investigating the consequences of deregulation upwards along the supply chain. This endeavor yields novel theoretical insights into the consequences of deregulation, and allows the identification of empirically relevant channels through which the policy affects efficiency. Our analysis is cast in terms of the restructuring of the U.S. electricity market, which has received special attention in the past due to a combination of political salience and data availability (e.g. Borenstein, Bushnell, and Wolak, 2002; Fabrizio, Rose, and Wolfram, 2007; Davis and Wolfram, 2012; Cicala, 2015) and is an industry where input costs are significant.[1]

We develop a theoretical model to analyze how deregulation impacts coal procurement contracts signed between electricity generators and coal mines. An established literature identifies the key dimensions along which long-term contracts are negotiated in the price adjustment mechanism and the length of the contract (e.g., Joskow, 1987, 1988). Accordingly, our model captures the negotiation between the parties in terms of the rigidity of the price setting mechanism and the duration of the contract, and focuses on the changes in the degree of risk faced by generators following the electricity market restructuring. The key insight we derive is that one would expect to observe more rigid (e.g., fixed-price), shorter contracts in restructured markets as a consequence of risk-sharing attempts. While previous work has noted that "*firms that do not have the security of a guaranteed rate of return on their investments will be more prudent in* [...] *the way they manage risk*" (Borenstein and Bushnell, 2000), we are the first to formally derive these results.

We then take these theoretical predictions to the data and exploit the peculiar history of restructuring in the United States to identify a suitable control group for the plants exogenously 'treated' with restructuring.[2] This enables us to identify the effects of restructuring on the deregulated plants. Using data on actual contracts signed by electricity generators with coal mines, we find empirical support for our theoretical insights.

[1] For the large coal-fired electricity generators at the center of our analysis, fuel costs contribute over 80% to total variable costs (Cicala, 2015).

[2] Restructuring was exogenous to coal contracting as a State's decision to restructure was driven by the lack of cheap hydroelectric generation opportunities and by costly generation investments dating back to the 1970s and 80s (Borenstein and Bushnell, 2000).

In the final part of our work, we discuss the implications of our results for the overall efficiency of the industry. On the one hand, rigid prices in contracts make the coal mine the residual claimant to any efficiency gain, and provide higher-powered incentives for cost reductions. Using data on coal mines' labor productivity, we conclude that shipping coal to deregulated plants is causally linked to productivity gains. On the other hand, shorter and more rigid contracts are, in theory, more prone to being renegotiated. Our final empirical effort confirms that the changes in contracting practices we identify imply more frequent renegotiations, which might lead to an increase in transaction costs.

Our goal in this paper is to understand how the contracting behavior of electricity generators adapts as the regulatory framework for the industry changes. While under cost-of-service regulation, electricity generators are all but guaranteed the recovery of (prudently incurred) costs and an adequate rate of return, in an unregulated environment they are faced with volatile fuel prices and unpredictable (wholesale) electricity prices. Thus, attitudes towards risk play an important role.

While risk-neutrality is a commonly made assumption in the theoretical literature on procurement and regulation, the more recent literature has moved away from it. Arve and Martimort (2016), for example, argue convincingly in favor of incorporating risk aversion in the analysis of long-term procurement relationships. According to these authors, risk neutrality hinges upon two key assumptions, which are both hard to substantiate. Firstly, it requires that firms have perfect access to financial markets; and secondly, that there are no agency problems.

As pertains to the first aspect, it is true that in principle a variety of financial instruments – forward contracts, futures contracts, options, etc. – are available to generators to hedge against risk. In practice, however, given the limited possibility to efficiently store electricity, the severe constraints that exist on its transmission (both in physical and in reliability terms), and the inelastic nature of (short-run) electricity demand, electricity prices on deregulated wholesale markets are substantially more volatile than commodity prices, making effective hedging much more difficult (e.g. Liu, Wu, and Ni, 2006; Yu, Somani, and Tesfatsion, 2010). Furthermore, Gross, Blyrth, and Heptonstall (2010) discuss at length the difficulty of hedging against long-run fuel price uncertainty. As a result, electricity generators need to accept the impossibility of perfectly hedging against the types of risk mentioned above. In this sense, our analysis can be seen as a study into how the *residual* risk (after hedging) from both the downstream wholesale electricity price volatility, and the upstream fuel price uncertainty shapes the contractual arrangements on the upstream market.

As for the second issue, agency constraints due to asymmetric information, adverse selection or moral hazard are well studied in regulated industries.[3] These issues are likely to be especially severe in the case of coal-fired electricity generation, where the opportunity costs of failing to produce are large,[4] and transportation and storage costs are substantial given the bulky nature of the inputs, limiting operative flexibility in the short-run. Moreover, in a recent contribution, Jha (2016) offers an alternative, non-agency-based theoretical

[3]Excellent reviews of the literature can be found in Laffont (1994), and Armstrong and Sappington (2006).

[4]It is generally understood that the state and electricity utilities entered a "regulatory compact" where consumers accepted a monopolistic provider, whereas the utility accepted an obligation to produce (McDermott, 2012). Moreover, as discussed by Gilbert and Newbery (1984) the utility regulators followed the "used and useful" standard, according to which state commissions could refuse compensation to generators for their idle capacity.

mechanism through which output price regulation induces risk aversion among regulated coal-fired generators. Based on this discussion, it seems, therefore, plausible that firms operating in such an environment would be concerned not only with the expected returns of their decisions, but also with the associated risks.[5]

Recent empirical evidence also lends support to the risk-aversion hypothesis. By accounting for the endogenous match between sellers and buyers, Ackerberg and Botticini (2002) have convincingly shown empirically, that different degrees of risk aversion play a significant role in contract choice. More recently, and more closely related to our work, Jha (2016) provides further empirical evidence among U.S. regulated coal-fired power plants that is consistent with the risk-aversion behavior derived in their theoretical framework.

With this in mind, we adopt the classical Markowitz (1952) framework and model the choice of contract similarly to a problem of portfolio selection. In our case the value of a contract can be expressed as a function of its expected profitability and riskiness. Rather than resorting to the variance of profits as our proxy for risk, however, we build on current practice in the financial literature and use the concept of Conditional Value at Risk to capture the risk associated with the contract (Rockafellar and Uryasev, 2000; Yamai and Yoshiba, 2005). Conditional value at risk (CVaR) is a statistic in the family of percentile risk measures that is a weighted average of the value at risk (VaR) and the losses exceeding the VaR. Due to its attractive properties (convexity, coherence, mathematical tractability, etc.), the CVaR can be easily incorporated in constrained reward optimization problems allowing for general distributions of losses and varying confidence levels across constraints.[6]

Our work is in the spirit of the seminal contribution by Cheung (1969) – given that we explicitly study the trade-off between transaction costs and risk distribution between parties across different contractual arrangements – and it is related to the vast literature on procurement contracts.[7] Among the many theoretical contributions on optimal procurement contracts and asymmetric information, our paper is closest to those that study moral hazard in procurement. McAfee and McMillan (1986) is a classic reference in this respect. There the optimal contract offered by the buyer to the risk averse seller implements a partial reimbursement rule that trades off incentives for cost reduction effort and the need to share risk. Similarly, Bajari and Tadelis (2001) focus on the trade-off between the cost reduction incentives and ex-post renegotiation inefficiencies. We adopt a similar approach in that in our framework the optimal contract identifies the best combination of price rigidity and duration to balance the cost of contracting against the exposure to upstream risk (due to fuel price).

Several authors have empirically investigated the determinants of contract choice using different proxies for the characteristics of the principal, the agent and the task being contracted.[8] Laffont and Matoussi (1995), Ackerberg and Botticini (2002), and Bandiera (2007)

[5] In moving away from risk-neutrality, we also follow a number of very influential theoretical contributions dealing with firms operating under price uncertainty. Seminal papers in this context are Baron (1970); Sandmo (1971); Holthausen (1979).

[6] See Krokhmal, Palmquist, and Uryasev (2002) for a discussion on the advantages of using CVaR over other measures such as the VaR and the variance in constrained optimization problems .

[7] The literature review in Asker and Cantillon (2010) provides an excellent overview of the key contributions in this field.

[8] For two recent surveys of this literature see Chiappori and Salanié (2002), and Corts and Singh (2004).

focus on the determinants of agrarian contracts, Leffler and Rucker (1991) look at timber harvesting, while Martin (1988) discusses contract choice in business franchising. Closer to our work, Corts and Singh (2004) study the impact of repeated interaction on the choice of fixed-price versus cost-plus contracts in the offshore drilling industry, while Joskow (1987), Kerkvliet and Shogren (2001) and Kozhevnikova and Lange (2009) look specifically at the determinants of contractual duration in coal procurement using U.S. data. In the present paper, we study the interaction between the price rigidity decision and the length of the contract, explicitly modeling the two decisions as simultaneously chosen characteristics of the optimal contract. In this respect our work is related to that of Bandiera (2007) who stresses the importance of the joint analysis of these two mechanisms in order to identify the contractual incentives for investment in land tenancy agreements. Our focus is instead on the consequences for productive efficiency in the coal industry.

The rest of the paper proceeds as follows, Section 2 provides a concise overview of the market for coal in the U.S. in the period covered by our analysis and discusses the restructuring process started in the early 1990s. Section 3 contains our theoretical discussion. Section 4 presents the empirical strategy, describes the data and discusses the results. In Section 5 we discuss the implications of our theoretical and empirical analysis for mine productivity and contract renegotiation. Finally, Section 6 concludes.

2 An overview of procurement choices in the U.S. coal-fired generation industry

Our analysis focuses on the period between 1990 and 2001, which corresponds to the peak of coal usage in the U.S. electricity market, as the oil shocks of the 1970s created the conditions for an expansion in coal-fired capacity. Coal supplied around 50% of the U.S. electricity through the 1980s, 1990s, and the early 2000s (U.S. EIA, 2010). Since coal plants tend to have higher start-up and shut-down costs relative to oil and gas plants, coal capacity was generally built to supply the base-load of the electricity system, meaning that it was expected to run at all hours of the day. Hence, the main operational concern for operators of coal-fired boilers was to ensure an adequate and consistent supply of coal to meet base-load electricity demand. This led plants to utilize complex long-term forward contracts for fuel procurement. Different types of contracts were developed, with varying degree of price rigidity. At one end of the spectrum, 'fixed-price' contracts would specify a single delivery price for the entire duration of the contract; at the other end of the spectrum, so-called 'evergreen' contracts stipulated that the price would be renegotiated at predetermined intervals, usually once a year. Other contracts had intermediate degrees of price rigidity, such as contracts that would specify a base price and a formula to compute increases or decreases from this base price, depending on economic and market conditions ('base-price plus escalation' contracts).[9] These contracts proved to be surprisingly resilient to changes in the market such as railroad market restructuring, and the emergence of a large spot market in the Western coal-producing states (Joskow, 1985, 1990).

[9]Table 1 presents the most common types of contracts, along with the definition provided by the Federal Energy Regulatory Commission (FERC) to plants in the documentation of Form 580 "Interrogatory on Fuel and Energy Purchase Practices", our main source of information on coal contracts.

The desire for quantity and quality certainty, and the associated use of long-term forward contracts, was re-enforced by the structure of economic regulation in the electricity sector. Plants were regulated under cost-of-service regulation, where the price of electricity was guaranteed by the state, depending on the plant's cost of generation. Crucially, once the state public utility commission approved a coal contract, they would then allow the plant to be compensated for the prices paid under that contract. The regulator put large weight on ensuring supply would meet demand, rather than focusing on the cost of electricity. Moreover, most plants were part of an integrated utility that also managed the transmission and distribution grids, so they had a great deal of certainty with respect to both the price and quantity of the electricity they would sell. In this situation, it was very difficult for new entrants to gain access to the market, given that the incumbents managed the grid. This state of affairs considerably reduced the generators' incentives to minimize their generation costs, and left coal mines with little pressure to improve their efficiency.

In 1992, the Federal Energy Policy Act mandated that non-discriminatory access to the transmission grid be guaranteed, in an effort to encourage new generators to enter the market. Many states were also interested in encouraging lower cost generators to enter the generation market, and thus held hearings on how to reform their regulation of the electricity market.[10] These hearings addressed possible ways to bring competition to the generation of electricity through potential legislation that separated transmission and distribution services from the generation and retail services of the electricity market. States that fully went through with electricity market restructuring set up a market where plants generally had to bid for the right to put electricity onto the transmission system and thus sell their output. This process was more straightforward for some states, such as in the Northeast, where most states already shared an electricity balancing authority previous to the restructuring decision. As a result, it was easier to form an independent system operator as the premise for a competitive wholesale market. Other states, like Oregon, which passed restructuring legislation, never had a formal wholesale market given the decisions made by their balancing authority. While restructuring introduced a number of changes to the way in which electricity markets were structured (both on the retail and the generation side), restructured electricity markets also introduced a significant degree of risk in the output market compared to the economic regulation that had existed before the mid-1990s. Indeed, in restructured markets little guarantee existed as to either the price or the quantity facing the generators. In the next section we present a theoretical model to analyze how uncertainty might affect the choice of contract in the negotiation between electricity generators and coal mines.

3 A model of fuel procurement in electricity generation

Our goal is to understand how changes in the regulatory environment on the wholesale electricity market, might affect the contractual choices made by coal-fired generators and coal mines.[11] The generator needs to source coal to generate electricity for sale on the

[10] Table 2 gives a list of the years when hearings were held and restructuring legislation passed, by State.

[11] In what follows we use 'producer', 'generator', 'buyer' or simply 'plant' interchangeably. Instead, we refer to the coal producer as the 'mine', or simply the 'seller'.

downstream market. The mine extracts coal from the ground and sells it.[12]

3.1 The value of a contract

While coal contracts can be very complex, for our purposes here it suffices to focus on two elements of the procurement contract, namely the price paid for each unit of coal, p^c, and the duration, d, of the contract itself. We simplify our analysis by assuming that the quantity of coal contracted for delivery is given and can be normalized to one.[13] Furthermore, building on the insights provided by Crio and Condren (1984), we treat all aspects of the contract that refers to the quality of coal as exogenous.[14]

As regards the price of coal, the contract specifies how it is to be determined over the whole duration of the agreement. Different price adjustment provisions may be included in procurement contracts (see Section 2). To reflect the varying degree to which the price of coal is linked to the mining costs, we write the delivery price of coal as the sum of a component that allows the seller to recoup its operating costs and a fixed part that allows for an appropriate rate of return on its assets. The degree of rigidity of the pricing mechanism can then be captured by the value of $r \in [0,1]$ as follows:

$$p^c = (1-r)x(\chi, e) + \delta(r), \tag{1}$$

where $r = 1$ represents a fixed-price contract. In the expression above $x(\chi, e)$ represents the production costs incurred by the mine. Extracting coal from the ground is a complex process, which entails drilling and blasting, collecting, crushing, separating by-products, stockpiling and shipping the coal. These activities entail uncertain costs, that depend on the physical properties of the seam, as well as other characteristics of the mine such as the degree of unionization of the labor force.[15] Here, we assume that mining costs depend positively on a random variable, χ, whose probability distribution is known to the mine at the time the contract is written, but whose actual realization is not.[16] The mine may affect the level of its mining costs by exerting effort, $e \geq 0$, for example in order to increase its productivity. Effort is costly, and the cost of effort, $g(e)$, is increasing and convex, i.e. $g(0) = 0$, with $g' > 0$, and $g'' \geq 0$. We also assume that these private costs are unobservable by the generator.[17]

[12] Between 1990 and 2001, on average 92% of all coal mined in the United States was used to generate electricity. Thus, neglecting alternative uses of mined coal is unlikely to be a significant omission in this context.

[13] Most coal-fired generators served as base-load generation during our sample given their low marginal cost of generation, and their high cost of ramping production up or down. Hence, such generators produced continuously and their main concern in terms of procurement was the availability of a sufficient quantity of coal. In this market segment, then, the quantity of coal to be delivered each period was very closely related to the productive capacity of the electricity generator, and can thus be considered constant.

[14] Crio and Condren (1984) remark that long term contracts specify the physical attributes of the coal in order to match the design specifications of the boilers. Hence, the physical attributes specified in the contract (usually the heat, sulfur, ash, and moisture content) are a function of the technical characteristics of the boiler, and as such are exogenous to the choice of contract.

[15] See Hartman (1990) for a classical text on the uncertain nature of mining costs. For the purposes of our empirical analysis we will use the fact that these costs vary across locations to control for them in our estimations.

[16] Later on in the analysis for the sake of analytical tractability we take $x(\chi, e)$ to be normally distributed with mean $\mathbb{E}(x)$ and variance σ_x^2.

[17] Notice that, in this context, contracting on the degree of price rigidity is equivalent to contracting on effort given the monotonic relationship between effort and rigidity. This is formally shown in Lemma 1 below.

In line with the moral hazard literature, we assume that effort may reduce the expected level of costs, but becomes gradually less effective, i.e. $\partial \mathbb{E}(x)/\partial e < 0$ and $\partial^2 \mathbb{E}(x)/\partial e^2 \geq 0$. Effort might also affect the variance of the mining costs. Cost-reducing efforts could, for example, be aimed at reducing administrative costs with little effect on actual production activities, such that $\partial \sigma_x^2/\partial e = 0$. This is equivalent to saying that, for any effort level $e < e'$, $x(\chi, e)$ first order stochastically dominates $x(\chi, e')$. Alternatively, effort could be directly aimed at reducing the variance of production costs. This could be achieved, for example, by prioritizing the development of shallower seams or by continuous production scheduling. In such cases, we would expect that $\partial \sigma_x^2/\partial e < 0$. Finally, certain types of efforts targeted at reducing the level of costs in mining may lead to an increase in the probability of injuries or fatalities (Buessing and Weil, 2014), implying $\partial \sigma_x^2/\partial e > 0$. Our framework nests all these three alternative scenarios.

Several types of contracts have long coexisted in this industry (see Section 2). To allow for this, we impose that the level of the price of coal be the same, *ex-ante*, across contracts. We thus need to adjust the level of the fixed component such that the expected price remains the same, irrespective of the degree of contractual price rigidity. It follows that δ is an increasing function of r. To see this, consider a fixed price contract where $r = 1$ and $p^c = \delta(1) = \overline{\delta}$. For the *ex-ante* price of coal to be the same across contracts with different degrees of price rigidity, it must hold that $\mathbb{E}(p^c) = \delta(r) + (1-r)\mathbb{E}(x) = \overline{\delta}$, or, equivalently,

$$\delta(r) = \overline{\delta} - (1-r)\mathbb{E}(x). \tag{2}$$

In line with the theoretical underpinnings of the transaction cost approach to contracting (e.g. Cheung, 1969), we assume that for both sellers and buyers negotiating an agreement, writing the contract, and managing the ensuing relationship entails potentially large costs, including the opportunity cost of devoting resources to contracting and administering the contract, rather than to alternative, more productive activities. We also assume, as discussed at length below, that different types of contracts entail different transaction costs, and that more complex relationships – in particular those that require higher level of relation-specific assets – are more costly to shape and maintain (Joskow, 1987). Crucially, most of these costs cannot be practically attributed to specific contracts and, as a consequence, they cannot be included among the costs recovered under a cost-plus contract by the seller, and under cost-of-service regulation by the buyer. In other words, transaction costs always contribute negatively to profits, irrespective of the regulatory environment and the pricing mechanism.

Given (1), we can parameterize the price setting mechanism by r, and define a 'contract' as a pair, $\boldsymbol{\gamma} = (r, d)$. From the set of all possible contracts, Γ, the parties select the contract $\boldsymbol{\gamma}$ that maximizes their payoff. Similarly to the familiar Markowitz (1952) setup, we assume that both types of agents value contracts according to their perceived tradeoff between risk and expected return. In line with recent practice in the financial contracting literature, rather than measuring risk using the variance of the portfolio returns, we adopt the concept of *Conditional Value-at-Risk* ($CVaR_\alpha$) (Rockafellar and Uryasev, 2000).[18] Both types of firm choose the contract that provides the best combination of expected profits and the size of

[18] For any given confidence level α, the *Value-at-Risk*, or VaR_α, of a portfolio is given by the smallest number v such that the probability that the loss in portfolio value exceeds v is not greater than $(1-\alpha)$. The $CVaR_\alpha$ of a portfolio is, instead, defined as the expected loss in portfolio value during a specified period, conditional on the event that the loss is greater than or equal to VaR_α. Thus, $CVaR_\alpha$ informs a portfolio holder about the size of

the potential adverse consequences associated with the contract. The per-period value of contract $\boldsymbol{\gamma} = (r, d)$ to firm type $i = \{g, m\}$, can thus be written in general terms as follows:

$$V^i(\boldsymbol{\gamma}) = \mathbb{E}(\pi^i) - \theta^i \, CVaR_{\alpha_i}(-\pi^i), \text{ for } i = \{g, m\}, \tag{3}$$

where g and m are the generator's and the mine's identifiers, respectively, and θ^i is the relative weight attached to risk by type i in its objective function.

3.2 The mine

We start by specializing (3) for the case of the coal mine. Having extracted and processed the coal, the mine delivers it to the generator in exchange for the agreed price, p^c. Taking into account that the mine incurs production costs, $x(\chi, e)$, effort costs, $g(e)$, and – as discussed above – transaction costs, k^m, we can write the mine's profits as

$$\pi^m = p^c - x(\chi, e) - g(e) - k^m(r, d; \mathbf{A}). \tag{4}$$

Our assumptions regarding the transaction cost component k^m, which are derived from the literature and from our understanding of the industry, warrant some discussion. It is quite natural to think that the transaction costs k^m would change with the pricing mechanism, and the duration of contract being stipulated (e.g. Tadelis and Williamson, 2012). On the one hand, a more rigid contract is more costly to negotiate, as there are simply more contingencies to contemplate (Bajari and Tadelis, 2001); on the other hand, a contract that specifies the price more rigidly reduces demands on the mine to account for, document and report its operating costs. As such, it entails lower administrative costs for the seller (Joskow, 1985). We assume that the latter effect is particularly relevant from the point of view of the mine and let $\partial k^m / \partial r < 0$. As refers to the duration stipulated in the contract, a longer contract allows the setup costs to be spread over a longer period of time, reducing the per-period administrative costs. The longer the contract duration, however, the higher the probability that the seller might find it advantageous to breach the agreement. This might be due to the desire to pursue more lucrative alternative opportunities – a situation discussed, for example, by Joskow (1988) – or to negative developments in productive conditions. As discussed in Section 2 above, coal procurement contracts specify in great detail the characteristics of the coal to be delivered. If the productive conditions of the mine change – because of an unexpected deterioration in the quality of the coal seam, for example – the mine might find it very costly to keep operating within the framework of current contractual obligations. Either way, breaching the contract adds transaction costs and potentially large litigation costs to the total. We conclude that k^m is likely to be increasing with contractual duration, d, i.e. $\partial k^m / \partial d > 0$. In what follows we also assume that transaction costs are strictly convex in both arguments, i.e. $\partial^2 k^m / \partial r^2 > 0$, and $\partial^2 k^m / \partial d^2 > 0$. Since the likelihood of breach of contract is particularly high for contracts with more rigid price setting mechanisms, we also let $\partial^2 k^m / (\partial r \partial d) > 0$.[19] Finally, this type of transaction costs may be affected by relation-specific

the expected loss, conditional on the occurrence of an unfavorable event. A rich literature discusses the relative merits of $CVaR_\alpha$ and VaR_α (see, e.g. Yamai and Yoshiba, 2005). For examples of papers using $CVaR_\alpha$ in the context of electricity markets, see Liu et al. (2006) and Yu et al. (2010).

[19] Joskow (1988) writes "*While almost any price-adjustment provision could lead to large disparities between contract prices and "market prices" if certain contingencies arise, and thereby provide incentives for either the buyer or the seller to breach, a fixed-price contract almost guarantees that these problems will arise*", (*ibid.*, p. 52).

investments (Joskow, 1987). Hence, we write transaction costs as $k^m(r,d;\mathbf{A})$, where $\mathbf{A}$ is a vector of cost-shifters. The need to incur relation-specific investments tends to increase the cost of entering the contract; at the same time, the presence of relation-specific assets is likely to reduce the attractiveness of alternative opportunities. Both arguments imply that a longer contractual duration becomes more desirable as the sunk costs may be spread over more periods, and the likelihood of breaching the contract is reduced.[20] Thus, we let the marginal costs of a longer contractual duration decrease with $\mathbf{A}$, i.e. $\partial^2 k^m/(\partial d\,\partial A_i) < 0$ for each component A_i of $\mathbf{A}$.[21]

Importantly, it is possible, by plugging (4) into (3), to fully characterize the optimal choice of effort as a function of the degree of price rigidity only, as emerges from the following,

Lemma 1. *Given equations* (3) *and* (4) *and any exogenous contact* $\boldsymbol{\gamma} = (r,d)$, *the mine's optimal choice of effort,* e^*, *is*

i. a monotonic function of the level of rigidity r *provided that*

$$\frac{\partial^2\left(\frac{\partial CVaR_{\alpha_m}(-\pi^m)}{\partial e}\right)}{\partial r^2} = 0.$$

ii. an increasing function of the level of rigidity r, *provided that*

$$\frac{\partial \mathbb{E}(x(\chi,e^*))}{\partial e} + \theta^m \frac{\partial\left(\frac{\partial CVaR_{\alpha_m}(-\pi^m)}{\partial e}\right)}{\partial r} < 0.$$

Proof. See Appendix A.1. □

The implications of this result are clear: as long as rigidity does not have a second-order effect[22] on the way the CVaR is affected by effort, the relation between the equilibrium level of effort and rigidity is monotonic; moreover, as long as effort is "worth it"[23], contracts with more rigid price provisions introduce higher powered incentives for cost-reduction by making the mine the residual claimant of any efficiency gain.

It directly follows from Lemma 1 that, from the point of view of the mine's decision, it suffices to concentrate on the choice of contractual rigidity. Accordingly, with a slight abuse of notation, we let $V^m(\boldsymbol{\gamma}) \equiv V^m(\boldsymbol{\gamma}, e^*(\boldsymbol{\gamma}))$.

[20] In this respect, Joskow (1987) concludes that "*The empirical results [...] provided strong support for the hypothesis that buyers and sellers make longer ex ante commitments to the terms of future trade, and rely less on repeated negotiations over time, when relationship-specific investments are more important*", (*ibid.*, p. 168).

[21] Since we have no priors about the impact of changes in relation-specific investments on the degree of rigidity of the pricing mechanism, nor could we think of a mechanism through which a change in A would *directly* affect the cost of r, in what follows we assume $\partial^2 k^m/(\partial r \partial A) = 0$.

[22] As it will become clear later in the discussion, once we make assumptions about the distribution of the random component of the costs, this condition will be trivially satisfied.

[23] From the point of view of the mine both a higher expected level and a higher variance of the costs represent negative attributes, the requirement that the marginal effect of effort on the weighted sum of the expected cost level and the CVaR be negative is in effect just saying that effort should be effective in reducing the negative impact of x on the maximand in (3) when specialized for the mine. Naturally, the weighting depends both on the mine's preference parameter for risk avoidance, θ, and on the level of its risk tolerance α.

3.3 The electricity generator

The generator derives revenues from the sale of electricity, which may occur either on a regulated or a liberalized market. When the generator operates within a regulated market, the unit price of electricity (p^e) is set by the regulator to cover the firm's operating costs (c) and allow for a fair rate of return on its assets. In this case, we write $p^e = \mu + c$, where μ represents the unitary mark-up over costs recognized by the regulator.[24] When the generator operates in a liberalize environment, instead, it faces conditions of perfect competition, and takes the price of electricity as given. Since the price of electricity is *ex-ante* unknown, this introduces uncertainty in the generator's objective function.

In this simplified set-up, we focus purely on fuel costs and abstract from all remaining operating costs.[25] This assumption allows us to transparently bring to the fore the role of input-cost risk, as in this context c simply equals p^c, the price of one unit of coal.

In addition to these operating costs, we consider the transaction costs, k^g, associated with the contract. We assume that k^g is increasing with the degree of price rigidity as writing a more rigid contract is more costly and, contrary to the seller, the buyer doesn't save on administrative costs by entering in a more rigid contract. Thus, $\partial k^g / \partial r > 0$. Furthermore, we assume that for the generator the cost of contracting declines with duration. Trivially in this case the costs are incurred less frequently, and the generator does not face the costs of an expected breach of contract, so that $\partial k^g / \partial d < 0$.[26] We also allow for the possibility that transaction costs depend on a set of cost shifters, $\mathbf{A}$. In this case, an increase in $\mathbf{A}$ further reduces the marginal cost of duration. Thus, $k^g = k^g(r, d; \mathbf{A})$, and $\partial^2 k^g / (\partial d \, \partial A_i) < 0$, for each $A_i \in \mathbf{A}$.[27]

If we let $\lambda = \{0, 1\}$ be an indicator of the regulatory context, which is 1 in a restructured market and 0 otherwise, we can write the generator's profits as:

$$\pi^g = \lambda p^e + (1 - \lambda)(\mu + p^c) - p^c - k^g(r, d; \mathbf{A}), \text{ for } \lambda = \{0, 1\}.$$

This implies that the value of contract $\boldsymbol{\gamma} = (r, d)$ for the generator is:

$$V^g(\boldsymbol{\gamma}) = \mathbb{E}(\pi^g) - \theta^g CVaR_{\alpha_g}(-\pi^g). \tag{5}$$

3.4 The optimal choice of contract

We consider a large number of potential sellers relative to the number of buyers, so that we let the generator make a take it or leave it offer to the mine, offering a contract that

[24] For simplicity, we assume that one unit of electricity requires one unit of coal.

[25] Elsewhere in the literature, the role of capital investments features prominently. Most recently, Fowlie (2010) discusses the possibility that firms' choices of compliance options in the NO_x Budget Program were driven by the difference in capital cost recovery possibilities between restructured and regulated electricity markets. In the context of the present paper, however, capital investment is not a crucial determinant of the contractual behavior of generators *vis à vis* coal mines. Thus, we abstract from this aspect in our theoretical discussion. We return to this topic when discussing our empirical results.

[26] This is because the generator has lower incentives to breach the contract than the mine, and it most likely would be on the receiving end of any compensation in case of breach of contract by the mine.

[27] We again assume that changes in $\mathbf{A}$ do not affect the marginal cost of rigidity, i.e. $\partial^2 k^g / (\partial r \, \partial A_i) = 0$.

guarantees the mine a value of zero.[28] The problem of the generator reduces to selecting from the menu of all contracts, Γ, the one that maximizes its objective function, (5), while guaranteeing the participation of the mine[29], i.e.:

$$\boldsymbol{\gamma}^* \equiv \underset{\boldsymbol{\gamma}\in\Gamma}{\arg\max} \left\{ V^g(\boldsymbol{\gamma}) \middle| V^m(\boldsymbol{\gamma})) \geq 0 \right\}. \tag{6}$$

For the sake of analytical convenience, it is necessary to make further assumptions about the probability distribution of the two random variables in our set-up:[30] the costs of mining, $x(\chi, e)$, and electricity prices, p^e. In particular, we take $x(\chi, e)$ to be normally distributed with mean $\mathbb{E}(x)$ and variance σ_x^2; and p^e to be normally distributed with mean $\mathbb{E}(p^e)$, and standard deviation σ_e. The assumptions of normality imply that both profit functions of the mine and the generator are normally distributed, which allows us to derive explicitly the CVaR factors for both agents.[31]

We are now in a position to derive our first result, which refers to the impact of deregulation in the downstream market on the characteristics of the optimal procurement contract:

Proposition 1. *The degree of price rigidity specified by the optimal contract, r^*, is monotonically non-decreasing in the degree of market liberalization, λ, while the optimal duration of the contract, d^*, is monotonically non-increasing in λ.*

Proof. See Appendix A.2 □

According to this result, as the downstream market is deregulated the generator finds it more profitable to offer more rigid, shorter contracts to its coal provider. The result accords with our intuition. In a regulated market, cost-of-service regulation *de facto* insulates the generator from adverse realizations of the mining cost. In this context, the generator only needs to pick the right combination of price rigidity and duration to minimize its transaction

[28] We make this assumption for the sake of simplicity. While this implies that the generator is able to extract all the rents, it is without loss of generality in terms of Propositions 1 and 2. In fact, any other non-cooperative bargaining procedure that reallocates rents differently implies qualitatively similar results. To see that this is indeed the case, consider the other polar case that assigns the role of proposer of the take it or leave it offer to the mine. While this implies reversing roles in problem (6), it does not change the sign of any of the derivatives in Appendices A.2 and A.3. Hence, our comparative statics results go through without amendments.

[29] The versatility CVaR deserves a further remark. Unlike other measures of dispersion, Krokhmal et al. (2002) show that the CVaR can be used in constrained optimization problems where agents attach different weights to the risk of losses, θ_i, as well as adopt different confidence levels α_i.

[30] These assumptions are sufficient but not necessary for our next results to hold. In particular, Krokhmal et al. (2002) show that it is not necessary for the probability distribution to be continuous for the CVaR to be employed in a well-defined constrained optimization problem. An explicit formula for the CVaR when the underlying probability distribution of losses is not normal, however, is more challenging and numerical simulations may be needed. Such exercise goes beyond the scope of the current project.

[31] While admittedly restrictive, the assumption that both costs and prices follow a normal distribution has a long tradition and is not without empirical relevance. Zimmerman (1977) in his classical analysis of depletion in the mining industry, shows that mining costs for coal are related to seam thickness and that seam thickness is log-normally distributed. This implies that also the costs of coal mining are log-normal. Similar discussions can be found in standard references such as Hartman (1990) and Darling (2011). In terms of our model, if we interpret χ, the relevant random variable as the log of mining costs, then χ is indeed normally distributed. As refers to electricity prices, the assumption of normality is broadly used, see e.g. Weron (2007), and is supported by at least some empirical evidence, e.g., Zhou, Chen, Han, and Zhang (2009).

costs, at the same time ensuring the participation of the mine. As the market gets liberalized, however, the generator is left facing the prospect of potential losses via the uncertainty associated with the variable output and input prices – see the last term in equation (5). Since the electricity market is perfectly competitive by assumption, the generator can only limit the uncertainty associated with the price of coal, in order to reduce its exposure to risk. The generator, thus, offers the mine a contract with a higher degree of price rigidity which protects its profits from bad realizations of χ. To satisfy the mine's participation constraint, the buyer needs to offer a shorter contractual duration, which reduces the cost of contracting for the mine and makes the new contract more palatable.

The optimal choice of procurement contract is also sensitive to changes in the key parameters of the problem, as shown in the following result:

Proposition 2. *The signs of the derivative of the optimal choice of contract rigidity and duration with respect to changes in the values of key parameters are as follows:*

	Choice variable	
Parameter	r^*	d^*
A_i	≤ 0	≥ 0
σ_e^2	≤ 0	≥ 0
σ_x^2	?	≥ 0

Proof. See Appendix A.3. □

An increase in any of the transaction cost-shifters, A_i, reduces r and increases d. Since more relation-specific assets reduce the transaction costs associated with a longer contract, longer, less rigid contracts will naturally emerge from situations where sunk costs of this type are more pervasive, e.g. for mine-mouth plants-mine relationships (Joskow, 1987). The mechanism at work here will help us in our identification efforts in the empirical part of the paper, as the lengthening of the contractual duration is *directly* caused by the change in the level of relation-specific assets, whereas the change in the pricing mechanism only emerges indirectly.

Next, we turn to the consequences of an increase in the volatility of the price of electricity, and the variance of the extraction costs. Since the $CVaR$ component of V^g is increasing in both σ_e^2 and σ_x^2, it is evident that operating in a more uncertain environment carries the risk of higher losses for the generator. The generator, however, has no instrument to insulate herself from an increase in σ_e^2, which also limits the marginal effectiveness of r in reducing $CVaR$. Indeed, the impact on $CVaR$ of an increase in the rigidity of the price setting mechanism is smaller, the more volatile the electricity prices (see Appendix A.3). It follows that an increase in r is not attractive in this context, as the higher transaction costs are no longer compensated by a sufficient reduction in $CVaR$. The generator therefore prefers *less* rigid contracts, compared to what is optimal in a low-σ_e^2 environment. As V^g is increasing with contractual duration, however, the generator prefers to increase the contract duration instead. From the point of view of the mine, the value of the contract is decreasing with d, and may also be decreasing with r. When this is the case, the mine would be indifferent between the "high-volatility" less rigid, but longer contract, and the "low-volatility" more rigid, shorter contract.

An increase in the dispersion of the extraction costs, σ_x^2, has less a clear-cut effect on the characteristics of the optimal contract. On the one hand, from the point of view of the generator a higher level of σ_x^2 implies higher $CVaR$. Thus, the generator may want to shelter from the increase in riskiness upstream by offering a more rigid contract to the mine. This is clearly the case when the mine attaches no weight to risk in its objective function, i.e. when $\theta^m = 0$. Furthermore, if the value of the contract for the mine, V^m, is increasing in rigidity, r, the generator can satisfy the mine's participation constraint and offer a longer contract, which reduces her transaction costs. If, however, the mine attaches a positive value on risk in its objective function (i.e., $\theta^m > 0$), the generator needs to accommodate the tightening of the mine's participation constraint in equation (6), as the value of the contract for the mine unequivocally falls with σ_x. In this case, the effect of an increase in σ_x^2 on the optimal level of rigidity is ambiguous as it depends on whether the contract value for the mine is overall increasing or decreasing in r. It is, however, clear that this will never result in a contract with shorter duration, as this would lead to a further tightening of the mine's participation constraint.

For our empirical identification strategy, it is important to note here that changes in the level of risk exposure affect *directly* the optimal level of r, but only indirectly the choice of contractual duration.

4 An empirical investigation of contract choices

Next, we confront the implications of Propositions 1 and 2 with the data. The first step is obviously to assess the impact of electricity market restructuring on the optimal choice of procurement contracts. Three aspects of this empirical endeavor are worth noting here: Firstly, and crucially, the U.S. experience with electricity market restructuring leads us to cast our analysis as a quasi-experiment with plants in regulated states acting as control group to assess the behavior of plants in restructured states. This allows us to causally attribute differences in contracting behavior to restructuring. Secondly, according to the theoretical discussion above the optimal contract choice entails a simultaneous decision of rigidity and duration, whereas the available data only captures the observed equilibrium outcomes of this process. This raises concerns about endogeneity and the related potential biases in coefficient estimates. To correct for such biases, an instrumental variable (IV) approach can be utilized, whereby instruments for both rigidity and duration are employed. Finally, the choice of contractual rigidity and duration depends – among other things – on the riskiness of the operating environment for the generators and on the volatility of coal production costs. Both of these variables are not directly observed in our data and can only be proxy-ed with error. As pointed out by Ackerberg and Botticini (2002), in such a context, the presence of endogenous matching between plants and mines might lead to biases in the estimated coefficients. To control for this possibility, we augment our model with a matching equation. We return to the last two aspects in the next section, when we discuss identification strategies.

In general terms, the model we estimate in this section can be written as:

$$r_i = \alpha_0 + \alpha_1 d_i + \alpha_2 \Delta_i + \alpha_3 \mathbf{X_i} + \alpha_4 \mathbf{Z_{1,i}} + \varepsilon_{1,i}; \tag{7}$$

$$d_i = \beta_0 + \beta_1 r_i + \beta_2 \Delta_i + \beta_3 \mathbf{X_i} + \beta_4 \mathbf{Z_{2,i}} + \varepsilon_{2,i}. \tag{8}$$

These equations reflect the simultaneous decision of rigidity and duration, that are also explained by a difference-in-difference variable (Δ), which identifies the treatment group, a set of control variables (**X**), which includes the year when the contract is signed, and a distinct set of instrumental variables (**Z**), for each of the regressions. Finally, $\varepsilon_{1,i}$ and $\varepsilon_{2,i}$ are error terms.

4.1 Identification

We use the variation over time and across U.S. states in the restructuring of the electricity market to identify the effect of changing regulation on procurement choices. Only about half of the states passed legislation to deregulate their electricity markets (See Table 2). Out of 1,242 contracts in our dataset 584 are signed by plants located in states that undergo restructuring at some point in the sample period; of these 19 per cent are signed after restructuring takes place. This peculiarity of the U.S. experience and data availability provides us with the quasi-experimental set-up necessary to test whether the restructuring of the electricity market has lead to a change in the nature and the duration of the procurement contracts signed between generators and coal mines. By being able to use generators in non-restructured states as our control group, we are able to isolate the effect of restructuring on the choice of procurement contracts in restructured states. This methodology is only justified, however, if we can argue, on the one hand, that the decision to restructure was exogenous to contract rigidity and duration, and, on the other hand, that, absent restructuring, plants operating in states that did in fact restructure would have mirrored the behavior of plants operating in non-restructured markets.

To argue the first condition – i.e. the exogeneity of treatment – we draw on the discussion of Joskow (2003) and Borenstein and Bushnell (2000) who attribute the decision to restructure to differences in natural resource endowments and to poor investments and contracting decisions made during the 1960s, 1970s, and 1980s. States that restructured generally had higher than average electricity prices due to the lack of hydroelectric generation and to investments in generation that had proven more expensive than expected – notably, nuclear and co-generation facilities. One of the main reasons for restructuring was to improve investment decisions in new generation capacity, as opposed to improving existing generation, and to transfer the risk from investment in new generation from consumers to electricity suppliers (see also Bushnell and Wolfram, 2005). Furthermore, the consensus is that restructuring would have eventually spread to the entire country had it not been for the California electricity crisis and Enron's financial collapse, hence the treatment would not have been contained to one specific type of state (Joskow, 2003).[32]

It is impossible to formally test the second condition discussed above given that the counter-factual is not observed. We are going to argue, however, that plants in the treatment and control groups exhibited similar behavior prior to the treatment (controlling for other confounding factors), and that the contracting behavior of plants in the control group did

[32] The exogeneity of treatment has been similarly argued in a number of other papers that also use restructuring as a natural experiment (e.g., Bushnell and Wolfram, 2005; Fabrizio et al., 2007; Fowlie, 2010; Davis and Wolfram, 2012; Cicala, 2015).

not change as a consequence of restructuring elsewhere.[33] We start our discussion with Figures 1 and 2. The figures describe how the rigidity and duration of contracts signed by treated plants vary over the period of our analysis relative to the corresponding values for control plants. Following the standard approach in the literature in the presence of a staggered treatment process within a treatment-control framework (e.g. Gentzkow, Shapiro, and Sinkinson, 2011; Oliva and Hanna, 2010), we use dummies that measure time relative to the year of deregulation, rather than calendar time when constructing the graphs. Overall, both graphs show no significant differences in the trends over the pre-treatment period, i.e. before the passing of restructuring legislation. Figure 1 suggests that contractual rigidity significantly increased immediately after deregulation. The figure also suggests that, following deregulation, the parties entered a learning phase about the characteristics of the optimal contract, as the degree of rigidity increases with the passage of time.

Next, we verify that, net of common confounding factors, the observable characteristics of the control group have remained sufficiently stable over time. This would suggest that the control has not been affected by the treatment, or by other unobservable shocks, suggesting that, absent treatment, the treated group itself would have developed similarly to the control. The average rigidity and duration of contracts signed by control plants – graphed in Figure 3 and 4, respectively – do not seem to exhibit a break or a change in trend throughout the sample period. This impression is supported by the difference-in-means statistics of the key variables (see Table 3). Overall, the exogenous variables that are directly linked to the contractual behavior appear quite stable over time for the control group as a whole, as shown in the last column of Table 3. The share of contracts written with a known counterpart, the characteristics of the coal, the minimum amount contracted for, as well as the relative size of contract to the total quantity of coal sold (by the mine) and purchased (by the plant) are all not statistically different for the average control plant, before and after treatment. The one notable exception refers to the contractual treatment of sulfur, which can be seen to have radically changed across the sub-samples. This is in all probability due to the introduction of the Acid Rain Program (ARP), whose first trading phase started in 1995. Table 3 shows that the mean Z-score increases over time, as power plants move towards contracts that give them a higher probability of receiving coal that would allow them to meet their compliance targets. The need to source different types of coal to comply with the more stringent environmental regulation is also evidenced by the change in the provenance of coal shipped to control plants, who seem to have substituted higher-Btu, lower-SO_2 Appalachian coal for lower grade Interior coal. This discussion leads us to conclude that, while it is important to control for the introduction of the ARP in our empirical analysis, the overall behavior of the control group as refers to their rigidity and duration choices have remained consistent over time.

Overall, we are convinced that the assumptions behind our identification strategy are supported by both economic and historical arguments, and, most importantly, they hold true in the data. We can, therefore, attribute differences in procurement strategies between the treated and the control group after restructuring to the policy change itself. We return to this aspect when we discuss placebo tests, and one possible deviation from the Stable Unit Treatment Value Assumption (SUTVA).

[33]The assumption that the control group is not affected by the treatment, or "Stable Unit Treatment Value Assumption" (SUTVA) is crucial for a satisfactory 'experimental design' that allows a proper causal interpretation of the results (Rubin, 1980). We discuss this aspect at length later in the paper.

4.2 Data

Our data are derived from several sources; the main source of information on coal procurement contracts is the Coal Transportation Rate Database, taken from the FERC Form 580 "Interrogatory on Fuel and Energy Purchase Practices". This is a representative survey of investor-owned, interstate electric generator plants with steam-electric generating stations with more than 50 Megawatts of installed capacity. Our database contains information on contracts signed for the years 1990-2001, including the price-setting mechanism specified in the contract and its duration, the lower and upper bounds for a number of coal quality attributes included in the contract, plant characteristics and identifiers for the county of origin of coal purchases.[34]

Although the data identifies contracts and any subsequent renegotiation, we only use information on newly signed contracts. This is because changes to contract terms when renegotiated are necessarily the product of a very different bargaining process from the one modeled above, as they crucially depend on the pre-existent conditions. Each contract provides a different status-quo and different sets of threat points to the renegotiating parties that not only depend on the original terms of contract, but also on the idiosyncratic way in which the relationship between the parties has evolved over time. Moreover – and crucially – since we do not have access to the actual contracts, when we observe changes in some of the parameters of the contract, we cannot be sure whether the remaining parameters were not renegotiated by choice, or rather because they were excluded from future renegotiations under the terms of the original contract. This is of particular concern in relation to the pricing mechanism and the contractual duration. This prevents comparability across renegotiated contracts irrespective of policy changes, thus rendering our identification strategy void. Excluding renegotiations leaves us with a cross-sectional dataset of newly signed contracts, each signed at a different time during our sample period.[35] The data lists the contract as having one of seven types of price adjustment mechanisms: Base price plus escalation; Price renegotiation; Price tied to market; Cost-Plus with a fixed fee provision; Cost-Plus with an incentive fee provision; Fixed price; Other (see Table 1, which also lists the FERC definition). We code contract types from 1 to 4 in increasing order of rigidity, and drop the category "Other".[36] Given the nature of this variable, both ordered probits and continuous variable specifications are utilized. Duration is calculated subtracting the year the contract was signed from the expiration year indicated in the data.

[34]The original dataset also contains information on pre-1990 contracts. The coal market, however, went through major changes in the 1980s (Joskow, 1988) so that contracts signed during this time are not proper controls for post-1990 ones. We therefore exclude these contracts from our analysis.

[35]In the interest of completeness, we want to verify that our sample selection strategy does not lead to the over-representation of either the control or treated group, which would be the case if the proportions of newly signed contracts were statistically different between regulated and deregulated states following restructuring. Starting in 1996, the proportion of newly signed contract in regulated states is 81%, whereas in deregulated states the same percentage is 83%. The corresponding difference-in-means test fails to reject the null of equal means with a p-value of 0.46 (t=0.73), suggesting that our sample selection is unlikely to bias our results. In addition, in our sample deregulation does not predict new contracts conditional upon observable characteristics in a probit regression of newly signed vs renegotiated status. The p-value of the diff-in-diff variable in this regression is 0.236. Full results are available from the authors upon request.

[36]Alternative forms of this ordinal ranking for rigidity were specified, and robustness checks conducted using these alternative dependent variables for r. The result were found to be qualitatively very similar. The full results of these tests are available from the authors upon request.

In our empirical analysis, we need to be able to distinguish 'treated' plants from 'control' plants via a difference-in-difference indicator that we call `Post Restructuring`. In our preferred specification the treatment indicator is a categorical variable that assumes the value of 1 for new contracts signed by electricity generators in restructured states after legislation was passed and zero otherwise. In what follows we refer to this specification as the state-level treatment. In our view, this treatment specification has the advantage of being consistent with the theoretical view that procurement contracts are forward-looking instruments, and are thus expected to change once the plant is certain of the change in regulation. Our specification is similar to that of Fabrizio et al. (2007) in that all plants in a state that passed deregulation legislation are considered treated, irrespective of their ownership status. Borenstein et al. (2002) point out that most states that passed deregulation legislation had Independent System Operators running wholesale markets by the year 2000, lending support to our view that deregulation had taken hold quickly. This strategy for the identification of the treatment group differs from the one used by Cicala (2015), for example, who uses a plant-level treatment beginning in the year that the restructured market came into effect according to the FERC. In the interest of completeness, we generate an alternative treatment indicator, to which we refer as to the plant-level treatment, which assumes the value of 1 for new contracts signed by plants listed as deregulated in the EIA-Form 923, operating in restructured states after legislation was passed, and zero otherwise.[37]

To account for changes in the regulatory environment and for idiosyncrasies in contractual relationships, we also introduce a number of additional variables in our empirical specification.

To control for the passing of the Clean Air Act Amendments of 1990, we include a dummy called "Post SO_2 Regulation", which equals 1 for all contracts signed in 1991 and later, and zero for those signed in 1990. Furthermore, we identify plants involved in Phase I of the ARP by means of a "`Mandatory Phase I Plant`" dummy. It is important to notice that, by design, plants regulated under the ARP were free to choose how best to comply with the regulation. Fuel switching and mixing was one possible route, the adoption of end-of-pipe abatement technology was another. These choices have a potentially significant impact for the type of coal to purchase, and hence for the procurement decisions of power plants. Plants that invested in a flue gas desulfurization unit, a 'scrubber', would be arguably less constrained in terms of the sulfur content of their feedstock than plants that decided not to invest in such technology, for example. It is therefore important that in our regressions we control for the presence of scrubbers at the power plants. To do this, we construct a dummy variable, called "`Scrubber`" which takes the value of one after a scrubber is installed at a plant, and is zero otherwise. To further account for any idiosyncratic behavior by power plants that might be correlated with the specificities of the coal they source, we add dummies that identify the coal basin their coal comes from (Appalachia, Interior, West), alongside a variable – "`Maximum Sulfur Allowed`" – that refers to the maximum sulfur content (in lbs/MBtu) specified in the contract.

The dummy variable "`Previous Interaction`" takes the value of one if the plant and

[37] In some states the history of the restructuring process was more complicated than in others. To reflect this aspect, in what follows we verify that the results of our estimation of (7) and (8) are robust to removing a number of states which first started and subsequently stopped restructuring their electricity market. See Section 4.3 for details.

mine had already been involved in a contractual relationship with each other prior to signing the current one and is zero otherwise. Furthermore, a "`Restructured Plant`" dummy is created to control for time-invariant differences between groups. In our state-level treatment assignment, the dummy assumes a value of 1 if it refers to a plant located in a state that ever restructures, and zero otherwise. In the plant-level treatment case, the dummy is 1 to identify a plant that is ever listed as deregulated by the EIA, and zero otherwise.

To correct for the potential endogeneity problems discussed above, one needs to choose appropriate instruments, i.e. variables that only affect one of the choice variables directly, while not directly impacting on the other. Our choice is informed by our theoretical framework, and in particular by the discussion of the results of Proposition 2. In the proof of Proposition 2, we showed that the choice of price rigidity is directly impacted by risk (i.e. by σ_e^2 and σ_x^2), whereas such parameters do not impact directly on the choice of duration (see Section A.3 in the Appendix). Conversely, the transaction-cost shifters, **A**, only directly affect the choice of duration. This leads us to identify risk proxies as plausible instruments for rigidity, whereas transaction cost shifters are candidates as instruments for duration.

In order to capture the degree of price uncertainty faced by electricity generators, one would ideally use a measure of dispersion for the wholesale electricity price. For regulated markets, however, a wholesale price does not exist, and the so-called "system lambdas" – measures of the marginal cost of production – while generally available are often not directly comparable to prices. For the sake of comparability between treated and control plants, we use the standard deviation of capacity utilization for gas and oil fired generators (`Utilization Variability`) to measure the degree of price uncertainty faced by the plants. The rationale for this approach is simple: plants which are primarily fired with oil and gas represent high-cost alternatives to coal-fired generation. For this reason, they are only utilized under conditions of high demand, usually associated with high prices. Hence, the variability in the utilization of oil and gas-fired plants proxies for the variability in the price of electricity. To proxy for input-cost risk, instead, we include an indicator for whether the mine is an underground mine (`Underground Mine`), and create dummies that control for the provenance of coal using the coal-producing regions defined by the Energy Information Administration (EIA), and include "`Interior Mine`" and "`Western Mine`" in our regressions.[38] The understanding here is that, since both the physical characteristics of coal seams and the specific mining practices differ across basins, underground mines and mines in different basins have different cost structures. Besides this rather crude measure of input-cost risk, we also include measures that take into account the match between coal characteristics and boiler types. When plants write a contract with mines for monthly delivery of coal, they specify the acceptable bounds for each attribute.[39] Crio and Condren (1984) and Kerkvliet and Shogren (1992) point out that plants often use long-term contracts to procure coal that match the design parameters of their boiler, so that the attributes specified in the contract depend on the (exogenous) technical characteristics of the boiler. Thus, the degree of input-cost risk a plant is exposed to is a function of both the physical characteristics of the available coal and of the technical characteristics of the

[38] The omitted category refers to mines located in Appalachia.

[39] Generally, in long-term contracts the maximum (minimum) levels of attributes such as ash, sulfur, and heat (Btu) that are allowed are specified. Ash and sulfur are undesirable attributes, therefore specifying lower maximum levels of these attributes in a contract imply the requirement to source higher quality coal. Btu's, on the other hand, are a positive attribute; therefore a higher minimum level specified implies a higher quality coal.

plant. To capture these aspects we include Z-scores for different coal attributes (`Z-Ash`, `Z-Btu`, `Z-Sulfur`) for each Bureau of Mines coal producing district. The Z-score – i.e. the difference between the allowable level of an attribute and the mean value of that attribute for coal mined in the district, divided by the standard deviation of the attribute at the district level – measures the probability that the average mine in a given district is able to deliver coal that meets the plant's technical requirements.[40]

As empirical counterparts for transaction cost shifters, we focus on variables that proxy for the likelihood of breach of contract, in particular we consider proxies for the availability of alternative contracting partners and for the relative importance of a specific contract to each of the parties (Joskow, 1987; Kerkvliet and Shogren, 2001). As discussed in Section 3, factors that increase the availability of alternative options might be correlated with shorter duration, whereas higher levels of dedicated assets ought to be correlated with longer contracts. The instruments we use are: "`Plant Dedicated Assets`" and "`Mine Dedicated Assets`", calculated as the ratio of an individual contract quantity to the sum of the plant's (mine's, respectively) overall contract quantity; the minimum quantity of coal to be transacted each month, "`Minimum Quantity`"; and a dummy that indicates whether the plant can receive deliveries through multiple modes of transportation,"`Multiple Mode of Delivery`". "`Multiple Mode of Delivery`" is a good candidate as an instrument because it is clearly exogenous to the rigidity decision being the outcome of previous investment decisions and as such predetermined. Moreover, the possibility to receive coal deliveries using multiple means of transportation makes the plant less dependent on any given supplier, and thus affects the optimal choice of contractual duration. The remaining instruments are also likely correlated with a predetermined variable, the plant's output rating (i.e. its productive capacity), since most long-term contracts signed between mines and coal-fired power plants specify a minimum take linked to the productive capacity of the boiler.[41] As productive capacity is given at the time the contract is signed, it is uncorrelated with the rigidity decision. On the other hand, the relative importance of a given contract to both mine and plant influences the stability of the contractual relation, as the parties are less likely to walk away from a large contract. Thus, the probability of a breach of contract decreases with the minimum take, as does, for the reasons discussed in Section 3, the marginal cost of duration. Hence, duration is likely correlated with minimum take. Our discussion suggests that all the instruments mentioned above should be both exogenous and relevant.[42]

As previously mentioned, Ackerberg and Botticini (2002) point out that, when empirically estimating the determinants of contract choices via reduced-form regressions that use sellers' and buyers' characteristics, if these characteristics are imperfectly measured and buyers and sellers are not randomly matched, a simple OLS approach risks providing biased

[40] The average and standard deviations in the Z-scores are calculated using the population of coal mines from the FERC Form 423, then brought to our sample of coal contracts. As a result, the sample mean of the Z-scores reported in Table 3 is not exactly zero.

[41] Coal-fired plants tend to be targeted at base-loads and operate continuously. Since coal is bulky and storage capacity limited, one of the main concern of coal-fired generators is not to run out of fuel.

[42] A number of other instruments are available to us, as we have information on whether the plant owns the transportation equipment used to deliver coal, the number of mines active in the county the contracted coal is being shipped from, and finally, the boiler rated output. We use these instruments both as an alternative to and in combination with the ones discussed in the main text. In all cases, the results are extremely robust to the choice of instruments.

estimates. Our theoretical insights from Section 3 do not depend on how sellers and buyers are matched, in the sense that, irrespective of the matching procedure, an increase in the degree of market liberalization leads to more rigid, shorter contracts. There are reasons, however, to believe that in reality the matching between mines and plants might depend on some of the characteristics of the agents. For example, one could think that plants operating in high-risk environments have stronger preferences for rigid contracts relative to plants facing less volatile prices. Similarly, low-cost-volatility mines would not dislike rigid contracts quite as much as mines that tend to experience large shocks to their extraction costs. It is thus easy to imagine that some form of assortative matching may occur between high-risk plants and low-risk mines. To alleviate the potential endogeneity issues, we introduce a 'matching' equation which regresses our proxy for revenue uncertainty, `Utilization Variability`, on a set of destination state dummies, and the same dummies interacted (as appropriate) with our proxies for extraction cost volatility (`Z-Ash`, `Z-Btu`, `Z-Sulfur`, `Underground Mine`, `Interior Mine`, and `Western Mine`). The predicted values of `Utilization Variability` are subsequently included in the estimation of equations (7) (see Ackerberg and Botticini, 2002).

4.3 Results

Tables 4 and 5 report the results of the estimation of equations (7) and (8), respectively. In Table 4 we first present an ordered probit model without controls, in which the dependent variable is regressed only on the treatment variables, followed by a naive ordered probit regression in which none of the endogeneity concerns discussed above are addressed. Next, we introduce our preferred ordered probit specification which aims at controlling for both the potential endogeneity due to the contemporaneous choice of rigidity and duration, and to the possibility of assortative matching between sellers and buyers, *à la* Ackerberg and Botticini (2002). The first three columns use the State-level treatment assignment discussed in Section 4.1. Column (4) presents instead the results from our preferred ordered probit specification, this time using the Plant-level assignment to treatment. The following two columns detail the results of the estimation using an instrumental variable approach to control for endogeneity of duration, without the correction for endogenous matching. Finally, the results from a system estimation of (7) and (8) are presented, which allows for possible correlation in the error terms across equation. All standard errors are clustered at the state level to correct for potential serial correlation.[43]

The results of Table 4 support the theoretical predictions of Proposition 1: electricity market restructuring does lead to the signing of more rigid contracts. This emerges as a robust finding of our analysis as the coefficient of `Post Restructuring` is everywhere positive, substantially stable in magnitude, and statistically significant in all IV specifications. Our results also show that rigidity and duration are substitutes, as the coefficient on `Duration` is

[43] To ensure the robustness of our results to the quality of the control group, we undertook a propensity score matching estimation. We matched contracts in the treatment and control groups based on their observable characteristics (quantity, where the mine is located, allowed sulfur content, and more). This analysis suggests that only four of our treated contracts are not on the common support. We re-ran all the analyses in this section based on this matched sample. The results we obtained were qualitatively indistinguishable from those discussed below. In the interest of brevity, these results are not shown here but are available from the authors upon request.

indeed negative throughout and statistically significant in all cases. The coefficient is also fairly stable, in particular across models (2)-(4) and (7), all of which treat rigidity as a categorical variable. The F-test for excluded instruments in the first stage is highly statistically significant in all IV models. Based on the Column (5), a series of tests for the validity of our instruments are conducted. Hansen's test fails to reject the null that the instruments are valid (J-test=6.44, p-value=0.17), and the model passes the Kleinbergen-Paap underidentification test (LM statistic=12.35, p-value=0.02). The results of these tests confirm that the instruments we use are both exogenous and relevant.[44]

The passing into law of the CAAA 1990 does not seem to be significantly correlated with contract rigidity, whereas the contracts signed with Phase I plants seem to be significantly more rigid. While the statistical significance of the coefficient varies across the different models, the presence of a scrubber appears to be not significantly correlated with the choice of rigidity. Interestingly, and consistent with our theoretical insights, a more generous limit on the maximum sulfur content of coal, correlates with more rigid contracts. Intuitively, mines would be more likely to find rigid contractual terms along the pricing dimension acceptable, knowing that a wider range of coal quality can potentially be delivered to fulfill their obligations.

The signs of the coefficients of the other controls conform to our theoretical expectations. Higher levels of `Z-Ash` and `Z-Sulfur` – and lower levels of `Z-Btu` – are associated with lower uncertainty, as the mines operating in the specified district are more likely to be able to deliver coal that meets the boiler's technical specifications. These mines, thus, ought to be more willing to sign relatively rigid contracts, as they face less risk. The estimated coefficient of `Z-Ash`, `Z-Sulfur`, and `Z-Btu` have consistently the expected sign, even if they are not always statistically significant. Underground coal is more costly to extract, and underground mines face higher probability of industrial accidents. Hence, we would expect that such mines would be reluctant to sign rigidly-priced contracts. As expected, the coefficient's estimates for `Underground Mine` are negative, albeit significant in only one instance. Appalachian mines have more challenging technical problems and have traditionally had a more unionized work-force, thus they are both more risky and more exposed to macroeconomic shocks that affect the labor market, relative to interior and western mines. Accordingly, the coefficients for both `Interior Mine` and `Western Mine` are expected to be positive. The relevant coefficients are, indeed, all positive and, at least for `Western Mine`, statistically significant across all specifications. The coefficient of `Utilization Variability` is always statistically insignificant.

The results for the duration equation are found in Table 5. Once again the first column only includes treatment variables, while in this case the second and third columns report on the results of the naive estimation which doesn't account for endogeneity. Columns (4) and (5) control for endogeneity using instruments that proxy for input-cost and output-price risk, using the State- and Plant-level assignment to treatment, respectively. Our strategy for the selection of instruments here deserves some discussion. In columns (4) and (5) of Table 5 we report IV estimates of equation (8) carried out using the complete set of instruments discussed above: `Z-Ash`, `Z-Sulfur`, `Z-Btu`, `Western Mine`, `Interior Mine`, `Underground Mine` and `Utilization Variability`. These instruments as a set comfort-

[44]As a robustness check, we replicated these estimations both with subsets of the current instruments, and including the variables described in Footnote 42. The results are consistent with our conclusions.

ably pass Hansen's J test for exogenity in both regressions (J-tests of 7.86 and 8.26, respectively with corresponding p-values of 0.25 and 0.22), and perform reasonably well in terms of the tests for under-identification and for weak identification (see table notes for the details). Some concerns, however, arise from the F-statistics of the test for the relevance of the instruments, whose values (4.34 and 7.88) are some way from the recommended value of 10. In order to determine the validity of our instruments, we experimented with all possible combinations of the original instruments. The only case for which we obtain an F-test in excess of 10 is in the exactly identified model which uses `Western Mine` as the only instrument (see Column (3) of Table 5) . In this case, the F-test for excluded instruments in the first stage is 11.92, the Kleibergen-Paap χ^2 LM statistic is 12.53 (p-value=0.00), and the Cragg-Donald Wald F-statistic equals 15.87. Since in this case we are unable to compute Hansen's over-identification statistic, we compute the J-statistic for the next best model for which we can test for the orthogonality of `Western Mine` in isolation. This model is the one which uses `Western Mine`, `Z-Sulfur`, and `Interior Mine` as instruments for rigidity. In this case the J test statistic for the joint test of over-identification of all instruments equals 0.126 (p-value=0.94), whereas the C-statistic for the orthogonality of `Western Mine` is 0.050 (p-value=0.78). We conclude that `Western Mine` is a valid instrument for rigidity. Finally, the last column once again reports the results of the 3SLS system estimation of (7) and (8).

The `Post Restructuring` results are in line with the implications of our theoretical analysis, as the coefficient is generally not statistically significant. Joskow (1987); Kerkvliet and Shogren (2001), and Kozhevnikova and Lange (2009) have all shown that the duration of contracts has been falling over time – and indeed our time control variables are statistically significant and negative in sign. One might suggest that against this backdrop, the identification of a further decrease in duration for contracts signed by restructured plants might be difficult.

`Rigidity` is negative and statistically significant throughout, and instrumenting for it – Columns (4)-(7) – leads to larger negative coefficients. This is consistent with our theoretical insights that rigidity and duration are substitutes. Overall, however, the changes are of no great import to our key question here, as the coefficient of `Post Restructuring`, while slightly larger, remains mostly insignificant. This result is robust to the changes in the set of instruments discussed above. The costs shifters discussed in Section 4.2 appear here as controls for `Duration`. `Mine Dedicated Assets` and `Minimum Quantity` have the correct sign and are generally statistically significant. `Plant Dedicated Assets` has the correct sign throughout, but is not statistically significant. The sign of the coefficient of `Multiple Mode of Delivery` is unexpected: one would imagine that where plants can easily get coal from alternative sources, the contract would be less stable and hence shorter.

4.4 Discussion

The results presented thus far confirm our theoretical insight that in response to changes in the market environment that expose them to more output-price risk, coal-fired power plants will strive to introduce more rigid pricing in their procurement contracts, to limit their exposure to input-price risk. Three further remarks on our results are in order here.

First, Fowlie (2010) suggests that restructured plants may have chosen not to undertake new capital investment to comply with the NO_x Budget Programme (NBP), preferring to buy permits. If fuel switching had led power plants to contract with mines with lower extraction cost risk, and thus lower aversion for rigidity, it might have been the cause of the increase in contractual rigidity that we identify. In other words, the NBP, not restructuring, would be the cause of the increase in rigidity. For this to be a convincing explanation, however, we should observe a significant shift in the geographical origin of the coal sourced by deregulated plants. Table 3, however, shows the distribution of contracts signed across the three coal basins is constant for restructured plants before and after restructuring.[45] Additionally, the contractual rigidity increases immediately upon restructuring. Thus, for the first deregulated states the changes in contractual rigidity pre-date the introduction of the NBP by at least four years.[46] Furthermore, in the rigidity equation we control for potential differences in mine's preferences for rigidity with the Z-scores, a coal basin dummy, and an `Underground Mine` dummy.

Second, as in every 'quasi-experimental' setting, our challenge lies in convincingly attributing the observed changes in behavior to the treatment. While our discussion of the identification strategy in Section 4.1 goes a long way towards justifying our research design, in the interest of completeness we also want to rule out to the extent possible, that the results obtained above are purely due to chance. To do this, we perform a so-called 'placebo test' whereby, after dropping the treated observations from the sample, we randomly allocate states to two groups, the placebo group and the control group. This reassignment completed, we replicate our analysis assigning treated status to contracts signed in placebo states after 1996. Failure to reject the null that the coefficient of the placebo treatment is zero would suggest that the increase in rigidity we identify above is in fact due to the treatment. Figure 5 in the appendix presents the distribution of the coefficient estimates for both the rigidity, and the duration regression, obtained replicating the experiment described above 10,000 times. At each iteration a new random assignment of States into groups is performed, and the models in Table 4, column (3), and Table 5, column (3) are re-estimated. We cannot reject the null that both coefficients are indeed statistically insignificant, and conclude that the increase in rigidity for contract signed by plants in restructured states is indeed due to the treatment.

Finally, in our study, the units used to form the control group participate in the coal market alongside treated ones, hence one could be concerned that the treatment might somehow spill over to the control group, thus invalidating the SUTVA. In particular, mines in our dataset contract with plants in restructured states and in regulated states at the same time. One might worry, for example, that a mine forced into more rigid contracts by its customers in restructured states could compensate by pushing for less rigid contract with its regulated customers than it would have done absent restructuring. In this case, our estimates of the effect of the treatment on the treated would be biased upwards. To test for such treatment spillovers, we identify mines that sell coal to both regulated and unregulated plants and test whether they behave differently than mines that only sell coal to regulated plants. Table 6 reports the results of this procedure. The variable of interest, "`Mine Selling to Both Plant Types`", emerges as insignificant across all specifications. We conclude that, at least

[45] The t-statistics, and the associated p-values, for the tests for difference in means across different coal basins, before and after treatment are: Appalachia, $t = 0.26$, p-value$= 0.79$; West, $t = 0.10$, p-value$= 0.92$; Interior, $t = -0.72$, p-value$= 0.47$.

[46] The first restructuring laws were implemented in 1996, whereas the US Court of Appeals upheld the NBP in early 2000. The deadline for full compliance was set for May 2004.

as refers to this potential spillover channel, the SUTVA seems to hold.[47]

5 Contract changes, mining efficiency, and transaction costs

Our theoretical discussion and empirical evidence so far have illustrated that restructuring in the downstream market has real effects on the contractual behavior of parties upstream. In particular, the move to more rigidly priced contracts emerges prominently from both the theoretical and empirical analysis. In what follows, we address some of the implications of more rigid contracts.

5.1 Productivity

Changes in contractual rigidity, by changing the mines' incentives to exert cost-reducing effort, might lead to increases in mining efficiency (see Lemma 1). It implies that, following restructuring, mines that sell coal to plants in restructured states should become more efficient relative to mines that do not. To test this hypothesis, we again use a difference-in-difference design:

$$p_{i,t} = \zeta_i + \gamma_1 \Sigma_{i,t} + \gamma_2 \mathbf{X_{i,t}} + \varepsilon_{i,t}. \tag{9}$$

Here $p_{i,t}$ is county i's coal mines average labor productivity in year t, measured as the average number of short tons of coal produced per mine employee in any given year by mines located in the county i; ζ_i is the county fixed effect, $\Sigma_{i,t}$ is the differences-in-differences variable indicating whether a mine sold coal under a new contract to a plant in a restructured state after restructuring, $\mathbf{X_{i,t}}$ is a set of control variables, and $\varepsilon_{i,t}$ an idiosyncratic error term.[48,49]

The data is taken from the Mine Health and Safety Administration (MHSA) Part 50 Address/Employment Dataset. Our treatment variable, "`Coal to Restructured State`", equals one if any of county i's mines sold any coal, under a new contract to a plant located in a state that had passed restructuring legislation and is zero otherwise. In an alternative specification, we account for the intensity of the exposure to deregulation by substituting the variable above with a variable called "`Share of coal to Restructured State`", which measures the percentage of total coal sales from a given county destined to treated plants in any given year. Information on sales of contract coal is taken from the FERC 423 dataset. As control variables we use the number of injuries per worker in year t, and its squared term, a variable indicating the proportions of mines in the state-county that have been producing continuously (i.e. they did not shut down) during year t, and its squared term, together with

[47] For completeness, we performed the same test for duration. Mines that operate across regulatory regimes are shown to behave not differently when negotiating with plants in regulated states, relative to mines that only sell to such plants. Once again, these results support the SUTVA.

[48] The data used in the estimation of (7) are derived from a representative sample of all contracts, and are too few per mine-year to use in this analysis. The data used in the current section, instead, refer to the entire population of transactions between plants and mines. While this data allows us to obtain a full picture of the impact on mines of selling coal to restructured plants, it does not contain other contract-specific information.As a result, we cannot use the rigidity of the price adjustment mechanism directly here.

[49] Data on plant purchases do not link to a specific mine but rather to the county of origin. This is the level utilized in the productivity analysis.

year dummy variables. "Injuries per worker" and "Continuous Production" data also come from the MHSA Part 50 Address/Employment Dataset. Summary statistics are in Table 3.

To support our identification strategy we refer back to the discussion of the exogeneity of treatment in Section 4.1, and focus here only on the appropriateness of the control group. First, we focus on the stability of the trend in the control group. Figure 6 plots the evolution of the average productivity of mines in our control group over the period covered by our analysis. The graph does not suggest any breaks or changes in trend once the legislation is passed. Second, we concentrate on the comparability of the treatment and control groups before treatment. Figure 7 describes the evolution of labor productivity at treated mines relative to control mines.[50] The productivity of the two groups trends similarly before restructuring, whereas it tends to increase faster for the treatment group after treatment. Overall, this evidence supports our identification strategy.

Two points are worth raising here. In the first place, it is a well known fact that the late 1980s were years of rapid expansion of Western coal mine production (e.g. Ellerman and Montero, 1998; Ellerman, Joskow, Schmalensee, Montero, and Bailey, 2000). On the other hand, Stoker, Berndt, Ellerman, and Schennach (2005) emphasize the large productivity advantage of Western coal mines over the remaining ones, as well as the differential trends in productivity growth among the two groups. To make sure that our empirical analysis is not biased by these two aspects, we re-estimate the evolution of labor productivity for treated mines relative to control ones excluding Western mines from our sample. In so doing, we can ensure that our treatment and control groups have been producing similar levels of coal for an extended period, before the treatment is applied. Figure 8 shows the evolution of the relative productivity for non-Western mines over time. The pattern that emerges is, if anything, even more clear-cut from the one given in Figure 7. We conclude that our interpretation of the changes in productivity as being due to deregulation is strongly supported by the evidence.

Table 7 shows the results of the estimation of equation (9) both with and without additional controls, and with the different samples described above. Columns (1)-(4) exclude additional controls, whereas (5)-(8) include the controls discussed above. In (1)-(2), and (5)-(6) we use the dummy specification for treatment status discussed above for the full sample of mines and non-Western mines only, respectively. Using the ratio of coal sold to treated plants over all coal sold and its square, instead, columns (3)-(4) and (7)-(8) show that the intensity of treatment has a non-linear, convex relation to productivity, given the statistically significant and positive coefficient on the squared term for both the complete sample and for the non-Western mines. Overall, the results in the Table 7 show that the treatment effects are unchanged when adding control variables. Based on the specification in column (5), our results suggest that mines that sold coal to plants in restructured states became on average 17.4% more productive than the control group. The effect is even more pronounced among non-Western mines, whose productivity increased by 21.2% on average.[51] These findings

[50] As described above, our baseline treatment assignment, which we apply here, allocates mines to the treatment group if they are located in a county where at least one mine sold coal under a new contract to plants in restructured states after restructuring. The control group, thus comprises mines located in counties where no mines ever sold to a plant in a state that eventually deregulated.

[51] The average productivity of control mines in 1996 was 8,817 for the complete sample, and 6,567 for the

support the argument that the move to higher-powered incentives in contracts written by restructured plants did lead to a sizable increase in mines' productivity.

Our results in this section are consistent with the evidence discussed by both Cicala (2015) and Chan, Fell, Lange, and Li (2017), that plants in restructured states pay a statistically lower price for their coal, as more efficient mines would be able to provide coal at lower prices. Interestingly, even the magnitude of our effect in Table 7 is broadly consistent with the drop in coal prices found in Cicala (2015) and Chan et al. (2017). The former finds a 12% drop in coal prices, while the latter estimate the drop to be closer to 10%. As neither of these papers discusses a specific mechanism that could have lead to lower coal prices or have information on the type of price adjustment mechanism in the contracts in their sample, our analysis complements theirs by suggesting that changes in price rigidity due to restructuring could have strengthened the incentives for cost savings. Thus, changes in the nature of procurement contracts might have brought about productivity increases, and ultimately, through competitive pressures, the decreases in prices documented in the literature.

Cicala (2015) points at a potential alternative explanation for our results when he notes that plants in restructured states are more likely to switch to out-of-state coal mines to procure fuel, and that after divestiture the labor content of coal purchased by plants in restructured states decreases. It is conceivable that the increase in productivity we report in Table 7 might be linked to the sorting of highly productive mines into contracts with plants in restructured states, and low productivity mines with plants in traditionally regulated states, a change that need not imply any actual productivity gain. If our results were being driven by such a re-ordering of mines, however, we would expect to find evidence that some mines that previously were not selling coal to plants in restructured states would start doing so, after restructuring. In our dataset, however, we could find no county whose mine were not initially selling to a plant in a would-be restructured state that started selling after treatment commenced. A more subtle way to test Cicala's hypothesis is to look at mines that stopped shipping coal to restructured markets after restructuring took place (the 'discontinuing' group), and compare their productivity levels with those of mines that kept selling even after restructuring (the 'continuing' group). According to the sorting hypothesis, the latter group should exhibit higher productivity levels in the period before restructuring. Using our data, we can test the (one-sided) hypothesis that the average labor productivity of the continuing mines be higher than that of the discontinuing ones. The results of this test (see Table 8) suggest that there is no statistical difference in the level of productivity between (groups of) mines that stopped selling to restructured states, and those who, instead, continued to do so. We conclude that the type of sorting hypothesizes by Cicala (2015) is unlikely to be driving our results.[52]

non-Western sub-sample.

[52]The apparent contradiction between our work here and the conclusions of Cicala (2015) may in fact be easily resolved by realizing that in our analysis the treatment period is 1996-2001, whereas in Cicala (2015) the focus is on 2002-2009. It is conceivable that the productivity gains driven by the higher-powered incentives we identify here would subsequently allow more productive coal mines to gain market share relative to mines with more stagnant productivity. This is something that might be worth of additional investigation in the future.

5.2 Renegotiations

Against the gains due to the improved productivity highlighted above one needs to weigh the potential losses due to changes in procurement contracts. In particular, one aspect often discussed in the literature is the fact that more rigid contracts are more costly to negotiate and prone to more frequent renegotiations (e.g., Tadelis and Williamson, 2012). Thus, the increase in contract rigidity identified in Section 4.3 could imply an increase in transaction costs. While it is not possible, given the available data, to ascertain directly whether transaction costs have increased, one possible – albeit indirect – test of this hypothesis is to test whether more rigid contracts are actually renegotiated more frequently. To analyze the effect of contract rigidity on renegotiation, we estimate the following model,

$$m_i = \theta_0 + \theta_1 r_i + \theta_2 d_i + \theta_3 \mathbf{X_i} + \varepsilon_i, \tag{10}$$

where m_i is the time to the first renegotiation of the contract, r_i and d_i are the rigidity of the price adjustment mechanism and the intended contractual duration of contract i, X_i is a vector of control variables, and ε_i is an idiosyncratic error term.

Table 9 shows the results of the estimation of equation (10) performed using a Poisson model. A more rigid price adjustment mechanism is associated with a shorter time until the first renegotiation of the contract, whereas a longer contractual duration has the opposite effect, increasing the number of years until first renegotiation.

These results conform to our theoretical priors. A more rigid pricing mechanism, by exposing the mine to the full cost of adverse realizations of extraction costs, tends to make the contractual relationship more vulnerable *vis-à-vis* such shocks. This evidence is suggestive of the fact that restructuring could have harmful effects in as far as frequent renegotiations imply an increase in the industry-wide transaction costs.

6 Conclusions

A substantial body of literature attempts to assess the economic impacts of industry liberalization. This literature, however, mostly focuses on how deregulation impacts directly on the regulated entities. In this paper we break with this tradition and analyze the consequences of deregulation on the contractual relationships that characterize the supply chain upstream from the deregulated market. We use electricity generation in the U.S. as our case study, and conclude that this previously overlooked aspect of deregulation is likely to have substantial efficiency implications.

During the 1990s, a number of U.S. states restructured their electricity market so that power plants could no longer be assured of cost recovery or a dedicated buyer for their output. Restructuring thus increased the uncertainty under which such plants operated. We have presented a theoretical discussion of the likely impact of these changes on the optimal choice of procurement contracts. Our analysis predicts that plants would respond to the increased uncertainty by signing contracts for coal delivery with a more rigid price adjustment mechanism. In our model, the higher price rigidity reduces the plant's exposure to risk in upstream prices, offsetting the downstream increase in uncertainty. Our empirical analysis uses coal contracts data for 1990-2001 and finds evidence that strongly supports our theoretical predictions.

One effect of the change to a more rigid price adjustment mechanism is that it provides higher-powered cost-reduction incentives to the upstream supply chain, coal mines in this instance. Results here show that these increased incentives did lead to a significant improvement in coal mine productivity. Our estimate of the magnitude of this increase in productivity is very close to the estimated reduction in coal prices recently discussed by Cicala (2015) and Chan et al. (2017). We argue that the evidence provided here may be the mechanism behind the price drops found by these authors.

On the other hand, economic theory suggests that more rigid price adjustment mechanisms entail higher transaction costs, due to higher initial negotiation costs, more frequent renegotiations, and more likely breaches of contract. To assess this aspect, we estimated the impact of price rigidity on the time to first renegotiation for the contracts in our sample. Our findings reveal that more rigid prices are indeed associated with a shorter time to first renegotiation. One might then be concerned that the productivity improvements discussed above be offset by increases in transaction costs.

Clearly, more work is needed to assess the net impact of deregulation on efficiency in upstream markets. An important area of future research that emerges from our work is to disentangle and empirically assess the welfare implications of deregulation by looking at the whole supply chain affected by the regulatory change.

Finally, we are convinced that the general mechanisms discussed here through which deregulation impacts supply chains by shifting risk up-stream from the deregulated industry are relevant beyond our specific case study. Given the move to natural gas that has occurred over the past two decades in the US, for example, we would expect similar effects in the context of gas extraction. Obviously, the two industries are quite different. Natural gas extraction is not linked to its end users quite as clearly as coal is, for example. Coal power plants write contracts with coal mines, whereas natural gas power plants procure their fuel through mid-stream gas marketers and pipeline companies. This is partially due to the fact that natural gas is a homogeneous products (i.e. once it goes in the pipeline you do not know which gas was put in, by whom) while coal is quite heterogeneous, facilitating the need to secure coal from specific mines. Interestingly, however, one of the debates in the natural gas industry in the recent past has been the surprising absence of long-run procurement contracts. Many authors have linked the shortening of gas supply contracts to restructuring. On this issue, for example, Petrash (2006) writes: "*There is no question that the terms of contracts – both gas supply and transportation – have shortened over the last decade.* [...] *The dramatic change in natural gas markets, from highly regulated to market-driven, dynamic, and volatile, has plainly played a critical role in changing perceptions of the market by participants, shortening forecasting horizons, increasing market risk, and increasing the reliability of gas supply*". While this is merely suggestive evidence of the kind of effects we identify, we are comforted in the relevance of our analysis. Moreover, as the electricity industry grows more competitive over time – more regions are moving to economic dispatch and larger geographic area are being considered in dispatch decisions – and as non-dispatchable renewables grow more prominent, electricity generators become less certain than ever over their output price and revenues. As a result, our insights relating to risk and the desire to shift it up-stream are likely to become even more relevant.

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A Proofs of the Theoretical Results

A.1 Proof of Lemma 1

Consider a fixed contract $\boldsymbol{\gamma} = (r, d)$. Substituting the expression (1) for the expected price of coal into the profit function of the mine given in (4), we obtain the expected per-period profit:

$$\mathbb{E}(\pi_m) = \delta(r) - r\mathbb{E}(x(\chi, e)) - k^m(r, d; \mathbf{A}) - g(e)$$

Recalling the general form of the mine's per-period value of contract $\gamma = (r, d)$, given in (3), allows us to write down the mine's optimal choice of effort given contract (r, d) as the solution to the following maximization problem:

$$\max_{e \geq 0} V^m(\gamma, e) = \delta(r) - r\mathbb{E}(x(\chi, e)) - k^m(r, d; \mathbf{A}) - g(e) - \theta^m CVaR_{\alpha_m}(-\pi^m),$$

Differentiating the objective function with respect to e we obtain that at the optimal level, e^*, we have

$$-r\frac{\partial \mathbb{E}(x(\chi, e^*))}{\partial e} - \frac{\partial g(e^*)}{\partial e} - \theta^m \frac{\partial CVaR_{\alpha_m}(-\pi^m)}{\partial e} = 0 \quad \text{(A.1)}$$

Recall that by assumption $\partial\mathbb{E}(x(\chi, e))/\partial e < 0$ and $\partial g(e)/\partial e > 0$, thus an interior solution for e^* is possible.

To verify that at e^*, we obtain a maximum, we study the second order condition:

$$\frac{\partial^2 V^m(\boldsymbol{\gamma}, e)}{\partial e^2} = -r\frac{\partial^2 \mathbb{E}(x(\chi, e^*))}{\partial e^2} - \frac{\partial^2 g(e^*)}{\partial e^2} - \theta^m \frac{\partial^2 CVaR_{\alpha_m}(-\pi^m)}{\partial e^2} < 0,$$

where the last inequality follows from the assumptions that $\partial^2\mathbb{E}(x(\chi, e))/\partial e^2 > 0$, $\partial^2 g(e)/\partial e^2 > 0$ and $\partial^2 CVaR_{\alpha_m}(-\pi^m)/\partial e^2 > 0$ which follows form the fact that the CVaR is convex with respect to the choice variable (here, e) when losses $(-\pi)$ are convex with respect to that variable (cf. Rockafellar and Uryasev (2000)) for a technical discussion).

Monotonicity of e^* with respect to r can be derived by using the implicit function theorem. From equation (A.1), we get,

$$\frac{\partial e^*}{\partial r} = -\frac{\left(-\frac{\partial \mathbb{E}(x(\chi, e^*))}{\partial e}\right) - \theta^m \frac{\partial\left(\frac{\partial CVaR_{\alpha_m}(-\pi^m)}{\partial e}\right)}{\partial r}}{-r\frac{\partial^2 \mathbb{E}(x(\chi, e^*))}{\partial e^2} - \frac{\partial^2 g(e^*)}{\partial e^2} - \theta^m \frac{\partial^2 CVaR_{\alpha_m}(-\pi^m)}{\partial e^2}}; \quad \text{(A.2)}$$

whose denominator is always negative as shown above. Therefore, to establish monotonicity of the relation (part i. of Lemma 1), it is sufficient to point out that the numerator does depend on the level of rigidity if and only if

$$\frac{\partial^2\left(\frac{\partial CVaR_{\alpha_m}(-\pi^m)}{\partial e}\right)}{\partial r^2} = 0$$

Moreover, the direction of monotonicity depends on the sign of the numerator of (A.2). Clearly, if the numerator is positive, then e^* increases with r. This is the case only when

$$\frac{\partial \mathbb{E}(x(\chi,e^*))}{\partial e} + \theta^m \frac{\partial\left(\frac{\partial CVaR_{\alpha_m}(-\pi^m)}{\partial e}\right)}{\partial r} < 0,$$

which confirms the statement of part ii. of Lemma 1.

A.2 Proof of Proposition 1

Here we make use of the assumption that profits π follow a normal distribution. In such case, Rockafellar and Uryasev (2000) show that

$$CVaR_\alpha(-\pi) = -\mathbb{E}(\pi) + b(\alpha)\sqrt{\mathrm{Var}(\pi)}, \tag{A.3}$$

where

$$b(\alpha) = \left(\sqrt{2\pi}\exp\left(\mathrm{erf}^{-1}(2\alpha-1)\right)^2(1-\alpha)\right)^{-1},$$

and $\mathrm{erf}(z) = (2/\sqrt{\pi})\int_o^z \exp(-s^2)\mathrm{d}s$ is the Gauss error function.

This allows us to derive the optimal contract choice (6) as the solution to the following problem:

$$\begin{aligned} \max_{r,d} \quad & (1+\theta^g)\left\{\lambda\left[\mathbb{E}(p^e)-\overline{\delta}-\mu\right]+\mu-k^g(r,d;\mathbf{A})\right\}-\theta^g b(\alpha)\lambda\sqrt{\sigma_e^2+(1-r)^2\sigma_x^2}, \\ s.t. \quad & (1+\theta^m)\left[\overline{\delta}-\mathbb{E}(x(\chi,e^*(r))-k^m(r,d;\mathbf{A})-g(e^*(r))\right]-\theta^m b(\alpha)r\sigma_x \geq 0. \end{aligned} \tag{A.4}$$

The associated Lagrangian is

$$\begin{aligned} \mathscr{L} = {} & (1+\theta^g)\left\{\lambda\left[\mathbb{E}(p^e)-\overline{\delta}-\mu\right]+\mu-k^g(r,d;\mathbf{A})\right\}-\theta^g b(\alpha)\lambda\sqrt{\sigma_e^2+(1-r)^2\sigma_x^2}+ \\ & +\eta\{(1+\theta^m)\left[\overline{\delta}-\mathbb{E}(x(\chi,e^*(r))-k^m(r,d;\mathbf{A})-g(e^*(r))\right]-\theta^m b(\alpha)r\sigma_x\}, \end{aligned}$$

and the necessary first-order conditions for a maximum are:

$$\begin{aligned} \frac{\partial\mathscr{L}}{\partial r} = {} & -(1+\theta^g)\frac{\partial k^g}{\partial r}+\theta^g b(\alpha)\lambda\left[\sigma_e^2+(1-r)^2\sigma_x^2\right]^{-1/2}(1-r)\sigma_x^2- \\ & -\eta(1+\theta^m)\left[\frac{\partial k^m}{\partial r}-\frac{\partial\mathbb{E}(x(\chi,e^*(r)))}{\partial e}\frac{\partial e^*}{\partial r}-\frac{\partial g}{\partial e}\frac{\partial e^*}{\partial r}\right]-\eta\theta^m b(\alpha)\sigma_x = 0, \end{aligned} \tag{A.5}$$

and

$$\frac{\partial\mathscr{L}}{\partial d} = -(1+\theta^g)\frac{\partial k^g}{\partial d}-\eta(1+\theta^m)\frac{\partial k^m}{\partial d} = 0. \tag{A.6}$$

Well know results in monotone comparative statics (see Milgrom and Shannon, 1994, theorem 5) assert that if $\mathscr{L}$ is supermodular in $(r,-d)$ and exhibits increasing returns in $(r,-d,\lambda)$, then the solutions to the maximization problem $r(\lambda)$, and $d(\lambda)$ are monotone non-decreasing and non-increasing, respectively.

To show that our objective function, $\mathscr{L}$, is supermodular in $(r,-d)$ and exhibits increasing differences in $(r,-d,\lambda)$ it suffices to show that the cross derivatives with respect to these three variables are non-negative (Milgrom and Shannon, 1994, theorem 6). Differentiating (A.5) with respect to $-d$ yields

$$\frac{\partial^2 \mathcal{L}}{\partial r \partial(-d)} = (1+\theta^g)\frac{\partial^2 k^g}{\partial r \partial(d)} + \eta(1+\theta^m)\frac{\partial k^m}{\partial r \partial(d)} > 0, \tag{A.7}$$

where the last inequality follows from the properties of $k^g(r,d)$, and the positivity of η. Differentiation of (A.5) and (A.6) with respect to λ yields

$$\frac{\partial^2 \mathcal{L}}{\partial r \partial \lambda} = \theta^g b(\alpha)(1-r)\sigma_x^2\left[\sigma_e^2 + (1-r)^2\sigma_x^2\right]^{-1/2} > 0, \quad \text{and} \quad \frac{\partial^2 \mathcal{L}}{\partial(-d)\partial\lambda} = 0, \tag{A.8}$$

respectively, which concludes our proof. □

A.3 Proof of Proposition 2

The previous proof establishes that $\mathcal{L}$ is supermodular in $(r, -d)$. Differentiating the first-order conditions (A.5) and (A.6) with respect to $-A_i$, and $-\sigma_e^2$ one gets

$$\frac{\partial^2 \mathcal{L}}{\partial r \partial(-\sigma_e)} = \theta^g b(\alpha)\lambda(1-r)\sigma_x^2\left[\sigma_e^2 + (1-r)^2\sigma_x^2\right]^{-3/2}\sigma_e > 0, \quad \text{and} \quad \frac{\partial^2 \mathcal{L}}{\partial(-d)\partial(-\sigma_e)} = 0;$$

$$\frac{\partial^2 \mathcal{L}}{\partial r \partial(-A_i)} = 0, \quad \text{and} \quad \frac{\partial^2 \mathcal{L}}{\partial(-d)\partial(-A_i)} = -(1+\theta^g)\frac{\partial^2 k^g}{\partial(-d)\partial(-A_i)} - \eta(1+\theta^m)\frac{\partial k^m}{\partial(-d)\partial(-A_i)} > 0;$$

that immediately establish that $\mathcal{L}$ exhibits increasing differences in $(r, -d, -\sigma_e^2, -A_i)$, implying that r^* is non-increasing in σ_e, and A_i, while d^* is non-decreasing in both.

Finally, differentiating (A.5) and (A.6) with respect to σ_χ yields

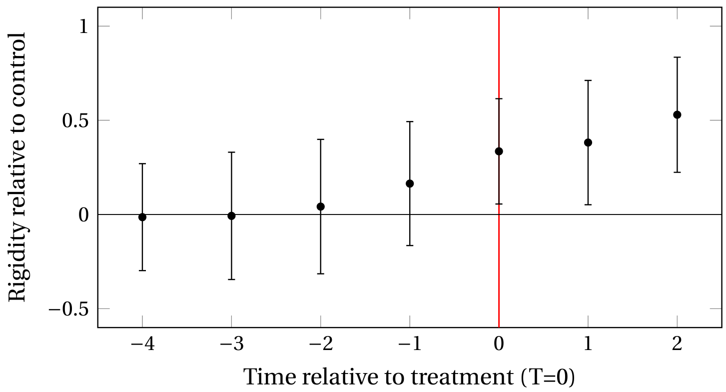
$$\frac{\partial^2 \mathcal{L}}{\partial r \partial \sigma_x} = \theta^g b(\alpha)\lambda(1-r)\sigma_x\left[\sigma_e^2 + (1-r)^2\sigma_x^2\right]^{-1/2}\left\{2-(1-r)^2\sigma_x^2\left[\sigma_e^2+(1-r)^2\sigma_x^2\right]^{-1}\right\} - \eta\theta^m b(\alpha),$$

and,

$$\frac{\partial^2 \mathcal{L}}{\partial(-d)\partial\sigma_x} = 0,$$

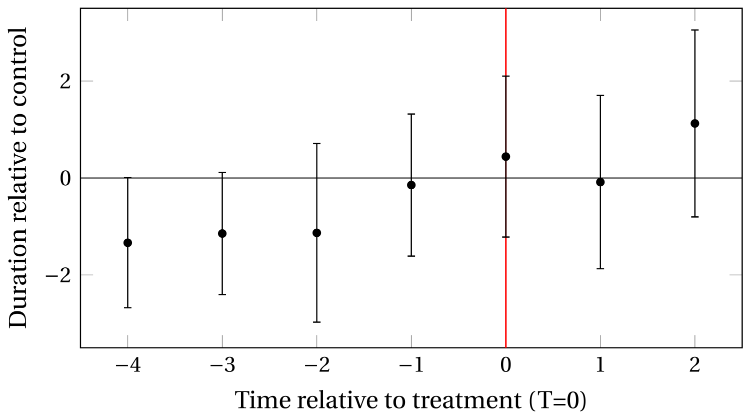
where it is apparent that it is not possible to sign in general the first cross derivative. This completes our proof. □

Figure 1: Average contract rigidity of treatment group relative to control – Normalized time.



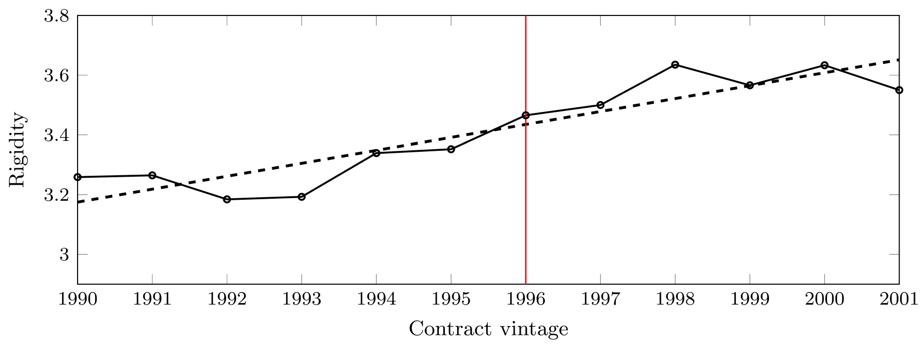
This figure shows the year-by-year estimated coefficient and the 95% confidence interval for duration in treated contracts relative to control, before and after the treatment. Time is normalized relative to the year that the state the plant is located in passed restructuring legislation. Contracts are included in the treatment group if they are a new contract signed with a plant in a state which has passed restructuring legislation. The estimating equation is based on Equation (7). Standard errors are clustered at the level of the state the plant is located in.

Figure 2: Average contract duration of treatment group relative to control – Normalized time.



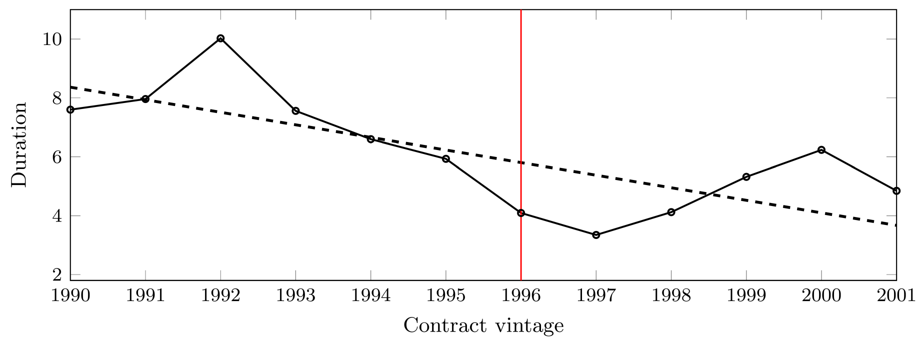
This figure shows the year-by-year estimated coefficient and the 95% confidence interval for duration in treated contracts relative to control, before and after the treatment. Time is normalized relative to the year that the state the plant is located in passed restructuring legislation. Contracts are included in the treatment group if they are a new contract signed with a plant in a state which has passed restructuring legislation. The estimating equation is based on Equation (8). Standard errors are clustered at the level of the state the plant is located in.

Figure 3: Average contract rigidity for control group (1990-2001).



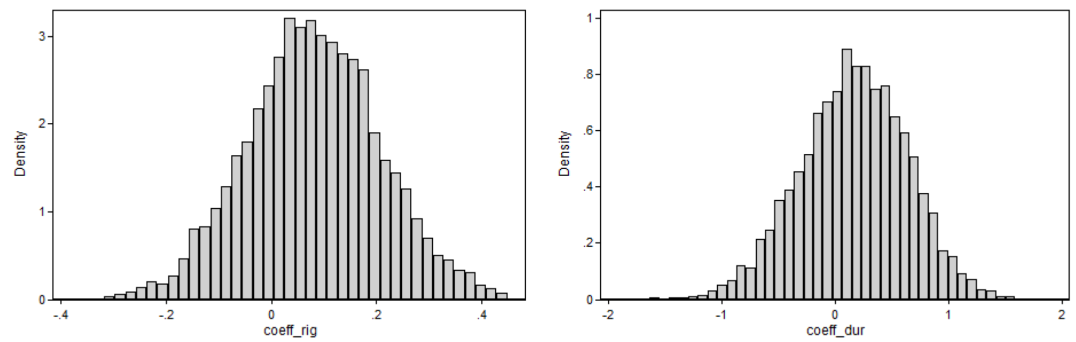
This figure shows the average yearly contractual rigidity for contracts in the control group, i.e. contracts signed by plants operating in states that have not passed restructuring legislation. The dashed line is the estimated trend over the entire period. The vertical line indicates the first year that a state passed restructuring legislation.

Figure 4: Average contract duration for control group (1990-2001).



This figure shows the average yearly contractual duration in years for contracts in the control group, i.e. contracts signed by plants operating in states that have not passed restructuring legislation. The dashed line is the estimated trend over the entire period. The vertical line indicates the first year that a state passed restructuring legislation.

Figure 5: Results of the placebo test - 10,000 iterations.

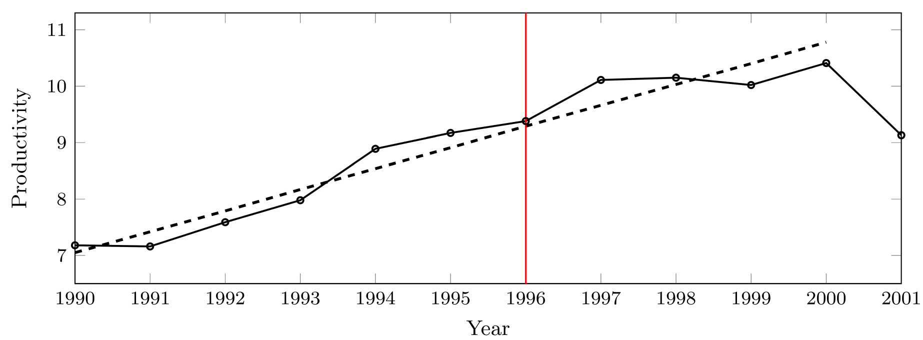


(a) Rigidity

(b) Duration

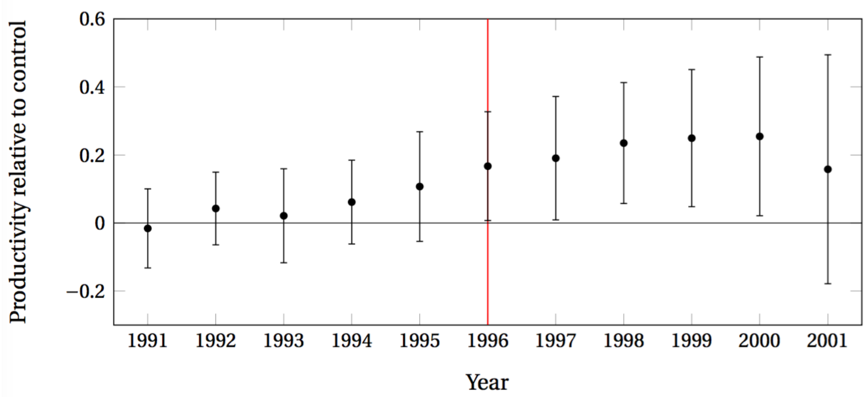
This figure reports the results of the Placebo test conducted assigning at each iteration half of the plants located in regulated states to the placebo group. This procedure was repeated 10,000 times. The figure shows the distribution of the estimated coefficients of the placebo indicator obtained from a regression of contractual rigidity, panel (a), and duration, panel (b). The estimated equations replicate the instrumentation carried out in Table 4, Column (3), and Table 5, Column (3), respectively.

Figure 6: Average productivity for control group (1990-2001).



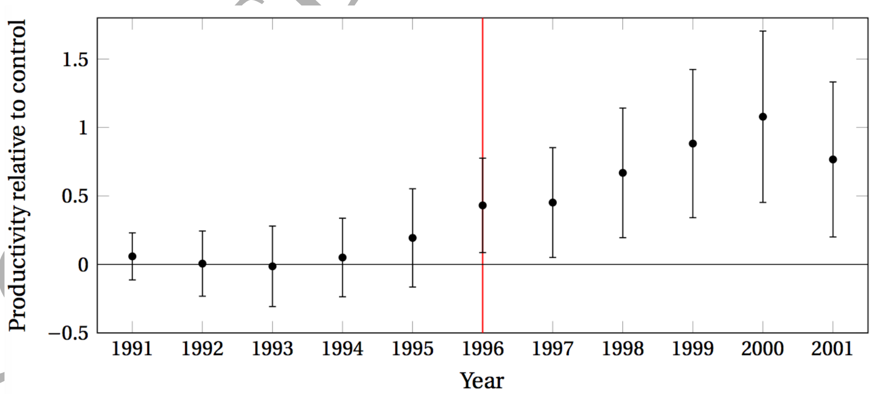
This figure shows the average yearly labor productivity for mines (counties) in the control group, i.e. for counties from which no coal was shipped to any of the restructured states. The dashed line is the estimated trend over 1990-2000. The vertical line indicates the first year that a state passed restructuring legislation. Coal productivity dropped across the industry in 2001 as documented in U.S. EIA (2010).

Figure 7: Average labor productivity of treatment group relative to control, full sample (1991-2001).



This figure shows the year-by-year estimated coefficient and the 95% confidence interval of (the log of) labor productivity (in million tons per employee), for treated counties relative to control, before and after the treatment. Counties are included in the treatment group if at least one mine in the county has signed a new contract with a plant in a state which has passed restructuring legislation. Time is normalized relative to the time of inclusion of the county in the treatment group. The estimating equation is based on Equation (9). Standard errors are clustered at the county level.

Figure 8: Average labor productivity of treatment group relative to control, Eastern mines only (1991-2001).



This figure shows the year-by-year estimated coefficient and the 95% confidence interval of (the log of) labor productivity (in million tons per employee), for Eastern, treated counties relative to control, before and after the treatment (see main text for details). Counties are included in the treatment group if at least one mine in the county has signed a new contract with a plant in a state which has passed restructuring legislation. Time is normalized relative to the time of inclusion of the county in the treatment group. The estimating equation is based on Equation (9). Standard errors are clustered at the county level.

Table 1: Description of Pricing Mechanisms

Ordinal Designation	Description
4, Most Rigid	Fixed-Price Contract. Price is fixed over the life of the contract.
3	Base Price Plus Escalation. Different components of the price escalate (or de-escalate) as a function of changing economic conditions (indices).
2	Price Tied to Market. Price tied to the price of coal being sold in a particular market. Product and market area are defined in the contract. Contract may contain a "Most Favored Nations" clause, i.e., supplier will not sell to any generator at a price lower than yours is paying.
2	Cost-Plus Contract with a Fixed Fee Provision. Purchaser agrees to pay all producer's costs plus a management fee. Some contracts provide for payment of both a management fee and a profit. This contract has a Fixed Fee provision.
2	Cost-Plus Contract with an Incentive Fee. Provision Purchaser agrees to pay all producer's costs plus a management fee. Some contracts provide for payment of both a management fee and a profit. This contract has an Incentive Fee provision, i.e., a variable fee that is tied to various productivity and cost reduction incentives.
1, Least Rigid	Price Renegotiation. The price is renegotiated at predetermined intervals, usually one year. This type of contract, frequently known as an *Evergreen Contract*, may also contain provisions for price adjustments between renegotiations.

Source: FERC form 580

Table 2: Status of Electricity Restructuring

State	Hearing Held	Law Passed	Contracts in Data	Contracts after Restructuring
Alabama	1997		38	
Alaska	1998			
*Arizona	1995	1998	5	4
Arkansas	1997	1999	3	
California	1994	1996		
Colorado	1998		12	
*Connecticut	1994	1998	1	
*Delaware	1995	1999	18	
*District of Columbia	1996	2000		
Florida	2000		41	
Georgia	1998		16	
Idaho	1997			
*Illinois	1995	1997	50	10
Indiana	1995		97	
Iowa	1996		79	
Kansas	1996		30	
Kentucky	1996	1999	54	
Louisiana	1997		5	
*Maine	1995	1997		
*Maryland	1995	1999	48	7
*Massachusetts	1994	1997	39	4
*Michigan	1994	2000	50	3
Minnesota	1997		24	
Mississippi	1997		3	
Missouri	1997		31	
Montana	1996	1997	1	
Nebraska	1996			
Nevada	1994	1996	7	
*New Hampshire	1994	1996	17	2
*New Jersey	1996	1999	16	
New Mexico	1995	1999		
*New York	1993	1996	21	1
North Carolina	1998		40	
North Dakota	1997		0	
*Ohio	1996	1999	59	4
Oklahoma	1995	1997	13	
*Oregon	1995	1999		
*Pennsylvania	1994	1996	134	55
*Rhode Island	1994	1996		
South Carolina	1997		29	
South Dakota	1998		1	
Tennessee	1997			
*Texas	1997	1999	26	2
Utah	1997		5	
Vermont	1995			
*Virginia	1995	1999	100	20
Washington	1995		3	
West Virginia	1995	1999	52	
Wisconsin	1997		57	
Wyoming	1997		17	

Source: U.S. Energy Information Administration.
Asterisks indicate States assigned to the treated group in our analysis.

Table 3: Summary Statistics

	All Data[a]	(A) Control before 1996[a]	(B) Treated before treatment[a]	(C) Control after 1996[a]	(D) Treated after treatment[a]	(A)-(B)[b]	(A)-(C)[b]
Rigidity	3.33	3.42	3.02	3.66	3.49	7.33	-4.04
	(0.79)	(0.70)	(0.87)	(0.63)	(0.63)	(0.00)	(0.00)
Duration	1.23	1.39	1.28	1.02	1.05	0.21	5.85
	(0.71)	(0.80)	(0.67)	(0.65)	(0.46)	(0.84)	(0.00)
Post SO_2 Regulation	0.65	0.56	0.58	0.85	0.80	2.43	-8.06
	(0.48)	(0.50)	(0.49)	(0.36)	(0.41)	(0.02)	(0.00)
Post Restructuring (State treatment)	0.09	0.00	0.00	0.00	1.00	–	–
	(0.28)	(0.00)	(0.00)	(0.00)	(0.00)	–	–
Restructured Plant (State treatment)	0.46	0.00	1.00	0.00	1.00	–	–
	(0.50)	(0.00)	(0.00)	(0.00)	(0.00)	–	–
Post Restructuring (Plant treatment)	0.05	0.00	0.00	0.00	0.61	–	–
	(0.23)	(0.00)	(0.00)	(0.00)	(0.49)	–	–
Restructured Plant (Plant treatment)	0.28	0.01	0.55	0.06	0.61	-19.90	-2.89
	(0.45)	(0.10)	(0.50)	(0.23)	(0.49)	(0.00)	(0.00)
Previous Interaction	0.63	0.64	0.61	0.60	0.73	0.78	0.97
	(0.48)	(0.48)	(0.49)	(0.49)	(0.45)	(0.44)	(0.33)
Z-Ash	-0.04	0.04	-0.11	-0.03	-0.08	2.09	0.85
	(0.92)	(1.01)	(0.87)	(0.90)	(0.85)	(0.04)	(0.40)
Z-Sulfur	0.19	0.12	0.06	0.38	0.51	2.89	-2.74
	(1.04)	(1.05)	(0.96)	(1.08)	(1.12)	(0.00)	(0.01)
Z-Btu	0.13	0.09	0.21	0.01	0.18	-3.13	1.38
	(0.60)	(0.50)	(0.58)	(0.76)	(0.50)	(0.00)	(0.17)
Scrubber	0.10	0.11	0.08	0.14	0.00	0.19	-0.91
	(0.30)	(0.32)	(0.28)	(0.35)	(0.00)	(0.85)	(0.36)
Maximum Sulfur Allowed	1.05	0.76	1.01	1.15	1.99	-2.45	-3.70
	(1.14)	(1.07)	(0.93)	(1.29)	(1.30)	(0.01)	(0.00)
Minimum Quantity	0.49	0.58	0.37	0.62	0.32	4.47	-0.61
	(0.72)	(0.83)	(0.54)	(0.84)	(0.46)	(0.00)	0.54
Appalachia Mine	0.58	0.30	0.82	0.47	0.83	-16.78	-4.14
	(0.49)	(0.46)	(0.39)	(0.50)	(0.38)	(0.00)	(0.00)
Interior Mine	0.15	0.33	0.03	0.15	0.05	11.02	5.24
	(0.36)	(0.47)	(0.17)	(0.36)	(0.21)	(0.00)	(0.00)
Western Mine	0.27	0.37	0.15	0.38	0.13	7.33	-0.30
	(0.44)	(0.48)	(0.36)	(0.49)	(0.33)	(0.00)	(0.76)
Mine Dedicated Assets	0.14	0.16	0.11	0.15	0.15	2.94	0.65
	(0.25)	(0.27)	(0.21)	(0.28)	(0.25)	(0.00)	(0.52)
Plant Dedicated Assets	0.19	0.22	0.18	0.21	0.15	3.16	0.44
	(0.25)	(0.27)	(0.23)	(0.26)	(0.22)	(0.00)	(0.66)
Mandatory Phase I Plant	0.32	0.39	0.26	0.28	0.42	2.06	2.66
	(0.46)	(0.49)	(0.44)	(0.45)	(0.50)	(0.04)	(0.01)
Log of Utilization Variability	8.16	7.34	8.83	7.71	9.38	-14.33	-3.25
	(1.41)	(1.36)	(1.12)	(1.29)	(0.59)	(0.00)	(0.00)
Time to First Renegotiation	3.34	3.57	3.66	2.87	2.46	-1.82	3.75
	(3.14)	(3.52)	(3.31)	(2.49)	(2.00)	(0.07)	(0.00)
Mine-mouth Plant	0.01	0.01	0.01	0.00	0.00	-1.35	2.00
	(0.08)	(0.08)	(0.11)	(0.00)	(0.00)	(0.18)	(0.05)
Mine Productivity	8462.19	7265.31	7796.35	9277.57	11243.47	-0.88	-5.92
	(8872.44)	(6872.99)	(9900.84)	(8689.90)	(13464.32)	(0.38)	(0.00)
Injuries Per Worker	0.07	0.07	0.09	0.06	0.07	-2.40	0.90
	(0.20)	(0.28)	(0.07)	(0.15)	(0.05)	(0.02)	(0.37)
Continuous production	0.58	0.60	0.56	0.58	0.52	2.39	1.76
	(0.30)	(0.29)	(0.24)	(0.33)	(0.22)	(0.02)	(0.08)
Underground Mine	0.25	0.23	0.36	0.22	0.33	-7.30	0.27
	(0.30)	(0.31)	(0.27)	(0.31)	(0.25)	(0.00)	(0.79)

[a] Sample means and standard deviations in parentheses.
[b] t-test for the difference in means and p-value in parentheses.
See Sections 4.2, 5.1, and 5.2 for detailed descriptions of all data series, including sources.

Table 4: Contract Choice – Rigidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Oprobit (State)	Oprobit (State)	Oprobit+EM (State)	Oprobit+EM (Plant)	IV (State)	IV (Plant)	3SLS (State)
Post Restructuring	0.66***	0.22	0.22**	0.19*	0.34***	0.26**	0.21**
	(0.16)	(0.24)	(0.11)	(0.11)	(0.10)	(0.10)	(0.09)
Restructured State	-0.73***	-0.58***	-0.33***	-0.26**	-0.38***	-0.21**	-0.30***
	(0.20)	(0.19)	(0.11)	(0.11)	(0.11)	(0.11)	(0.06)
Log of Duration	–	-0.79***	-0.36***	-0.34***	-0.27**	-0.21**	-0.37***
	–	(0.12)	(0.10)	(0.09)	(0.10)	(0.09)	(0.07)
Previous Interaction	–	0.08	0.00	0.01	-0.01	0.01	-0.01
	–	(0.09)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
Post SO_2 Regulation	–	-0.13	-0.06	-0.08	-0.04	-0.07	-0.06
	–	(0.09)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Mandatory Phase I Plant	–	0.35***	0.18**	0.21***	0.15**	0.17***	0.21***
	–	(0.12)	(0.08)	(0.08)	(0.06)	(0.06)	(0.05)
Scrubber	–	0.06	0.08	0.13	0.07	0.10	0.13*
	–	(0.20)	(0.09)	(0.09)	(0.09)	(0.09)	(0.07)
Maximum Sulfur Allowed	–	0.14**	0.07*	0.08*	0.07*	0.07**	0.05**
	–	(0.07)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)
Z-Ash	–	0.10**	0.04*	0.05*	0.07***	0.08***	0.03
	–	(0.05)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Z-Sulfur	–	0.01	0.01	0.00	-0.00	-0.00	0.01
	–	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Z-Btu	–	-0.21	-0.13*	-0.12**	-0.15**	-0.15**	-0.10***
	–	(0.14)	(0.07)	(0.06)	(0.07)	(0.06)	(0.03)
Underground Mine	–	-0.33	-0.16	-0.10	-0.16	-0.11	-0.14*
	–	(0.22)	(0.12)	(0.11)	(0.11)	(0.11)	(0.08)
Interior Mine	–	0.14	0.01	0.09	0.12	0.22	0.12*
	–	(0.25)	(0.16)	(0.16)	(0.16)	(0.15)	(0.06)
Western Mine	–	0.43**	0.23**	0.30***	0.30***	0.36***	0.32***
	–	(0.17)	(0.09)	(0.09)	(0.08)	(0.08)	(0.06)
Log of Utilization Variability	–	-0.02	-0.01	-0.03	0.04	-0.00	-0.00
	–	(0.07)	(0.04)	(0.03)	(0.04)	(0.03)	(0.02)
Year Signed	–	0.04***	0.00	0.01	0.01	0.03**	0.02*
	–	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	–	–	-3.30	-23.65	-23.24	-57.52**	-34.80
	–	–	(22.30)	(23.44)	(28.84)	(25.59)	(21.18)
Observations	1090	1037	1201	1201	1008	1008	1008
R^2	–	–	–	–	0.27	0.25	–
Test for instruments' relevance	–	–	126.61	139.83	24.53	25.52	90.81
p-value	–	–	0.00	0.00	0.00	0.00	0.00

Notes: *, **, *** indicate 10%, 5% and 1% statistical significance, respectively. Time period for all regressions is 1990-2001. Standard errors corrected for State-level serial correlation in parentheses. In (1), (2), (3), (5), and (7) treatment status is assigned based on the signatory plant being located in a deregulated state, after deregulation legislation is passed. In (4) and (6) treatment status is assigned based on the EIA Form 923 identifiers, after the law pass. Rigidity is treated everywhere as a categorical variable, except in (5) and (6), where it is treated as continuous. In (3)-(7), the instruments for Duration are: Mine Dedicated Assets, Plant Dedicated Assets, and Minimum Quantity. In (3), (4), and (7) we report the χ^2 test statistic for the joint significance of the instruments, in (5) and (6) the Angrist-Pischke F test of excluded instruments. In (3) and (4) the endogenous matching (EM) equation specifies the Log of Utilization Variability as a function of Interior, Western Mine, and State dummies, as well as State dummies interactions with Z-Ash, Z-Sulfur, Z-Btu, and Underground Mine. In (3) and (4) the F-test for the matching equation is 54.94 (p-value=0.00), the adjusted R^2 is 0.85. In (5) Hansen's test fails to reject the null that the instruments are valid (J-test=5.02, p-value=0.17), the model passes the Kleinbergen-Paap under-identification test (LM statistic=15.25, p-value=0.00); the Kleinbergen-Paap Wald test for weak identification is 24.53. In (6), Hansen's J is 4.78 (p-value=0.19), the Kleinbergen-Paap under-identification test statistic is 14.67 (p-value=0.00), the Kleinbergen-Paap Wald test for weak identification is 25.52.

Table 5: Contract Choice – Duration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	OLS	OLS	IV	IV	IV	3SLS
	(State)	(State)	(Plant)	(State)	(Plant)	(State)	(State)
Post Restructuring	-0.26***	0.07	0.12	0.12	0.11	0.17	0.16*
	(0.05)	(0.09)	(0.10)	(0.09)	(0.08)	(0.12)	(0.09)
Restructured State	0.09	-0.05	-0.17***	-0.13	-0.21***	-0.33***	-0.20***
	(0.11)	(0.09)	(0.06)	(0.09)	(0.07)	(0.11)	(0.06)
Rigidity	–	-0.28***	-0.29***	-0.41***	-0.44***	-0.96***	-0.59***
	–	(0.06)	(0.06)	(0.15)	(0.16)	(0.24)	(0.09)
Previous Interaction	–	-0.02	-0.01	-0.02	-0.01	0.01	-0.01
	–	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)
Post SO_2 Regulation	–	1.04***	1.02***	0.96***	0.87***	0.60*	0.82***
	–	(0.17)	(0.17)	(0.19)	(0.21)	(0.34)	(0.18)
Mandatory Phase I Plant	–	0.16**	0.17**	0.14**	0.21***	0.29***	0.21***
	–	(0.07)	(0.07)	(0.07)	(0.08)	(0.06)	(0.05)
Scrubber	–	0.19	0.20*	0.23**	0.23**	0.26**	0.22***
	–	(0.12)	(0.11)	(0.11)	(0.11)	(0.12)	(0.07)
Mine Dedicated Assets	–	0.14*	0.14	0.20***	0.18**	0.05	0.12*
	–	(0.08)	(0.09)	(0.07)	(0.07)	(0.11)	(0.07)
Plant Dedicated Assets	–	-0.09	-0.09	-0.10	-0.05	-0.03	-0.05
	–	(0.08)	(0.08)	(0.07)	(0.07)	(0.11)	(0.07)
Multiple Mode of Delivery	–	0.15**	0.16**	0.15**	0.17***	0.23**	0.08**
	–	(0.07)	(0.07)	(0.06)	(0.06)	(0.09)	(0.04)
Minimum Quantity	–	0.28***	0.28***	0.25***	0.26***	0.25***	0.26***
	–	(0.04)	(0.04)	(0.03)	(0.04)	(0.06)	(0.03)
Constant	1.19***	2.09***	2.12***	2.53***	2.59***	4.28***	3.15***
	(0.09)	(0.25)	(0.23)	(0.51)	(0.53)	(0.84)	(0.31)
Observations	1234	1033	1033	1008	1008	1020	1008
R^2	0.01	–	–	0.30	0.30	0.17	0.22
Test for instruments' relevance	–	–	–	3.62	4.91	11.53	18.10
p-value	–	–	–	0.00	0.00	0.00	0.00

Notes: *, **, *** indicate 10%, 5% and 1% statistical significance, respectively. Time period for all regressions is 1990-2001. Vintage dummies are included in all regressions. Standard errors corrected for State-level serial correlation in parentheses. In (1), (2), (4), (6) and (7) treatment status is assigned based on the signatory plant being located in a deregulated state, after deregulation legislation is passed. In (3) and (5) treatment status is assigned based on the FERC identifiers, after the law pass. In (4) and (5), the instruments for Rigidity are: Z-Ash, Z-Sulfur, Z-Btu, Underground Mine, Log of Utilization Variability. For (4) and (5), the F test for omitted instruments are reported. In (4), Hansen's test fails to reject the null that the instruments are valid (J-test=6.49, p-value=0.17), the model passes both the Kleinbergen-Paap under-identification test (LM statistic=11.54, p-value=0.04) and the Kleibergen-Paap Wald F test for weak identification (F-test=3.62). In (5), Hansen's test fails to reject the null that the instruments are valid (J-test=6.47, p-value=0.17), the model passes both the Kleinbergen-Paap under-identification test (LM statistic=12.35, p-value=0.03) and the Cragg-Donald Wald F test for weak identification (F-test=4.91). In (6), the only instrument for Rigidity is Western Mine, the F test for excluded instruments is reported in the table. In (6), the model passes both the Kleinbergen-Paap under-identification test (LM statistic=8.34, p-value=0.00) and the Kleinbergen-Paap test for weak identification (F-test=11.53).

Table 6: Test of Stable Unit Treatment Value Assumption (SUTVA)

	(1)	(2)	(3)
	Ordered Probit	IV-Oprobit	IV
Duration	-0.87***	-0.35***	-0.46***
	(0.08)	(0.07)	(0.08)
Mine Selling to Both Plant Types	0.07	-0.03	-0.03
	(0.23)	(0.10)	(0.06)
Previous Interaction	0.24	0.06	0.05
	(0.15)	(0.06)	(0.07)
Post SO_2 Regulation	-0.09	-0.04	-0.02
	(0.13)	(0.06)	(0.05)
Mandatory Phase I Plant	0.21	0.11	0.13*
	(0.15)	(0.09)	(0.07)
Z-Ash	0.10*	0.03**	0.02
	(0.06)	(0.02)	(0.02)
Z-Sulfur	-0.03	-0.04	-0.04
	(0.06)	(0.03)	(0.03)
Z-Btu	-0.12	-0.04	-0.05
	(0.09)	(0.05)	(0.03)
Maximum Sulfur Allowed	0.18**	0.11**	0.13***
	(0.09)	(0.05)	(0.04)
Scrubber	0.18	0.10	0.14**
	(0.16)	(0.10)	(0.06)
Underground Mine	-0.53**	-0.24*	-0.29**
	(0.27)	(0.14)	(0.12)
Interior Mine	0.03	-0.08	-0.16
	(0.26)	(0.20)	(0.14)
Western Mine	0.43***	0.20***	0.18***
	(0.15)	(0.08)	(0.07)
Log of Utilization Variability	-0.05	0.01	0.03
	(0.06)	(0.04)	(0.03)
Year Signed	0.03***	0.01	0.00
	(0.00)	(0.01)	(0.01)
Constant	–	-16.87	1.89
	–	(22.06)	(24.04)
Observations	558	635	541
R^2	–	–	0.26
Test for instruments' relevance	–	92.20	16.45
p-value	–	0.00	0.00

Notes: *, **, *** indicate 10%, 5% and 1% statistical significance, respectively. Time period for all regressions is 1990-2001. Standard errors corrected for State-level serial correlation in parentheses. In (2)-(3), the Instruments for Duration are: Mine Dedicated Assets, Plant Dedicated Assets, and Minimum Quantity. In (3), Rigidity is treated as a continuous variable, Duration as not truncated; in this model Hansen's test fails to reject the null that the instruments are valid (J-test=1.078, p-value=0.58), the model passes both the Kleinbergen-Paap underidentification test (LM statistic=10.96, p-value=0.01) and the Kleibergen-Paap Wald test for weak identification (F-test=16.45).

Table 7: Mine Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mine Sample:	All	Non-Western	All	Non-Western	All	Non-Western	All	Non-Western
Coal to Restructured State	1756.47**	1615.21***	–	–	1538.04**	1391.76***	–	–
	(688.15)	(496.27)	–	–	(657.43)	(454.52)	–	–
Share of coal to Restructure State	–	–	-9838.95*	-7164.17	–	–	-10351.84**	-7825.42
	–	–	(5351.76)	(5406.67)	–	–	(4893.51)	(4954.92)
(Share of coal to Restructure State)^2	–	–	19609.16**	17255.56*	–	–	19394.65**	17275.90**
	–	–	(9223.22)	(9571.67)	–	–	(8166.53)	(8607.24)
Injuries per worker	–	–	–	–	484.82	917.52	654.14	845.71
	–	–	–	–	(1078.29)	(1003.72)	(1268.38)	(1254.88)
(Injuries per worker)^2	–	–	–	–	-81.78	-128.15	-98.91	-118.22
	–	–	–	–	(115.14)	(105.56)	(134.21)	(132.02)
Continuous production	–	–	–	–	8316.31***	7156.29***	8472.80***	7197.81***
	–	–	–	–	(1561.90)	(2208.52)	(1528.46)	(1945.18)
(Continuous production)^2	–	–	–	–	-5240.56***	-5063.61**	-5837.45***	-5071.47***
	–	–	–	–	(1346.69)	(1958.67)	(1390.30)	(1744.98)
Constant	7224.07***	5186.44***	7469.52***	5323.21***	4296.42***	2842.19***	4721.35***	2963.08***
	(200.22)	(160.02)	(201.66)	(160.75)	(523.03)	(620.22)	(495.10)	(543.86)
Observations	2793	1789	2527	1652	2793	1789	2527	1652
R^2	0.12	0.17	0.16	0.24	0.16	0.21	0.19	0.28
F-test	–	–	–	–	13.30	11.80	9.56	10.17
p-value	–	–	–	–	0.00	0.00	0.00	0.00

Notes: *, **, *** indicate 10%, 5% and 1% statistical significance, respectively. Time period is 1990-2001. Standard errors clustered at the county-state level in parentheses. Year dummies are included in all regressions but not shown. Odd columns refer to the whole sample, even columns refer to a sample restricted that excludes western mines. The F-test entries refer to the test of the hypothesis that the coefficient on `Injuries per worker` and `(Injuries per worker)`^{2} be jointly insignificant. The productivity (in short tons per employee) of the average firm in the control group at the time of treatment in 1996 was 8817 for the whole sample and 6567 for the restricted sample. Using the estimated coefficients in (5) and (6), the increase in productivity due to sales to plants in restructured states is 17.4% and 21.2%, respectively.

Table 8: Average productivity of continuing and discontinuing mines (million short tons/employee, 1990-1995).

Year	Continuing (A)	Discontinuing (B)	t-statistic	$Pr(A-B>0)$
1990	6949.06	7143.93	-0.15	0.56
1991	7123.79	6949.96	0.13	0.45
1992	7527.05	7252.52	0.20	0.43
1993	7771.06	7919.12	-0.10	0.54
1994	8429.09	8459.41	-0.02	0.51
1995	8978.05	8667.59	0.17	0.43

Notes: The Table reports the average productivity per year among counties which continue to supply to restructured generators and those which discontinue supplying restructured generators after restructuring, the t-statistic for the test of difference in means, and the associated p-values for the one-sided hypothesis that $A > B$.

Table 9: Contract Renegotiations

	Poisson
	Time to Renegotiation
Rigidity	-0.19***
	(0.02)
Duration	0.03***
	(0.01)
Post Restructuring	-0.03
	(0.05)
Mine-mouth Plant	0.36*
	(0.21)
Constant	1.96***
	(0.10)
Observations	1,826
Psuedo R^2	0.12

Notes: *, **, *** indicate 10%, 5% and 1% statistical significance, respectively. Robust standard errors in parentheses. Time period is 1990-2001. Vintage dummies included but not shown.