PRODUCTIVITY AND ACQUISITIONS IN U.S. COAL MINING

by

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Abstract

This paper extends the literature on the productivity incentives for mergers and acquisitions. We develop a stochastic matching model that describes the conditions under which a coal mine will change owners. This model suggests two empirically testable hypotheses: i. acquired mines will exhibit low productivity prior to being acquired relative to non-acquired mines and ii. extant acquired mines will show post-acquisition productivity improvements over their pre-acquisition productivity levels. Using a unique micro data set on the universe of U.S. coal mines observed from 1978 to 1996, it is estimated that acquired coal mines are significantly less productive than non-acquired mines prior to having been acquired. Additionally, there is observable and significant evidence of post-acquisition productivity improvements. Finally, it is found that having been acquired positively and significantly influences the likelihood that a coal mine fails.

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I. Introduction

Firms regularly alter their physical and financial configurations as optimal responses to changing economic conditions. Depending on the prevailing circumstances, firms can open de novo facilities or scrap existing ones. They can expand into new product lines or exit current ones. Alternatively, mergers and acquisitions are an often used method for affecting the changes in firm configurations. In the United States from 1963 to 1997, the number of completed acquisition transactions ranges from a low of 1,361 in 1963 to a high of 7,800 in 1997. Additionally, the nominal value of these transactions ranges from $11.8 billion in 1975 to $657.1 billion in 1997; from 1970 to 1997, the value of completed mergers and acquisitions increased 1407.11%--far outpacing any price index or even the growth in the S&P 500 index over the same interval of time.[1]

This seemingly increasing reliance on mergers and acquisitions to affect changes in firm structure has sparked debate over the motivations for and consequences of mergers and acquisitions. Much of the early concern emphasized market power and public interest issues (Stigler, 1950). While it is likely that the desire for market power represents some small part of the motivation for mergers and acquisitions, it is unclear in general that the anticipated gains have materialized as industrial concentration had not markedly increased during the two most recent merger waves. Still, as a strategic goal, one cannot discount entirely the search for market control as representing some part of the motivation behind mergers and acquisitions.

[1] SOURCE: Mergerstat Historical Trends. See the website http://www.mergerstat.com/mod01/mod01-04.htm. The number of completed mergers and acquisitions represents the number of completed merger and acquisition transactions representing at least one million dollars, and the values stated are for those transactions where a price was stated.

More recently, interest has focused on the implications which merger and acquisition activities have on the relationships between managers and owners. These concerns involve what may motivate managers to acquire whole or parts of other businesses. These motivations include strengthening managerial control over financial resources by siphoning off free cash flow from dividend payouts (Jensen, 1988; Roll, 1986), empire building (Baumol, 1987; Mueller, 1969 and 1993), and management entrenchment through maximizing objectives other than owner wealth (Shleifer and Vishny, 1989; Morck, Schleifer, and Vishny, 1990; Brandenburger and Polak, 1996). Common to all of these possible motivations for mergers and acquisitions is that they represent unchecked divergences between the interests of owners and managers.[2]

All of the above potential sources of the value gains represent uncompensated transfers of wealth from one group to another, and in this way, they represent potential sources of welfare loss. However, it is possible to have gains to mergers and acquisitions that represent true value creations. Jarrell, Brickley, and Netter (1988), Jensen and Ruback (1983) and Jensen (1988) argue that since there is no significant statistical evidence of transfer effects, the sources of the gains come from productivity windfalls resulting from freeing resources from poorly performing managers. To this end, there will be an active market among management teams for the control of corporate resources (Manne, 1965; Meade, 1968; Jensen and Ruback, 1983). Acquiring

[2] Another direction the literature has taken is to argue that the gains from mergers and acquisitions could come from unfunded transfers from implicit labor contracts. See Summers and Schleifer (1987) and Ritter and Taylor (1999). Though an interesting claim, there is no statistical evidence that this sort of effect is present. Brown and Medoff (1987) find that employment and wages actually increase in acquired plants in Michigan. Additionally, McGuckin, Nguyen, and Reznek (1995) find that employment and wages increase in acquired manufacturing plants in the food and beverage industry. These findings are inconsistent with the notion that the gains to mergers and acquisitions come from violating implicit labor contracts.

firms will target less productive firms or parts of firms, acquire them, replace the management structure, and institute programs to raise productivity.

The empirical literature on the productivity incentive for mergers and acquisitions is relatively sparse. Two general approaches have been taken. The first is to examine the pre- and post-acquisition productivity performance, and the second approach is to examine what affects the likelihood that an asset experiences an ownership change.

As an example of the pre- and post-acquisition event studies literature, Lichtenberg and Siegel (1987, 1990, 1992a, 1992b) examine the relationship between productivity and ownership change using a matching model that suggests that if productivity is a measure of the goodness-of-fit between management teams and assets, then low (high) productivity implies a poor (good) fit between management and a particular manufacturing plant, and thereby the probability of experiencing an ownership change rises (declines).

Using a balanced panel of manufacturing plants observed in the Census Bureau's Longitudinal Research Database, these authors look for productivity differences between acquired and non-acquired plants.[3] Total Factor Productivity (TFP) is assumed to capture the quality of the match between owners and assets. In reduced form regressions, they find that acquired plants are less productive prior to being acquired than non-acquired plants—which is consistent with their matching story. Additionally, their panel exhibits post-acquisition productivity gains—to the extent that plants surviving seven years after having been acquired are

[3] Lichtenberg and Siegel use the Wall Street Journal index to identify manufacturing plants that have undergone an acquisition or a leveraged buy-out.

not statistically different in terms of productivity than non-acquired plants; prior to being acquired, these plants performed significantly worse than non-acquired plants.

More recently, Maksimovic and Phillips (1999) use a simple neoclassical model of firm organization and profit maximization to examine the productivity-acquisition nexus. Using the Census Bureau's Longitudinal Research Database for the period 1974 to 1992, they find significant productivity gains in acquired assets in U.S. manufacturing plants—especially from assets moving from peripheral divisions of the selling firm to the main division of the purchasing firm. They find also that these productivity gains are significantly higher the more productive the acquiring firm.

The second general approach in examining the productivity incentive for mergers and acquisitions is to examine what influences the likelihood of an asset changing owners. McGuckin and Nguyen (1995) examine a sample of food and beverage plants observed in the Census Bureau's Longitudinal Research Database that change owners between 1977 and 1982. In probit regressions aimed at modeling the probability that a plant changes ownership, these authors find that there is a statistically significant positive relationship between productivity and the likelihood of being acquired[4]—suggesting in part that *high* productivity plants are *more* likely to be acquired than low productivity plants.[5]

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[4] Using financial data, Ravenscraft and Scherer (1987) and Matsusaka (1993a, 1993b) find that firms involved in mergers and acquisitions are highly profitable prior to the buyout and that there were little if any financially measured gains post-merger.

[5] McGuckin and Nguyen (1995) find similar results to Lichtenberg and Siegel when using a balanced panel of plants constructed from the Annual Survey of Manufactures; when using their unbalanced panel, however, the result is reversed to suggest that higher productivity plants are more likely to be acquired. This finding is interpreted as evidence that the Lichtenberg-Siegel estimates suffer from a sample biased in favor of large plants.

This paper extends the literature on the productivity incentive for mergers and acquisitions. The contributions here are twofold. First, productivity differences using microdata over time are examined in order to investigate whether the productivity differences between acquired and non-acquired assets are fundamentally related to the acquisition event. Second, the findings of Lichtenberg and Siegel and of Maksimovic and Phillips are confirmed in that acquired coal mines are between 5.23% and 12.46% less productive than non-acquired mines prior to the acquisition, and there are significant post-acquisition productivity gains.

In the empirical analysis, a data set on the U.S. coal mining industry containing observations on the statistical universe of coal mines from 1978 to 1996 is used. The benefits of these data are threefold. First, ownership changes of coal mines are observed at a number of points in time. Thus, is it possible able to examine whether the observed productivity differences between acquired and non-acquired coal mines manifest themselves repeatedly. Second, these data are not contained in the manufacturing universe. Virtually all of the empirical studies examining the relationships between ownership changes and productivity come from manufacturing data.

Third, the U.S. coal mining industry has undergone a good deal of acquisition activity over time. Between 5.8% and 12.2% of mines are involved either in whole company acquisitions or partial company carve-outs. This activity is a product of a number of influences—not the least of which is the decline of the steel industry in the United States. U.S. iron, coke, and steel companies suffered a good deal during the recession of the early 1980s. As the production of coke and pig iron declined, companies needed less coal as a factor of production and at the same time had (generally) poor cash flows. Divesting of coal divisions is a natural mechanism to correct both problems. U.S. Steel, Republic Steel, ARMCO, LTV Corporation, and others divested much of their coal properties. For example, Inland Steel sold its coal assets to Consolidation Coal in 1986.

Additionally, large oil and gas conglomerates sold many coal properties to concentrate on their "core" businesses. Houston Natural Gas sold Ziegler Coal Company to an investment group, Amoco spun off Cyprus Minerals, British Petroleum sold Old Ben Coal to Ziegler, and Eastern Gas and Fuel Associates sold its mines to Peabody—to name a few of these such transactions. Table 1 presents some selected acquisitions that occurred during the 1978 to 1992 period; to be sure, the transactions listed on Table 1 are separated into both whole company purchases and partial company "carve-outs." For a very informative and more complete survey of these events, see <u>The Changing Structure of the U.S. Coal Industry: An Update</u>.

In the next section, a stochastic matching model very similar to that used by Lichtenberg and Siegel is presented. Section III details the sources of data for the U.S. coal mining industry and also presents some interesting features of the productivity series in this industry. Section IV details the empirical analysis. Section V concludes.

II. Acquisitions and Productivity

To organize the empirical agenda, a market search model similar to Jovanovic (1979) is adapted. This adaptation (which is very similar to the setup used by Lichtenberg and Siegel) implies that mergers and acquisitions are mechanisms to correct deteriorating productivity performance. Productivity performance provides owners with a valuable signal about the quality of the match between the owner and the property. If productivity is declining, then current owners infer that there is some intrinsic incompatibility between the owner and the coal mine. If an owner's comparative advantage with a given mine is unknown initially, then it is only through market tenure that true relative productivity is revealed. The effect is that a heterogeneous group of owners constantly re-examines the "fit" between an owner and a coal mine.

When deciding whether or not to purchase a coal mine, the purchaser has incomplete information about how well that operation can be managed, and it is reasonable to assume that purchasers are interested in maintaining control only over operations that can be managed effectively. Hence, a buyer constantly evaluates opening or acquiring decisions, and the longer a mine is operated, the more information is gained about the quality of the match between owner and coal mine.

The process would proceed in the following way: mines and owners are matched initially. The quality of this match (assume to be indexed by productivity) varies randomly. Lower productivity provides a signal that the quality of the match between owner and mine is low. Further, lower productivity implies that the mine would be more likely to change owners—representing the desire of an owner to maintain control over operations that can be operated effectively. If some lower bound of productivity is reached, a current owner will divest or close any mine that cannot be operated effectively. A mine is sold or closed, and the same sort of constant evaluation and re-evaluation of the comparative advantage of operating a coal mine ensues with the new owner(s).

The theoretical considerations surrounding the merger and acquisition process can be expressed formally using simple stochastic dynamic programming arguments. The problem is twofold: to describe the decision process of the current owners and to describe the decision process of a potential purchaser of a mine, given that it is offered for sale. First assume that productivity evolves according to the following stochastic process:[6]

(1) $x(t) = \alpha t + \sigma z(t) \;\forall\; t > 0$

where α and σ are constants, and $\sigma>0$. z(t) is a standard Wiener process with time independent increments. Assume that σ is the same for each owner-mine match and that in general α, which is learned over time, differs across owner-mine matches. In this way, α can be interpreted as an index of the quality of the match between the owner of a mine and the mine itself. High realizations of α denote relatively good match between owner and mine, while a low realization of α represents a relatively poor match. Let α be normally distributed and assume that changing owners involves drawing a new value of α from the distribution where successive draws are independent.[7]

Firms maximize the expectation of net revenues discounted by the rate, ρ. Let π(x;u,t) denote the net revenues as a function of the random state variable x and a vector of exogenous parameters, u. Assume that $\pi(\cdot)$ increases in x and that x and x' (where x'=x+dx) are positively serially correlated such that x is first-order stochastically dominated by x'. Let Λ(x'|x) represent the cumulative density function of x. One should be clear that all heterogeneity is driven by

[6] Dixit and Pindyck (1994) use a very similar model throughout their text. For a detailed discussion on the properties of these sorts of models, the reader is referred to that text.
[7] Another possibility is that there could exist "bad" mines—mines that are located in places that are difficult to mine, that are plagued with unionization problems, etc. In cases such as this, there would be serial

different realizations of the productivity state variable, x, which in turn is a function of the realization of the goodness-of-fit between an owner and a mine, α.

Current owners compare the expected value of continuing control over a mine versus the expected value of the payoff from selling or scrapping a mine; denote the latter as $\Omega(x)$ (the payoff from selling a mine) and θ (the scrap value of a mine), respectively. If $\Omega(x)>\theta$, then a current owner who does not desire to continue with a mine would sell the mine to another owner, but if $\theta>\Omega(x)$, then the current owner would find it better to close a mine and recoup its exogenously determined scrap value. Assume that $\Omega(x)$ is known to all firms.

Formally, current owners make the intertemporal optimization calculation suggested by the following Bellman Equation:

$$V(x) = \max\left\{\boldsymbol{q}, \Omega(x),\ \boldsymbol{p}(x;u,t) + (1+\boldsymbol{r})^{-1} E\left[V(x'|x)\right]\right\} \tag{2}$$

where x'=x+dx.[8] This problem is essentially one of an optimal stopping calculation in the sense that an owner decides when to cease operating and/or owning a particular coal mine. The solution techniques to this class of problems are well known, and for ease of exposition, only the relevant decisions are discussed here. Suppose there is a single-valued threshold level, x^*, which demarcates the continuation region in (x,t) space from the stopping region. Realizations of $x>x^*$ will result in the present owner continuing ownership, while values of $x<x^*$ will result in

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correlation among the draws on α. Although this could be a very real possibility, it does not present any implications for the empirical agenda below since all of the estimates are from reduced-form regressions.

8 Making the resale value of a mine a function of its productivity requires two additional technical assumptions. First, there must be a value-matching property to the boundary condition; that is, in the stopping region, we have $V(\cdot)=\Omega(x)$. By continuity, we can impose $V(x^*;\cdot)=\Omega(x^*)$ where the function $x^*(\cdot)$ represents a free-boundary. However, this formulation also implies curvature in $\Omega(x)$—suggesting a potential continuity problem at the boundary. To avoid this problem, we assume that $V(\cdot)$ and $\Omega(x)$ meet tangentially at the boundary: $\partial V(x^*(t),t)/\partial x=\partial\Omega(x^*(t),t)/\partial x$—which is known as the high-order contact property. Dixit and Pindyck (1994) have a detailed discussion of these properties.

the divestiture or closure of the mine. It is clear that the present owner will continue ownership and operation if the maximum is attained at the third argument of equation (2) (when Ω(x)>θ); that is, if

$$(3)\quad p(x;u,t)+(1+r)^{-1}\int V(x')d\Lambda(x'|x)>\Omega(x)$$

is true. Optimal stopping occurs if the opposite inequality holds—which is to say that the maximum of (2) is obtained at either of the first two arguments.[9]

This suggests that low realizations of the random productivity state variable, to the extent that those low realizations are manifest in lower profitability, lead to the divestiture or scrapping of a mine. Here is our first empirically testable hypothesis: ownership change and exit are negatively related to productivity. Hence, taken to the data, one should observe that mines changing owners (or exiting) are less productive than those that do not.

The potential owner's problem also is simple. Keep in mind that the new owner takes a draw on α which is independent of previous draws, and now the evolution of the random state variable, x, begins anew. So, the problem for the new owner when deciding whether to purchase a mine is to compare the expected profitability with the sale price of the mine. Formally, if the expected profitability of the new owner is at least as great as the sale price of the mine, then the potential owner will purchase the mine; that is, if

$$(4)\quad V(x)=\max\left\{(1+r)^{-1}E\left[V(x')\right]\right\}\geq\Omega(x)+c$$

where c is a parametrically determined (possibly trivial) constant representing sunk transactions costs, etc, then the mine will be purchased. Though it does not follow immediately from (4), mine acquisitions ought to result in productivity improvements for those mines. Since productivity is assumed to be randomly distributed, the expected value of a new match is higher on average than the realized value of old matches—given that subsequent owners draw from the same distribution as previous owners.

Two testable implications arise from these theoretical considerations. First, poor matches induce ownership changes. Deteriorating productivity at a mine indicates that current owners possess a comparative disadvantage with that mine relative to other current owners, and the owner likely will divest of or close that mine. Hence, one ought to see that acquired mines have lower productivity prior to the acquisition than non-acquired mines. Second, changes in ownership should result in productivity improvements over pre-acquisition levels, other things equal. This prediction reflects the notion that the expected value of a new match is on average higher than the realized value of an old match.

III. Data and Measurement

This section outlines the data used to classify acquisitions in the coal mining industry as well as the data used to measure mine productivity. Additionally, some details are given that describe how productivity is measured and how productivity differs across a number of important dimensions.

A. The Data

The data used in this analysis come from the Mine Safety and Health Administration of the U.S. Department of Labor. These data contain the statistical universe of coal mines in a

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[9] It is simple to show that x^* exists uniquely. For a very simple and intuitive proof, see Dixit and Pindyck

year and are collected under the regulatory and oversight authority of the Mine Safety and Health Administration. Among other things, these data contain information on employment, hours, production, the number of injuries at a mine, and certain descriptive/classificatory information for each mine. A mine is tracked using a unique mine identification number that allows intertemporal linkages of mine observations.

For present purposes, a sample of mines observed from 1978 to 1996 is used. Each mine must have a classification code indicating that it was active in a year and must have had positive employment, hours, and production; additionally, coal processing facilities and coal contractors are not included. This leaves a large number of coal mines in each sample year. This industry has undergone a number of very unique adjustments over time—some of which are detailed in Figure 1. Figure 1 documents the patterns of mine employment, production, and hours over time. Production has increased tremendously over the sample period. In 1978, the industry produced just around 600 million short tons of coal, and at the end of the sample in 1996, industry production was just under 1 billion short tons—a 98% increase in production over the 1978 level. One interesting aspect to this increase is that it happened while there was a general decline in the number of workers employed and hours worked; this equates to large gains in labor productivity at the industry level.

B. Measuring Productivity

Productivity is measured for each active mine in the industry for each year of the sample. Because of data limitations regarding the employment of non-labor factors, only labor productivity is observed—which is measured as short tons of coal produced per worker hour.

(1994).

Admittedly, this measure of productivity lacks the completeness of broader multi-factor productivity measures, but it is believed that labor productivity will serve as a good proxy for total factor productivity for a couple of reasons.

First, labor represents the largest share of inputs in terms of output value. From 1948 to 1991, labor inputs accounted for approximately 40% of output value, materials about 30%, and capital and energy account for about 15% each.[10] There has been a slight tendency for labor's share of output value to decline while there is a slight trend for material's share of output value to rise. Berndt and Ellerman (1997) document a significant labor-saving bias to technical change in the coal industry. This bias in technical change also could explain divergences between total factor productivity and labor productivity. [11]

Before turning to the empirical analysis, there are a few important observations to make about exogenous differences in productivity that are not necessarily related to acquisitions. First, Figure 2 shows that there are clear differences in productivity stemming from differences in the type of mine.[12] Ignoring the type of mine as an explanation for observable differences in labor productivity among coal mines could lead one to misstate the importance of ownership change to differences in labor productivity—representing an omitted variables bias. Second, Figure 2 also shows a clear upward trend in labor productivity over the sample period; this

[10] I offer my thanks to Dale Jorgenson and Kevin Stiroh for making these industry aggregate data series available.
[11] It should be noted that simple time series correlations between Jorgenson's total factor productivity series and the labor productivity series used here are estimated at +0.9377 (p<0.0001).
[12] The type of mine is thought of as representing an exogenous constraint on the type of technology used when mining coal. That is, given the geographic and geologic characteristics of mines, the type of coal extraction technique is at least partly determined. Underground mines because of their particular exogenous characteristics can be mined only in certain ways—irrespective of an owner's comparative advantage, and likewise for surface mines.

result is true both for the industry aggregate and for the mine type sub-aggregates. This fact suggests that year effects are important controls as well.

Third, Figure 3 plots the productivity series separately by geographic region.[13] Generally speaking, there are three broadly defined coal producing regions: the Appalachian Region, the Interior Region, and the Western Region. Appalachian mines typically are smaller, underground, and more labor intensive. Interior mines generally are larger than the typical Appalachian mine—though smaller than the average Western Region mine. Interior mines are slightly less labor intensive and are divided between surface and underground mines. Finally, the Western Coal Region is populated by remarkably larger surface mines with thick coal seams located near the surface. Figure 3 makes clear that there are distinct productivity differences between coal producing regions, and in the productivity equation, it will be important to control for this regional effect.

C. Identifying Acquisitions

Identifying acquisitions in the coal mining industry requires a second data source from the Mine Safety and Health Administration.[14] The records in this file are identified with the same unique mine identification numbers mentioned above—making it possible to link acquisition indicators to the production and employment files. In addition to other information relevant to the assessment of fines and fees, this data set tracks the ownership of all coal mines by recording the beginning and ending dates of ownership regimes. Changes in ownership are

[13] Joskow (1987) adds this control to his analysis of price contracts in the U.S. coal mining industry.
[14] Specifically, this file is the Coal Information File and is maintained by the Office of Assessments, U.S. Mine Safety and Health Administration. For a fee, the Office of Assessments will make various extracts of

indicated when there is an entry on the record listing an ending date to an ownership period. If there is a valid ending date (viz., an entry not showing a missing value code and an entry containing a real calendar value) to a regime (in year t) and a start date for a new regime (also in year t), then a mine is said to have been acquired in year t.[15] Given that determination, a dichotomous variable is created indicating that a mine was acquired in that year.

III. Empirical Analysis

Recall that the matching model presents two broad empirical hypotheses. For convenience, they are as follows: 1) mines that are acquired should exhibit lower productivity relative to mines that are not acquired and 2) extant acquired mines should exhibit post-acquisition productivity gains. Each of these hypotheses are examined and discussed in terms of the productivity incentive for acquisitions. Additionally, the role of acquisitions in coal mine failure is examined.

A. Pre-Acquisition Productivity Differences

To examine differences in productivity prior to acquisition, total annual worker hours for all active coal mines and total annual short tons of coal produced are observed. Denote these quantities H_{it} and Q_{it}, respectively for i=1,2,…N, t=1,2,…T. These are combined to form an index of labor productivity: Q_{it}/H_{it}—short tons of coal per worker hour. Additionally, a mine may be acquired in period t. Define this event as a dichotomous indicator variable, x_{it}, which is governed by the following rule:

this file available. I offer my thanks to the Carnegie Mellon Census Research Data Center for providing the financial resources to acquire these data.

[15] It is possible to determine the difference between changes in ownership and scrapping. Scrapped mines will not have a *valid* ending date listed in the sense that the ending date field for these mines will contain a missing value code.

$$x_{it} = \begin{cases} 1 \text{ if mine i is acquired in period t} \\ 0 \text{ otherwise.} \end{cases}$$

Recalling from the previous section that there are clear, observable differences in productivity attributable to the type of coal mine (i.e., underground or surface mine), time, and broadly defined coal producing regions, the following pooled ordinary least squares (OLS) model is estimated:

$$\text{(1)} \qquad \ln\left(\frac{Q_{it-1}}{H_{it-1}}\right) = \alpha + \beta x_{it} + \delta m_i + \sum_{t=1}^{18} \gamma_t d_t + \sum_{s=1}^{3} \phi_s r_{is} + \varepsilon_{it}$$

where x_{it} is the acquisition dummy, m_i is a dichotomous variable equally one if a mine is an underground mine, d_t are year effects, r_{is} are dichotomous variables representing each of the coal producing regions, and ε_{it} is Gaussian error independent over time and across coal mines. From Section II, it is expected that β ought to be negative—suggesting that acquired coal mines are less productive prior to being acquired. Additionally, δ ought to be negative representing that underground mines are less productive than surface coal mines. Finally, all of the γ_t and ϕ_s estimates ought to be negative (with the omitted classes being the last year (1996) and the Western coal region, respectively); this represents that the estimates of the remaining year and region effects are interpreted relative to the omitted class: earlier years have lower productivity than 1996, and the Interior and Appalachian mines are less productive (generally) than Western coal mines.

Column 1 of Table 2 presents the OLS estimates of this model. There are a number of things to note. First, controlling for the type of mine effect, year effects, and region specific effects, the estimates indicate that acquired coal mines are 12.46% less productive prior to being acquired than mines that were not acquired. This finding is consistent with the matching model of Section II. Next, consistent with Figure 2, all of the estimates on the time dummies are negative and significant—indicating that productivity has risen almost monotonically over the entire period The region specific effects also capture significant differences in productivity; these controls work as anticipated: relative to the Western Region mines, ceteris paribus, Appalachian mines are on average 68.8% less productive while Interior mines are on average 54.3% less productive. Finally, note that the estimate on m_i is highly significant and indicates that on average underground mines are about 31% less productive than surface mines—also consistent with Figure 2.

Ellerman, Stoker, and Berndt (1998) find significant evidence that the scale of a coal mining operation is an important determinant of productivity growth in U.S. coal mining.[16] Although it is unclear exactly how omitted size effects would bias the estimate of β, regressors are included to control for the size of a coal mine. Specifically, dummy variables for a mine's employment size quartile in a given year are created. The following pooled regression model is estimated by OLS:

$$(2) \qquad \ln\left(\frac{Q_{it-1}}{H_{it-1}}\right) = \alpha + \beta x_{it} + \delta m_i + \sum_{t=1}^{18} \gamma_t d_t + \sum_{s=1}^{3} \phi_s r_{is} + \sum_{j=1}^{4} \psi_j s_{jit} + \varepsilon_{it}$$

All of the regressors are the same as before, and the s_{jit} are dummies representing a mine's employment quartile in year t. Non-singularity requires that one of these dummies be omitted, and the largest quartile is chosen; the interpretations of the ψ_j, then, are relative to the largest

[16] Bailey, Hulten, and Campbell (1992) find that in manufacturing data, the size of a plant is an important determinant of productivity growth. Jensen and McGuckin (1997) present a detailed discussion of the known empirical regularities of U.S. manufacturing microdata—including size effects.

quartile. Column 2 of Table 2 lists the estimates of this model—again including the important type of mine effect, year effects, and region effects. Including these mine size effects does not qualitatively alter the conclusions of the base specification of Column 1. That is, even with these controls, it is estimated that acquired mines are 11.79% less productive than non-acquired mines. This finding also is consistent with the model in Section II.

It is very likely that there are other important, but unobservable, mine idiosyncrasies that drive productivity differences—like capital intensity, union status, mine age, et cetera. To examine the importance of these omitted mine-specific characteristics, the following error-components model is estimated:

$$(3) \qquad \ln\left(\frac{Q_{it-1}}{H_{it-1}}\right) = \beta x_{\mathrm{it}} + \sum_{\mathrm{t}=1}^{18} \gamma_{\mathrm{t}} d_t + \eta_{\mathrm{it}}$$

where η_{it} is an error term consisting of a mine-specific component and Gaussian error: $\eta_{it} = \nu_i + \varepsilon_{it}$. It is believed that ν_i captures the mine-specific idiosyncrasies that could lead to differences in productivity but that are unobservable in practice. In this model, some observable mine characteristics are omitted since there is no time variation with which to identify them, e.g., mine type and coal producing region; they are, however, part of the mine-specific component of η_{it}. Year effects, however, can be identified and are included as controls in this model. Column 3 of Table 2 lists the estimates of this error-components model. Again, the omitted year effect is 1996, and the estimates on the year effects are interpreted relative to that year. The estimate of β, controlling for year effects and mine-specific idiosyncrasies, shows that acquired mines are 5.23% less productive than non-acquired mines. Even when controlling for mine fixed effects and year effects, the empirical evidence is consistent with the theoretical predictions from Section II.

To put all of this into perspective then, all of the estimates suggest that prior to having been acquired, acquired coal mines are between 5.23% and 12.46% less productive than non-acquired mines. Irrespective of the sets of controls that are used to capture differences in productivity that are not attributable to acquisitions, acquired mines are found to be less productive ex ante than non-acquired mines. These findings are consistent with the predictions of Section II.[17]

B. Post-Acquisition Productivity Performance

The second theoretical prediction of Section II is that acquired mines ought to exhibit post-acquisition productivity gains. This reflects the notion that the expected value of a new owner-mine match is higher than the realized value the old match. To examine this issue, the productivity growth equations of the general form below are estimated by OLS:

$$(4) \qquad \%\Delta Y_{it} = \boldsymbol{a} + \boldsymbol{b}\mathrm{x}_{\mathrm{it}} + \boldsymbol{d}m_i + \sum_{t=1}^{18} \boldsymbol{g}_t d_t + \sum_{s=1}^{3} \boldsymbol{f}_s r_{is} + \boldsymbol{e}_{it}$$

$$(5) \qquad \%\Delta Y_{\mathrm{it}} = \boldsymbol{a} + \boldsymbol{b}\mathrm{x}_{\mathrm{it}} + \boldsymbol{d}m_i + \sum_{t=1}^{18} \boldsymbol{g}_t d_t + \sum_{s=1}^{3} \boldsymbol{f}_s r_{is} + \sum_{j=1}^{4} \boldsymbol{j}_j s_{jit} + \boldsymbol{e}_{it}$$

$$(6) \qquad \%\Delta Y_{\mathrm{it}} = \boldsymbol{b}\mathrm{x}_{\mathrm{it}} + \sum_{t=1}^{18} \boldsymbol{g}_t d_t + \boldsymbol{h}_{it} \text{ where } \boldsymbol{h}_{\mathrm{it}} = \boldsymbol{n}_i + \boldsymbol{e}_{it}$$

where Y_{it} is labor productivity measured as short tons of coal per worker hour. All three specifications are the same as in Table 2; the difference between those models and these is that the dependent variable is average annual productivity growth between the year of the acquisition and t+1, t+2, and t+3. Note also that the samples for these models are different than those of Table 2 in the sense that these samples are conditioned on survival. That is, to be in the sample supporting the productivity growth equation for a one year horizon, a mine must have survived after the acquisition for at least one period. The same is true for t+2 (t+3): a mine must have survived at least two (three) periods after the acquisition.

Table 3 presents the estimates of β for all nine regressions. In every case, the effect of the acquisition on productivity growth is positive and significant. For extant mines surviving at least one year after the acquisition, acquired mines' productivity growth is between 5.8% and 6.5% higher than non-acquired mines. Even at the three-year horizon, acquired mines have productivity growth between 2.5% and 3.4% higher than non-acquired mines. This evidence supports the theoretical prediction of Section II that extant acquired mines ought to exhibit positive productivity gains.

As would be expected, the magnitude of the acquisition effect declines in the time horizon away from the acquisition period. This is for two reasons. First, the material importance of any event would decline naturally in the time since that event. Second, sample selection bias likely enters the problem since the samples are limited to extant mines.[18] This bias would tend to understate the importance of the acquisition to productivity growth since

[17] The two OLS specifications also were estimated using more detailed geographic controls. That is, both models were estimated using state dummies and county dummies. In all four cases, the estimates on the change in ownership dummy increase in magnitude and are all significant at conventional levels.

[18] Comparing the different sample selection criteria, one observes that the estimates on the acquisition dummy decline by roughly half. In a very important paper on (among other things) the effects of sample selection bias on productivity estimates, Olley and Pakes (1996) find similar results in the sense that they

continuing mines tend to be more productive than failing mines—irrespective of whether or not they had been acquired. Still, even if such a bias is present in the data, the acquisition has a significant and positive impact on productivity growth—consistent with the theoretical prediction of Section II.

C. Post-Acquisition Death

While it appears that acquisitions work as a corrective force for extant mines that experienced deteriorating productivity (consistent with Section II), the story does not end there. That is, acquired mines tend to have higher failure rates than non-acquired mines—a finding somewhat at odds with the predictions of Section II. To address the issue of what role acquisitions play in mine closure, failure probits are estimated. One must be careful to control for effects that might influence the probability of failure that are not necessarily related to the acquisition event itself. To this end, the same controls are introduced as in the OLS regressions of Tables 2 and 3. Recall that these controls were important in determining productivity differences that were not related to acquisitions. Productivity also is included as a control to separate explicitly productivity effects from acquisition effects. Specifically, probit models of the following basic form are estimated:

$$\text{(7)} \qquad \Pr\{Y_{it+1} = 1\} = f(\alpha + \beta x_{it} + \chi p_{it} + \tau(x_{it} * p_{it}) + \delta m_i + \sum_{t=1}^{15} \gamma_t d_t + \sum_{s=1}^{3} \phi_s r_{is} + \varepsilon_{it})$$

where Y_{it+1} is a dichotomous variable equal to one if a coal mine closed in year t+1 and zero otherwise, p_t is a three-year moving average of the log of labor productivity, and all other

observe wild swings in the magnitudes of parameter estimates when moving from balanced panels to unbalanced panels.

controls are the same as before.[19] The estimate of τ on the interaction of the acquisition dummy and productivity gives some indication of whether productivity impacts on mine failure differently among acquired and non-acquired firms.[20]

Table 4 presents the direct estimates of equation 7 as well as a number of alternative specifications.[21] There are a number of things to note. First, though not reported, all of the probit models of Table 4 include year and region controls. These controls work qualitatively the same as before. That is, Western mines are less likely to fail than Interior mines which are less likely to fail than Appalachian mines (the omitted class); the year controls likely capture business cycle effects and do not lend themselves to easy interpretation relative to the omitted year (1981). Second, consistent with traditional models of industrial evolution, productivity is negatively and significantly related to the probability of mine failure. Third, Table 4 shows that larger mines are less likely to fail than smaller mines—given that the omitted size class is the

[19] To be sure, including a three-year moving average of labor productivity conditions the sample to those mines that had been active for three consecutive years. Mines that do not meet this criterion are excluded from the sample supporting Table 4. Additionally, the sample is limited to the years 1981 to 1995; this is because mines are not observed prior to 1978 or after 1996.

[20] The theoretical motivation for including this interaction comes from the idea that when a mine is acquired, the new owner takes a draw on α that is independent of previous draws, and the productivity process starts over—essentially implying that the mine is "new" at least from an information standpoint. Dunne, Roberts, and Samuelson (1989) argue that failure boundaries decline in age since older plants have more refined information about the distribution from which production cost expectations are drawn. This is an artifact of older plants having more observations on production costs than newer plants which tends to reduce the variance of the cost distribution: new information causes smaller revisions in cost expectations and hence reduces the exit threshold. As another alternative, Pakes and Ericson (1998) present a very simple example where hazard rates may rise and then fall in age; again, this suggests that there is reason to believe that age differences may have differential impacts on exit. Empirically, then, one needs to control for the interaction of the state variable and age when examining failure probabilities; the state variable (productivity) may impact differentially depending on the age of the mine (where "age" in this case is a function of having been acquired).

[21] The only differences between specifications 7 through 9 are the definitions of the acquisition event relative to the exit date. In specification 7, x_{it} is equal to one if a mine had been acquired in period t—recalling that the exit dummy is always dated in period t+1. Specification 8 has x_{it} equal to one if a mine had been acquired in period t *or* t-1 *or* t-2. Finally, specification 9 includes lags of x_{it} in order to show how the lagged effect of having been acquired influences period t+1 exit decisions.

smallest class. Fourth, underground coal mines are significantly more likely to fail than surface mines—likely because underground mines are generally less productive than surface mines. Fifth, the estimate on the interaction term is negative but not statistically significant; this suggests that productivity has the same impact on coal mine failure irrespective of whether a mine had been acquired or not. Finally, having been acquired within one to three years prior to the failure year significantly raises the probability that a coal mine fails relative to mines that were not acquired. These findings are somewhat at odds with the predictions of Section II.

To examine whether there are unobserved sources of serial correlation present that might lead one to overstate the relevance of acquisitions to coal mine failure, specifications 7 through 9 were re-estimated as random effects probit models; see Butler and Moffitt (1982). Referring to the columns in Table 4 labeled 10 through 12, this extra control does not qualitatively alter the results of the specifications that do not control for unobserved serial correlation. That is, it still is the case that acquisitions are significantly and positively related to the probability of mine failure—irrespective of the definition of the acquisition dummy. At the same time, the estimate of the serial correlation parameter (ρ) in a one-factorized multinomial probit model is significant at conventional levels indicating the presence of serial persistence among the participation patterns of coal mines. Again, these findings, *prima facie*, are somewhat at odds with the theoretical predictions of Section II.

That acquisition events are significantly and positively related to the probability of mine failure could be explained in a way that is not inconsistent with Section II; this finding could be an artifact of data limitations in the sense that *firms* are not uniquely identifiable in the data. That is, it is likely the case that the merger decision occurs at the firm level rather than the mine level, viz., firms are targeting firms (or large parts of firms) and not individual mines. Certainly, Table 1 strongly suggests that this is true. In this scenario, a firm would buy all or part of another firm and then would operate some of the new mines and closes some others. If this were the case, then this finding would not necessarily be inconsistent with the theoretical predictions of Section II since firms would be making the same mine level participation decisions as before. Managers of firms would look at each mine owned by that firm and determine the comparative advantage of operating it; it would be the same optimal stopping problem described in Section II.

V. Conclusion

In this paper, the relationship between productivity and acquisition activity in the U.S. coal mining industry has been examined. Deriving from a stochastic matching model, there are two broad hypotheses that describe this relationship. First, acquired mines should exhibit lower productivity prior to having been acquired—representing an intrinsic incompatibility (poor match) between an owner and a coal mine. Second, acquired mines ought to exhibit gains in productivity after having been acquired—representing that the expected value of a new match is higher than the realized value of an old match.

It is found, consistent with this stochastic matching model, that acquired coal mines were between 5.23% and 12.46% less productive before being acquired than non-acquired coal mines. This comparative disadvantage is the impetus for the acquisition: current owners are willing to sell because of the substantially lower productivity and buyers are willing to buy in order to capture the productivity windfalls of mines which can be operated more efficiently.

Additionally, there is significant evidence of productivity improvements for acquired mines. In regressions of productivity growth on the acquisition dummy and other controls, acquisitions are positively and significantly correlated with productivity growth. At all of the horizons examined (one, two, and three years post-acquisition), extant acquired mines have faster productivity growth than their non-acquired counterpart—between 5.6% and 6.5% faster in the year immediately after the acquisition. This evidence is consistent with the notion that acquisitions are corrective forces for poorly performing coal mines.

It also is found that having been acquired significantly and positively influences the likelihood of coal mine failure. Controlling for other factors that may contribute to mine failure (both observed and unobserved) and controlling directly for productivity, acquisition events significantly raise the probability of mine failure. This finding is somewhat at odds with the model of Section II. However, it could be the case that this finding is a result of limitations in the data since only mines (and not firms) are identified uniquely.

In closing, this paper is an extension on the literature that examines the productivity incentive for mergers and acquisitions. This paper confirms the findings of Lichtenberg and Siegel and Maksimovic and Phillips by finding that acquired mines are less productive prior to being acquired and that acquired mines exhibit persistent post-acquisition productivity gains. These findings are consistent with a stochastic matching model that suggests that acquisitions are corrective forces in the evolution of the U.S. coal mining industry—at least in the sense that acquisitions are corrections for mines exhibiting relatively poor productivity. These findings are confirmed using data outside the manufacturing universe and with a number of acquisition events occurring at different points in time—where virtually all other work has focused on manufacturing and on cross-sectional datasets. Altogether, these findings suggest that acquisitions promote the reallocation of resources from firms less able to exploit then to firms more able to profit from them.

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Table 1. Selected Whole and Partial Company Acquisitions

Whole Company Acqusitions	
Aquirer	Seller
Bow Valleys Industries, Ltd.	Coal Reserves Group
Patrick Petroleum Corp.	Belibe Coal
Sun Company, Inc.	Elk River Resources
Trafalfar Industries	Avery Coal Co.
Gulf Resources and Chemical Corp.	R. D. Baughman Coal Co.
Chevron Corp.	Pittsburgh and Midway Coal
Drummond Coal Co.	Alabama By-Products Corp.
DuPont (Consolidation Coal Co.)	Inland Steel Coal Co.
Investor Group	Ziegler Coal Co.
Arch Minerals	Diamond Shamrock Coal
AOI Coal Co.	Kitanning Coal Co.
Hanson PLC	Peabody Holding Company
Ziegler Coal Holding Co.	Franklin Coal
Ziegler Coal Holding Co.	Old Ben Coal
Drummond Coal, Inc.	Mobil Coal Producing, Inc.
Carve-Out Acquisitions	
Consolidation Coal Co.	Exxon Coal and Minerals Company
Drummond Coal Co.	ARMCO
Peabody Holding Group	Arch Minerals Corporation
Mitsubishi Corporation	Cyprus Minerals Company
AMVEST Corporation	Bethlehem Steel Corp.
Arch Minerals Corporation	Quaker State Corporation
Ashland Coal Inc.	Bethlehem Steel Corp.
A. T. Massey Coal Company, Inc.	Bethlehem Steel Corp.
Montana Coal Company	A. T. Massey Coal Company, Inc.
Great Northern Properties LP	Burlington Resources, Inc.

Source: The Changing Structure of the U.S. Coal Industry: An Update, Energy Information Administration, July 1993.

Table 2. Productivity Differences Between Acquired and Non-Acquired Coal Mines: (Student's t)

Regressor	**Base Model**	**Size Effects**	**Fixed Effects**
	(1)	(2)	(3)
Intercept	-1.9185	1.9271	----
	(77.61)	(77.86)	
Changed	-0.1246	-0.1179	-0.0523
Owner	(-10.21)	(-9.67)	(-5.37)
Underground	-0.3110	-0.3380	----
	(-47.00)	(-49.28)	
Year78	-0.6257	-0.6270	-0.2990
	(-28.94)	(-29.10)	(-16.78)
Year79	-0.6191	-0.6200	-0.3179
	(-28.46)	(-28.61)	(-18.00)
Year80	-0.5261	-0.5263	-0.2606
	(-24.09)	(-24.19)	(-14.87)
Year81	-0.4934	-0.4941	-0.2447
	(-22.67)	(-22.79)	(-14.07)
Year82	-0.5233	-0.5241	-0.2927
	(-23.58)	(-23.70)	(-16.68)
Year83	-0.4451	-0.4460	-0.2374
	(-19.91)	(-20.02)	(-13.55)
Year84	-0.3946	-0.3950	-0.1921
	(-17.96)	(-18.04)	(-11.09)
Year85	-0.3908	-0.3913	-0.2126
	(-17.37)	(-17.46)	(-12.15)
Year86	-0.3413	-0.3416	-0.1721
	(-15.02)	(-15.08)	(-9.82)
Year87	-0.2944	-0.2942	-0.1277
	(-12.87)	(-12.91)	(-7.29)
Year88	-0.2462	-0.2465	-0.0893
	(-10.69)	(-10.75)	(-5.10)
Year89	-0.2277	-0.2273	-0.0810
	(-9.80)	(-9.82)	(-4.63)
Year90	-0.2111	-0.2105	-0.0888
	(-9.00)	(-9.01)	(-5.08)
Year91	-0.1654	-0.1647	-0.0728
	(-6.95)	(-6.95)	(-4.14)
Year92	-0.1076	-0.1076	-0.0374

	(-4.43)	(-4.45)	(-2.12)
Year93	-0.0834	-0.0837	-0.0192
	(-3.37)	(-3.39)	(-1.08)
Year94	-0.0502	-0.0505	-0.0338
	(-1.99)	(-2.00)	(-1.92)
Year95	----	----	----
Appalachia	-0.6725	-0.6567	----
	(-38.76)	(-36.73)	
Interior	-0.5320	-0.5346	----
	(-26.17)	(-26.28)	
Western	----	----	----
First Quartile	----	-0.1009	----
		(-10.35)	
Second Quartile	----	-0.0121	----
		(-1.28)	
Third Quartile	----	0.0755	----
		(8.04)	
Fourth Quartile	----	----	----
N=	50,549	50,549	12,255
R^2	0.1301	0.1363	0.7240

Table 3. The Effect of Acquisition on Productivity Growth:
Estimates of β at Various Horizons
(Student's t)

Average Productivity Growth	**Base Model** (4)	**Size Effects** (5)	**Fixed Effects** (6)
One Year	0.0586 (5.41) N=36,304	0.0632 (5.80) N=36,304	0.0650 (4.81) N=8,417
Two Years	0.0367 (5.31) N=26,784	0.0401 (5.78) N=26,784	0.0285 (3.53) N=5,889
Three Years	0.0292 (5.08) N=20,403	0.0339 (5.86) N=20,403	0.0252 (3.82) N=4,450

Table 4. Post-Acquisition Failure
(standard errors)

Regressor	Probits			Random Effects Probits		
	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	-0.5352 (0.0353)	-0.5410 (0.0356)	-0.5384 (0.0356)	-0.4956 (0.0390)	-0.5029 (0.0392)	-0.5017 (0.0391)
Changed Owners (t)	0.2517 (0.0556)	----	0.2100 (0.0566)	0.2080 (0.0599)	----	0.1855 (0.0602)
Changed Owners in Last Three Years	----	0.2250 (0.0389)	----	----	0.1930 (0.0429)	----
Changed Owners (t-1)	----	----	0.2293 (0.0583)	----	----	0.2223 (0.0618)
Changed Owners (t-2)	----	----	0.0943 (0.0585)	----	----	0.0626 (0.0620)
Productivity	-0.1309 (0.0164)	-0.1298 (0.0171)	-0.1315 (0.0170)	-0.1848 (0.0198)	-0.1804 (0.0205)	-0.1810 (0.0203)
Changed Owners * Productivity	-0.0654 (0.0624)	-0.0281 (0.0414)	-0.0490 (0.0632)	-0.0617 (0.0671)	-0.0311 (0.0453)	-0.0483 (0.0673)
Changed Owners (t-1) * Productivity	----	----	-0.0567 (0.0646)	----	----	-0.0652 (0.0686)
Changed Owners (t-2) * Productivity	----	----	0.0846 (0.0623)	----	----	0.0794 (0.0662)
Underground Mine	0.2777 (0.0208)	0.2589 (0.0211)	0.2540 (0.0211)	0.2741 (0.0251)	0.2580 (0.0252)	0.2526 (0.0252)
First Size Quartile	----	----	----	----	----	----
Second Size Quartile	-0.1491 (0.0254)	-0.1566 (0.0255)	-0.1552 (0.0255)	-0.1894 (0.0292)	-0.1938 (0.0431)	-0.1916 (0.0290)
Third Size Quartile	-0.3074 (0.0263)	-0.3163 (0.0264)	-0.3129 (0.0264)	-0.3787 (0.0313)	-0.3823 (0.0311)	-0.3781 (0.0310)
Fourth Size Quartile	-0.8615 (0.0317)	-0.8569 (0.0317)	-0.8496 (0.0318)	-0.9780 (0.0389)	-0.9685 (0.0387)	-0.9597 (0.0387)
Rho	----	----	----	0.1310 (0.0130)	0.1243 (0.0130)	0.1226 (0.0129)
N=	24,027	24,027	24,027	24,027	24,027	24,027
Pseudo R^2	0.0606	0.0620	0.0627	0.0560	0.0567	0.0573

Log Likelihood	-11,860.10	-11,942.78	-11,833.82	-11,789.16	-11,779.29	-11,772.02

Note: All of these regressions also have region and year controls.

Figure 1. Total Hours, Employment and Production: 1978 to 1996

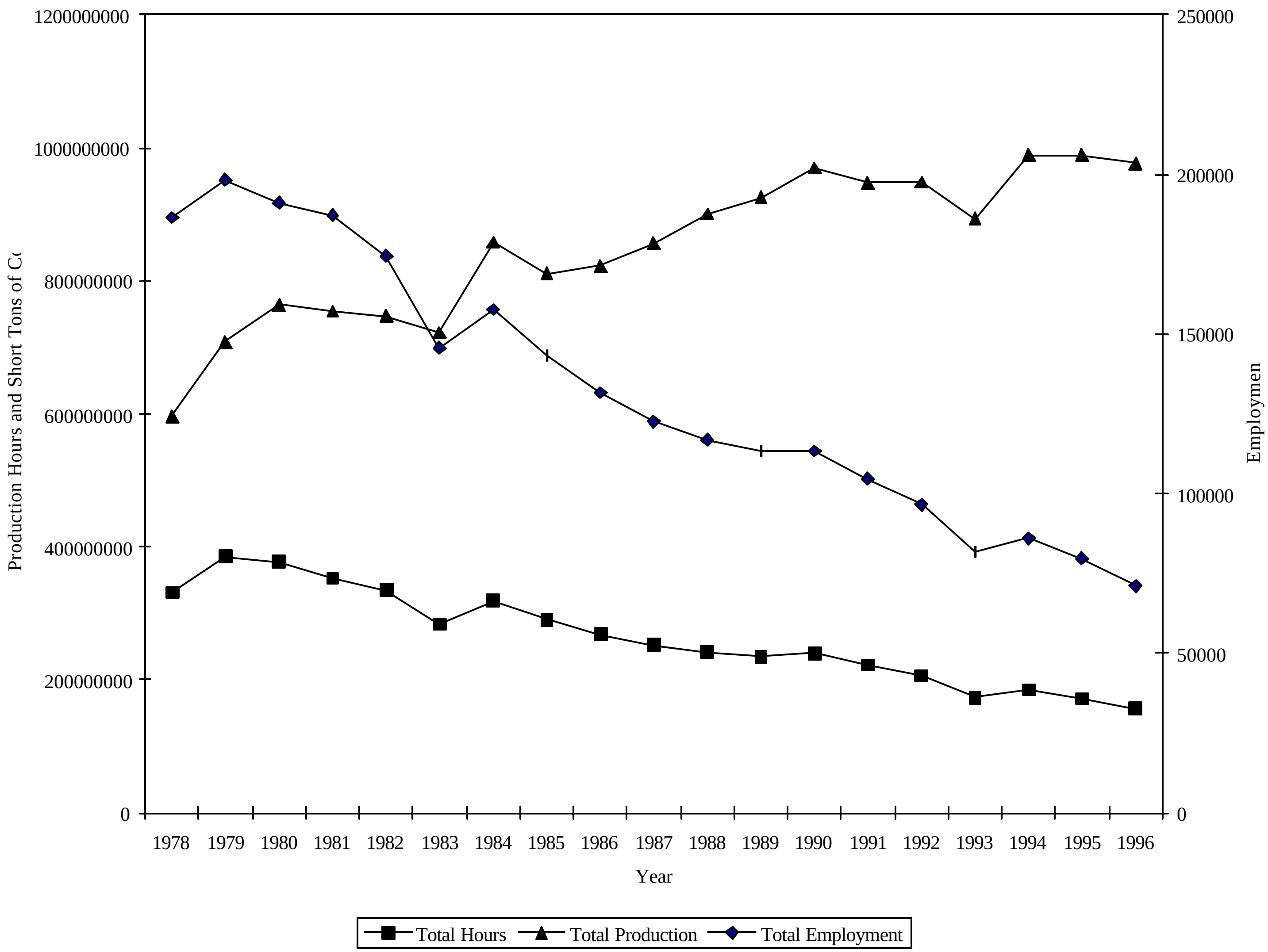

Figure 2. Short Tons of Coal per Worker Hour by Type of Mine

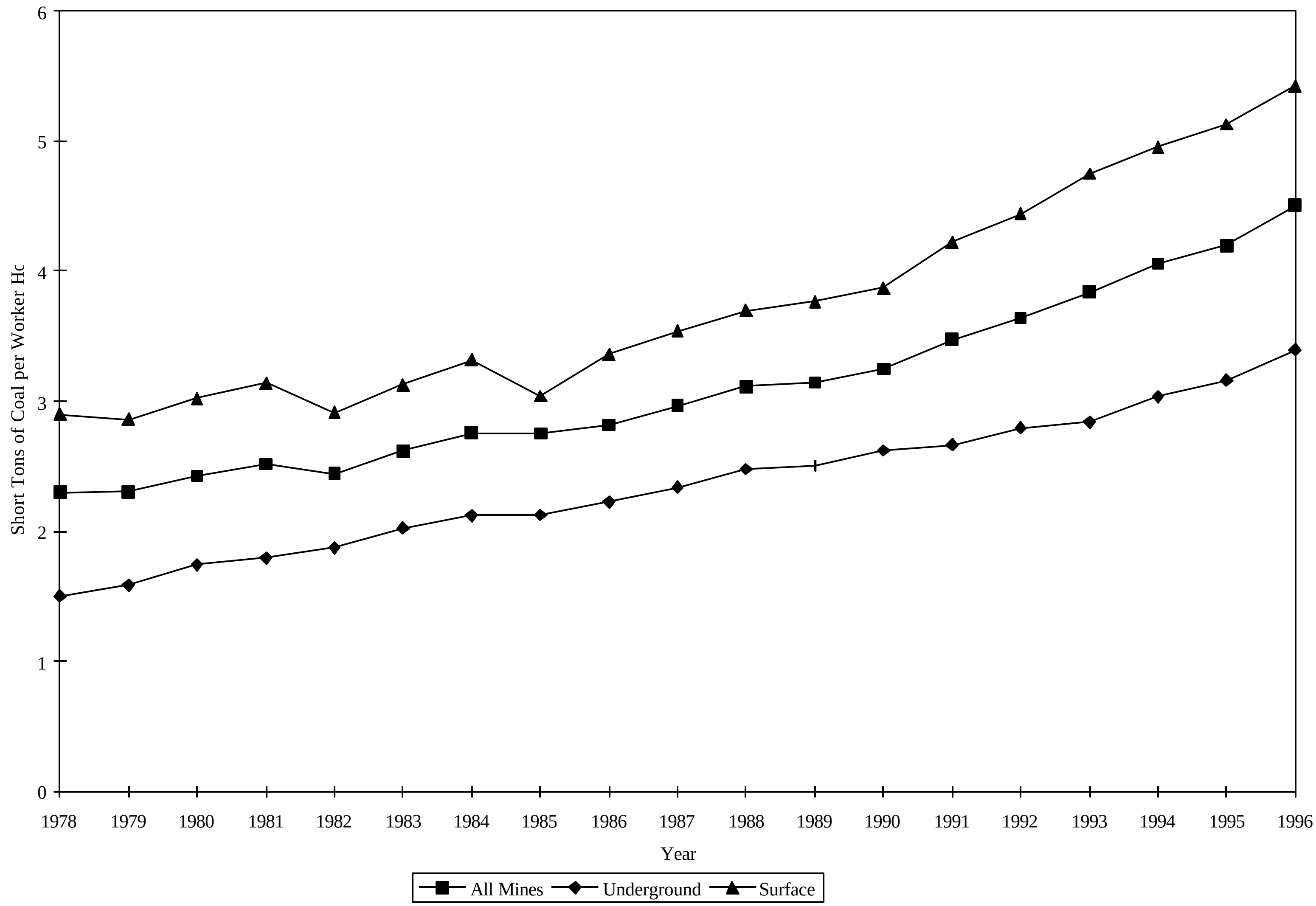

Figure 3. Short Tons of Coal per Worker Hour by Coal Region