Management, Productivity, and Technology Choices: Evidence from U.S. Mining Schools

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Online Appendix

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February 10, 2022

O.1 Model extensions

Three theories of management

In this section, I provide a more general framework to think about how managers affect productivity. I start with a stylized model of production to distinguish three theoretical mechanisms through which managers can affect productivity. Consider a firm i that produces a homogeneous good Q_i using a variable input V_i, and one of $J \geq 2$ capital inputs K_i^j, with $j = 1, ..., J$, which are substitutable. The index j indicates the production technology, which alters the production function coefficients $\boldsymbol{\beta}^j$ and the total productivity residual Ω_i^j. The firm can use only one technology j. The production function $F(.)$ is given by equation (1).

$$Q_i = F(V_i, K_i^j; \boldsymbol{\beta}^j)\Omega_i^j \tag{1}$$

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Denote the input prices as W_i^v and $W_i^{k,j}$ and the goods price as P_i. Using technology j requires paying a fixed cost ϕ_i^j, which consist of a monetary component $\tilde{\phi}_i^j$ and a non-monetary component $\hat{\phi}_i^j$. One can think of this non-monetary cost as a search cost, for instance.

$$\phi_i^j = \tilde{\phi}_i^j + \hat{\phi}_i^j.$$

The firm employs a manager with a continuous quality level X_i. The manager earns a wage W_i^x, which can depend on the quality level. Accounting profits are denoted $\tilde{\Pi}_i$, and the dummy $\mathbb{I}(K_i^j > 0)$ indicates the usage of technology j.

$$\tilde{\Pi}_i \equiv P_i Q_i - W_i^v V_i - W_i^x X_i - \sum_j (W_i^{k,j} K_i^j) - \sum_j \tilde{\phi}_i^j \mathbb{I}(K_i^j > 0)$$

The profit function that the firm maximizes is $\Pi_i \equiv \tilde{\Pi}_i - \sum_j \hat{\phi}_i^j \mathbb{I}(K_i^j > 0)$. For now, I consider managers, and their wages, to be exogenous. Firms choose the bundle of inputs that maximizes profits: $\max\limits_{V_i, \mathbf{K}_i} \Pi_i$.

Theory 1 *Managers are Hicks-neutral productivity shifters.*

A first possibility is that managerial quality increases the productivity residual Ω_i^j, as in equation (1a). This implies that it shifts the isoquant outwards. In a Cobb-Douglas production function, this is equivalent to adding managerial quality as an additional production input.

$$Q_i = F(V_i, K_i^j; \boldsymbol{\beta}^j)\omega_i^j(X_i) \quad \text{with} \quad \frac{\partial \omega_i^j}{\partial X_i} > 0 \tag{1a}$$

In order to test the first theory, one has to estimate the production function (1a), and regress the productivity residual on the management indicator X_i.[1] Alternatively, the man-

[1] This approach corresponds to a large set of articles in the management literature, such as Bertrand and Schoar (2003) or Bloom and Van Reenen (2007), among many others, although most use a revenue-generating production function rather than a production function in quantities.

agement indicator X_i could be added as a production input, for instance if $F(.)$ is a Cobb-Douglas function. The usual simultaneity problem between total factor productivity and input usage needs to be addressed (Marschak and Andrews, 1944). If management would be an endogenous choice by the firm, it would also be correlated with productivity.

Theory 2 *Managers change the output elasticity of other inputs in the production function.*

A second view of managers is that they change the output elasticities of the other production inputs. This is usually meant when categorizing inputs as being complements to other inputs, as in Brynjolfsson and Milgrom (2013). Using the notation from equation (1), this implies that the parametrization $\boldsymbol{\beta}^j$ depends on management, as shown in equation (1b).

$$Q_i = F(V_i, K_i^j; \boldsymbol{\beta}^j(X_i))\omega_i^j \tag{1b}$$

Testing the second theory requires estimating the complementarities between managers and the other inputs. Depending on the functional form of the production function, these complementarities can be estimated using interaction effects between managers and capital.

Theory 3 *Managers change the cost of using other inputs in the production function*

In the third mechanism, managers change the costs of using a technology j.

$$\phi_i^j = \phi_i^j(X_i) \tag{1c}$$

By decreasing fixed costs of the technologies with the highest isoquant, managers can increase productivity. Denote the technology that corresponds to the highest productivity level as j^*. The firm may not use this technology, and hence not produce at the production frontier, because of high fixed costs $\phi_i^{j^*}$. If managers lower this cost, the firm may end up choosing j^*, and hence produce at a higher productivity level. This effect of managers on productivity is, however, conditional on technology usage j: the isoquant does not move when one changes management but keeps all other inputs constant.

This third theory can, in contrast, not be identified using the production function. Supposing that the first two theories do not hold but the third theory does, and that the production function is correctly specified and identified, adding managerial quality to the production function as an input should yield an insignificant output elasticity on managerial quality, and insignificant interaction effects between managerial quality and the other inputs. If the technology fixed costs ϕ_i^j are purely monetary, meaning that $\hat{\phi}_i^j = 0$, a part of the effect could be detected by looking at balance-sheet profits $\tilde{\Pi}_i$ or by relying on a revenue-generating production function with input expenditure on the right-hand side.[2] If managers lower non-monetary fixed costs, however, this is no longer the case.

When examining complementarities between inputs, the alternative to relying on the production function is to estimate correlations between the input demand functions, as proposed by Bresnahan, Brynjolfsson, and Hitt (2002). If inputs are complementary, in the meaning of theory 2, demand for these inputs should move together. The demand for each capital type can be written as a function $D^j(.)$ of all input prices $\mathbf{W}_i$, of the output price, of the other input quantity, of the production function coefficients, of total factor productivity, and of fixed costs. Assuming that the production function is identified, all the covariates of the capital demand function are known, except for the vector of fixed costs $\boldsymbol{\phi}_i$.

$$K_i^j = D^j(\mathbf{W}_i, P_i, V_i, \boldsymbol{\beta}, \Omega_i^j; \boldsymbol{\phi}_i(X_i)),$$

Brynjolfsson and Milgrom (2013) argue that in order to estimate input complementarities, estimating the interaction effects in the production function and estimating the input demand correlation $\frac{\partial K_i^j}{\partial X_i}\frac{X_i}{K_i^j}$ are equivalent, abstracting from unobserved input demand shifters. I ar-

[2]The usual caveats when using revenue production functions apply, as discussed in De Loecker and Goldberg (2014).

gue, however, that this is not the case when managers change technology fixed costs, rather than their marginal products, as in theory 3. If theories 1 and 2 do not apply, meaning that managers do not change the production function coefficients and TFP, then capital demand and managerial capital should not co-move, unless technology fixed costs depend on management.[3] Comparing the interaction effects in the production function with correlations in the input demand functions can hence be informative about whether complementarities come from the marginal product side, as in theory 2, or from the fixed cost side, as in theory 3.

Market for managers

The main model focused on demand for mining college managers. What about the supply of these managers? Superintendents probably have some choice of which mine to join. Suppose superintendents have a utility function that depends on their wage W_t^X and on mine characteristics $\boldsymbol{\zeta}_{it}$. Both superintendent wages and mine characteristics are latent, and assumed exogenous to the mine. These characteristics are likely to be serially correlated: mines that are attractive to managers today are likely to be so in the future. An example of a mine characteristic that enters superintendent utility is how close it is located to a city. To what extent are these unobservable 'amenities' $\boldsymbol{\zeta}_{it}$ problematic for identification of the input demand and production functions? For the production function identification approach in the main text, this unobserved variation in mine characteristics is not problematic because the auto-regressive productivity specification allows for serially correlated latent shifters of input demand and supply, see Shenoy (2021). For the ACF specification in Online Appendix O.2, in contrast, it is problematic if these unobservable amenities would be serially correlated. For identification of the capital choice model, the unobserved amenities are problematic if they include the unobserved shocks to locomotive costs or returns, as mentioned in the main text.

[3]This again assumes that all unobserved heterogeneity is captured by total factor productivity, which is identified.

During the time period studied, the supply of college-educated managers was low, which explains their low share of the managerial corps. Eventually, nearly all coal mine managers would have formal mining college education, so the relative gains from employing mining college graduates compared to other firms are temporary. The same holds for the locomotive types: steam and compressed air locomotives were gradually phased out at coal mines for underground usage during the 1920s and 1930s, and were eventually replaced by diesel-electric engines. The benefits from increased management and technology adoption are hence temporary. This holds in many other settings in which their are shocks to management and technology, such as the introduction of 'six sigma' quality management during the 1980s, which became a common practice, or the introduction of enterprise resource systems.[4]

O.2 Production function identification: alternatives

Auto-regressive approach

In order to identify the production function, I relied on the joint assumptions that all mines have the same variable input prices in a given year, and on a Cobb-Douglas functional form. Both these assumptions can be relaxed. In this section, I rely on the timing assumptions from Ackerberg, Caves, and Frazer (2015) in combination with a linear productivity transition to identify all output elasticities jointly, that is, both the variable and fixed inputs. This approach allows to estimate interaction terms between the inputs and does not impose homogeneous input and coal prices.

I estimate two functional forms of the production function. First, I use a Cobb-Douglas specification, in order to compare with the main text. Next, I allow for interaction effects between each locomotive type and the variable inputs using Equation (2). The coefficients $\boldsymbol{\beta}^{lk}$ and $\boldsymbol{\beta}^{mk}$ capture the extent to which mining locomotives change the output elasticities

[4]Thanks to an anonymous reviewer for pointing this out.

of labor and materials. I refer to section 4 in the paper for a specification in which I also add an interaction term between managerial education and each locomotive type.

$$q_{it} = \beta^l l_{it} + \beta^m m_{it} + \boldsymbol{\beta}^k \mathbf{K}_{it} + \boldsymbol{\beta}^x \mathbf{X}_{it} + \boldsymbol{\beta}^{lk} \mathbf{K}_{it} \circ l_{it} + \boldsymbol{\beta}^{mk} \mathbf{K}_{it} \circ m_{it} + \omega_{it} + \beta^t t + \varepsilon_{it} \quad (2)$$

Identification

I keep all the input timing assumptions from the main text, and the AR(1) productivity transition process. Variable input prices and coal prices are now $W_{it}^M, W_{it}^L, P_{it}$ and can vary across mines and time. Without relying on the revenue shares approach, the output elasticities of all inputs, fixed or variable, can now be estimated using the moment condition in (3). The unexpected shock to productivity and measurement error, $\upsilon_{it} + \varepsilon_{it} - \rho\varepsilon_{it-1}$, is now assumed orthogonal to the current *and* past capital and managerial choices, and to past labor and material choices. For the production function with interaction effects, Equation (2), the moment conditions are analogous but now include the (lagged) interaction terms as well in the instrumental variables list.

$$\mathbb{E}\Big[\upsilon_{it} + \varepsilon_{it} - \rho\varepsilon_{it-1} | \left\{ \begin{matrix} l_{it-1} \\ m_{it-1} \\ \mathbf{K}_{it-1} \\ \mathbf{X}_{it-1} \\ \mathbf{K}_{it} \\ \mathbf{X}_{it} \\ t \end{matrix} \right\} \Big] = 0 \quad (3)$$

Given that no input inversion takes place, this identification approach is consistent even if wages are endogenous. When relying on input inversion, unobserved markdown variation across mines is problematic as differences in input usage can be due to both productivity or markdown differences. This problem does not apply to the auto-regressive productivity estimator, as it does not rely on inverting input demand functions.

Results

The estimates for the Cobb-Douglas model when using the autoregressive productivity identification approach for all inputs are in column (I) of Table 1. The mining college coefficient is -0.03 with a 95% confidence interval of [-0.103;0.043], which is similar to the baseline estimates in the main text. The locomotive coefficients are slightly smaller compared to the ones estimates in the baseline model, and their ordering in terms of magnitudes remains the same. The output elasticities of labor and materials are similar in terms of magnitude compared to the factor shares approach used in the main text.

The interaction effects between the locomotive type of interest, electrical locomotives, and the variable inputs, in column (III), are all insignificant, although imprecisely estimated. Hence, there is insufficient statistical power to draw conclusions regarding the factor-biased effects of the electrical locomotives. The main estimate of interest, the output elasticity of mining college graduates, is very similar between the factor-biased model and the Cobb-Douglas model: it has a 95% confidence interval of [-0.106;0.012], so the Hicks-neutral productivity effect of mining college graduates is negative at the 10% confidence level.

Ackerberg, Caves and Frazer (2015)

A second alternative identification strategy is to follow Ackerberg et al. (2015) with the input demand inversion for total factor productivity. The upside of this approach is that it can cope with endogenous exit of mines.[5] The drawback is that it cannot cope with serially correlated unobserved variables that affect input demand, such as coal or input prices. The latent coal

[5] Moving to an unbalanced panel should, however, also help to cope with the endogeneity of market structure. Ackerberg et al. (2015) also does not require a linear productivity transition.

and input prices hence have to be serially uncorrelated, which is unlikely to hold in practice.

Identification

The productivity transition still follows the AR(1) process. Intermediate inputs are used as the flexible input for the first stage inversion. In line with Olley and Pakes (1996), I now allow for endogenous exit. I regress a mine exit dummy on all locomotive type dummies, mining college graduates, and year dummies using a probit regression. Then, I include the imputed exit probabilities $\hat{pr}_{it}$ as covariates in the first stage regression of Ackerberg et al. (2015), which is used to recover measurement error ε:

$$q_{it} = \psi_t(l_{it}, m_{it}, \mathbf{K}_{it}, \hat{pr}_{it}, \mathbf{X}_{it}, t) + \varepsilon_{it}$$

Total factor productivity can now be recovered as a function of data and parameters to be estimated, with $\hat{\psi}$ denoting the estimate of ψ:

$$\omega_{it} = \hat{\psi}_{it} - h(l_{it}, m_{it}, \mathbf{K}_{it}, \mathbf{X}_{it}, \boldsymbol{\beta}, t)$$

I use a third-order polynomial for this first-stage regression. The productivity innovation υ_{it} is given by the difference between productivity and its expected value from the equation of motion.

$$\upsilon_{it} = \omega_{it} - \mathbb{E}\Big(\omega_{it}|\omega_{it-1}\Big)$$

Still assuming that all locomotive types and managers are chosen prior to observing the shock υ_{it}, but labor and materials afterwards, the moment conditions to identify $\boldsymbol{\beta}$ are given by:

$$\mathbb{E}[\upsilon_{it}| \left\{ \begin{matrix} l_{it-1} \\ m_{it-1} \\ \mathbf{K}_{it} \\ \mathbf{X}_{it} \\ \mathbf{K}_{it-1} \\ \mathbf{X}_{it-1} \\ t \end{matrix} \right\}] = 0$$

In order to obtain correct standard errors for this two-step procedure, I bootstrap the standard errors with 250 iterations. I use a 'block-bootstrapping' procedure that resamples while keeping the mines fixed.

Results

The estimates are in column (II) of Table 1. The mining college coefficient is similar to the other specifications, but is less precisely estimated: its 95% confidence interval is [-0.171;0.091]. The locomotive output elasticities are all similar to the estimates in the main text.

O.3 College graduates database and matching procedure

Mining college graduates list

As shown in Table 3, I access the alumni registries or catalogs through *Ancestry.com* for 14 of the 40 programs. For 26 programs, I collected either the alumni registries or course catalogs myself, and digitized them in order to get a full list of college graduates in mining engineering from these institutions. For 10 programs, I do not observe the names of the college graduates. Based on the numbers of mining engineering student reported by the

1912 Report of the Commissioner of Education, my data set covers 87.7% of all mining engineering graduates in the U.S.A. and 99.1% of graduates excluding the Western states.[6]. Matching the college data sets with the managers in the mining data set reveals that Pennsylvania coal mines only hired mining engineering graduates from Pennsylvanian colleges, which are 100% covered by the data set. Because of this, the omission of some Western U.S. mining colleges is very unlikely to result in false negative observations for the mining college graduate dummy.

Matching using Ancestry.com

I start by describing how I match the managers in the data set to the college registries on Ancestry.com. The given, middle and surnames of all managers, superintendents, and foremen are observed in the coal mine inspection reports. As explained in the paper, I only focus on mine superintendents. I match full manager names with population census records using *Ancestry.com*, in order to know their age and address. In case of multiple matches, I select the right match based on whether the location of the person was in Pennsylvania during the years they are observed in the mining data set. This information is observed for 73.5% of the superintendents in the data set. Next, I look up the educational background of the managers based on their last name and initial(s) using the alumni registries and school catalogs on *Ancestry.com* to find possible matches. I flag matches as false positives if the age from the census data cannot reasonably correspond to the age imputed from the college alumni registries (e.g., if the manager would have obtained a college degree at age 5). I also flag matches as false positives if the middle names are given in both the census and college data, and do not overlap. I checked whether the listed occupations of the resulting mining college graduates in the census records were correct (e.g. 'Coal operator' or 'Mine superintendent'). This procedure results in 17 college graduates, of which 7 graduated with a degree in mining

[6]Arizona, California, Colorado, Idaho, Montana, New Mexico, Oregon, and Washington

engineering, from *Lehigh University* and *Lafayette College*, both located in Pennsylvania.

Matching using hand-collected alumni records

For 26 colleges offering mining engineering programs, but which are not included on Ancestry.com, I manually collect and digitize lists with the full names of all mining engineering graduates from either alumni records or course catalogs. This results in a data set of 4841 mining engineering graduates across the U.S.A. between 1886 and 1914. Table 4 in the Online Appendix lists all sources used to construct this data set. First, I match the last names and initials of the middle and first names in both the coal mine data and the graduate registries data. This does not yield any matches. Second, I match only the last names and initials of the first names, because the middle names could be unobserved in either the coal mines data or the college alumni data. This does not yield any matches either. Hence, none of the mining engineering graduates in the college alumni data set are employed as superintendents by the coal mines in the data set.

This matching learns us that Pennsylvanian coal mines during the time period studied in this article exclusively hired mining college graduates from local Pennsylvanian colleges. Given that the matching rate in Pennsylvania is 100%, and close to 100% outside of the Western states, this implies that the probability of false negatives in the mining college dummy – managers that are flagged as having no mining degree while they had one in reality – is very small.

More details on mining college curricula

The average mining college program structure for the mining colleges from table 4 is in Table 2. For the two mining engineering programs in the data set, Lehigh University and Lafayette College, excerpts from the course catalog are included in Appendix 1 and Figures 2, covering

1890 and 1899. The specialized coursework in the last two years contained various classes that were informative for choosing and operating locomotives. Class 161 at Lehigh was about coal haulage and covered underground mining locomotives, just as the class ‘Haulage’ in the senior year at Lafayette college. Both programs included compulsory field work in local coal mines. More general engineering classes such as ‘Machinery and Motors’ at Lafayette and ‘Mechanics of Machinery’ at Lehigh (included in the general engineering sequence in the sophomore year) were equally relevant to the understanding of automated locomotive technologies. Both schools also offered introductions to electrical engineering in the mining school curriculum, which was relevant to the operation of electrical mining locomotives.

[Table 2 here]

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Table 1: Production function: robustness

	(I) log(Output) Estimate	(I) S.E.	(II) log(Output) Estimate	(II) S.E.	(III) log(Output) Estimate	(III) S.E.
1(Mining col. grad.)	-0.030	0.037	-0.040	0.067	-0.047	0.030
1(Other grad.)	0.018	0.103	0.031	0.176	0.172	0.084
log(Labor)	0.767	0.064	0.610	0.044	0.682	0.096
log(Materials)	0.085	0.065	0.232	0.038	0.268	0.076
1(Elec. loc.)	0.121	0.035	0.179	0.038	1.678	0.606
1(Air loc.)	0.065	0.031	0.016	0.042	-0.364	0.461
1(Steam loc.)	0.124	0.036	0.148	0.051	1.097	0.526
Year	0.007	0.003	0.006	0.004	0.010	0.003
1(Air loc.)*log(Labor)					-0.081	0.052
1(Elec. loc.)*log(Labor)					-0.146	0.116
1(Steam loc.)*log(Labor)					0.114	0.092
1(Air loc.)*log(Materials)					0.096	0.051
1(Elec. loc.)*log(Materials)					-0.065	0.115
1(Steam loc.)*log(Materials)					-0.182	0.083
Model	Cobb-Douglas		Cobb-Douglas		Interaction effects	
Method	Autoregressive		ACF(2015)		Autoregressive	
Observations	3429		3429		3429	
R-squared	.78		.325		.801	

Notes: Column (I) reports the estimates for the Cobb-Douglas model with the autoregressive model being used to recover both the variable *and* the fixed input output elasticities. Column (II) reports the estimates for the Cobb-Douglas model when estimated with ACF (2015). Column (III) reports the model with interaction effects between the mining engineer dummy and both log labor and log intermediate inputs, estimated using the auto-regressive productivity model.

Table 2: Mining school curricula

Subject	Course examples	% Credits	Usual phase
Science	Mathematics, Chemistry, ...	33.7	Freshman / Sophomore
Mining engineering	Drilling, Mine construction, Geology, ...	34.3	Junior / Senior
Other engineering	Electricity, Mechanics, ...	24.3	Sophomore / Junior
Languages	Foreign languages, writing, retorics	4.7	Freshman
Thesis	Master project	2.0	Senior
Management	Mining economics, mining law, contracts, ...	1.0	Senior

Table 3: Matching managers to college alumni lists

Nr.	College	Source	E.M. students in 1911*
1	Alabama Polytechnic Institute	Not included	11
2	University of Alabama	Ancestry.com	NN
3	Arizona School of Mines	Alumnal records	16
4	Arkansas Industrial University	Ancestry.com	3
5	University of California	Not included	144
6	Stanford University	Not included	6
7	Colorado School of Mines	Alumnal records	216
8	North Georgia Agricultural College	Not included	NN
9	University of Idaho	Not included	18
10	University of Illinois	Ancestry.com	22
11	Iowa State College of Agri. and Mech. Arts	Ancestry.com	26
12	University of Kansas	Ancestry.com	NN
13	State University of Kentucky	Alumnal records	39
14	Massachussetts Institute of Technology	Alumnal records	79
15	Michigan College of Mines	Alumnal records	191
16	University of Minnesota	Alumnal records	72
17	University of Missouri	Alumnal records	146
18	Montana State School of Mines	Alumnal records	40
19	Missouri School of Mines	Ancestry.com	134
20	New Mexico School of Mines	Alumnal records	10
21	Cornell University	Ancestry.com	NN
22	Columbia School of Mines	Alumnal records	143
23	University of North Dakota	Not included	NN
24	University of Nevada	Alumnal records	32
25	Case School of Applied Science	Not included	NN
26	Ohio State University	Ancestry.com	39
27	University of Oklahoma	Not included	NN
28	Oregon Agricultural College	Ancestry.com	21
29	Lafayette College	Ancestry.com	NN
30	University of Pittsburgh	Alumnal records	41
31	Lehigh University	Ancestry.com	NN
32	South Dakota School of Mines	Alumnal records	30
33	University of Tennessee	Ancestry.com	5
34	University of Utah	Alumnal records	61
35	Virginia Agri. and Mechanical College	Ancestry.com	14
36	University of Virginia	Alumnal records	NN
37	State College of Washington	Not included	27
38	University of Wisconsin	Ancestry.com	31
39	University of Wyoming	Not included	NN
40	Penn State School of Mines	Alumnal records	61
Total			1678
Matched			1472 (87.7 %)
Total - Non-Western			1180
Matched - Non-Western			1169 (99.1 %)

* Sources: Education Inspector Report, vol. 2, 1912; and own data. NN implies that the class size is unknown.

Table 4: College alumni records: sources

School	Source	Year of volume used
(a) Alumni registries:		
Arizona School of Mines	Alumnal Record of the University of Arizona	1916
Michigan College of Mines	Graduates of the Michigan College of Mines	1910
Penn State School of Mines	Alumni Directory	1913
West Virginia University	Register of Faculty, Alumni and Students	1920
(b) Annual catalogs:		
Colorado School of Mines	Quarterly of the Colorado School of Mines	1908, 1912-1914
University of Kentucky	The Kentucky Alumnus	1909-1914
Columbia College of Mines	Catalogue of Columbia University	1867-1914
Massachussetts Institute of Technology	Catalog ”Technique”	1887-1914
Michigan College of Mines	Year Book of the Michigan College of Mines	1910-1914
Missouri School of Mines	School of Mines and Metallurgy Bulletin	1914
Montana School of Mines	Annual Catalogue	1908-1914
Nevada Mackay School of Mines	Register of the University of Nevada	1908-1914
New Mexico School of Mines	Register of the New Mexico School of Mines	1909-1914
South Dakota School of Mines	Annual Catalogue	1912
University of Minnesota	School of Mines Announcement	1897-1914
University of Utah	Catalogue of the University of Utah	1901-1915
Virginia Agricultural and Mechanical College	Catalogue of Virginia Ag. and Mech.	1900-1913

Figure 1: Mining engineering curriculum at Lehigh University

MINING ENGINEERING.

PROFESSOR WILLIAMS, MR. MILLER.

159. MINING ENGINEERING. Prospecting, valuation of property, boring, timbering, shaft sinking. Lectures, references to text-books, monographs and periodicals. Visits to mines. Preparation required: 146 or 147. First term. (3)

160. MINING. Blasting, development of deposits, systems of winning underground and at daylight. Lectures, etc. First term. (2)

161. MINING ENGINEERING. Haulage by track and wire, hoisting, drainage, ventilation and lighting. Lectures, etc. Second term. (2)

162. MINING ENGINEERING. Accidents, their cause, means of prevention, rescue, etc., police of mines, hygiene, rules, and laws. First term. (1)

163. MINING ENGINEERING. Theory of ore dressing. Physical principles on which it depends. Machines used in wet, dry, and magnetic methods, with the order in which they are arranged. The location of dressing works. The preparation of anthracite. Lectures, etc., and visits to dressing works. Second term. (3)

164. MINE SURVEYING. Location of stations underground. Temporary and permanent side notes. Connecting surface and underground work through shafts or slopes. Mapping by coordinates. Care of maps, and variations due to temperature and moisture. Permanent forms of records. Detection of errors. Rectification of bore holes. Lectures, etc., followed by practice with a mine corps and construction of map from notes of actual survey. Preparation required: 77. First term. (2)

165. MINING DESIGN. The design of mining plant to meet assigned conditions, with detailed working drawings and estimates of cost. Each problem is accompanied by a memoir containing all calculations and descriptions, with which are bound tracings or blue prints of all drawings. Preparation required: 159, 161. First term. (2)

166. THESIS FOR THE DEGREE OF E. M. Candidates are required to present a thesis on some topic connected with this subject.

Note: Source: Register of the Lehigh University, 1899-1900

Figure 2: Mining engineering curriculum at Lafayette College

JUNIOR YEAR.

First Term.

Mechanics.
Analytical Chemistry.
Descriptive Geometry (continued).
Practice with the Blow-pipe.
Triangular Surveying (Field and Office Work); Plan of Survey.
Leveling; Contour Map; Mine Surveying (Theory).

Second Term.

Physics (begun).
Analytical Chemistry.
Mine Surveying (practice in the mines in the spring vacation).
Geology (begun).
Integral Calculus.
Assaying.
Lithology.
Maps of Surveys.

Third Term.

Physics (completed).
Topographiclal and Hydroghraphical Surveys.
Adjustment of Instruments.
Map of Mine Survey.
Geology (completed).
Analytical and Applied Mechanics.
Analytical Chemistry.
Economic Geology.

Throughout the Year.—Declamations, Themes, and the Bible.

SENIOR YEAR.

First Term.

Mining Law.
Prospecting.
Deep Boring.
Blasting. Quarrying.
Metallurgy.
Analytical Chemistry.
Machine Drawing.
General Theory of Machines.

Second Term.

Shaft Sinking.
Tunneling.
Exploitation.
Haulage.
Analytical Chemistry.
Stability of Structures.
Machinery and Motors.
Strength of Materials.
Political Economy.
Metallurgy.

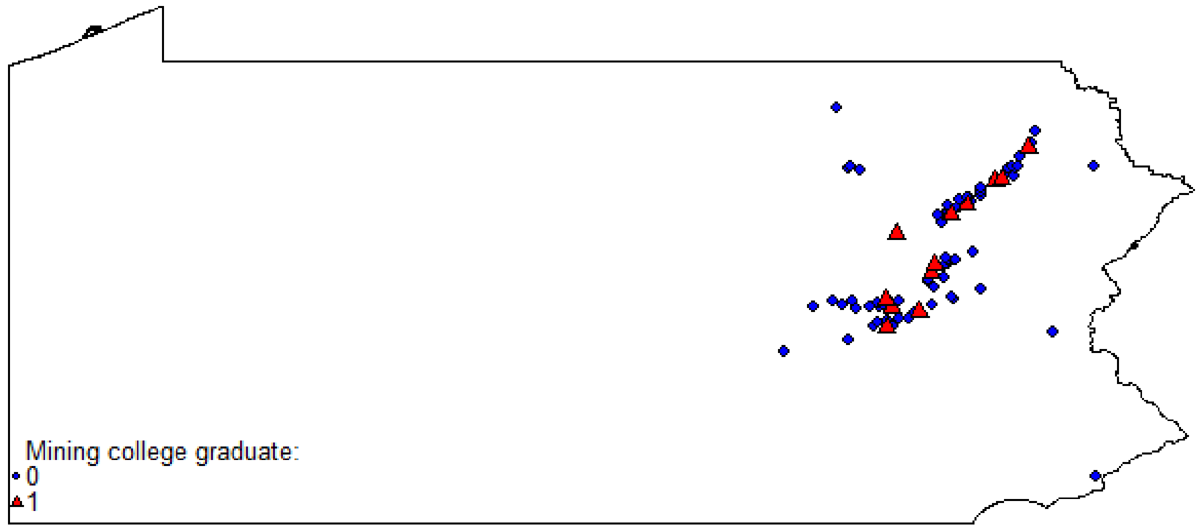
Third Term.

Winding.
Ventilation.
Mechanical Separation of Ores.
Designs for and Reviews of Special Metallurgical and Mining Operations.
Drainage.
Graphical Statics.
Analytical Chemistry.
History.
Graduation Theses.

Throughout the Year.—Themes, Speaking, and Biblical Studies.

Note: Source: Annual Catalog of the Officers and Students of Lafayette College for the year 1890-1891.

Figure 3: Map with mining towns



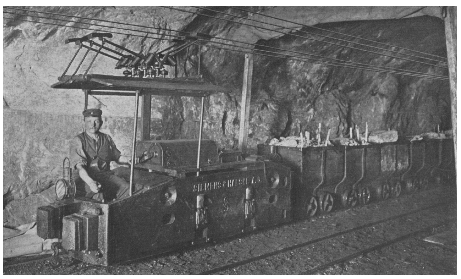
Note: Red triangles are towns in which there was at least one mining college graduate managing an anthracite mine between 1900 and 1914. Blue circles are towns where this was not the case. Source: own data.

Figure 4: Haulage technologies

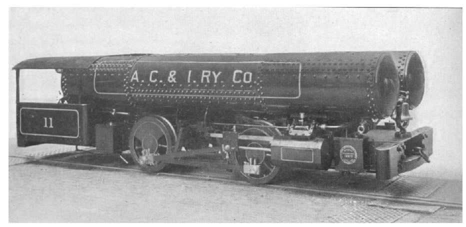
(a) Mules

(b) Steam locomotive

(c) Electrical locomotive



(d) Compressed air locomotive



Source: Images (b)-(d) are from Gairns (1904), image (d) from the New York Public Library.