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Evaluating the Learning-by-Doing Theory of Long-Run Oil, Gas, and Coal Economics

Justin Ritchie and Hadi Dowlatabadi

1616 P St. NW
Washington, DC 20036
202-328-5000 www.rff.org

RESOURCES FOR THE FUTURE

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Abstract

Energy and climate policy studies with a long-term outlook need to anticipate potential developments in technology and the temporal nature of today's resource-reserve definitions for oil, gas and coal. Accordingly, economic concepts of learning formulated from research on manufacturing industries inspire a common approach to modeling technological change in hydrocarbon energy resource production. This theory expects future costs of fossil energy supply to benefit from a cumulative learning effect which results from ongoing extraction. With three decades of data since the initial formulation of this theory by Rogner (1997), some key regions of conventional oil and gas production have matured. Fresh data on industry cost trends are now available, allowing for a closer examination and validation of whether this learning model hypothesis is relevant for long-run cost projections.

Empirical cost and productivity data challenge the broad application of a learning model to the total geologic occurrences of fossil energy resources. We find that oil and gas industry operating costs indicate a learning effect, but capital expenditures do not. Coal resource-reserve dynamics have not developed as anticipated. Nordhaus (2009) suggests technological change models of energy supply calculated with a learning curve will consistently overestimate productivity gains, producing biased cost estimates of future technologies. This paper considers the Rogner (1997) *learning-by-extracting* model for fossil energy supply as a specific case of Nordhaus' argument.

Key Words: energy resources, oil, gas, coal, learning-by-doing

JEL Classification Numbers: Q40, Q47, Q35, Q30, Q33, Q31

Contents

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Justin Ritchie and Hadi Dowlatabadi*

1. Introduction: A Learning-by-Extracting Theory of Total Geologic Oil, Gas, and Coal Occurrences

Long-term climate and energy policy studies inherently extend beyond the scope of today's knowledge, requiring a dynamic approach to future technological possibilities and the frontiers of currently available information. Understanding fossil energy resources in this context commonly starts with assessments of total geologic oil, gas, and coal occurrences. After data limitations are acknowledged, hypotheses can be applied to anticipate future developments in the production technologies that could enable economic access to the full extent of these deposits.

Rogner (1997) addresses these questions of inherent long-run uncertainty with an innovative methodology, grounding the total geologic presence of fossil energy resources in a theory of learning-by-doing. This seminal assessment combines diverse reports from governments and international agencies to formulate internally consistent cumulative availability curves for each hydrocarbon fuel (known as the H-H-R supply curve).

Rogner's hypothesis is that ongoing production will reduce the cost of accessing future resources, inducing a learning curve effect independent of market prices. This learning effect leads to compounding annual productivity improvements for the supply of oil, gas, and coal from conventional and unconventional production technologies. In this theory, today's reserves are understood as a "flow" continually replenished by the "stock" of total geologic occurrences, with a dynamic boundary characterized by learning that accumulates from increasing knowledge.

Learning curves draw from a long history of studies on manufacturing, and in macroeconomics through endogenous modeling of technical change (Anzanello and Fogliatto

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* Ritchie and Dowlatabadi: Institute for Resources, Environment and Sustainability, University of British Columbia, 429-2202 Main Mall Vancouver, BC Canada V6T 1Z4l. Correspondence may be directed by email at emailjustinritchie@gmail.com or by phone at 919.701.9872.

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2011; Arrow 1962; Yelle 1979). Since Wright (1936) observed productivity gains that resulted from repetitive tasks on airplane assembly lines, learning curves have provided effective and accurate mathematical accounts of performance improvements in continuous manufacturing processes.

The learning-by-doing in economic models of productivity results from ongoing use of tools and techniques by workers, which leads to shortcuts and process optimizations that reduce the time, cost, and materials involved in executing a specific task. Macroeconomic concepts of learning-by-doing have drawn from these strong microeconomic foundations, as in the work by Arrow (1962) and Lucas (1988), which consider learning effects for an endogenous model of technical change in neoclassical growth theory.[1]

Rogner (1997) adapts the concept of learning-by-doing to create an elegant foundation for energy models, condensing the complex factors shaping hydrocarbon resource economics into a numerically tractable solution. This *learning-by-extracting* (LBE) theory calculates future fossil energy supply potentials with a non-price–induced learning rate of (ρ) – an outcome of ongoing production. The resulting cost-quantity curve for future supply is then simplified to focus on two dimensions: assumptions varying the rate of future learning and the total geologic stock of the resource.

Long-run studies on the economics of climate change and energy futures conducted with integrated assessment models (IAMs) regularly apply the LBE theory to develop fossil resource supply curves (Clarke et al. 2014; IPCC 2000; IPCC WGIII 2014; Joint Global Change Research Institute 2016; Luderer et al. 2013; Masui et al. 2011; Riahi et al. 2011; van Vuuren 2007). Detailed and publicly accessible data on global oil, gas and, coal productivity are often outside the budget of public and academic researchers, making the original H-H-R supply curve one of the very few available to the research community.

Though each IAM applies unique variations of Rogner's initial concept, the basic theoretical approach has remained consistent for decades. McCollum et al. (2014) review the details of learning-driven fossil energy resource supply costs in a range of IAMs. Recent efforts by Bauer et al. (2016a) place this method within a framework that scales fossil availability curves based on scenario assumptions for trajectories of future socioeconomic development.

[1] Lucas (1988) articulated a case for learning-by-doing in macroeconomics where each good has a different potential for learning-induced productivity gains.

However, this geologic learning model has yet to be empirically assessed for the oil, gas, and coal industries (Bauer et al. 2016a), leaving studies reliant on the LBE theory with an unverified concept of technological change which is inherently sensitive to its key parameter: the chosen learning rate.

To illustrate the influence a selected learning rate can have on cost projections of future energy supply, Figure 1 reproduces the original H-H-R supply curve for oil with annual rates of learning driven productivity gains (ρ) that vary from +1.0 to -1.0 percent. Each cost-quantity curve for oil intersects with its equivalent amount of carbon dioxide emissions (top x-axis) at a common backstop price for low-emission oil alternatives of roughly $120 per barrel of oil equivalent (BOE). Calculating the next century of oil economics with this 2 percent total variation in learning rates results in a span of uncertainty across the supply curve of 1,800 gigatons of carbon dioxide (CO_2)—roughly a half-century of current annual total CO_2 emissions from all fossil fuels. The total price effect contributed by learning (**P**)[2] in this case estimates an aggregate productivity improvement for oil supply costs across the century as high as +170 percent, or as low as -60 percent.[3]

Nordhaus (2009) argues that learning curve models of future energy technologies produce estimates of long-run productivity with a consistent upward bias. He suggests this is "dangerous" because costs for any energy supply strategy calculated from this technique are highly sensitive to a chosen learning rate that is difficult to validate (and possibly indistinguishable from model or data artifacts or normative preferences). This paper considers LBE assessments of fossil energy resources as a specific illustration of Nordhaus's argument. We highlight that physical and geological factors related to oil, gas, and coal recovery add further complexity to the issues raised by Nordhaus through analyzing the suitability of each hypothesis developed by Rogner (1997) for long-run fossil resource economics with contemporary data.

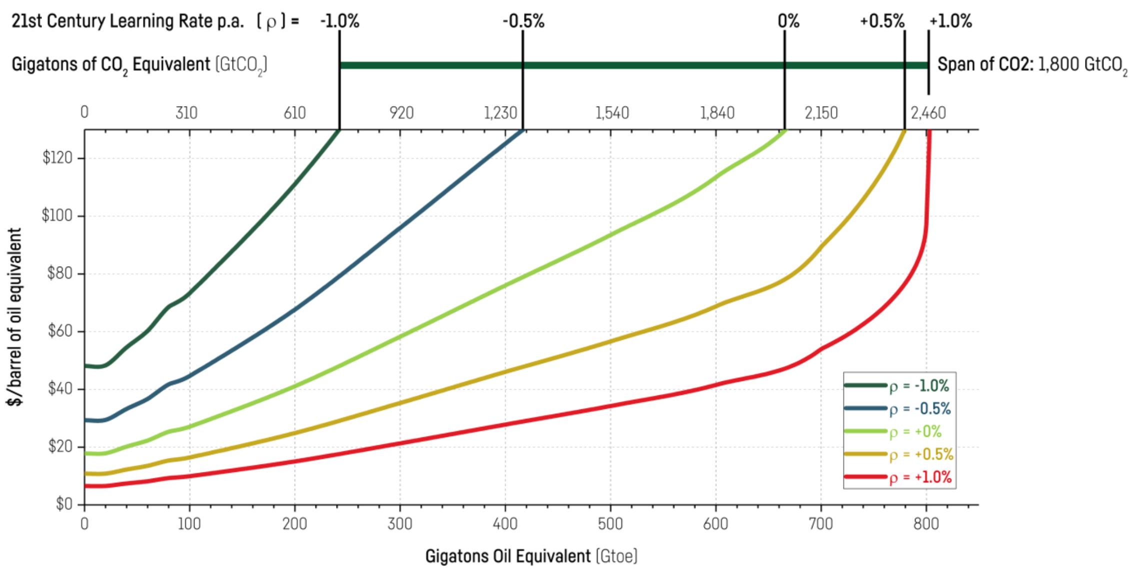
To develop this case, in Section 2 we revisit trends in upstream oil and gas productivity since the LBE model was developed in the mid-1990s, as a first step in linking the theory

[2] Throughout this paper we denote the annual learning-by-extracting effect as ρ: the rate of learning driven productivity gain, or dollar value of upstream cost reduction, while P is the cumulative productivity gain induced by learning over the duration of the projection.

[3] Note: Each curve starts at a different place on the y-axis as it reflects the learning effect throughout the entire century.

proposed by Rogner (1997) to empirical validation. In Section 3, we briefly examine the hypotheses of LBE for the context of coal. Section 4 extends the theoretical case of Nordhaus (2009) to the specific context of energy resources. Section 5 concludes by summarizing the paper and takes initial steps toward proposing solutions that can address inherent limitations in the LBE theory.

Figure 1. Influence of Learning Rates on Calculations of Future Oil Supply Costs



Notes: Rogner (1997) oil supply curve *(bottom x-axis in gigatons oil equivalent)* modeled with varied assumptions on the rate of productivity gains from learning (ρ = +1.0% to = -1.0%). The equivalent amount of emissions from carbon dioxide ($GtCO_2$) are shown on the top x-axis; the range of $GtCO_2$ spanning the variation in each learning driven supply curve is shown on the top bar *(green)*.

2. Empirical Trends in Oil and Gas: Production Costs, Market Influences, and Reserve Base Trends

We have now experienced more than 15 percent of the period Rogner (1997) originally projects to illustrate the LBE theory for future hydrocarbon energy resource supply, allowing its basic tenets to be revisited for empirical evidence of: (i) autonomous compounding upstream productivity driven by learning, (ii) long-term stable upstream costs independent of price effects, and (iii) the relevance of a reserve-to-production (R-P) equilibrium range for future oil and gas availability.

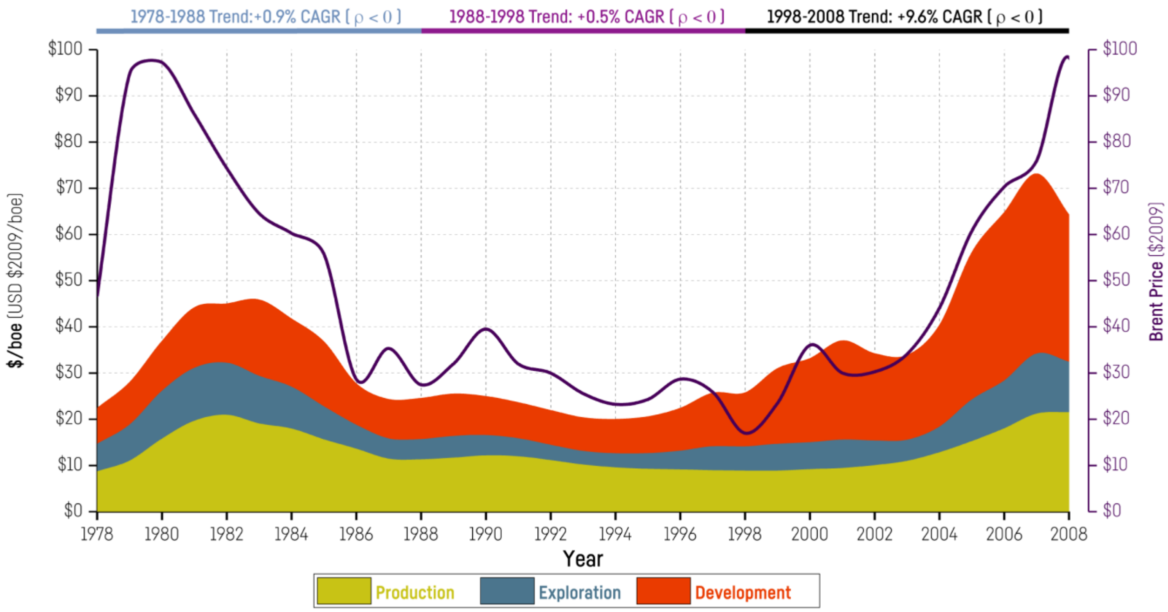
2.1. Data on Oil and Gas Upstream Costs: Evidence of Compounding Productivity Driven by Learning?

The US Energy Information Administration (EIA) conducted a regular survey of major US energy companies with its Financial Reporting System (FRS) through 2011. Subsequent FRS reports analyzed data on the financial performance of domestic and worldwide operations for companies that included ExxonMobil, Shell, ConocoPhillips, Chevron, and BP. The latest EIA FRS publication provides internally consistent time-series data from 1977 through 2009 that allow for examination of aggregate industry productivity data (US Energy Information Administration 2011). Figure 2a-b displays these reported FRS company cost trends for two elements of oil and gas production: total upstream expenditures per barrel of oil equivalent (BOE) for oil and gas (Figure 2a) and production costs less royalties (Figure 2b).

Figure 2a overlays the upstream cost trends for each decade of available FRS data, calculated by compound annual growth rate (CAGR) with a three-year moving average (top axis). Decadal trends in upstream costs indicated by these FRS data are: +0.9 percent (1978–1988), +0.5 percent (1988–1998) and +9.6% (1998–2008). Assuming a stable declining trend for total upstream costs would be inconsistent with the FRS data since the calculated productivity rate appears negative in each ten-year period ($\rho < 0$).[4]

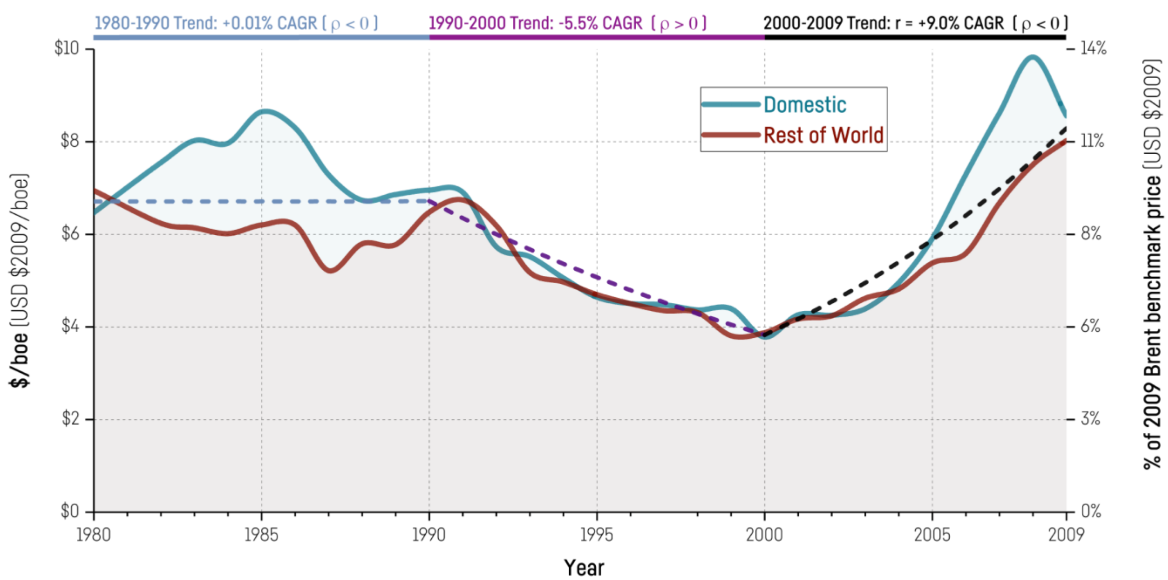
[4] The resolution of trend analysis is of importance to note: while the 1978-1988 trend shows a slight increase in costs, a smoothed compound annual growth rate would miscalculate the costs in nearly every year during the decade, missing the extreme cost increase from 1979-1983 and decline from 1984-1987. This reflects price volatility in the market for a global commodity. Alternative supply strategies that compete with oil through demand for manufactured products (such as wind turbines or solar panels) may have price trends that more directly relate to the learning-by-doing model for manufacturing.

Figure 2a. Upstream Trends in Oil and Gas Productivity (1978–-2008)



Note: EIA FRS reporting on worldwide expenditures for exploration, development, and production of oil and gas output in BOE with a three-year moving average (MA); (right-axis) annual Brent crude benchmark price (purple line) in constant dollars (2009$); (top-axis) the decadal compound annual growth rate (CAGR) trend for upstream costs.

Figure 2b. Trends in Direct Lifting Costs per BOE for EIA FRS Companies (1980–2009)



Note: Domestic trends (blue) and rest of world (red); (right axis) proportion of 2009 Brent benchmark price; (top axis) CAGR trends for each decade with dotted lines that correspond with each decadal trend.

Across the full three decades in the FRS data, total upstream costs increased at a rate of +3.6 percent per year. The right-axis (dark purple) of Figure 2a overlays the Brent market price in constant dollars (2009$). Exploration costs show the highest stability, fluctuating between 10 and 30 percent of Brent crude. Production costs dominate throughout the early portion of the time series (1978–1996) until development expenditures become the highest proportion of upstream spending from 1997 onward. Notably, the three-year moving average of upstream FRS expenditures exceed the Brent market price for much of the period during 1997–2002—signaling market prices that reached unsustainable levels for the industry in the long term. The increasing dominance of development costs in the late 1990s indicates a growth trend in industry capital expenditures, contributing to the supply-side conditions for the following decade's oil bull market.[5]

Industry trends for production, development, and exploration costs reported in the FRS (Figure 2a) align with the initial formulation of the LBE model in the period leading up to its original publication. From 1988–1996, total upstream costs per BOE of oil and gas output experienced an average -1.1 percent annual cost decline ($\rho \approx +1$ percent). Though these productivity gains did not translate to subsequent decades, this portion of the time series shows gradual improvements in oil and gas production costs as a learning effect one would expect for a homogenous product.

The closest equivalence between the cost ranges reported in the H-H-R supply curve and industry metrics are reported direct lifting costs.[6] Lifting costs account for the expenditures required to extract developed reserves after they are found and acquired. EIA FRS data on direct lifting costs provided in Figure 2b indicate that the technical cost of extracting oil and gas rose +0.7 percent per year from 1980 to 2009.

The three decadal cost trends range from negligible (1980–1990), to a sharp compound annual decline of -5.5 percent (1990–2000), and a rapid increase (+9.0 percent) in the first decade of the twenty-first century. From 1980–1992 the trend indicates a -1.0 percent annual cost decline from improving productivity. This sub-period appears to show the effect of learning from continuous production with conventional technologies in well-characterized geographic regions,

[5] The FRS data report aggregate oil and gas production, so these values are not directly indicative of actual producer marginal cost, or useful for calculating profit margin. While providing an internally consistent data set for upstream costs and production, the aggregation of oil and gas data makes disaggregation dependent on a series of complex assumptions.

[6] Though Rogner (1997) argues full upstream costs from exploration, development and production are captured in this model because of evidence suggested by development in the United States and production in the North Sea, and we contend that supply curves produced by the LBE approach more closely correspond to the direct lifting costs associated with production (e.g. operational expenditures). This case is argued throughout the following Section 2.2.

shaping the initial formulation of the LBE concept, which anticipates that these productivity gains would extend and continue for all geologic oil and gas resources.

Although the EIA is only one source for data on industry productivity, these upstream cost trends mirror the general features of other academic studies (Fantazzini, Höök, and Angelantoni 2011; Mitchell and Mitchell 2014); financial institution publications (Syme et al. 2013; Deloitte 2015; Goldman Sachs 2014, 2013; JP Morgan Asset Management 2015; Lewis 2014); and reports from oil industry consulting agencies (e.g., Kopits 2014; Rystad Energy 2015). We have elected to focus on the EIA FRS data because it is the highest quality dataset we could find in the public domain and available to readers for additional scrutiny. Additional efforts can harmonize these data with upstream trends from the most recent decade. Admittedly, while including worldwide measures for Canada, Europe, the former Soviet Union, Africa, the Middle East, and other parts of the world, these data are biased toward US operations. Therefore, an immediate question arises about the application of these upstream trends to studies of global oil and gas supplies, where OPEC producers play a major role.

We agree with Watkins (2006) that the deregulation of US oil prices in 1981 plugged the domestic market into the world, allowing information from the United States to provide a window into reserve prices and costs in all regions open to new investment. As non-US companies develop and explore for oil in the United States with operations around the world, the EIA FRS data series can be considered to generally represent the "shape" of costs in many parts of the world. Global price trends have mirrored these upstream costs, suggesting they are generally representative of industry marginal cost and performance trends.[7]

The LBE theory expected that compounding gains in performance would lead to ongoing cost declines from accumulated learning. Yet total upstream costs indicate an extended period of aggregate performance declines for total global oil supply. Despite specific performance increases in some regions and the rapid diffusion and innovation in new upstream technologies (e.g., especially horizontal drilling post-2005), sustained periods of productivity trends from 1978–2009 break from LBE projections. This discontinuity indicates that a model of autonomous non-price–induced learning for conventional oil and gas supply technologies does not capture relevant characteristics of the frontier between production technologies of the past and those of

[7] Operations in the United States are less subject to political instability than in many regions; however, they may be more expensive due to concerns about litigation and social license.

the future. A continuous learning effect applied to a heterogeneous resource base will thus face essential constraints in modeling the productivity of new technologies needed to access different types of resources in varied geologic formations.

The analysis in this section leads us to propose that specific manufacturing processes for future oil and gas production must be considered in models of long-run technological change to resolve contradictions between empirical trends and theoretical expectations for contributions from learning. The importance of introducing higher resolution modeling for extraction technologies is further illustrated by the context of capital expenditures.

2.2. Market Prices and Measured Productivity: Distinct Patterns for Operational and Capital Expenditures

The LBE theory expects that a learning effect independent of market price is a suitable explanation for productivity improvements in upstream energy resource extraction costs. However upstream costs are also contingent on a range of non-technical factors, including taxes and royalties, land valuations, political intentions and business cycles.

Osmundsen and Roll (2016) explore evidence of industry cycles on upstream expenditures and provide evidence that bullish periods lead to increases in costs per unit of output, reducing measured productivity. In periods of rapid expansion, oil rigs and other oilfield service equipment experience a faster hike in wages and rig prices, which reduces measured productivity, due to pressure from higher rates of capacity utilization. Conversely, in a market slump, equipment utilization rates decline, rig rates fall, and upstream productivity measures increase.

The FRS upstream costs we analyze mirror patterns in market price, but are these fluctuations in productivity more clearly shaped by demand- or supply-driven gains from learning? Rogner (1997) equates long-term price in LBE supply curves to marginal costs (P = MC) determined by technology that improves with learning to formulate cost projections dominated by supply-side factors. If learning-by-doing dominates upstream costs, an autonomous stable productivity trend is an appropriate model, since the costs of investing in supply expansion are largely independent of demand. However, Osmundsen and Roll point to one important way that demand-led prices shape marginal cost profiles, suggesting that point estimates of upstream productivity independent of market conditions may not be applicable.

While the EIA FRS data do not have enough resolution to develop a test of causality between market price and upstream productivity with robust econometric analysis, we broadly examine these relationships in Figure 3a-b. Production costs are summarized as operational expenditures (opex) and development plus exploration costs as capital expenditures (capex).

Figure 3a plots the year-to-year change in Brent price (top) alongside measured productivity gains for opex (middle) and capex (lower) from the FRS data in Section 2.1. Price declines visibly precede productivity gains through the early 1980s, suggesting much of the "learning effect" measurable over this period resulted from industry consolidation. Parallel productivity gains in this series for opex are far less volatile than capex, and consistent with what a learning model would expect: 1991–1999 shows an eight-year stable improvement in operational productivity (ρ ~ +3 percent). Because long-term models smooth trends to maintain numerical tractability, the histograms (right-side) highlight empirically consistent normal distribution fits with mean values over the entire time series for opex of $\rho =$ -4 percent (dashed yellow line*)* and $\rho =$ -5 percent for capex (dashed orange line).

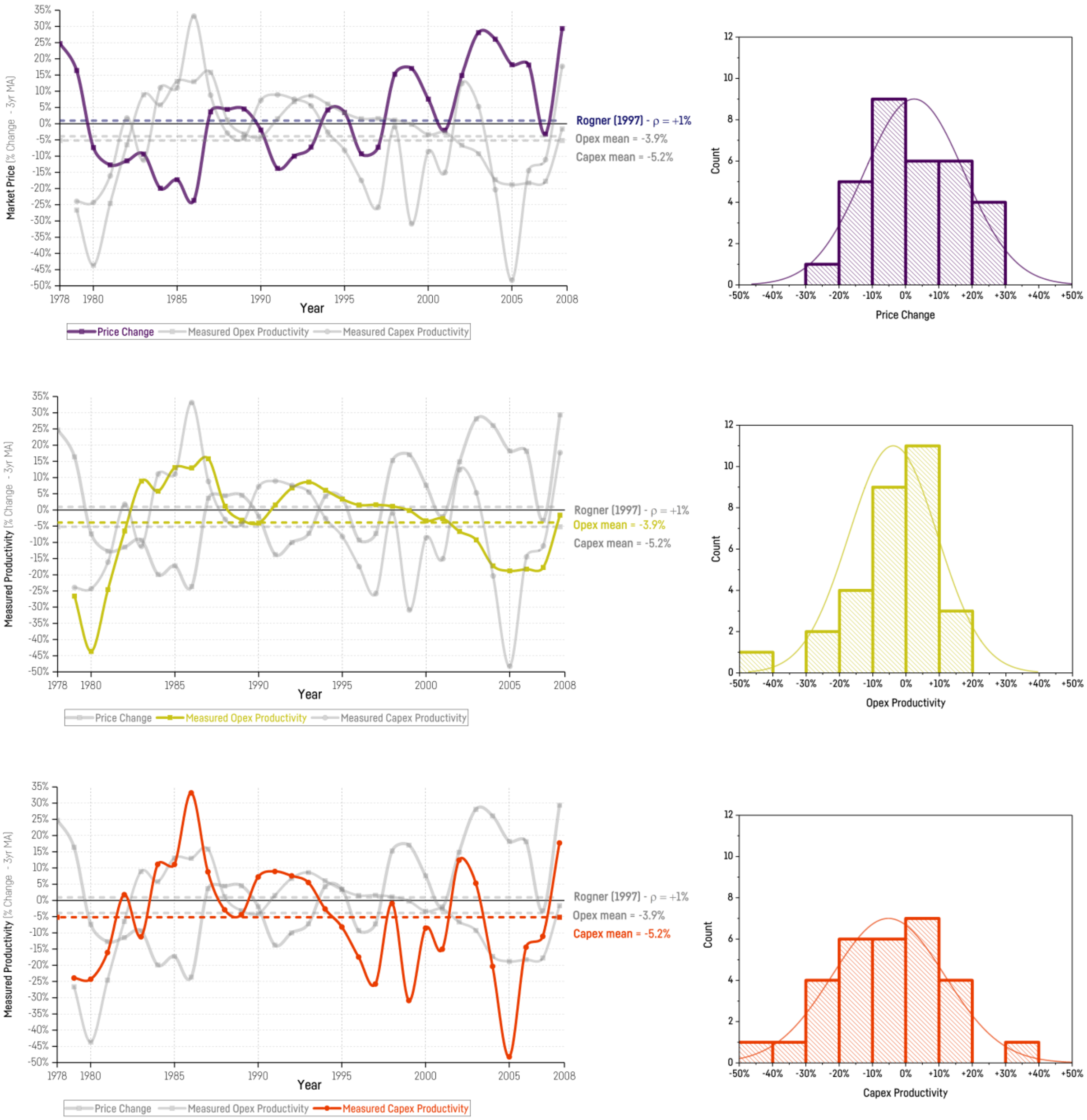
To test for the relevance of price effects, Figure 3b shows the influence of market fluctuations with year-to-year marginal changes in productivity measured per dollar of market price ($\frac{d\rho}{d\$}$). Once again, the theoretical framework of LBE shows close correspondence to opex trends: production expenditures experience little sensitivity to market price throughout the time-series, as Rogner (1997) originally assumes for total hydrocarbon energy supply.

A simple time series average for opex indicates the productivity of operational expenditures fell by 0.08 percent for every dollar increase in market price ($\frac{d\rho}{d\$} =$ -0.08), but an equilibrium value is close to zero. We interpret this as further confirming the validity of a non-price–induced productivity model for opex. However, this assumption does not extend to capital expenditures where marginal productivity rates fluctuate significantly from 1979–2008.

The overall relationship between price and capex in this time-series is broadly negative ($\frac{d\rho}{d\$} < 0$), suggesting the industry tends to commit capital investments when market prices increase. The cyclical nature of this trend indicates the industry adjusts expenditures based on what the market outlook allows over any multi-year period. Large positive values for capex in 1990, 1997, and 2003 may indicate points where the industry was temporarily starved for capital from underinvestment over the preceding period, and it is playing catch-up. Significant increases in amplitude during the latter half of the series may account for the scale-up of capital investments needed to extend production into areas that required deepwater drilling and hydraulic fracturing, alongside boom times for the industry in the early twenty-first century.

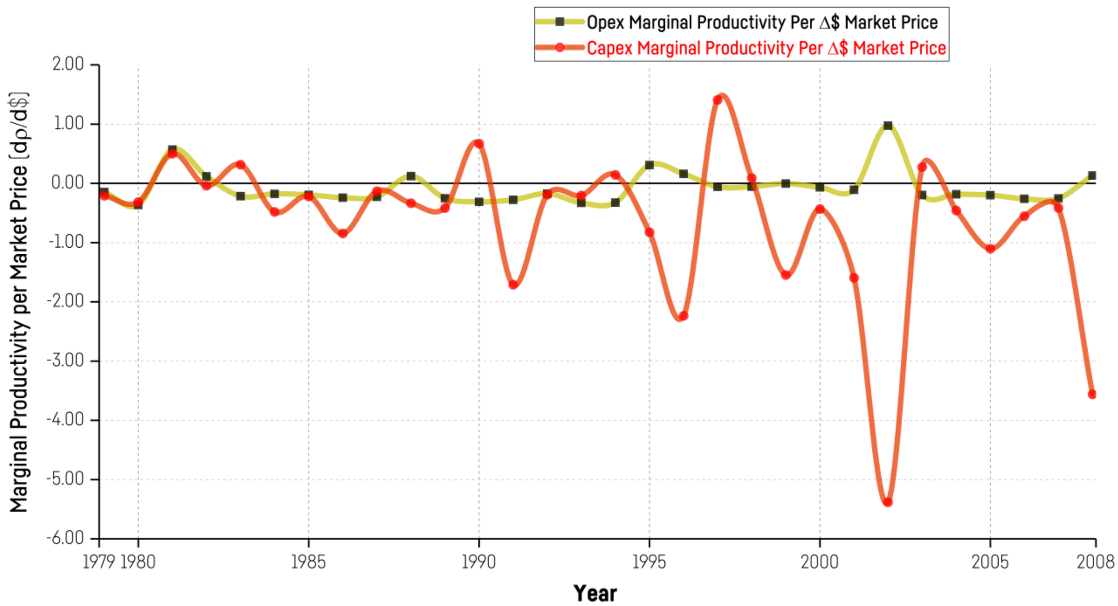
Figure 3. Relationships between Upstream Spending, Measured Productivity Changes and Market Price (1978–2008) for EIA FRS companies (3-yr MA)

Figure 3a. Market Price and Upstream Productivity Trends Multi-Plot



Notes: 1978–2008 time-series (left column) and histogram with normal distribution fit (right column) for 3-yr MA change in Brent market price (purple line, upper); measured productivity improvement for operational expenditures (yellow line, middle); and capital expenditures (orange line, lower). The original Rogner (1997) estimation of 1% annual productivity gain is overlaid on the time series (dark blue dotted line, upper) along with the average productivity improvement for opex (dashed yellow line, middle) and capex (dashed orange line, lower); each plot includes gray lines for the other two data series out of focus.

Figure 3b. Marginal Upstream Productivity Rate per Dollar of Change in Market Price - ($\frac{d\rho}{d\$}$) for Operational Expenditures (yellow line) and Capital Expenditures (orange line)



Since many oil and gas companies employ significant teams for forecasting and strategy, decisions to commit development costs are undoubtedly contingent on scenarios for market outlooks. This analysis suggests the relevance of simulating market conditions for projections of upstream productivity over the long run. It seems difficult to harmonize an outlook for optimal investments that result in supply-led marginal costs determined by a 1 percent per year learning improvement with an industry that undertakes marginal capital investments under an expectation of higher market prices.

As visible in the FRS data from 1998–2008, development expenditures continue to accelerate in line with market prices (Figure 2a and 3a), indicating that the projects expanding marginal supply from the expensive end of the cost curve receive a green light under outlooks for continually increasing prices. If a 1 percent per year improvement in total upstream productivity had occurred from 1988–2008, total upstream costs would have fallen from $24.50 per barrel to $20 per barrel by 2008, and expenditures on capex would have declined from $13 to $11 per barrel. Such a projection would have underestimated total upstream costs over these two decades by an average of 60 percent per year and capex by 100 percent per year. In this case, the LBE theory would have anticipated an equilibrium Brent market price of $26 per barrel through the period from 2000–2008 over which Brent market prices averaged $60.[8]

Overall, it is unlikely that year-to-year average productivity measures for capital would maintain such distinct volatility across the industry. We therefore interpret these fluctuations of measured annual productivity in capex as indicating the dominance of essential business cycle elements over a measurable level of pure endogenous learning in this time series. These are the factors originally discussed by Schumpeter (1934; 1939): during an upturn, wages increase and labour productivity decreases; during downturns, the opposite occurs, as companies throttle expenditures for production capacity based on market outlooks.[9]

FRS data illustrate important and relevant macro-scale aspects of the trends explored at the micro level by Osmundsen and Roll (2016): short- and medium-run constraints on production equipment during booms drive up costs because limited supplies of oil-field capital and labor may command higher prices. Accounting for such demand-led marginal costs in a long-run supply model is necessary: socioeconomic conditions of many long-run policy models are predicated on a "long boom" of equilibrium growth in economic output (Clarke et al. 2014).

Total upstream costs per unit of production decline in a market bust, but resulting productivity measures are dominated by the expenditure reductions driven by responses to market conditions—and not the influence of learning. Capex productivity improvements in these data under such an economic environment seem to primarily reflect curtailed expansion of production to new areas. Even though market pressures drive innovation, aggregate industry productivity data require a careful analysis that accounts for explicit technological improvements alongside potential bear or bull market conditions—an insight particularly relevant for oil, gas, and coal production data collected during the commodity bear market that started in 2014.

While short, multi-year downturns merely constrain future output growth, extended periods of low capital investment will eventually lead to maturing production and well depletion,

[8] This projection of market prices maintains average mark-up per barrel in the FRS series of 30%.

[9] These measures are further complicated because of the long-run outlooks required to develop new fields, i.e. market price outlooks for development expenditures must look beyond 3-year moving averages. However, this comparison is developed with 3-year MA market prices to make a one-to-one comparison with the original FRS data. In many regards, a year-to-year measure of capex productivity is limited but this is provided to match the annual point estimates in the LBE model.

a 9 percent annual decline that sustained investment tends to reduce by 3 percent in aggregate.[10] Measured productivity gains due to a period of oversupply and falling oil prices do not inherently translate to increased long-run output potential because the production of oil resources are inherently different from manufacturing of an homogenous product: the production profile of specific wells and fields declines over time.

This analysis of FRS data indicates that: (i) the LBE model accurately captures non-price–induced secular trends for spending on operations; and (ii) the performance of energy-sector capex is poorly represented in a homogenous formulation of marginal costs driven by the accumulation of learning.

Accordingly, some element of observable market price effects must inform a model of long-term industry productivity trends to overcome biases introduced by aggregating operational and capital investment dynamics in the LBE theoretical approach to upstream cost. Plausible simulations of long-run oil and gas supply costs require an explicit representation of the industry decision context for capital expenditures.

2.3. How Relevant Is an Equilibrium Reserve-to-Production Range for Calibrating Future Upstream Cost Profiles?

The LBE theory draws from a reserve-to-production (R-P) ratio for oil and gas, which maintained relative consistency over the twentieth century, suggesting that recoverable reserves can be conceptualized as a flow that continually draws from the total stock of geologic resources. Therefore, resources are continually reclassified as reserves with production at costs subject to productivity improvements driven by learning. This is the underlying concept for an equilibrium R-P ratio—it is maintained within a consistent range of values by ongoing development of resources into reserves. The equilibrium R-P ratio intends to represent the behavioral dynamic of producers who otherwise have little incentive to invest in knowledge of energy resources at lower production rates. However, the last few decades of data challenge the relevance of this assumption to projections of upstream costs driven by learning and the accumulation of knowledge.

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[10] The IEA World Energy Outlook 2016 highlights that depletion rates for global mature fields are around 9%, but sustained investment reduces decline of producing fields to 6% (IEA, 2016). Fustler et al. (2016) review the academic literature on decline rates, estimating a 6.2% per annum rate post-peak.

Even as R-P ratios for oil and gas can remain relatively stable, the expenditures necessary to develop reserves into production have varied. A growing reserve base doesn't inherently ensure that oil is getting cheaper to produce, and can often mean the opposite. The costs of converting proven reserves into a producing well are accounted as development expenditures. In the LBE theoretical approach, development expenditures represent the costs of moving the dynamic boundary that differentiates the total geologic stock of an energy resource from its reserves, and their eventual production. Figure 4a-c plots several relationships between production, reserves, and development costs for oil and gas. Figure 4a depicts the proportion of exploration, production, and development costs in the EIA FRS. Development as a fraction of upstream costs remained relatively stable from 1978–1991 but grew steadily from 1992–2005. Data from EIA FRS companies indicate that total expenditures on development grew from $7.50 per BOE in the mid-1990s to $36.50 per BOE in the mid-2000s. Over this period, development costs grew 4.8 percent per year from 1978–2008, outpacing growth in operating costs by 56 percent.

As an aspect of total industry marginal cost, development costs will be reflected in market price. Over the last few decades, development costs have mirrored trends in market prices much closer than trends in exploration or production costs (see Section 2.2). We suggest that by focusing on the technical operating costs of producing wells, the LBE supply curves applied thus far in the literature reflect only one-third of the marginal cost of oil and gas production. This has neglected the cost and performance dynamics of the boundary between resources, reserves, and production—especially as significant unconventional resources were being developed. Development costs are highly sensitive to aspects of technical difficulty introduced by geology or geography.

Adelman (1995) characterizes essential features of industry behavior with a warehouse metaphor, where reserves are the dynamic inventory. This warehouse inventory is replenished from the resource base and depleted through production, with reserves established by expenditures on development. Adelman highlights that production capacity is likely to increase if development costs are below the equilibrium market price, but intensive periods of development raise the marginal cost per barrel of output, continually testing the equilibrium value. This interplay between supply and demand converts the marginal warehouse inventory of reserves into production as fast as the equilibrium market can rise.

Accordingly, we suggest that the relationship between expenditures on reserve development and demand drives cycles of marginal cost and market price that fluctuate around the base of proved reserves. An autonomous equilibrium R-P ratio provides little information on the availability of long-run supply if applied independently of development cost trends. [11]

A stylized version of these cycles is illustrated by a ratio of proven reserves and market prices (R-to-Price).[12] When plotted (Figure 4b), industry data suggest the realization of reserves has fluctuated through two major cycles between 1955 and 2015. Each point on the curve in Figure 4b represents the size of the global oil reserve warehouse and the cost of converting it into production. A lower value indicates fewer reserves or higher costs (more expensive warehouse withdrawals) and vice-versa. In this series, peaks in the ratio of proven reserves-to-price occur in 1970 and approximately 1997–2001; troughs occur in the mid-1950s, 1980, and perhaps 2016.[13]

In this cycle, increasing overall costs test the maximum threshold of market demand. Once market equilibrium no longer supports further growth in development costs, pressure eases on the need to sustain high production growth rates. At this point, upstream costs consolidate around ongoing viable operating production at a lower market price level (the 1980s and 2014–2016). Regardless of the exact mechanism generating these two cycles, they indicate that the industry conditions that lead to increasing reserves at lower cost only characterize one-half of each cycle since 1955. The presence of reserve base cycles suggest the initial formulation of the LBE theory is based on a convention that projects dynamics consistent with the upward swing (1980–2000).[14]

Though the LBE supply model as applied in Rogner (1997) and subsequent studies allows the total size of the warehouse to grow, development costs that would govern the rate and costs of "warehouse withdrawals" are noticeably missing—such as Adelman's (1995)

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[11] The snapshot of a reserve base at a point in time will include a portfolio of projects with a range of necessary development costs to realize production consistent with today's output. The view of Adelman (1995) is that the stock of geologic oil resources is irrelevant, and what matters is the development cost needed to provide a regular flow of oil production.

[12] Market prices are assumed to reflect some aspect of medium-run marginal costs related to mobilizing reserves—i.e., reserves anticipated to be economically viable are developed at expected market prices.

[13] Data for oil prices and reserves were collected from the BP Statistical Review (2015) and for 1948-1980 from the Oil Economists' Handbook (Jenkins, 2005).

[14] One possible interpretation of these cycles could build from structural adoption of present and future oil demand that generates alternating states of pressure and release on the reserve base. As the reserves in the present become cheaper (upward ascent of each cycle), development costs accelerate to keep production capacity growing on pace with the demand that readily results from increased availability. As the rate of adoption increased from the 1990s through the early 2000s, development costs increased as a proportion of upstream spend (Figure 4a).

observation that development costs increase rapidly during periods of high capacity use. Therefore, we argue that the LBE conceptualization of dynamic oil and gas resources focuses on inputs to the reserve warehouse but poorly captures aspects of realizing the warehouse inventory's potential for production.

Because development costs are an important element of marginal production cost largely missing from long-term supply curves shaped by the LBE theory, the resource-to-reserve-to-production dynamic applied to future oil, gas, and coal are only consistent with an outlook for permanently optimal investment, where supply is expanded at the lowest possible cost in perfect foresight. Costs of oil and gas supply estimated by the LBE model are unmoderated by the development costs and market prices that could diminish reserve growth, lower demand, or decrease production in a competitive marketplace with a diversity of energy supply strategies.

The projection of a learning effect point-estimate from any single state in this reserve-price cycle will result in an overabundant or overly scarce depiction of oil and gas supply. Each point in the historic time-series of Figure 4b is a valid representation of the supply-demand balance for the reserve base at a snapshot in time. Projecting a learning trend that smooths this cycle by starting with a selected baseline period is likely to considerably miscalculate the cost of mobilizing reserves in all future periods by establishing overly bearish or bullish conditions from the outset.

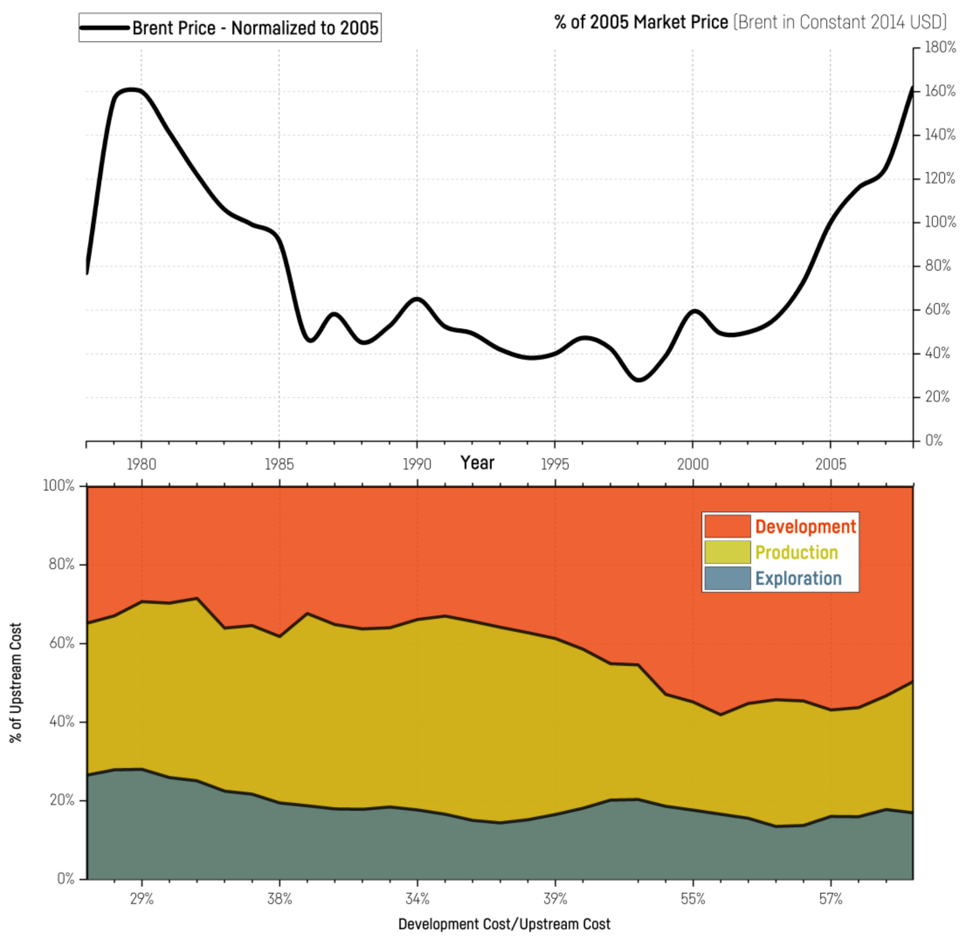
To illustrate how this distortion is likely to occur, we conduct a Monte Carlo (MC) simulation with 200 runs that randomly select a base year R-$ value (1950-2014) from a uniform distribution of the underlying data from Figure 4b for calculation of compounded learning across the twenty-first century. Projections of this reserve-to-price ratio are overlaid on Figure 4c for 600 gigatons of oil equivalent (Gtoe) (>140 years of supply at 2014 levels) from Rogner (1997), GCAM (Joint Global Change Research Institute 2016) and 570 Gtoe from MESSAGE (Riahi et al. 2012). Historical trends across a five-year moving average for proved reserves (P1) to constant 2014 US$ (R/$) are illustrated by the solid black line which reproduces Figure 4b.

The mean year-2100 value from the results of our MC simulation is R-to-$ = 70.43, which represents a steady-state reserve-base condition 55 percent higher than data indicate the industry has ever experienced. By midcentury, the average value of all runs has surpassed previous peaks in the late-1990s and early-1970s.

Though the projections of Rogner (1997), GCAM, and MESSAGE may appear like conservative median estimates when plotted against the full range of simulations, they are consistent with the MC simulations which have already reached the most bullish observed industry conditions by 2050. Representing these states as the baseline for industry operation will significantly underestimate the cost and overstate net economic benefits of future supply.

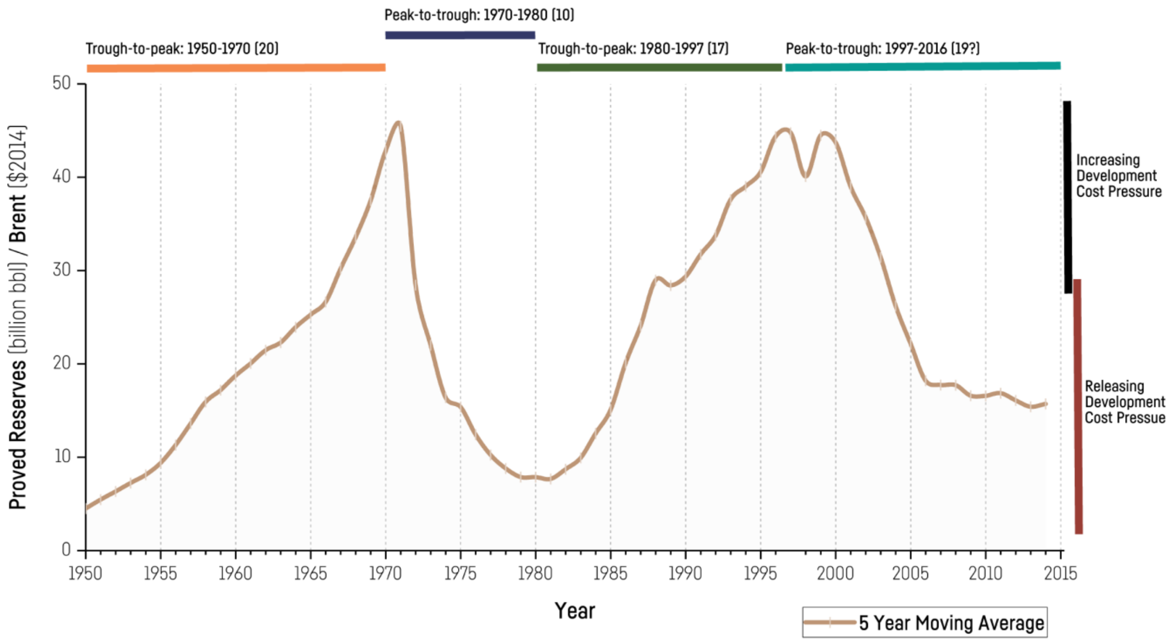
Figure 4. Oil Reserves, Production, and Development Cost Trends

Figure 4a. Development Costs as a Proportion of Upstream Costs (1978–2009)



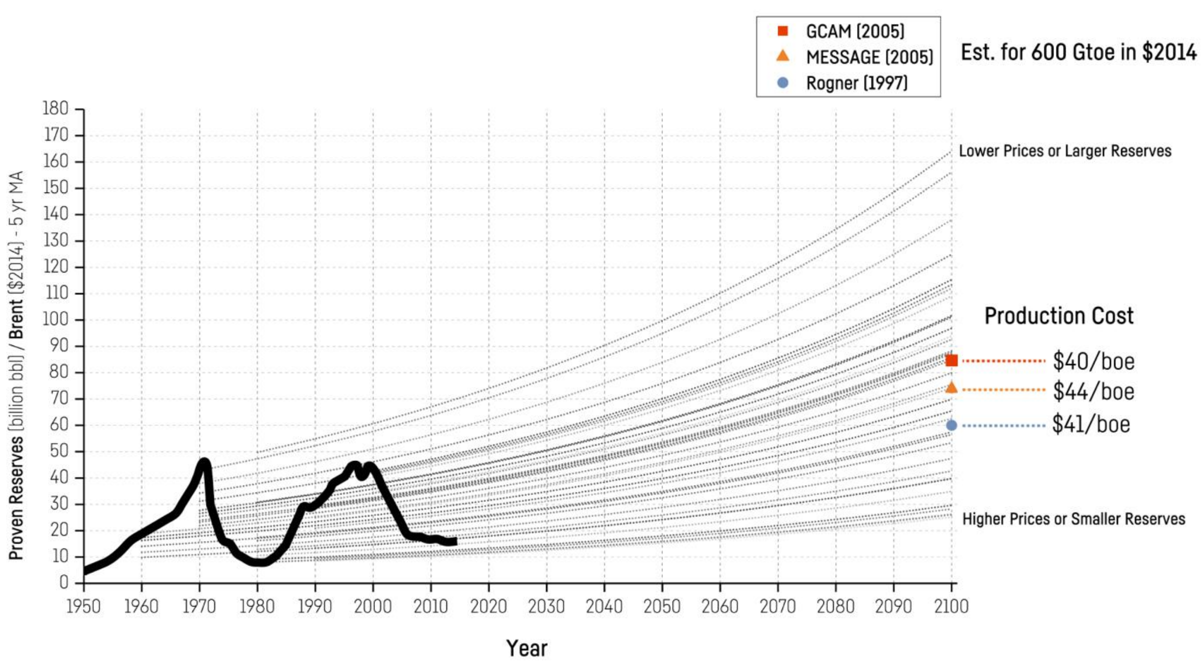
Notes: As reported by EIA FRS (2011), with top chart displaying normalized Brent price normalized to 2005 for comparison.

Figure 4b. Two Distinct Cycles in Reserves: Quantity of Proved Reserves-to-Brent Prices for Oil (1955–2015)



Notes: Right-axis indicates regions of each cycle which lead to increasing pressure on development costs and declining pressure on development costs; top-axis notes duration of cycle states from trough-to-peak and peak-to-trough.

Figure 4c. Range of Estimates from Relative Ratio of Proven Reserves to Price for Oil



Notes: Historic trend with 5-year moving average (solid black); a Monte Carlo simulation of 200 runs randomly selects from a base year R-$ value between 1950–2014 with uniform distribution and projects this value at ρ = 1% per year (thin lines); values for 600 Gtoe of oil (>140 years of supply at 2014 levels) are provided for Rogner (1997) and GCAM (2012) and 570 Gtoe for MESSAGE (Riahi et al., 2012)

As these cycles indicate, the relationship between reserves and price is more dynamic than a monotonic decline in upstream costs and stable replenishment of reserves. When the original LBE model was published in 1997, data from the preceding period would have undoubtedly been influenced by the upward swing of the reserve-price cycle of 1980–2000. A sustained negative slope in this reserves-to-price ratio is likely to create perception of increasing scarcity, while a sustained positive slope could lead to a perception of increasing abundance.

Future research on long-term energy resources must strike a balance that recognizes the cyclical nature of industry operations that moderate bullish and bearish periods. The boundary between producing reserves and resources can move in directions that allow production of more reserves at lower cost, and vice-versa.

Similar equilibrium R-P trends in conventional oil and gas are applied by the LBE theory to characterize the total occurrences of geologic coal. We now examine the validity of a learning-by-doing model with a dynamic reserve boundary for the coal resource base.

3. Assessing the Learning Hypothesis for Total Geologic Coal Occurrences

Despite varied development costs for recovery of oil and gas, increasing knowledge has generally led to the discovery and classification of more reserves over time (e.g., Adelman and Watkins 2008; Watkins 2006). LBE supply curves hypothesize that the resource-to-reserve dynamics of oil and gas can characterize the future of the coal resource base. While increasing knowledge of oil and gas has discovered more economically recoverable reserves, coal resources have followed the opposite pattern (Ritchie and Dowlatabadi 2017).

As coal deposits are generally easier to discover and assess than oil and gas, coal availability studies often start by establishing the largest possible quantity of total coal resources (Fettweis 1976; Höök et al. 2010; Rutledge 2011). After an initial assessment determines the amount of coal in a deposit, a process of ongoing subtraction clarifies the portion recoverable as reserves (e.g., accounting for those that are too deep or for which the seam is too thin). An economic assessment further shrinks the reserve base by eliminating portions of a deposit that are not viable for profitable production. Several dimensions of hard coal resource assessments relevant to an evaluation of the LBE theory are provided in Figure 5.

The process used by the US Geological Survey (USGS) to assess the coal resource base (Figure 5a) demonstrates how increasing knowledge continually subtracts from initial coal availability studies (Luppens et al. 2009). The original availability studies at the root of this process are rarely updated. Recent documents from the USGS and the EIA still cite Averitt (1975) as establishing primary data on the national coal resource base in many areas. Recoverability studies are updated with more regularity, but tend to focus on specific regions where coal mining is already ongoing (such as for the United States with Luppens 2009 and Ruppert et al. 2002).[15]

The 1913 International Congress of Geologists (IGC) in Toronto established an original aggregate assessment for global coal resources. Since then, the World Energy Council (WEC), previously the World Power Council (WPC), and the German Federal Institute for Geosciences and Natural Resources (Bundesanstalt für Geowissenschaften und Rohstoffe, BGR) have maintained regular publications on global coal reserves and resources. As vintage editions of these assessments can be difficult to procure, we rely on the twentieth-century values of the IGC, WPC, WEC, and BGR reported by Fettweis (1976), Rogner (1997), Gregory and Rogner (1998), Höök (2010), and Rutledge (2011).

These data indicate global coal reserve base trends have mirrored the USGS process of ongoing subtraction. In other words, more of what used to be considered recoverable reserves has been reclassified as resources over time, or simply removed from the records. Recent WEC and BGR data are consistent with these trends.

The global reserves-to-resources dynamic for coal is depicted in Figure 5b, which plots the Rogner (1997) synthesis of BGR (1989) and WEC (1992) next to recent BGR studies (BGR 2014, 2010) used by the IEA (2006–2015) and against Rogner (2012). To maintain consistency with the H-H-R supply curve, energy units (Gtoe) for each coal assessment (Figure 5b) are harmonized with physical units (gigatons) based on values used by Rogner (1997).[16]

An empirical learning curve for increasing knowledge about the global coal resource base measures a -4.5 percent annual decline in reserves from Rogner (1997) to the BGR (2014) assessment. A similar trend is present in the WEC and BGR vintage reserve data reported by

[15] Initial availability figures for several nations come from assessments in the late 19th-century, such as the initial figure for China of 1,000 Gt provided by German geographer von Richthofen during his surveys from 1877-1911 (Fettweis 1976). Recent data available from the UK indicate that coal supply figures are consistent with those from the 1870s (Department for Business, Energy, & Industrial Strategy 2015). Rutledge (2011) writes that in the UK, the 1871 Royal Commission provided the reserve estimate until 1968, after which the updated quantities of reserves fell rapidly.

[16] To ensure internally consistent comparisons, we follow the methodology of Rogner (1997) by using average primary energy content values of each region.

Höök (2010), which includes lignite. Consequently, the global coal R-P ratio of more than 200 years (1980–2000) has fallen to approximately 100 years (2014).

However, any trend is difficult to ascertain because inconsistencies in data over time make useful comparisons of dubious quality. Fettweis (1976) argues that the primary changes in total world coal resources reported to the IGC (1913) and subsequent assessments through 1970s were: (i) changes in reporting definitions on the depth limit of resources (up to 1,200m, 1,800m, or no limit); (ii) the addition or subtraction of hypothetical “prognostic resources;” and (iii) the correction of errors. These factors still appear to contribute to the notorious reputation of modern global coal data.

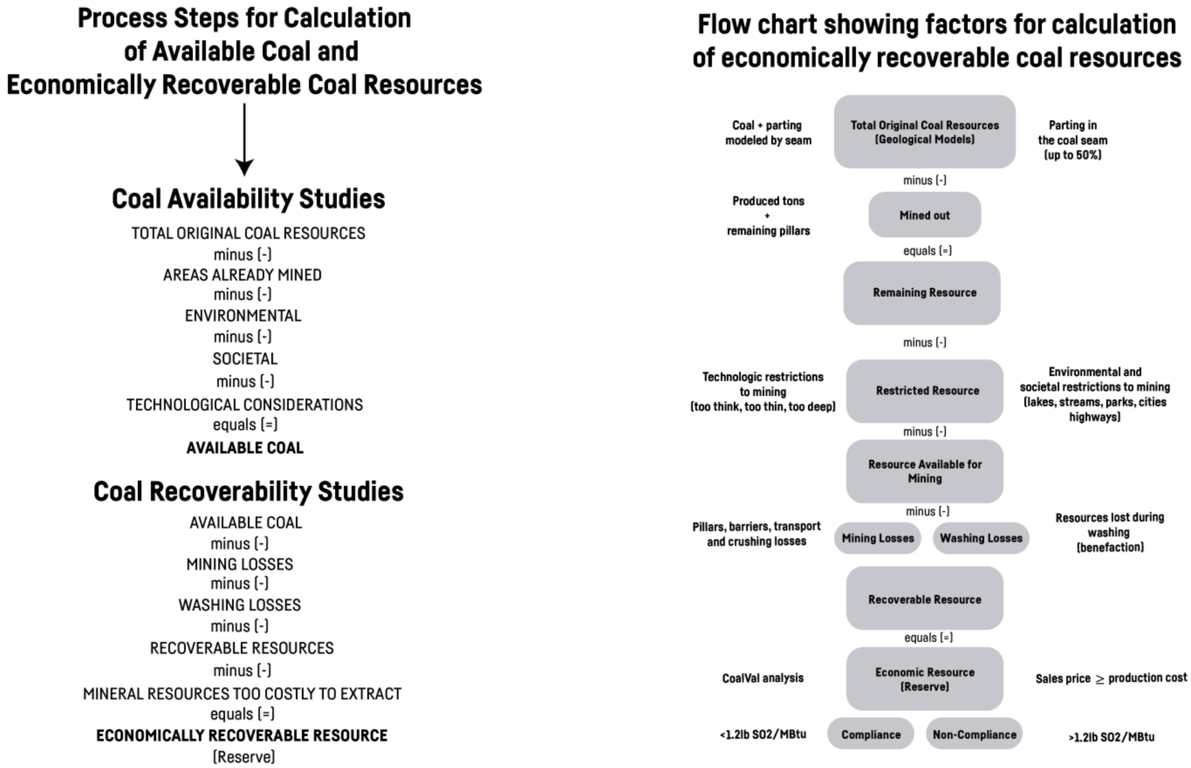
IEA coal database figures on domestic coal supply do not consistently match reserve or resource numbers in annual *Coal Information* reports (IEA 2015). Despite growing production, China’s reported coal reserves remained relatively static since 1992—confusion has resulted from definitions of economically viable *reserves* and coal classified as *basic reserves* (Wang, Davidsson, and Höök 2013).

Heterogeneous national definitions of reserves and resources further muddle varied assessment techniques that blur the line between whether a nation’s coal reserves have been quantified with a focus on economic or geologic factors (Fettweis 1979; Wang et al. 2013) or whether a recovery rate has been applied in determining “recoverability” (BGR 2015). In recent years, WEC has omitted reporting on global coal resources, focusing only on reserves.

More consistent reporting standards and definitions applied in the early twenty-first century have increased overall knowledge of the global coal resource base. The learning that has accumulated over this period about geologic coal has decreased the assessed quantity of reserves (CIM 2014; Hartnady 2010; JORC 2012; Wellmer 2008). Despite upward revisions to reserves in some regions over this period, cumulative production figures indicate that at least 20 percent of the aggregate decline has resulted from factors attributable to learning: increasing knowledge and improved reporting (Ritchie and Dowlatabadi 2017).

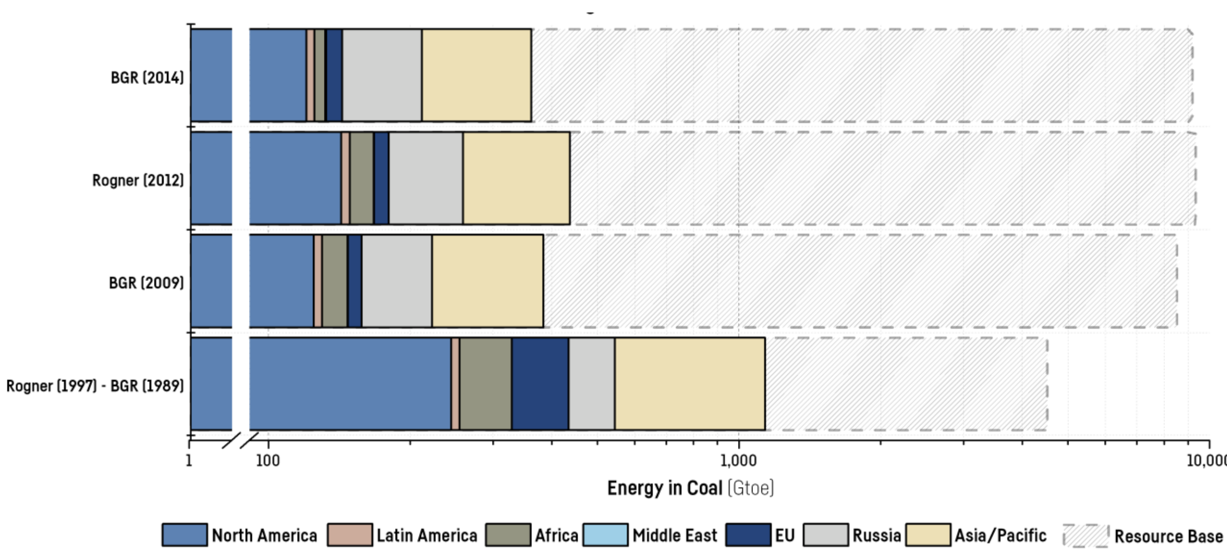
Figure 5. Assessing the Global Coal Resource Base over Time

Fig. 5a Process for Calculating Economically Recoverable Coal



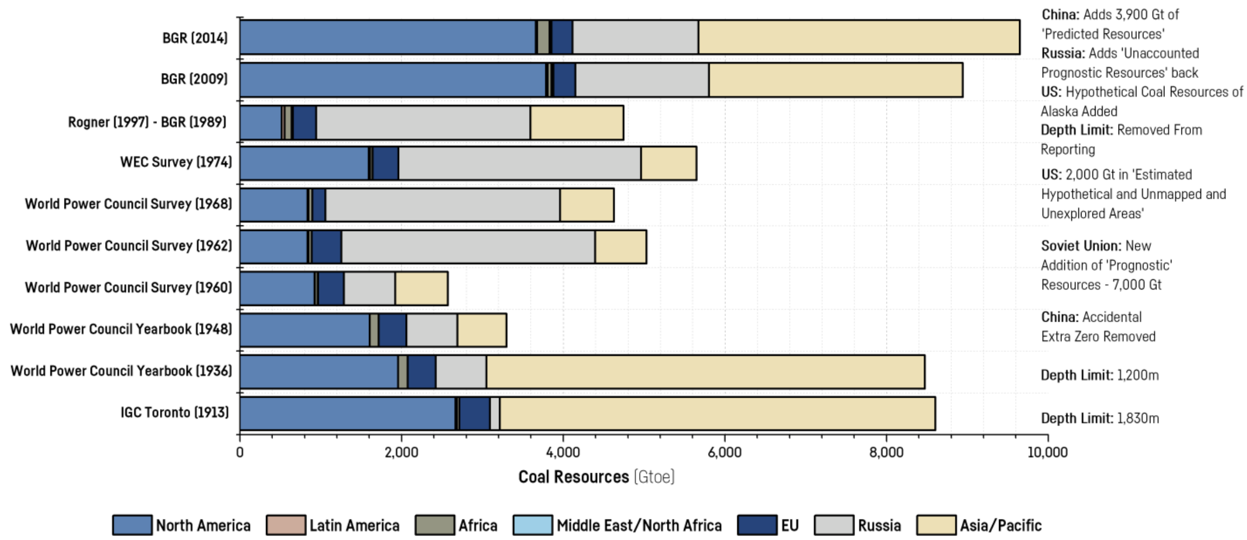
Source: Adapted from USGS (2009)

Figure 5b. Coal Reserves as a Fraction of Recent Coal Resource Assessments



Sources: BGR 2014, 2010; Rogner et al. 2012; Rogner 1997.

Figure 5c. Total Coal Resource Base over Time with Key Points Noted



Sources: BGR, 2014, 2010; Fettweis 1976; Höök et al. 2010.

The assessed size of the total global coal resource base (Figure 5c) has only recently surpassed values from the early twentieth century. Much of the known geologic coal resource base (about 70 percent) is in the hypothetical prognostic resources of Alaska (28 percent), Siberia (20 percent) and China (22 percent) (BGR 2014; Flores et al. 2004). Quantities of assessed prognostic resources are based on a favourable geological environment assumed from projections and assumptions of the probable dimensions of a potential deposit (Henley 2004). Applying a learning-induced productivity gain to quantities of energy from prognostic resources does not constitute a plausible context for learning-by-doing.

Since the R-P ratio for coal maintained a value of more than 200 throughout the twentieth century, the incentive to explore for coal reserves was small. If the R-P ratio continues to fall during the twenty-first century toward a new equilibrium value similar to oil and gas (40–60 years), the interest in exploring for coal will undoubtedly grow. Any assessment of future coal supply must consider this possibility.

Will exploration discover more geologic coal resources in the twenty-first century? Absolutely. The hypothetical occurrences of coal in the Earth's crust are possibly far more extensive than even the total resource base of BGR (2015) indicates: 440,000 exajoules (EJ; or 10,500 Gtoe). Yet the likely discovery of more coal in extreme locations is insufficient to justify the projection of oil and gas reserve dynamics on the occurrences of hypothetically combustible carbon in the Earth's crust, since reserves provide a benchmark for our understanding of recoverable coal. Sustained declines in the coal R-P ratio over the last decade has not followed the trend of oil and gas, where increased consumption has also increased reserves.

The economic and market conditions that may allow reserves downgraded since Rogner (1997) to be reclassified as recoverable would also face stringent competition from a range of other options of energy supply and demand. There are further issues with procuring enough water, establishing social license, and navigating the legislative constraints necessary to realize ambitious coal supply figures. As Figure 5a illustrates, social and environmental factors play a major role in subtracting from the total coal resource base.

Including the full extent of the coal resource base in a twenty-first century supply curve requires normative choices for coal supplies and technology, such as those Rogner (1997) describes: drastic, specific progress in technology at a sustained rate several times the historically observed average. This requires radical shifts from today's coal mining technologies, outside the scope of reasonable productivity improvements that could constitute plausible projections of a learning rate or equilibrium reserve value.

Still, even if perfect data were available on cost trends of oil, gas, and coal production so that aggregate productivity trends could be robustly interpreted, would it be possible to identify and fully distinguish improvements attributable to learning?

4. Nordhaus (2009) on the Perils of the Learning Model: Applications to Energy Resources

The LBE theory for future hydrocarbon supply is conceptualized by Rogner (1997) with market prices determined by marginal production costs over the long-run (P = MC). Market prices are exogenous in this supply-led model, calibrated by the influence of endogenous learning, which drives production costs with the cumulative experience that results from continued extraction of the geologic resource base.

Though markets for energy commodities are global in scale, resources are locally produced under myriad conditions dictated by firm structure, international politics, royalty and tax accounting, technology, geology, and access to markets. Surmising an aggregate estimate of macro-level productivity improvements is at best a speculative venture, as demonstrated by the volatile year-to-year productivity rates described in Section 2.2.[17]

Nordhaus (2009) argues policy models that apply a learning curve to assess future technological change for energy supply strategies are potentially dangerous: they are highly sensitive to artificial learning rates that could be indistinguishable from measurement errors and normative choices. He develops a theoretical case for a generic industry to illustrate that productivity gains explained as “learning-by-doing” will always lead to upwardly biased estimates of long-run productivity, because the influence of pure endogenous learning is difficult to isolate and identify. His general theoretical case is summarized in the Appendix.

From this generic industry, Nordhaus suggests that: (a) there is a fundamental statistical identification problem in separating an endogenous learning effect from exogenous productivity gains; (b) the subsequent estimated learning coefficient is generally biased upwards; (c) model parameters intended to represent learning effects are not robust to alternative explanations and specifications; (d) overestimates of learning coefficients will underestimate the total marginal cost of output for a technology; and (e) optimization models that rely on learning curves are likely to simply choose technologies that incorrectly or arbitrarily specify a high learning coefficients (e.g., an upwardly biased long-run learning rate for any technology will allow it to “rise above the rest”).

Though Nordhaus (2009) agrees that productivity benefits follow as workers in firms gain experience with a production process, he expresses skepticism that embodied learning can be measured reliably for large global systems. The “supply” of accumulated learning could be embodied in a firm, a group of workers, an individual worker, or it could result from international or interindustry spillovers. Further, a measured learning improvement may not be durable.

The case developed by Nordhaus (2009) for exaggerated learning in a generic industry (see Appendix) can be adapted to examine the theory of LBE by considering specific technical features of oil and gas extraction.

[17] We agree with Rogner (1997, 250): “Because data are consistently poor and have limited availability, estimating productivity gains over extended periods of time is a risky undertaking. Hence, there could be a wide margin for error around this productivity estimate. The projection of a long-term 1% per year growth rate may well prove too conservative (or too optimistic).”

4.1. Drilling into Factors of Oil and Gas Productivity: More than Learning-by-Doing

Hamilton (2012) analyzes the impact of technology and price on oil production over the last century in the United States (1859–2010) and across the world (1973–2010), extending far beyond the small window covered by EIA FRS data in Section 2 of this paper. Hamilton draws on these data to conclude that individual oil-producing regions have not demonstrated a pattern of continuously increasing productivity from ongoing technological progress.

In Hamilton's view, price incentives and technology have reversed declines in output resulting from geological or geographic factors, but only temporarily. Measured productivity gains in oil-producing regions initially increase as new fields are developed, followed by productivity declines dominated by the natural depletion rate of wells. Hamilton suggests that the historical source of industry productivity gains and increasing global oil production during the twentieth century has been the exploitation of new geographical areas.

While Hamilton is only focused on empirical aspects of the past and does not consider the potential long-run theoretical contribution of learning and unspecified technological breakthroughs to productivity, his analysis serves as a reminder of the engineering factors related to geology and geography that distinguish the oil and gas industry from other forms of manufacturing.[18] The determination of a true learning rate for oil and gas could be further distorted by such complex industry conditions, adding another element to the issues raised by Nordhaus (2009). For energy resources, it is unclear whether the role of learning and upstream technology improvements can always be fully distinguished from productivity gains resulting from specific geographic or geologic factors.

This dilemma mirrors echoes Adelman (1990): that the oil industry is an "endless tug-of-war between diminishing returns and increasing knowledge." As currently formulated, the LBE model projects future supply costs as determined by a function of increasing knowledge, which pulls Adelman's tug-of-war in a single direction.

[18]Further, given the important role of oil in the economy, wholly political decisions have resulted in rapid growth of output and subsequent price declines (outside of what any would consider as free-market equilibrium conditions) at the moment these political concerns are left aside, as well as oligopoly or monopoly features that could create price declines to consolidate market share. The Nordhaus (2009) model could further extend to capture price declines induced by cartel decisions.

The cycles of cost and reserves reviewed in Section 2 suggest that Adelman's metaphor is apt: the reserve base does get pulled in both directions. Though application of an LBE supply curve generally uses lowest-cost resources first, this weakly captures the effect depletion may have on costs of accessing the full geologic resource stock over the long run, and misses an opportunity to understand the investments needed to offset declines.

The use of compounded learning as the prime determinant of projected future costs of oil and gas supply develops Adelman's industry metaphor in a way that confirms the concern of Nordhaus (2009). Hamilton's analysis highlights the factors of oil production that counter the increasing returns from knowledge and learning, indicating a path toward integrating the insights of Nordhaus and Adleman. Global oil and gas production in the twenty-first century will balance, benefit, and suffer from both increasing knowledge and diminishing returns.

4.2. A Case of Measuring Learning-by-Extracting alongside Geological and Geographical Factors

Accordingly, the case of Nordhaus (2009) can include a factor relevant to productivity in the oil and gas industry. We introduce o to represent a parameter for upstream productivity that results from geographic expansion and geological conditions. When the price, cost, output, and growth assumptions of Nordhaus (2009; see Appendix) are adopted, the original equation for declines in price (p) as a function of productivity gains results as Equation 1.

$$p = h + o + r(\epsilon + z) \tag{1}$$

In this equation, the rate of true endogenous learning is denoted by r, exogenous technical change by h, constant price elasticity by ϵ, and z is a function of autonomous, non-price–induced growth.With this modification, the industry cost function is assumed to involve factors specific to engineering for oil and gas extraction (o), which may also influence productivity independent of learning-induced technical change.

In a case that considers production from an oil well in Texas, r would capture endogenous learning that leads to productivity improvements for onsite extraction (e.g., the local crew gets better at operating the well). The specific location and geologic nature of the oil well would impose productivity considerations captured by o, such as favorable drilling conditions resulting from the initial pressure at the wellhead or the natural profile of production increases and declines indicative of a maturing oil well.

Following from Equation 1, a calculation of the learning coefficient ρ for this case results in Equation 2, where exogenous and true endogenous learning are combined with productivity gains enabled by geology and geography. If we adopt the values of exogenous technical change, used by Nordhaus (see Appendix), with a true learning rate of r = 0.25 and consider that geology or geography may contribute a 1 percent productivity gain (o = 0.01), then the learning coefficient would be measured at ρ = 0.5, twice the true rate of learning (r).

$$\rho = \frac{p}{g} = \frac{h+o+rz}{z+\epsilon h+\epsilon o} = \frac{0.01+0.01+.25\times 0.04}{0.01+0.01+0.04} = 0.5 \tag{2}$$

With these plausible values for exogenous technical change, autonomous growth and demand elasticity, the sensitivity of ρ to o and its relationship to r can be further considered: with $o \to 2r$ the marginal contribution of o to ρ rapidly declines as the calculated learning curve approaches unity. Following from this case, even if o were twice the value of r, the calculated effect would remain roughly unchanged from when $o < 0.8r$.

If we interpret the H-H-R (1997) assumption of 1 percent endogenous learning for global oil and gas as $\rho = 0.01$, using the structural form of Equation 2, we can isolate the relationship between o and r in Equation 3, with a learning curve effect summarized by $\Omega = \frac{0.2375}{r}$, where the negative slope indicates that o and r are inversely correlated.[19]

$$\frac{r}{o} = -(24.75 + \Omega) \tag{3}$$

It follows from Equation 3 with the learning rate of +1 percent: (i) o and r are highly sensitive to each other and could easily be conflated, or mask their relative contribution. Furthermore, that (iia) the sustained high level of true learning is needed to compensate for a slightly negative contribution by o; or, conversely, (iib) a high level of learning could appear low with a slightly negative contribution from o.

In a case where geological conditions result in a negative contribution to productivity and increasing prices, such that o = -1.5 percent, then the equivalent learning rate to sustain a +1.0 percent productivity gain on average in Equation 3 would need to sustain 13 percent per year; further a -2.0 percent contribution by o would need a continual 25 percent true learning rate.

[19] We simplify Equation 3 with Ω which describes a *learning curve effect on geography and geology*: a higher value for r reduces Ω and calculates a smaller negative slope for the relationship between learning productivity and geological/geographical productivity. Though the elasticity of demand for Equation 3 is consistent with Nordhaus's example in this case ($\epsilon = 1$), an updated value for long-run oil demand elasticity for oil of $\epsilon = -0.072$ (International Monetary Fund 2011) yields only a slightly different equation of $\frac{r+0.2402}{o} = -25.02$, which doesn't significantly change the relationship of the variables here.

Conversely, a high true learning rate of 25 percent could be misconstrued by this slightly negative value of o, underestimating the influence of technological change.

In summary, a measurement of learning-induced productivity that fails to capture the effect of o could readily obtain a biased value for the effect of learning-by doing on oil and gas production. These considerations illustrate that truly disentangling the contribution of endogenous learning from geology, geography, or exogenous factors is extremely difficult without explicit studies of producing fields. Establishing the appropriate value of a learning parameter for long-term fossil energy supply is a complex process that needs a further robust modeling effort to remain relevant in future studies on climate and energy policy.

For the FRS data considered in Section 2, the mean value for decadal upstream productivity appears to be negative ($\rho < 0$), further complicating the picture. Was endogenous learning negative or did geology, geography, or exogenous factors dominate cost increases? Presuming a deterministic level of true learning over a long time frame needs to overcome measurement issues such as these to become a plausible description of future hydrocarbon economics. When an observable productivity trend is the product of two unknowns, guessing the value of each without an empirically constrained distribution of plausible values is difficult to separate from a normative choice.

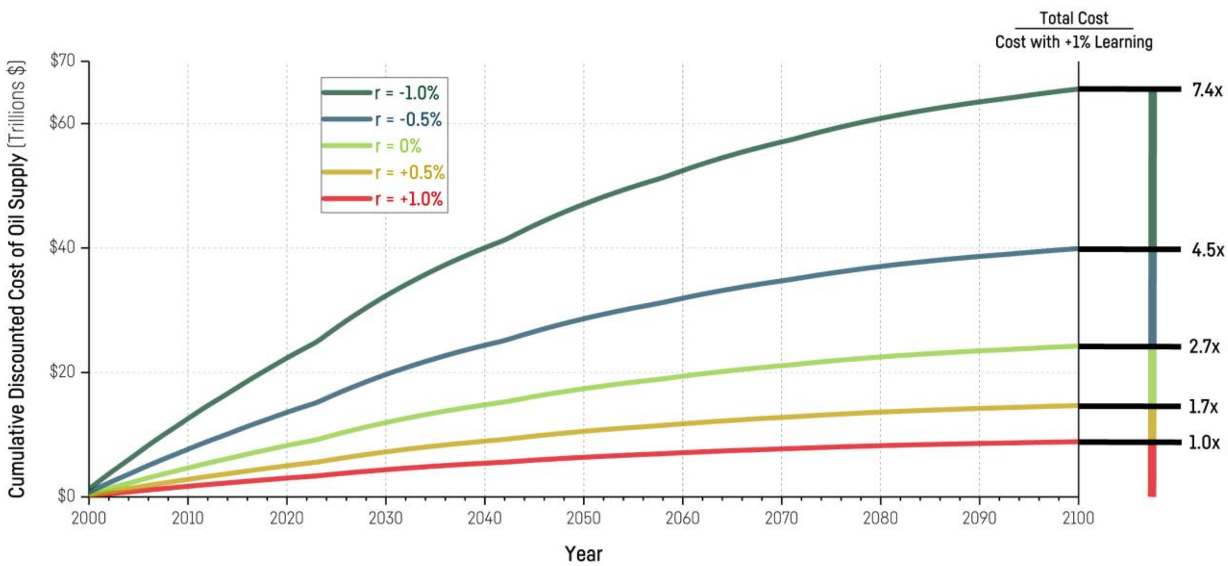
4.3. Implications of Learning Effects for Long-Run Energy Economics and Climate Change Mitigation Cost Projections

Fossil energy supply curves constructed with the LBE theory generally indicate that the vast quantity of fossil occurrences in the Earth's crust will readily dominate twenty-first century choices for energy supply. Policy goals for reducing carbon emissions to limit future climate change thus face stringent competition from the low-cost hydrocarbon deposits expected to result from compounded learning. The projected cost of any backstop technology that could readily substitute for these resources can also receive a bias from any selected learning rate. We provide a simple example to illustrate the sensitivity of future backstop and policy costs to a chosen learning rate.

If annual oil production growth continues across the twenty-first century at 1.1 percent per year (2000–2014 trend), 660 Gtoe is withdrawn from the H-H-R supply curve. Varied rates of productivity from +1 to -1 percent applied to the oil cost ranges calculated by Rogner (1997) (Figure 6) adjusts the total discounted cost of supply by more than a factor of 7. As this case for oil demonstrates, a greenhouse gas emission reference scenario adopted as a mitigation policy baseline that relies on an upwardly biased learning rate for twenty-first century fossil energy supply can easily underestimate the cost of future oil supply by 1.6 to 7.4 times per barrel.

Understating the cost of oil supply will also overstate the investment required to mitigate its greenhouse gas emissions with a low-carbon alternative. If we equate the cost of future oil supply in the ρ = + 1.0 percent case to an average market price of $50 per barrel over the century, a $120 per barrel zero-carbon backstop oil substitute available today appears as a significant cost: a 60 percent reduction in the backstop cost is required for substitution with no deadweight loss. Yet with an oil supply calculated at ρ = -1.0 percent, this backstop is already 200 percent more cost-effective than oil over the long run—optimal energy policy in this case calculates that short-run substitution should be incentivized because of negligible deadweight losses.[20]

Figure 6. Cumulative Discounted Cost of Twenty-First Century Oil Supply



Notes: Growth in oil production at a 2000–2014 consistent level (1.1% per year) with H-H-R price bands at learning rates of ρ = +1%, 0.5%, 0%, -0.5% and -1% for discount rate of 5%; right bar multiples of total twenty-first century oil supply cost compared to the ρ = +1% case.

This simple case depicts how slight changes to the learning rate applied for an oil-, gas-, and coal-dependent policy baseline can frame a consistent series of mitigation steps as either net

[20] Learning calculated at 0% also considers that the $120 backstop is already more effective than oil.

costs or net benefits—substantiating Nordhaus's concern that a learning model for developing long-term energy strategies is potentially "dangerous."

5. Summary and Conclusions: Revising Our Hypotheses for Long-Term Fossil Energy Supply

This paper has considered empirical and theoretical aspects of a learning-by-doing framework for long-term resource assessments in climate and energy policy studies. Rogner (1997) articulates a theory of future hydrocarbon energy supply driven by annual productivity gains that result from learning, applied to the global oil, gas, and coal resource base at a rate of 1 percent per year (ρ = +1.0 percent). When compounded across a century, an aggregate productivity improvement results that reduces the cost of fossil energy extraction by more than 170 percent (**P** = 170 per BOE). This approach is widely used in integrated assessments of climate change and energy economics with no systematic studies available in the literature to calibrate learning rates per resource and industry.

EIA data on the financial metrics of US and worldwide oil and gas production indicate that decadal productivity trends may significantly vary (Section 2.1). From 1988–1996 they were broadly consistent with a +1.0 percent upstream productivity improvement as projected by Rogner (1997); overall, depending on the measure, oil and gas productivity declined by 3.0 percent (total upstream) to 5.2 percent (capex) per year from 1977–2009.

The volatility of year-to-year productivity changes in these data indicate the relevance of modeling stochastic processes of discovery, innovation, and market conditions when calibrating long-term costs: projection of aggregate productivity gains in oil and gas as a secular trend over a century is likely to mislead any model of fuel adoption patterns. Further, it appears likely that sustained periods of high demand (i.e., bull markets) reduce short-run and medium-run productivity, dominating any gains induced by learning during the same period (Section 2.2). Because conditions of sustained rapid fossil energy adoption are often projected in many long-term energy reference cases scenarios, these factors will be of explicit interest to the research community (Bauer et al. 2016b). Conversely, productivity estimates drawn from recent industry bear market conditions for cost reductions in US shale and unconventional technologies must be understood in the full context of producer investment decisions for labor, capital, and markets. Recent upstream cost declines may not immediately translate to the next bull market.

LBE supply curves have accurately captured secular trends in operational expenditures for oil and gas production; however, these are one-third of the marginal costs reported by producers. A focus on learning-driven productivity gains as a primary determinant of long-run energy resource costs has blurred the distinction between the specific processes, technologies and decisions on capital expenditures required to produce fossil energy commodities. Each fuel type, geography, and geology is not a single manufacturing process, but requires a portfolio of technologies with their own learning rates and potentials. However, there is reason to expect that operational learning curves can extend well into the future to capture potential effects from automation, machine learning, and information technology.

Across a century time span, the production of fossil energy will require multiple manufacturing processes. The history of oil illustrates a dramatic span of technology between the horizontal and deepwater drilling of today and original nineteenth-century wells. This study suggests the present generation of fossil supply curves structured by the LBE theory have extended a learning model suitable for a single manufacturing process in a given facility beyond its plausible boundaries. Recent expansion in supply has required new technologies with a different pattern of development costs, indicating the confines of this framework.

Though the LBE model poorly captures development costs, these expenditures play a significant role in driving marginal cost throughout cycles of demand on the “warehouse stock” of reserve vintages (Section 2.3). EIA FRS data suggest development expenditures constitute more than half of oil and gas production in times of fast-growing demand, a dynamic articulated by Adelman (1995).

While an equilibrium R-P ratio describes essential features of oil and gas producer behavior for knowledge of energy resources, this heuristic appears of limited value for determining future costs and availability. Varied costs of developing reserves into production have contributed to distinct cycles in the oil and gas reserve base over the last six decades (Section 2.3).

The learning-driven productivity modeled in LBE supply curves is explained by Rogner (1997) to result from optimal investment: this is only possible in an environment where prices may increase without a maximum threshold of demand on market price (i.e., where demand faces no constraints). We show that industry investment in capital expenditures is not optimal but cyclical, facing boundary conditions at regular intervals. Relaxing the assumption of optimal investment for supply expansion opens an avenue for recalibrating long-term outlooks on fossil energy supply.

The LBE theory has anticipated that the global warehouse of coal reserves will emulate oil and gas, where the broader resource base will be reclassified as reserves over time (Section

3). There is no evidence that this has occurred on a wide scale, or that it will in the future. Increasing knowledge about the world's coal deposits has led to fewer assessed reserves. Consequently, a learning dynamic should not be applied to the global coal resource base in reference cases, only to reserve recovery rates. Studies that choose to tap into the vast geologic coal resource base must overcome decades of evidence to the contrary.

Nordhaus (2009) argues a learning model of productivity is dangerous for long-term energy studies: there are too many exogenous factors to isolate the contribution of learning-by-doing for a homogenous global energy resource (Section 4). Consequently, the assessed contribution of learning is generally biased upwards.

Where Adelman (1990) sees the future of the oil and gas industry determined by a tug-of-war between diminishing returns and increasing knowledge we argue that the LBE theory of fossil supply curves have only pulled this rope in one direction.

Section 4 indicates that Nordhaus’s concerns apply to the LBE model of future fossil energy, which appears to underestimate the total twenty-first century cost of oil, gas, and coal supply, potentially overstating its resulting net benefit to society and necessary policy costs for lowering future greenhouse gas emissions. A brief example (Section 4.3) illustrates how estimates of energy resources based on autonomous learning can readily bias energy system reference cases for energy and climate policy: projected costs of mitigation and backstop technologies can easily be distorted with slight changes to a chosen learning rate. Therefore, a rigorous justification is necessary for any selected learning rate in studies that apply Rogner's theory.

The evaluation of the LBE theory in this paper is developed in the context of constructing a more robust assessment of long-term fossil energy supply economics. All possible solutions to the issues raised in this paper extend far beyond the scope of a single manuscript. However, based on this analysis, we suggest that a more empirically grounded theory of long-run resource supply can draw from the introduction of new hypotheses for technological change in fossil energy production with stronger empirical consistency and an attention to finer resolution for specific geologic formations and technologies. To this aim, we offer the following proposals:

- **Proposal 1:** The LBE theory of future fossil energy supply did not anticipate the last three decades of oil and gas upstream productivity trends (Section 2.1). To capture essential observed elements of demand and supply conditions on industry productivity, solutions will need to develop an alternative to autonomous non-price–induced extraction productivity gains applied to a homogenous geologic resource base.

- **Proposal 2:** Productivity gains for operations and capital expenditures have followed distinctly different trends (Section 2.2). An empirically grounded long-term industry model will need to capture an explicit representation of capital expenditures necessary for oil and gas extraction. These investments are not optimal for expansion of the cheapest possible supply; they are deeply influenced by market cycles and rates of output.
- **Proposal 3:** The LBE model has captured aspects of operational costs for oil and gas, which are around one-third of upstream marginal cost (Section 2.3). Oil and gas resources are heterogeneous and require different extraction technologies; future solutions must explicitly consider the technologies and manufacturing processes needed to access future supplies.
- **Proposal 4:** The LBE theory considers that coal will follow the pattern of oil and gas: the quantity of reported reserves will tend to grow with annual production and resources will become reserves. Conversely, over the last twenty years, global coal reserves have declined as production increased. The accumulation of knowledge has led to fewer assessed coal reserves (Section 3). Studies on future coal supply uncertainties will need to examine how many coal reserves are recoverable, rather than asking how many resources will become reserves (Ritchie and Dowlatabadi 2017); this question can be further addressed through modeling coal mining technologies and equipment as with Proposal 3 for oil and gas.
- **Proposal 5:** Nordhaus (2009) argues that actual learning rates for aggregate energy technologies are difficult to identify and tend to receive an upward bias (Section 4). Energy resources encompass even more complex factors than the example of a generic manufacturing industry (Section 4.1 and 4.2). In the case of oil and gas production, an upwardly biased learning rate could readily underestimate the total discounted cost of future supply by as much as 600 percent (Section 4.3). A revised model for global oil and gas supply can start with specific studies on producing regions to distinguish the influence of geological conditions from pure technological improvements and the essential elements of producer behavior.

Because the LBE theory for future energy resource production holds a prominent role in many long-term studies and scenarios, there are consequently many possibilities for research that can adapt this body of work to an empirically consistent context while solutions to these proposals are developed in a broader research program.

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Appendix

Nordhaus (2009) argues that the policy models using a learning curve to assess the economics of energy supply strategies can be dangerous. This appendix summarizes the case Nordhaus (2009) uses to illustrate this danger for a generic industry. Nordhaus develops the example further with considerable detail in his original paper. This appendix covers relevant factors to the main paper with consistent notation.

Nordhaus (2009) Derivation of Generic Industry Case

To explore whether exogenous factors could result in cost declines mistakenly measured as productivity gains created by learning, Nordhaus develops a case where exogenous technical change is denoted as h and true endogenous learning as r. The price function p_t for a generic industry is assumed to equal instantaneous marginal cost c_t , where the rate of cost declines equals the decline in price as in Equation A1, with g_t representing a constant growth rate for industry output.

$$p_t = c_t = h + rg_t \tag{A1}$$

With a constant marginal cost, price is determined exogenously to current demand. Growth in output (i.e., demand) can be expressed as in Equation A2 with constant price elasticity (ϵ), an elasticity of per capita demand with respect to total output (λ), a growth of aggregate per capita output (w_t), and a constant population growth of

$$g_t = \epsilon p_t + \lambda w_t + n = \epsilon p_t + z. \tag{A2}$$

Nordhaus summarizes the autonomous, non-price–induced growth as $z_t = \lambda w_t + n$. Substituting Equation A1 into Equation A2, the total price decline (p) results (Equation A3), and time subscripts are dropped since this is an example of constant growth. Output growth (g) is then determined by Equation A4.

$$p = h + rg = h + r(\epsilon p + z) = \frac{h+rz}{1-r/\epsilon} \tag{A3}$$

$$g = \epsilon(h + rg) + z = \frac{\epsilon h+z}{1-\epsilon r} \tag{A4}$$

The contribution of learning to declining prices would be calculated as ρ, where the learning curve is the ratio of price to growth, $\frac{p}{g}$, which is illustrated in Equation A5.

$$\rho = \frac{p}{g} = \frac{h + rz}{\epsilon h + z} \qquad \text{(A5)}$$

Nordhaus argues that in Equation A5, the exact contribution of learning is difficult to determine because so many coefficients are present: it is challenging to know the price declines that can be specifically attributed to learning in Equation A5 unless we know the exact values of exogenous technical change, the demand elasticity, and the rate of autonomous demand growth. In the case of oil and gas, there could be a further variable denoting political goals to capture the influence of cartels.

Nordhaus (2009) Illustrates a Quantitative Case

Nordhaus uses this formulation to develop a quantitative case that illustrates calculations of learning in a generic industry by assuming plausible values for price elasticity (ϵ = 1), exogenous demand growth (z = 0.04), and a rate of exogenous technical change (h = 0.01). When true learning is zero (r = 0), substituting these values into Equation A5 results in a calculation of "learning" at 20 percent (ρ =0.20) from Equation A6.

$$\rho = \frac{0.01 + 0 \times 0.04}{1 \times 0.01 + .04} = \frac{0.01}{0.05} = 0.20 \qquad \text{(A6)}$$

Nordhaus then considers that if the true learning value were greater than zero (r = 0.25) then the calculated learning rate receives a larger upward bias (ρ = 0.4).

Nordhaus uses this example to conclude that the learning curves applied in models of endogenous technical change will tend toward a consistent upward bias because of complications induced by the interactions between demand, output growth, and exogenous technical change. Disentangling the explicit effect of learning-induced price declines independent of all other exogenous factors requires a detailed study of specific industry conditions.