Received: 5 October 2014 | Revised: 18 March 2018 | Accepted: 20 March 2018 | Published on: 18 July 2018

DOI: 10.1002/smj.2915

WILEY STRATEGIC MANAGEMENT JOURNAL

RESEARCH ARTICLE

Time compression (dis)economies: An empirical analysis

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Funding information
HEC Foundation, Grant/Award Number: 4F73DRRR - F1202 - O2200PFF1; University of Colorado Boulder

***Research Summary*:** To investigate time compression diseconomies (TCD), this study estimated time–cost elasticities using 459 oil and gas global investment projects (1997–2010). Results show that the average cost of accelerating investments is negative: a firm could cut \$6.3 million in costs of a single project by accumulating asset stocks 1 month faster. About 88% of the projects exhibit negative time–cost elasticities with over 39% of unrealized *economies* of time compression. Only 12% of the projects are subject to TCD. These time inefficiencies or frictions do not negate the existence of TCD, but suggest they are less prevalent than assumed in the literature. Management experience, R&D investment, firm size, economic development, and political stability are shown to be associated with greater time compression efficiency.

***Managerial Summary*:** How fast should firms invest? The conventional view is that acceleration increases market revenues but also inflates costs. However, there is no recent empirical evidence of this tradeoff. Our article systematically investigates the costs of compressing time in investment projects. Results show that most firms in the oil and gas industry are significantly time inefficient in their operations. Specifically, by accelerating investments, firms would also substantially decrease costs. We estimate the magnitude of these time inefficiencies for specific oil and gas industries and firms and study which strategies might mitigate this problem. This fine-grained analysis should help firms assess their financial incentives to accelerate projects and prove informative to stock market analysts' valuations of firm investment timing.

KEYWORDS

sustainable competitive advantage, temporal frictions, time compression diseconomies, time inefficiencies, time–cost tradeoff

1 | INTRODUCTION

Can money buy time? The classical view in strategy is that firms can accelerate the accumulation of nontradeable assets—but at increasing costs. For example, to accelerate R&D, firms can assign more engineers to a project but each additional person will contribute incrementally less to overall productivity due to diminishing returns. "Time compression diseconomies are the[se] additional costs incurred by firms seeking to quickly reach a given level of an asset stock when this stock could be accumulated more economically over a longer period of time" (Cool, Dierickx, & Almeida, 2016, p. 1). While time compression diseconomies (hereafter, TCD) may be prohibitive at high levels of acceleration, in most cases firms can—and should—strategically decide how fast to invest. This time compression decision is particularly critical because TCD apply to the accumulation of any type of asset, including intangibles (e.g., R&D know-how or reputation) and tangibles (e.g., physical capital). Indeed, "time compression diseconomies and the notion of 'strictly convex adjustment costs' in the theory of capital investment (…) express the same fundamental mechanism" (Lucas, 1967; Gould, 1968; Dierickx & Cool, 1989, p. 1507).

The importance of TCD has long been accepted and extensively theorized about in different fields. In strategy, TCD are a well-known isolating mechanism that helps sustain competitive advantage of early-mover firms: "if diseconomies are large, they provide extra protection to the firms that were the first to build resources; their resources stay unique for a longer time" (Cool et al., 2016, p. 2). TCD are also hypothesized to curb the benefits of speed, thereby imposing an optimal level of acceleration in firm activities, including in innovation and imitation (Pacheco-de-Almeida & Zemsky, 2007; Pacheco-de-Almeida & Zemsky, 2012), internationalization (Vermeulen & Barkema, 2002; Wagner, 2004), diversification (Markides & Williamson, 1994), capital investment (Pacheco-de-Almeida, Hawk, & Yeung, 2015), and alliance formation (Garcia-Canal, López Duarte, Rialp Criado, & Valdés Llaneza, 2002). In economics, TCD have been a central assumption in prominent game-theoretical models of the timing of new technology adoption (Fudenberg & Tirole, 1985; Hoppe, 2002; Reinganum, 1981), R&D investment competition (Scherer, 1967), and the speed and cost of industrial innovation and imitation (Mansfield, 1988; Mansfield, Rapoport, Schnee, Wagner, & Hamburger, 1971; Mansfield, Schwartz, & Wagner, 1981). Time compression diseconomies have also been a standard and widespread feature in operations research on reduced new product development cycle times (e.g., Babu & Suresh, 1996; De, Dunne, Ghosh, & Wells, 1995; Elmaghraby, 1977; Lamberson & Hocking, 1970; Roemer, Ahmadi, & Wang, 2000).

However—for all this literature that has assumed and theorized about TCD—limited empirical evidence has actually documented their existence and magnitude. To our knowledge, only six studies in strategy, economics, and operations have offered explicit estimates of the time–cost tradeoff. This empirical evidence of TCD dates back to the 1970s and 1980s and is based on studies with small sample sizes of 5–59 observations per estimate (e.g., Graves, 1989). Recent empirical studies of TCD have been lacking not only because the time-consuming nature of firm's actions is often unobservable, but also due to the technical challenges inherent in the empirical estimation of time–cost elasticities when individual projects and different firms exhibit varying levels of time compression efficiency. In sum, TCD have been a longstanding theoretical principle with important implications for multiple strands of literature in management science; yet, we have only sparse and outdated empirical evidence of their existence.

Our article addresses this gap in the literature by using a large dataset of 459 global investment projects to (a) empirically estimate TCD and (b) investigate their determinants. Our empirical setting is the oil and gas industry, specifically investments in new refinery and petrochemical production facilities from 1997 to 2010. The advantage of using the oil and gas industry as our empirical setting is threefold. First, data on project investment lags and costs is readily available worldwide because the industry is highly regulated. Second, oil and gas is the industry with the most reliable past empirical estimates of TCD, which increases the comparability of our results with prior literature (Mansfield, 1988; Teece, 1977). Third, global investment projects in oil and gas involve tangible and intangible asset stock accumulation (physical capital and technology transfer)—and both are subject to TCD. Our sample is substantially larger than the datasets used in previous empirical studies of TCD; in addition, we use real project data, whereas much of the previous work used counterfactual observations from survey data.

The results show that the cost of accelerating investments in the oil and gas industry during the period of analysis is, on average, negative. An average firm could have cut \$6.3 million (in 1996 dollars) in costs by accumulating physical and intangible asset stocks 1 month faster when developing a new productive facility. This corresponds to an average estimated time–cost elasticity in our sample of approximately −0.556. Negative time–cost elasticities are indicative of *economies* of time compression, a situation in which investment acceleration reduces firm costs. For about 88% of the 459 projects in our sample that exhibit negative time–cost elasticities, firms could have both reduced costs and compressed time in asset stock accumulation (with a minimum elasticity of −1.887). The remaining 12% of the projects are subject to TCD, or a time–cost tradeoff (with a maximum elasticity of 6.982). In our sample, over 39% of project time and costs represent unnecessary delays and overspending.

A word of caution is in order in the interpretation of our results. Pervasive negative time–cost elasticities do not negate the existence of TCD, but indicate that TCD are not an active constraint for the majority of the projects in our sample. In other words, TCD are still expected to kick in for high levels of time compression; however, most firms insufficiently accelerate their investments—and, thus, do not experience a time–cost tradeoff. The limited evidence of TCD implies that TCD have not been the main isolating mechanism sustaining competitive advantage in this industry during the period of analysis. This suggests that the time–cost tradeoff—a central assumption in much of the strategy, economics, and operations literatures—should not always be taken at face value as an unquestionable empirical fact. Nevertheless, since firms are shown to take longer than they should to accumulate asset stocks, lead time may arguably be an even more important instrument to protect firms' market positions (Cohen, Nelson, & Walsh, 2000).

The economies of time compression demonstrated in our study are evidence of time inefficiencies. These "temporal frictions" are a yet new type of frictions that add to the long list of disturbances identified in strategy and economics that hinder markets from clearing or allocating resources optimally (e.g., see strategic factor market frictions or firm matching frictions in Barney, 1986; Chade, Eeckhout, & Smith, 2017). The magnitude of these "temporal frictions" is also striking. In this context, our firm-specific estimates of time–cost elasticities may be informative for capital allocation decisions, stock market valuations, and firms' investment timing decisions. Without accurate empirical measures of the marginal costs of speeding up, it is difficult to estimate the returns to and limits of acceleration strategies—and issue normative statements on this subject.

But what explains these results? The determinants of time–cost elasticities and their average economic impact have also been analyzed. First, new-to-the-firm technology is associated with an investment slowdown of about 7 months and a decrease in time–cost elasticities of 1.521. This large deceleration evidently increases total costs: the rise in indirect costs (i.e., overhead costs that are fixed per unit of time) more than offsets the direct cost savings from slower investments. Second, a 10% increase in firm size is related to a 0.032 reduction in time–cost elasticities. This is because larger firms have greater indirect (overhead) costs—and lower direct costs likely due to a deeper pool of in-house capabilities and resources that reduce TCD. Third, a 10% increase in project size is accompanied by a 15-day investment deceleration and a 0.043 decrease in elasticity. Larger projects have more coordination costs and, thus, higher direct costs. But larger projects also amplify indirect overhead costs and take longer to complete, which decrease elasticities overall. Fourth, trade barriers are associated with a 1.3-month investment acceleration and a 0.109 increase in time–cost elasticities. Trade barriers typically curb firms' exports, growing the expected revenues from building new production facilities in the host country—which, in turn, accelerates investments and increases elasticities.

Fifth, broad investment experience is related to a 0.031 increase in time–cost elasticities for each additional completed past project. This prior experience—unspecific to project types or technologies—is expected to enhance overall managerial capabilities. While managerial capabilities do not offer superior technical know-how to reduce TCD in project acceleration, they likely prevent excessive delays in project scheduling, thereby increasing elasticities. Sixth, a one-standard deviation increase in R&D intensity is accompanied by a 3.351 decrease in time–cost elasticity. Investment in R&D arguably boosts in-house technical capabilities and innovation, making human capital more competent at compressing time in the accumulation of intangible and physical technical asset stocks, which reduces TCD. Seventh, each additional year in firm age is associated with an increase of 0.154 in elasticities. Presumably, older firms with more organizational inertia face greater difficulties to compress time and, thus, have higher TCD. Eighth, a large increase of one standard deviation in our measure of country economic development leads to a 2.810 decrease in time–cost elasticities. More developed countries typically have better infrastructure and superior local suppliers, which facilitate investment acceleration. Finally, a one standard deviation increase in country political constraints is associated with a 1.750 increase in elasticity. With increased political risk, project financing is often subject to higher discount rates, which reduces the net present value of future investment cash flows—thereby decreasing firms'' incentives to compress time and reducing time–cost elasticities.

Although, to our knowledge, this article is the first large-sample empirical study of time–cost elasticities—and the first to show pervasive economies of time compression, our results are consistent with prior anecdotal evidence. A recent report by PricewaterhouseCoopers' consulting arm "Strategy&" (formerly Booz & Company) documented oil and gas companies' systematic "difficulty delivering large capital projects on time and within budget" with delays of several years and cost overruns as high as 350% (Tideman, Tuinstra, & Campbell, 2014, p. 3). Teece (1977) also acknowledged the possibility of negative time–cost elasticities in petroleum refining investment projects when he qualitatively reported that "costs would have increased if the expected time were doubled" for a few observations in his sample (p. 832). More generally, the idea that "by reducing the consumption of time, (…) companies also reduce costs" has been a central feature in the practitioner's literature on time-based competition (Stalk, 1988, p. 46; Stalk & Hout, 1990).

2 | LITERATURE REVIEW

The time–cost tradeoff, or TCD, has been a central assumption in much of the management science literature. Time compression diseconomies are generally accepted to apply to any process or activity that involves the accumulation of nontradeable assets—resources or inputs that firms cannot instantaneously purchase in strategic factor markets (e.g., Barney, 1986; Dierickx & Cool, 1989). These investments take time, and any acceleration is likely to inflate costs—at an increasing rate.[1]

There are four main reasons for the existence of TCD (for a review, see Graves, 1989). First, firms often accelerate a project by committing more resources to the project. For example, an investment project may be accelerated by allocating more manpower to it. However, more human capital typically aggravates coordination costs, which leads to diminishing returns and higher total costs. Second, firms also speed up investments by bringing previously sequentially scheduled activities into parallel processing. This results in the loss of information that used to flow from the first to the second activity, which creates a higher incidence of mistakes and rework and increased costs in the second activity. Third, firms often resort to hedging by concurrently pursuing multiple alternative approaches to an uncertain technical problem so as to find a solution faster. This approach, however, also comes at a cost premium. Fourth, project acceleration based on PERT (Program Evaluation Review Technique) analysis will compress first those activities with the cheapest individual acceleration costs and only afterward activities that are more expensive to speed up. This acceleration pattern creates a convex time–cost tradeoff for the overall project.

It is sensible to expect TCD to decrease over time due to technological progress. Better technology is expected to help coordination, reducing the diminishing returns associated with allocating more resources to a project. Technological advancements may also facilitate hedging strategies and PERT acceleration by making it easier to pursue multiple potential solutions to uncertain tasks simultaneously or by reducing the costs of speeding up individual activities.

While the time–cost tradeoff has been discussed at length theoretically, there have been relatively few empirical investigations of this phenomenon. We could find only six studies in strategy, economics, and operations that explicitly offered estimates of time–cost elasticities (Boehm, 1981; Hartley & Corcoran, 1978; Mansfield, 1988; Mansfield et al., 1971; Putnam & Fitzsimmons, 1979; Teece, 1977). Table 1 summarizes these results. More recently, indirect empirical evidence of the effect of TCD on resource accumulation was also found by Knott, Bryce, and Posen (2003), but no estimates of time–cost elasticities were reported.

The six previous studies of time–cost elasticities are dated and based on small sample sizes of 5–59 observations per estimate. Five studies used ex-post data, which was collected after project completion; in one study, estimations were based on ex-ante time–cost predictions based on a PERT analysis of one real project (Putnam & Fitzsimmons, 1979). "*Ex-post* data (…) might differ from planned behavior" due to unexpected shocks such as delays (Hartley & Corcoran, 1978, p. 210). Of the five ex-post data analyses, two studies used real-project observations and three studies were based on counterfactual data with only one real-project observation and $(n - 1)$ hypothetical observations. In these counterfactual studies, "the *ex-post* trade-off function is based on expected values from the subjective probability distribution which exists after the actual innovation has been completed. (…) [It is] hypothetical in the sense that only one time-cost point is ever realized"—the other observations are collected by asking project managers the question: "Looking back on the project, how much do you think it would have cost to have completed it in various alternative lengths of time?" (Mansfield et al., 1971, pp. 128, 129).

[1]Note that we do not examine the time-quality tradeoff in this article, which is less relevant in our empirical setting.

TABLE 1 Overview of time–cost elasticities estimated in prior literature

Industries	Data[a]	Compression: Time / Minimum Time (%)[b]						
		1.00–1.05	1.06–1.15	1.16–1.25	1.26–1.30	1.31–1.50	1.51–1.80	1.81–2.50
Chemicals, machinery, and electronics (Mansfield et al., 1971)	$n \in [6, 10]$ Ex-post, counterfactual data (total elasticities: 29)	1.6	1.6	1.6	1.6	0.5	0.5	0.25
Chemicals, petroleum refining, and machinery (Teece, 1977)	$n = 5$ Ex-post, counterfactual data (total elasticities: 20)	1.76	1.76	1.76	1.30	1.30	n/a	n/a
Airline manufacturing (Hartley & Corcoran, 1978)	$n = 18$ Ex-post, real data (total elasticities: 1)	....	....	....	1.35	....	....	....
Software (Putnam & Fitzsimmons, 1979)	$n = 1$ Ex-ante, PERT analysis (total elasticities: 1)	....	....	....	2.00	....	....	....
Software (Boehm, 1981; Graves, 1989)[c]	$n = 59$ Ex-post, real data (total elasticities: 5)	1.13	0.96	0.60	n/a	n/a	n/a	n/a
Chemicals, electrical and instruments, machinery (Mansfield, 1988)	$n \in [6, 10]$ Ex-post, counterfactual data (total elasticities: 32)	....	....	....	6.73	....	....	....

[a] n is sample size per estimate; ex-*ante* (*ex-post*): data collected before (after) project completion; counterfactual data: one real project observation and $(n - 1)$ hypothetical observations obtained by asking project managers about the predicted costs of a project if counterfactual levels of time compression had occurred; real data: data from real projects.

[b] Lower values indicate higher time compression: for, e.g., at 1.05 a project is completed at 105% of the minimum possible completion time; all elasticity figures in the table are mean values except for Mansfield et al. (1971) and Teece (1977) who reported median values; n/a denotes also compression intervals with unreliable data; the max elasticity in Mansfield (1988) was 15.7.

[c] Estimated by Graves (1989) using Boehm (1981)'s data.

Notably, all of these prior studies reported positive time–cost elasticities. Also, with the exception of Mansfield (1988) that documented higher elasticities, all other work estimated elasticities to be less than 2.00 and relatively similar across six different industries: chemicals, machinery, electronics, petroleum refining, airline manufacturing, and software. As expected, elasticities were also found to generally increase with more severe levels of time compression. For an investment executed at less than 130% of its minimum completion time (*Time*/*Minimum Time* < 1.30), all studies with the exception of Graves (1989) reported elastic time compression diseconomies, or time–cost elasticities greater than 1. For the largest elasticity estimate (Mansfield, 1988), a 1% increase in time compression increases costs by 6.73%: for example, a 2-week acceleration of a $100 million investment that would take 1 year to complete would cost approximately $28 million.

For nearly 30 years since these early studies, estimates of the time–cost tradeoff have been lacking—due not only to the limited availability of investment time data, but also to the technical challenges associated with empirically estimating time–cost elasticities, as discussed in the next sections. These two reasons may also explain the main caveats of prior studies, namely, the use of small samples and counterfactual data. This methodology raises questions about the reliability of these prior TCD estimates: indeed, "Mansfield cautions that there may be considerable errors in the manager's estimate of the time-cost tradeoff" (Graves, 1989, p. 6). This suggests an opportunity for a recent, large-sample empirical study of real projects to derive more robust estimates of the time–cost tradeoff. Our article undertakes that task.

3 | ESTIMATES OF TIME–COST ELASTICITIES: BASELINE MODEL

Our baseline model follows Mansfield et al. (1971) and Teece (1977) for two reasons. First, this is the only model—out of the six prior empirical studies of time–cost elasticities (see Table 1)—that complies with all the expected properties of TCD, as theorized in the previous literature (e.g., Dierickx & Cool, 1989; Scherer, 1967). It is also one of the simplest possible model specifications with these features. Second, sharing the same baseline model with two of the six prior studies of TCD increases the comparability of our results. In our model, cost is a negative and convex function of time, as follows[2]:

$$C(V,\phi,t,\alpha) = Ve^{\frac{\alpha}{(t/\phi-1)}} \tag{1}$$

In Model 1, C is project cost and t is the time that the project takes to develop. Parameter $\phi > 0$ is the time asymptote representing the minimum theoretical time to complete the project if firms had unlimited resources, or the maximum level of time compression with infinite project development costs (thus, $t > \phi$). Parameter $V > 0$ is the cost asymptote that denotes the minimum theoretical cost for the project without scheduling constraints ($t \to \infty$). Coefficient $\alpha > 0$ is a function of the direct costs associated with accelerating the project and affects the convexity of the cost curve with respect

[2]Theoretically, TCD are assumed to have the following properties: (a) cost is a negative and convex function of time, (b) time–cost elasticities increase for more severe levels of time compression, and (c) positive vertical and horizontal asymptotes set the minimum possible time and cost for projects (i.e., investment in nontradeable assets cannot be instantaneous or costless). Hartley & Corcoran, 1978, Putnam & Fitzsimmons, 1979, and Mansfield (1988) violate assumptions (b) and (c). In particular, Hartley & Corcoran, 1978 and Putnam & Fitzsimmons, 1979 assumed constant time–cost elasticities, whereas Mansfield (1988) only reported compression-invariant arc elasticity averages without specifying a formal analytical model. Finally, Graves (1989) estimation using Boehm's (1981) data violates assumption (c): "th[e] formula was developed (…) through a quadratic fit of Boehm's data" (Graves, 1989, p. 7) with no vertical asymptote—rather, the curve was "truncated" below a certain level of acceleration. Finally, note that parameter α in our Model 1 is denoted by ϕ in Mansfield et al. (1971) and Teece (1977), and vice-versa. We changed the notation so that α and β always denote the main coefficients to be estimated across all our regression models.

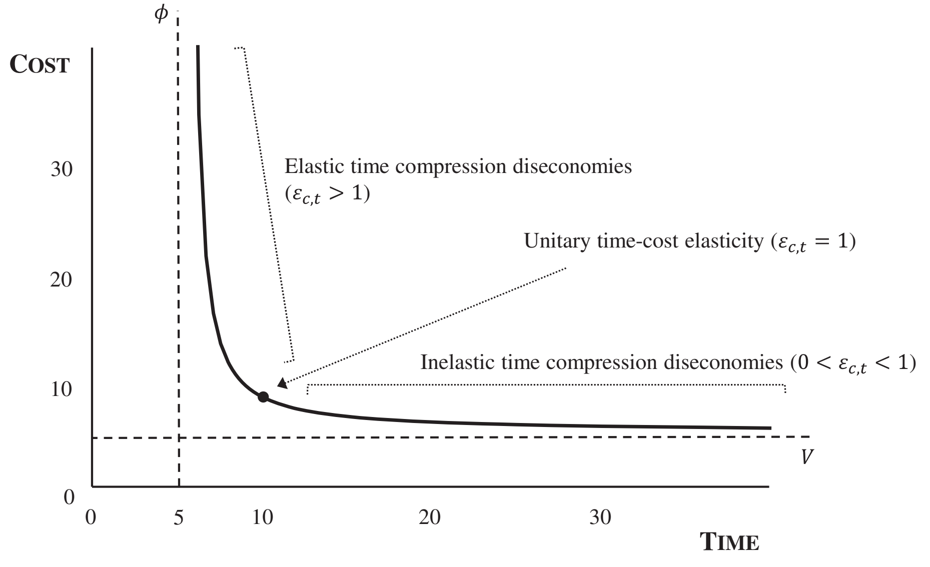

FIGURE 1 The baseline Model 1 ($V = \phi = 5$, and $\alpha = 0.5$)

to time t. In particular, for a given value of t/ϕ, α determines the elasticity of cost with respect to time, or the extent of TCD:

$$\varepsilon_{c,t} = \frac{\alpha t/\phi}{(t/\phi - 1)^2} \tag{2}$$

Figure 1 is a graphical representation of Model 1. The time–cost function is negatively sloped and convex to the origin because its first derivative is negative and the second derivative is positive ($\partial C/\partial t < 0$, $\partial^2 C/\partial t^2 > 0$). All time–cost elasticities for all values of t are strictly positive ($\varepsilon_{c,\,t} > 0$), with elastic time compression diseconomies occurring for t sufficiently small ($t < 10$ or $t/\phi < 2$, in the example). Note also that an appealing property of this model is that elasticities strictly increase as time is compressed ($\partial \varepsilon_{c,\,t}/\partial t < 0$), as expected.

We transform model (1) into a linear estimable form by taking logs:

$$\ln C = \ln V + \alpha \left(\frac{t}{\phi} - 1 \right)^{-1} + \xi \tag{3}$$

In Model 3, variables C, t, and ϕ are data and $\ln V$ and α are coefficients to be estimated. The error term ξ is assumed to be distributed with mean zero and constant variance. Our main hypothesis is that the direct costs (or TCD) coefficient $\hat{\alpha}$ is positive with a low p value so that compressing time t in the development of an investment project increases costs. This is equivalent to hypothesizing that the cost curve in Figure 1 is downward sloping in t and that the time–cost elasticity in Equation (2) is always positive.

3.1 | Data and Estimation

Our empirical setting is the planning, engineering, and construction of new petrochemical and refinery production facilities worldwide from 1997 to 2010, similarly to Teece (1977) whose sample included 15 out of 20 projects also from this industry. These global investment projects require the accumulation of both intangible and tangible asset stocks: specialized know-how through technology transfer and physical capital, amassed during the planning/engineering and construction development phases (respectively).

Accelerating technology transfer and physical capital accumulation while investing in new oil and gas plants should produce TCD. The four main mechanisms behind the time–cost tradeoff described in the literature review section—diminishing returns, information loss with acceleration, hedging, and PERT-based acceleration—are particularly salient in our setting (see also discussion in Teece, 1977). For example, the transfer of firm technology to other domestic and foreign sites often involves substantial uncertainty, which favors hedging strategies. Also, firms often speed up projects by soliciting early bids from suppliers—before plants are actually designed—for equipment needed only in the last stages of plant construction. This helps compress time by several weeks, but firms often incur substantial cost penalties when design specifications are subsequently modified. The alternative strategy of bypassing regular equipment-bidding protocols by negotiating cost-plus contracts with suppliers is also known to be cost inefficient. Finally, most U.S. firms' standard practice of importing skilled U.S.-based labor to staff plant development abroad helps accelerate projects, but also substantially increases costs.

Besides exhibiting TCD, two other features of the oil and gas industry make it a good empirical setting for our study. The sizeable and irreversible nature of investment in new oil and gas plants—with the average cost of a petrochemical facility in our sample being approximately \$660 million—makes the timing of this type of decision inherently strategic. Finally, data on investment time, costs, and other project characteristics is available from several industry sources.

The dataset used in this study comes from the *Oil and Gas Journal* (*OGJ*) and only includes ex-post, real-project data. We focus on the subset of 459 projects in our dataset that are petrochemical plants and refineries with available data for our covariates. To estimate Model 3, we partition our data by project type according to standard industry classifications to create comparable project pools (Burdick & Leffler, 2001; Leffler, 2000). In particular, we consider four main project types, two in petrochemicals (olefins and plastics) and two in refineries (simple and complex). We estimate our model at the project level within each project subgroup using ordinary least squares (OLS) and a number of different control variables. We report as baseline results the regression estimates using control dummies for different geographic regions (Asia and the Pacific, Eastern Europe, Former U.S.S.R., Latin America and the Caribbean, North Africa and the Middle East, North America, Sub-Saharan Africa, and Western Europe). This seems sensible given the international nature of our data.

The operationalization of the variables in Model 3 is as follows: C is project cost in millions of dollars (deflated to 1996) and t is the number of months of plant development. Variable ϕ represents the vertical asymptote in Figure 1 and is a measure of the minimum theoretical time for each project if firms had unlimited resources, or the maximum level of time compression with infinite project development costs. By definition, $t = \phi$ is impossible to attain and is empirically unobservable in project data. Mansfield et al. (1971) and Teece (1977) measured ϕ by asking "project managers (…) to estimate the minimum *possible* time in which the project could be completed" (Teece, 1977, p. 832), which is an imperfect proxy for this construct. In contrast, we assume that ϕ is a positive step function of project size—or that the minimum theoretical time of a project increases with increments in plant capacity (we consider quartile increments in capacity as the baseline case, although other step increments have also been examined). Our data was checked for inconsistencies with this assumption. We also assume that ϕ varies by project type, due to differences in project type complexity. Thus, by definition, it must be that ϕ lies in the interval between 0 and the minimum recorded time in our dataset for each project type and capacity quartile ($0 < \phi < \min t$). Since ϕ is unobserved, we estimate our models for a range of possible values of ϕ in 10% increments from the minimum to the maximum

TABLE 2 Summary statistics for first-stage Models 3 and 7

Variable	Mean	*SD*	Min	Max	1	2	3
1. ln C	4.38	1.77	−0.09	8.67	1		
2. $\left(\frac{t}{\phi}-1\right)^{-1}$	0.11	0.31	0.00	3.03	0.16	1	
3. ln t	3.23	0.67	1.62	4.98	0.29	−0.19	1

TABLE 3 Baseline Model 3 OLS estimation with region dummies (DV: ln C)

							Point Elasticity				
Project type	N	$\hat{V}$ ($M)	$\overline{\phi}$ (months)	$\hat{\alpha}$	R^2	$\bar{t}$ (months)	Mean	*SD*	Min	Max	% <0
Petrochemicals: Olefins	70	42.407	7.831	−0.227	0.269	37.968	−0.278	0.536	−2.776	−0.014	100%
		(p = 0.000)		(p = 0.496)							
Petrochemicals: Plastics	60	84.424	1.342	−20.886	0.201	32.530	−1.196	0.582	−2.469	−0.309	100%
		(p = 0.001)		(p = 0.003)							
Refineries: Simple	145	97.669	0.533	−1.709	0.355	29.825	−0.053	0.044	−0.183	−0.007	100%
		(p = 0.000)		(p = 0.789)							
Refineries: Complex	184	16.373	0.527	−8.012	0.199	29.363	−0.250	0.201	−0.911	−0.028	100%
		(p = 0.029)		(p = 0.065)							
Sample	459	—	1.749	—	—	31.235	−0.316	0.478	−2.776	−0.007	100%

Note. Variable $\hat{V}$ is the natural antilogarithm of the constant estimate. OLS = ordinary least squares; DV = dependent variable.

value of this interval. We then use as the baseline case the value of ϕ that maximizes the log-likelihood of model estimation. In later estimations and in the robustness checks section, we adjust our estimation to mitigate concerns regarding the sensitivity of our results to the method used to set the value of ϕ. Finally, the remaining variables in Model 3, α and ln$V$, are coefficients to be estimated. For a given estimated value of $\hat{\alpha}$ per project type, the time–cost elasticity for each of the projects of that type is obtained by substituting the realized values of t/ϕ recorded in our sample into Equation (2). Table 2 presents the summary statistics for the variables in Model 3.

3.2 | Results

Table 3 summarizes our estimation results and distribution of elasticities for our estimation of Model 3. Projects are partitioned into two project type categories for petrochemicals and two project type categories for refineries. Our results are substantially different from Mansfield et al. (1971) and Teece (1977). Most importantly, the central hypothesis that the direct costs (or TCD) coefficient α should be positive with a small p value is not supported in our sample. Specifically, our estimates of $\hat{\alpha}$ are negative for each project type, with some project types having large negative coefficient sizes and small p values ($\hat{\alpha} = -20.886$, $p = 0.003$ for Plastics; $\hat{\alpha} = -8.012$, $p = 0.065$ for Complex Refineries) and other project types having small negative coefficient sizes and large p values ($\hat{\alpha} = -0.227$, $p = 0.496$ for Olefins; $\hat{\alpha} = -1.709$, $p = 0.789$ for Simple Refineries). This finding is robust across different Model 3 runs and alternative variable measurements, and it has profound qualitative implications. It suggests that, for our sample, the time–cost curve in Models 1 and 3 and in Figure 1 is either time-invariant or upward sloping. This is equivalent to saying that, according to this initial set of results, TCD are not an active investment constraint. Seemingly, firms can accelerate without affecting—or even while reducing—direct project development costs. At face value, this would imply that our sample firms are time-inefficient in global investment projects.

Similar conclusions can be reached by analyzing the point elasticities for each of the project types in Table 3. While prior work only reported positive elasticities (Table 1), in our baseline model results all elasticities are negative. This is because the sign of elasticities depends only on the sign of the estimated coefficient $\hat{\alpha}$, as per Equation (2): when $\hat{\alpha}$ is negative, all elasticities for that project type are also negative, independently of the realized value of t/ϕ. For petrochemical plastics, for example, the mean elasticity estimate means that, on average, accelerating investments in productive facilities by 1% would also decrease costs by 1.196%. Since firms spent an average of 32.5 months and $363.7 million (in 1996 dollars) to build a plastics plant in our sample, our baseline results imply that firms would have saved about $13.4 million, on average, if they had compressed time marginally by 1 month. These time–cost efficiency gains in investment would have been more modest for complex refineries, with savings of about $1.0 million (in 1996 dollars) per month shaved off in project development.

4 | ESTIMATES OF TIME–COST ELASTICITIES: EXTENDED MODEL

The existence—and large number—of negative elasticities in our results is the fundamental difference between our baseline model and previous literature. There are two main possible explanations for this difference. We use these two explanations to extend our initial analysis.

4.1 | Explanation (A): Direct and Indirect Project Costs

The first explanation for negative elasticities is that new project development involves not only *direct* costs—as assumed in prior work and in Model 3—but also *indirect* project costs. Direct project costs are intrinsically associated with project activities (e.g. salaries, project materials, equipment) and increase as the pace of activities accelerates due to diminishing returns, information loss, or concurrent investments—as extensively discussed earlier in the article. In contrast, indirect project costs are overhead costs not associated with specific project activities, but fixed per unit of time over the life of a project. Thus, unlike direct costs, indirect costs *increase* as projects take longer to develop. Examples of indirect costs include supervision and administration, transportation of labor to the working site, insurance, security and maintenance, office rent, and taxes (Badiru, 2005; Baker, 1991; Smith & Reinertsen, 1998). Therefore, taking excessively long to complete projects likely increases total costs: the rise in indirect costs more than offsets the direct cost savings from slower investment.

Since most investments in our sample were substantially slower than those in Mansfield et al. (1971) and Teece (1977)—over 90% of our projects have realized values of t/ϕ above the maximum reported by these studies—indirect costs are likely more prominent in our data. This suggests levels of time compression well below those documented in prior research. As a result, for most of these projects with large time-to-build, total project costs increased in development time, thereby giving rise to an upward-sloping cost curve and negative elasticities. For all other projects with shorter time-to-build, direct costs and TCD still governed the time–cost curve. The combination of these two effects produces a U-shaped time–cost curve, as illustrated in the left panel of Figure 2. We denote by minimum efficient time (MET) the level of time that minimizes total costs in Figure 2. Observations to the right of MET (left) are expected to have negative (positive) time–cost elasticities.

Interestingly, prior literature has explicitly acknowledged the existence of indirect project costs and theorized about the possibility of a U-shaped time–cost curve. However, this empirical possibility

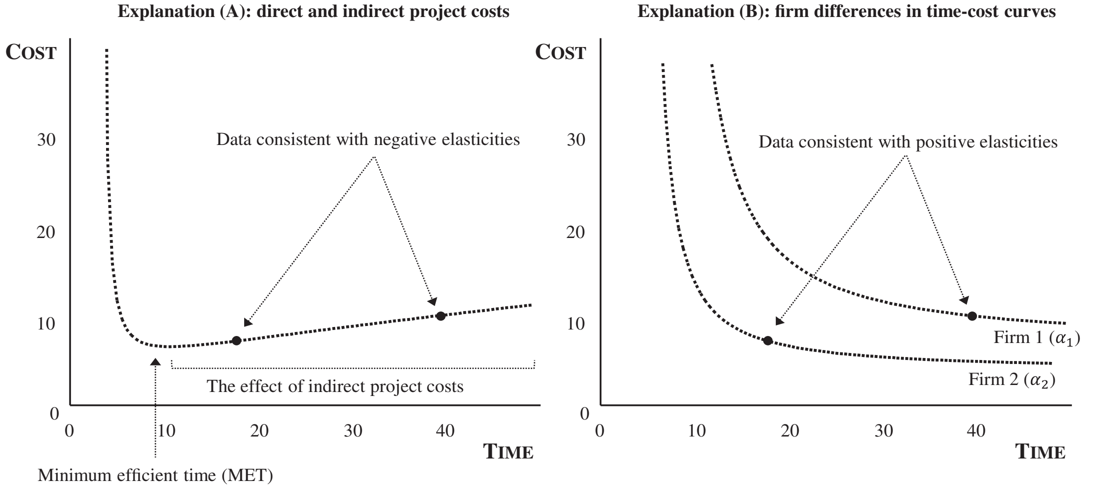

FIGURE 2 The two alternative explanations for negative elasticities (left panel: Models 1 and 4 with $v = 1$, $\phi = 2.5$, $\alpha = 1.5$ and $\beta = 0.6$; right panel: model (1) with $V = 4$, $\phi = 2, \beta = 0$ and $\alpha_1 = 5$ versus $\alpha_2 = 20$)

was either not allowed by past model specifications and estimations or discarded altogether—even when some evidence of indirect costs was unambiguously found in the data.[3]

In our model extension, we allow for indirect project costs in Model 1 by assuming that:

$$V = vt^{\beta} \tag{4}$$

where $v > 0$ and $\beta \geq 0$ so that indirect projects costs increase in t. In Model 4, constant v rescales the magnitude of indirect project costs and no longer represents the minimum theoretical cost of a project. Thus, our estimates of v in this model extension and V in Model 3 are not directly comparable. Note that indirect costs are a linear function of time t when $\beta = 1$ and that Model 4 simplifies to Mansfield et al.'s (1971) and Teece's (1977) functional form when $\beta = 0$. Indirect costs were modeled as a multiplicative term in exponential form to respect the original model structure. An additive specification for indirect costs would have been intractable as the model would not have been estimable using a log transformation. Another advantage of this specification is that there is a simple

[3]Teece (1977, p. 831) stated that "if the existence of some fixed costs is also postulated, then increasing project time need not always lower expected costs". Mansfield et al. (1971) explained that "Economists generally assume that, within the relevant range, the trade-off function is negatively sloped. But little or nothing is really known about the shape of the trade-off function. (…) To what extent do the data confirm the hypothesis that the trade-off function has a negative slope? (…) There is widespread agreement that the time–cost trade-off function is likely to be negatively sloped and convex *only over a particular range*" (p. 131). Some "projects are carried out so slowly that important economies are lost. (…) projects are inefficiently carried out" (p. 82). Swink, Talluri, and Pandejpong (2006, p. 543) agreed that "the relationship between project time and development expense is u-shaped (…). A given project's position on this tradeoff curve is determined by the 'effectiveness' of the project, that is, the degree to which the managers of the project have made use of 'techniques' which improve the efficiency of project execution. Thus, [some] NPD projects (…) have the potential to reduce both project time and project expense by better utilization of techniques and resources available to them. However, projects that already have high levels of execution competence are more likely to face a tradeoff; faster product development will require greater development expense." Early anecdotal evidence of negative time–cost elasticities has also been reported. For example, Teece (1977, p. 832) stated that "Although it was decided to estimate only the negatively sloped portion of the time–cost tradeoff, it is of interest to note that for 13 [out] of the [20] projects in the sample, costs would have increased if the expected time were doubled. Several respondents pointed out that inept management could quite easily create situations where it might be realized ex post that a project had proceeded on the positively sloped portion of the tradeoff." Mansfield et al. (1971, p. 132) and Graves (1989, p. 7) also found at least one project in the positively sloped part of the time–cost curve in their studies.

closed-form solution for MET, the stationary point in the time–cost curve represented in the left panel of Figure 2[4]:

$$MET = \frac{\phi}{2\beta}\left(\alpha + 2\beta + \sqrt{\alpha^2 + 4\alpha\beta}\right) \tag{5}$$

To obtain the model to estimate, we substitute Equation (4) in Model 1 and take logarithms:

$$ln\ C = ln\ v + \alpha\left(\frac{t}{\phi} - 1\right)^{-1} + \beta\ ln\ t + \xi \tag{6}$$

4.2 | Explanation (B): Firm Differences in Time–Cost Curves

While the existence of both direct and indirect project costs is the first obvious explanation for negative elasticities in our baseline model results, a second plausible explanation exists. The right panel in Figure 2 offers a stylized graphical illustration of this possibility. Even without indirect costs in Model 1, the exact same pattern of time–cost observations represented by the two dots in Figure 2 can be explained by the existence of firm differences in time–cost curves. In particular, if firms differ in their capabilities to compress time (e.g., Hawk, Pacheco-De-Almeida, & Yeung, 2013; Helfat et al., 2007; Mansfield, 1988; Pacheco-de-Almeida et al., 2015; Stalk & Hout, 1990), the slope of their time–cost curve also varies. In Model 1, this implies that different firms have different coefficients associated with TCD, or direct project costs, α_i (where i denotes firm). For example, in the right panel of Figure 2, Firm 2 buys time at a lower cost than Firm 1, that is, Firm 2 experiences lower TCD. It has been shown that the optimal development time for firms with lower TCD is also usually faster: specifically, when choosing the development time that maximizes the difference between project revenues and costs, firms with lower TCD not only accelerate more but also incur lower costs (Pacheco-de-Almeida & Zemsky, 2012). Empirically, this implies a positive relationship between time and cost in econometricians' samples, as illustrated by the two observations in the right panel of Figure 2.

The problem with our baseline Model 1 is that it was estimated using OLS for each project type, which de facto assumes that all firms within a project type have the exact same direct cost (TCD) coefficient α—and, thus, the same time compression capabilities and time–cost curve. When forced to fit only one curve to data that exhibits a positive relationship between time and cost (as in Figure 2), OLS necessarily estimates an upward-sloping curve, with a negative coefficient α that produces negative time–cost elasticities.

One solution to this problem that accommodates this explanation for negative elasticities is to estimate Model 6 using a random coefficient model (RCM) (see Alcacer, Chung, Hawk, & Pacheco-de-Almeida, 2018). Unlike standard regression techniques, RCM estimation offers the possibility to test if firms differ in model coefficients (i.e., have different α and β in Model 6). If this is proven to be the case, then an RCM can predict post-estimation the values of firm-specific coefficients (α_i and β_i). Another appealing feature of RCMs is that the econometrician does not need to define how firm heterogeneity affects the firm-specific model coefficients: firm differences are assumed to be unobserved. This property is particularly suited to our empirical context because the source of firm differences in our model is firm capabilities, which cannot be empirically measured. The graphical

[4]From the first-order condition for minimum in the extended model, a stationary point exists when $\beta(t - \phi)^2 - t\alpha\phi = 0$, which is a well-behaved polynomial in t with two solutions: $t_1 = \frac{\phi}{2\beta}\left(\alpha + 2\beta - \sqrt{\alpha^2 + 4\alpha\beta}\right)$ and $t_2 = \frac{\phi}{2\beta}\left(\alpha + 2\beta + \sqrt{\alpha^2 + 4\alpha\beta}\right)$. It is easy to show that $t_1 < \phi$, so the only possible solution is $MET = t_2$.

example in the right panel of Figure 2 shows how RCM estimation would allow the model coefficients to vary by firm, ultimately fitting downward-sloping time–cost curves to the data—thereby producing positive TCD direct cost coefficients ($\alpha_i > 0$) and positive elasticities. Thus, the same time–cost observations that would have generated negative elasticities in OLS could now be consistent with positive elasticities under RCM estimation.

In this second extension, we estimate Model 7 with direct and indirect costs using an uncorrelated RCM (by firm i) in two pooled regressions—for refineries and petrochemicals:

$$ln\ C = ln\ v + \alpha_i \left(\frac{t}{\phi} - 1\right)^{-1} + \beta_i\, ln\ \mathrm{t} + \xi \tag{7}$$

where the intercept ln$v$ is nonrandom but α_i and β_i vary by firm. Notation subscripts are simplified for exposition purposes, but the panel structure of the data remains unchanged (different projects per firm over time). RCM estimation per project type (as before) is not feasible because more project observations per firm are needed to accommodate firm-level variation in the model coefficients. To increase the comparability of this set of results with prior model runs, we keep the level of aggregation across project types to a minimum (refineries versus petrochemicals) and estimate Model 7 including project-type dummies (olefins, plastics, and simple or complex refineries) as controls. Region dummies are also added.[5]

Using the predicted values of $\hat{\alpha}_i$ and $\hat{\beta}_i$ per firm and the realized values of t/ϕ, the time–cost elasticity and MET for each of the projects can be calculated as:

$$\varepsilon^i_{c,t} = \frac{\alpha_i t/\phi}{(t/\phi - 1)^2} - \beta_i \quad \text{and} \quad MET = \frac{\phi}{2\beta_i}\left(\alpha_i + 2\beta_i + \sqrt{\alpha_i{}^2 + 4\alpha_i\beta_i}\right) \tag{8}$$

Note that, analytically, time–cost elasticities are positive when development time is smaller than MET (and negative otherwise) and that β_i is the partial elasticity with respect to indirect costs. As before, time–cost elasticities increase with time compression ($\partial\varepsilon^i_{c,t}/\partial t<0$).

4.3 | Results

Tables 4, 5, and 6 present the results for our extended model. Table 4 tabulates the regression results for Model 7, in which the direct and indirect cost coefficients (α and β, respectively) are allowed to be random. The first moment of these coefficients' distributions characterize the common mean parameters for all firms in that subsample (petrochemicals vs. refineries). The second moment of these distributions represent the estimated standard deviation (*SD*, in the table) of the two random parameters. A random coefficient's standard deviation estimate with a low p value suggests that this coefficient likely differs from one firm to the next due to unobserved firm heterogeneity (for a review of RCM estimation, see Alcacer et al., 2018). We report the p value within brackets below each estimate.

[5]RCM estimation results of Mansfield et al.'s (1971) and Teece's (1977) Model 3 without indirect project costs are not reported in the article due to space constraints. We run an uncorrelated RCM in Model 7 because there are no obvious theoretical reasons to expect direct and indirect costs to covary (i.e., $cov(\alpha, \beta) = 0$). The model intercept ln$v$ is nonrandom because it works as a constant that rescales indirect costs over time and our theory does not offer any explicit rationale for why it should vary across firms. Another advantage of RCM estimation is that it allows us to study the time–cost tradeoff simultaneously at the industry level (the common mean coefficients) and the firm level (the firm-specific coefficients). Also, by predicting firm-varying time–cost elasticities, RCM estimation enhances our second-stage analysis to include firm-level determinants of time–cost elasticities. Finally, RCM estimation provides a more efficient estimation of the common mean coefficients than the alternative method of running separate OLS regressions for each firm in our sample.

TABLE 4 Extended Model 7 RCM estimation with region and project type dummies

	Petrochemicals		Refineries	
DV: ln *C*	**Mean**	***SD***	**Mean**	***SD***
$\widehat{\ln v}$	−3.196	—	−1.039	—
	(p = 0.000)	—	(p = 0.415)	—
$\hat{\alpha}$ (direct costs coefficient)	1.519	0.889	16.994	15.575
	(p = 0.002)	(p = 0.065)	(p = 0.081)	(p = 0.000)
$\hat{\beta}$ (indirect costs coefficient)	1.940	0.203	1.100	0.207
	(p = 0.000)	(p = 0.000)	(p = 0.001)	(p = 0.000)
Region dummies	Yes		Yes	
Project type dummies	Yes		Yes	
Number of observations	130		329	
Log-likelihood	−204.660		−580.253	

Note. All p values are two-tail probabilities for mean coefficient estimates, one-tail probabilities for *SD* estimates. DV = dependent variable; RCM = random coefficient model.

TABLE 5 Extended Model 7 RCM estimation with region and project type dummies (continued)

					Point Elasticity				
Project type	***N***	$\overline{\phi}$ **(months)**	$\overline{MET}$ **(months)**	$\bar{t}$ **(months)**	**Mean**	***SD.***	**Min**	**Max**	**% <0**
Petrochemicals: Olefins	70	4.351	12.368	37.968	−1.253	0.595	−1.887	0.723	93%
Petrochemicals: Plastics	60	6.709	19.363	32.530	−0.548	1.121	−1.864	3.110	79%
Refineries: Simple	145	2.663	10.149	29.825	−0.374	1.226	−1.179	6.982	87%
Refineries: Complex	184	2.633	9.946	29.363	−0.438	1.003	−1.305	5.176	90%
Sample	459	3.437	11.615	31.235	−0.556	1.096	−1.887	6.982	88%

Note. Average results across the nine different levels of ϕ; $\overline{MET}$ represents the average minimum efficient time. RCM = random coefficient model.

In Table 4, the common means of the direct and indirect cost coefficients for both refineries and petrochemicals are positive and have small-to-reasonably-sized or large magnitudes with low p values, as expected ($\hat{\alpha} = 1.519$, $p = 0.002$ and $\hat{\beta} = 1.940$, $p = 0.000$ for Petrochemicals; $\hat{\alpha} = 16.994$, $p = 0.081$ and $\hat{\beta} = 1.100$, $p = 0.001$ for Refineries). These results suggest that, on average, both direct and indirect costs impact the projects in our sample and (should) affect investment speed in oil and gas. On the one hand, TCD is a constraint when firms sufficiently accelerate the development of new production facilities; on the other hand, taking too long may also cause substantial diseconomies. In addition, the estimated standard deviations for both direct and indirect costs have small-to-reasonably-sized or large magnitudes with low p values across the petrochemical and refinery subsamples ($SD(\hat{\alpha}) = 0.889$, $p = 0.065$ and $SD(\hat{\beta}) = 0.203$, $p = 0.000$ for Petrochemicals; $SD(\hat{\alpha}) = 15.575$, $p = 0.000$ and $SD(\hat{\beta}) = 0.207$, $p = 0.000$ for Refineries). This finding gives credence to our second explanation (B) for negative elasticities: there seems to exist firm differences in time–cost curves that are caused by unobserved firm heterogeneity. Different firms likely have different model coefficients for direct costs (α_i) and indirect costs (β_i). As illustrated in the right panel of Figure 2, allowing different firms to have different time–cost curves helps with model identification in that we get more accurate estimates of the specific model parameterization that is generating the time–cost observations in our sample. Thus, certain time–cost elasticities that were initially reported as negative in our replication of Teece (1977) are now expected to turn positive.

TABLE 6 Estimated time inefficiencies in investment in the oil and gas industry during the 1997–2010 period for the extended Model 7 RCM

	Time inefficiencies		
	Insufficient acceleration		Ineffective time compression
	Magnitude of delay[a]	Magnitude of overspending[b]	TCD differentials[c]
Oil and gas industry average	45.1%	39.4%	—
Firms with below-average delay (and $N_i \geq 10$)			
BP	37.1%	36.1%	−12.9%
Hellenic Petroleum SA	26.2%	32.0%	33.0%
Petróleo Brasileiro SA	42.2%	42.1%	39.0%
Valero Energy Corp	30.1%	21.8%	19.8%

[a] Percentage of project time above minimum efficient time (*MET*), $(t - MET)/t$, on average across projects

[b] Percentage of predicted project cost above the predicted cost at *MET*, $\left(\hat{C}(t)-\hat{C}(MET)\right)/\hat{C}(t)$, on average across projects;

[c] Percentage of the time compression diseconomies coefficient above (or below) the industry average, $(\hat{\alpha}_i-\hat{\alpha})/\hat{\alpha}_i$, on average across projects. Note that this measure is also a proxy for the percentage of the time–cost elasticity above (or below) the industry average, $(\hat{\varepsilon}_i-\overline{\varepsilon})/\hat{\varepsilon}_i$, when $\hat{\beta}_i$ is sufficiently small. RCM = random coefficient model.

In order to summarize elasticity estimates from our extended model, an additional consideration is whether our results might be sensitive to the value chosen for the vertical asymptote ϕ. To address this concern, we reestimate Model 7 for a range of possible values of ϕ in 10% increments from the minimum to the maximum value of the interval (0, min t)—where min t denotes the minimum time observed in our data for each project type and capacity quartile. We then take the average of elasticity estimates across the nine estimations. This should help mitigate concerns about the sensitivity of our findings to the selection of ϕ. Table 5 presents these elasticity summary statistics for Model 7. This approach was not possible for Tables 3 and 4 because they report the p values for the estimated parameters, which is meaningless for average results (Tables 3 and 4 use the log-likelihood maximizing value of ϕ). In the online appendix, we also show summary statistics for the elasticity estimates for Model 7 using the log-likelihood maximizing ϕ (Table S1). The conclusions are qualitatively similar.

In Table 5, the time–cost elasticity estimates still have slightly negative mean values for most project types. The distribution of time–cost elasticities now span both positive and negative values, and the maximum values are now positive for all project types. Olefins exhibit the largest negative mean value for elasticity: strategies aimed at shaving project time by 1% would save costs by 1.253%. In absolute terms, firms would have saved about $26.1 million (in 1996 dollars) with a one-month investment acceleration. Table 5 also shows a high percentage of negative elasticities for each project type: 93%, 79%, 87%, and 90% for olefins, plastics, simple refineries, and complex refineries (respectively). The high number of negative elasticities in our sample is because most firms take too long to develop new projects, thereby incurring substantial indirect costs. Indeed, average time $\bar{t}$ is larger than average $\overline{MET}$ for all project types in Table 5.

Table 6 presents the estimated time inefficiencies in investment in the oil and gas industry during 1997–2010 based on our extended Model 7 RCM results. Two main types of time-related inefficiencies can be identified in our model: (a) insufficient acceleration, characterized by project development times greater than MET that result in larger-than-desirable indirect costs and (b) ineffective time compression, when a firm has worse capabilities to compress time than the industry average and, thus, faces greater direct cost or TCD from project acceleration. In Table 6, we offer two measures of insufficient acceleration—the magnitude of delay and the magnitude of overspending—and one measure of ineffective time compression dubbed TCD differentials. These three measures are defined below Table 6.

Our results show that the oil and gas industry exhibited substantial undue investment delays: to be efficient, the industry should have shaved over 45% of its project development time, on average. These delays resulted in unnecessary overspending: 39% of the industry costs could have been saved by compressing time to MET. As Teece (1977) put it, "clearly (…) firms [should] not wish to operate to the right of (…) [MET] under any sort of sensible conditions" (p. 832). These findings are consistent with recent qualitative reports from oil and gas industry consulting bodies, as discussed in the conclusion section.

Next, in Table 6, we analyze time (in)efficiency in technology transfer for a few select companies with at least 10 projects in our sample and magnitudes of delay inferior to the industry average (45.1%). Even for these better-performing firms, substantial average delays and cost overruns are identified: 26–42% of development times and 21–42% of project costs could have been saved through acceleration. These results are for firms from a variety of home countries (United Kingdom, United States, Greece, and Brazil). Interestingly, three out of these four better-than-average firms in project scheduling are predicted to be ineffective at compressing time (last column in Table 6). With the exception of BP, all other three companies must spend marginally more than the industry average to accelerate investment projects (i.e., have positive TCD differentials). The case-in-point is Petróleo Brasileiro SA: with 39% of its TCD (or direct cost) coefficient α above the industry average, the company is more inefficient at buying time than its peers. In contrast, BP arguably has above-average technical capabilities to compress time at lower costs (with a TCD coefficient 12.9% below average), but its insufficient acceleration suggests it might have poor managerial capabilities. The drivers of these time inefficiencies and differences in time–cost elasticities are discussed next.

5 | DETERMINANTS OF TIME–COST ELASTICITIES

Thus far, the main finding of our study is the high frequency of negative time–cost elasticities and a higher-than-expected level of time inefficiency exhibited by the firms in our sample. A remaining question is why we observe these results. Here, we develop a second-stage analysis to investigate the drivers of the time–cost elasticities in Equation (8) by regressing these elasticities on project and firm regressors.

The starting point of our approach is similar to Teece's (1977) second-stage analysis: our initial set of explanatory variables are designed to be as close to that article as possible. We then estimate an extended second-stage model with additional variables that are theoretically expected to also affect time–cost elasticities. Since our results for time–cost elasticities $\hat{\varepsilon}^{i}_{c,t}$ depend on how the different explanatory variables affect the main components of elasticity in Equation (8), we also run supplemental regressions using these elasticity components as dependent variables—specifically, for the direct and indirect cost coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ and time t. These auxiliary regressions facilitate the interpretation of our second-stage results. It is also important to note that using these estimated coefficients from stage one as dependent variables may cause econometric problems in stage two (e.g., heteroskedasticity). We correct for this using Hornstein and Greene's (2012) adjusted Saxonhouse weighted GLS procedure by weighting all independent observations by the inverse of the variance of the dependent variable. All elasticities are taken from the estimation of Model 7 using the log-likelihood maximizing value for ϕ. We do not use the elasticities averaged across the nine different levels of ϕ reported in Table 5 because Hornstein and Greene's (2012) correction was only developed for single-point RCM estimates in the first stage—not for averages of estimates.

Our hypotheses follow. The first four regressors were studied by Teece (1977) but our predictions differ. This is because our model is an extension of Teece's (1977) original model (in Equation (3)) to include both direct and indirect project costs and firm differences in cost curves. First, we expect that firms take longer to develop projects associated with new-to-the-firm technology because it is harder to accelerate practices that are implemented for the first time. Increasing observed time t pushes projects along the time–cost curve to the right—toward the region where indirect costs matter more than direct costs. Thus, new-to-the-firm technology should reduce the importance of direct costs in projects, that is, have a negative or a high p value effect on $\hat{\alpha}_i$ in Equation (8). Also, we have no obvious reason to believe that new-to-the-firm technology impacts projects' indirect costs ($\hat{\beta}_i$). These inferences jointly point to the fact that new-to-the-firm technology should reduce overall time–cost elasticities ($\hat{\varepsilon}_{c,t}$ and $\hat{\varepsilon}^i_{c,t}$).

Second, the influence of firm size on elasticities is less straightforward. Larger firms typically have greater overhead costs and thus, by definition, higher indirect project costs ($\hat{\beta}_i$ increases), which reduces elasticities. However, this effect may be either offset or reinforced by how firm size affects direct costs. On the one hand, it is plausible to think that larger firms have more inertia, which thwarts time compression, thereby increasing direct costs ($\hat{\alpha}_i$) and elasticities. On the other hand, larger firms also have access to larger pools of in-house talent, which should make acceleration easier, decreasing direct costs ($\hat{\alpha}_i$) and elasticities. Since it is also unclear how firm size affects project completion time t, our net prediction for elasticities is ambiguous.

Third, project size should have a well-defined impact on elasticities. Larger projects imply higher coordination costs, which increases time compression diseconomies and direct costs ($\hat{\alpha}_i$). At the same time, larger projects should have more overhead costs and, thus, higher indirect costs ($\hat{\beta}_i$). Although these two effects have opposite consequences for elasticities, larger projects also take longer time (t) to complete, which makes the indirect costs effect more dominant, thereby decreasing elasticities.

Fourth, trade barriers affect elasticities through project revenues rather than (direct or indirect) project costs. Host country trade barriers limit firms' ability to supply through exporting, which increases the expected revenues from building a new production facility on the host country. Thus, firms have more incentives to accelerate projects and time t should decrease, thereby increasing elasticities. No changes in direct or indirect costs ($\hat{\alpha}_i$ or $\hat{\beta}_i$) are expected.

Our operationalization of these first four explanatory variables is as follows. New-to-the-firm technology is a dummy variable equal to 1 if the firm has not done a similar project within our data prior to the current project. Firm size is constructed as the natural log of total firm sales deflated to 1996 using the consumer price index. Project Size is the natural log of project cost. Trade barriers is the average level of tariffs in the host country interacted with a dummy that equals 1 if the firm has not executed a project in the host country in the past. We further include region and project type dummies due to the aggregation of our projects across project type and geography. These dummies may also help control for the degree of planning used in each project if planning differs systematically by project type or geography. Note that we do not study Teece's (1977) "front-end loading" variable because it is unobservable in our data.

We then go beyond Teece (1977) to include additional firm-specific and country-specific variables that capture other potential theoretical drivers of time–cost elasticities. We presume that elasticities generally vary with three types of factors: (a) capabilities, or whether firms have the know-how and human capital to compress time and manage projects efficiently; (b) incentives, in particular, how competition may induce firms to speed up investments; and (c) constraints, internal and external to the firm. We discuss each of these categories of explanations in turn.

The article includes two proxies for firm capabilities. On the one hand, we expect managerial capabilities to improve with past broad project experience, which should curb excessive investment delays—thereby increasing elasticities. Managerial capabilities are unspecific to project types or technologies, so they should not affect direct project costs. Broad project experience is measured as a count of all oil and gas projects (gas processing, petrochemicals, pipelines, refineries, sulfur facilities) listed in the *Oil and Gas Journal* as executed by the firm before the current project during our sample period. On the other hand, we hypothesize that in-house technical capabilities and innovation increase with R&D investment—making human capital more competent at accelerating investments at lower costs, which reduces elasticities (see also our discussion of the effect of technology on TCD in the literature review section). Firm technical capabilities are measured by R&D intensity (R&D expense divided by total assets).

For incentives, we argue that firms that are exposed to lower levels of competition (i.e., live a "quiet life"), have fewer reasons to reduce time inefficiencies and are more likely to take longer to invest—thereby decreasing time–cost elasticities. We measure competition by rival entry, operationalized as the number of firms completing projects in the same year as the focal project.

Internal and external constraints are measured in multiple ways. Older firms are expected to face more organizational inertia and, thus, have greater difficulty to compress time, which raises time–cost elasticities. Firm age is operationalized as the number of years since the firm's founding date. For external, country-specific constraints, two explanatory variables are included. We predict that in more economically developed countries, with greater availability of local suppliers and better infrastructure, firms should have lower time–cost elasticities. Country development is measured as the gross national income (GNI) per capita in the host country. Finally, in countries with greater political risk, project financing is likely subject to higher discount rates, which reduces the net present value of future cash flows—thereby decreasing firms' incentives to compress time and, thus, reducing time–cost elasticities. Our measure of political risk is reverse-coded: the POLCON political constraints index (Henisz, 2000) assumes larger values for more constrained governments, which implies lower political risk.

Our last set of variables are controls. Since investment acceleration costs may differ for foreign direct investment (FDI) projects, we created a dummy FDI indicating 1 if the project is completed in a foreign market and 0 otherwise. The use of subcontractors may also affect the cost of time compression, so we created a dummy Subcontractor indicating 1 if a subcontractor was used in the project and 0 otherwise. We also include project type, geographic region, firm, parent industry, and year fixed effects to further control for omitted heterogeneity across observations. Table 7 presents summary statistics and a correlation matrix for these variables, and Table 8 summarizes the variable definitions and data sources.

5.1 | Results

Table 9 reports our second-stage OLS regression results on the determinants of time–cost elasticities using Hornstein and Greene's (2012) adjusted-Saxonhouse weighted-GLS correction (see p. 26). Each column shows the dependent variable (DV) used in that model. The first three regressions, Models A to C, are supplemental regressions that use the elasticity components as DVs. Models A and B use as DV the firm-specific direct and indirect cost coefficients, $\hat{\alpha}_i$ and $\hat{\beta}_i$ (respectively). Model C uses time t as the DV. The final second-stage estimation results are in Models D and E with the time–cost elasticities from the first-stage extended RCM Model 8.

TABLE 7 Summary statistics for the second-stage model

Variable	Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. $\hat{\varepsilon}^{i}_{c,t}$ (Stage 1 RCM)	−0.71	1.22	−2.25	9.00	1															
2. $\hat{\alpha}_i$ (Stage 1 RCM)	13.95	11.55	0.47	33.18	0.30	1														
3. $\hat{\beta}_i$ (Stage 1 RCM)	1.43	0.45	0.87	2.28	−0.30	−0.63	1													
4. t (actual time)	27.88	20.20	5.7	114.63	−0.42	−0.04	0.23	1												
5. New-to-the-firm technology	0.57	0.50	0	1	−0.15	−0.32	0.10	−0.06	1											
6. Firm size	10.16	1.27	7.09	12.37	−0.12	−0.20	0.18	0.01	−0.21	1										
7. Project size	4.45	1.71	0.90	8.20	−0.18	−0.00	0.46	0.54	−0.22	0.06	1									
8. Trade barriers	2.68	4.39	0	28.90	−0.01	−0.25	0.20	−0.13	0.36	−0.06	0.05	1								
9. Broad project experience	27.60	28.52	0	133	−0.14	0.05	0.09	0.22	−0.43	0.63	0.22	−0.20	1							
10. R&D intensity	0.01	0.01	0	0.07	−0.05	−0.29	0.35	−0.03	0.12	0.09	0.06	0.20	−0.17	1						
11. Rival entry	103.83	33.52	34	170	0.04	−0.04	0.09	−0.40	0.39	−0.16	−0.30	0.33	−0.53	0.27	1					
12. Firm age	65.60	40.27	0	139	−0.01	−0.38	0.30	−0.30	0.15	0.23	−0.10	0.21	−0.02	0.49	0.35	1				
13. Country development	25.55	18.08	0.50	53.77	0.07	−0.09	−0.30	−0.46	0.14	−0.17	−0.47	−0.23	−0.38	−0.02	0.16	0.19	1			
14. Political constraints	0.36	0.20	0	0.72	0.35	0.41	−0.38	−0.46	0.01	−0.14	−0.38	−0.17	−0.30	−0.01	0.43	0.09	0.37	1		
15. FDI (dummy)	0.29	0.46	0	1	−0.08	−0.41	0.33	−0.05	0.05	0.43	0.11	0.42	0.24	0.30	0.04	0.39	−0.23	−0.20	1	
16. Subcontractor (dummy)	0.89	0.32	0	1	−0.07	−0.08	0.12	0.10	−0.26	0.21	0.04	−0.24	0.20	0.14	−0.08	0.15	−0.01	0.03	0.01	1

Note. RCM = random coefficient model; FDI = foreign direct investment.

TABLE 8 Variable definitions and data sources

Variables	Definition	Data Source
$\hat{\varepsilon}_{c,t}$	Time–cost elasticity estimated in OLS in Stage 1	*Oil and Gas Journal* (*OGJ*)
$\hat{\varepsilon}^{i}_{c,t}$	Firm-specific time–cost elasticity predicted by RCM in Stage 1	*OGJ*
$\hat{\alpha}_i$	Firm-specific direct cost coefficient predicted by RCM in Stage 1	*OGJ*
$\hat{\beta}_i$	Firm-specific indirect cost coefficient predicted by RCM in Stage 1	*OGJ*
C	Project actual cost (deflated to 1996)	*OGJ*
t	Number of months of plant development	*OGJ*
New-to-the-firm technology	= 1 if firm invests in this project type for the first time (in our data)	*OGJ*
Firm size	Logarithm of total firm sales, deflated to 1996	Compustat, Consumer Price Index from the Bureau of Labor Statistics
Project size	Measures: (a) project expected cost, (b) project actual cost, (c) project capacity. All measures logarithmized. All costs deflated to 1996	*OGJ*, Consumer Price Index from the Bureau of Labor Statistics
Trade barriers	Average level of tariffs in the host country interacted with a dummy = 1 if the firm has not executed a project in the host country in the past	World Development Indicators (WDI) from the World Bank, *OGJ*
Broad Project Experience	Number of oil and gas projects (gas processing, petrochemicals, pipelines, refineries, sulfur facilities) executed by firm in data in the past	*OGJ*
R&D intensity	R&D expenses divided by total assets	Compustat
Rival entry	Number of projects completed by other firms in the same year as the focal project	*OGJ*
Firm age	Number of years since firm founding	Compustat, web-based reports
Country development	Gross national income (GNI) per capita	WDI from the World Bank
Political constraints	Political constraints index: higher values indicate more constraints on host country government and lower political risk	Henisz (2000)
FDI (dummy)	= 1 if the firm country differs from the project country	*OGJ*, web-based reports
Subcontractor (dummy)	= 1 if a contractor was used on the project	*OGJ*

Note. OLS = ordinary least squares; FDI = foreign direct investment.

Our initial set of results in Models A through D essentially support our hypotheses. Due to space constraints, we will not repeat again here our hypotheses. The only additional note worth making about these results regards firm size because we had ambiguous theoretical predictions about its effect on elasticities. Empirically, firm size is shown to have a modest negative effect on the direct costs coefficient ($\hat{\alpha}_i$) with a low p value (effect estimate = −0.667, p = 0.063), which suggests that larger firms access to deeper pools of in-house talent helps reduce TCD and makes acceleration easier. This result, together with the fact that indirect costs increase in firm size, is shown to reduce time–cost elasticities.

Our results in Model E add six additional explanatory variables, two controls (for FDI and subcontractors), and firm, industry, and year dummies. Out of the 10 main regressors in Model E, all but three have the hypothesized effects on elasticities. We focus only on the three exceptions to our predictions. Specifically, new-to-the-firm technology and trade barriers have low p values with the expected sign in Model D (new-to-the-firm technology effect estimate = −1.521, p = 0.001; trade

TABLE 9 The determinants of time–cost elasticities, OLS estimation

	Stage 1: RCM Extended model				
	DV: $\hat{\alpha}_i$	DV: $\hat{\beta}_i$	DV: t	DV: $\hat{\varepsilon}^i_{c,t}$	
Variable	**A**	**B**	**C**	**D**	**E**
Constant	−4.888	1.688	16.265	3.537	−7.009
	(p = 0.436)	(p = 0.000)	(p = 0.365)	(p = 0.181)	(p = 0.582)
New-to-the-firm technology	−0.764	0.009	6.993	−1.521	0.113
	(p = 0.483)	(p = 0.674)	(p = 0.026)	(p = 0.001)	(p = 0.776)
Firm size	−0.667	0.015	−0.718	−0.320	0.640
	(p = 0.063)	(p = 0.026)	(p = 0.481)	(p = 0.034)	(p = 0.400)
Project Size	2.206	0.026	4.855	−0.428	−0.248
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.004)	(p = 0.073)
Trade barriers	−0.072	−0.004	−1.304	0.109	0.005
	(p = 0.539)	(p = 0.118)	(p = 0.000)	(p = 0.028)	(p = 0.934)
Broad Project Experience					0.041
					(p = 0.054)
R&D intensity					−335.128
					(p = 0.002)
Rival entry					0.041
					(p = 0.575)
Firm age					0.154
					(p = 0.009)
Country development					−0.156
					(p = 0.000)
Political constraints					8.752
					(p = 0.000)
FDI (dummy)					0.208
					(p = 0.822)
Subcontractor (dummy)					−0.312
					(p = 0.618)
Control dummies:					
Region/Project type	Yes	Yes	Yes	Yes	Yes
Firm/Industry/Year	No	No	No	No	Yes
Number of observations	126	126	126	126	123
F-test for model	42.38	249.54	4.13	6.63	12.09
	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)	(p = 0.000)
R^2	0.831	0.967	0.324	0.435	0.934

Note. Results use Hornstein and Greene's (2012) adjusted-Saxonhouse weighted-GLS correction for the estimated RCM coefficients as dependent variables in a second-stage regression. OLS = ordinary least squares; RCM = random coefficient model; DV = dependent variable; FDI = foreign direct investment.

barriers effect estimate = 0.109, p = 0.028) but have high p values in Model E (new-to-the-firm technology effect estimate = 0.113, p = 0.776; trade barriers effect estimate = 0.005, p = 0.934). The explanation for this change in results is the fact that Model E includes an additional set of aggressive firm, industry, and year controls that pick up much of the variation previously explained by these variables. This is particularly the case for new-to-the-firm technology because Model E also adds a more fine-grained measure of a similar construct, broad project experience. The same reasoning applies to trade barriers, as Model E adds two additional country-specific variables, country development and political constraints. We also note that rival entry in Model E has a high p value (effect estimate = 0.041, $p = 0.575$), but this is likely due to the inclusion of year controls since rival entry varies by year. As for controls, the FDI and subcontracting dummies have high p values (FDI effect estimate = 0.208, $p = 0.822$; Subcontracting effect estimate = −0.312, $p = 0.618$). The FDI nonresult may be explained by the fact that we already have several country-specific controls.

Finally, the average economic impact of our results in our second-stage regressions follows. In Models A through D, when technology is new to the firm, projects slow down by 7.0 months and time–cost elasticity decreases by 1.521. A 10 % increase in firm size reduces elasticity by 0.032, whereas a 10 % increase in project size slows down projects by 15 days and cuts elasticity by 0.043. Trade barriers reduce project development time by 1.3 months and raises elasticities by 0.109. In Model E, an increase of broad project experience by one project is associated with a .041 increase in time–cost elasticity. A large, one-standard deviation increase in R&D intensity is associated with a 3.351 decrease in time–cost elasticity, whereas each additional year in firm age increases elasticities by 0.154. A large increase in country economic development of one standard deviation leads to a 2.810 decrease in time–cost elasticity. Finally, a one standard deviation increase in political constraints is associated with a 1.750 increase in elasticity.

6 | ROBUSTNESS CHECKS

We conducted multiple robustness checks. First, we tried alternative econometric specifications. In our results, we ran both OLS and RCM models and obtained comparable results. As an additional check, we tried firm fixed effects and firm random effects in the first stage and received qualitatively similar findings. Second, temporal factors such as changes in technology over time could affect the time–cost tradeoff. In Model E in stage two, we included year effects to account for this possibility. As a robustness check, we also tried including year dummies in the first-stage estimations and obtained identical results.

Third, involvement of subcontractors could also affect the time cost tradeoff. In Model E in the second stage, we included a dummy for whether a subcontractor was involved in the project, and it came out with a high p value. We also tried including the subcontractor dummy in the first-stage runs and received similar results. Fourth, for the second-stage estimations, we tried alternative ways to construct variables. For project size, we tried the natural log of project capacity, the natural log of expected cost, and the natural log of actual cost and found similar results across. We also used alternative firm size variables (total assets and total employees) and other firm innovativeness measures (R&D/Sales) and received comparable results.

Fifth, our results could be sensitive to the values set for the vertical asymptote ϕ. The percentage of negative elasticities remains large across different values of ϕ. When we set ϕ to different values between 0 and minimum t (moving in 1/10th increments), the frequency of negative elasticities range from 76.67 to 97.14%.

Sixth, we tried an alternative approach to setting MET. As an exercise, we set MET based on the empirical results of Teece (1977). According to Teece, for 13 out of his 20 projects (65% of the sample), cost would have increased if time would have doubled (footnote 5 in Teece, 1977). This implies that, for these projects, MET was between t and $2t$. From Table 2 in Teece (1977), we also know that t/ϕ varies between 1 and 2. To be conservative, since larger MET decreases the percentage of negative elasticities, we took the largest of both values and set MET equal to 4ϕ. Using this method to set MET, we took our sample, made random draws of 65% of our projects, and calculated the frequency that projects had actual time t greater than MET—that is, a negative elasticity. We tried 100, 500, and 1,000 random draws, and we consistently found negative elasticities to comprise over 60% of our sample. If we take the same approach but set ϕ equal to 9/10th of the interval from 0 to minimum actual time t within each project type, we would still get negative elasticities for over 30% of the sample. These results suggest the core results of the article—a high frequency of negative elasticities—would still be observed across multiple approaches to setting MET and ϕ.

7 | DISCUSSION AND CONCLUSION

Time compression diseconomies have been a central assumption in much of the strategy, economics, and operations literatures. This article carried out a large-sample study of TCD, also known as time–cost tradeoff in operations research (e.g., Graves, 1989; Roemer et al., 2000) and adjustment costs in capital investment theory (e.g., Gould, 1968; Lucas, 1967). Specifically, we estimated time–cost elasticities and investigated their determinants using 459 global investment projects in the oil and gas industry (1997–2010). Our results complement the sparse and dated TCD estimates in six prior studies from the 1970s and 1980s (Boehm, 1981; Hartley & Corcoran, 1978; Mansfield, 1988; Mansfield et al., 1971; Putnam & Fitzsimmons, 1979; Teece, 1977).

Our findings differ from previous work. We show that the average cost of investment acceleration in the oil and gas industry is negative, which is evidence of *economies* of time compression. TCD are often not an active constraint when firms develop new production facilities in this industry. The average firm in our sample is time inefficient in the accumulation of intangible and physical asset stocks: a one-month investment acceleration is associated with a \$6.3 million reduction in the costs of a single project (in 1996 dollars). The frequency of negative time–cost elasticities is also high in our sample, varying between 79% and 93% for different project types. Petrochemical olefins exhibited the largest negative mean elasticity value: −1.253, which corresponds to \$26.1 million (in 1996 dollars) of savings associated with a one-month investment acceleration. Despite hovering around negative mean values, our overall distribution of time–cost elasticities also spans to positive values. The maximum average elasticity in our sample was 6.982, which is consistent with estimates in earlier articles (e.g., Mansfield, 1988)—in this case, accumulating asset stocks 1 month faster would have increased investment costs by \$104.7 million (in 1996 dollars).

To our knowledge, this is the first time that widespread negative time–cost elasticities are documented in the literature. The difference in results between our article and previous work can be explained as follows. The six previous studies of time–cost elasticities used only small samples of 5 to 59 observations per estimate. In addition, past data was often collected through surveys of project managers with questions about the hypothetical costs of a project if counterfactual levels of acceleration had occurred (e.g., Mansfield, 1988; Mansfield et al., 1971; Teece, 1977). This approach led "Mansfield [to] caution that there may be considerable errors in the manager's estimate of the time-cost tradeoff" (Graves, 1989, p. 6). This concern found some support in our analysis: our use of a substantially larger sample with actual data revealed levels of project acceleration well below those previously reported. For example, about 90% of the projects in our data were developed more slowly than the slowest project in Teece's (1977) sample. And, as Teece (1977) conceded, taking too long to develop projects also causes substantial diseconomies as firms incur indirect project costs (i.e., overhead costs not associated with specific project activities, but fixed per unit of time). While prior research did not explicitly focus on indirect project costs, we extended our model to allow for this possibility. This approach made it possible for us to empirically observe that a large fraction of the projects in this industry are developed past their minimum efficient time—in a region of the time–cost curve where indirect costs prevail and total costs increase with further delays. As Teece (1977) put it, "clearly (…) firms [should] not wish to operate to the right of (…) [MET] under any sort of sensible conditions" (p. 832).

Insufficient investment acceleration is prevalent in our sample. Our estimates indicate that the industry could have shaved over 45% of its project development time, on average. These delays resulted in overspending: 39% of the industry costs could have been saved by compressing time down to MET. Table S2 shows how time–cost elasticities are predicted to increase as firms accelerate investments in the oil and gas industry. Also, our random coefficient model estimation showed that even the best-performing firms sometimes incurred large average time and cost overruns. Overall, these findings are consistent with qualitative industry evidence. For instance, Strategy&'s recent study documented oil and gas companies' systematic "difficulty delivering large capital projects on time and within budget" (Tideman et al., 2014, p. 3). The authors advance a number of different reasons for these severe time inefficiencies—one of the most salient being the exact same reason offered by Teece's (1977) survey respondents for project delays: "inept management" (p. 832).[6]

The determinants of time–cost elasticities were also examined. We show that time–cost elasticities decrease with the newness of technology, firm size, and project size mostly due to a substantial slowdown in project development. Investments in R&D also cut elasticities, arguably by reducing diminishing returns associated with allocating more resources to accelerate projects. In addition, it is easier to compress time in more developed countries, likely due to better existing infrastructure. In contrast, older firms exhibit higher levels of time–cost elasticity, probably as a result of organizational inertia. Trade barriers and country political risk impact the revenue incentives from investment acceleration, thereby affecting time–cost elasticities. Higher host-country trade barriers and lower political risk are expected to give firms more incentives to accelerate projects, which increases time–cost elasticities. Finally, more managerial experience curbs excessive delays, thereby increasing elasticities.

The main limitation of our study remains "the problem of identification (…) because it is only possible to observe one combination of time and cost for any project, so that the estimated relationship might simply reflect points on different development isoquants" (Hartley & Corcoran, 1978, p. 210). This is the advantage of counterfactual data over real project data: hypothetical observations for one same project automatically control—by definition—for any unobserved variation in project characteristics. However, our use of random-coefficient model estimation controlling for potential sources of heterogeneity should help alleviate this concern.

7.1 | Strategy Implications

Our results do not refute the existence of TCD, but suggest that they may be less pervasive than assumed in the literature. The limited evidence of TCD in our sample also implies that TCD have not been the main isolating mechanism sustaining competitive advantage in the oil and gas industry during the period of analysis. However, since investment delays are shown to be substantial, investment time lags may be even more important to protect firms' market positions than previously accepted in strategy (Cohen et al., 2000).

The time inefficiencies documented in this article arguably constitute "temporal frictions" and supply-side rigidities that hinder markets from clearing quickly or allocating resources optimally.

[6]Most other causes—labor shortages, labor cost increases, policy changes, etc.—are manifestations of risks that could be identified with better management practices (e.g., with more extensive up-front project planning). A related BCG study by Bascle et al. (2012, p. 2) has also reported differences in time efficiencies across firms in fast-moving consumer goods: "For standard new-product development, a seven-month time-to-market gap separates best-in-class from average players—15 versus 22 months for development."

One important source of supply-side rigidities in our setting is slow technology transfer during the development of a new production facility. It has long been assumed that technology transfer is often slowed down because "the information used in technical problem solving is costly to acquire, transfer, and use in a new location—[that is, knowledge] is (…) 'sticky'" (Von Hippel, 1994). The literature has extensively discussed the characteristics of knowledge, the transferor, and the transferee that create these costs of knowledge transfer (e.g., Bozeman, 2000; Szulanski, 1996). Interestingly, however, cost impediments do not seem to be the main cause of knowledge "stickiness" in our setting because accelerating technology transfer would, on average, have reduced costs. On a related note, our findings also imply lower-than-expected actual costs of faster technology diffusion within an industry.

Our time–cost elasticity estimates should also help firms gauge their marginal financial incentives to accelerate projects. This data may also prove informative to stock market analysts' valuations of firm investment timing. Our analysis of the determinants of time–cost elasticities points to levers that firms may use to control their time–cost investment profile.

Finally, this study will hopefully motivate additional research on time–cost elasticities in other empirical settings. For example, one might intuit that in industries with fast clockspeed—such as fast-moving consumer goods with low standard NPD cycles—the frequency and extent of time inefficiencies should be considerably reduced. In these industries, TCD should also be more salient empirically and actively constrain firms' investments. In addition, it would be interesting to investigate if more R&D-intensive industries where firms often concurrently pursue multiple alternative approaches to uncertain technical problems also exhibit larger minimum efficient times in firm activities.

ACKNOWLEDGEMENTS

The authors are listed in alphabetical order and contributed equally to the article. Gonçalo Pacheco-de-Almeida is a member of the CNRS unit GREGHEC, UMR CNRS 2959. For their helpful comments, we wish to thank editors Richard Bettis, Constance Helfat, and J. Myles Shaver, two anonymous reviewers, Emilie Feldman, Javier Gimeno, Rahul Kapoor, Marvin Lieberman, Nydia MacGregor, Joseph Mahoney, Jason Snyder, Liang Wang, Todd Zenger, Maurizio Zollo, and seminar participants at the 2016 Darden Judge Entrepreneurship and Innovation Research Conference, the University of Colorado Boulder, the 2016 BYU-Utah Winter Strategy Conference, the 2014 Academy of Management Conference, the Cambridge Judge Business School, the HEC SnO Research Day, the 2014 Midwest Strategy Meeting, and the 2013 Strategic Management Society Conference. Financial support from the HEC Foundation (grant number 4F73DRRR - F1202 - O2200PFF1) is also gratefully acknowledged.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Hawk A, Pacheco-de-Almeida G. Time compression (dis)economies: An empirical analysis. *Strat Mgmt J*. 2018;39:2489–2516. https://doi.org/10.1002/smj.2915