THE COST OF ACCELERATING TECHNOLOGY TRANSFER: AN EMPIRICAL ANALYSIS OF TIME COMPRESSION DISECONOMIES[1]

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ABSTRACT

We empirically investigate acceleration costs in technology transfer via a replication of Teece's (1977) early work on time-cost elasticities. Our dataset on the development of oil production facilities worldwide between 1997 and 2010 is similar to Teece (1977), but over 20 times larger. Our results contrast with previous studies. On average, the cost of accelerating technology transfer is negative: firms could have cut $7.2 million in costs by developing projects one month faster. For 87% of our projects, time compression diseconomies are not binding. Industry-average technology transfer inefficiencies are significant: over 36% of project time and costs are unnecessary delays and overspending. Finally, we estimate the determinants of time-cost elasticities. Our findings reassess firms' capital allocation decisions and the role of time in Strategy theories.

MOTIVATION

Most prior research has postulated that accelerating a firms' pursuit of any strategic goal (competitive advantage, industry leadership, or technology transfer) typically comes at the expense of extreme investment inefficiencies. Compressing time substantially raises costs – at an increasing rate. These adjustment costs are known in the strategy literature as time compression diseconomies (TCD). The existence of TCD critically affects strategy fundamentals and, thus, has been central to multiple strands of literature. For example, competitive strategy and the resource-based view have emphasized that TCD are a necessary and sufficient condition for sustainable competitive advantage: if speed were costless, rivals would imitate instantaneously (and vice versa) (Dierickx and Cool 1989). The existence of TCD implies that there is an optimal level of acceleration in firm activities.

Although the notion of TCD is pivotal for the strategy literature, few empirical studies have documented its existence. The most recent empirical evidence of TCD dates back to the 1970s and 1980s and is based on a sparse number of observations, with sample sizes typically varying between 5 and 30 observations (Graves, 1989; Teece, 1977). Recent empirical studies of TCD have been lacking because time is often an elusive and unobservable construct; thus, measuring the time-consuming nature of firm actions is difficult.

Our paper addresses this gap by investigating TCD and its determinants in the context of technology transfer projects. The time efficiency of technology transfer – the timely and effective deployment of productive knowledge to new facilities – is at the heart of successful organizational growth and performance. The speed and costs of the technology transfer process determine a firm's ability to enter new industries, adapt to market changes, develop new products, and respond to rivals. Our paper replicates the early work by Teece (1977) on the estimation of time-cost elasticities that measure the cost of accelerating technology transfer in global investments projects. The reason to replicate Teece (1977) is threefold. First, Teece (1977) provided perhaps the most structured and formal empirical study of TCD in technology transfer to date. Its precise model specification increases the comparability of results. Second, Teece's (1977) empirical setting of the oil and gas industry is highly regulated, which facilitates data collection. Third, the economic fundamentals of the oil and gas industry have remained relatively stable over time, thereby enhancing comparisons and inferences.

This replication study is long overdue. The timing of this paper is also a response to the mounting attention that strategy dynamics and technology transfer have received from scholars and practitioners. A growing body of work suggests that firms should innovate and imitate increasingly faster in most industries (e.g. Agarwal and Gort, 2001; D'Aveni, 1994; Jovanovic and MacDonald, 1994; Wiggins and Ruefli, 2005). However, without accurate empirical measures of the marginal costs of speeding up, it is difficult to estimate the returns and limits to acceleration strategies – and issue normative statements on this subject. Our paper aims at contributing empirical evidence of TCD to help calibrate these inferences.

Our priority in this paper is the strict reproducibility of Teece's (1977) results to the extent that our data allows. Therefore, we follow a similar research design in terms of empirical model, variable measurements, and estimation strategy. We then explore two necessary extensions to our model and estimation methodology to accommodate the specificities of our data. Specifically, our sample is over 20 times larger than the dataset used in Teece (1977) and comes from petrochemical and refinery plant construction projects worldwide from 1997 to 2010. In addition, our sample is based on real project data, whereas Teece (1977) used counterfactual observations from survey data.

Our results are considerably different from Teece (1977) – and from all other prior studies. We show that the average cost of accelerating technology transfer in the oil and gas industry is negative. This implies that the average firm in our sample is time inefficient in technology transfer: firms could simultaneously accelerate and cut costs in project development. Thus, TCD are often not binding in our data. The sheer magnitude of time inefficiencies in this industry is also striking. Our estimates indicate that, on average, oil and gas firms should have shaved over 36 percent of their project development time. These delays resulted in unnecessary overspending: at least 37 percent of the industry costs could have been saved. Overall, these findings are consistent with qualitative industry evidence. A recent study 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 percent (Tideman, Tuinstra, and Campbell, 2014: 3). Our study has important managerial implications, as it reveals the existence of sizeable gains to be had by firms that use time strategically in technology transfer. Our estimates of time-cost elasticities may also be informative for capital allocation decisions and for stock market valuations of firms' timing of technology transfer and innovation.

BRIEF LITERATURE REVIEW

The time-cost investment tradeoff, or the general principle that 'money buys time' in various types of projects, is a core component of the theory of capital investment and asset accumulation. Any large investment project takes time, and an acceleration of project development time is likely to inflate costs – at an increasing rate.

There are three main reasons for this time-cost tradeoff, or time compression diseconomies (TCD). First, firms often accelerate a project by committing more resources to the project. For example, an R&D project may be accelerated by allocating more engineers 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, 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 (Graves, 1989; Mansfield, 1968; Scherer, 1966).[2]

While the time-cost tradeoff has been discussed at length theoretically, there have been relatively few recent empirical investigations of this phenomenon. Researchers in the 1970s and 1980s pioneered efforts to estimate the time-cost tradeoff. Mansfield (1971) collected survey data from project managers who considered 29 hypothetical innovation projects in the chemical, electrical and machinery industries. He found that for projects completed at less than 130% of the minimum completion time, the median elasticity was 1.75. This means that a one percent reduction in duration increases cost by 1.75%. To illustrate, these estimates imply that a two-week compression of Intel's 386 development project, which took 48 months to complete, would have resulted in a $3.5 million increase in development costs (Casadesus-Masanell et al. 2005).

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[2] Note that the three mechanisms leading to time compression diseconomies are affected differently by improvements in technology. Better technology is expected to help with coordination, reducing the diminishing returns associated with allocating more resources to a project. Technological advancements may also facilitate hedging strategies by making it easier for firms to pursue multiple potential solutions to uncertain tasks simultaneously. It is unclear whether better technology would have any effect on information loss from acceleration due to parallel processing of previously sequential activities. Overall, it is sensible to expect TCD to decrease over time. Finally, note also that other tradeoffs are associated with project development, such as the time-quality tradeoff. However, we keep these considerations constant and restrict our focus to the time-cost relationship in this paper.

Teece (1977) conducted a follow up study using survey data for 20 manufacturing projects, and he, too, found the elasticity to be above 1% for 15 of the projects. Similar studies of software engineering development projects by Boehm (1981) and Putnam and Fitzsimmons (1979) found that elasticity estimates generally are positive and range between 1% and 2%. Graves (1989) concludes that time cost elasticities are generally in the 1-2% range.

Since these early studies, direct estimates of the time-cost tradeoff have been lacking during the last 30 years. Notably, all of these prior studies found very similar findings of positive elasticities. We believe that given these results, the field of Strategy has generally assumed that TCD work as an active constraint at all times – almost as a 'law of nature': since firms' actions cannot be instantaneous, it would make intuitive sense that costs should always increase as time is compressed. Note, however, several caveats with these prior findings. All of these studies used small sample sizes and many were based on surveys asking questions about counterfactual hypothetical changes to time and cost for a given project, potentially creating concerns about how representative these results are of reality. This suggests an opportunity for a recent, large data empirical study of real-world projects to obtain estimates that are more generalizable and, thus, have greater external validity. This paper undertakes that task.

ESTIMATES OF TIME-COST ELASTICITIES: STAGE 1 REPLICATION

Model

Our replication model strictly follows Teece (1977).[3] Specifically, cost is a negative and convex function of time and assumes the form:

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[3] Note that parameter α in model (1) is denoted by ϕ in 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.

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

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 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 time compression diseconomies (TCD):

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

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.

Insert Figure 1 here

Following Teece (1977), we transform model (1) into a linear estimable form by taking logs:

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

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. As in Teece (1977), our main hypothesis is that the direct costs (or TCD) coefficient $\hat{\alpha}$ is positive and significant 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.

Data and Estimation

Our empirical setting is the planning, engineering, and construction of new petrochemical and refinery production facilities worldwide between 1997 and 2010. This setting is similar to Teece (1977), which enhances the comparability of the replication.

Technology transfer is central to the oil and gas industry, in particular during the development of new production facilities, as discussed in Teece (1977). Several key oil and gas industry bodies, such as the Petroleum Technology Transfer Council (PTTC), herald technology transfer as their primary mission. The PTTC is a national not-for-profit organization established in 1994 by the Department of Energy to "provide a forum for transfer of technology (…) within the producer community", as a "clearinghouse to disseminate drilling and production technology" (PTTC website). The Society of Petroleum Engineers (SPE) has also stressed that it is now ever more critical to "build technology transfer into the company's operations". According to SPE, oil firms are "engaging in an increasing number of [plant development] growth projects around the world" and the standard practice of "staff[ing] them almost entirely with US-based members" is no longer viable (Sumrow, 2002, in the Oil and Gas Journal). Oil and gas technology transfer in FDI has also become a focal issue in public policy. Multinational oil companies are often contractually forced to transfer technology to host-country partner firms during new plant development projects to be granted government construction permits overseas.

As explained by Teece (1977), technology transfer during new oil plant development projects typically exhibits time compression diseconomies (TCD). The three main drivers of the time-cost tradeoff identified in the literature review section are particularly salient in our setting. First, the deployment of firm technology to other domestic and foreign sites often involves substantial technological uncertainty. This uncertainty results from the need to adjust plant design parameters to different market-based scales of operation, material inputs, operator skills, and engineering standards. “When uncertainty precludes immediate identification of the best design, it may be desirable to ‘hedge’ by supporting several different designs. By incurring higher project costs, hedging can reduce the project time relative to a procedure which explores different designs sequentially” (p. 831). This probabilistic approach to technology transfer is known to create TCD. Second, crashing plant investment projects by assigning more resources such as chemical engineers to plant design or engineering increases job segmentation, coordination costs, and diminishing returns, which also results in TCD. Third, project acceleration by bringing sequentially-scheduled tasks (e.g. plant design, engineering, and construction) into parallel processing reduces information flows between tasks, causing mistakes, rework, and TCD. A case-in-point is firms’ attempts to speed up projects by soliciting bids from suppliers for equipment to be used in the last stages of plant development (i.e. construction) before the initial plant design phase is finalized. 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, as mentioned in SPE’s quote above, most US firms' conventional practice of importing skilled US-based labor to staff plant development abroad helps accelerate projects, but also significantly increases costs.

Besides exhibiting TCD in technology transfer, two other features of the oil and gas industry also make it a good empirical setting for our replication study. The sizeable and irreversible nature of investment in new oil plants – with the average cost of a petrochemical facility in our sample being approximately $660 million – makes the timing of these type of decisions inherently strategic. Finally, data on time-to-build and investment project characteristics is available from several industry sources, which facilitates empirical work.

The dataset used in this replication study comes from the Oil and Gas Journal (OGJ). We collected data on all oil and gas projects carried out worldwide from 1997 to 2010 that contained information on project cost and time-to-build. To mirror the sample used in Teece (1977), we only focus on the subset of 452 projects in our dataset that are petrochemical plants and refineries with available data for our covariates. Our sample is over twenty times larger in number of projects than Teece's (1977) sample, which only had 20 projects. The structure of our data also differs. While all the observations in our sample consist of actual time-cost project data, Teece (1977) used a mix of actual data and hypothetical data from a survey of project managers. Specifically, for each of his 20 projects, Teece (1977) asked project managers to make four counterfactual estimates of how project costs would have changed if the project would have taken (a) half its actual time, (b) twice its actual time, (c) 90 percent of its actual time, and (d) 110 percent of its actual time. Thus, each project in Teece (1977) had five observations, one actual – or realized – time-cost observation and four hypothetical observations. This difference in data structure has profound implications for the reliability of the results, but it also requires an adjustment to our estimation strategy, as discussed next.

To estimate model (3), we partition our data by project type according to standard industry classifications to create comparable project pools (Leffler, 2000; Burdick and Leffler, 2001). In particular, we consider five main project types, two in petrochemicals (olefins and plastics) and three in refineries (simple, complex, and very complex). We estimate our model at the project level within each project subgroup using OLS and a number of different control variables.[4] Our results are generally consistent across the different sets of controls that we used, as discussed in the robustness checks section. We report as baseline results the regression estimates using control dummies for different geographic regions (Asia and the Pacific, Eastern Europe, Former USSR, 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. Teece (1977) measured ϕ by asking "project managers (…) to estimate the minimum *possible* time in which the project could be completed" (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,

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[4] Teece (1977) needed no controls because he ran separate OLS regressions for each of the 20 projects in his sample.

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 value of this interval. Our results are generally consistent across runs (namely, for ϕ equal to 10, 50, and 90 percent of the minimum recorded time), as mentioned in the robustness checks section. For reporting purposes in the paper, we use as the baseline case the value of ϕ that maximizes the log-likelihood of model estimation. 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). Appendix Table 1 presents the summary statistics for the variables in model (3).

Results

Table 1 summarizes our estimation results for Teece (1977) stage 1 replication model (3). Table 2 presents the distribution of elasticities based on the same replication model. Teece's (1977) original results can be found in Appendix Tables 3 and 4. In Table 1, projects are partitioned into two project type categories for petrochemicals and three project type categories for refineries. In contrast, Teece (1977) reported results for the 20 projects in his sample after running separate OLS regressions for each project (with five observations each), as explained above.

Our replication results in Table 1 are substantially different from Teece (1977). Most importantly, Teece's (1977) central hypothesis that the direct costs (or TCD) coefficient α

should be positive and significant is not supported in 98% of our sample. Specifically, our estimates of $\hat{\alpha}$ are either not significant or negative and significant – except for very complex refineries where $\hat{\alpha}$ is positive and significant, as predicted. This finding is robust across different model (3) runs and alternative variable measurements, and it has profound qualitative implications. It suggests that, for 98% of 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, in this industry and with the exception of very complex refineries, time-compression diseconomies (TCD) are not a constraint in technology transfer. Seemingly, firms can accelerate without affecting – or even while reducing – direct project development costs. At face value, this implies that, for the large majority of projects in our sample, firms are time-inefficient in technology transfer. The finding that $\hat{\alpha}$ is only positive and significant for very complex refineries should be interpreted with caution given our small sample size. However, this result is consistent with existing theories that show that complexity generally amplifies TCD (Pacheco-de-Almeida and Zemsky, 2007).

Insert Table 1 here

Similar conclusions can be reached by analyzing the point elasticities for each of the project types in Table 1 and the elasticity distribution in Table 2. While Teece (1977) only had positive elasticities (Appendix Table 4), in our replication study most 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 technology transfer in plant development 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 results imply that firms would have saved about $13.4 million by reducing plant development time by one month. This time-cost efficiency gains in technology transfer would have been more modest for complex refineries, with savings of approximately $1.1 million (in 1996 dollars) per month shaved off in project development. In contrast, for very complex refineries, the positive time-cost elasticity of 1.161 suggests that being simultaneously faster and cheaper in technology transfer for this project type is not possible: companies would need to devote the equivalent of $2.1 million (in 1996 dollars), on average, to reduce time by one month. Therefore, we cannot infer that firms are being time inefficient in the development of very complex refinery projects.

Insert Table 2 here

Finally, Tables 1 and 2 show three remaining differences between Teece's (1977) original results and our replication study. Interestingly, 98% of the projects in our sample have realized values of t/ϕ above the maximum reported in Teece (1977). This denotes levels of time compression in our sample well below those documented by Teece (1977) – that is, the firms in our dataset accelerate their projects significantly less than those in Teece's sample. This finding is generally robust across the different possible values of ϕ ($0 < \phi < \min t$). This empirical regularity also explains why a disproportionately large number of projects have time-cost elasticities in the -0.49 to 0.00 range: for sufficiently large values of t/ϕ, marginal variations in time t or α have very little impact on elasticity. Intuitively, this occurs because the cost curve flattens when t/ϕ is large, independently of the sign of α (mathematically, it is easy to show that $\partial \left|\partial \varepsilon_{c,t}/\partial \left(\frac{t}{\phi}\right)\right| / \partial \left(\frac{t}{\phi}\right) < 0$ and $\partial \left|\partial \varepsilon_{c,t}/\partial \alpha\right| / \partial \left(\frac{t}{\phi}\right) < 0$). The last two differences between Tables 1 and 2 and Teece (1977) are that the values of R^2 are considerably lower in our replication and that our estimates of the minimum theoretical cost of projects ($\hat{V}$) are larger than in Teece (1977), as expected given the 20-year hiatus between the two samples. The next section aims at explaining the discrepancies in results between Teece (1977) and our replication study.

TWO EXTENSIONS TO STAGE ONE REPLICATION

The existence – and large number – of negative elasticities in our results is the fundamental difference between our replication and Teece (1977). There are two main possible explanations for this difference. We use these two explanations to extend and fine-tune our replication study.

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 Teece (1977) 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 paper. 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 2014; Baker 1991; Smith and Reinertsen 1998). Since most projects in our sample took substantially longer to complete than in Teece (1977) – as evidenced by the larger realized values of t/ϕ in Table 2 – indirect costs were likely more prominent in our replication than in Teece's original study. 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 time compression diseconomies 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 (left) of MET are expected to have negative (positive) time-cost elasticities.

Insert Figure 2 here

Interestingly, Teece (1977) explicitly acknowledged the potential consequences of indirect project costs: “If the existence of some fixed costs is also postulated, then increasing project time need not always lower expected costs” (p. 831). The u-shaped time-cost curve in Figure 1 of his paper also graphically illustrated this effect. However, Teece (1977) decided not to allow for this empirical possibility in his model and estimation, even if evidence of indirect costs was unambiguously found in his data:

> “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” (p. 832)

In our replication study, assuming away indirect costs when theory and data strongly suggest the opposite would cause estimation biases and incorrect inferences. Therefore, the first extension to our stage one replication of Teece (1977) allows for the existence of 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 Teece's (1977) functional form specification when $\beta = 0$. Indirect costs were modeled as a multiplicative term in exponential form to respect Teece's (1977) 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 closed-form solution for minimum efficient time (MET), the stationary point in the time-cost curve represented in the left panel of Figure 2:[5]

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

The extended model to estimate is obtained by substituting equation (4) in model (1) and taking logarithms:

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

In this first extension, the data and estimation of model (6) is identical to those used in model (3). As before, we estimate model (6) at the project level within each of the same five project subgroups (olefins, plastics, and simple, complex and very complex refineries) using OLS with control dummies for different geographic regions. Our results are generally consistent across different sets of controls. The operationalization of the model variables remains unchanged. For a given estimated value of $\hat{\alpha}$ and $\hat{\beta}$ per project type in model (6), 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 the new equation for time-cost elasticity for this first model extension:

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[5] 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 $MET = t_2$.

$$\varepsilon_{c,t} = \frac{\alpha\, t/\phi}{(t/\phi - 1)^2} - \beta \qquad (7)$$

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

Due to space constraints, we report and discuss our estimation results for this first extension to our replication in the Appendix (see Appendix Tables 5 and 6). In short, our results from this first extension with both direct and indirect costs appear to be a substantial improvement over our initial Teece (1977) replication. However, our analysis can be further fine-tuned by also considering the second explanation for negative elasticities.

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 replication, 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. Dierickx and Cool, 1989; Helfat *et al.*, 2007; Mansfield, 1988; Pacheco-de-Almeida, Hawk, and Yeung, 2015), 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 time compression diseconomies (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 and 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 replication study is that model (1) 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 (even if the minimum theoretical time ϕ varies per project quartile). 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 explanation (B) for negative elasticities is to estimate model (1) (with or without indirect costs) using a Random Coefficient Model (RCM) (see Alcacer *et al.*, 2015). 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 models (1) and (4) above). If this is proven to be the case, then RCM estimation can predict the values of firm-specific coefficients (α_i and β_i). Another appealing feature of RCM estimation 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 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 to the replication, we estimate model (6) with both direct and indirect costs using an uncorrelated RCM (by firm i) in two pooled regressions – for refineries and petrochemical projects:

$$\ln C = \ln v + \alpha_i \left(\frac{t}{\phi} - 1\right)^{-1} + \beta_i \ln t + \xi \tag{8}$$

, where the intercept $\ln v$ is non-random 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 (8) including project type dummies (olefins, plastics, and simple, complex or very complex refineries) as controls. Region dummies are also added.[6]

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 minimum efficient time (MET) for each of the projects can be calculated as:

[6] RCM estimation results of Teece's (1977) model (3) without indirect project costs are not reported in the paper due to space constraints. We run an uncorrelated RCM in model (8) because there are no obvious theoretical reasons to expect direct and indirect costs to co-vary (i.e. $cov(\alpha, \beta) = 0$). The model intercept $\ln v$ is non-random 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 trade-off 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.

$$\varepsilon_{c,t}^{i} = \frac{\alpha_i t/\phi}{(t/\phi-1)^2} - \beta_i \text{ and } MET = \frac{\phi}{2\beta_i}\left(\alpha_i + 2\beta_i + \sqrt{\alpha_i{}^2 + 4\alpha_i\beta_i}\right) \quad (9)$$

Tables 3 through 6 present the results for this second extension to the replication model. Table 3 tabulates the regression results for model (8), 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 versus refineries). The second moment of these distributions represent the estimated standard deviation (S.D., in the table) of the two random parameters. A significant standard deviation for a random coefficient suggests that this coefficient likely differs from one firm to the next due to unobserved firm heterogeneity (see Alcacer *et al.,* 2015, for a review of RCM estimation). We report the standard error within brackets below each estimate.

Insert Table 3 here

In Table 3, the common means of the direct and indirect cost coefficients for both refineries and petrochemicals are positive and very significant, as expected. These results suggest that, on average, both types of costs impact the projects in our sample and (should) affect the timing of technology transfer 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 are significant across the petrochemical and refinery subsamples. This finding gives credence to explanation (B): 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.

Insert Table 4 here

Tables 4 and 5 present the elasticity distribution and summary statistics for model (8). In Table 4, results are tabulated by project type to facilitate comparisons with our previous tables. The time-cost elasticity estimates still have slightly negative mean values for most project types, similar to the OLS extended model results (in Appendix Table 5). The distribution of time-cost elasticities continue to span both positive and negative values, and the maximum values are now positive for four out of five project types. Plastics exhibit the largest negative mean value for elasticity: strategies aimed at shaving project time by 1% would save costs by 1.856%. In absolute terms, firms would have saved about $20.8 million (in 1996 dollars) with a one-month acceleration in plant development technology transfer. Very complex refineries still is the only project type with a positive mean time-cost elasticity. As mentioned above, this finding is consistent with the analytical result that TCD increase in the level of project complexity (Pacheco-de-Almeida and Zemsky, 2007). However, the mean elasticity of 0.141 for very complex refineries still is about one order of magnitude smaller than Teece (1977) estimates, which represents substantially lower time compression diseconomies. On average, companies developing very complex refineries would need to spend an extra $250,000 to crash their investments by one month. Table 5 also shows that only 57 out of 452 projects have positive time-cost elasticities and that mean elasticities turn positive and gradually increase with higher levels of time compression (smaller values of realized t/ϕ), as theoretically expected. The high number of negative elasticities in our sample is due to the fact that most firms take too long to develop new projects, thereby incurring significant indirect costs. Indeed, average time $\bar{t}$ is larger than average $\overline{MET}$ for all but one project types in Table 4. Similar evidence at the project level can be found in Appendix Figure 1 for our entire sample.

Insert Table 5 here

Figure 3 compares the time-cost elasticity distributions for Teece (1977), our initial replication results, and our final extended model (8) that includes explanations (A) and (B) (direct and indirect project costs and unobserved firm differences in time-cost curves). Teece's (1977) all-positive elasticity distribution, based on 20 projects, is characteristic of time-efficient technology transfer, with firms operating at levels of time compression below minimum efficient time. However, Teece's (1977) results are unlikely to be representative of larger samples. As Teece (1977) acknowledged, it is not uncommon for oil and gas firms to be time inefficient. Our findings support this idea, with the large majority (87%) of our 452 projects exhibiting negative time-cost elasticities in our final elasticity distribution for extended model (8). Unlike in our replication, this final distribution is less concentrated and spans both negative and positive values after corrections (A) and (B) discussed above. Appendix Figure 2 shows the weight of these two corrections in explaining the prevalence of negative elasticities in our sample. Our initial replication overestimated the true number of negative elasticities in our sample by about 12%.

Insert Figure 3 here

Table 6 presents the estimated time inefficiencies in technology transfer in the oil and gas industry during 1997-2010 based on our second extension results in model (8). 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. For comparison purposes, we also report industry-wide OLS inefficiency estimates using model (6).

Our results across models (6) and (8) show that the oil and gas industry exhibited substantial undue delays in technology transfer: to be efficient, the industry should have shaved over 36% of its project development time, on average. These delays resulted in unnecessary overspending: at least 37% 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 conclusions section.

Insert Table 6 here

Next, 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 (47.3% in model (8)). Even for these better-performing firms, significant average time and cost overruns are identified: 20% to 40% of development times and 16% to 30% of project costs should have been saved through acceleration. These results are for firms from a variety of home countries (US, Greece, Brazil, and Taiwan). Interestingly, three out of these four better-than-average firms in project scheduling are predicted to be ineffective at compressing time: with the exception of Chinese Petroleum Corp, all other three companies must spend marginally more than the industry average to accelerate investment projects. The case-in-point is perhaps Petróleo

Brasileiro SA with 41.2% of its TCD (or direct cost) coefficient α above the industry average. This company is more inefficient in buying time during technology transfer than its peers.

DETERMINANTS OF TIME-COST ELASTICITIES: STAGE TWO REPLICATION AND EXTENSION

Teece (1977) conducted a second stage estimation where the time-cost elasticities were regressed on a series of project and firm explanatory variables. We replicate this second stage regression using as dependent variables the time-cost elasticities estimated by extended models (6) and (8) – elasticities $\hat{\varepsilon}_{c,t}$ and $\hat{\varepsilon}^{i}_{c,t}$ in equations (7) and (9), respectively. Our explanatory variables are designed to be as close to Teece (1977) as possible. We also estimate an extended second-stage model with additional variables that are theoretically expected to 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 (9), 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 our 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.

Teece (1977) originally hypothesized that time-cost elasticities should be lower when engineers spend more time planning projects. This 'front-end loading' of plant development allows firms to accelerate subsequent project development stages while making fewer mistakes, thereby reducing rework and costs. In contrast, Teece (1977) postulated that time-cost elasticities should be higher for new-to-the-firm technology because it is usually harder to accelerate processes requiring know-how that the firm is implementing for the first time. Teece (1977) also predicted that time-cost elasticities should increase for larger firms (due to inertia) and larger projects (due to coordination costs). Lastly, Teece (1977) also anticipated time-cost elasticities to increase in locations that have higher trade barriers because of firms' greater firm incentives to develop projects faster given that exporting is not a viable alternative to supply those markets. These variables were labeled A_i, U_i, S_i, C_i, and X_i in Teece (1977), respectively.

In our paper, the operationalization of these explanatory variables follows closely Teece (1977). 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. Note that we do not observe the variable capturing the length of the planning stage in each project. 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. Appendix Table 7 summarizes our variables and data sources.

Although our central explanatory variables are identical to Teece's (1977), our hypotheses differ. The reason is that our elasticities are estimated using an extended model. As explained in the previous sections of the paper, our extended model (8) departs from Teece (1977) by allowing for (A) both direct and indirect project costs and (B) firm differences in cost curves.

Thus, we must interpret the effects of the explanatory variables on elasticity by taking into account these two extensions. Our predictions follow.

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 – towards 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 not significant effect on $\hat{\alpha}_i$ in equation (9). 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.

In our extension to the second stage estimation, we go beyond Teece (1977) to include additional firm-specific and country-specific regressors that capture other potential drivers of time-cost elasticities. For instance, firms with less experience with a given technology should take longer to execute projects, which reduces time-cost elasticities. Technology experience is measured as the number of similar projects executed by the firm before the current project within our data. We also expect more innovative firms to have better human capital, which should reduce time compression diseconomies or the direct costs from acceleration and, thus, elasticities. Investment in R&D and technology may have a similar effect on elasticities by (a) facilitating coordination with increasing job segmentation and, thereby, reducing the diminishing returns associated with allocating more resources to speed up a project or by (b) helping firms pursue multiple potential solutions to uncertain tasks concurrently via better information sharing, which reduces time compression diseconomies. Firm innovativeness is measured in our study by R&D intensity, that is, R&D expense divided by firms' total assets. We also include a more direct proxy for organizational inertia given by firm age. Specifically, we hypothesize that older firms with more inertia face greater difficulties to compress time and, thus, have higher time-cost elasticities. Firm age is operationalized as the number of years since the firm's founding date. As for country-specific factors, two additional 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, we expect project financing to be 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. Note that our measure of political risk is reverse-coded: we use the POLCON political constraints index (Henisz, 2000) that assumes larger values for more constrained governments, which is a measure of lower political risk.

Our final set of variables are controls. Technology transfer costs may also 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. 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 project, firm, industry, or temporal heterogeneity across projects.

Results

Table 7 presents our second stage OLS regression results on the determinants of time-cost elasticities. Each column shows the dependent variable (DV) used in that model. Models (i) and (ii) use the time-cost elasticities from the first stage extended model (6) OLS estimation. Since model (6) is not our final first stage results, models (i) and (ii) in Table 7 are only reported for comparison purposes and not commented on in detail. Models (iii) through (vii) represent our final second stage estimation results and use the time-cost elasticities from our first stage extended model (8) RCM estimation.

Our pure replication results of Teece (1977) in model (vi) and the auxiliary regressions (iii) through (v) essentially support our hypotheses. Due to space constraints, we will not repeat again here our hypotheses. The only additional note worth making about this set of results is about firm size because we had ambiguous theoretical predictions about its effect on elasticities. Empirically, firm size is shown to have a negative and significant effect on the direct costs coefficient ($\hat{\alpha}_i$), which suggests that larger firms access to deeper pools of in-house talent help reducing time compression diseconomies and make acceleration easier. This result, together with the fact that indirect costs increase in firm size, is shown to reduce time-cost elasticities. All other results conform to our hypotheses.

Insert Table 7 here

Our extension results in model (vii) add five additional explanatory variables and two controls that are theoretically expected to affect time-cost elasticities. Out of the nine main regressors in model (vii), all but three have the hypothesized effects on elasticities. For space constraints, we do not repeat here the hypotheses that find empirical support and only focus on the three exceptions to our predictions. Specifically, new-to-the-firm technology, firm size, and trade barriers are significant with the expected sign in our replication model (vi) but turn insignificant in model (vii). The explanation for this change in results is the fact that model (vii) 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 (vii) also adds a more fine-grained measure of a similar construct, experience with technology. The same reasoning applies to trade barriers, as model (vii) adds two additional country-specific variables, country development and political constraints. As for controls, the FDI and subcontracting dummies are not significant in model (vii). The FDI non-result may be explained by the fact that we already have several country-specific controls.

Finally, the average economic impact of our results in models (v) and (vi) is as follows. When technology is new to the firm, projects slow down by 7.4 months and time-cost elasticity decreases by 1.557. A ten percent increase in firm size reduces elasticity by 0.031, whereas a ten percent increase in project size slows down projects by 15 days and cuts elasticity by 0.048. Trade barriers reduce project development time by 1.3 months and raises elasticities by 0.123. In model (vii), a large, one-standard deviation increase in R&D intensity is associated with 3.647 decrease in time-cost elasticity, whereas each additional year in firm age increases elasticities by 0.172. A significant increase in country economic development of one standard deviation leads to a 3.370 decrease in time-cost elasticity. Finally, a one standard deviation increase in political constraints is associated with a 1.583 increase in elasticity.

ROBUSTNESS CHECKS

We conduct multiple robustness checks. First, we tried multiple alternative econometric specifications. In our results, we present runs using both OLS and RCM and obtained very comparable results. As an additional check, we tried firm fixed effects and firm random effects in stage one, and we received qualitatively similar results. Second, temporal factors such as changes in technology over time could affect the time cost tradeoff. In the stage two extended estimations, we included year effects to account for this possibility. As a robustness check, we also tried including year dummies in stage one estimations, and we obtained similar results.

Third, involvement of subcontractors could affect the time cost tradeoff. In our second stage extended estimations, we included a dummy for whether a subcontractor was involved in the project, and it came out insignificant. We also tried including the subcontractor dummy in stage one runs, and we received similar results. Fourth, for our stage two 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 we found similar results across the alternative approaches. We also tried alternative firm size variables (using total assets) and firm innovativeness measures (using R&D/Sales), and we received similar results. Fifth, we reran our stage two analysis using only stage one elasticities for project types that had significant direct and indirect cost coefficients in the extended model OLS (olefins and simple refineries in Appendix Table 5). While our second stage sample size shrinks substantially with this restriction, we continue to get results for our stage two replication that look similar to our baseline results.

Sixth, our results could be sensitive to the values set for the vertical asymptote ϕ. We set ϕ to the value in the interval between 0 and minimum t (moving in 1/10$^{\text{th}}$ increments) that maximized the log-likelihood function of the replication model. We also tried numerous alternatives such as setting ϕ equal to 1/10$^{\text{th}}$, ½, and 9/10$^{\text{th}}$ the interval, and we continued to obtain a similar frequency of negative elasticities. Sixth, we tried an alternative approach to setting minimum efficient time (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 1000 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 result suggest the core results of the paper, a high frequency of negative time-cost elasticities, would be observed across multiple approaches to setting MET and ϕ.

DISCUSSION AND CONCLUSION

This paper examines the cost of accelerating technology transfer for investments in oil and gas production facilities worldwide from 1997 to 2010. Specifically, we replicate and extend Teece's (1977) estimation of time-cost elasticities and their determinants using a similar empirical setting. Our results are of topical interest because the timing of technology transfer continues to be central to organizational performance and no other studies have been conducted on this subject since the 1980s.

Our findings lie in stark contrast with Teece (1977) and all other previous studies. We show that the average cost of accelerating technology transfer in the oil and gas industry is negative. This suggests that time compression diseconomies (TCD) – a tradeoff between time and costs – are often not binding in this industry. The average firm in our sample is time inefficient in technology transfer: firms could simultaneously shave time and cut costs in project development. This result is also striking by its incidence and magnitude. While in Teece (1977) all time-cost elasticities were positive, in our sample 87 percent of the 452 projects and all but one project type exhibited negative elasticities. Petrochemical plastics displayed the largest negative mean value for elasticity: firms would have saved about $20.8 million (in 1996 dollars) with a one-month acceleration in plant development technology transfer. Despite hovering around negative mean values, our overall distribution of time-cost elasticities also spans to positive values. Very complex refineries were the only project type with a positive mean elasticity, which is evidence of time compression diseconomies (TCD). Interestingly, this is consistent with the theoretical finding that TCD generally increase in the level of project complexity (Pacheco-de-Almeida and Zemsky, 2007). On average, companies developing very complex refineries would need to spend an extra $250,000 to crash their investments by one month. The maximum value assumed by time-cost elasticities in our sample was 15.6, which is equivalent to the maximum estimates in other early papers (e.g. Mansfield, 1988). Another empirical regularity in our sample is that mean elasticities turn positive and gradually increase with higher levels of time compression, as theoretically expected.

The difference in results between our paper and previous work can be explained as follows. Most classical studies on time-cost elasticities used small samples (e.g. 28 projects in Mansfield, 1971; 20 projects in Teece, 1977). In addition, this 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. This approach led "Mansfield [to] caution that there may be considerable errors in the manager's estimate of the time-cost tradeoff" (Graves 1989: 6). This concern found support in our analysis: our use of a sample with actual data that is over 20 times larger than Teece's (1977) revealed levels of project acceleration well below those previously reported. About 98 percent of the projects in our data were developed more slowly than the slowest project in Teece's (1977) sample. And, as Teece (1977: footnote 5) 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 Teece (1977) did not focus on indirect project costs (p. 832), we extended our model to allow for this possibility. This approach allowed us to empirically observe that a large fraction of the projects in this industry are developed past their minimum efficient time (MET) – 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).

Time inefficiencies in the oil and gas industry can be significant. Our estimates indicate that the industry should have shaved over 36 percent of its project development time, on average. This delays resulted in unnecessary overspending: at least 37 percent of the industry costs could have been saved by compressing time down to MET. Also, our random coefficient model estimation showed that even the best-performing firms incurred in significant average time and cost overruns. Overall, these findings are consistent with qualitative industry evidence. For instance, PricewaterhouseCoopers' consulting arm "Strategy&" (formerly Booz & Company) issued a recent study on the oil and gas industry that documented companies' systematic "difficulty delivering large capital projects on time and within budget" (Tideman, Tuinstra, and Campbell, 2014: 3). According to this report, "delays can be on the order of years, and cost overruns can reach as high as 350 percent" (p. 6). 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).[7,8]

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[7] 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).

[8] A recent BCG study has also reported time inefficiencies in fast-moving consumer goods industries (Bascle *et al.*, 2012). Our preliminary analysis of the semiconductor industry has also found early evidence of negative elasticities.

Our results have several implications for the strategy and business economics literature. First, we show that TCD exist but are not an active constraint for the time regimes in which most of the firms in our sample operate. Prior work has generally assumed that TCD and lead time are effective mechanisms to sustain competitive advantage and protect intellectual property assets (e.g., Cohen et al. 2002; Dierickx and Cool, 1989; Pacheco-de-Almeida and Zemsky, 2007). In contrast, our study found evidence of 'reverse TCD', or *economies* of time compression.

Second, 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., Szulanski, 1996; for a review, see Bozeman, 2000). Interestingly, 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.

Third, our study also has a number of lateral implications for other literatures. It may imply lower-than-expected actual costs of faster technology diffusion within an industry – where technology diffusion costs have long been assumed to protect first-mover advantages (Lieberman and Montgomery, 1988). Our empirical setting also seems far from the relentless, ever-increasing, rent-dissipating patterns of time competition assumed in the technology adoption, hypercompetition, Red Queen, and time-based competition literatures (Barnet and Hansen, 1996, D'Aveni, 1994; Fudenberg and Tirole, 1985; Stalk, 1990).

Finally, our second stage results on the determinants of time-cost elasticities contribute to our understanding of investment lags and adjustment costs in the theory of capital investment and firm growth. Specifically, we show that time-cost elasticities decrease with the newness of technology, firm size and project size mostly due to an indirect positive effect on project development delays. 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.

Our study has important managerial implications, as it revealed the existence of a sizeable gain to be had by firms that sufficiently accelerate technology transfer. On average, oil and gas firms should consider cutting their project development times by at least 36 percent. The mean time-cost elasticity estimates for each level of time compression provided in our tables should also help firms gauge their marginal financial incentives to accelerate projects and optimize the timing of technology transfer. This data may also prove informative to stock market analysts' valuations of firm technology transfer and innovation timing. Our analysis of the main determinants of time-cost elasticities points to additional levers that firms can often use to more accurately control their time-cost investment profile.

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FIGURES AND TABLES

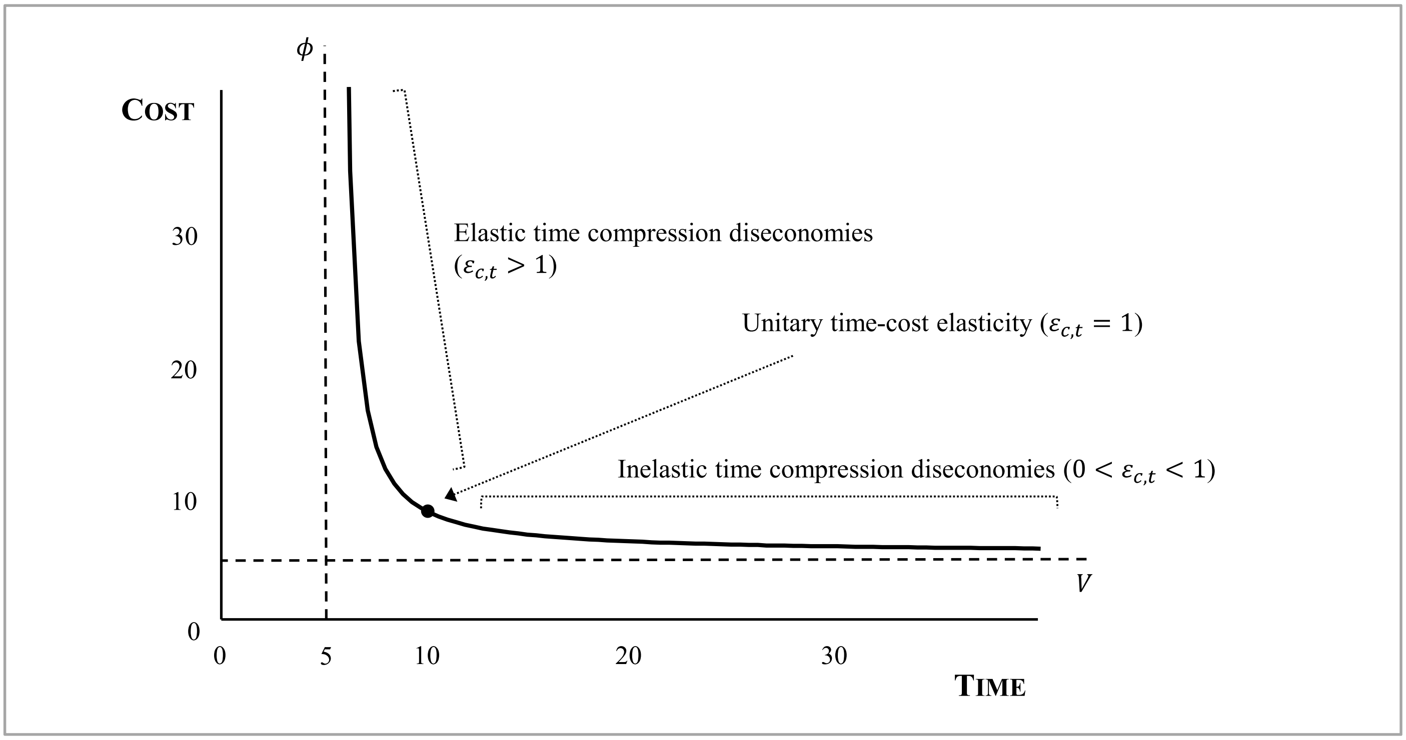


Figure 1: The original model (1) estimated by Teece, 1977 ($V = \phi = 5$, and $\alpha = 0.5$).

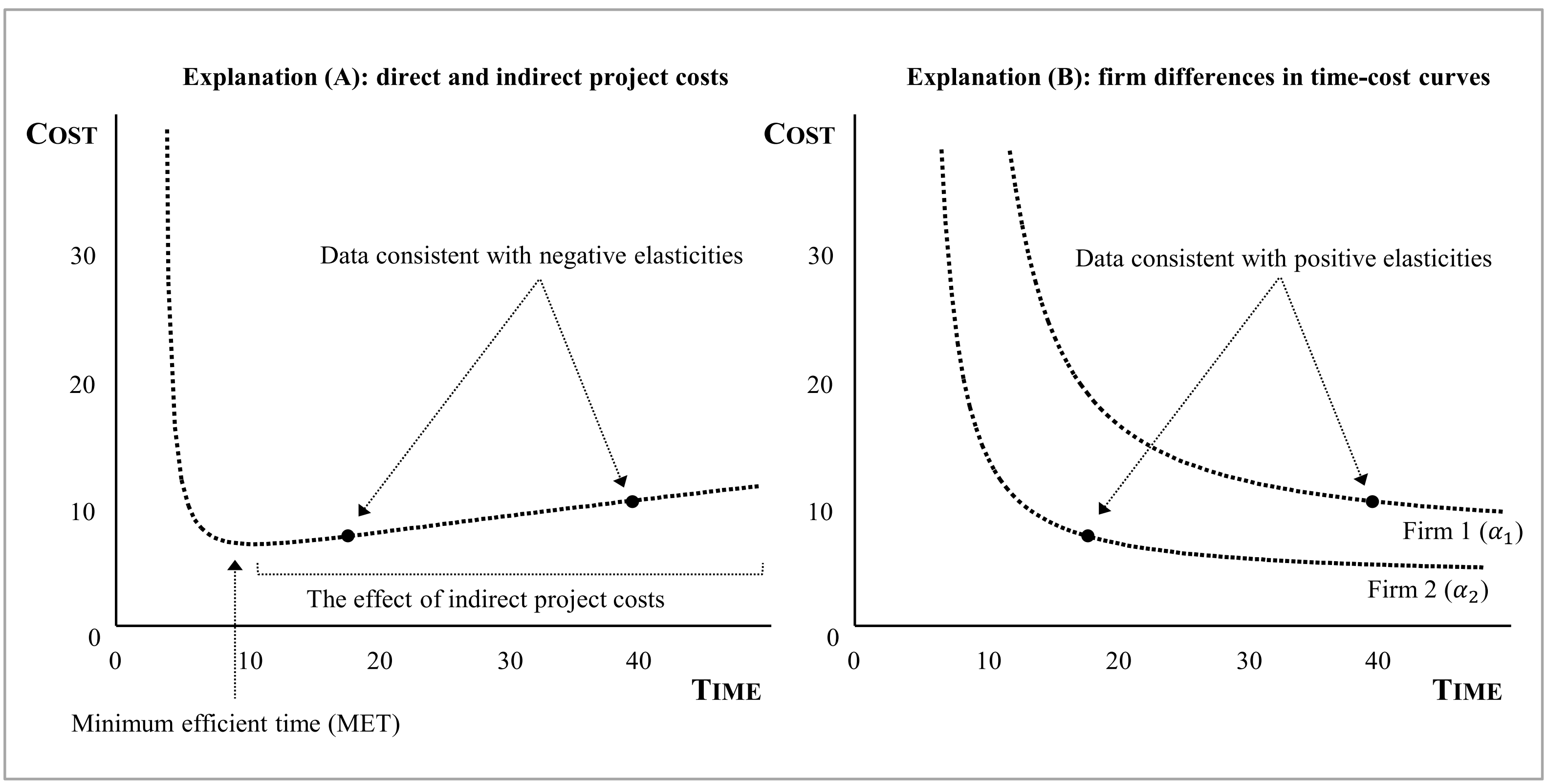


Figure 2: The two alternative explanations for negative elasticities (left panel: models (1) and (4) with $v = 1$, $\phi = 2.5, \alpha = 1.5$ and $\beta = 0.6$; right panel: model (1) with $V = 4$, $\phi = 2, \beta = 0$ and $\alpha_1 = 5$ versus $\alpha_2 = 20$).

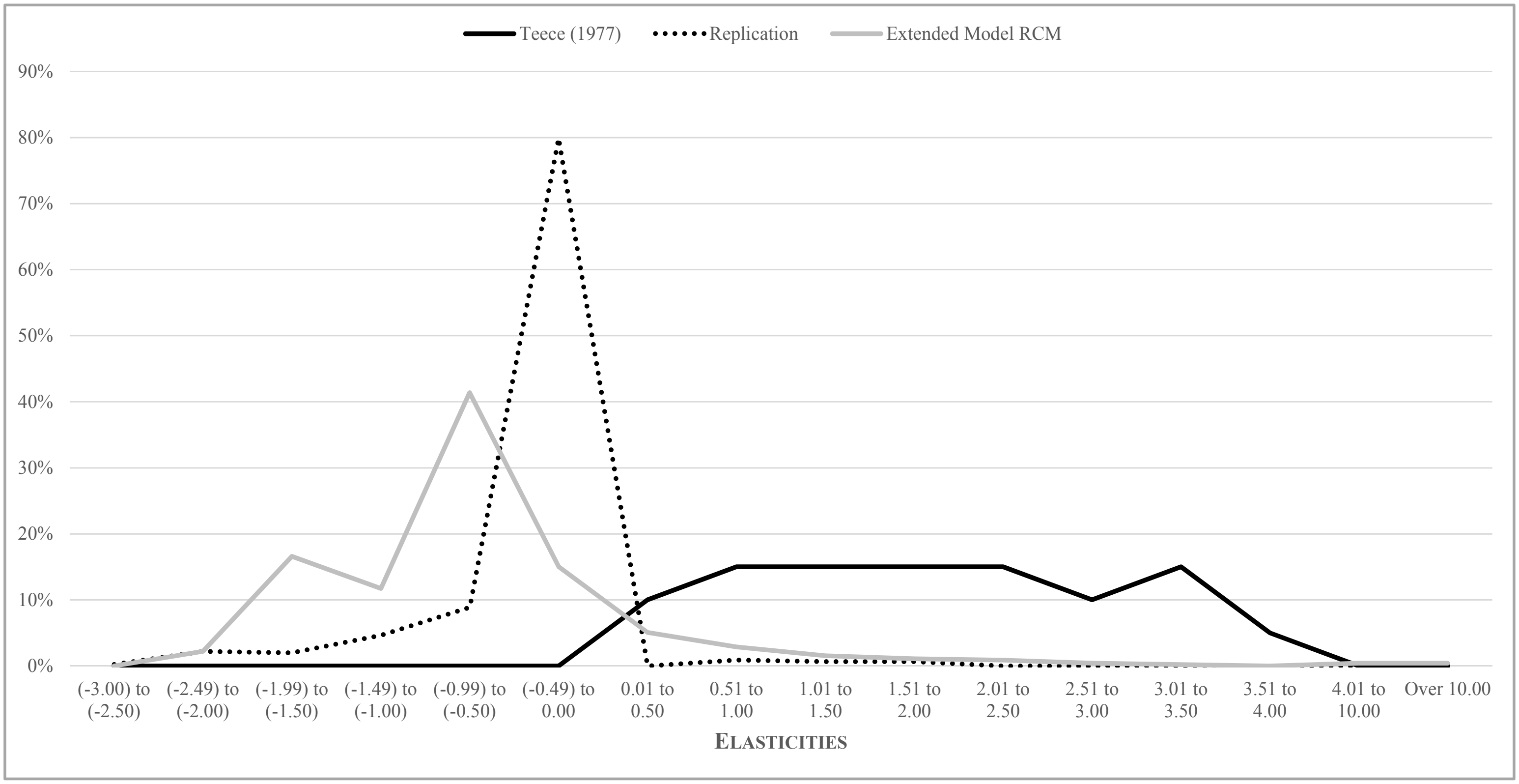


Figure 3: The distribution of estimated elasticities for Teece (1977), our replication model (3), and the extended model (8) RCM (with direct and indirect project costs and firm differences in time-cost curves).

Table 1: Replication model (3) OLS estimation with region dummies (DV: $\ln C$)

Project type	N	$\hat{V}$ ($M)	$\bar{\phi}$ (months)	$\hat{\alpha}$	R^2	Point elasticity		
						Mean	Min	Max
Petrochemicals: Olefins	70	42.407***	7.831	-0.227	0.269	-0.278	-2.776	-0.014
		(0.742)		(0.332)				
Petrochemicals: Plastics	60	84.424***	1.342	-20.886***	0.201	-1.196	-2.469	-0.309
		(1.247)		(6.771)				
Refineries: Simple	145	97.669***	0.533	-1.709	0.355	-0.053	-0.183	-0.007
		(0.876)		(6.364)				
Refineries: Complex	167	16.643**	0.531	-8.279*	0.195	-0.269	-0.963	-0.029
		(1.263)		(4.274)				
Refineries: Very complex	10	55.536***	2.341	16.086*	0.939	1.161	0.554	1.937
		(0.708)		(7.466)				
Total	452	—	—	—	—	—	—	—

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; $\hat{V}$ is the natural antilogarithm of the constant estimate; Note: the parameter α is denoted by ϕ in Teece (1977), and vice-versa

Table 2: The distribution of elasticities for the replication model (3) OLS estimation with region dummies (DV: $\ln C$)

Point elasticity	Realized t/ϕ										Total
	1.00–1.25	1.26–1.50	1.51–1.75	1.76–2.00	2.01–10.00	10.01–20.00	20.01–30.00	30.01–40.00	40.01–50.00	Over 50.00	
Mean	—	-2.213	-1.047	—	-0.132	-0.659	-0.433	-0.227	-0.156	-0.070	—
Min	—	-2.776	-1.097	—	-0.426	-2.469	-1.141	-0.731	-0.527	-0.381	—
Max	—	-1.538	-0.965	—	-0.029	1.937	0.761	0.554	-0.036	-0.007	—
S.D.	—	0.513	0.072	—	0.102	0.935	0.425	0.211	0.133	0.065	—
(-3.00) – (-2.50)	0	1	0	0	0	0	0	0	0	0	1
(-2.49) – (-2.00)	0	2	0	0	0	8	0	0	0	0	10
(-1.99) – (-1.50)	0	1	0	0	0	8	0	0	0	0	9
(-1.49) – (-1.00)	0	0	2	0	0	11	8	0	0	0	21
(-0.99) – (-0.50)	0	0	1	0	0	19	9	9	2	0	40
(-0.49) – 0.00	0	0	0	0	55	33	36	60	44	133	361
0.01 – 0.50	0	0	0	0	0	0	0	0	0	0	0
0.51 – 1.00	0	0	0	0	0	1	2	1	0	0	4
1.01 – 1.50	0	0	0	0	0	3	0	0	0	0	3
1.51 – 2.00	0	0	0	0	0	3	0	0	0	0	3
2.01 – 2.50	0	0	0	0	0	0	0	0	0	0	0
2.51 – 3.00	0	0	0	0	0	0	0	0	0	0	0
3.01 – 3.50	0	0	0	0	0	0	0	0	0	0	0
3.51 – 4.00	0	0	0	0	0	0	0	0	0	0	0
4.01 – 10.00	0	0	0	0	0	0	0	0	0	0	0
Over 10.00	0	0	0	0	0	0	0	0	0	0	0
Total	0	4	3	0	55	86	55	70	46	133	452

Note: the parameter ϕ is denoted by α in Teece (1977)

Table 3: Extended model (8) RCM estimation with region and project type dummies

DV: $\ln C$	Petrochemicals		Refineries	
	Mean	S.D.	Mean	S.D.
$\widehat{\ln v}$	-3.196***	—	-2.060	—
	(0.898)	—	(1.732)	—
$\hat{\alpha}$	1.519***	0.889*	18.936**	12.451***
	(0.491)	(0.582)	(9.081)	(4.000)
$\hat{\beta}$	1.940***	0.203***	1.154***	0.216***
	(0.260)	(0.045)	(0.314)	(0.043)
Region dummies	Yes		Yes	
Project type dummies	Yes		Yes	
Number of observations	130		322	
Log-likelihood	-204.660		-571.299	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; S.D. significance reported for a one-tail t-test

Table 4: Extended model (8) RCM estimation with region and project type dummies (contd.)

Project type	N	$\bar{\phi}$ (months)	$\overline{MET}$ (months)	$\bar{t}$ (months)	Point elasticity		
					Mean	Min	Max
Petrochemicals: Olefins	70	7.831	18.065	37.968	-0.312	-2.183	15.613
Petrochemicals: Plastics	60	1.342	3.127	32.530	-1.856	-2.247	-1.542
Refineries: Simple	145	0.533	10.286	29.825	-0.505	-1.200	3.091
Refineries: Complex	167	0.531	10.358	29.094	-0.494	-1.152	2.075
Refineries: Very complex	10	2.341	42.173	40.410	0.141	-0.300	0.789
Total	452	—	—	—	—	—	—

Table 5: The distribution of elasticities for the extended model (8) RCM estimation with region and project type dummies (DV: $\ln C$)

Point elasticity	Realized t/ϕ										Total
	1.00–1.25	1.26–1.50	1.51–1.75	1.76–2.00	2.01–10.00	10.01–20.00	20.01–30.00	30.01–40.00	40.01–50.00	Over 50.00	
Mean	—	9.355	4.689	—	-1.090	-0.374	-0.767	-0.694	-0.761	-0.911	—
Petrochemicals	—	9.355	4.689	—	-1.090	-1.833	-1.843	-1.816	-1.780	-1.937	—
Refineries	—	—	—	—	—	0.627	-0.285	-0.529	-0.664	-0.887	—
Min	—	0.877	2.794	—	-2.183	-2.247	-2.124	-2.046	-1.842	-2.072	—
Max	—	15.613	8.476	—	2.425	3.091	0.255	-0.266	-0.373	-0.554	—
S.D.	—	6.266	3.280	—	0.870	1.366	0.757	0.450	0.337	0.211	—
(-3.00) – (-2.50)	0	0	0	0	0	0	0	0	0	0	0
(-2.49) – (-2.00)	0	0	0	0	3	4	1	1	0	1	10
(-1.99) – (-1.50)	0	0	0	0	15	30	16	8	4	2	75
(-1.49) – (-1.00)	0	0	0	0	21	1	0	0	0	31	53
(-0.99) – (-0.50)	0	0	0	0	6	2	3	39	38	99	187
(-0.49) – 0.00	0	0	0	0	4	9	29	22	4	0	68
0.01 – 0.50	0	0	0	0	2	15	6	0	0	0	23
0.51 – 1.00	0	1	0	0	2	10	0	0	0	0	13
1.01 – 1.50	0	0	0	0	1	6	0	0	0	0	7
1.51 – 2.00	0	0	0	0	0	5	0	0	0	0	5
2.01 – 2.50	0	0	0	0	1	3	0	0	0	0	4
2.51 – 3.00	0	0	2	0	0	0	0	0	0	0	2
3.01 – 3.50	0	0	0	0	0	1	0	0	0	0	1
3.51 – 4.00	0	0	0	0	0	0	0	0	0	0	0
4.01 – 10.00	0	1	1	0	0	0	0	0	0	0	2
Over 10.00	0	2	0	0	0	0	0	0	0	0	2
Total	0	4	3	0	55	86	55	70	46	133	452

Table 6: Estimated time inefficiencies in technology transfer in the oil and gas industry during the 1997-2010 period

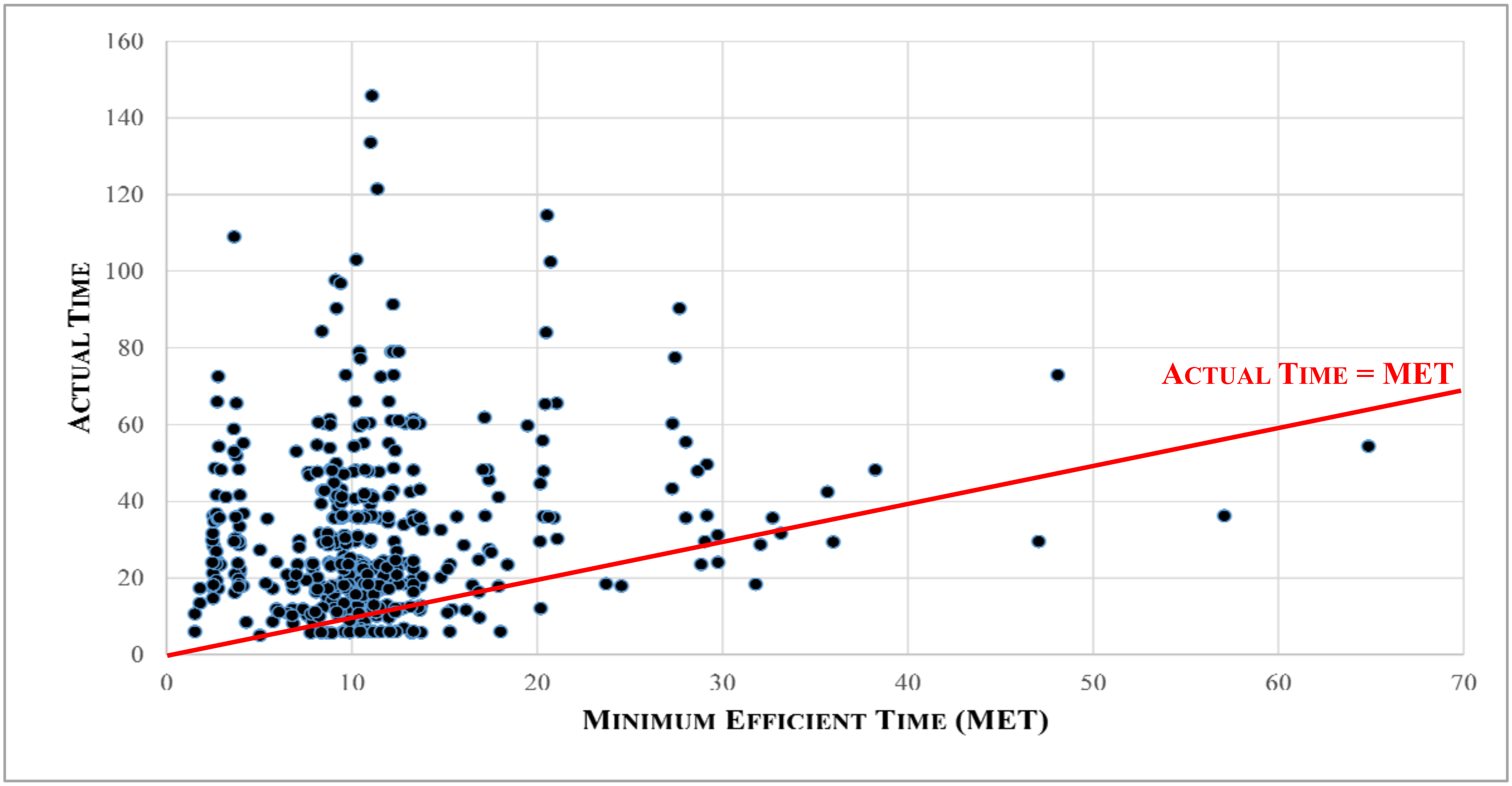
	Time inefficiencies in technology transfer		
	Insufficient acceleration		Ineffective time compression
	Magnitude of delay[a]	Magnitude of overspending[b]	TCD differentials[c]
Oil and gas industry average: Extended model (8) RCM	47.3%	43.3%	—
Oil and gas industry average: Extended model (6) OLS	36.9%	37.9%	—
Firms with below-average delay (and $N_i \geq 10$): Ext. model RCM			
Chinese Petroleum Corp	39.9%	30.0%	-39.6%
Hellenic Petroleum SA	33.8%	31.0%	21.2%
Petróleo Brasileiro SA	35.1%	34.1%	41.2%
Valero Energy Corp	26.6%	16.6%	19.1%

[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, $(\hat{\varepsilon}_i - \bar{\varepsilon})/\hat{\varepsilon}_i$, when $\hat{\beta}_i$ is sufficiently small.

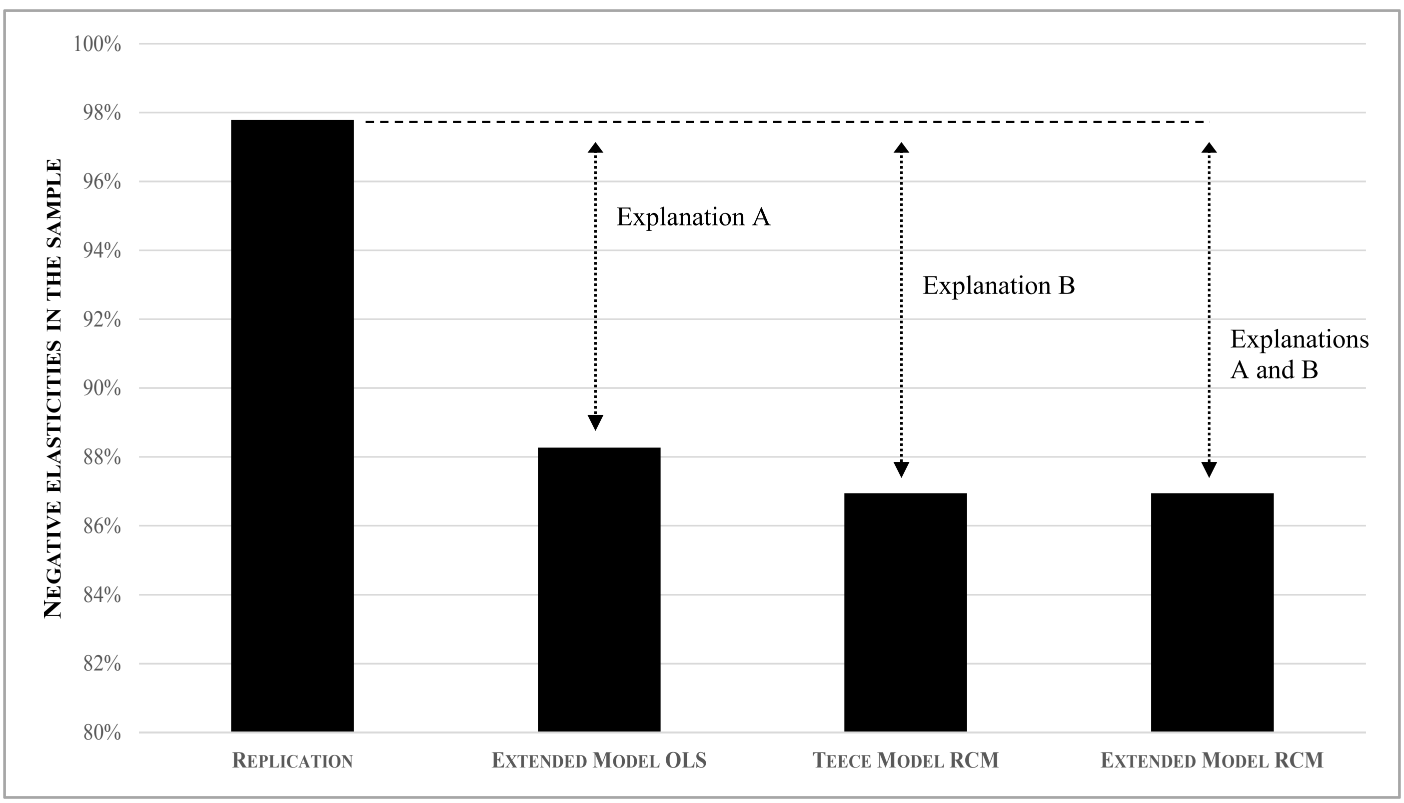
Table 7: The determinants of time-cost elasticities, OLS estimation

Variable	Stage 1: Ext. model OLS		Stage 1: Extended model RCM				
	DV: $\hat{\varepsilon}_{c,t}$		DV: $\hat{\alpha}_i$	DV: $\hat{\beta}_i$	DV: t	DV: $\hat{\varepsilon}^i_{c,t}$	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
Constant	9.349**	-16.752	16.592***	0.825***	15.803	4.762*	-22.044***
	(4.420)	(15.125)	(4.459)	(0.122)	(17.213)	(2.544)	(7.440)
New-to-the-firm technology	-1.974***	0.660	-0.685	0.005	7.466**	-1.557***	0.313
(U_i dummy in Teece, 1977)	(0.640)	(0.850)	(0.814)	(0.022)	(3.144)	(0.465)	(0.434)
Firm size	-0.174	1.384	-0.465*	0.017**	-0.823	-0.310**	0.898
(S_i variable in Teece, 1977)	(0.196)	(1.583)	(0.264)	(0.007)	(1.020)	(0.151)	(0.752)
Project Size	-0.945***	-0.837***	1.605***	0.028***	5.018***	-0.477***	-0.286**
(C_i variable in Teece, 1977)	(0.191)	(0.252)	(0.256)	(0.007)	(0.988)	(0.146)	(0.135)
Trade barriers	0.065	-0.009	-0.054	-0.003	-1.344***	0.123**	0.001
(proxy for X_i dummy in Teece, 1977)	(0.063)	(0.112)	(0.088)	(0.002)	(0.341)	(0.050)	(0.059)
Experience with technology		0.419*					0.225**
		(0.217)					0.110
R&D intensity		-438.685**					-364.740***
		(192.461)					(92.859)
Firm age		0.024					0.172***
		(0.030)					(0.053)
Country development		-0.219**					-0.188***
		(0.087)					(0.039)
Political constraints		9.713***					7.917***
		(3.466)					(1.739)
FDI (dummy)		-0.989					-0.090
		(1.887)					(0.913)
Subcontractor (dummy)		-0.380					-0.538
		(1.178)					(0.598)
Control dummies:							
Region / Project type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm / Industry / Year	No	Yes	No	No	No	No	Yes
Number of observations	125	122	125	125	125	125	122
F-test for model	9.74***	5.46***	88.81***	220.58***	4.69***	7.46***	12.83***
R^2	0.511	0.860	0.905	0.959	0.335	0.444	0.935

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; variable A_i in Teece (1977) N/A (the percentage of time allocated to the project planning stage); Estimation includes Hornstein and Greene's (2012) correction for the use of estimated coefficients as dependent variables in the second stage



Appendix Figure 1: Actual time versus minimum efficient time (MET) for all sample observations in the extended model (8) RCM.



Appendix Figure 2: The prevalence of negative elasticities in the different estimated models (explanation (A): direct and indirect project costs; explanation (B): firm differences in time-cost curves).

Appendix Table 1: Summary statistics for first stage models (3), (6), and (8)

Variable	Mean	S.D.	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

Appendix Table 2: Summary statistics for the second stage model

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. $\hat{\varepsilon}_{c,t}$ (Stage 1 OLS)	-0.48	1.77	-2.28	14.45	1															
2. $\hat{\varepsilon}^{i}_{c,t}$ (Stage 1 RCM)	-0.73	1.22	-2.25	9.00	0.85	1														
3. $\hat{\alpha}_i$ (Stage 1 RCM)	14.79	11.22	0.47	32.20	0.09	0.29	1													
4. $\hat{\beta}_i$ (Stage 1 RCM)	1.47	0.43	0.91	2.28	-0.10	-0.31	-0.72	1												
5. t (actual time)	28.25	20.16	5.70	114.63	-0.36	-0.43	-0.07	0.23	1											
6. New-to-the-firm technology	0.58	0.49	0.00	1.00	-0.15	-0.14	-0.30	0.09	-0.06	1										
7. Firm size	10.06	1.44	4.07	12.38	0.05	-0.11	-0.19	0.20	0.02	-0.21	1									
8. Project size	4.50	1.71	0.90	8.20	-0.19	-0.21	-0.09	0.47	0.53	-0.20	0.08	1								
9. Trade barriers	2.74	4.37	0.00	28.90	0.06	-0.00	-0.26	0.20	-0.13	0.37	-0.06	0.05	1							
10. Experience with technology	1.59	3.12	0.00	16.00	0.04	0.03	0.50	-0.14	0.19	-0.60	0.16	0.10	-0.28	1						
11. R&D intensity	0.01	0.01	0.00	0.07	0.05	-0.05	-0.32	0.34	-0.03	0.12	0.09	0.06	0.20	-0.08	1					
12. Firm age	65.28	40.59	0.00	139.00	0.12	-0.00	-0.39	0.30	-0.29	0.16	0.23	-0.09	0.21	-0.21	0.49	1				
13. Country development	25.36	17.90	0.503	53.77	-0.06	0.08	-0.04	-0.30	-0.45	0.14	-0.19	-0.46	-0.23	-0.27	-0.02	0.19	1			
14. Political constraints	0.36	0.20	0.00	0.72	0.16	0.35	0.43	-0.38	-0.45	0.01	-0.16	-0.37	-0.17	0.00	-0.01	0.08	0.36	1		
15. FDI (dummy)	0.30	0.46	0.00	1.00	0.10	-0.07	-0.41	0.35	-0.04	0.07	0.42	0.14	0.42	-0.21	0.30	0.38	-0.26	-0.22	1	
16. Subcontractor (dummy)	0.89	0.32	0.00	1.00	-0.03	-0.07	-0.08	0.12	0.11	-0.26	0.21	0.04	-0.24	0.18	0.14	0.15	-0.02	0.03	0.00	1

Appendix Table 3: Original Teece (1977) estimation (DV: $\ln C$)

Project	$\hat{V}$ (\$K)	ϕ (months)	$\hat{\alpha}$	R^2
1	260	9	0.024	0.61
2	1,998	20	0.068	0.69
3	3,964	14	0.065	0.99
4	796	11	0.146	0.99
5	578	32	0.174	0.90
6	1,808	28	0.070	0.98
7	9,228	24	0.089	0.55
8	3,197	15	0.030	0.95
9	111	3	0.279	0.96
10	459	10	0.072	0.94
11	1,615	21	0.007	0.82
12	11,395	30	0.119	0.96
13	29,971	61	0.028	0.98
14	2,470	20	0.115	0.95
15	654	12	0.053	0.94
16	3,901	22	0.122	0.91
17	12,100	27	0.560	0.79
18	4,745	36	0.185	0.78
19	10,872	36	0.021	0.97
20	620	17	0.041	0.97

Note: the parameter α on this table is denoted by ϕ in Teece (1977), and vice-versa

Appendix Table 4: The distribution of elasticities in Teece (1977) original estimation (DV: ln C)

Point Elasticity	Realized t/ϕ				Total
	1.00 – 1.25	1.26 – 1.50	1.51 – 1.75	1.76 – 2.00	
0 – 0.50	1	0	1	0	2
0.51 – 1.00	2	1	0	0	3
1.01 – 1.50	1	1	0	1	3
1.51 – 2.00	3	0	0	0	3
2.01 – 2.50	2	1	0	0	3
2.51 – 3.00	1	1	0	0	2
3.01 – 3.50	2	1	0	0	3
Over 3.50	1	0	0	0	1
Total	13	5	1	1	20

Note: the parameter ϕ on this table is denoted by α in Teece (1977); the original table had two typos in the second column

We present here the estimation of the first extension to our replication regarding explanation (A). Appendix Table 5 reports the results. If we compare these results to our initial replication in Table 1 in the paper, a few stark differences are visible. First, as hypothesized, in Appendix Table 5 all of the estimated parameters for direct costs (α) and indirect costs (β) are positive – unlike in Table 1 – and some are significant. Specifically, for olefins and simple refineries both α and β are positive and significant; for plastics, β is positive and significant but α is not significant. These findings suggest that time compression diseconomies take effect in olefins and simple refineries when projects are sufficiently accelerated. The significance of β for olefins, simple refineries, and plastics implies that indirect costs are particularly relevant for these project types. The interpretation of the constant estimate in Table 1 and Appendix Table 5 is non-comparable: while V denotes the minimum theoretical cost of a project, v simply rescales the magnitude of indirect project costs. Thus, unlike Table 1, Appendix Table 5 does not report the natural antilogarithm of the constant estimate. The lack of significance of the model constant across most project types implies that there is no rescaling adjustment needed for indirect costs.

Insert Appendix Table 5 here

Second, the fit of extended model (6) is better for most project types than the fit of Teece's (1977) model (3) reported in our initial replication results. In Appendix Table 5, R^2 is substantially higher for Olefins and Plastics and slightly higher for simple and complex refineries than in Table 1, whereas R^2 is comparable across models for very complex refineries.

Third, summary statistics for the estimated time-cost elasticities per project type can be found on the right-hand side of Appendix Table 5 and the distribution of elasticities is presented in Appendix Table 6. Overall, we obtain fairly similar mean estimates of time-cost elasticities as in the replication model. However, the maximum values of elasticities are more positive in the extended model. While in the replication we received strictly negative time-cost elasticity estimates for four out of five project types, we now obtain some positive values using the extended model for three out of five project types. The maximum elasticity gets as high as 17 for Olefins and 2.7 for simple refineries. Appendix Table 6 shows that 53 out of 452 projects in the extended model have positive time-cost elasticities. Elasticities turn positive and gradually increase as t/ϕ is reduced, which means that time compression diseconomies intensify as firms accelerate projects, as expected. This observation has another profound implication: while in Table 1 negative elasticities are due to the negative direct cost coefficients (α), in Appendix Tables 5 and 6 negative elasticities result from firms taking too long to develop projects and, thus, incurring substantial indirect project costs. To see this, consider the two project types for which both direct and indirect cost coefficients are significant, olefins and simple refineries. In both cases, the average project development time ($\bar{t}$) is well beyond the average minimum efficient time ($\overline{MET}$) for the projects, that is, firms are operating in the upward sloping part of the time-cost curve. This finding suggests substantial time inefficiencies in technology transfer.

Insert Appendix Table 6 here

Appendix Table 5: Extended model (6) OLS estimation with region dummies (DV: $\ln C$)

Project type	N	$\widehat{\ln v}$	$\bar{\phi}$ (months)	$\hat{\alpha}$	$\hat{\beta}$	$\overline{MET}$ (months)	$\bar{t}$ (months)	R^2	Point elasticity		
									Mean	Min	Max
Petrochemicals: Olefins	70	-5.877***	7.831	1.634***	2.428***	17.409	37.968	0.524	-0.429	-2.330	17.556
		(1.790)		(0.423)	(0.425)						
Petrochemicals: Plastics	60	-4.095	1.342	11.909	2.078***	10.197	32.530	0.331	-1.396	-1.902	-0.670
		(2.941)		(12.138)	(0.659)						
Refineries: Simple	145	-1.779	0.533	40.277**	1.583***	14.600	29.825	0.389	-0.330	-1.429	2.730
		(2.455)		(16.410)	(0.573)						
Refineries: Complex	167	1.067	0.531	3.897	0.475	5.370	29.094	0.205	-0.348	-0.461	-0.022
		(1.757)		(9.558)	(.334)						
Refineries: Very complex	10	3.200	2.341	17.938	0.205	209.351	40.410	0.939	0.491	0.413	1.955
		(4.150)		(12.587)	(1.022)						
Total	452	—	—	—	—	—	—	—	—	—	—

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table 6: The distribution of elasticities for the extended model (6) OLS estimation with region dummies (DV: ln C)

Point elasticity	Realized t/ϕ										Total
	1.00–1.25	1.26–1.50	1.51–1.75	1.76–2.00	2.01–10.00	10.01–20.00	20.01–30.00	30.01–40.00	40.01–50.00	Over 50.00	
Mean	—	13.502	5.111	—	-1.475	-0.030	-0.492	-0.519	-0.627	-0.769	—
Min	—	8.640	4.519	—	-2.216	-2.330	-1.652	-1.744	-1.813	-1.902	—
Max	—	17.556	5.471	—	0.638	2.730	0.643	0.413	-0.373	-0.394	—
S.D.	—	3.696	0.517	—	0.733	1.410	0.764	0.470	0.390	0.374	—
(-3.00) – (-2.50)	0	0	0	0	0	0	0	0	0	0	0
(-2.49) – (-2.00)	0	0	0	0	16	8	0	0	0	0	24
(-1.99) – (-1.50)	0	0	0	0	18	0	11	9	4	3	45
(-1.49) – (-1.00)	0	0	0	0	10	18	6	0	0	36	70
(-0.99) – (-0.50)	0	0	0	0	5	9	0	3	20	29	66
(-0.49) – 0.00	0	0	0	0	3	22	25	57	22	65	194
0.01 – 0.50	0	0	0	0	0	0	8	1	0	0	9
0.51 – 1.00	0	0	0	0	3	7	5	0	0	0	15
1.01 – 1.50	0	0	0	0	0	7	0	0	0	0	7
1.51 – 2.00	0	0	0	0	0	6	0	0	0	0	6
2.01 – 2.50	0	0	0	0	0	2	0	0	0	0	2
2.51 – 3.00	0	0	0	0	0	7	0	0	0	0	7
3.01 – 3.50	0	0	0	0	0	0	0	0	0	0	0
3.51 – 4.00	0	0	0	0	0	0	0	0	0	0	0
4.01 – 10.00	0	1	3	0	0	0	0	0	0	0	4
Over 10.00	0	3	0	0	0	0	0	0	0	0	3
Total	0	4	3	0	55	86	55	70	46	133	452

Appendix Table 7: Variable definitions

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
Experience with technology	Number of projects of the same type executed by firm in data in the past	OGJ
R&D intensity	R&D expenses divided by total assets	Compustat
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