When Does a Firm Have Faster Speed Despite Inferior Capability? Disintegrating Capability and Incentive Effects When Examining Firm Speed

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Firm speed has long been a construct of interest among managers and researchers. Although both a firm's capabilities and incentives to be fast determine observed firm speed, practitioners and academic scholars have typically focused on the capability mechanism alone. However, the omission of incentives in understanding firm speed can lead to mistaking faster firm speed for superior firm capability. To address this shortcoming, we develop a theoretical framework considering both capabilities and incentives simultaneously to examine faster firm speed. Our developed framework allows us to discern whether superior capabilities or greater incentives lead to a faster speed. We also show how to apply our framework to empirical analysis by analyzing actual firm data in the Liquefied Natural Gas industry from 1996 to 2007. In this way, the current paper contributes to the literature on firm speed by providing a theoretical framework that enables a more nuanced understanding of firm speed.

Keywords: data envelopment analysis, firm speed, industry frontier, speed capability, time compression diseconomies

INTRODUCTION

Management literature has emphasized speed as a potential source of superior firm performance (Cohen, Nelson, & Walsh, 2000; Dierickx & Cool, 1989; Teece, Pisano, & Shuen, 1997). Faster firms can preempt key inputs, such as scarce natural and human resources, increase consumer-switching costs, and build technological lock-in by getting to the market early. These maneuvers allow the faster firms to restrict, or at least severely limit, a slower firm's range of actions (Dixit, 1992; Ghemawat, 1991; Lieberman & Montgomery, 1988; Rumelt, 1984). In addition, for those firms making commitments later than other firms, faster speed can increase the relative benefit of late action by decreasing preemption risk, which allows them to wait longer until the uncertainty is mitigated (Bar-Ilan & Strange, 1996; Pacheco-de-Almeida & Zemsky, 2003).

These advantages of faster speed have led researchers and practitioners to investigate the source of faster speed (Hawk *et al*., 2021; Vesey, 1991; Vinton, 1992). In their investigations, faster speed is often assumed to indicate superior capabilities (Chen & Hambrick, 1995; Clark & Fujimoto, 1989; Eisenhardt, 1989; Pacheco-de-Almeida *et al*., 2008), but this assumption is not always true. According to time compression diseconomies (Dierickx & Cool, 1989; Teece, 1977), firms can accelerate speed by incurring higher costs. When higher returns driven by accelerated speed offset these costs, a firm can wind up with incentives to accelerate its speed despite cost increases. In such a case, speed is an outcome of adjusting to incentives, not superior capabilities. This challenges the assumption that faster speed always indicates better capability.

Despite the general acknowledgment of time compression diseconomies, the current literature on firm speed maintains a lopsided focus on the capability mechanism, even to the extent of omitting the incentive mechanism. This lopsided focus on capability partly stems from the lack of a theoretical framework considering both capabilities and incentives simultaneously. Without that, researchers have little way of knowing whether capabilities or incentives drive faster speed. Also, due to the general misunderstanding of faster speed as a capability, researchers largely overlook incentive-driven faster speed. This misunderstanding can be a critical problem in strategy literature because mistaking the mechanism for speed can produce ill-advised recommendations. Capability-driven speed typically requires investments in interrelated and co-specialized resources, which are costly and time-consuming for others to imitate (Ghemawat, 1991). In contrast, incentive-driven speed can be a relatively short-term calibration of firm resources related to economic decisions considering opportunity cost (Arora & Nandkumar, 2011). If we were to misunderstand incentive-driven speed for capability-driven speed, then we overestimate a firm's capability or miss out on the opportunity to understand a firm's maneuvers for faster speed unrelated to capability.

We seek to address this shortcoming by developing a theoretical framework that generates distinctive comparative statics such as speed, cost, and distance to industry speed-cost frontier (i.e., best practice regarding speed and cost) *a priori* for all scenarios of capability and incentives changes simultaneously. With this framework, we can corroborate whether incentive, capability, or both lead to a faster speed in reverse by estimating speed, cost, and distance to the industry speed-cost frontier empirically and comparing these results to the predicted comparative statics for each scenario. Thus, our framework allows researchers to discern whether capabilities or incentives lead to a faster speed.

As an illustration, we analyze actual firm data in the Liquefied Natural Gas (LNG) industry, within which a positive demand shock was caused by market liberalization, to discern whether capabilities or incentives cause the faster speed of post-shock firms. We find that post-shock firms have faster speed, higher cost, and farther distance to the industry speed-cost frontier than pre-shock firms in building a plant. These results are predicted by our framework when and only when post-shock firms' incentives to be fast are higher but their capabilities are lower than pre-shock firms. We thus conclude that post-shock firms have faster speed than pre-shock firms despite their inferior capability. Our framework thus yields a surprising result given the current literature's dominant focus on capability mechanisms.

We contribute to the literature by helping researchers and practitioners discern the mechanisms behind observed faster speed by bringing back the incentive mechanism. By showing that a firm can have faster speed despite inferior capabilities when positive incentive effects are strong enough to outweigh the negative capability effect, we reinforce the concept that faster speed differs from speed capability (Hawk *et al*., 2013). Our paper highlights the importance of a nuanced understanding of firm speed, as faster speed may not necessarily equate to superior capability.

PRIOR RESEARCH ON FIRM SPEED

The literature defines 'faster speed' as a shorter time lag between initiating and completing an event of interest. Examples of faster speed include shorter time-to-decision-making (Eisenhardt, 1989; Judge & Miller, 1991; Wally & Baum, 1994); time-to-initial public offering (IPO) (Beckman & Burton, 2008; Chang, 2004; Gompers, 1996); time-to-acquisition (Bauer & Matzler, 2014); time-to-respond to rivals' competitive actions (Chen & Hambrick, 1995; Más-Ruiz *et al*., 2005); time-to-commercialization (Markman *et al*., 2005); time-to-product development (Atuahene-Gima, 2003; Clark & Fujimoto, 1989); and time-to-build a plant (Holloway & Parmigiani, 2016; Pacheco-de-Almeida *et al*., 2008). The current paper investigates the last example in its empirical analysis.

Research on firm speed commonly suggests that a firm with superior capability has fast speed. Superior capability is the power or ability to do things better; thus, if a firm has superior capability, it can have faster speed, all else equal. Relatedly, research in various areas has examined the source of faster speed based on the idea that superior capabilities lead to faster speed. In the M&A literature, for example, Aktas and colleagues (2013) find that firms with more learning from previous acquisition experience have a shorter time lag between acquisition deals. In the competitive strategy literature, researchers have presented arguments for whether a smaller or larger firm has better capabilities to respond to rivals' competitive actions faster. Chen and Hambrick (1995) find that smaller firms respond faster to rivals' competitive actions; Más-Ruiz and colleagues (2005) find instead that larger firms have a faster response speed to the same. In the decision-making literature, researchers maintain that capable firms make quick strategic decisions (Eisenhardt, 1989; Judge & Miller, 1991) due to executives' cognitive ability, intuition, risk tolerance, and propensity to act, correlating with organizational centralization and formalization (Wally & Baum, 1994). In the entrepreneurship literature, a startup with better resources, such as more support from venture capital (Chang, 2004; Honjo & Nagaoka, 2018), more complete functional structures, and broadly experienced team members (Beckman & Burton, 2008), has a shorter time-to-IPO. For example, university startups commercialize faster with lower skill assembly needs, high-level technology transfer, infrastructure access, informal colleague support, and competent university technology transfer offices in client matching (Markman *et al*., 2005; Müller, 2010). In the international business literature, firms with earlier initiation of internationalization, greater knowledge intensity (Autio *et al*., 2000), cumulative entry experience (Gao & Pan, 2010), business intelligence (Cheng *et al*., 2020), and more strategic alliances (Kabongo & Okpara, 2019) grow faster. In the product development literature, firms with organizational capability (Clark & Fujimoto, 1989), cultural competitiveness (Hult *et al*., 2002), and inter-firm human asset co-specialization (Dyer, 1996) have shorter lead times, with these features considered superior capabilities driving faster speed. Firms using bricolage and effectuation (Wu *et al*., 2017; Wu *et al*., 2020) are positively associated with new product development speed. Platform synergy has a positive impact on innovation speed within the platform (Wu *et al*., 2022). In all these kinds of literature, the features positively related to faster firm speed are viewed as superior capabilities and drivers of faster speed.

In a second stream of research, however, faster speed can result from a firm's choice to incur higher costs in response to incentives rather than superior capabilities. According to time compression diseconomies (Dierickx & Cool, 1989), a firm can accelerate its speed by incurring increasingly higher costs. In a positive demand shock, for example, a firm can have incentives to increase its speed despite higher costs because the higher returns from accelerated speed can more than compensate for the corresponding cost increases. In this case, speed is an outcome of a firm's speed calibration to respond to the changing incentives, not an outcome of superior capabilities. Thus, a firm with the same or even inferior capabilities can have faster speed by expecting higher net benefits from increased costs and even more increased returns. Although the concept of time compression diseconomies is well-received by researchers as an isolating mechanism (Rumelt, 1984; Srikanth *et al*., 2021), only a few researchers have explained faster speed based on the incentive mechanism in their empirical research. Rare examples include Arora & Nandkumar (2011), Gompers (1996), and Lewis & Bajari (2011). Arora & Nandkumar (2011) find that high-opportunity-cost entrepreneurs have a shorter time to cash out (e.g., IPO or acquisition). Instead of assuming that high-opportunity-cost entrepreneurs have superior capability, these researchers maintain that these entrepreneurs have faster speed because of a higher incentive to be fast. They find that entrepreneurs with high opportunity costs are not only more likely to cash out more quickly but are also more likely to fail faster. Gompers (1996) finds that young venture capital firms take startups public earlier than older venture capital firms. He explains that young venture capital firms have a greater marginal return of shorter time-to-IPO from establishing a reputation and raising capital for new funds. Gompers (1996) implicitly focuses on rejecting the capability effect in explaining time-to-IPO because the capability mechanism would predict the opposite of his conclusion, namely, that younger venture capitals can have less capability and a slower time-to-IPO. Lewis and Bajari (2011) show that scoring design reduces contract delivery time by giving contractors explicit incentives for accelerated delivery.

This review makes clear that, although both capabilities and incentives drive faster firm speed, the current literature on firm speed has a lopsided focus on the capability mechanism and overlooks the incentive mechanism. This imbalance can lead researchers to misunderstand incentive-driven speed as capability-driven speed, which is problematic. The resources and activities required of a firm to achieve faster speed by developing capability can differ from those needed to achieve faster speed by adequately responding to changing incentives. This is because capability-driven speed typically requires costly and time-consuming investments in interrelated and cospecialized resources (Ghemawat, 1991), whereas incentive-driven speed can be achieved with short-term calibration of resources considering opportunity cost (Arora & Nandkumar, 2011). If we misidentify the mechanism behind the firm speed, our recommendation to achieve fast speed can be misguided. Thus, we propose a framework considering both the mechanisms of capabilities and incentives in explaining faster firm speed to address this imbalance.

THEORETICAL FRAMEWORK

Setting for Framework Development

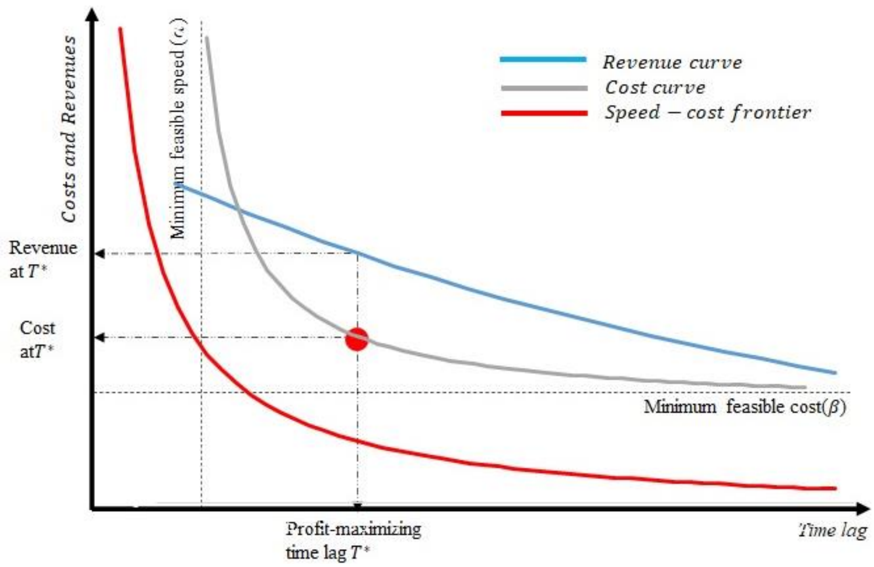
We begin our framework development by relying on a simple model. This model aims to obtain distinctive comparative statics of speed, cost, and distance to the industry speed-cost frontier (i.e., best practice regarding speed and cost) when a firm's capability and incentives change *a priori*. By developing these distinctive predictions for each scenario, we can corroborate which specific scenario plays out by comparing empirically estimated values with the theoretically predicted statics. Therefore, the framework does not explain a firm's reasons for capability and incentive changes or the interaction of capability and incentive. The decision-theoretic approach is suitable for the LNG industry, where firms are price-takes and monopoly power is not a concern, with the largest firm holding just 5.2% of constructed plant capacities (Kellogg, 2014; Santalo, 2002). Instead, the changes in incentive and capability are treated exogenously. Our focus is to observe changes in the speed, cost, and distance to the industry speed-cost frontier when including the incentive and capability effects.

We set our model following the literature but in a simple manner. We begin with the revenue curve of a firm with respect to a time lag. A time lag between the initiation and completion of an event is denoted as T; thus, a shorter time lag means faster speed. The return that a firm starts receiving when the event completes is denoted as r. Once a firm has calculated its T^*, it has determined its calendar time for the completion of an event. A common discount rate $\delta \in (0, 1)$ reflects a firm's capital cost. The revenue function of a firm's speed is then expressed as:

$$R(T) = \int_T^\infty re^{-\delta t}dt \tag{1}$$

The blue curve in Figure 1 represents the revenue curve. As a firm shortens its time lag, its revenue increases, as we can see in the figure because it can advance the date of the event of interest (e.g., an acceleration in commercial operation on the product market).

FIGURE 1
THE REVENUE CURVE AND COST CURVE OF A FIRM REGARDING ITS TIME-TO-BUILD



On the cost side, as a firm shortens the time lag, its cost increases due to time compression diseconomies (Dierickx & Cool, 1989; Teece, 1977). More strictly speaking, under time compression diseconomies, a 1% decrease in a firm's speed typically requires more than a 1% increase in the firm's cost (Boehm, 1981; Graves, 1989; Scherer, 1967, 1984). Thus, any cost function of a firm with respect to a time lag satisfying the following convexity conditions is under time compression diseconomies:

$$c(T) > 0c'(T) < 0, c''(T) > 0, \lim_{T\to 0} c'(T) = -\infty, \lim_{T\to \infty} c'(T) = 0, and\ T > 0 \quad (2)$$

In this cost function, we consider a firm's minimum feasible speed (i.e., time which is independent of cost), denoted as α, and a firm's minimum feasible cost (i.e., cost, which is independent of time), denoted as β. Thus, the cost function of a firm's speed is then expressed as:

$$C(T) = c(T - \alpha) + \beta\ where\ a, \beta > 0 \quad (3)$$

The grey curve in Figure 1 represents the cost curve above. As seen in the figure, the cost function meets the convexity condition and, thus, is under time compression diseconomies.

Consistent with the literature, this figure also shows the tradeoff between revenue and cost for a firm deciding its optimal time lag. The red circle in the figure represents the optimal time lag a firm strategically chooses to maximize its profit. It shows that a firm neither continues to decrease its time lag due to time compression diseconomies nor continues to increase its time lag due to the opportunity cost of revenues.

The industry's speed-cost frontier is the best practice regarding speed and cost (i.e., minimum attainable cost at any time lag). Industry speed-cost frontier also follows time compression diseconomies. The cost at a given time lag on the frontier is always lower than or equal to a firm's cost at the same time lag by definition. The red curve represents the industry speed-cost frontier in Figure 1. A firm's cost change *along* the cost curve does not change the distance to the industry frontier, but a firm's cost change caused by the cost curve *shift* impacts the distance to the industry frontier.

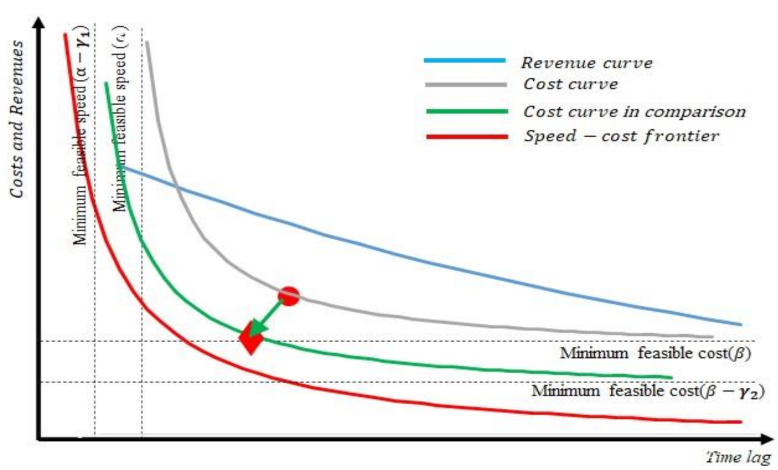
Using Figure 1 as a reference, the next section describes two fundamental dynamics of a firm's faster speed that maximizes its profit: superior-capability-driven faster speed and higher-incentive-driven faster speed.

Superior-Capability-Driven Faster Speed

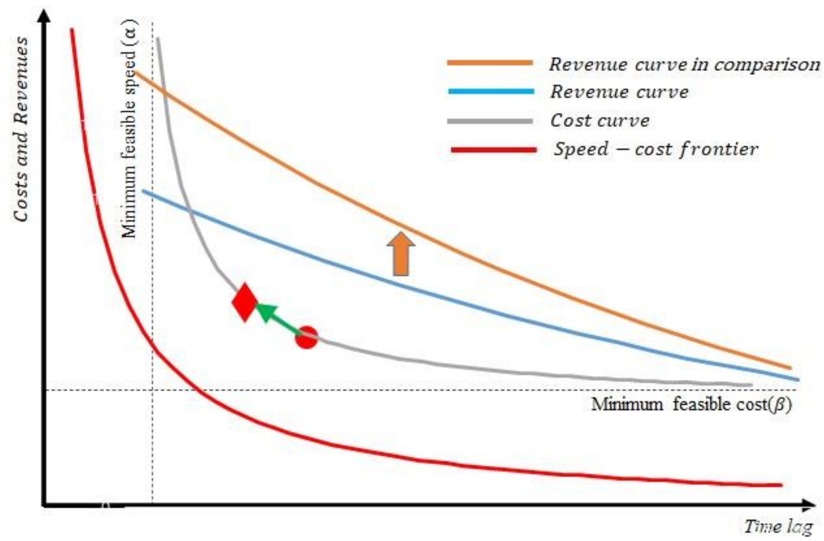
Firms with superior capabilities can have faster speed because they can advance revenue flow sooner without incurring more costs, as shown in Figure 2(a). The red circle in this figure represents the same reference point as in Figure 1, at which the firm maximizes its profit when it has a grey-colored cost curve. This point becomes the reference point; a firm's time lag when costs get lower will be compared to it. A firm's cost decreases for the same time lag is captured by its cost curve shifting downwards, as marked by the green-colored cost curve. Formally put, the cost function of a firm's speed when the cost curve shifts downwards can be expressed as $C(T) = c(T - \alpha + \gamma_2) + \beta - \gamma_1$ where $\beta \geq \gamma_1 \geq 0$ and $\alpha \geq \gamma_2 \geq 0$. We assume the shape of both curves is the same for convenience, but results are robust to different shapes of the new cost curve (i.e., a green-colored cost curve) than the one in the reference case (i.e., a grey-colored cost curve). One critical assumption is that the cost curves of the reference and comparison cases do not intersect, which will be mostly valid when comparing the same firm's change in its cost curve over time. A downward shift in a firm's cost curve typically suggests a firm's capability improvements by making a long-term commitment. It is unlikely that the firm will increase its cost-to-build in one area while decreasing its cost-to-build in another during this improvement in its cost curve. This assumption is consistent with our empirical analysis because we compare the post-shock firm with the pre-shock firm using a within-firm estimator while controlling for other firm characteristics. Therefore, the assumption of no cost curve intersection is valid for within-firm variation analysis over time. This assumption is less likely to be valid when comparing two different individual firms simultaneously using a between-variation estimator or a weighted average of between- and within-variations in empirical analysis. A red diamond represents the point of a firm's time lag and cost at which it maximizes its profit for the downward-shifted green-colored cost curve. Again, the downward cost curve shift represents better firm capabilities because faster speed is achieved by incurring lower costs at any given point of the time lag.

As seen in the figure, a firm's new point that maximizes its profit (i.e., a red diamond) will have a shorter time lag and a lower cost relative to the reference point (i.e., a red circle). This change means that decreasing the time lag is a profit-maximizing decision when a firm's cost curve shifts downward because firms can advance revenue flow sooner while incurring no more costs. In addition to the changes in time lag and cost, Figure 2(a) shows what happens to a firm's distance to the industry speed-cost frontier: a firm's distance to the industry speed-cost frontier decreases because a firm's lower costs are caused by its cost curve's downward shifts, not by its movement along the existing cost curve. Therefore, the distance to the industry speed-cost frontier will be shorter.

FIGURE 2
BASIC DYNAMICS OF HIGHER-INCENTIVE-DRIVEN FASTER SPEED AND SUPERIOR-CAPABILITY-DRIVEN FASTER SPEED



(a) Superior-capability-driven fast speed



(b) Higher-incentive-driven fast speed

In sum, a firm will have faster speed, lower cost, and shorter distance to the industry speed-cost frontier when its speed capability increases, as captured by the downward cost curve shift.

Higher-Incentive-Driven Faster Speed

Firms facing higher marginal returns for the same speed can have faster speed because they expect a higher revenue flow sooner that can more than compensate for any additional costs incurred by accelerating their speed. To explain how a higher incentive leads to a firm's faster speed, we use Figure 2(b). Again, the red circle in this figure represents the reference point of a firm's time lag and cost at which it maximizes its profit in Figure 1. Formally put, the revenue function of a firm's speed when a firm's returns for the same speed are higher can be expressed as:

$$R(T) = \int_T^\infty r_T e^{-\delta t} dt \; where \; r_T > r \quad (4)$$

When a firm's returns for the same speed increase, its revenue curve shifts upwards with a steeper slope, as marked by the orange-colored revenue curve in Figure 2(b). A red diamond represents the point of a firm's time lag and cost at which it maximizes its profit for the upward-shifted orange-colored revenue curve. In this figure, a change in a firm's optimal speed to maximize its profit has nothing to do with its capability because the change does not result from the cost curve shift but from the change along the same cost curve, and thus, the cost incurred at any time lag is identical for both firms facing different returns.

As seen in the figure, a firm's new point that maximizes its profit (i.e., a red diamond) will have a shorter time lag and a higher cost relative to the reference point (i.e., a red circle). This change means that when a firm's marginal returns from the same speed are higher, it has a greater incentive to accelerate its speed, even if it involves some increases in cost along the cost curve. In other words, for firms with higher returns for the same speed, decreasing the time lag is a profit-maximizing decision because a higher revenue flow is expected to occur sooner. This revenue flow can more than compensate for any additional costs incurred by decreasing their time lag. In addition, Figure 2(b) shows what happens to a firm's distance to the industry speed-cost frontier: Because the cost curve does not shift for firms facing different marginal returns, there is no change in the distance to the industry speed-cost frontier. In sum, a firm facing higher marginal returns will have faster speed, higher cost, and unchanged distance to the industry speed-cost frontier as captured by the upward revenue curve shift.

Comparative Statics for Exhaustive Scenarios

We provide all scenarios of capability and incentive changes in Table 1. Each scenario provides theoretically distinctive predictions on the three comparative statics of time lag, cost, and a firm's distance to the industry speed-cost frontier. For example, a positive α_1 in Table 1 means that comparison firms have a longer time lag than reference firms and, thus, have a slower speed. Likewise, a positive β_1 in Table 1 means that comparison firms have a higher cost than reference firms. A positive γ_1 in Table 1 means that comparison firms have a longer distance to the industry speed-cost frontier than reference firms.

TABLE 1
THEORETICAL PREDICTIONS ON COMPARATIVE STATICS WHEN CAPABILITY AND INCENTIVES CHANGE

		α_1: change in the time lag β_1: change in the cost γ_1: change in the distance to industry speed-cost frontier		
		Incentive		
		1. No change	2. Higher incentive	3. Lower incentive
Capability	A. No change	α_1: 0 β_1: 0 γ_1: 0	α_1: – β_1: + γ_1: 0	α_1: + β_1: – γ_1: 0
	B. Superior capability	α_1: – β_1: – γ_1: –	α_1: – β_1: indefinite γ_1: –	α_1: indefinite β_1: – γ_1: –
	C. Inferior capability	α_1: + β_1: + γ_1: +	α_1: indefinite β_1: + γ_1:+	α_1:+ β_1:indefinite γ_1: +

Note 1. 'Zero' means that there is no significant change.
Note 2. 'Indefinite' means the sign can be anything (i.e., positive, negative, or zero). The relative strength of each dynamic determines the sign in this case.

Our theoretical framework suggests that relying on capability alone is insufficient in understanding faster firm speed. As seen in Column 2, Row C in Table 1, a comparison firm with inferior capability can have a shorter time lag (i.e., negative α_1) when its incentive to be faster is substantially high to make the high incentive effect outweigh the inferior capability effect. Likewise, as seen in Column 3, Row B, a comparison firm with superior capability can have a longer time lag (i.e., positive α_1) when its incentive is substantially low enough that the low incentive effect outweighs the superior capability effect. Thus, our framework highlights the need to consider incentives and capabilities for a more nuanced understanding of faster firm speed. It also makes clear that simply relying on the time lag (i.e., α_1 in Table 1) can lead to inaccurate inferences about the source of faster speed. In this paper, triangulation occurs by theorizing three different comparative statics: a firm's speed, cost, and distance to the industry speed-cost frontier rather than simply relying on speed. Such triangulation disentangles the capability and incentive dynamics behind the observed speed and boosts the reliability of the theoretical arguments by generating additional information (Van de Ven, 2007).

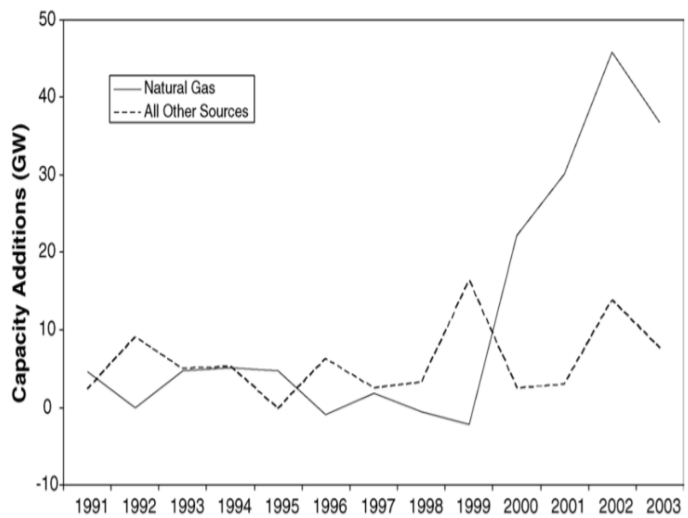
In the next section, we show how to apply our framework to empirical analysis using actual firm data in the LNG industry, which experienced a positive demand shock.

METHOD

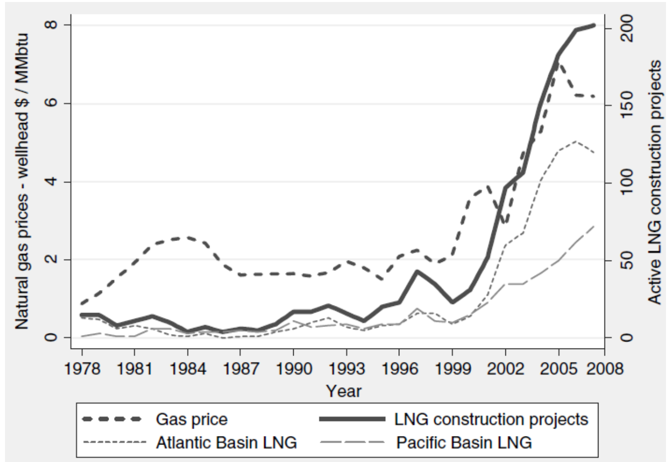
Empirical Context

The empirical analysis aims to compare a firm's speed, cost, and distance to the industry speed-cost frontier between pre- and post-shock firms and compare these observed results with the predicted statics in our framework to identify which scenario – capability or incentive or both – plays out. The current research examines a firm's time-to-build and cost-to-build plants and its distance to the industry speed-cost frontier in the global LNG industry from 1996 to 2007. This empirical context has an attractive feature of a positive demand shock, which was experienced by the LNG industry in 2000 due to energy market liberalization and subsequent increases in the number of gas power plants. Specifically, the liberalization allowed private electricity entities to participate in the market price system that replaced the state-determined price system, creating a wholesale electricity market with time-varying prices. Under this market, *gas* power plants' operational flexibility to respond better to demand (e.g., easier startup/shut-down) became more advantageous than traditional power plants. Figure 3(a) (Blumsack *et al*., 2006) illustrates the effects of gas power plants' attractiveness: electricity-generating capacity addition through natural gas rapidly increased after 1999 relative to all other sources. Adding more gas power plants created a demand shock, leading to sharp increases in natural gas prices and LNG plant construction activities around 2000. As shown in Figure 3(b) (Hawk *et al.* 2013), in the pre-shock period, entry occurred at a prolonged and steady rate, and natural gas prices remained low and steady historically. However, in the post-shock period until the end of our sample, entry into the LNG industry dramatically increased, and natural gas prices rose to more than five times the typical price level.

FIGURE 3
DEMAND SHOCK IN LIQUEFIED NATURAL GAS (LNG) INDUSTRY



(Source: Blumsack, Apt, & Lave, 2006)
(a) Generating Capacity Additions in Electric Power Generation, 1991-2003



(Source: Hawk *et al.* 2013)

(b) Global Liquefied Natural Gas (LNG) Industry, 1978-2007

Sample and Data

We first identified the proposed contemporary LNG construction projects from the *Oil & Gas Journal* (OGJ), Tusiani and Shearer's (2007) LNG: A Non-technical Guide, firm Web sites, Web searches, and other sources. We hand-collected samples based on other plant-level data, such as plant costs, plant quality, construction start date, commercial operation date, and delay events. This process identified 72 LNG plant construction projects that started construction in our sample period. In most cases, multiple firms conduct each project. We then use this project dataset to construct firm panel data.

To match the plant-level data with the firm-year panel data of the parent company, we used the ownership information collected during our data work, such as Oil & Gas Productions and Reserves and financial information. After deleting observations due to missing data for needed variables, our final panel data set corresponded to 45 firms over 12 years, from 1996 to 2007, and produced a sample of 500 firm-year records in the yearly panel data. These data comprise a reasonably comprehensive panel data set covering most of the entrants into the LNG industry with available and useable data for covariates.

For nominal time-to-build per ton capacity, we collected data on construction dates and used the EPC contract award date or final investment decision date as proxies if needed. Nominal time-to-build per ton capacity was calculated by dividing nominal time-to-build by plant capacity. To obtain nominal cost-to-build per ton capacity, we collected plant construction cost estimates and used the most updated figures. Costs in non-USD currencies were converted using yearly-averaged exchange rates and deflated to 1996 prices with CPI. The nominal cost-to-build per ton capacity was calculated by dividing the deflated cost by plant capacity.

The following section explains how we operationalized our main variables of adjusted time-to-build, cost-to-build, and distance to industry speed-cost frontier.

Time-to-Build Per Ton Capacity (Adjusted)

Our first goal is to obtain comparable firm-level time-to-build per ton capacity and cost-to-build per ton capacity from project-level time-to-build and cost-to-build. We look to enable a comparison of the *same firm*'s post-entry speed efficiencies for building the *same plant* in the *same market* in the pre-shock and post-shock periods. To assist in this comparison, we parse out how heterogeneous plants, firms, and markets influence a firm's time-to-build and cost-to-build plant. We address plant-level heterogeneity and some elements of market-level heterogeneity when we operationalize two of the variables of comparable time-to-build per ton capacity and cost-to-build per ton capacity in these pre- and post-shock periods. In the final regression, we address firm-level heterogeneity and the rest of the market-level heterogeneity through control variables. Addressing heterogeneity in all levels of plant, firm, and market, as described above, helps us to compare the same firm's speed and cost in building the same plant in the same market in both pre-shock and post-shock periods and thus to operationalize comparable time-to-build data.

We take five steps to obtain comparable firm-level time-to-build per ton capacity and cost-to-build per ton capacity. These steps build on those in Hawk *et al*. (2013) and Pacheco-de-Almeida *et al*. (2015) but are improved by including the quality of the plant in the first step of the operationalization. For a detailed explanation of these five steps, refer to Hawk *et al*. (2013) and Pacheco-de-Almeida *et al*. (2015). We begin with time-to-build per ton capacity. In the first step, we adjusted nominal time-to-build per ton capacity for plant-level variables (e.g., plant size, usage, quality, and type) and market-level variables (e.g., demand growth, geography, and year). In this approach, we decomposed the time-to-build per ton capacity of each plant into a systematic component (i.e., average time-to-build in the sample) and a plant-specific component (corresponding to the degree to which a firm has a shorter or a longer time-to-build per ton capacity than the average time-to-build in the sample). Specifically, we pulled plant-level data from all firms for all facilities (indexed by *f*), all geographic regions (indexed by *l*), and all years (indexed by *t*) in our sample by running the following regression:

$$lnT_{f,l,t} = \beta_1 lnE_{f,l,t} + \beta_2 lnE_{f,l,t}{}^2 + \beta_3 P_{f,l,t} + \beta_4 Q_{f,l,t} + \beta_5 NDUM_{f,l,t} + \beta_6 ln\overline{\Delta}_{l,t} + \beta_7 LDUM + \beta_8 YDUM + \theta \tag{5}$$

where T is the nominal time-to-build per ton capacity, E is the ton capacity of a plant, P is the plant usage dummy, Q is the plant quality dummy, NDUM is the plant type dummy, $\overline{\Delta}$ is the proxy for local demand growth, and LDUM and YDUM are geographic region dummies and year dummies, respectively. First, we included a ton capacity of a plant variable, as well as a squared term of that variable, because the ton capacity of a plant could affect time-to-build per ton capacity due to economies of scale and diseconomies of scale. The ton capacity of a plant is measured as capacity figures in million tons per year. Second, we included a plant usage variable because different usage specificity can influence time-to-build. Plant usage is measured as one if a plant is a liquefaction plant and zero if a plant is a regasification plant. Third, we included a plant quality variable because quality can influence the time-to-build per ton capacity. Plant quality is a new variable that was not included in the original study of Hawk, Pacheco-de-Almeida and colleagues, but that we believe is essential to partial out plant quality when operationalizing comparable time-to-build measures. Plant quality is measured as one if a plant is shut down for maintenance within a year of commercial operation and zero otherwise. Fourth, we included plant-type dummies because plant type (whether new, expansion, or revamp) can influence the time-to-build per ton capacity. Fifth, local demand growth ($\overline{\Delta}_{l,t}$) is measured by the yearly growth rate in the real GDP of the country of the plant using the World Bank Development Indicators database. Finally, we included geographic region and year dummy variables to capture year-specific and geography-specific effects (i.e., bureaucratic delays). We use the following geographic areas: Asia and the Pacific; Eastern Europe; Former USSR; Japan; Latin America and the Caribbean; North Africa and the Middle East; North America; Sub-Saharan Africa; and Western Europe. Using these different variables, we applied the first step necessary to adjust nominal time-to-build per ton capacity for plant- and market-level variables.

As a result of applying this first step, we decomposed the time-to-build per ton capacity of each plant into a systematic component (i.e., average time-to-build in the sample), and a plant-specific component (corresponding to the degree to which a firm has a shorter or a longer time-to-build per ton capacity than the average time-to-build in the sample). The estimated residual $\theta_{f,l,t}$ associated with a plant for a given firm (denoted $\theta^j_{f,l,t}$ for firm *j*) from our estimation of Equation 1 represents the plant-specific component of the time-to-build, and the predicted value from Equation 1 represents the systematic component. A positive residual indicates that the plant construction was finished slower than average, whereas a negative residual implies that plant construction was completed faster than average.

In the second step, we standardized the measure within each regional subgroup for each year for comparability. We calculated the mean and standard deviation of $\theta^j_{f,l,t}$ within each regional subgroup for each year. The mean is calculated as $\bar{\theta}_{l,t} = \frac{\sum_j \sum_f \theta^j_{f,l,t}}{n_{l,t}}$ and standard deviation as $\sigma_{l,t} = \left[\frac{\sum_j \sum_f \left(\theta^j_{f,l,t} - \bar{\theta}_{l,t}\right)^2}{n_{l,t}-1}\right]^2$. We then standardized each observation of $\theta^j_{f,l,t}$ using mean ($\bar{\theta}_{l,t}$) and standard deviation ($\sigma_{l,t}$) as follows: $\tilde{\theta}^j_{f,l,t} = \frac{\theta^j_{f,l,t} - \bar{\theta}_{l,t}}{\sigma_{l,t}}$.

In the third step, we built our measure of time-to-build per ton capacity for firm *j* by summing up the standardized plant time-to-build per ton capacity $\tilde{\theta}^j_{f,l,t}$ for all of the plants that firm *j* begins in year t and then taking the average.

In the fourth step, we mapped our averaged, standardized, time-to-build per ton capacity measure from the fourth step into a panel of firm-year observations. Our goal was to have a firm time-to-build per ton capacity measure for when a firm initiated construction. Thus, we took the following approach: we carried forward our time-to-build per ton capacity measure to future years when no new information was available. For years in our panel before any time-to-build information was available for a firm, we assumed neutral time-to-build (i.e., we replaced the missing time-to-build per ton capacity observations by zeroes for years before any time-to-build per ton capacity information was available for a firm in our panel).

In the fifth and final step, we shifted a firm's time-to-build in the firm panel data by its minimum value and then added one so that all the values of the time-to-build per ton capacity were positive. This approach enabled us to capture the real-world characteristic that time-to-build and cost-to-build are both positive without affecting the coefficients of each regression.

Cost-to-Build Per Ton Capacity (Adjusted)

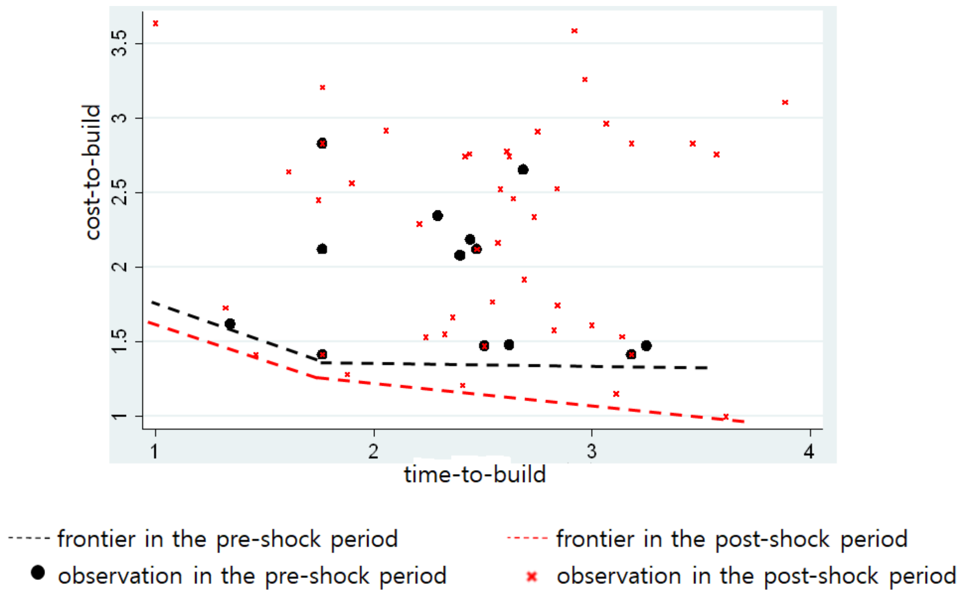
For the cost-to-build per ton capacity measure, we took the same five steps that we followed in the operationalization of a comparable time-to-build (per ton capacity) variable in the previous section, except that we replaced time-to-build per ton capacity with cost-to-build per ton capacity in equation 1 of the first step. We then repeated the rest of the steps.

Distance to Industry Speed-Cost Frontier

To measure the distance to the industry speed-cost frontier, we applied a Data Envelopment Analysis (DEA) (Banker *et al*., 1984). DEA is a frontier method in which a firm's efficiency is measured in terms of distance to the efficient frontier (Banker *et al*., 1984; Charnes *et al*., 1978). DEA's technical features and effectiveness have been established in the literature (Chen *et al*., 2015; Gelada & Gilbert, 2003; McWilliams *et al*., 2005).

We transformed the adjusted cost-to-build data to apply the DEA approach without changing their relative distance from the efficient frontier. This transformation is necessary because DEA typically identifies the efficient frontier as the *maximum* attainable output, whereas the current paper identifies the efficient frontier as the *minimum* attainable cost. First, we symmetrically transposed the observation of adjusted time-to-build and adjusted cost-to-build on the X-axis by multiplying adjusted cost-to-build values by negative one. We then added the absolute values of the minimum adjusted cost-to-build values transposed. Through this transformation, we shifted each value without changing its relative distance to the industry speed-cost frontier. After transformation, we calculated efficiency scores using the user command *dea* in *Stata* (Ji & Lee, 2010) with a variable return to scale (*vrs*) option. Efficiency scores range from 0 to 1; in this approach, a higher efficiency score represents a shorter distance to the industry frontier. Because our goal is to measure the relative distance to the industry frontier, not the efficiency score per se, we multiplied efficiency scores by negative one and added its minimum value to them so that all values are positive. In this way, we could measure the distance of each firm to the industry speed-cost frontier: the higher the value, the longer the distance to the industry frontier. Figure 4 illustrates the positions of the firms in our data in the coordinates of adjusted time-to-build (as the X-axis) and cost-to-build (as the Y-axis) a plant. In this figure, the industry speed-cost frontier appears as the outer surface, in red, that envelopes the firms in the sample market.

FIGURE 4
INDUSTRY SPEED-COST FRONTIERS AND FIRMS' TIME-TO-BUILD AND COST-TO-BUILD IN THE PRE-AND POST-SHOCK PERIODS



Demand Conditions

To capture the different demand conditions that firms face, we create a variable *post shock*, equal to '1' for firms in the post-shock period (after 2000) and '0' for firms in the pre-shock period (before 2000). This variable results from the empirical context and the quantitative structural break analysis. In our robustness check, we use the year 2001 as an alternative cut-off date between regimes since practitioners' perceived timing for regime change may be less clear-cut. Results are robust to the different cut-off dates.

Control Variables

We controlled for price level and price volatility as market characteristics. *Price* is measured using U.S. natural gas wellhead price data from the Energy Information Administration of the U.S. Department of Energy. *Price volatility* is the conditional variance of the U.S. natural gas price estimated from the ARCH process (Episcopos, 1995). A demand shock in the product market might influence input prices in the factor market, which might influence firms' post-entry speed for the same cost. To rule out this factor market explanation, we included two measures: EPC cost and construction raw material price. *EPC cost* is measured by averaging EPC contract amounts in the current year. EPC costs for each year were deflated to 1996 prices using the CPI. For the years when EPC cost data (i.e., 1997, 1998, and 2001) are not available, we extended the value from the previous year. *Construction raw material price* was measured using the Producer Price Index by the Commodity for Special Indexes: Construction Materials data from the Federal Reserve Bank database.

We next set our control variables for firm differences (Mitchell, 1989). In this case, we considered firm size, age, expansion, and possession of complementary assets. *Firm size* is the natural log of the firm's sales for the current year, deflated to 1996 prices using the CPI. When sales data were unavailable for a time period, we used a regression imputation procedure (Little & Rubin, 1987) to impute missing values and complete the data. *Age* is the difference between the year of incorporation for the firm and the plant construction year. We captured firm expansion with two measures: *Total Project Capacity Initiated* and *Total Project Number under Construction. Total Project Capacity Initiated* measured a focal firm's total LNG capacity initiated in the current year. *Total Project Number under Construction* measured the number of LNG plant projects under construction in the current year. To account for *the possession of* *complementary assets*, we included several measures. We created *a variable, LNG fleet*, as the number of LNG fleets owned by a focal firm in the current year. We measured *oil and gas production* and *oil and gas reserves* as the natural log of the firm's oil and gas production and reserves for the current year, respectively, measured in millions of barrels of oil equivalent (MMboe). When oil and gas production and reserves data were not available for a time period, we used a regression imputation procedure (Little & Rubin, 1987) to impute missing values and complete the data. In these various ways, we accounted for firm size, age, prior experience, and possession of complementary assets to control for firm differences. To further account for systematic differences in entry incentives across parent industry categorizations (i.e., a parent company's related diversifications), we included a set of related industry dummies that may represent how parent companies diversify. These industry dummies included Oil and Gas Extraction (SIC code 13), Petroleum and Coal Products (SIC code 29), and Electric and Gas Services (SIC code 49), among others. Second, to capture the actual nature of time compression diseconomies more accurately, we controlled for delay events during plant construction: *delay by extreme weather* and *delay by hurricane* when a firm experienced a delay event in its schedule in the current year.

Statistical Method: Structural Equational Modeling and a Within-variation Estimator

We use structural equation modeling (SEM) with clustering because we simultaneously analyze more than one dependent variable (Jöreskog *et al.*, 1999; Shook *et al.*, 2004). The fit index of the SEM model indicates that the models fit the data well (SRMR = 0.051).

Regarding the choice of the estimator, the question was whether to use a within-variation estimator (e.g., a fixed-effects model), a between-variation estimator, or an average estimator of within- and between-variation (e.g., a random-effects model) (Certo *et al*., 2017). As stated in the theory section, the developed framework is valid under the assumption that the cost curves do not intersect. Such an intersection could happen when comparing two different firms. Therefore, the assumption of non-intersecting cost curves might not be valid in empirical analysis when using a between-variation estimator or a weighted average of between- and within-variations. However, it is unlikely that the cost curves of the same firm over time intersect because it is highly likely that the firm will decrease its cost-to-build at a specific time lag and decrease its cost-to-build at another time lag during this improvement in its cost curve over time. As a result, the assumption of non-intersecting cost curves would be valid when using a within-variation estimator. We, therefore, use a firm fixed-effect model for our estimator. Hausman tests also corroborate that a within-variation estimator is consistent and efficient.

EMPIRICAL RESULTS

We first provide summary statistics and a correlation matrix for the panel data set in Table 2. We observe that the time-to-build per ton capacity, cost-to-build per ton capacity, and distance to industry speed-cost frontier variables demonstrate substantial variation, so a lack of variation is less of a concern when finding statistically significant results.

We also examined potential collinearity in the yearly panel data using variance inflation factors (VIFs). Kennedy suggests a VIF above 10 indicates 'harmful collinearity' (1992: 183). For our data, the mean VIF is 5.01 for all models. The VIFs for most variables in the panel data are less than 10, except for Yearly Price Level, Yearly Price Volatility, and Construction Raw Material Cost. The first two have a ready explanation. A high VIF for price level and price volatility is due to the empirical context, where the pre-shock period is characterized by a low price level coupled with low price volatility, whereas the post-shock period is characterized by a high price level coupled with high price volatility. Multicollinearity is not, therefore, a concern, and our regression analysis produces statistically significant results.

Table 3 provides results regarding post-shock firms' time-to-build (i.e., α_1 in Table 1), cost-to-build (i.e., β_1 in Table 1), and distance to industry speed-cost frontier (i.e., γ_1 in Table 1) from the SEM. Column I provides the results for time-to-build (per ton capacity). The coefficients for post-shock firms are negative and statistically significant ($\beta = -0.125, p = 0.028$); thus, α_1 in Table 1 is negative. This result means that post-shock firms have a short time lag and faster speed in building a plant than pre-shock firms. Column

II provides the results for cost-to-build (per ton capacity). The coefficients for post-shock firms are positive and statistically significant ($\beta = 0.124, p = 0.037$); thus, β_1 in Table 1 is positive. This result means that post-shock firms have higher cost-to-build than pre-shock firms. Column III provides the results for distance to industry speed-cost frontier. The coefficients for post-shock firms are positive and statistically significant ($\beta = 0.033, p = 0.038$); thus, γ_1 in Table 1 is positive. This result means that the distance to the industry speed-cost frontier is longer for the post-shock firms than for pre-shock firms.

If we only examine the observed time lag in building a plant, we may conclude that post-shock firms have superior capabilities than pre-shock firms because post-shock firms have faster speed than pre-shock firms. If we do not consider the possibility of higher incentive-driven speed, we would be more likely to interpret post-shock firms' faster speed as superior speed capability. However, when we consider all three comparative statics and interpret the findings based on our developed framework, we reach the opposite conclusion that post-shock firms have an inferior capability to pre-shock firms. Negative α_1, positiveβ_1, and positive γ_1 are consistent with our model prediction *when and only when* post-shock firms' incentives are higher than those of pre-shock firms and their capabilities are inferior in the same comparison (i.e., Column 2 and Row C in Table 1). Our findings indicate that post-shock firms have faster speed due to higher incentives resulting from the positive demand shock despite the inferior capability. The higher incentive effect outweighs the inferior capability effect in this context. Using our developed framework, we can discern that the faster speed of post-shock firms is caused by the higher incentive stemming from the positive demand shock and not by their superior capability.

TABLE 2
DESCRIPTIVE STATISTICS AND CORRELATION MATRIX

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Post-shock Firm	0.57	0.50	1.00																
2. Time-to-build	2.47	0.51	-0.17	1.00															
3. Cost-to-build	2.06	0.51	0.07	-0.28	1.00														
4. Distance to industry speed-cost frontier	0.25	0.14	0.03	-0.11	0.98	1.00													
5. Price Level	4.10	1.81	0.78	-0.18	0.06	0.02	1.00												
6. Price Volatility	0.11	0.13	0.69	-0.16	0.07	0.03	0.97	1.00											
7. Construction Raw Material Price	1.53	0.15	0.62	-0.15	0.09	0.05	0.88	0.89	1.00										
8. EPC cost	1.69	1.28	0.09	-0.01	0.10	0.09	0.18	0.24	0.51	1.00									
9. Firm Size	9.48	2.43	-0.01	0.10	-0.06	-0.05	0.03	0.05	0.07	0.06	1.00								
10. Age	0.32	0.96	0.05	0.01	0.07	0.08	0.06	0.06	0.06	0.03	0.29	1.00							
11. Total Project Number under Construction	1.07	1.53	0.34	0.02	0.20	0.19	0.37	0.35	0.32	0.07	0.30	0.13	1.00						
12. Total Project Capacity Initiated	18.41	29.77	0.32	-0.01	0.22	0.22	0.39	0.38	0.39	0.16	0.27	0.23	0.74	1.00					
13. LNG Fleet	0.41	0.49	0.02	-0.19	0.24	0.23	0.01	0.01	0.01	-0.00	-0.33	-0.04	-0.32	-0.16	1.00				
14. Oil Gas Production	2.21	5.31	0.09	0.06	0.10	0.10	0.11	0.10	0.11	0.06	0.30	0.12	0.48	0.42	-0.24	1.00			
15. Oil Gas Reserves	6.12	0.82	0.05	0.11	-0.04	-0.02	0.04	0.03	0.03	0.02	0.35	0.40	0.31	0.36	-0.28	0.29	1.00		
16. Delay by Extreme Weather	10.54	0.62	-0.01	-0.04	0.13	0.13	0.03	0.03	0.04	0.04	0.06	-0.26	0.20	0.17	0.02	0.12	-0.03	1.00	
17. Delay by Hurricane	0.08	0.27	0.17	0.39	-0.31	-0.26	0.16	0.12	0.10	-0.02	0.05	-0.02	0.00	-0.04	-0.23	-0.11	0.01	-0.01	1.00

Note. N=500

TABLE 3
THE EFFECT OF A POSITIVE DEMAND SHOCK ON TIME-TO-BUILD, COST-TO-BUILD, AND DISTANCE TO INDUSTRY SPEED-COST FRONTIER

	I. **Time-to-build ($\boldsymbol{\alpha_1}$)**	**II. Cost-to-build ($\boldsymbol{\beta_1}$)**	**III. Distance to speed-cost frontier ($\boldsymbol{\gamma_1}$)**
Post-shock Firms	**-0.125**** **(0.057)**	**0.124**** **(0.060)**	**0.033**** **(0.016)**
Price Level	-0.077* (0.045)	0.004 (0.047)	0.001 (0.013)
Price Volatility	0.624 (0.432)	-0.362 (0.437)	-0.098 (0.126)
Construction Raw Material Cost	-0.248 (0.375)	0.212 (0.270)	0.038 (0.077)
EPC Cost	0.018 (0.018)	0.020 (0.018)	0.007 (0.005)
Firm Size	0.005 (0.021)	0.029 (0.023)	0.008 (0.006)
Age	0.381 (0.618)	-0.422 (0.518)	-0.164 (0.153)
Total Project Number under Construction	-0.005 (0.041)	0.015 (0.042)	0.003 (0.011)
Total Project Capacity Initiated	0.001 (0.002)	0.002 (0.003)	0.001 (0.001)
LNG Fleet	-0.036** (0.016)	0.046* (0.028)	0.011 (0.008)
Oil & Gas Production	0.020 (0.047)	0.093** (0.037)	0.026*** (0.010)
Oil & Gas Reserves	-0.095*** (0.027)	-0.013 (0.030)	-0.010 (0.008)
Delay by Extreme Weather	0.734*** (0.175)	-0.329*** (0.252)	-0.112*** (0.039)
Delay by Hurricane	0.076 (0.123)	-0.327 (0.292)	-0.087 (0.084)
N	500	500	500

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$
Standard errors are in parentheses. They are robust to clustering by firm. A constant is included in the regressions, but those results are not reported in the Table.

Robustness Checks

Several checks confirm the robustness of our findings. First, we tested different operationalizations for the independent variable. For example, we used *the interaction term of price and price volatility* to measure product-market demand. The signs and statistical significances for the coefficients β_1 and γ_1 remain the same, while α_1 becomes insignificant. Although the coefficient α_1 becomes insignificant, this does not change the conclusion from the developed framework of Table 1. Therefore, the results are robust to the different operationalization of independent variables. Second, we used different operationalizations for some control variables, such as firm size, oil & gas productions, and oil & gas reserves. The signs for the coefficients α_1, β_1, and γ_1 remain the same and significant at a p-value of 0.052, 0.033, and 0.036, respectively. Therefore, the results are robust to these different operationalizations of control variables.

Third, we included the squared term of age. The signs for the coefficients α_1, β_1, and γ_1 remain the same and significant. Therefore, the results are robust to including the squared term of age. Finally, we conducted robustness checks regarding price data using the future natural gas price. The signs and statistical significances for the coefficients α_1 and β_1 remain same, but the coefficient γ_1 becomes statistically insignificant. However, this change in the coefficient γ_1 does not change the conclusion from the developed framework of Table 1 that faster speed is caused by increasing returns, not decreasing costs. Therefore, the results are robust to using the future natural gas price. As a result, all robustness checks corroborate our model.

DISCUSSION

By bringing the incentive mechanism back to the examination of faster speed, our paper contributes to the literature by developing the framework that enables us to discern whether and to what extent the effects of capabilities and incentives are substantially at play. Our empirical analysis of actual firm data in the LNG industry is an example of how our framework can contribute to the literature by finding that post-shock firms have faster speed because of high incentives despite inferior capabilities. Without the framework, we could have mistakenly identified a firm with inferior post-shock capabilities as one with superior capabilities. Our paper's direct contribution to the literature is to help researchers and practitioners identify the correct mechanism behind firm speed.

In addition, by indirectly comparing the previous research in the literature, our paper opens up interesting and new research opportunities. For instance, Hawk *et al*. (2013) find that firms with superior *pre-entry* speed capability in building their plants in adjacent industries, such as refinery and petrochemicals, are more likely to enter the LNG industry in the post-shock period. Although these divergent findings seem to contradict each other, they do not necessarily: our research analyzes *post-entry* capability, which is a firm's capability *after* it enters the focal LGN market, whereas the previous study focuses on *pre-entry* capability, namely a firm's capability in the adjacent markets, such as refinery and petrochemicals *before* it enters the focal LNG market. Our different focuses offer a more nuanced view of firm capability, indicating that post-entry capability can diverge from pre-entry capability. It will be fruitful to answer questions such as when pre-entry and post-entry capabilities can diverge from each other and how a firm can realize its potential superior pre-entry capabilities when entering a market. This is one example of how our framework can generate interesting research opportunities. Revisiting previous research with our framework can create more opportunities.

Another example is revisiting contradictory findings in the literature and providing a reconciliation of the contradictory findings. Taking our review for example, in the competitive strategy literature, Chen and Hambrick (1995) find that smaller firms have a faster response speed to rivals' competitive actions, whereas Más-Ruiz *et al*. (2005) find that larger firms have a faster response speed to the same. These contradictory findings can be reconciled within our framework in a way that allows some firms to have better capability while the other firms have a greater incentive to be fast. In this case, we can observe that both small and large firms have faster speeds depending on the context and other moderating factors.

In light of these findings, our research has implications for understanding speed. First, we reinforce that faster speed differs from speed capability (Hawk *et al*., 2013). For one thing, faster speed does not necessarily mean better capability. For another, a firm can also have faster speed despite inferior capabilities because when the effect of positive incentives is strong enough to outweigh the negative capability effect, a firm with inferior capability can have faster speed. Second, we provide a theoretical framework to discern the mechanisms behind the observed faster speed. This framework allows researchers to distinguish whether superior capabilities or higher incentives lead to faster speed by triangulating comparative statics of a firm's speed, cost, and distance to the industry speed-cost frontier. The distinctive predictions of the three comparative statics for each scenario can be beneficial when the effects of capability and incentives oppose each other in a way that one outweighs the other, as in the empirical context of this paper. Our model will help researchers identify the suitable mechanism behind the faster firm speed in various contexts.

In conclusion, our paper highlights the importance of taking caution in understanding faster speed for researchers and practitioners, as faster speed may not necessarily equate to superior capability.

Direction for Future Research and Limitations

Our empirical analysis suggests that post-shock firms have faster speed despite their inferior capability because the positive incentive effects caused by a positive demand shock outweigh a negative capability effect. Although this finding is interesting, in that previous research finds that a firm with superior capabilities is more likely to enter the post-shock market, our research does not address why post-shock firms have inferior capabilities compared to pre-shock firms. Given that a firm with superior capability is more likely to enter the post-shock market in our context and that a firm's capability typically improves over time by accumulating more experiences and benefiting from evolving technologies, our finding that post-shock firms have inferior capabilities can be counterintuitive. One potential explanation is that experience derived from early technological choices is not translated from a different industry or submarket (de Figueiredo & Silverman, 2007; Mitchell, 1989) but is directly related to the focal market and strategic choices made by managers after the decision to pursue a new opportunity (Eggers, 2013). Another possible explanation is the positive demand shock effect, which leads to firm growth because it requires conducting more projects and enables the firm to capitalize on product-market conditions. Leveraging the demand conditions, however, means trading off capabilities because conducting more projects requires allocating non-scale free resources across additional projects (Levinthal & Wu, 2010; Penrose, 1959). This is only conjecture; we leave it as an opportunity for future research.

As in all research, the current paper is also subject to some limitations. First, it used data from a single industry, a feature that potentially limits generalizability. While the theoretical mechanisms at play are likely robust, we do not know whether context influences the mechanism in explaining firm speed. Second, we assumed that the cost curves do not intersect in our theory development. Such an intersection could happen when comparing two different firms. Therefore, the assumption of non-intersecting cost curves might be valid only when we compare the same firm's change over time (i.e., a fixed-effects model in empirical analysis), as was the case for the current study. Applying our theoretical framework would not be appropriate if we use a between-variation estimator in the empirical analysis. Third, we used the decision-theoretic approach in our theory development. Although it makes sense, given our purpose and empirical setting, future research can adopt game-theoretic approaches to see how competitive force on the market influences the mechanisms of capabilities and incentives. Despite these limitations, our work retains important strengths. To the best of our knowledge, it is the first study to propose a theoretical framework that disentangles the capability and incentive mechanisms and empirically investigates the mechanism of faster speed.

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