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THE RIGHT SPEED AND ITS VALUE

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Slow investments cause substantial revenue losses, yet acceleration increases costs. This tradeoff implies that an optimal investment speed usually exists; it is faster the higher a firm's intrinsic speed capability. We hypothesize that it is a firm's intrinsic speed capability, rather than its speed relative to industry competitors per se, that boosts firm value. Using data on oil and gas facilities (1996–2005), we find that intrinsic speed capabilities augment firm value in a varied way: their value is larger with better corporate governance, lower cost of capital, and higher ability to draw value from R&D investment. Our work elevates the discussion of speed from a project-level consideration to a firm-level competitive advantage issue and raises the need to further explore its strategic value.

INTRODUCTION

Empirical evidence shows that rivals imitate increasingly faster, and the race to take on new market opportunities has accelerated (Agarwal and Gort, 2001; D'Aveni, 1994; Gort and Klepper, 1982; Jovanovic and MacDonald, 1994; Wiggins and Ruefli, 2005). Firms that invest more rapidly gain more revenues. But should firms always invest faster than competitors? Accelerating investments also raises costs—at an increasing rate (Dierickx and Cool, 1989; Graves, 1989; Mansfield, 1971; Scherer, 1967).

An example helps illustrate the point. In 1996, Westlake and Exxon started investing in two competing ethylene plants in the United States. Westlake finished its investment three months faster than Exxon. At $411,000 of gross margin per day for an average ethylene plant (Spletter, Ruwe, and Killen, 2002), Westlake may have earned $37 million more in gross revenues than Exxon at the front end of the investment. But did Westlake necessarily outperform Exxon? For an average oil and gas firm, accelerating the development of a new chemical plant by three months may inflate costs by approximately $87 million (Mansfield, 1971; Teece, 1977). Thus, Westlake only created value by being faster if its acceleration was due to better-than-average speed capabilities.

The example shows that firms need to balance the benefits and costs of being fast, which implies that an optimal investment speed usually exists. This optimal speed is fundamentally affected by a firm's intrinsic speed capability, which is the ability to complete an investment project faster than others given the same cost and conditions. The goal of this paper is to show that it is a firm's intrinsic speed capability—rather than its speed relative to industry competitors per se—that ultimately contributes to firm value.

Multiple confounding effects render an empirical analysis of speed's value technically challenging. The value of speed varies not only

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with firm capabilities but also from one project to another and with firm heterogeneity in corporate governance, capital cost, and outsourcing practices. Therefore, simple estimates of a firm's speed do not have a uniform relationship with the value of speed. The implication is that, in empirical tests, researchers have to pay attention to firm-level and project-level nuances that affect the relationship between observed speed and firms' intrinsic speed capability—as well as the relationship between intrinsic speed capability and firm value.

In this paper, we use a simple firm-level model to facilitate the empirics. We use an optimization model to derive an expression for optimal project completion time—the key to deriving a defensible proxy for intrinsic speed capability. We then estimate the value of intrinsic speed through a reduced-form random-parameter model that accommodates variations in the valuation of intrinsic speed across firms.

Our data are based on publicly available firm-level data and on investment project completion time of oil and gas facilities worldwide from 1996 to 2005. We find a positive relationship between firm value (as measured by Tobin's q) and our proxy for intrinsic speed, and the relationship indeed varies across firms. We further find important complementary factors that raise intrinsic speed's value. First, intrinsic speed is more valued in firms with good corporate governance as these firms utilize corporate resources and adopt investment opportunities more optimally. Second, intrinsic speed generates more value in firms with lower discount rates; a lower discount rate raises the valuation of a project's stream of revenues and thus the returns from speed. Third, intrinsic speed is more valuable to firms that benefit more from their R&D investments. To the extent that value created by R&D investments stems from successful product or process innovation, more innovative firms benefit more from being intrinsically fast. Finally, we also show that our results are robust to investment outsourcing, that is, after controlling for the subcontractors that firms used in each stage of plant development. These results elevate the discussion of speed from a project-level issue to a firm-level competitive advantage issue; they also highlight the synergies between intrinsic speed capabilities and other firm-level competitive advantages that create profitable investments.

THE INVESTMENT SPEED TRADEOFF AND EMPIRICAL PROPOSITIONS

The strategy literature has extensively emphasized the importance of speed for firm competitive advantage. Fundamentally, speed enables a firm to realize the revenue streams from an investment project early, while prolonging project development time leads to potentially severe opportunity costs. Firm speed in the execution of investment projects matters in many strategic contexts, such as entering new markets, catching up with industry leaders, and competing in a dynamically changing environment. These ideas have been discussed at length in the dynamic capabilities (Helfat *et al.*, 2007; Teece, 2007; Teece, Pisano, and Shuen, 1997) and time-based competition literatures (Stalk, 1988; Stalk and Hout, 1990). Most recently, Hawk, Pacheco-de-Almeida, and Yeung (2013) show that firms that can complete investment projects fast face less preemption risk in waiting for demand or technical uncertainty to subside before investing, and thus their investments generate greater value.

Balancing the benefits of speed are the costs of hastening investment execution. Internal resource accumulation is generally subject to time compression diseconomies: reducing project development time often raises costs at an increasing rate (Boehm, 1981; Dierickx and Cool, 1989; Scherer, 1967, 1984). Several possible explanations exist for time compression diseconomies. Speeding up a project usually involves crash investments, with the deployment of more resources to the project at each point in time. The law of diminishing returns (where one input, *viz.*, time, is held constant) typically limits overall productivity and drives up investment costs. Also, investment acceleration often requires parallel processing of previously sequential development steps, which reduces internal information flow across stages of the development process and increases mistakes, rework, and costs. Note, however, that these costs are dependent on firms' intrinsic capabilities: firms that are better at internal communication and coordination can accelerate project completion at a lower cost. The operations research literature has extensively examined this time-cost tradeoff (e.g., Graves, 1989).

This literature review suggests that firms face an important strategic decision with each investment: they need to decide on the optimal speed of completion of the investment project that balances the aforementioned benefits and costs of speed. We expect this optimal speed to be firm and project specific but also to be fundamentally shorter with firms' intrinsic speed capabilities, *ceteris paribus*.

Empirical propositions

A firm with higher intrinsic speed capabilities can finish an investment project faster than slower firms at identical cost. The implication is that intrinsic speed capabilities are an intangible competitive advantage that augments firm value. Let us reiterate the advantages that slower counterparts cannot mimic: (1) propelled by intrinsic speed capabilities, firms with speedy investment implementation gain more revenues earlier in any investment project than their slower competitors; (2) firms with high intrinsic speed capabilities have high strategic flexibility in that they can afford to wait longer before entering new market opportunities. These considerations suggest our first empirical proposition:

> *Proposition 1 (P1): Instrinsic speed capabilities augment firm value.*

The value of intrinsic capabilities varies across firms according to their other capabilities. First, the value of intrinsic speed capabilities stems from a firm's profitable investment. Firms with good corporate governance tend to make more optimal investment decisions. For well-governed firms, intrinsic speed capabilities can thus bring in more firm value because the underlying investment projects are more optimally chosen. Second, the advantage of intrinsic speed capabilities is the ability to gain a stream of revenues earlier and faster at identical investment cost. This means that the lower a firm's discount rate, the higher the stream of cash flows and thus the higher the value of intrinsic speed capabilities. Third, intrinsic speed capabilities are more value enhancing for more innovative firms that generate better investment ideas because intrinsic speed capabilities allow firms to bring these innovations to market faster. These ideas lead to the following illustrative propositions:

> *Proposition 2a (P2a): The value of intrinsic speed capabilities generally varies across firms.*

> *Proposition 2b (P2b): The value of intrinsic speed capabilities is higher in firms with better corporate governance, lower cost of capital, and greater ability to benefit from innovation efforts.*

A REDUCED-FORM MODEL: INTRINSIC SPEED CAPABILITIES AND FIRM VALUE

To empirically explore these empirical propositions, we proceed in two steps. First, we derive an empirical model of the determinants of project completion time. By controlling for market conditions, location-specific factors, and industry- and project-specific characteristics, we are able to isolate the part of investment speed that is due to firm-specific factors. We use this information to build a proxy for firms' intrinsic investment speed. Our second step is to use a random parameters model (RPM) to regress firm value on this proxy. The RPM allows us to estimate the effect of intrinsic speed capabilities on firm performance and thus test P1. As well, the model allows us to explore firm-level nuances that moderate the relationship, that is, to explore P2a and P2b. These two steps of our analysis are described in the following two subsections.

The determinants of project completion time

We study the determinants of investment time by estimating the following empirical model:

$$\ln \widetilde{T}_{\mathbf{f,i},t} = \beta_{0\mathbf{i}} + \beta_1 \ln K_{\mathbf{f,i},t} + \beta_2 \ln E_{\mathbf{f,i},t} + \beta_3 \ln \overline{\Delta}_{\mathbf{f,i}} + \theta_{\mathbf{f,i},t} \quad (1)$$

While this methodology is general, exposition-wise it is convenient to link the empirical model to the intended application, which is the construction of oil and gas facilities. We describe the analytical derivation of the model in the online supporting information.

Intuitively, Regression Equation 1 uses a number of systematic factors that are known to affect new plant construction to estimate average project completion time. We expect average project time to vary by industry type and location conditions, and to accelerate when the economy grows. Also, it will take longer for larger and

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more complex projects. Regression Equation 1 is structured accordingly, as follows.

$\widetilde{T}_{\mathbf{f,i},t}$ is a discounted transformation of the time-to-build of a new production facility **f** in industry **i** at time t.[1] Each production facility **f** represents the n^{th} $(n \geq 1)$ investment of firm j, identified by vector $\mathbf{f}=(j,n)$. Every industry subgroup **i** is defined by a different project type p (refineries, petrochemical plants, and gas-to-liquids plants) and geographic market g, $\mathbf{i}=(p,g)$. Intercept β_{0i} is a vector of project type (p) and geographic location (g) dummies that accounts for the expected variation in average project time-to-build across geographies and project type (results are robust to the additional inclusion of year (t) dummies).

Coefficients $\beta_1, \beta_2 \geq 0$ represent the elasticity of development time with respect to the stock of intangible and physical resources needed to build a new oil and gas plant, respectively. Intangible resources are typically accumulated during the first two phases—planning and engineering—of a new oil and gas plant development project. When planning and engineering a new plant, oil and gas companies primarily accumulate technological and managerial knowledge $K_{\mathbf{f,i},t} > 0$ that depends on the technical complexity of the project (e.g., the feedstock processes, mechanical and piping engineering specifications, and electrical design to be used in the new facility). The physical resources and equipment $E_{\mathbf{f,i},t} > 0$ needed to start production are accumulated and assembled during the third and last phase—construction—of a new plant development project. For each project type, the amount of equipment required for production is usually directly proportional to the size of the investment or a plant's production capacity.

We assume that $K_{\mathbf{f,i},t}$ and $E_{\mathbf{f,i},t}$, the knowledge and equipment factors affecting a firm's project completion time ($T_{\mathbf{f,i},t}$), are predetermined before a firm decides on completion time (see supporting information). Finally, coefficient $\beta_3 = -\frac{\gamma}{2} \leq 0$ corresponds to the revenue $\left(\overline{\Delta}_{\mathbf{f,i}}\right)$ elasticity of development time. In sum, the expected signs of the model coefficients in Regression Equation 1 ($\beta_1, \beta_2 \geq 0, \beta_3 \leq 0$) reflect our expectations that the more (intangible and physical) resources needed to develop an oil and gas facility and the lower the project's revenues, the longer firms take to bring new investments online.

Our critical focus in Regression Equation 1 is on the error term, $\theta_{\mathbf{f,i},t}$. Intuitively, a negative (positive) residual implies that firm j completed facility **f** faster (slower) than the industry average speed after controlling for project type, location, and time fixed effects. The deviations are due to either suboptimal acceleration or deceleration of a project or the fact that individual firms' speed capabilities differ from the industry-time average. Both factors are included in the error term as they are unobservable at the project level.

We describe each of these two factors and their effects on the estimation properties of the error term as follows. The structure of the error term is given by $\theta_{\mathbf{f,i},t} = \varepsilon_{\mathbf{f,i},t} + \beta_0 \ln\left(\frac{1-d_{\mathbf{f,i},t}}{1-d_i}\right)$ (see the supporting information for technical details). As explained above, the first term $\varepsilon_{\mathbf{f,i},t} \neq 0$ allows for the possibility that individual firms may suboptimize the investment speed of specific projects at given points in time. This may stem from exogenous shocks in the construction process (e.g., disruptions in the supply of third-party technical equipment) or simple managerial mistakes. It may also be due to agency problems (Jensen, 1993; Jensen and Meckling, 1976), as managers may excessively accelerate "pet projects" or cause delay because of lackluster efforts. Note that we also assume that, *on average*, firms operating in the oil and gas industry during our period of analysis (from 1996 to 2005) chose their development time $T_{\mathbf{f,i},t}$ to maximize their projects' profits, $E(\varepsilon_{\mathbf{f,i},t})=0$. This assumption that oil companies collectively optimize on project speed is central to our estimation procedure and reasonable in our empirical setting for several reasons. During this period, governments offered fewer subsidies to render uneconomic projects financially viable or distort the returns from speed in the execution of investments in oil facilities. Companies were also increasingly subject to the discipline of global capital markets due to the current maturity stage of the oil industry.

The second term in our model residual $\theta_{\mathbf{f,i},t}$, $\ln\left(\frac{1-d_{\mathbf{f,i},t}}{1-d_i}\right)$, captures firms' intrinsic speed capabilities relative to the industry average. Note that

[1] The functional form of the discounting is given by $\widetilde{T}_{\mathbf{f,i},t} = \left(1 - e^{-rT_{\mathbf{f,i},t}}\right)/r$, where $T_{\mathbf{f,i},t}$ is the measure of time-to-build of a plant development project in months. This positive monotonic transformation compresses the distribution of development time-to-build from the infinite interval $(0,\infty)$ to the finite interval $(0, 1/r)$. See the supporting information for further details on the analytical derivation of the regression model.

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$d_{\mathbf{f,i},t} \in (0,1)$ is a parameter that shifts firms' time-cost tradeoff such that, for any fixed level of expenditures, a more capable firm (with a higher $d_{\mathbf{f,i},t}$) develops projects faster. Firms' intrinsic speed capabilities include any organizational factors that allow firms to develop investment projects more quickly than competitors. For example, in our empirical setting of the oil and gas industry, firms differ in their ability to speedily accumulate and deploy the stock of tangible and intangible resources required to bring new oil plants online. Some firms may be intrinsically faster at project development because of more efficient project management processes or culture. For example, "an organization that has an outcome-oriented culture and is able to navigate the regulatory environment can speed up plant development" (senior oil and gas industry consultant). Also, ample evidence exists that, in oil and gas, a firm's "[ability to pursue] a modular investment approach ... speeds construction" (Stell, 2003; see also Ganapati *et al.*, 2000). Prior experience and skilled labor is another important source of investment speed, as extensively documented in the *Oil and Gas Journal* (OGJ) (e.g., Ganapati *et al.*, 2000; 1990).

Firms' intrinsic speed capabilities ($d_{\mathbf{f,i},t}$), although an unobservable intangible construct, affect the estimation properties of the error term ($\theta_{\mathbf{f,i},t}$). Specifically, $E\left(\theta_{\mathbf{f,i},t}\right) = \beta_0 E\left[\ln\left(\frac{1-d_{\mathbf{f,i},t}}{1-d_i}\right)\right] \leq \beta_0 \ln E\left(\frac{1-d_{\mathbf{f,i},t}}{1-d_i}\right) = 0$ because of Jensen's inequality and that $E\left(\frac{1-d_{\mathbf{f,i},t}}{1-d_i}\right) = 1$ (by construction). Since $E(\varepsilon_{\mathbf{f,i},t}) \leq 0$, the ordinary least squares (OLS) estimates of the intercepts $\beta_{0\mathbf{i}}$ may be biased (but not the coefficients of the remaining variables).

To conclude, our first-stage regression error term $\theta_{\mathbf{f,i},t}$ constitutes our empirical proxy for *project speed*, or how much firms' development time $T_{\mathbf{f,i},t}$ deviates from the industry average, after controlling for project-specific characteristics. Note that $\theta_{\mathbf{f,i},t}$ can include firm-project specific considerations that go beyond the controlled factors: sheer randomness and nonsystematic considerations to occasionally speed up or slow down project completion. Our next step is to examine how these deviations from industry average speed affect firm value.

Intrinsic speed capabilities and firm value

By construction, nonzero project speed $\theta_{\mathbf{f,i},t}$ implies that a firm's project completion time differs from the project-location-time average because of randomness, suboptimal behavior, or firm-specific speed capabilities. Also, it can be affected by other firm specific factors, e.g., a firm-specific lower cost of capital likely raises the appeal of speedy completion of profitable investment. The implication is that there is firm heterogeneity in the relationship between the systematic component of speed estimate and performance. As well, we need to incorporate relevant firm-level controls to delineate the impact on firm value by firm-specific speed capabilities and by other firm-specific factors. Accordingly, we use the following RPM (see the supporting information for associated discussion and derivation):

$$\prod\nolimits_{j,t} = \delta^0_{\mathbf{i},t} + \delta^1_j \Theta_{j,t} + \delta^2_j \Lambda_{j,t} + \mu_{j,t} \qquad (2)$$

In Regression Equation 2, $\prod_{j,t}$ is a measure of firm j's performance at time t, $\delta^0_{\mathbf{i},t}$ are industry subgroup $\mathbf{i}$ (product, geography) and time t dummies plus a random constant term. The coefficients $\delta^x_j = \delta^x + \zeta^x_j$ $(x = 1, 2)$ vary per firm j, where δ^x is the common-mean coefficient across firms and ζ^x_j is a random term. Vector $\Lambda_{j,t}$ includes all necessary control variables that are known to affect performance, and $\mu_{j,t}$ is a mean zero i.i.d. stochastic error term.

The focal independent variable $\Theta_{j,t}$ is our proxy for intrinsic speed capabilities. To calculate this firm-level measure, we first compute the mean and standard deviation of speed for *all* projects in each industry $\mathbf{i}$ at time t using the residuals from Regression Equation 1 (where each industry is defined by $\mathbf{i} = (p,g)$, its project geography). Analytically, the mean speed in industry $\mathbf{i}$ is given by $\overline{\theta}_{\mathbf{i},t} = \sum_{\mathbf{f}} \frac{\theta_{\mathbf{f,i},t}}{n_{\mathbf{i},t}} = \sum_j \sum_n \frac{\theta_{\mathbf{f,i},t}}{n_{\mathbf{i},t}}$, where each facility project $\mathbf{f} = (j,n)$ represents the n^{th} investment of firm j in industry $\mathbf{i}$ at time t, and $n_{i,t}$ is the total number of projects in industry $\boldsymbol{i}$ at time t. Similarly, the standard deviation is given by $\sigma_{\mathbf{i},t} = \left[\sum_{\mathbf{f}} \left(\theta_{\mathbf{f,i},t} - \overline{\theta}_{\mathbf{i},t}\right)^2 / \left(n_{i,t} - 1\right)\right]^{1/2}$.

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We then standardize each project speed observation, $\frac{\theta_{\mathbf{f},\mathbf{i},t}-\overline{\theta}_{\mathbf{i},t}}{\sigma_{\mathbf{i},t}}$. Finally, we construct our measure of intrinsic speed capability for each firm j in our sample by taking the average of the standardized speed of all $n_{j,t}$ projects completed at time t by firm j across all industries $\mathbf{i}$. The averaging mitigates the influence of randomness and nonsystemic factors in $\theta_{\mathbf{f},\mathbf{i},t}$, including firm-level strategic considerations pertaining to each individual project. We reverse code it so that positive values indicate faster firms, $\Theta_{j,t} = -\left(\sum_{n,\mathbf{i}} \frac{\theta_{\mathbf{f},\mathbf{i},t}-\overline{\theta}_{\mathbf{i},t}}{\sigma_{\mathbf{i},t}}\right)/n_{j,t}$.

Our main independent variable $\Theta_{j,t}$ captures by construction a firm's intrinsic speed capability relative to the industry average as well as each firm's average suboptimization behavior. Therefore, we acknowledge that our proxy for firm speed capability $\Theta_{j,t}$ may be influenced by corporate suboptimization due to, for example, agency problems as well as other firm-level heterogeneity. However, after controlling for them in $\Lambda_{j,t}$, the resulting random parameter estimate δ_j^1 associated with our main independent variable $\Theta_{j,t}$ captures the varying effect of firms' intrinsic speed capabilities on performance. Thus, a positive δ_j^1 supports P1. At the same time, the variation of δ_j^1 across firms supports P2a.

The estimated correlations between the random parameters of speed and of the controls for firm characteristics (δ_j^1 and δ_j^2) reveal information on the determinants of the value of intrinsic speed capabilities. These correlations present evidence for P2b.

The next section describes our sample and empirical steps in more detail. In particular, we shall present our empirical measures for firm value and various control measures.

EMPIRICAL ANALYSIS

We conducted our empirical analysis in the worldwide oil and gas industry from 1996 to 2005. The speed of investment in new oil plants has a significant impact on firm performance, as the loss of a single day's revenue due to plant construction delays can cost a company hundreds of thousands of dollars. For instance, Spletter *et al.* (2002) estimated the gross margin loss per day of an average size ethylene cracker in the U.S. Gulf Coast during 1997–2002 at approximately \$411,000 (in 1997 dollars). The oil and gas industry also serves as an appropriate setting for this study because of public reporting of data on project execution time and the possibility of studying various regions and products simultaneously while maintaining a homogeneous sample.

Data and variables

Our data sample contains investment and timing information we collected from OGJ on a total of 2,659 refinery, petrochemical, and gas-to-liquids (GTL) plant construction projects. This sample covers virtually all plants built worldwide from 1996 to 2005. These plant investments were carried out by 847 firm subsidiaries in 99 different countries.[2] We matched each firm in our OGJ project dataset to their ultimate parent company using the *Directory of Corporate Affiliations*. Finally, we merged the investment dataset with financial information from Compustat on each publicly traded company. Our final sample size varies between 151 and 198 firm-year observations, depending on which measures we used for the independent variables in each regression.[3]

The operationalization of the variables in Regression Equation 2 is as follows. The dependent variable—firm j's performance at time t ($\prod_{j,t}$)—is measured by Tobin's q, which is defined as the ratio of a firm's market value to replacement costs of tangible assets. We proxy market value by the sum of market value of equity, book value of preferred stock, book value of long-term debt, and current liabilities less current assets. The replacement costs of tangible assets are measured as total assets less current assets and intangibles, plus the book value of inventory. Tobin's q

[2] Only a small fraction of the firms in the dataset invested in GTL plants (15 firms, as opposed to 386 and 527 firms that invested in refineries and petrochemicals, respectively). A total of 81 firms invested in at least two different types of projects during the period of analysis. The three countries with the highest number of projects by different firms included the United States (97 firms), China (71 firms), and India (63 firms).

[3] Note that we are using only information on publicly traded firms. The objective functions for private firms are less uniform than public firms; they are more affected by owner's private benefit considerations and less driven by financial value-based objectives. Therefore, besides the critical issue that data for private firms may be incomplete, there is a real advantage in focusing on public firms.

is often used to capture the value of firms' intangibles (e.g., Dowell, Hart, and Yeung, 2000; Morck and Yeung, 1991). Our conceptualization is that intrinsic speed capabilities are an intangible asset.

As reported in the previous section, our proxy for intrinsic firm speed capabilities ($\Theta_{j,t}$) is the average standardized speed of all projects that firm j completed at time t across all industries, where project speed ($\theta_{\mathbf{f,i},t}$) is the residual of Regression Equation 1. In model 1, project development time ($T_{\mathbf{f,i},t}$) is the lag between the start and end dates of plant development reported in the OGJ.[4] The industry discount rate (r) is proxied by the average WACC (weighted average cost of capital) across all oil companies with Compustat-CRSP Merged financial data from 1996 to 2005.[5] Another alternative is to use the average EBIDA to proxy for industry discount rate, and we obtained qualitatively similar results. To save space, we focus on results obtained using the WACC measure. The increase in revenues from plant development $\left(\overline{\Delta_{\mathbf{f,i}}}\right)$ is operationalized as the average demand growth, which we proxy by the annual growth rate in real GDP in each location from the World Bank Development Indicators database. The amount of physical resources and equipment ($E_{\mathbf{f,i},t}$) required for a project is directly proportional to a plant's production capacity. We operationalized this variable accordingly using OGJ data (in volume and mass units for refinery, GTL plants, and petrochemical plants, respectively). Technological knowledge ($K_{\mathbf{f,i},t}$) depends on the technical complexity of each project. Complexity data is only available for refinery plants (see Nelson's Complexity Index in Leffler, 2000: 216). However, restricting our dataset exclusively to refineries would create an unreasonably small final sample in Regression Equation 2 (after merging with Compustat-CRSP financials). Also, the complexity variable proved *not* statistically significant or only marginally significant in Regression Equation 1 with the restricted refinery sample. Therefore, we use our whole dataset (refinery, petrochemical, and GTL projects) and exclude the complexity measure from the estimation of the project speed residuals in Regression Equation 1. Model 1 included industry dummies as column vectors of product dummies (for refinery, petrochemical, GTL plants) and geography dummies (17 regions were identified; we assigned a dummy to each country with over 2% of the dataset projects and aggregated the remaining countries to prevent an excessive loss

[4] The official start (end) of plant development is assumed to be the date in which the project is first (last) reported in the OGJ minus (plus) 90 days. The 90-day lag occurs because the OGJ reports the status of each plant development project only twice per year, in April and October. Thus, if a project appears for the first time in one issue of the journal, we can only infer that development started sometime after the prior issue and before the current one. For simplicity, we assume that development started exactly in between the two consecutive issues of the OGJ, thus the 90-day (three-month) lag. A similar logic applies to the official end date of the project, unless an expected completion date was reported, in which case, the latter is assumed to be the official end date. Since the OGJ lists updated, self-reported expected completion dates for almost all plants (90.5% of the sample), our official end date measure is reasonably accurate and should be consistent with firms' internal records. The measurement error associated with the official start date of a project varies between zero and three months and corresponds, on average, to 7.14% of the total development time of a plant (21 months). This relatively small project-specific error is likely washed out as we have several project observations per firm. We also do not expect substantial biases in firms' timing of announcements of new projects (e.g., for strategic reasons). Bluffing in this industry is not very effective because firms' actions are externally visible. The extremely regulated oil and gas industry is the center of attention of several government bodies, consulting companies, and subcontractors. Even at the very early stages of projects, the extent of under- or over-reporting is limited by the fact that firms need to apply in advance for construction permits from regulators, order plant components from a few global suppliers ahead of time, and often outsource the initial stages (study/planning) to external contractors. Bluffing is also not a sustainable long-term strategy because it reflects on companies' reputations—especially in a setting with repeated interactions between incumbent firms that have operated in a mature industry for a long period of time. Finally, there are strong reasons to believe that, when plant development projects are reported for the first time in the OGJ, firms are credibly committed to the investment. This is the case because companies abandon or cancel only a very small fraction of the projects listed (about 1.5%). Finally, $T_{\mathbf{f,i},t}$ is reported in months.

[5] Compustat-CRSP Merged financial data was collected for a universe of firms operating from 1996 to 2005 in the oil products industry (SIC code 29) and the chemical industry (SIC code 28 excluding pharmaceuticals—SIC code 283). In contrast with our original sample from Compustat, the Compustat-CRSP Merged dataset was not restricted to only companies that invested in an oil plant during the period of analysis. This approach allows for a more accurate approximation to the industry discount rate. For each company, EBIDA = (operating income before depreciation – income taxes)/total assets. We construct WACC as a weighted average between the equity cost of capital (ECC, proxied by the earnings yield = earnings per share/year end price) and the debt cost of capital (DCC = interest expense/(long-term debt + current liabilities) using market capitalization as weights. Formally, WACC = ECC × (market capitalization)/(market capitalization + long term debt + current liabilities) + DCC × (long-term debt + current liabilities)/(market capitalization + long-term debt + current liabilities). For both the average EBIDA and the average WACC, we account for yearly differences in inflation by subtracting the inflation rate (calculated using the growth rate in the CPI-U from the Bureau of Labor Statistics). Therefore, we use the real discount rate in the model (Equation 1).

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of data in the standardization of the project speed residuals).

In Regression Equation 2, one of the key control variables (in $\Lambda_{j,t}$) reflects the quality of a firm's corporate governance. Corporate governance refers to designs that monitor and discipline managers so that they take actions in shareholders' interest. The financial economics literature has well established that good corporate governance is comprised of efficient management monitoring and shareholder protection and that these measures positively affect firm value (Tobin's q), which is our dependent variable in Regression Equation 2 (Denis and McConnell, 2003; Gompers, Ishii, and Metrick, 2003; Morck, Shleifer, and Vishny, 1988; Shleifer and Vishny, 1997).

In the context of our Regression Equation 2, corporate governance not only impacts firm value directly (as explained above), but it also affects the performance of the intrinsic speed variable ($\Theta_{j,t}$). First, better corporate governance reduces the weight of suboptimal behavior in our proxy for intrinsic speed. With good corporate governance, observed speed should mostly be due to firms' capabilities. Second, firms with better corporate governance likely make more and better use of their intrinsic speed capabilities and also make more optimal investment choices. Therefore, in better-governed firms our proxy for intrinsic speed should generate a higher impact on firm value. This observation suggests a possible interaction effect between corporate governance and speed capabilities. In our model, this is accommodated by allowing the random parameters to be correlated.

We use two well-accepted measures of corporate governance, but to save space we report only one. (1) *Blockholding* represents the percentage of common stock held by institutional investors owning at least 5 percent of a company's outstanding common stock. Larger stockowners can better monitor and control a company using voting rights associated with their holding. We obtain this variable by averaging quarterly institutional ownership data from Thomson Financial 13F Filings for each firm-year in our oil dataset. (2) In our robustness checks, we use *S&P Score*, which is a percentile score based on each firm's Standard and Poor's Transparency and Disclosure Index (S&P Index). Standard and Poor's generates this index by examining the annual reports and standard regulatory filings of 1,443 companies worldwide for 98 financial, governance, and ownership disclosure items. We sum the S&P Index across these reported disclosure ratings for each company and convert the total into a percentile score defined within our final company sample. Prior literature has used the S&P Index as an indicator of stockholders' protection (Bushee, 2004; Durnev and Kim, 2005; Khanna, Kogan, and Palepu, 2006).

To control for important firm-level factors that affect Tobin's q, we include firms' R&D Intensity (R&D expenditures over total assets), Leverage (long-term debt over total assets), and Advertising Intensity (advertising expenditures over total assets). Note that each of these factors could have an impact on the value of intrinsic speed capabilities. The first variable captures innovation effort; q will be higher the greater a firm's R&D efficacy. Tobin's q is negatively related with high leverage if the variable is associated with high cost of capital. Advertising Intensity represents marketing intangibles. It is not reported in the final estimations because it proved statistically insignificant in all exploratory regressions of model 2 and is missing in many of our sample firms.

Finally, we include year, industry, and country dummies based on parent-level data in our estimation of Regression Equation 2. For industry effects, we use two-digit SIC codes (13 for Oil and Gas Extraction, 28 for Chemicals and Allied Products, 29 for Petroleum and Coal Products, and 50 for Wholesale Trade-Durable Goods). We base country dummies on parent company's home country.

Statistical method

As discussed above, we estimate Regression Equation 2 using RPM regression methods (e.g., see Chung and Alcácer, 2002; Greene, 2004; Layton and Brown, 2000; McFadden and Train, 2000; Revelt and Train, 1998; Train, 1998, 2003). The RPM provides a distributional characterization of the relationship between our independent variables and performance, the estimated mean, and the estimated standard deviation across firms, which is assumed to follow a normal distribution $\delta_j^x \sim N\left(\delta^x + \zeta_j^x, \sigma^2\right)$. In the case of the parameter associated with our intrinsic speed measure ($\Theta_{j,t}$), the common mean (δ^1) reveals the average impact of intrinsic speed capabilities on firm value. Additionally, the use of simulation within the random parameter model allows us to obtain firm-specific coefficient estimates (δ_j^1) in order to study the nature of the speed-performance relationship at the firm level.

We estimate the RPM using simulated maximum likelihood. For the simulation, we use 100 "smart" draws using the Halton sequence as in Greene (2001) (Halton draws avoid the "clumpy" draws that can occur with random draws and accelerate the convergence in the estimation process).

We allow five key independent variables to have random coefficients: our measure of intrinsic firm speed capabilities, Blockholding, R&D intensity, leverage, and the intercept. Our interest focuses on the mean and standard deviation estimates for the firm intrinsic speed capabilities random coefficient. These estimates allow us to infer whether intrinsic firm speed capabilities create value for firms on average (based on the significance of the mean estimate δ^1) and whether firm heterogeneity plays an important role in the relationship (based on the significance of the standard deviation estimate). The random intercept acts as a random effect, addressing concerns regarding possible forms of omitted firm heterogeneity. The other three key control variables (Blockholding, R&D intensity, and leverage) are standard controls for Tobin's q regressions and also allow us to examine how different kinds of firm heterogeneity covary in their valuation. Accordingly, we allow the random parameters in our model to be freely correlated. The underlying issue is the *correlation* between the *coefficients* in the random parameter estimation of these five variables, i.e., the correlation of δ_j^1 and δ_j^2 in Regression Equation 2 and as depicted in P2b. We describe the details below.

First, we expect the regression random coefficients δ_j^1 of the speed proxy and δ_j^2 of corporate governance (Blockholding) to covary *negatively*. For well-governed firms, further incremental improvements to their governance practices enhance firm value little (δ_j^2 is lower). At the same time, for these well-governed firms, speed is also less driven by suboptimal behavior and more a function of intrinsic speed capabilities. In addition, intrinsic speed capabilities will be more often applied in optimally chosen projects. Therefore, our intrinsic speed proxy should have a larger positive relationship with firm value (δ_j^1 is higher).

Second, we expect the covariance between the coefficient δ_j^1 of the intrinsic speed proxy and δ_j^2 of firm leverage to be positive. Leverage directly affects unobserved heterogeneity in firm discount rates. Debt erodes firm value more (i.e., the negative effect of leverage on firm value is exacerbated) for firms facing greater liquidity constraints and higher external cost of capital; for these firms the leverage regression coefficient is more negative. But these firms also typically have a higher discount rate, which lowers project investment profits and thus reduces the value of investment speed—that is, the speed coefficient δ_j^1 is also lower.

Third, we expect the coefficients of intrinsic speed and R&D intensity to covary positively. To the extent that larger value created by R&D investments correlate with successful product or process innovation, more innovative firms should also benefit more from intrinsic speed capabilities. This is because they can then speed up plant development at controlled cost to capture returns from their successful innovations early; intrinsic speed capabilities and R&D efficacy thus have a synergistic relation.

Since the random parameters are allowed to be freely correlated, we obtain and report the random parameters covariance matrix Ω_δ. Our estimation produces the Γ matrix, where Γ is a lower triangular Cholesky factor of the random parameters covariance matrix ($\Omega_\delta = \Gamma\Gamma'$). While the elements of Γ have no direct interpretation, it allows us to determine whether a correlated RPM is a more appropriate econometric specification than an uncorrelated RPM by looking at the significance of the elements of Γ. Specifically, if the off-diagonal terms of the Γ matrix are significant, an uncorrelated RPM would result in model misspecification. We proceed to determine the significance of (1) the estimated standard deviations of the random parameters, and (2) the estimated covariance terms between the random parameters. We use the delta method to calculate the asymptotic standard errors of the estimated (co)variance of each parameter: (1) with the function $f = \sqrt{\Gamma(i) * \Gamma(i)'}$ for the estimated standard deviations ($\Gamma(i)$ is the i^{th} row of the Γ matrix); (2) with the function $f = \Gamma(i) * \Gamma(j)'$ for the ij^{th} estimated covariance term. The delta method uses a Taylor series approximation to the asymptotic standard errors of the standard deviation and covariance terms, which

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by construction are functions of several random variables (the elements of Γ).

Finally, the RPM also allows us to obtain firm-specific coefficients in the speed-performance relationship. The use of simulation allows for the estimation of firm-specific parameters using Bayes' theorem (Greene, 2004). These firm-specific parameters enable vivid comparisons across firms and allow us to empirically identify firms that excel or lag in intrinsic speed capabilities. These firms should, then, become natural candidates for in-depth case study analyses.

ESTIMATION RESULTS

We present descriptive statistics and correlation matrices for our variables in Tables 1–3. All variables show substantial empirical variation. The mean and standard deviation of project development time for the 2,659 plant investments in our dataset are 20.796 and 14.584 months, respectively (with a maximum of 109 months). Tobin's q also varies widely by more than one order of magnitude (i.e., a factor of 10) during the period of analysis and positively correlates with firm speed, which suggests that faster firms generally have higher firm value.

We proceed to our multivariate analyses. We first use OLS to estimate our Regression Equation 1 and then use the residuals to produce the firm-level proxy for intrinsic speed capabilities. These first-stage results are presented in Table 4. We find that the multivariate OLS regression results of Equation 1 are consistent with our theoretical predictions. Table 4 uses WACC as the discount rate, but similar results were obtained using EBIDA.

As expected, the revenue (GDP rate) elasticity of development time is negative and significant ($\beta_3 = -0.553, p < 0.1$ for the complete sample). Greater forecasted project revenues (or foregone revenues from investment delays) give firms more incentive to compress time in project development. Also, as predicted, the elasticity of development time with respect to the stock of physical resources (equipment) needed to build a plant is positive and highly significant ($\beta_2 = 0.053, p < 0.01$ for the complete sample). Firms take longer to complete larger investment projects. On average, reducing the real GDP annual growth rate by one percentage point slows down investment projects by more than fifty days. An equivalent investment deceleration would only be achieved by more than tripling project size. As for the effect of complexity on development time, inferences can only be made for projects in the refineries subsample because

Table 1. Descriptive statistics and correlation matrix for the first-stage regression (complete sample)

Variable	Number of observations = 2,659				1	2	3	4	5
	Mean	*S.D.*	Minimum	Maximum					
1 $T_{\mathbf{f,i},t}$	20.796	14.584	3.033	108.767	1.000				
2 EBIDA	0.128	0.011	0.109	0.151	0.086	1.000			
3 WACC	0.050	0.012	0.032	0.074	0.018	0.936	1.000		
4 GDP rate	0.041	0.039	−0.131	0.179	0.066	0.294	0.286	1.000	
5 Capacity (10^6 units)	0.307	4.694	0.000	182.5	−0.007	−0.026	−0.013	−0.004	1.000

Table 2. Descriptive statistics and correlation matrix for the second-stage regression (Blockholding sample)

Variable	Number of observations = 151				1	2	3	4	5
	Mean	*S.D.*	Minimum	Maximum					
1 Tobin's q	1.306	0.504	0.276	3.003	1.000				
2 Speed	0.047	0.752	−1.626	1.991	0.124	1.000			
3 Blockholding	11.975	13.476	0.000	50.293	−0.125	0.058	1.000		
4 R&D intensity	0.007	0.012	0.000	0.052	0.171	0.087	0.155	1.000	
5 Leverage	0.213	0.118	0.012	0.637	−0.371	0.044	0.527	−0.036	1.000

Table 3. Descriptive statistics and correlation matrix for the second-stage regression (S&P score sample)

	Number of observations = 198								
Variable	Mean	*S.D.*	Minimum	Maximum	1	2	3	4	5
1 Tobin's q	1.247	0.526	0.447	3.102	1.000				
2 Speed	0.072	0.760	−1.281	2.732	0.040	1.000			
3 S&P score	59.005	17.785	18.000	84.000	0.302	−0.113	1.000		
4 R&D intensity	0.007	0.013	0.000	0.069	0.068	0.048	0.237	1.000	
5 Leverage	0.183	0.113	0.000	0.517	−0.230	0.058	−0.385	−0.130	1.000

Table 4. First-stage OLS regression results of the determinants of project completion time ($\ln \widetilde{T}_{\mathbf{f,i},t}$)

Variable	Refineries subsample	Complete sample
Constant	1.924***	2.091***
	(0.140)	(0.190)
Complexity (ln)	0.034*	—†
	(0.019)	
Capacity (ln)	0.034***	0.053***
	(0.013)	(0.008)
GDP rate	−0.863**	−0.553*
	(0.429)	(0.331)
Industry dummies	Yes	Yes
Number of observations	1,357	2,659
F-test for model	10.72***	17.33***
R^2	0.120	0.106
Adjusted R^2	0.109	0.100

Standard errors are reported in parentheses.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; †unavailable for complete sample

complexity data is only available for refineries. Within this subsample, technological complexity slows down investments (as hypothesized) by an elasticity factor comparable to that of capacity. However, this effect is shown to be marginally significant or statistically insignificant ($\beta_1 = 0.034, p < 0.1$ for the refineries subsample). One possible explanation for this result is that project complexity matters less when firms already possess much of the technical knowledge in-house, a likely case when most firms are incumbents in a mature industry such as oil and gas. Since restricting our dataset exclusively to refineries would leave us with an unreasonably small final sample (after merging with Compustat-CRSP financials), we proceeded by excluding the complexity measure from the first-stage estimation and used the entire dataset observations (i.e., refinery, petrochemical, and GTL projects).

Using the residuals from our first-stage results, we construct our measure of intrinsic speed capabilities. Figure 1 graphically shows that our speed measure has substantial variation in project and firm speed for the 2,659 investments by the 847 oil and gas firm subsidiaries in our sample from 1996 to 2005. The distribution of the estimated speed residuals from Regression Equation 1 exhibits positive skewness, with the model firm and project being slower than the industry average. While firms accelerated investments up to five standard deviations above the industry norm, they were never more than two standard deviations slower than the industry. By construction in our model, the speed residuals in Figure 1 represent the joint distribution of speed capabilities and speed suboptimization across projects and firms in our dataset. Assuming that speed capabilities are normally distributed in the population of oil firms, the positive skewness in Figure 1 is suggestive of suboptimal project acceleration. We would expect that deliberate speed suboptimization is more likely to be biased towards excessive project acceleration than deceleration because of the extensive foregone revenues typically associated with delays in investment projects in the oil and gas industry. The estimates in Figure 1 confirm this expectation.

We then conduct our second-stage estimations of Regression Equation 2 using a linear random parameter model with freely correlated coefficients. These results are presented in Table 5 using WACC industry discount rate and the Blockholding corporate governance measure (similar results were obtained with EBIDA and S&P Score). All common mean coefficients across firms reported in the second column of Table 5 have the predicted sign and are very significant (at the 1% level). In particular, the coefficient for our proxy for intrinsic firm speed capabilities (δ^1) is positive, which suggests that possessing intrinsic speed

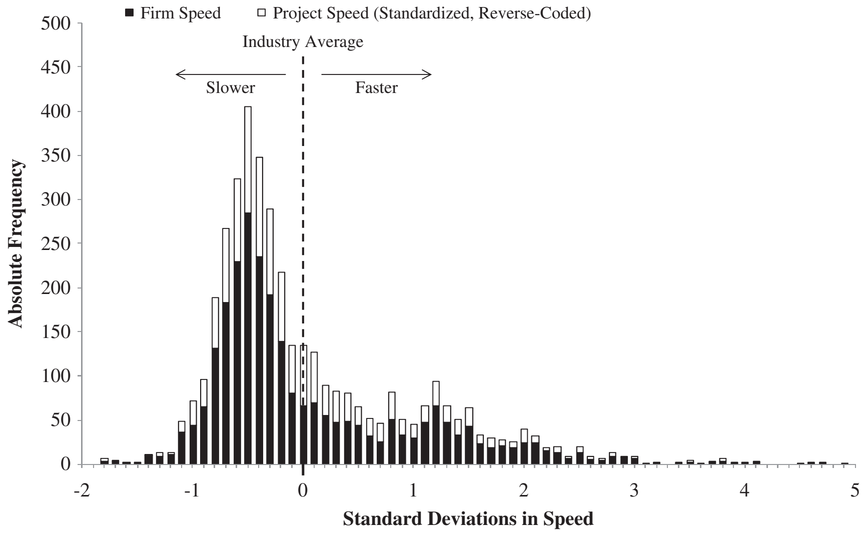

Figure 1. Firm speed ($\Theta_{j,t}$) and standardized, reverse-coded project speed ($-\left(\theta_{\mathbf{f},\mathbf{i},t}-\overline{\theta}_{\mathbf{i},t}\right)/\sigma_{\mathbf{i},t}$)

capabilities boosts firms' market value, as captured by Tobin's q; the result supports P1. Firms with higher intrinsic speed capabilities can accumulate more quickly the technological knowledge and physical resources required to bring new oil plants online at low costs. The magnitude of this effect is shown to be considerably large. On average, accelerating a firm's investments by 5 percent (or one month) below the industry norm due to organizational capabilities increases market value by \$214.3 million, which is about 1 percent of the asset value of an average oil firm.[6]

The mean parameter associated with the Blockholding variable (δ^2) is positive, a finding consistent with the financial economics literature. Firms with high institutional Blockholding are more efficiently monitored and thus better managed, which results in higher firm value (Gompers and Metrick, 2001). The other control variables also behave as expected. A firm's R&D intensity boosts a company's market value indicating that R&D is an intangible asset stock. Firm leverage is associated with lower values of Tobin's q suggesting that greater than average leverage raises the cost of capital. Note that we have industry and year dummies in our regressions, and they are generally significant.

All random parameters in the estimation of Regression Equation 2 have very significant estimated standard deviations (at the 1% level), as shown in the last column of Table 5. This offers compelling evidence that there is unobserved firm heterogeneity so that the impact of the independent variables on firm value (Tobin's q) varies across firms, which supports P2a. The improvement in fit of the RPM versus the corresponding OLS model, measured by a likelihood ratio test, is highly significant ($\lambda = 57.998, p < 0.005$ for χ^2_{16}). Thus, the RPM specification is preferable to assuming fixed coefficients in our model. Critically, for the same proxy value for intrinsic speed capabilities, different firms will experience a different impact on their respective market value. We did a centipede plot that represents 95 percent confidence intervals and point estimates for the individual speed parameters of the 51 firms in our sample. These estimates indeed indicate high variations on firm value when a firm accelerates investments.

Very importantly, the implied covariance terms of the random parameters in Table 6 provide further evidence of how unobserved firm heterogeneity influences the effect of speed on firm

[6] From Regression Equation 1, we have that $\partial\theta_{\mathbf{f},\mathbf{i},t}/\partial T_{\mathbf{f},\mathbf{i},t} = re^{-rT_{\mathbf{f},\mathbf{i},t}}/\left(1-e^{-rT_{\mathbf{f},\mathbf{i},t}}\right)$. In our sample, for a hypothetical oil firm that owns one investment project per industry $\mathbf{i}$ at time t, a simultaneous identical acceleration in all of its projects relative to each industry $\mathbf{i}$ affects firm speed by $\partial\Theta_{j,t}/\partial\theta_{\mathbf{f},\mathbf{i},t} = -\sum_{n,\mathbf{i}}\left({}^{1}/_{\sigma_{\mathbf{i},t}}\right)/n_{j,t}$. The marginal variation in Tobin's q due to changes in firm speed for an average oil firm is given by the estimated common-mean coefficient $\delta^1 = 0.112$ (in Table 5). Finally, firm value varies with Tobin's q proportionally to a firm's replacement costs of tangible assets. Using the average asset value of \$26.151 BN for firms with financials from Compustat North America in the sample establishes the result.

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Table 5. Second-stage regression results of the effect of firm intrinsic speed on Tobin's q using a correlated random parameter model

		Elements of Γ					
Variable	Mean	Constant	Speed	Blockholding	R&D intensity	Leverage	*S.D.*
Constant	1.632***	0.525***					0.525***
	(0.103)	(0.031)					(0.031)
Speed	0.112***	0.051***	0.143***				0.152***
	(0.018)	(0.019)	(0.020)				(0.020)
Blockholding	0.004***	−0.000	−0.017***	0.003*			0.017***
	(0.002)	(0.001)	(0.002)	(0.001)			(0.002)
R&D intensity	8.268***	−8.378***	8.156***	−0.181	1.687		11.815***
	(1.806)	(1.275)	(1.554)	(1.261)	(1.185)		(1.464)
Leverage	−0.943***	−1.238***	1.574***	−0.585***	−0.403***	0.135**	2.129***
	(0.179)	(0.149)	(0.113)	(0.102)	(0.065)	(0.058)	(0.126)
Industry dummies	Yes						
Year dummies	Yes						
Number of observations	151						
Log-likelihood	−50.230						

Standard errors are reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6. Implied covariance terms of the random parameters

Variable	Constant	Speed	Blockholding	R&D intensity	Leverage
Constant	—				
Speed	0.027***	—			
	(0.010)				
Blockholding	−0.000	−0.002***	—		
	(0.000)	(0.000)			
R&D intensity	−4.396***	0.742***	−0.137***	—	
	(0.799)	(0.306)	(0.034)		
Leverage	−0.650***	0.162***	−0.028***	22.631***	—
	(0.110)	(0.043)	(0.004)	(3.579)	

Standard errors are reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

value. All but one covariance term are highly significant. A significant covariance term means that some of the underlying reasons for coefficient heterogeneity are shared by two independent variables. That is, if differences between firms simultaneously impact the effects of multiple independent variables on firm value, the marginal effects of these variables are correlated across firms.

The implied correlations of the coefficients in Table 6 conform to our theoretical expectations as in P2b. We focus on the correlations discussed in the statistical method section, that is, the covariances associated with the coefficient of our focal independent variable—the proxy for firm intrinsic speed capabilities. This proxy and the corporate governance (Blockholding) parameters covary negatively, as expected. This indicates that better-governed firms benefit less from additional monitoring and more from being intrinsically faster. Also, the parameters associated with the proxy for intrinsic speed capabilities and leverage correlate positively. A firm for which debt has a more negative impact on firm value generally faces more severe liquidity constraints—thus, more debt drives up the cost of capital which, in turn, increasingly erodes the benefits from investment speed. Finally, the intrinsic speed and R&D intensity parameters covary positively. Firms that create more value by investing in R&D have high innovative efficacy. The positive correlation indicates that firms that create more value from R&D investment also benefit more

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from intrinsic speed capabilities, which allows fast capitalization on successful innovations. Thus, innovative efficacy and intrinsic speed capabilities are complementary.

Finally, we note here that, in our second-stage RPM regression, the intercept is random; it picks up unobserved firm heterogeneity that stems from systematic differences in a firm's environment not already captured by the included firm-level characteristic variables. This random intercept will essentially capture these effects on a firm's Tobin's q, and our RPM treatment allows these effects' impact on Tobin's q to be linked to different marginal effects of speed on firm performance. Table 6 shows that the more these effects raise a firm's Tobin's q, the more the firm benefits from intrinsic speed capability.

This information on the factors that qualify the value of intrinsic speed provides useful managerial pointers on when it pays off to invest in intrinsic speed. For example, firms with higher cost of capital will likely benefit less from investing in speed capabilities; firms whose poor governance makes it hard to implement projects according to schedule should also benefit less from intrinsic speed. At the same time, firms that benefit more from R&D investment would also benefit more from developing intrinsic speed capabilities (and vice versa).

ROBUSTNESS CHECKS

We conducted many robustness checks on our first- and second-stage regressions, as follows. First, we checked robustness pertaining to the variables in the first-stage regression. We find that our results are robust to the choice of discount rates: using WACC or EBIDA as the industry discount rate produced identical results. We constructed alternative measures of project complexity. Since technology is essentially standardized by industry subsector, we constructed a more refined set of project dummies capturing different project types within refineries (simple, complex, and very complex), petrochemicals (olefins—or the basic building blocks of the industry, first and second generation derivatives, plastics and resins compositions such as thermoplastics, thermosets, and fibers, and a final category including all other types of petrochemicals) and gas-to-liquids. Along the same line of thought, expansion and greenfield investments may have different levels of complexity. We constructed a dummy to identify expansion versus greenfield investments. Across all regressions, the new dummies created came out not significant.

We then turned to sampling issues. We found that restricting our sample exclusively to the refinery subindustry observations (where complexity data is available) also did not change the estimations for the key variables of interest. We collected OGJ data on all subcontractors that firms used in each stage of plant development and then reran Regression Equation 1; adding variables representing the use of subcontractors did not qualitatively change our results (we did, however, lose significance in the corporate governance measure, possibly reflecting lower agency costs with the involvement of additional contracted parties involved in the project).

Considering the statistical integrity of regressions, we first worried about important missing variables. We included uncertainty in project revenues, defined as the standard deviation of four years' worth of the GDP growth rate prior to the year under consideration. The variable was not significant. This may be due to the maturity of the oil industry since the 1980s, where "demand forecasts reflect a strong consensus, the difference between the highest and lowest of less than 10 percent. This compares with the 100 percent difference which was prevalent in the 1970s" (*Chemical Insight*, 1987).

Our findings were also robust to the inclusion of year dummies (together with industry dummies), with the exception of the GDP Growth Rate that turned insignificant. The latter result occurs because the GDP growth rate only varies per industry and over time.

Finally, we examined endogeneity in the first-stage regression. The fact that project characteristics (e.g., capacity) are endogenously chosen by firms suggests the possibility that these variables can be contemporaneously correlated with firms' speed capabilities and thus the error term. However, the Hausman test rejected this hypothesis (after estimating model 1 with instruments for project-specific variables).

We proceeded to explore the robustness of our second-stage results by examining alternative variable definitions, econometric specifications, outliers problems, reverse causality, and sample selection bias.

The findings in our estimation of second-stage regression are not qualitatively affected by adopting any of the various modified estimations of firm speed in Regression Equation 1 described in the previous paragraphs. Likewise, using the alternative measure of corporate governance (S&P Score) did not fundamentally change our results.

We explored alternative econometric specifications by using multivariate OLS with standard errors robust to clustering by firm instead of random parameter regressions. Our results stayed broadly consistent across both econometric specifications, with similar estimates across the common-mean coefficients. The Blockholding variable became insignificant, which could indicate that the impact of Blockholding on firm value varies across firms—another justification for using the RPM model. Besides being statistically more appropriate, the RPM provides richer information as we have reported in the previous section.

The value of intrinsic capability may be specific to a firm's country environment. To deal with this, we introduced home country dummies in the second-stage regression. Our results did not qualitatively change.

Our estimation results were also robust to an analysis of speed outliers. Only two firms were identified as potential outliers influencing our regressions; their exclusion did not change the main results of the paper.

We explored the possibility of reverse causality in interpreting our second-stage regression. Given the substantial time lags involved in each facility, potential endogeneity from contemporaneous reverse causality wherein firms rush to finish fast as the market value of their investment soars should not be an issue in the current specification of our model. To explore the possibility of lagged reverse causality, we also ran several multivariate OLS regressions where firm speed was regressed on lagged Tobin's q (and controls). We did not obtain any significant statistical results.

Finally, we examined a possible sample selection bias. To do so, we studied the pool of all U.S. firms listed in the Compustat-CRSP Merged database as oil companies in 2000 and found that the majority (between 67 and 78%) of oil firms invested in an oil facility from 1996 to 2005. Moreover, the market capitalization (in 2000 dollars) of firms with at least one project in our OGJ investment dataset was 97.8 percent of the total market capitalization of all U.S. oil companies in 2000. Hence, most oil companies invested during the period of analysis and those that did not were very small (mostly private) firms, suggesting that our OGJ database constitutes a relatively complete and inclusive company investment sample.

DISCUSSION AND CONCLUSIONS

This paper examines the speed issue—the time it takes to complete an investment project. Most would intuitively agree that speed is desirable, and yet firms should recognize the cost associated with it. Few would disagree that speed is valuable. We push the discussion to a deeper level.

Our premise is that it is a firm's intrinsic speed capability—rather than its speed relative to industry competitors per se—that matters. Firms with superior intrinsic speed capabilities accumulate and deploy the physical and intangible resources needed for project investment faster and at less cost than rivals. Intrinsic speed capabilities are a competitive advantage and augment firm value. As a competitive advantage that strengthens a firm's front-end competitiveness, intrinsic speed capabilities have a synergistic relationship with other firm-level characteristics. For example, the value of intrinsic speed capabilities rises with a firm's R&D innovation capability and with its ability to control cost of capital and to contend with agency behavior. As such, the value of intrinsic speed capabilities varies across firms.

Empirical validation of these ideas can be challenging because observed project completion speed is project and location specific besides being influenced by other firm-level factors. As well, the relationship between speed and firm value ought to vary across firms. We overcome these challenges by developing a proxy for intrinsic speed capabilities by integrating firms' speed tradeoff in a reduced-form model of investment acceleration in oil and gas facilities worldwide (1996–2005). We then find empirical support for our proposition using a random-parameter model using data from oil and gas facilities worldwide (1996–2005).

This paper contributes to the strategy literature on strategy dynamics and firm capabilities in several ways. From a technical standpoint, we clarify that the driver of speed advantage is intrinsic speed capabilities and then advance an empirical proxy. We examine its relationship with firm value

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using an appropriate empirical methodology, random parameter regression models. Consequently, we can credibly account for and explore firm-level heterogeneity in the relationship between intrinsic speed capabilities and firm value. The correlations between the random regression coefficients for our proxy for intrinsic speed, corporate governance, cost of capital, and innovation capabilities conform to theoretical expectations and thus validate the sources of speed capabilities' value. Furthermore, our results are robust to outsourcing arrangements, which suggests that intrinsic speed capabilities are imperfectly tradable assets and thus, indeed, a source of firm-specific competitive advantage.

From a nontechnical perspective, attaining empirical and conceptual clarity on speed capabilities is useful in the field of strategy for several reasons. First, speed is a relevant consideration when firms try to race ahead of competitors in any strategic goal—be it the pursuit of competitive advantage, industry leadership, or technology and plant development. Understanding the tradeoff between the benefits and cost of being fast can help us to avoid erroneous estimation of the expected returns from being fast, leading to over-acceleration in investment and suboptimal capital allocation decisions.

Second, our results help clarify that the benefits of speed are limited by the extent of a firm's intrinsic speed capabilities. It also elevates the concept of speed from a project-level issue to a firm-level competitive advantage issue. Our results usefully highlight the complementarity of intrinsic capabilities as an intangible, with good corporate governance, ability to successfully innovate, and ability to contend with the cost of capital. Thus, the value of speed builds on the contributions of a firm's fundamental capabilities. These synergistic relationships validate as well as expose the nature of intrinsic speed capabilities as a competitive advantage. Moreover, they suggest interesting considerations when investing to develop these intangibles.

Third, seeing intrinsic speed capabilities as an intangible also helps us understand the role of speed in strategic investment timing. In particular, it leads us to appreciate the concept of a fast mover. Being able to enter new markets more rapidly than rivals, a firm can afford to wait longer for market uncertainty to be resolved. This highlights an important distinction between *first*-mover advantages and *fast*-mover advantages. Being fast allows a firm not to be first, while still reaping the benefits of early entry. We thus shed light on the long-standing mixed empirical results on the existence of first-mover advantages (e.g., Franco *et al.*, 2009; Lieberman and Montgomery, 1988, 1998; Mitchell, 1991).

We believe that there are many unexplored strategy issues related to firms' intrinsic speed capabilities. Several possible conjectures follow. For example, we speculate that firms with high intrinsic speed capabilities may belong to the oft-quoted category of "successful innovators." As fast movers, these firms do not need to pioneer new markets with original innovations; rather, they can quickly learn from precedent and implement other firms' best—and proven—innovations. Furthermore, we speculate that intrinsic speed capabilities are effective in deterring new market entry because fast movers can leapfrog would-be imitators, thereby reducing the returns to new market entry. These speculations await further theoretical development and empirical tests.

The limitations of this paper are as follows. First, our analysis is limited to firms with publicly available financial data. An exploration of the returns from speed for private firms would reveal further useful information. Second, the magnitude of the effect of intrinsic speed on firm value reported in this paper typifies mature industries, such as oil and gas. In growing markets, the potential foregone profits from delaying investments tend to be greater, and thus the benefits of intrinsic speed may be even more noticeable. It is unclear how other structural characteristics of an industry (e.g., the rate of technological innovation, market structure, the degree of outsourcing and subcontracting) or strategic interactions among firms (e.g., preemption, pricing, or innovation games) calibrate the impact of intrinsic speed capabilities on firm value. More generally, it would be useful to develop further more fine-grained understanding of the market and firm-level determinants of the value of intrinsic speed capabilities.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. Model derivation.