Speed and Tobin’s q

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Slow execution of investment projects often means substantial revenue losses for companies. However, accelerating investments generally results in higher investment costs. Our paper integrates this investment speed tradeoff in a reduced-form model of project development to create an empirical proxy for firm speed. We examine how deviations from industry-average speed in the execution of large investments in oil and gas facilities worldwide from 1996 to 2005 affect firm value, as measured by Tobin’s q. We find substantial variation in investment speed among firms in the oil and gas industry. Using a linear correlated random parameter model to allow for unobserved firm heterogeneity, we show that firms’ speed capabilities have high market value. On average, accelerating a firm’s investments by 5% (or 1 month) relative to the industry norm due to organizational capabilities increases market value by $214.3 million. Additionally, we show that the effect of speed on firm value varies widely among firms and is amplified by good corporate governance but often mitigated by the level of firms’ debt.

Key words: time-based competition; speed capabilities; strategy dynamics; firm value; project management; correlated random parameters

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1. Introduction

“Is Your Company Fast Enough?” asked a recent cover of BusinessWeek (Hamm 2006). "If the 1980s were about quality and the 1990s were about reengineering, then the 2000s will be about velocity” and “everybody must realize that if you don’t meet customer demand quickly enough (…), a competitor will” (Microsoft’s Chairman Bill Gates, in Gates 1999: p. 143). Indeed, “a good idea for a new business tends not to occur in isolation, and often the window of opportunity is very small. So speed is of the essence” (Virgin Group’s Founder Richard Branson, in Hamm 2006: 70). Recent empirical evidence shows that the time interval between the commercial introduction of a new product and rival imitation has substantially decreased over the last century (Gort and Klepper 1982, Agarwal and Gort 2001). Firms have also reportedly enjoyed increasingly shorter periods of persistent superior economic performance over time (Ghemawat 1991, Waring 1996, Wiggins and Ruefli 2002, 2005). Competition has created a race to take on new market opportunities swiftly and achieve economies of scale early in the industry life cycle, while prices are still relatively high (e.g., Jovanovic and MacDonald 1994). Speed is, thus, an important metric of firm performance in strategy practice.

Despite its managerial relevance, the speed of execution of investment projects has received insufficient attention in strategy research. Some scholars have argued that speed is beneficial because firms that are slow to execute investment projects often incur substantial revenue losses (Eisenhardt 1989, Stalk and Hout 1990, D'Aveni 1994, Teece et al. 1997, Smith and Reinertsen 1998). Other researchers, though, have asserted that speed is detrimental, as accelerating investments generally results in higher investment costs (Scherer 1967, Mansfield 1971, Dierickx and Cool 1989, Graves 1989). Hence, an important unresolved empirical question remains: do deviations from industry-average speed improve or deteriorate overall firm performance? More fundamentally, can some firms profitably move faster than others and, if so, to what extent and why?

In this paper, we consider the execution speed of investment projects a product of firm choice and, thus,
endogenous to our analysis. In particular, we investigate the microdeterminants of investment speed and the heterogeneous impact of firm speed on performance, as measured by Tobin’s q. We build on the growing body of work on dynamic capabilities, time-based competition, and time compression diseconomies from strategy, economics, and operations research (for a review, see Graves 1989, Stalk and Hout 1990, Teece 2007). By doing so, we directly integrate these (thus far) largely disconnected concepts and make them concrete in an empirical setting.

The worldwide oil and gas industry from 1996 to 2005 comprises the empirical setting of this study. In this industry, the speed of investment in new oil plants can have a significant effect on firm performance – the loss of a single day’s revenue to plant construction delays, for example, can cost a company hundreds of thousands of dollars. In addition, the oil and gas industry represents an appropriate setting for this study because the trade press publicly reports data on project execution speed.

We show that there is substantial heterogeneity in firm speed during the period of analysis. We then estimate our main econometric model using linear correlated random parameter regression to allow unobserved firm heterogeneity to moderate the effect of the independent variables on Tobin’s q. We find that accelerating investment projects relative to the industry average substantially increases firms’ market value, especially when speed results from firms’ superior capabilities. Good corporate governance amplifies this effect of speed on firm performance by limiting the extent of suboptimal project acceleration. The returns from speed are reduced for firms that experience greater value erosion from debt and face higher discount rates. Finally, and most importantly, the market value of speed varies widely among firms. We used the random parameter model to estimate firm-specific coefficients that measure the value associated with a firm’s idiosyncratic speed capabilities. This methodology - underused in the field of strategy – offers a powerful engine to empirically assess firm heterogeneity and provide large sample support to case study analyses.

The paper proceeds as follows. The next section reviews the extant literature and introduces the fundamental tradeoff that firms face when deciding project investment speed. Next, we integrate this speed tra-
deoff in a reduced-form model of project development time to create an empirical proxy for firm speed and derive its effect on performance. We proceed to describe our sample, variables, and estimation methodology before testing our model in the context of the worldwide oil and gas industry. Finally, we check the robustness and consider the implication of our results, and we close with a discussion of suggested avenues for further investigation.

2. Prior Literature: The Investment Speed Tradeoff

The strategy literature has extensively emphasized the importance of time and timing decisions for a firm to gain competitive advantage. However, past contributions have not provided an integrated empirical analysis of the effect of investment speed on firm performance. Indeed, most prior work has either focused on aspects of time other than speed (in particular, entry timing and first-mover advantages) or offered only one-sided views (benefits vs. costs) of the project acceleration decision problem.¹

2.1 The Benefits of Speed

Firms that compete to develop valuable projects (product, service, technology) generally experience foregone revenues from delays in project development. For example, postponing the launch of a $10,000 car costs the automotive industry a daily expected $1 million loss in net revenues (Clark 1989); the PC industry saw an approximately $1.1 million per day revenue loss with the late introduction of the HP 930 computer (Waldman 1986). This opportunity cost of slower speed in the execution of investment projects also has a direct impact on a firm’s market value: delay announcements in new product introduction decrease firm market value by 5.25% (or $-119.3 million in 1991 dollars), on average (Hendricks and Singhal

¹ The research on first-mover advantages has examined the profit implications of a firm’s order of entry into a market. Theoretical contributions have generally assumed away firm differences in investment speed to ensure the analytical tractability of the underlying models (for a review, see Hoppe 2002). In this line of work, project “development is assumed to take place instantaneously” (Katz and Shapiro 1987: 405) and, thus, makes firm investments immediately productive (e.g., Reinganum 1981, Carpenter and Nakamoto 1990, Fershtman et al. 1990, Maggi 1996). Similarly, empirical contributions have mostly been “interest[ed] (…) in looking at profit differences between pioneers and followers solely attributable to the timing of market entry, and not differences due to other characteristics (e.g., resources) of pioneers and followers”, although “in all likelihood (…) firms’ resources and capabilities affect the choice of entry timing” (Boulding and Christen 2003: 372). Thus, firm heterogeneity in speed capabilities and its impact on the endogeneity of first-mover opportunities have also been overlooked empirically (for a review, see Lieberman and Montgomery 1988, 1998).
1997). These findings illustrate the penalties of lengthy project development and, thus, stress the benefits of firm speed.\(^2\)

Firm speed in the execution of investment projects matters particularly in the context of new market entry and rapidly changing competitive landscapes. Fast firms can afford to wait for demand or technical uncertainty to subside before investing and then quickly respond to business opportunities. These ideas have been discussed at length in the dynamic capabilities (Teece et al. 1997, Helfat et al. 2007, Teece 2007) and time-based competition literatures (Stalk 1988, Stalk and Hout 1990).\(^3\) However, these research streams have often overlooked the costs of investment speed, which we now describe.

### 2.2 The Costs of Speed

The speed of execution of investment projects intrinsically depends on a firm’s *internal pace* of resource accumulation. Strategic projects that support privileged market positions require the commitment and deployment of valuable and rare firm-specific resources to product markets (Barney 1991, Ghemawat 1991). These firm-specific resources cannot be instantaneously purchased on strategic-factor markets, but must be internally accumulated by firms over time (Barney 1986, Dierickx and Cool 1989).

Firms’ internal pace of resource accumulation is generally subject to time compression diseconomies: reducing project duration often raises costs, and more severe compressions are purchased at increasingly higher costs (Scherer 1967, Boehm 1981, Scherer 1984, Dierickx and Cool 1989). Early estimates of this time-cost tradeoff indicate that, on average, a 1% acceleration in project development time inflates investment costs by 1.75% (Mansfield 1971).\(^4\)

Several possible explanations exist for time compression diseconomies. Speeding up a project usually

\(^2\) Delay announcements may also signal unanticipated technical problems with projects, which affect market value independently of the magnitude of revenue loss during the delay.

\(^3\) See also the literature on time-pacing (Brown and Eisenhardt 1998, Eisenhardt and Brown 1998), red queen competition (Barnett and Hansen 1996, Barnett and Pontikes 2008), system dynamics (e.g., Lenox et al. 2007), and innovation and technology timing (Mitchell 1991, Salomon and Martin 2008, Katila and Chen 2009).

\(^4\) In addition to the time-cost tradeoff, accelerating investments may also lower the final quality of a project, particularly in the context of new product development (Cohen et al. 1996). However, the effect of speed on project quality matters less in the empirical setting of our paper, where building oil and gas facilities must meet rigorous technical performance standards at the end of the construction process and before market operations start.
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.

Conceptually, time compression diseconomies equate to the notion of strictly convex adjustment costs in economics (Lucas 1967, Gould 1968). The operations research literature has also extensively examined this time-cost tradeoff (e.g., Graves 1989). However, most studies of time compression diseconomies omit a complete characterization of a firm’s investment speed tradeoff, as they overemphasize the cost-side of the project-acceleration decision problem.

3. An Applied Reduced-Form Model of Investment Speed

We now derive the econometric model to be estimated empirically. In §3.1, we integrate firms’ investment speed tradeoff in a reduced-form model of project development to create an empirical proxy for firm speed. In §3.2, we develop a random-parameter model to examine how deviations from industry-average speed in project execution affect firm performance.

3.1 Suboptimal Acceleration and Deceleration with Heterogeneous Capabilities

In this subsection, we use the basic structure of Pacheco-de-Almeida and Zemsky's (2007) continuous-time model of investment speed, the first formal analysis of investment speed entirely consistent with our work. The authors treat speed as a product of firm choice, where the benefits and costs of speed depend on product-market dynamics and time compression diseconomies.

However, we go well beyond Pacheco-de-Almeida and Zemsky (2007) in three main ways. First, we relax the assumption of profit-maximizing firms to allow for the possibility of suboptimal project acceleration, which is more realistic empirically. Second, we introduce firm heterogeneity in speed capabilities, which is consistent with most prior strategy literature (e.g., Stalk and Hout 1990, Teece 2007). Third, we customize the structure of our model to reflect some of the key empirical regularities of the setting where
it will be tested, the oil and gas industry. For simplicity and tractability, we downplay the importance of strategic interactions among firms (e.g., preemption, pricing, or innovation games) in our analysis.

In our model, each firm must decide on its project development time, or how long it will take to build a new production facility \( f \) in industry \( i \) at time \( t \), which we denote by \( T_{f,i,t} \). Each production facility \( f \) represents the \( n^{th} \) \((n \geq 1)\) investment of firm \( j \) in industry \( i \), identified by the vector \( f = (j,n) \). Every industry \( i \) is defined by a different project type \( p \) (refineries, petrochemical plants, and gas-to-liquids plants) and geographical market \( g \), \( i = (p,g) \). The benefits and costs of faster project development are discounted at the cost of capital \( r > 0 \) and defined as follows.

The benefits of speed for firm \( j \) in industry \( i \) depend on project revenues. Once the new oil and gas facility \( f \) is brought on line (from \( t=T_{f,i,t} \) to \( t=\infty \)), the firm earns revenue flows \( \Delta_{f,i,t} \), where \( \Delta > 0 \). These revenues are net of all plant operation costs. We also assume that revenue flows are time-invariant so that \( \Delta_{f,i,t} = (\Delta_{f,i})^{\gamma} \) (where parameter \( \gamma \) is proportional to the revenue elasticity of development time) and sufficiently high to give firms incentive to develop the new oil and gas facility. There is no uncertainty about project payoffs, as oil and gas is a mature industry during the period of analysis (1996-2005).

The costs of speed exhibit time compression diseconomies: the faster a firm develops a plant, the greater its cost. In particular, firms’ investments at each point in time \( c_t, c_t \geq 0 \) are subject to diminishing returns such that each plant development project only progresses at a rate \( (c_t)^{\alpha} \) for some \( \alpha \in (0,1) \). In the oil and gas industry, investments in new facilities progress toward completion by going sequentially through three main phases: study and planning, engineering, and construction (see the Oil and Gas Journal Worldwide Construction Surveys, Pacheco-de-Almeida et al. 2008). In the first two phases (study/planning and engineering) firms accumulate intangible resources, primarily technological and managerial knowledge \( K_{f,i,t} > 0 \) that depends on the technical complexity of each project (e.g., feedstock processes, mechanical and piping engineering, electrical design). In the third and last phase of investment
in new production facilities (construction), firms accumulate and assemble the physical resources and equipment \( E_{t,i} > 0 \) to start production. 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.

Firms differ in their ability to amass rapidly the stock of tangible and intangible resources required to bring new oil plants online. 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, in Hawk 2008). 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., 1990, Ganapati et al. 2000). In this paper, we refer to these idiosyncratic organizational factors that allow firms to develop plants more quickly as *firm speed capabilities*.

We model firms’ speed capabilities in a certain project, \( d_{t,i} \in (0,1) \), as shifting a firm’s time-cost tradeoff such that, for a fixed level of expenditures, a more capable firm develops the project faster (or, for given development times, more capable firms build plants more efficiently).\(^5\)

We assume that firms’ initial choice to build a new plant with a certain capacity to produce a specific product by a certain date \( (T_{t,i}) \) – before the actual beginning of the development process – predetermines the two main types of resource stocks needed for the project (technological knowledge and equipment). For example, the National Cooperative Refining Association publicly announced in November 2002 the development of a new 30 MMcf/d hydrogen plant. This decision essentially defined, for the most part, the type of technology and equipment needed for the plant – therefore, at the time this decision was made, the

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\(^5\) Note that speed capabilities depend not only on (a) firm-specific resources that are likely to have remained stable over the period of analysis (e.g., a firm’s corporate culture), but also on (b) project-specific time-variant factors (e.g., cumulative technical experience in developing certain types of plants). The time-variant component of speed capabilities may partly reflect a firm’s dynamic capabilities (Helfat et al. 2007, Teece 2007). In fact, dynamic capabilities have often been referred to as "the capacity to [quickly] renew competences (...) required when time-to-market and timing are critical, [and] the rate of technological change is rapid" (Teece et al. 1997: 515; see also Stalk 1988, Stalk and Hout 1990).
firm also had a reasonably accurate understanding of the total amount of effort or progress that it needed to make to complete the project. Specifically, we assume that the total amount of progress or effort required to develop a new productive facility by time \( T_{t,i} \) is a Cobb-Douglas function of the two main types of resource stocks needed for the project (technological knowledge and equipment) and the level of firms’ capabilities such that

\[
\int_0^{T_{t,i}} (c_i) \, dt = A(1-d_{t,i})^{\beta_0} (K_{t,i})^{\beta_1} (E_{t,i})^{\beta_2}, \quad \text{where } A > 0 \text{ and } \beta_0, \beta_1, \beta_2 \geq 0.
\]

This functional form is consistent with the specification used on the ground by chemical engineers for investments in new plants. It allows for possible interactions between the project development phases (e.g., due to Front End Loading engineering-design processes) and allows for economies of scale from physical laws of investment (e.g., from the fact that the capacity of a pressure vessel can be doubled by using less than twice the surface area of steel). For tractability, we set \( \alpha = 1/2 \).

Under these assumptions, a profit-optimizing firm chooses the project development time that maximizes the difference between the benefits and costs of speed. We allow for suboptimal project acceleration or deceleration by including an observation-specific error around the optimal development time. Since project costs are empirically unobservable in our sample, we estimate a reduced-form econometric model conditional on firms’ decision to invest in an oil facility in industry \( i \) at time \( t \) (see Appendix A.1.)

\[
\ln \tilde{T}_{t,i} = \beta_0 + \beta_1 \ln K_{t,i} + \beta_2 \ln E_{t,i} + \beta_3 \ln \Delta_{t,i} + \theta_{t,i}\tag{3.1}
\]

, where \( \tilde{T}_{t,i} = (1-e^{-\lambda_{t,i}})/r \) and \( \beta_0 = -\ln A + \beta_0 \ln(1-d_i) \) are industry (product, geography) dummies.

\[\text{We measure heterogeneity in speed capabilities by changes in } d_{t,i}, \text{ not in } \alpha \text{ – for three main reasons. First, in our model, firms’ ability to experience lower diminishing returns (} \alpha \text{) during an investment project does not necessarily allow them to develop plants more quickly. This analytical property results from the specific functional form assumed for diminishing returns in our paper. In contrast, larger values of } d_{t,i}, \text{ denoting superior (in)tangible resources that confer firms a head start or a greater ability in plant development, have the desired effect of accelerating firms’ investments. Second, the alternative approach of letting } \alpha \text{ vary by firm is econometrically unappealing, as it produces an intrinsically nonlinear model for which there is not an obvious estimation strategy. The decision to parameterize } \alpha = 1/2 \text{ renders the model substantially more tractable. Finally, most anecdotal evidence in the specialized press appears to attribute speed capabilities to firms’ initial resource endowments, rather than to variance in diminishing returns to investment.}\]
Coefficients $\beta_1, \beta_2 \geq 0$ represent the elasticity of development time with respect to the stock of intangible resources (technological knowledge) and physical resources (equipment) needed to build a plant. The coefficient $\beta_3 = -\frac{\gamma}{2} \leq 0$ corresponds to the revenue ($\bar{\Delta}_{t,j}$) elasticity of development time. Intuitively, the more (intangible and physical) resources needed to develop an oil facility and the lower the project’s revenues, the longer firms’ take to bring new investments online. Although time compression diseconomies are not an independent variable in expression (3.1), they directly determine the specific functional form of our reduced-form model and the effect of resources and revenues on firms’ development time.

The error term $\theta_{t,j} = \varepsilon_{t,j} + \beta_0 \ln \nu_{t,j}$ captures two unobservable components of firms’ investments: (1) the degree of suboptimal speed (i.e., excessive acceleration or deceleration) in a specific project $\varepsilon_{t,j}$ and (2) the extent $\nu_{t,j} > 0$ by which a firm’s speed capabilities in a project fall above or below the industry average $d_i$, $\nu_{t,j} = \nu_{t,j} (1 - d_i)$ (such that $\nu_{t,j} < 1$ when $d_{t,j} > d_i$). The estimation properties of the error term $\varepsilon_{t,j}$ follow.

First, we assume that, on average, firms operating in the oil and gas industry from 1996 to 2005 chose their development time $T_{t,j}$ to maximize their projects’ profits, $E(\varepsilon_{t,j}) = 0$. 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. In addition, the growing worldwide energy crisis has forced firms to improve the level of efficiency of their operations.

Second, although we assume that, on average, oil firms optimize on investment speed, individual firms may be suboptimizing in specific projects at given points in time, $\varepsilon_{t,j} \neq 0$. Exogenous shocks in the
construction process (e.g., disruptions in the supply of third-party technical equipment) may lead to unexpected delays. Other investments may not be completed at their optimal scheduled time because of agency problems (Jensen and Meckling 1976, Jensen 1993). Managers may excessively accelerate “pet projects” or, alternatively, divert resources away from plant construction to other competing uses that generate higher private benefits at the expense of firm value. Managerial mistakes and bounded rationality may also cause suboptimal acceleration (Simon 1957, Cyert and March 1963, Bower 1970).7

Finally, firms’ time-based or speed capabilities \( d_{t,i} \) are typically unobservable in an empirical setting. Speed-based dynamic capabilities represent an intangible construct that depends on the “role of strategic management in appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competences” (Teece et al. 1997: 515). Therefore, firms’ speed capabilities affect the error term. Specifically, we have that \( E(\theta_{t,i}) = \beta_0 E(\ln v_{t,i}) \leq \beta_0 \ln E(v_{t,i}) = 0 \) because of Jensen’s inequality and the fact that \( E(v_{t,i}) = 1 \) (by construction). Since \( E(\theta_{t,i}) \leq 0 \), the ordinary least squares (OLS) estimates of the intercepts \( \beta_0 \) may be biased (but not the coefficients of the remaining variables).

The error term \( \theta_{t,i} \) constitutes our empirical proxy for project speed, or how much firms’ development time \( T_{t,i} \) deviates from the industry average, after controlling for project-specific characteristics.

### 3.2 The Effect of Speed on Performance

Nonzero project speed \( (\theta_{t,i} \neq 0) \) implies that firms differ from their industry average because they pursue suboptimal project acceleration or deceleration \( (\varepsilon_{t,i} \neq 0) \) or have idiosyncratic speed capabilities.

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7 We expect disturbances \( \varepsilon_{t,i} \) to be nonspherical. Heteroskedasticity likely exists. For example, larger oil production facilities require more equipment from suppliers, which makes the investment project more vulnerable to third-party delays and suboptimization. The possibility of autocorrelation also needs to be carefully considered. The probability that a certain firm suboptimizes in a specific project and industry is arguably higher if that firm already suboptimized in a prior project in that same industry. For example, the National Petrochemical Company (NPC), a subsidiary owned by the Iranian Petroleum Ministry and the government of the Islamic Republic of Iran, may have fewer incentives to consistently optimize its plant development decisions than British Petroleum (BP).
(\nu_{t,i,j} \neq 1). By definition, suboptimization is expected to decrease firm profits relative to the industry average. In contrast, superior speed capabilities enhance performance vis-à-vis the industry because firms can pursue speed at lower costs. Accordingly, we develop the following random parameters model (RPM) of the effect of firm speed on performance (see appendix A.2.)

$$\Pi_{j,t} = \delta_0^\text{i,j} + \delta^\text{j,t} \Theta_{j,t} + \delta^2_\text{j,t} \Lambda_{j,t} + \mu_{j,t}$$

(3.2)

where \(\Pi_{j,t}\) is a measure of firm \(j\)'s performance at time \(t\), \(\delta_0^\text{i,j}\) are industry \(i\) (product, geography) and time \(t\) dummies plus a random constant term, and the coefficients \(\delta^x_{j,t} = \delta^*_{j,t} + \zeta^x_{j,t} (x = 1,2)\) vary per firm \(j\), where \(\delta^*_{j,t}\) is the common-mean coefficient across firms and \(\zeta^x_{j,t}\) is a random term. The variable

$$\Lambda_{j,t} = -\left(\sum_{n,i} \delta_{j,n,i}\right)/n_{j,t}$$

is the average level of optimization in firm \(j\) at time \(t\). While optimization is unobservable at the plant (i.e., project) level in our sample, firm-level proxies for optimization exist for most publicly traded oil companies (see p. 15 for possible proxies). Optimization is expected to enhance firm performance \((\delta^2 > 0)\). The variable \(\Theta_{j,t}\) is a measure of firm speed (specifically, \(\Theta_{j,t}\) increases with faster firm speed). Formally, \(\Theta_{j,t} = -\left(\sum_{n,i} \frac{\theta_{j,n,i} - \bar{\theta}_{i,t}}{\sigma_{i,t}}\right)/n_{j,t}\) is the average standardized investment speed of all \(n_{j,t}\) projects of firm \(j\) completed at time \(t\) across all industries, where \(\bar{\theta}_{i,t}\) and \(\sigma_{i,t}\) are the average and standard deviation of project speed in industry \(i\) at time \(t\), respectively. Since we explicitly control for optimization in model (3.2) and the random parameters account for any other unspecified source of firm heterogeneity, the coefficient \(\delta^1_{j,t}\) mainly captures the effect of firms’ speed capabilities on performance (i.e., \(\delta^1 > 0\)).

The RPM specification in (3.2) allows unobserved firm heterogeneity to moderate the impact of the independent variables on firm performance. We let the random parameters be freely correlated, which is less restrictive and empirically more plausible than the alternative assumption of uncorrelated parameters.
We carefully characterize the implications of unobserved heterogeneity in subsection 4.2 after identifying the most important possible sources of unobserved firm differences in our data sample (in subsection 4.1). Finally, $\mu_{r,t}$ is a mean zero i.i.d. stochastic error term. For nontechnical readers, an intuitive explanation of our two-stage estimation methodology can be found at the beginning of subsection 5 (on p. 19).

4. 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. 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.

4.1 Data

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. 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). 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.

The operationalization of the variables in the RPM (3.2) follows. The dependent variable of the model – firm \(j\)'s performance at time \(t\) \((\Pi_{j,t})\) – is measured by Tobin’s q. We define Tobin’s q 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, 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 (as in Dowell et al. 2000). We consider the advantages of using Tobin’s q as our measure of firm performance as twofold. First, Tobin’s q captures the value of firms’ intangibles (such as speed capabilities and organizational suboptimization) based on contemporaneous market information on firms’ plant development projects. Second, Tobin’s q closely mirrors the conceptualization of performance in our theoretical model as the sum of all future discounted cash-flows of firms’ investments.

Firm speed \((\Theta_{j,t})\) is the average standardized speed of all projects that firm \(j\) completed at time \(t\) across all industries, where project speed \((\theta_{i,t})\) is the residual of regression (3.1). In model (3.1), project development time \((T_{i,t})\) is the lag between the start and end dates of plant development reported in the OGJ.\(^8\)

\(^{8}\) 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 (3-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 0 and 3 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 de-
The industry discount rate ($r$) is proxied by two different measures: the average WACC (weighted average cost of capital) and the average EBIDA (earnings before interest, depreciation, and amortization over total assets) across all oil companies with Compustat-CRSP Merged financial data from 1996 to 2005. The increase in revenues from plant development ($\Delta R_d$) is operationalized as the average demand growth, which we proxy by the yearly growth rate in real GDP in each location from the World Bank Development Indicators database. The amount of physical resources and equipment ($E_{t,i,e}$) 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 ($K_{t,i,s}$) 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 (3.2) (after merging with Compustat-CRSP financials). Also, the complexity variable proved not statistically significant or only marginally significant in regression (3.1) with the restricted refinery sample.

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%). $T_{t,i}$ is reported in months.

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, we have that

$$WACC = \frac{ECC \cdot Market\ Capitalization}{Market\ Capitalization + Long-Term\ Debt + Current\ Liabilities} + \frac{DCC \cdot Long-Term\ Debt + Current\ Liabilities}{Market\ Capitalization + Long-Term\ Debt + Current\ Liabilities}.$$ 

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 model (3.1).

Most prior work proxied demand growth by the four-year historical compound annual growth rate of production for the product-region (e.g., Gilbert and Lieberman 1987, Lieberman 1987, Henderson and Cool 2003). However, this operationalization is intractable in our empirical setting because our data covers a substantially greater number of plant locations (99 countries) and a wider spectrum of refining and chemical products and byproducts.
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 (3.1). Model (3.1) 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 of data in the standardization of the project speed residuals).

In RPM (3.2), the average level of optimization in firm $j$ at time $t$ ($\Lambda_{jt}$) is proxied by variables that reflect the quality of a firm’s corporate governance practices. The financial economics literature has well established that corporate governance plays an important role in efficient management monitoring and shareholder protection, which positively affects firm valuation and Tobin’s q (Morck et al. 1988, Shleifer and Vishny 1997, Denis and McConnell 2003, Gompers et al. 2003). Good corporate governance systems will likely enhance organizational optimization in firms’ operational decisions such as project development timing. We use two well-accepted measures of corporate governance in this paper. (1) Blockholding represents the percentage of common stock held by institutional investors owning at least 5% of a company’s outstanding common stock. Larger stockowners can often 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) S&P Score is a percentage 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 percentage score defined within our final company sample. Prior literature has widely used the S&P Index as an indicator of stockholders’ protection (Bushee 2004, Durnev and Kim 2005, Khanna et al. 2006).

We follow standard practice in the Tobin’s q literature and include a firm’s R&D Intensity (R&D expenditures over total assets), Leverage (long-term debt over total assets), and Advertising Intensity (ad-
vertising expenditures over total assets) as controls in model (3.2) (e.g., Morck and Yeung 1991). Advertising Intensity is not reported in the final estimations because it proved statistically insignificant in all exploratory regressions of model (3.2) and its inclusion makes our final sample extremely small. Also, Marketing plays a more limited role in affecting firm value in the oil and gas industry than in many others. Finally, model (3.2) includes industry and country dummies based on parent-level data. For industry effects, we use 2-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 based country dummies on the parent company’s home country and included year dummies as well. (See Appendix A.3. for a list of variables and measures included in our models).

4.2 Methods

In model (3.1) we use multivariate OLS regression analysis. Model (3.2) is estimated using two different methodologies: (1) multivariate OLS regression with the covariance matrix robust to clustering by firm (the dataset is treated as a pooled cross-section sample of firm-year observations) and (2) linear random parameter model regression with freely correlated coefficients. The latter estimation methodology is consistent with our model specification in subsection 3.2 and allows for unobserved firm heterogeneity to moderate the impact of the independent variables on firm value. For example, in the RPM regression the effect of speed on value may vary across firms with differences in organizational capabilities. A firm that makes an engineering breakthrough to accelerate the construction of a specific plant should experience a greater increase in value if the market recognizes its ability to transfer the new knowledge to other plants over time. Yet, we do not observe firms’ knowledge transfer capabilities in our sample.

Unobserved firm heterogeneity may also influence the correlation between the coefficients in RPM (3.2). We focus on the correlations with the parameter associated with firms’ speed capabilities. We consider two empirical possibilities below (see also Appendix A.4.).

First, we examine the correlation between the two main explanatory variable coefficients in the model. The random parameters $\delta^1_j$ and $\delta^2_j$ are expected to co-vary negatively. Increments to organizational op-
timization improve firm value less ($\delta^2_i$ is lower) the closer firms are to the optimum (by definition). But with superior levels of organizational optimization, enhancements in a firm’s speed capabilities should result in greater performance improvements ($\delta_i$ is higher). In empirical terms, better-governed firms should generate superior returns from speed capabilities, but have fewer incentives to further improve their governance practices (i.e., decreasing returns to good corporate governance).

Second, we analyze the correlation between the coefficients of speed and the controls in RPM (3.2). Leverage directly affects unobserved heterogeneity in firm discount rates (the latter are only available for a subset of the firms in the data). 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. These firms also typically have a higher discount rate, which lowers project investment profits because long-term revenues are more heavily discounted than shorter-term development costs. This reduces the returns from investment speed. Therefore, we expect the parameters associated with firms’ speed capabilities and leverage to co-vary positively.

The two correlation effects above encompass the most important sources of unobserved firm heterogeneity in the context of our reduced-form model of firm speed. However, the RPM regression allows for other unidentified differences between firms to influence the correlation patterns between the model coefficients, as carefully examined below in the results section.

Note that, although reported in the paper, standard OLS regressions of model (3.2) do not fully capture our theoretical model structure or the nature of our data. Unlike RPM, OLS does not easily accommodate coefficient heterogeneity and co-variation due to unobserved firm heterogeneity. By definition, if firm differences are not measured or proxied in the data, their effect on coefficient variation and co-variation cannot be directly specified as part of the econometric model structure to estimate. The alternative of interacting firm dummies with each variable coefficient in model (3.2) is also not feasible: it would imply the estimation of over 200 model parameters with an insufficient number of observations. Any attempt to deal with coefficient co-variation by including standard two-way interaction terms in model (3.2) would not be
entirely consistent with our theory: the marginal effects of the independent variables would depend on the
data values assumed by other variables – not on their intrinsic marginal effects, as predicted.\textsuperscript{11}

Generally, standard OLS regressions only estimate average model coefficients for the firms in the sample, which may potentially lead to estimation bias (see Levinsohn and Petrin 2003). This is the case if, for instance, there is correlation between speed and the unobserved firm-specific market value of speed. The intuition is simple: firms that experience more market returns from speed may respond by increasing speed.\textsuperscript{12} Since OLS coefficients are invariant across firms, positive contemporaneous correlation between speed and the error term may exist and, thus, a simultaneity problem in model (3.2) arises. In short, OLS models should be interpreted with caution: they are not fully representative of our theory and may also result in biased and inconsistent coefficient estimates. In contrast, RPM estimation allows unobserved firm heterogeneity to moderate the effect of the independent variables on firm value without requiring the econometrician to specify these relationships in the structure of the model.

The estimation of the linear RPM (3.2) requires the following econometric structure. We assume that, in aggregate, the firm-specific coefficients follow a normal distribution: $\delta^i \sim N(\delta^i + \zeta^i, \sigma^2)$ (the normal distribution allows for the estimated means of the coefficients to be positive or negative). Our statistical task is to estimate the mean and standard deviation of each coefficient. We proceed to estimate the RPM using simulated maximum likelihood. The use of simulation allows for the estimation of firm-specific parameters using Bayes theorem (see Greene 2004). 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). The estimation is obviously predicated on the assumption that stock markets cannot perfectly forecast the evolution of or-

\textsuperscript{11} Analytically, an OLS model of the following general form $Y = \alpha + \beta X + \delta Z + \gamma (XZ) + \varepsilon$ implies that the marginal effect of $X$ on $Y$ is a function of the data values assumed by variable $Z$: $\partial Y/\partial X = \beta + \gamma Z$. This structure is distinct from a specification where the marginal effects co-vary independently of the data.

\textsuperscript{12} Our theoretical model validates this intuition for the specific case of unobserved differences in firms’ cost of capital: firms with lower discount rates (due to lower cost of capital) should have higher speed coefficients and also optimally choose higher levels of project speed (see p. a9).
ganizational speed capabilities over time.

In contrast with most prior work and as mentioned above, we allow the RPM coefficients to be correlated. Our estimation produces the $\Gamma$ matrix, where $\Gamma$ is a lower triangular Cholesky factor of the random parameters covariance matrix $\Omega_{\delta}$ ($\Omega_{\delta} = \Gamma\Gamma'$). The elements of $\Gamma$ have no direct interpretation. 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. For more information on random parameter model estimation, see also Revelt and Train (1998), Train (1998), Layton and Brown (2000), McFadden and Train (2000), Chung and Alcácer (2002), Train (2003), and Greene (2004).

5. Estimation Results

As a preamble to the discussion of our estimation results, we review the overall methodological approach of the paper in nontechnical terms, which can be summarized as follows. In the first stage, we estimate an empirical model of project completion time to determine how fast a given project would normally take. The structure of this model is reasonably intuitive: project times vary by industry, accelerate when the economy grows, and take longer for larger and more complex projects. The functional form assumed for the first-stage regression is derived from a theoretical model where firms choose project times given diseconomies of accelerating investments (see A.1). This project completion time model allows us to estimate the speed for each project: speed is defined as the difference between the length of time an average firm would have used to complete the project and the actual time taken to complete the project. By construction, firms accelerate their projects relative to the industry in two main ways: (a) by using their intrinsic superior speed capabilities, or (b) by excessively spending on a project (i.e., suboptimizing).

---

13 We use the delta method: (1) with the function $f = \sqrt{\Gamma(i)\Gamma(i)'}$ for the estimated standard deviations ($\Gamma(i)$ is the $i$-th row of the $\Gamma$ 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 covariance terms, which by construction are functions of several random variables (the elements of $\Gamma$ above).
In the second-stage regression (see A.2), we use the first-stage speed measures to estimate the relationship between speed (faster or slower than average completion times) and profitability. Since speed may result from capabilities or suboptimization, its effect on performance may be positive (if acceleration is due to superior capabilities) or negative (if acceleration is due to suboptimization). We obtain a clear prediction about the expected sign of the speed coefficient by indirectly controlling for optimization in model (3.2) using corporate governance measures. Specifically, when we control for firms’ governance practices, the speed coefficient is hypothesized to be positive because it should mainly be capturing the effect of firms’ speed capabilities on performance. We estimate model (3.2) by first running a simple pooled OLS regression. The OLS regression tells us whether or not faster completion times, on average, improve performance. However, our real interest is whether firms differ in their ability to profitably complete projects faster. To investigate this question, we switch to a random parameters model (RPM). The RPM estimates a different relationship (i.e., coefficient) between speed and profitability for each firm. Firms with larger positive random parameters benefit more from project acceleration. In addition, the RPM also estimates the correlation between the model parameters, which yields important insights into how unobservable sources of firm heterogeneity affect our results.

Due to space limitations, tables with variable descriptive statistics appear in Appendix A.5. The key results from these preliminary analyses follow. First, all variables in regressions (3.1) and (3.2) show substantial empirical variation, in particular the dependent and main independent variables in our models. 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.

Second, the multivariate OLS regression results of model (3.1) are consistent with our theoretical predictions, independently of whether we use WACC or EBIDA as the industry discount rate in the complete sample or in the refineries subsample (see Table 1). Below we only comment on coefficient estimates that
use the WACC measure in the complete 2,659 oil and gas project observations because this is usually considered a better proxy than EBIDA for the cost of capital – the appropriate discount rate.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Refineries Subsample</th>
<th>Complete Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WACC</td>
<td>EBIDA</td>
</tr>
<tr>
<td>Constant</td>
<td>1.924***</td>
<td>1.714***</td>
</tr>
<tr>
<td></td>
<td>(0.140)</td>
<td>(0.084)</td>
</tr>
<tr>
<td>Capacity (ln)</td>
<td>0.034***</td>
<td>0.016**</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Complexity (ln)</td>
<td>0.034*</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>GDP Rate</td>
<td>-0.863**</td>
<td>-0.778***</td>
</tr>
<tr>
<td></td>
<td>(0.429)</td>
<td>(0.256)</td>
</tr>
<tr>
<td>Industry Dummies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>1,357</td>
<td>1,357</td>
</tr>
<tr>
<td>F-test for Model</td>
<td>10.72***</td>
<td>9.59***</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.120</td>
<td>0.109</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.109</td>
<td>0.097</td>
</tr>
</tbody>
</table>

Table 1: Multivariate OLS regression: model (3.1).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, † Unavailable for complete sample

As expected, the revenue (GDP Rate) elasticity of development time is negative and significant ($\beta_1 = -0.553, p < 0.1$). 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 ($\beta_1 = 0.053, p < 0.01$). 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 50 days (8%). 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 complexity data is unavailable for petrochemical and GTL plants. 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 not statistically significant. One possible explanation for this result is that project complexity matters less when firms already possess a fraction 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 whole dataset observations (i.e., refinery, petrochemical, and GTL projects).

Finally, Figure 1 shows 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 model (3.1) exhibits positive skewness, with the modal 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 suboptimization and speed capabilities 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 the consequence of suboptimal and extreme project acceleration. 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. This empirical regularity increases industry average speed but showed no further implications for our subsequent estimations.

We first estimated Model (3.2) using multivariate OLS with the covariance matrix robust to clustering by firm (see Table A.5.5 in Appendix A.5). These exploratory regressions provide widespread support to the hypothesis that faster firms tend to have higher firm values. The coefficient associated with firm speed is always positive and significant whether we use WACC or EBIDA as the industry discount rate with the corporate governance Blockholding measure (similar results are obtained with S&P Score). These preliminary results on the effect of speed on firm value are promising because OLS regressions do not fully capture our model structure or the nature of the data in terms of unobserved firm heterogeneity. The latter may also explain why corporate governance has a positive (as predicted) but insignificant impact on firm performance in this initial analysis. Finally, the control variables are also generally significant and with the expected sign: while R&D Intensity enhances firm value, leverage erodes it. As explained in section 4.1 of the paper (p. 15), Advertising Intensity is the only standard control variable in Tobin’s q regressions that comes out consistently insignificant in our OLS estimations. This can be explained because Marketing plays a more limited role in commodity industries such as oil and gas than in many other industries. Since Advertising Intensity makes our final sample extremely small, we excluded it from our final model estimation. Finally, note that the inclusion of the Blockholding variable also substantially reduces our sample in more than 30% (from about 222 to 151 observations), which affects overall significance levels.

Tables 2 and 3 below report the linear random parameter regression with freely correlated coefficients of model (3.2) using WACC industry discount rate and the Blockholding corporate governance measure.

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14 See subsection 4.2.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Elements of $\Gamma$</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant</td>
<td>Speed</td>
<td>Blockholding</td>
</tr>
<tr>
<td>Constant</td>
<td>1.632***</td>
<td>0.525***</td>
<td>0.525***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Speed</td>
<td>0.112***</td>
<td>0.051***</td>
<td>0.143***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Blockholding</td>
<td>0.004***</td>
<td>-0.000</td>
<td>-0.017***</td>
</tr>
<tr>
<td></td>
<td>(0.179)</td>
<td>(0.149)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>R&amp;D Intensity</td>
<td>8.268***</td>
<td>-8.378***</td>
<td>8.156***</td>
</tr>
<tr>
<td></td>
<td>(1.806)</td>
<td>(1.275)</td>
<td>(1.554)</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.943***</td>
<td>-1.238***</td>
<td>1.574***</td>
</tr>
<tr>
<td></td>
<td>(0.179)</td>
<td>(0.149)</td>
<td>(0.113)</td>
</tr>
</tbody>
</table>

Industry Dummies: Yes
Year Dummies: Yes

Number of Observations: 151
Log-likelihood: -50.230

Table 2: Linear random parameters model regression with correlated coefficients: model (3.2).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
<table>
<thead>
<tr>
<th>Variable</th>
<th>Constant</th>
<th>Speed</th>
<th>Blockholding</th>
<th>R&amp;D Intensity</th>
<th>Leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>— †</td>
<td>— †</td>
<td>— †</td>
<td>— †</td>
<td>— †</td>
</tr>
<tr>
<td>Speed</td>
<td>0.027***</td>
<td>— †</td>
<td>— †</td>
<td>— †</td>
<td>— †</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blockholding</td>
<td>-0.000</td>
<td>-0.002***</td>
<td>— †</td>
<td>— †</td>
<td>— †</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D Intensity</td>
<td>-4.396***</td>
<td>0.742***</td>
<td>-0.137***</td>
<td>— †</td>
<td>— †</td>
</tr>
<tr>
<td></td>
<td>(0.799)</td>
<td>(0.306)</td>
<td>(0.034)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.650***</td>
<td>0.162***</td>
<td>-0.028***</td>
<td>22.631***</td>
<td>— †</td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.043)</td>
<td>(0.004)</td>
<td>(3.579)</td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Implied covariance terms of the random parameters: model (3.2).
* p < 0.1, ** p < 0.05, *** p < 0.01, † reported in table 2

Figure 2: The marginal effect of speed on firms’ market value: model (3.2) uses the Blockholding measure.
Note that these results are generally robust to alternative operationalizations of both variables (see the robustness checks section). The RPM allows for unobserved firm heterogeneity to moderate the effect of all independent variables (excluding the industry and year dummies) on firm value (Tobin’s q). The estimation results deserve several comments. First, 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 $\chi^2_{16}$).  

This also occurs when we compare the correlated RPM with most uncorrelated specifications of the model. Thus, allowing the parameters in model (3.2) to vary randomly and to correlate freely offers a substantially better model specification than having fixed coefficients.

Second, all common-mean coefficients across firms reported in the second column of Table 2 have the predicted sign and are very significant (at the 1% level). As theoretically expected, the firm speed coefficient ($\delta^t$) is positive, which suggests that possessing speed capabilities boost firms’ market value, as measured by Tobin’s q. Superior speed capabilities confer firms the capacity to accumulate quickly the technological knowledge (e.g., on feedstock processes, mechanical and piping engineering, electrical design) required to bring new oil plants online when time-to-market is critical, thereby reducing the costs of speed. In addition, the magnitude of this effect is shown to be considerably large. On average, accelerating a firm’s investments by 5% (or 1 month) below the industry norm due to organizational capabilities increases market value by $214.3$ million.  

This represents the amount firms should be willing to pay, on average, to improve their speed capabilities to achieve 5% investment acceleration. Also as expected, the

---

15 The 16 degrees of freedom include the 15 elements of the $\Gamma$ matrix and the standard deviation of the error term.

16 From model (3.1), we have that $\frac{\partial \theta_{r,t,j}}{\partial T_{r,t,j}} = e^{r T_{r,t,j}} / (1 - e^{-r T_{r,t,j}})$. In our sample, for a hypothetical oil firm that owns one investment project per industry $i$ at time $t$, a simultaneous identical acceleration in all of its projects relative to each industry $i$ affects firm speed by $\frac{\partial \Theta_{j,t}}{\partial \theta_{r,t,j}} = -\sum_{n,t} (1/\sigma_{r,t}) / n_{j,t}$. 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 $\delta^t = 0.112$ (in Table 2). 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 of Table 1 establishes the result. Note that an increase of $\$214.3$ million in market value corresponds to nearly 1% of the asset value of an average oil firm.
mean parameter associated with the Blockholding variable ($\delta^2$) 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 control variables also affect Tobin’s q as anticipated. A firm’s R&D intensity boosts a company’s market value because current R&D investment flows add increments to the firm’s future stock of intangible resources, namely technological knowledge. Firms’ leverage is associated with lower values of Tobin’s q for two possible reasons: (a) the more the level of leverage deviates from the industry norm, the higher the cost of capital that firms face; (b) an increase in leverage may reflect firms’ poor past profitability and, thus, lower internal capital. This implies greater liquidity constraints and higher expected cost of capital (Myers and Majluf 1984). (Note, also, that the stronger this effect, the smaller the expected marginal returns from speed, as discussed below.) The industry and year dummies generally prove significant in the estimation.

Third, all random parameters in model (3.2) have very significant estimated standard deviations (at the 1% level), as shown in the last column of Table 2. This offers compelling evidence of parameter heterogeneity; that is, the effect of the independent variables on Tobin’s q is not uniform across firms. In other words, the coefficients associated with the independent variables vary randomly across firms and are affected by unobserved firm heterogeneity. Or, more simply, different firms will experience different changes in market value from the same increments in speed. The same conclusion applies to the remaining independent variables in model (3.2). Thus, as argued before, the RPM specification is preferable to assuming fixed coefficients in our model. Figure 2 illustrates this result for the key variable of interest, firm speed. The centipede plot represents 95% confidence intervals and point estimates for the individual speed parameters of the 51 firms in our sample. These estimates indicate how much firm value varies when a firm accelerates investments as a result of superior speed capabilities. Although our small sample size is large enough to support the estimation of the RPM, the wide confidence intervals produced by the simulation algorithm call for caution in the interpretation of the firm-specific coefficients. Note that the width of the confidence intervals is inversely proportional to sample size. Nevertheless, we can draw sev-
eral conclusions. Consistent with the positive common-mean speed parameter estimate, speed improves market value for the large majority of firms; however, this effect also shows substantial intra-industry variation. For firms such as China Petroleum and Chemical Corporation (Sinopec), accelerating oil and gas investments by 5% (or 1 month) below the industry norm increases market value by as much as $831 million (i.e., two-and-a-half times more than the expected average value increase from speed). Sinopec is the largest refiner and petrochemical producer in the fastest-growing world economy; thus, delays in project development entail high revenue losses and speed yields substantial benefits. In contrast, a small subset of the companies in our dataset generates negative returns from speed, which has two explanations. For some firms, ineffective corporate governance results in suboptimal project acceleration and speed is, "de facto", achieved by overinvesting in "pet projects". This likely occurs in the case of firms with poor corporate governance scores such as the semi-public company Petrobras Brasileiro, which owned Brazil’s oil monopoly until 1997. For other firms with better corporate governance practices such as BP, a negative speed parameter perhaps indicates important technological or organizational problems that hinder a firm’s ability to pursue speed. Indeed, BP experienced unreliable operational efficiency, delays in production at several oil rigs, and growing organizational complexity during the period of analysis. Solving these issues would have enhanced investment speed but would have required costly investments that would ultimately discount the benefits of improved speed capabilities.

Finally, the implied covariance terms of the random parameters in Table 3 provide further evidence of how unobserved firm heterogeneity influences the effect of speed on firm value (Revelt and Train 1998, Train 1998, Layton and Brown 2000, McFadden and Train 2000, Train 2003, Greene 2004). All but one covariance terms are highly significant, suggesting that it would have been a model misspecification to constrain the off-diagonal terms of the covariance matrix to be equal to zero. A significant covariance term means that some of the underlying reasons for coefficient heterogeneity are shared by two independent variables. In other words, 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.
For focus reasons, we only discuss the covariances associated with the coefficient of the main independent variable in the model, firm speed. The speed and the corporate governance (Blockholding) parameters co-vary negatively, as expected. For firms with low corporate governance, the marginal impact of an improvement in corporate governance is high. At the same time, because of poor governance, speed is likely due to sub-optimal acceleration and results in low marginal contribution to firm value. Also as predicted, the parameters associated with firms’ speed capabilities and leverage correlate positively. Firms for which debt has a more negative impact on firm value generally face more severe liquidity constraints and, thus, greater external costs of capital and discount rates. Higher time-cost of money lowers profits from investment projects because long-term revenues are more heavily discounted than shorter-term development costs. This reduces the returns from accelerating investments based on speed capabilities. Lastly, the remaining correlation of interest – between R&D intensity and speed – is positive. Firms that create more value from investments in R&D also benefit more from exploiting speed capabilities. Beyond any synergistic effects between technological and speed capabilities, this result may reflect firms’ general ability to deploy and capitalize on intangible assets to achieve privileged product-market positions.

The specific case of Exxon Mobil is a particularly well-suited example of how RPM is a powerful methodology that uses large samples to assess and explain firm heterogeneity and to empirically identify firms that excel along dimensions of interest to strategy researchers. These firms should, then, become natural candidates for in-depth case study analyses. Exxon Mobil is one of the companies in our sample with the largest speed coefficients, as documented in Figure 2 and, more clearly, in Figure A.6.1. Stated differently, Exxon Mobil seems to have a competitive advantage in speed in an industry where speed is an important driver of firm performance. Our covariance terms in Table 3 suggest that this advantage may be explained, among other reasons, if Exxon Mobil has superior governance practices. These RPM results proved to have external validity. Field interviews with oil and gas industry consultants and executives revealed that Exxon Mobil has a strict, engineering-minded, outcome-oriented culture that favors hard deadlines, clear performance metrics, and immediate accountability. These industry experts credited Ex-
xon Mobil’s culture with the company’s ability to accelerate projects without suboptimizing – that is, Ex-
exon Mobil’s ability to derive more value from speed than most oil companies.

To the extent that the ultimate goal of the field of strategy is the identification and explanation of com-
petitive advantage (i.e., the origins of firm differences that lead to superior performance), the RPM me-
thod may be the best econometric technique yet to assist strategy scholars in their empirical research.

6. Robustness Checks

Several checks confirmed the robustness of our findings in model (3.1). First, using WACC or EBIDA
as the industry discount rate produced identical results. Second, restricting our sample exclusively to the
refinery sub-industry observations (where complexity data is available) also did not change the estima-
tions for the key variables of interest. Third, the findings were robust to the inclusion of year dummies
(together with industry dummies) in regression (3.1), with the exception of the GDP Rate that turned in-
significant. The latter result occurs because the GDP Rate only varies per industry and over time. Fourth,
uncertainty in project revenues had no effect on speed. The inclusion of uncertainty, defined as the stan-
dard deviation of four years’ worth of the GDP Rate prior to the year under consideration, proved insigni-
ficant. This may be due to the maturity of the oil industry since the 1980s, where “demand forecasts re-
fect a strong consensus, there being a difference between the highest and lowest of less than 10%. This
compares with the 100% difference which was prevalent in the 1970s” (Chemical Insight 1987: 2). Fifth,
we directly tested for endogeneity in model (3.1). The fact that project characteristics (e.g., capacity) are
endogenously chosen by firms suggests the possibility that these variables can be contemporaneously cor-
related with firms’ speed capabilities and, thus, the error term. However, the Hausman test rejected this
hypothesis (after estimating model (3.1) with instruments for project-specific variables). Finally, we col-
llected OGJ data on outsourcing and controlled for the subcontractors that firms used in each of the differ-
ent stages of plant development, without changing the results in model (3.1). The findings in model (3.2)
are not qualitatively affected by adopting any of the various modified estimations of firm speed in regres-
In addition, the results in model (3.2) were robust to the following empirical tests. First, we ran a multivariate OLS regression using the two different measures of industry discount rate (WACC and EBIDA) and the two alternative operationalizations of corporate governance (Blockholding and S&P Score) with the covariance matrix robust to clustering by firm. The speed variable always came out positive and proved significant in all but one of the four models. Second, we estimated these same four models using a linear correlated random parameter regression. Consistent with Table 2, the common-mean coefficients for all the independent variables across the four models had the predicted sign and were very significant. We only report results using WACC because of space limitations and because this is a more accurate measure of industry discount rate than EBIDA, according to standard practice in the finance literature; indeed, WACC produces marginally better aggregate estimates than EBIDA in the baseline model (3.1). We present the results for the WACC-Blockholding measures in the body of the paper and those for the WACC-S&P Score in Appendix A.6. The reason is that the former is a more conservative test of our model (the sample is 25% smaller) and that Blockholding constitutes a more desirable measure of corporate governance because it directly captures the presence of dominant institutional investors with the power and strong incentives to monitor company managers actively. The S&P Score, a detailed index, incorporates extensive company financial disclosure information from annual reports and regulatory filings; however, it does not offer a comprehensive metric of corporate governance. The results with the S&P Score corporate governance metric confirm the findings in Tables 2 and 3, with the exception of the two correlations between the speed parameter and the Leverage and R&D Intensity parameters: although

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17 The only noticeable exception was the fact that controlling for subcontracting rendered the corporate governance measure (i.e., Blockholding) insignificant. One possible explanation for this result, consistent with the strategy and financial economics literatures, is that arm’s length market transactions (i.e., subcontracting) likely discipline firms’ actions and reduce agency problems. In other words, the “discipline of the market” seems a substitute mechanism for corporate-governance control in ensuring organizational optimization.

18 We predicated our estimation of model (3.2) on the assumption that our speed measure is statistically different across firms. We directly checked the robustness of this assumption by testing for the joint significance of firm fixed effects in model (3.1). We rejected the null hypotheses of nonsignificance at the 0.1% level.
positive, as expected, they are insignificant. Finally, our estimation results are 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.\textsuperscript{19,20}

7. Discussion and Conclusions

Investment speed represents an important performance metric in strategy practice; yet, strategy research has not provided a complete empirical analysis of its effect on firm performance. While some scholars have argued that speed is beneficial because slowness in the execution of investment projects often leads to revenue losses, others have stressed that speed is detrimental as it results in high investment costs.

This paper integrates firms’ investment speed trade-off in a reduced-form model of project development to create an empirical proxy for firm speed and offers the first comprehensive empirical account of the impact of firm speed on performance. Our analysis measured speed as deviations from industry-average time of execution of large investments in oil and gas facilities worldwide from 1996 to 2005. The data shows substantial variation in investment speed between firms in the oil and gas industry.

\textsuperscript{19} We also carefully analyzed the possibility of reverse causality (Tobin’s q influencing firm speed) in model (3.2). Contemporaneous reverse causality, or cases where high firm market value at year $t$ causes firms to speed up projects that are completed that same year, is less of a concern in our setting. On average, it takes approximately two years to build a new oil and gas facility (i.e., firms start investments in year $t-2$). The availability of more financial resources towards the end of a project (in year $t$) does not change investment speed prior to that date and is unlikely to make firms implement time-consuming and costly changes in the closing stages of a project. These effects are exacerbated by the fact that investments in the oil industry presuppose substantial initial pre-commitments to specific plant-development plans. Thus, potential endogeneity should not be an issue in the current specification of our model. This conclusion is reinforced by the fact that we lack empirical support even for the empirically more plausible scenario of lagged reverse causality. We ran several multivariate OLS regressions with and without the covariance matrix robust to clustering by firm where firm speed was regressed on lagged Tobin’s q (and controls). We did not obtain any significant statistical results.

\textsuperscript{20} Our reduced-form econometric model is conditional on firms’ decision to invest in an oil and gas facility in industry $i$ at time $t$. We examined the implications of this constraint for our empirical estimations. We created a pool of all US firms listed in the Compustat-CRSP Merged database (CCM) as oil companies in 2000. The majority (between 67% and 78%) of oil firms invested in an oil facility from 1996 to 2005. Moreover, the total market capitalization (in 2000 dollars) of firms with at least one project in our OGJ investment dataset was 97.8%. The remaining 2.2% of market capitalization corresponded to oil firms listed in the CCM dataset that did not invest in an oil facility from 1996 to 2005. Hence, most oil companies invested during the period of analysis and those that did not were very small (mostly private) firms. This result was robust whether we used 1996 or 2000 as the base comparison year. Since oil and gas is a mature industry where most investments are made by incumbent companies, these stylized empirical facts establish that our OGJ database constitutes a relatively complete and inclusive company investment sample. Thus, biases due to the estimation of our model conditional on firms’ decision to invest in an oil and gas facility from 1996 to 2005 are perhaps less likely.
Our data support the central hypotheses of the paper regarding the impact of speed on firm value. Firms that pursue speed by exploiting their intrinsic capabilities generate firm value, as measured by Tobin’s q. Superior speed capabilities generally reduce the costs of speed by allowing firms to accumulate quickly the technological knowledge required to bring new oil plants online when time-to-market is critical. The magnitude of this effect is shown to be considerably large. On average, accelerating a firm’s investments by 5% (or 1 month) below the industry norm due to capabilities is worth $214.3 million in market value. In addition, the effect of speed on Tobin’s q varies substantially among firms. Some oil companies in our sample create as much as two-and-a-half times more value from speed than the industry average, while a small subset of the companies in our dataset generates negative returns from speed. These intra-industry differences in the market value of speed can be explained by unobserved heterogeneity in firms’ product-market positioning, corporate strategies, cost of capital, or organizational capabilities. For example, the correlations between the random parameters in our model suggest that better-governed firms create more value from speed by curtailing the extent of suboptimal project acceleration. Firms that experience greater market value erosion by raising debt have higher external cost of capital and discount rates, which damps the returns from speed. Finally, firms that create more value from investments in R&D also benefit more from exploiting speed-based organizational capabilities; this result may reflect firms’ organizational ability to deploy and capitalize on intangible resources to achieve privileged product-market positions.

Our methodological contributions are twofold. First, the applied theoretical model offers a formal analysis of firms’ investment speed tradeoff grounded on the stylized empirical regularities of the oil industry. This approach made explicit and externally validated the key working assumptions of our study. The closed-form solution for optimal development time determined the econometric specification of our models, the distributional properties of the disturbances, and the central hypotheses to be tested. Second, we adopted a relatively novel empirical methodology. The linear correlated random parameter model (RPM) regression allows for unobserved (firm) heterogeneity to moderate the effect of the predictors on the dependent variable. To the extent that the ultimate goal of the field of strategy is the identification and ex-
planation of competitive advantage – the origins of firm differences that lead to superior performance, RPM may be the best econometric technique yet to assist strategy scholars in their empirical research. The RPM method enhances the inferences that can be drawn from the data and provides large sample validation for in-depth qualitative case studies of specific companies. For example, our results suggest that China Petroleum Corp and Exxon Mobil generate substantial returns from speed and, thus, should perhaps be studied in greater detail through extensive field work.

Generalizations and limitations of this paper follow. The magnitude of the effect of speed on firm value reported in this paper typifies, perhaps, mature industries with chronic excess capacity, such as oil and gas. In growing markets, the potential foregone profits from delaying investments tend to be greater and, thus, the benefits of 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 effect of speed on firm performance. This observation may constitute motivation for future work. Other possibilities for future research include examining whether our findings for investment speed in large production facilities also hold true in the context of speed in new product or technology development. Finally, it would be interesting to explore the influence of organizational speed capabilities on firms’ market entry timing decisions and the endogeneity of first-mover opportunities.

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Appendix

A.1. Suboptimal Acceleration and Deceleration with Heterogeneous Capabilities (in §3.1)

Model (3.1) Firms’ choose the investment profile \( c_t \) \((c_t \geq 0)\) that minimizes the net present value of investment subject to the constraint that all effort required to build a new productive facility is exerted by the completion time \( T_{t,i} \). Investments at each point in time are subject to diminishing returns such that each plant development project only progresses at a rate \( (c_t)^\alpha \) \((0 \leq \alpha \leq 1)\). The total amount of progress or effort required to develop a new productive facility is given by \( A(1-d_{t,i})^\beta_0 (K_{t,i})^\beta_1 (E_{t,i})^\beta_2 \) (where \( A > 0; \beta_0, \beta_1, \beta_2 \geq 0 \)). Thus, firms’ investment problem is given by

\[
C(T_{t,i}) = \min_{c_t \geq 0} \int_0^{T_{t,i}} c_t e^{-rt} dt
\]

s.t. \( \int_0^{T_{t,i}} (c_t)^\alpha dt = A(1-d_{t,i})^\beta_0 (K_{t,i})^\beta_1 (E_{t,i})^\beta_2 \).

Following Lucas (1971) and Pacheco-de-Almeida and Zemsky (2007), the cost minimizing investment profile for a general \( \alpha \) is \( c_t^*(T_{t,i}) = e^{rt/(1-\alpha)} \left( \frac{\alpha A(1-d_{t,i})^\beta_0 (K_{t,i})^\beta_1 (E_{t,i})^\beta_2 r}{e^{rt_{t,i} \alpha/(1-\alpha)} - 1} \right)^{1/\alpha} \). The present value of plant investment costs is given by \( C(T_{t,i}) = \int_0^{T_{t,i}} c_t^*(T_{t,i}) e^{-rt} dt \), which is equivalent to expression

\[
C_{t,i} = \frac{A^2(1-d_{t,i})^2 \beta_0 (K_{t,i})^2 \beta_1 (E_{t,i})^2 \beta_2 r}{e^{2rt_{t,i}} - 1}
\]

when \( \alpha = 1/2 \).

Firm revenues are given by \( R_{t,i} = \int_0^{\infty} \Delta_{t,i} e^{-rt} dt = \frac{\Delta_{t,i} e^{-rt_{t,i}}}{r} \). For tractability reasons, we assume that \( \Delta_{t,i} = (\kappa_{t,i})^\gamma \). Since our model of investment speed is conditional on firms’ decision to invest in a
new production facility in industry \( i \) at time \( t \), we further impose that
\[
\sqrt{\Delta_t} > A((1-d_{t,i})^\beta_i (K_{t,i})^\beta_i (E_{t,i})^\beta_i r),
\]
so that firms have enough incentives to develop the new production facility.

Because project costs are empirically unobservable in our oil and gas industry sample, we develop a reduced-form model based on firms’ optimal project development time. Firm profits are given by
\[
\Pi_{t,i} = R_{t,i} - C_{t,i}.
\]
Hence, the FOC for the optimal development time \( T_{t,i}^* \) is
\[
\left( \frac{1}{T_{t,i}^*} \right) = 0.
\]
Substituting \( T_{t,i}^* = \frac{\ln x}{r} \) where \( x > 1 \)
yields
\[
\frac{x-1}{x} = A((1-d_{t,i})^\beta_i (K_{t,i})^\beta_i (E_{t,i})^\beta_i r),
\]
which solves for a unique \( T_{t,i}^* \),
\[
T_{t,i}^* = \frac{1}{r} \ln \left( 1 - \frac{A((1-d_{t,i})^\beta_i (K_{t,i})^\beta_i (E_{t,i})^\beta_i r)}{\sqrt{\Delta_t}} \right)^{-1}.
\]
(A.1.1)

This is equivalent to having
\[
\ln \tilde{\theta}_{t,i}^* = \ln A + \beta_0 \ln (1-d_{t,i}) + \beta_1 \ln K_{t,i} + \beta_2 \ln E_{t,i} + \beta_3 \ln \Delta_t
\]
(A.1.2)
where \( \tilde{\theta}_{t,i}^* = \left( 1 - e^{-\alpha_{t,i}} \right) / r \) and \( \beta_3 = -\frac{\gamma}{2} \). In our current model, we allow for suboptimal acceleration of specific projects. This observation-specific error around the optimal development time is denoted in our model by \( \varepsilon_{t,i} \), such that
\[
\ln \tilde{\theta}_{t,i} = \ln \tilde{\theta}_{t,i}^* + \varepsilon_{t,i}
\]
and
\[
\tilde{\theta}_{t,i} = \left( 1 - e^{-\alpha_{t,i}} \right) / r.
\]
By construction,
\[
(1-d_{t,i}) = v_{t,i} (1-d_i),
\]
where \( v_{t,i} > 0 \) is unobservable. Thus, the error term of the final model to estimate in (3.1) is given by
\[
\theta_{t,i} = \varepsilon_{t,i} + \beta_0 \ln v_{t,i} + \beta_1 \ln (1-d_i).
\]

Figure A.1.1 shows a numerical example of model (3.1). The cost curve is downward sloping and convex due to time compression diseconomies. The revenue curve is also downward sloping because rev-
Appendix to Pacheco-de-Almeida, Hawk, and Yeung: Speed and Tobin’s q

Revenue discounting increases in development time. Firms’ optimal time \( T^*_{t,i} \) maximizes profits \( \Pi_{t,i} \), or the (vertical) difference between revenues and costs in the figure. The unobservable components of the error term \( (\varepsilon_{t,i}, \nu_{t,i}) \) affect the model differently: suboptimization implies deviations from \( T^*_{t,i} \); speed capabilities shift the cost curve inwards such that, at the optimum, firms develop projects faster. \( \square \)

**Figure A.1.1:** Suboptimal acceleration and deceleration (left panel) and heterogeneous capabilities (right panel). Parameter values: \( r = 0.1, A = 1, K_{t,i,j} = E_{t,i,j} = 4, \beta_0 = \beta_1 = \beta_2 = 0.1, \gamma = 1, d_{t,i,j} = 0 \) (left panel) versus \( d_{t,i,j} = 0.99 \).

**A.2. The Effect of Speed on Performance (in §3.2)**

**Model (3.2)** Denote by \( T^*_{t,i} \) the optimal plant development time for an average firm in the industry (with average speed capabilities \( d_i \)) and by \( \Pi^*_{t,i} = \Pi_{t,i} \left( T^*_{t,i} \right) \) the resulting industry average profits. As in section A.1., \( T^*_{t,i,j} \) denotes the optimal time for a specific project when firms have speed capabilities \( d_{t,i,j} \), where the corresponding profits are \( \Pi^*_{t,i,j} = \Pi_{t,i,j} \left( T^*_{t,i,j} \right) \). Then, the performance impact of project deviations in development time \( (T^*_{t,i,j}) \) from the industry average \( (T^*_{t,i}) \), as on average oil firms are assumed to optimize, is given by the following identity

\[
\Pi_{t,i,j} = \Pi_{t,i,j}^* + \left( \Pi_{t,i,j}^* - \Pi_{t,i,j}^* \right) + \left( \Pi_{t,i,j} - \Pi_{t,i,j}^* \right)
\]  

(A.2.1)
where \( (\Pi_{i,t}^* - \Pi_{i,t}^*) \) is the change in optimal profits resulting from a change in the level of speed capabilities relative to the industry average, and the term \( (\Pi_{i,t}^* - \Pi_{i,t}^*) \) measures the change in profits due to suboptimization.

A first-order approximation to the second term in (A.2.1) is \( (\Pi_{i,t}^* - \Pi_{i,t}^*) \approx \frac{\partial \Pi_{i,t}^*}{\partial d_{i,t}^*} (\Delta d_{i,t}^*) \). We have that \( \frac{\partial \Pi_{i,t}^*}{\partial d_{i,t}^*} = 2 \left( \frac{\beta_0 W}{1 - d_{i,t}^*} \right) \left( \overline{\Delta}_{i,t}^* \right)^{1/2} - rW > 0 \) where \( W = A(1 - d_{i,t}^*)^{\beta_0} (K_{i,t}^*)^{\beta_1} (E_{i,t}^*)^{\beta_2} \). Since \( \varepsilon_{i,t} = 0 \) (i.e., there is no suboptimization), \( \Delta d_{i,t} = d_{i,t} - d_i = (1 - d_i)(1 - v_{i,t}) \) and \( v_{i,t} = e^{\theta_{i,t}^*/\beta_0} \). Given that \( \beta_0 \geq 0 \), \( \Delta d_{i,t} \) is decreasing in project speed \( \theta_{i,t}^* \). Therefore, we can re-write

\[
(\Pi_{i,t}^* - \Pi_{i,t}^*) \approx \frac{\partial \Pi_{i,t}^*}{\partial d_{i,t}^*} \left( \theta_{i,t}^* - \overline{\theta}_{i,t}^* \right) (A.2.2),
\]

where \( \delta_{i,t}^1 = \delta^1 + \zeta_{i,t}^1 > 0 \). Specifically, \( \delta^1 \) is the common-mean coefficient across all projects and \( \zeta_{i,t}^1 \) is a random term that varies with observable and unobservable project-specific characteristics (consistently with \( \frac{\partial \Pi_{i,t}^*}{\partial d_{i,t}^*} \)). In (A.2.2), project speed \( \theta_{i,t}^* \) is reverse coded and standardized relative to its industry \( i \) at time \( t \), \( \overline{\theta}_{i,t} = \sum_{t} \theta_{i,t} / n_{i,t} \) and \( \sigma_{i,t} = \left[ \sum_{t} (\theta_{i,t} - \overline{\theta}_{i,t})^2 / (n_{i,t} - 1) \right]^{1/2} \) (\( n_{i,t} \) is the total number of projects in industry \( i \) at time \( t \)), which allows for a meaningful comparison of speed deviations between identical projects.21

By definition, the third term in (A.2.1) is always negative and decreasing in the extent of suboptimization. In addition, the FOC for the optimal development time \( T_{i,t}^* \) in appendix (A.1.), \( \frac{\partial \Pi_{i,t}^*}{\partial T_{i,t}^*} = 0 \), suggests that identical suboptimal deviations may have different effects on profits depending on project-

---

21 Although model (3.1) includes industry dummies, \( \overline{\theta}_{i,t} \) may not be zero because of time effects (or interactions between product, geography, and time effects), which are not part of our model specification. Even when \( \overline{\theta}_{i,t} = 0 \), the overall distribution of project development times may vary substantially across industries (and time periods) and, thus, the same absolute speed deviation can have very different impacts on performance in distinct industries.
specific characteristics. If we assume that symmetric suboptimal deviations (i.e., suboptimal accelerations and decelerations of equivalent absolute magnitudes) have an identical impact on profits, we can re-write

\[
\left( \Pi_{f,t,i} - \Pi_{f,t,i}^* \right) \approx \delta_{f,t,i}^2 \left( -|\epsilon_{f,t,i}| \right)
\]

(A.2.3), where \( \delta_{f,t,i}^2 = \delta^2 + \epsilon_{f,t,i}^2 > 0 \). In particular, \( \delta^2 \) is the common-mean coefficient across all projects and \( \epsilon_{f,t,i}^2 \) is a random term that varies with observable and unobservable project-specific characteristics (consistently with \( \partial \Pi_{f,t,i} / \partial T_{f,t,i} \)).\(^{22}\) Therefore, identity (A.2.1) can be proxied by

\[
\Pi_{f,t,i} = \delta_{f,t,i}^0 + \delta_{f,t,i}^1 \left( -\frac{\theta_{f,t,i} - \bar{\theta}_{f,t}}{\sigma_{f,t}} \right) + \delta_{f,t,i}^2 \left( -|\epsilon_{f,t,i}| \right) + \mu_{f,t,i}
\]

(A.2.4)

, where \( \delta_{f,t,i}^0 \) are industry (product, geography) and time dummies plus a random constant term, and \( \mu_{f,t,i} \) is a mean-zero i.i.d. stochastic error term. Consistent with our theory, the coefficient \( \delta_{f,t,i}^1 \) captures the effect of firms’ speed capabilities on performance because optimization is controlled for in the model.

Model (A.2.4) cannot be directly estimated because we do not empirically observe profits and timing optimization at the project (i.e., oil plant) level in our oil and gas industry sample. However, performance data and reliable proxies for organizational (sub)optimization exist at the firm level since most oil companies are publicly traded. Therefore, we average model (A.2.4) over the \( n_{j,t} \) projects of firm \( j \) completed at time \( t \) across all industries to derive the firm-level RPM (3.2) in §3.2, where

\[
\Pi_{j,t} = \sum_{i=1}^{\Pi_{f,t,i}} / n_{j,t},
\]

\[
\Theta_{j,t} = -\left( \sum_{i=1}^{\Pi_{f,t,i}} \frac{\theta_{f,t,i} - \bar{\theta}_{f,t}}{\sigma_{f,t}} \right) / n_{j,t}, \quad \text{and} \quad \Lambda_{j,t} = -\left( \sum_{i=1}^{\Pi_{f,t,i}} |\epsilon_{f,t,i}| \right) / n_{j,t}.
\]

Note that this transformation assumes that

\(^{22}\) In the context of our model, the assumption that suboptimal accelerations and decelerations of equivalent absolute magnitudes have an identical impact on project profits is only reasonable for small to moderate levels of suboptimization. For severe suboptimization, acceleration erodes profits more rapidly than deceleration (e.g., at the limit, a 100% deviation from the optimal development time reduces profits to \( \lim_{T_{f,t,i} \to 2T_{f,t,i}} \Pi_{f,t,i} = -\infty \) with acceleration, whereas we have that profits with deceleration are \( \lim_{T_{f,t,i} \to 2T_{f,t,i}} \Pi_{f,t,i} > 0 \)). This asymmetric effect of severe suboptimization on performance may be accommodated by the random project term \( \zeta_{f,t,i}^2 \). In particular, for equal levels of severe suboptimization, projects that are accelerated should have a higher coefficient \( \delta_{f,t,i}^2 \) than projects that are decelerated.
each random coefficient $\delta_{x,t}^{x'}$ ($x=1,2$) is time-invariant and independently distributed of its corresponding explanatory variable in model (A.2.4), so that $\delta_{j,t}^{x} = \delta_{j,t}^{x'} = \sum_{x} \delta_{x,t}^{x} / n_{j,t}$, $\forall t$. The latter assumption is reasonable in the context of our theoretical model for two reasons. First, the effect of speed capabilities on project profits depends ambiguously on the level of firms’ speed capabilities (analytically, $\delta^{2} \Pi_{x,t} / \partial (d_{t,x})^{2} = \frac{2\beta_{0}W}{(1-d_{t,x})^{2}} (\sqrt{\Delta_{t,x}}) (1+\beta_{0}) - rW (1+2\beta_{0})$, which may be positive or negative).

Second, the effect of suboptimization on profits should not depend on the level of suboptimization because it is unlikely that any one oil firm in our sample systematically pursued severe suboptimization across all of its projects from 1996 to 2005 (see footnote 22). □
A.3. Data (in §4.1)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project Time</td>
<td>$T_{t,i,e}$</td>
<td>Oil and Gas Journal</td>
</tr>
<tr>
<td></td>
<td>$= \left( \left( \text{Date Project First Reported in OGJ - 90 Days} \right) - \left( \text{Date Project Last Reported in OGJ + 90 Days} \right) \right) / 30 \text{ Days}$</td>
<td></td>
</tr>
<tr>
<td>Industry Discount Rate</td>
<td>$\frac{\sum \text{Operating Income Before Depreciation - Income Taxes}}{\text{Total Assets}}$</td>
<td>Compustat-CRSP</td>
</tr>
<tr>
<td></td>
<td>$= \frac{\sum \text{EBIDA}}{\text{Number of Firms in the Industry}}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\text{WACC} = \sum \left( \frac{\text{ECC}^* \text{Market Capitalization}}{\text{Market Capitalization + Long-Term Debt + Current Liabilities}} + \frac{\text{DCC}^* \text{Long-Term Debt + Current Liabilities}}{\text{Market Capitalization + Long-Term Debt + Current Liabilities}} \right) / \text{Number of Firms in the Industry}$</td>
<td>Compustat-CRSP</td>
</tr>
<tr>
<td></td>
<td>$, \text{ where } \text{ECC} = \text{Earnings Yield} = \frac{\text{Earnings Per Share}}{\text{Year End Price}} \text{ and } \text{DCC} = \frac{\text{Interest Expense}}{\text{Long-Term Debt + Current Liabilities}}$</td>
<td></td>
</tr>
<tr>
<td>Project Revenues</td>
<td>$\text{GDP Rate} = \frac{\text{GDP}<em>{\text{location g, year } t} - \text{GDP}</em>{\text{location g, year } t-1}}{\text{GDP}_{\text{location g, year } t-1}}$</td>
<td>World Bank</td>
</tr>
<tr>
<td>Project Technology</td>
<td>$\text{Complexity} = \text{Nelson's Complexity Index (only available for refinery projects)}$</td>
<td>Leffler (2000)</td>
</tr>
<tr>
<td>Project Equipment</td>
<td>$\text{Capacity} = \text{Plant Capacity Size}$</td>
<td>Oil and Gas Journal</td>
</tr>
</tbody>
</table>

Table A.3.1: Variable definitions: model (3.1).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
</table>
| Firm Performance       | Tobin’s q \[
\frac{\text{Market Value of Equity} + \text{Book Value of Preferred Stock} + \text{Long-Term Debt} + \text{Current Liabilities} - \text{Current Assets}}{\text{Total Assets} - \text{Current Assets} - \text{Intangibles} + \text{Book Value of Inventory}}\] | Compustat       |
| Firm Speed             | Speed \[
- \left( \sum \frac{\text{Project Speed} - \text{Industry Average Project Speed}}{\text{Standard Deviation of Project Speed per Industry}} \right) / \text{Number of Firm Projects}\] | Oil and Gas Journal |
| Firm Optimization      | Blockholding \[
\frac{\text{Common Stock of Institutional Investors Owning} \geq 5\% \text{of the Company's Stock}}{\text{Total Common Stock of the Company}}\] (%) | Thomson Financial |
|                        | S&P Score \[
\frac{\text{Sum of S&P Index Ratings on 98 Company Disclosure Items}}{\text{Sum of the Maximum S&P Index Ratings on 98 Company Disclosure Items}}\] (%) | Standard & Poor’s |
| Controls               | R&D Intensity \[
\frac{\text{R&D Expenditure}}{\text{Total Assets}}\] | Compustat       |
|                        | Leverage \[
\frac{\text{Long-Term Debt}}{\text{Total Assets}}\] | Compustat       |

**Table A.3.2:** Variable definitions: model (3.2).
A.4. Methods: Unobserved Firm Heterogeneity (in §4.2)

The RPM regression allows for unidentified or unobserved differences between firms to influence the correlation between the model coefficients. Below, we focus on the correlations between the parameters associated with (a) firms’ speed capabilities and leverage and (b) firms’ speed capabilities and organizational optimization.

Unobserved firm heterogeneity in discount rates (due to, for instance, differences in firms’ financial leverage) affects the incentives to and the returns from speed. Specifically,

$$\frac{\partial T^*_t}{\partial r} = \left( -e^{-\tau_{i,j}} / r \right) \frac{\partial e^{-\tau_{i,j}}}{\partial r} > 0 \quad \text{as} \quad \frac{\partial e^{-\tau_{i,j}}}{\partial r} = -\frac{W}{\sqrt{(\bar{A}_{r,i})}} < 0$$

(where 0 < 1) and, thus, firms take a longer time to develop investment projects with higher discount rates. Also, the returns from speed capabilities decrease in firms’ discount rate, as given by the following cross-partial derivative

$$\frac{\partial^2 \Pi_{t,k,j}^*}{\partial d_{t,i,j} \partial r} = -\frac{2\beta_0 W^2}{(1-d_{t,i,j})} < 0.$$  

The reason for both results is that long-term project revenues are more heavily discounted than shorter-term project development costs with higher discount rates. Since firms’ with greater leverage typically have larger discount rates and, thus, decreasing returns from additional debt, the random parameters associated with firms’ speed capabilities and leverage should co-vary positively in RPM (3.2).

As mentioned in §4.2, the random parameters $\delta^1_j$ and $\delta^2_j$ are expected to co-vary negatively by default. Increments to organizational optimization improve firm value less ($\delta^2_j$ is lower) the closer firms are to the optimum (by definition). But with superior levels of organizational optimization, enhancements in a firm’s speed capabilities should result in greater performance improvements ($\delta^1_j$ is higher).

Note, however, that this negative baseline correlation could hypothetically be mitigated or reversed by other patterns of unobserved firm heterogeneity. An example follows. In the unlikely event that different oil firms pursued projects that systematically differed in complexity and revenue impact, the parame-
Appendix to Pacheco-de-Almeida, Hawk, and Yeung: Speed and Tobin’s q

ters $\delta_j^1$ and $\delta_j^2$ would co-vary positively (note that complexity and variation in project revenue potential per location are unobserved in our sample). Specifically, suboptimization and inferior speed capabilities should erode value more for firms pursuing projects with larger revenue potential and greater complexity, whereas smaller and simpler projects should have less impact on firms’ financial performance. This inference is also supported by our model. Assume that $\sqrt{\left(\bar{X}_{t,1}\right)^2} = \eta(rW)$, where $\eta > 1$ is constant across projects. This assumption allows us to compare the effects of suboptimization and speed capabilities on performance with simultaneous heterogeneity in project complexity ($K_{t,1}$) and revenue potential ($\bar{X}_{t,1}$).

We have $\partial^2 \Pi_{t,1}^\ast / (\partial d_{t,1} \partial K_{t,1}) = 4 \beta_0 \beta W^2 (\eta - 1)r > 0$. Also, $\partial^2 \Pi_{t,1}^\ast / (\partial T_{t,1} \partial K_{t,1}) = \frac{2 \beta_1}{K_{t,1}} \frac{\partial \Pi_{t,1}^\ast}{\partial T_{t,1}}$, which is positive if and only if $T_{t,1}^* < T_{t,1}$ (negative otherwise). Hence, superior speed capabilities and timing optimization should have a greater impact on performance in projects that are technologically more complex and have higher revenue potential. This means that the random coefficients $\delta_{t,1}^1$ and $\delta_{t,1}^2$, in model (A.2.4) should co-vary positively. Therefore, if in our dataset different firms were to pursue projects that systematically differed in complexity and revenue impact, the parameters $\delta_j^1$ and $\delta_j^2$ should also co-vary positively in RPM (3.2). While this has shown not to be the case in our setting and, thus, it is not the hypothesized correlation between the parameters $\delta_j^1$ and $\delta_j^2$, this is a concrete example of the advantages of using a RPM specification to capture unobserved firm heterogeneity. □

23 We can only compare the effect of suboptimization (i.e., deviations from the optimal development time) across different projects if the optimal development time is identical for all projects, which holds if $\eta$ is project-invariant.
A.5. Estimation Results (in §5.)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Observations = 1,357</th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
<th>6.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
<td>Minimum</td>
<td>Maximum</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. $T_{r,k,t}$</td>
<td>20.581</td>
<td>15.424</td>
<td>3.167</td>
<td>108.767</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. EBIDA</td>
<td>0.129</td>
<td>0.011</td>
<td>0.109</td>
<td>0.151</td>
<td>0.069</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>3. WACC</td>
<td>0.051</td>
<td>0.012</td>
<td>0.032</td>
<td>0.074</td>
<td>0.034</td>
<td>0.941</td>
<td>1.000</td>
</tr>
<tr>
<td>4. GDP Rate</td>
<td>0.036</td>
<td>0.037</td>
<td>-0.131</td>
<td>0.179</td>
<td>0.112</td>
<td>0.341</td>
<td>0.309</td>
</tr>
<tr>
<td>5. Complexity</td>
<td>6.171</td>
<td>6.876</td>
<td>1.000</td>
<td>60.000</td>
<td>-0.017</td>
<td>0.011</td>
<td>0.013</td>
</tr>
<tr>
<td>6. Capacity (10^6 units)</td>
<td>0.033</td>
<td>0.050</td>
<td>0.000</td>
<td>0.800</td>
<td>0.063</td>
<td>0.003</td>
<td>-0.003</td>
</tr>
</tbody>
</table>

Table A.5.1: Variable descriptive statistics and correlations: model (3.1); refineries subsample.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Observations = 2,659</th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
<td>Minimum</td>
<td>Maximum</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. $T_{r,k,t}$</td>
<td>20.796</td>
<td>14.584</td>
<td>3.033</td>
<td>108.767</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>2. EBIDA</td>
<td>0.128</td>
<td>0.011</td>
<td>0.109</td>
<td>0.151</td>
<td>0.086</td>
<td>1.000</td>
</tr>
<tr>
<td>3. WACC</td>
<td>0.050</td>
<td>0.012</td>
<td>0.032</td>
<td>0.074</td>
<td>0.018</td>
<td>0.936</td>
</tr>
<tr>
<td>4. GDP Rate</td>
<td>0.041</td>
<td>0.039</td>
<td>-0.131</td>
<td>0.179</td>
<td>0.066</td>
<td>0.294</td>
</tr>
<tr>
<td>5. Capacity (10^6 units)</td>
<td>0.307</td>
<td>4.694</td>
<td>0.000</td>
<td>182.5</td>
<td>-0.007</td>
<td>-0.026</td>
</tr>
</tbody>
</table>

Table A.5.2: Variable descriptive statistics and correlations: model (3.1); complete sample.
### Variable descriptive statistics and correlations: model (3.2); complete sample with Blockholding observations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Observations = 151</th>
<th></th>
<th></th>
<th></th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Mean</strong></td>
<td><strong>S.D.</strong></td>
<td><strong>Minimum</strong></td>
<td><strong>Maximum</strong></td>
<td>1.</td>
<td>2.</td>
<td>3.</td>
<td>4.</td>
<td>5.</td>
</tr>
<tr>
<td>1. Tobin’s q</td>
<td>1.306</td>
<td>0.504</td>
<td>0.276</td>
<td>3.003</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Speed</td>
<td>0.047</td>
<td>0.752</td>
<td>-1.626</td>
<td>1.991</td>
<td>0.124</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Blockholding</td>
<td>11.975</td>
<td>13.476</td>
<td>0.000</td>
<td>50.293</td>
<td>-0.125</td>
<td>0.058</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. R&amp;D Intensity</td>
<td>0.007</td>
<td>0.012</td>
<td>0.000</td>
<td>0.052</td>
<td>0.171</td>
<td>0.087</td>
<td>0.155</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>5. Leverage</td>
<td>0.213</td>
<td>0.118</td>
<td>0.012</td>
<td>0.637</td>
<td>-0.371</td>
<td>0.044</td>
<td>0.527</td>
<td>-0.036</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table A.5.3: Variable descriptive statistics and correlations: model (3.2); complete sample with Blockholding observations.

### Variable descriptive statistics and correlations: model (3.2); complete sample with S&P Score observations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Observations = 198</th>
<th></th>
<th></th>
<th></th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Mean</strong></td>
<td><strong>S.D.</strong></td>
<td><strong>Minimum</strong></td>
<td><strong>Maximum</strong></td>
<td>1.</td>
<td>2.</td>
<td>3.</td>
<td>4.</td>
<td>5.</td>
</tr>
<tr>
<td>1. Tobin’s q</td>
<td>1.247</td>
<td>0.526</td>
<td>0.447</td>
<td>3.102</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Speed</td>
<td>0.072</td>
<td>0.760</td>
<td>-1.281</td>
<td>2.732</td>
<td>0.040</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. S&amp;P Score</td>
<td>59.005</td>
<td>17.785</td>
<td>18.000</td>
<td>84.000</td>
<td>0.302</td>
<td>-0.113</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. R&amp;D Intensity</td>
<td>0.007</td>
<td>0.013</td>
<td>0.000</td>
<td>0.069</td>
<td>0.068</td>
<td>0.048</td>
<td>0.237</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>5. Leverage</td>
<td>0.183</td>
<td>0.113</td>
<td>0.000</td>
<td>0.517</td>
<td>-0.230</td>
<td>0.058</td>
<td>-0.385</td>
<td>-0.130</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table A.5.4: Variable descriptive statistics and correlations: model (3.2); complete sample with S&P Score observations.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WACC</td>
<td>EBIDA</td>
<td>WACC</td>
<td>EBIDA</td>
</tr>
<tr>
<td>Constant</td>
<td>1.374*** (0.247)</td>
<td>1.312*** (0.244)</td>
<td>1.833*** (0.103)</td>
<td>1.239*** (0.251)</td>
</tr>
<tr>
<td>Speed</td>
<td>0.077** (0.032)</td>
<td>0.083** (0.032)</td>
<td>0.073** (0.033)</td>
<td>0.079** (0.034)</td>
</tr>
<tr>
<td>Blockholding</td>
<td>0.003 (0.005)</td>
<td>0.002 (0.004)</td>
<td>0.002 (0.004)</td>
<td>0.002 (0.004)</td>
</tr>
<tr>
<td>Leverage</td>
<td>-1.079** (0.512)</td>
<td>-0.967* (0.527)</td>
<td>-1.107** (0.527)</td>
<td>-0.990* (0.546)</td>
</tr>
<tr>
<td>Advertising Intensity</td>
<td>-7.446 (21.727)</td>
<td>-7.182 (21.799)</td>
<td>-8.962 (18.291)</td>
<td>-8.819 (18.083)</td>
</tr>
<tr>
<td>Industry Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>222</td>
<td>224</td>
<td>222</td>
<td>224</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.371</td>
<td>0.380</td>
<td>0.385</td>
<td>0.395</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.315</td>
<td>0.325</td>
<td>0.327</td>
<td>0.339</td>
</tr>
<tr>
<td>Likelihood Ratio $\lambda$ (RPM vs. OLS, $\chi^2_{16}$)</td>
<td>55.785***</td>
<td>29.754**</td>
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<td></td>
</tr>
</tbody>
</table>

Table A.5.5: Multivariate OLS regression with the covariance matrix robust to clustering by firm: model (3.2).

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
### A.6. Robustness Checks (in §6.)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Constant</th>
<th>Speed</th>
<th>S&amp;P Score</th>
<th>R&amp;D Intensity</th>
<th>Leverage</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.665**</td>
<td>0.538***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.538***</td>
</tr>
<tr>
<td></td>
<td>(0.266)</td>
<td>(0.065)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.065)</td>
</tr>
<tr>
<td>Speed</td>
<td>0.087***</td>
<td>-0.059***</td>
<td>0.075***</td>
<td></td>
<td></td>
<td></td>
<td>0.095***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.017)</td>
<td>(0.018)</td>
<td></td>
<td></td>
<td></td>
<td>(0.017)</td>
</tr>
<tr>
<td>S&amp;P Score</td>
<td>0.008**</td>
<td>0.005***</td>
<td>-0.005***</td>
<td>0.004***</td>
<td></td>
<td></td>
<td>0.008***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>R&amp;D Intensity</td>
<td>4.803**</td>
<td>2.193*</td>
<td>2.734**</td>
<td>3.465***</td>
<td>0.513</td>
<td></td>
<td>4.955***</td>
</tr>
<tr>
<td></td>
<td>(1.995)</td>
<td>(1.127)</td>
<td>(1.295)</td>
<td>(1.146)</td>
<td>(0.965)</td>
<td></td>
<td>(1.307)</td>
</tr>
<tr>
<td>Leverage</td>
<td>-0.897***</td>
<td>0.867***</td>
<td>0.754***</td>
<td>0.540***</td>
<td>-0.029</td>
<td>0.071</td>
<td>1.272***</td>
</tr>
<tr>
<td></td>
<td>(0.226)</td>
<td>(0.133)</td>
<td>(0.110)</td>
<td>(0.100)</td>
<td>(0.064)</td>
<td>(0.059)</td>
<td>(0.127)</td>
</tr>
<tr>
<td>Industry Dummies</td>
<td>Yes</td>
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</tr>
<tr>
<td>Year Dummies</td>
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</tr>
<tr>
<td>Number of Observations</td>
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<tr>
<td>Log-likelihood</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Table A.6.1: Linear random parameters model regression with correlated coefficients: model (3.2).

* \( p < 0.1 \), ** \( p < 0.05 \), *** \( p < 0.01 \)
Appendix to Pacheco-de-Almeida, Hawk, and Yeung: Speed and Tobin’s q

<table>
<thead>
<tr>
<th>Variable</th>
<th>Constant</th>
<th>Speed</th>
<th>S&amp;P Score</th>
<th>R&amp;D Intensity</th>
<th>Leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>— ‡</td>
<td>— ‡</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Speed</td>
<td>-0.032***</td>
<td>— ‡</td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P Score</td>
<td>0.003***</td>
<td>-0.001***</td>
<td>— ‡</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R&amp;D Intensity</td>
<td>1.179*</td>
<td>0.077</td>
<td>0.010</td>
<td>— ‡</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.625)</td>
<td>(0.126)</td>
<td>(0.009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leverage</td>
<td>0.466***</td>
<td>0.006</td>
<td>0.003**</td>
<td>5.821***</td>
<td>— ‡</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.023)</td>
<td>(0.001)</td>
<td>(1.749)</td>
<td></td>
</tr>
</tbody>
</table>

Table A.6.2: Implied covariance terms of the random parameters: model (3.2).

* p < 0.1, ** p < 0.05, *** p < 0.01, ‡ reported in table A.5.6

Figure A.6.1: The marginal effect of speed on firms’ market value: model (3.2) uses the S&P Score.
References

See references list in the main paper.