Integration and Cospecialization of Emerging Complementary Technologies by Startups

Edward G. Anderson Jr.
University of Texas
Edward.Anderson@mccombs.utexas.edu

Geoffrey G. Parker
Tulane University
gparker@tulane.edu

May 25, 2012
Forthcoming, *Production and Operations Management*

Abstract

We analyze the market entry problem faced by startups that must *integrate their service or product* with one or more complementary technologies. The problem is especially challenging when the complementary technologies have large but uncertain cost reduction potentials. The market for intermittent renewable power generation (e.g., wind, solar) combined with storage (e.g., battery, pumped reservoir, flywheel) provides a motivating context. Renewable generation technologies are immature; thus storage startups face high risks when making R&D investments to integrate with them.

The entrepreneurship literature often suggests that startups should pursue focused strategies for various reasons, including bounded rationality and budget constraints. This literature generally overlooks startups entering markets with complementary technologies. The advice for mature firms investing in complementary technologies is often to diversify their investment across multiple complements to manage technological uncertainty. Given competing guidance, we seek to extend the entrepreneurship literature by modeling startups' entry decisions for markets in which complementary technologies exhibit strong learning effects.

We find that, consistent with the extant entrepreneurship literature, startups generally achieve higher expected returns by channeling their integration investment to only one complementary technology. However, the mechanisms driving our results are very different from prior research findings and hinge primarily on nonlinear feedback effects that occur when firms concentrate integration investment in only one complementary technology. Interestingly, this focused strategy often does not yield the highest market share or the lowest likelihood of bankruptcy. We characterize the situations under which each finding holds and describe the implications of these findings for theory, practice, and policy.

Keywords: startups, entrepreneurship, complements, integration, learning curve, externalities, power storage, power generation, renewables

Support from the National Science Foundation (SES-0925004) is gratefully acknowledged.

1 Introduction

In many markets with either supply- or demand-side externalities, a startup's success is strongly tied to the availability of complementary technologies (Schilling 2002) that are often technologically distinct and rapidly evolving (Van de Ven 2005). Emerging complementary industries are those whose products and services involve a system of complementary technologies (or complements) with uncertain cost trajectories (from learning curves or network externalities) and uncertain market penetration. They include, for example, apps and smartphones, videogames and consoles, and smart meters and smart grids (Cusumano 2010; Eisenmann et al. 2011). A recent Google search of startups selling into such "two-sided" markets conducted on March 16, 2012 using the terms "two-sided market startup" identified hundreds of startups that claim to be pursuing strategies dependent on complementary technologies. These sites indicate that startups face a difficult investment decision because they must choose which complementary technology or technologies to focus their R&D efforts on. As a simple example, consider the energy storage market whose products smooth the volatility of power delivered by renewable generation technologies such as wind or solar power. An energy storage entrant can integrate its technology to work more effectively with that of wind technology, solar technology, or both. Because the complementary technologies are technically complex, investment in R&D to integrate the storage technology with a given complementary technology such as wind is generally complex, expensive, and difficult (Anderson et al. 2007; Makri et al. 2010). Moreover, investment in a complementary technology is typically idiosyncratic and hence will not fully and seamlessly transfer to a second complementary technology (Grant 1996).

Because capital is usually scarce for startups, managing the integration investment decision is critical to the startup in emerging complementary industries/markets. Yet the extant literature's guidance on this issue is contradictory and imprecise. For example, the entrepreneurship literature (e.g., Sandburg and Hofer 1987; Romanelli 1989) generally suggests that startups, because of their limited capital and other resources (such as limited technical staff), should pursue focused investment strategies in the face of uncertainty (e.g., they should invest in R&D

to tailor the product for only one of several potential markets). However, this entrepreneurship literature does not explicitly consider how integration investment affects complementary technologies. A separate product development literature (Arditti and Levy 1980; Ward et al. 1995; Srinivasan et al. 1997; Krishnan and Bhattacharya 2002) offers more nuanced guidance that includes spreading integration investment across complementary technologies to mitigate the risk of technology failure. However, few firms studied in this stream of literature are startups; most are established firms with access to significant capital, which greatly impacts outcomes.

To reconcile these contradictory recommendations, we carefully model the integration investment decision faced by startups that depend on emerging complementary technologies. Specifically, we analyze two decisions that a startup must make that critically impact its success: (1) how much to invest in integrating complementary technologies, and (2) whether to focus integration investments on one complementary technology or across multiple complementary technologies. Because this decision inherently involves numerous nonlinear market and learning feedback loops with embedded delays, it is difficult to analyze, either intuitively or through a closed-form analysis (Sterman 1994). To overcome this, we employ the system dynamics methodology (Forrester 1958) to create and explore a simplified, conceptual simulation model of the problem. For concreteness, we ground the simulation in the context of the aforementioned energy storage industry (which produces batteries, flywheels, molten salt storage, etc.) because it typifies emerging complementary industries. For example, an energy storage startup firm might decide to integrate its technology with wind power by cospecializing it through inverter selection, control electronics, and by adding capacitors (Xtreme Power 2010). However, integration with wind power does not make the startup's product fully compatible with photovoltaic solar power because of differences in electrical characteristics, generation volatility, and specific physical characteristics (LaMonica 2010). Any integration investment by the storage startup that makes a complementary technology, such as wind power, more attractive for purchase by power producers (e.g., utilities or independent power producers) will enhance the startup's learning efforts. This is because additional sales of storage will affect the rate of the storage startup's learning efforts, increasing both deliberate learning (because additional revenue is available for R&D investment) and autonomous learning (from the learning curve). Because this learning further increases the attractiveness of the startup's product to the market, an endogenous reinforcing loop is created. In addition, because both technologies involved (storage and generation) are rapidly evolving, the energy storage startup faces a complex and highly risky integration investment decision.

We develop a simulation model to explore how various factors, uncertainties, and scenario parameters influence the storage startup's integration investment decision using the system dynamics methodology (Forrester 1958; Sterman 2000). We capture uncertainty by varying the startup's technology learning curve, the learning curves of the complementary technologies, and the price of natural gas. Natural gas is a mature competitor to the startup's energy storage technology because natural gas plants can rapidly ramp up and down to compensate for the volatility inherent in wind and solar power generation. To test the sensitivity of our findings to the assumptions in our simulation model, we vary such parameters as technological uncertainty, technology costs, the amount of capital injected by an equity partner, the discount rate and time horizon, market sensitivity to price, technological spillovers, and "over-investment" in integration, among others.

In particular, this model shows that startups maximize value creation by investing in integrating with only one complementary technology. Our model's results generally agree with the earlier entrepreneurship literature's recommendation to focus R&D investment. Unlike earlier guidance from studies that hinge on the effects of bounded rationality and limited access to capital, however, our results derive from the nonlinear feedback effects that occur when a startup concentrates its integration investment on a single complementary technology. Moreover, our model can characterize the sensitivity of this decision. For example, increases in uncertainty or the strength of supply chain externalities increase the advantages of a one-technology focus, while favorable financial conditions (e.g., reduced interest rates, increased working capital) or increased transferability of the integration investment from one complementary technology to another (integration spillover) lessen the advantages of such focus. In addition, while focused technology strategies may optimize financial returns, they often do not optimize market share or lower bankruptcy rates. For example, from a managerial perspective, a focused integration investment strategy is often suboptimal with respect to market share when there are favorable market conditions (significant market growth or low market sensitivity to price), significant integration spillover, or a compressed decision horizon. With respect to bankruptcy, avoiding integration investment altogether is typically optimal.

Since our research questions have broad implications, as indicated earlier, but our simulation is specific, we extend the sensitivity analyses described earlier to explore the external validity of our model. The findings were extremely robust to variations in assumptions, giving us confidence that our model's findings are not only applicable to the energy storage industry, but are likely to apply to other emerging complementary industries as well. This allows us to address broader research issues at the interface of the operations and entrepreneurship literature. First, we reconcile competing advice from the entrepreneurship literature (Sandburg and Hofer 1987; Romanelli 1989) and flexible product development literature (Arditti and Levy 1980; Ward et al. 1995; Srinivasan et al. 1997; Krishnan and Bhattacharya 2002; Sommer and Loch 2004; Sommer et al. 2008) by characterizing the integration investment decision in emerging complementary markets. Specifically, we examine factors that drive the startup's decision to (1) invest in cospecialization with complementary technologies, and (2) to focus that investment on one complementary technology or spread it among multiple technologies. Secondly, we extend the integration (Anderson and Parker, Forthcoming) and "winner-take-all" two-sided market (Parker and Van Alstyne 2005; Eisenmann et al. 2011) literature to begin to address some operational issues and constraints specific to the startup environment.

The paper proceeds as follows. In Section 2, we discuss the relevant literature. Section 3 describes our model. Section 4 formally presents the various sensitivity and policy analyses performed on this model and extensively details how various factors affect the optimal integration investment decision. In Section 5, we discuss the limitations of this study and its implications for theory. Section 6 concludes by discussing implications for practice and policy.

2 Literature Review

To investigate the startup integration investment decision in emerging complementary industries, we must build upon several research streams relevant to the topic. The literatures on R&D investment decisions for business startups and venture financing and entrepreneurship success both discuss the investment decisions that must be made under the constraints that startups typically face. The complements and two-sided networks literature touches on the complements and externalities faced by firms in complementary industries. The product integration literature discusses integration investment directly, and the flexible product development literature examines investment in competing technologies under technological uncertainty. We also outline the system dynamics work in the field of renewable energy as it relates to our motivating example. The guiding logic behind our literature review is to include only papers that bear directly on the integration investment decision or are highly cited papers in a particular field touching on this topic. Finally, we offer a summary table (Table 1) that identifies the gaps in these literatures with respect to the factors underlying the questions investigated by this paper.

2.1 R&D Investment Decisions

Much of the literature that examines R&D in the startup context focuses on the flow of innovation either between firms (e.g., Shan et al. 1994; Gans and Stern 2000; Almeida et al. 2003; Rothaermel and Deeds 2004) or between firms and institutions (e.g., universities, government bodies) (e.g., Bania et al. 1993; Mansfield and Lee 1996). Other streams address the underpinnings of R&D success in startups, such as personnel quality or geographic location (e.g., Deeds et al. 2000). The literature that focuses directly on how startups make R&D investment decisions, and how best to make such decisions, is surprisingly limited. Shane and Ulrich (2004) point out that *Management Science* published only four articles between 1971 and 2004 that examine startup *decision making with respect to operational decisions*. Joglekar and Levesque (2009) note a gradual correction of this scarcity in recent years and model the trade-off between marketing and R&D investment in startups. Armstrong and Levesque (2002) model a startup's entry timing into a market as a function of the industry's overall R&D progress. Zott's (2003) simulation study traces the role of experimentation, imitation, timing, cost, and resource deployment in market entry decisions and subsequent success. Similarly, Hilmola et al. (2003) use a system dynamics model to examine how a reduction in software development lead time can improve financial outcomes for software startups by increasing the amount of working capital available for R&D. Related work on inventory and production decisions in startups includes Babich and Sobel (2004), Archibald et al. (2002), and Swinney et al. (2011). Interestingly, the latter two studies optimize long-term survival rather than shorter-term financial metrics. Finally, Tanrisever et al. (Forthcoming) characterize how a startup's debt influences the aggressiveness of its production and investment in process improvement.

2.2 Venture Financing and Entrepreneurship Success

An important stream of research examines sources of startup funding as a function of the startup's R&D decisions and other factors (Eckhardt et al. 2006; Hall and Lerner 2009), often by focusing on how venture capitalists make funding decisions (Gompers 1995; Amit et al. 1998; Zacharakis and Meyer 1998; Zacharakis and Meyer 2000). Another strand explores how venture capitalists oversee funded startups (Lerner 1995; Sapienza et al.1996). A review of venture capitalists' investment decision making appears in Soderblom and Wiklund (2006). A significant body of literature examines key drivers of startup success; most of these studies recommend that startups pursue tightly focused strategies, particularly in the context of working capital constraints and compressed time horizons (and associated high discount rates) that startups face. Bruderl et al. (1992) show that startups occupying a narrow niche in the market have a higher survival rate. Mitchell and Nault (2007) explore the role of cognition and bounded rationality in entrepreneurship success. Janney and Dess (2006) and Norton and Tenenbaum (1993) find that investors (especially venture capitalists) who specialize by industry improve their ability to control risk because they can better evaluate startups in that industry, and thus look for more focused firms in which to invest. Romanelli (1989) finds that aggressive market specialization is good for startups' survival; Sandberg and Hofer (1987) agree, but argue that it can also limit a product's functionality. This idea recalls the "lean startup" set of ideas championed by Ries (2011) that asserts that a "minimum viable product" in terms of functionality is necessary to gain rapid market feedback.

2.3 Complements and Two-Sided Networks

Studies on complementary assets include Teece (1986), Tripsas (1997), and Rothaermel (2001) and continue to the present. Gawer and Cusumano (2002) and Eisenmann et al. (2009) provide recent reviews. In general, papers in this literature stream consider the strategic question of whether a firm should best obtain cospecialized complementary assets through internal resources, alliances, open innovation (Chesbrough 2003), or some combination thereof (von Hippel 2005). In contrast, the two-sided network literature (Rochet and Tirole 2003; Parker and Van Alstyne 2005) focuses on pricing rather than the R&D investment required to tailor complements on one side of the market to the other in order to create more attractive bundles for end-consumer consumption (Boudreau and Hagiu 2008). However, recent research has begun to focus on R&D investment decisions, as exemplified by Gawer and Cusumano (2002), Prencipe et al. (2003), Iansiti and Levien (2004), Schilling (2009), Cusumano (2010), Eisenmann et al. (2006, 2011), and Boudreau and Hagiu (2008). They find that emerging sponsors (firms with significant market power) can create standards, encourage investment, or use other levers to prevent market failures and manage network effects to improve their own outcomes.

2.4 Product Integration

A relatively small strand of literature related to the investment integration decision examines product integration (for a review, see Anderson and Parker (Forthcoming)). Key results show that product integration is difficult in terms of expense, resources, and time (Parker and Anderson 2002; Prencipe et al. 2003; Makri et al. 2010), yet is often a decisive factor in the marketplace (Iansiti 1995a, 1995b). Teece (1986) and a number of other investigators on complementary assets also pursue this question, albeit within the context of either a vertically integrated firm or mature buyer-supplier dyads, whereas our study concerns emerging complementary markets like energy storage. Despite the type of industrial organization, however, Grant (1996) contends that any investment in integrating two disparate technologies will be idiosyncratic because so much of the knowledge underlying any technology is tacit, and tacit knowledge is notoriously difficult to transfer (Kogut and Zander 1992). For example, an energy storage startup's investment in integrating its storage technology with wind power technology, for example, cannot be repurposed later on to integrate with solar power without significant additional costs.

2.5 Flexible Product Development

For the most part, research in product development and management of technology in mature firms does not directly address the integration investment decision (Krishnan and Ulrich 2001; Shane and Ulrich 2004; Gaimon 2008). However, a closely related stream studies flexible product development (Nelson 1961; Arditti and Levy 1980; Ward et al. 1995; Srinivasan et al. 1997; Krishnan and Bhattacharya 2002; Sommer and Loch 2004; Sommer et al. 2008). This research suggests that it is often economically beneficial for firms to make R&D investments in two or more potential technologies in the presence of technological uncertainty. However, the firms studied in this stream of literature do not bear the startup's time compression and working capital constraints nor the supply-side externalities created by emerging complementary markets.

2.6 Systems Dynamics Energy Modeling

Because our motivating example of renewable energy employs a systems dynamics model, we note that system dynamics has a long and rich history of energy modeling. Most relevant to the context of the motivating example in this paper, Struben (2006) and Struben and Sterman (2007) analyze technological diffusion in the renewable energy industry and examine industry decisions at an aggregate level. In contrast, where they study aggregate industry decisions, we isolate and study the decision-making processes of an individual startup in the industry.

2.7 Literature Gap

To sum up, the extant literatures do not simultaneously consider all the major factors that bear on the integration investment decision for startups in emerging complementary industries—market growth, integration, supply side externalities, time horizon compression, working capital constraints, and focus (Table 1). In particular, although the most relevant and recent product development literature finds that mature firms facing uncertainty often create value by investing in integrating with multiple technologies, the literature on drivers of startup success *recommends focused R&D investment.* Both literatures have significant gaps. The flexible product development literature does not consider the constraints that startups face such as working capital constraints and time compression. The extant startup literature does not address how best to make R&D decisions in the presence of complementary technologies that exhibit the sort of supply- and demand-side network externalities characteristic of two-sided markets, which represent a growing segment of the economy (Eisenmann et. al. 2009). These gaps are important, not only because research strongly supports the correlation between the presence of complementary technologies and startup outcomes (Schilling 1999; Schilling 2002; Van de Ven 2005), but because entrepreneurs increasingly are basing their investment strategies on integrating with complementary technologies to harness externalities (Eisenmann et. al 2006). We propose to begin bridging these gaps by carefully examining the specific drivers of *startups'* integration investment decisions in the context of complementary technologies with supply-side externalities such as learning curves.

Table 1: Summary of Factors Considered in this Paper vs. That of the Reviewed Literatures

	Factors Considered in This Paper					
Literature	Market Growth	Integration	Supply Side Externalities	Time Horizon Compression	Working Capital Constraints	Focus
Startup R&D Investment Decisions	x	-	-	x	x	-
Venture Financing & Entrepreneurial Success	x	-	-	x	x	x
Complements/Two-sided Networks	x	x	x	-	-	-
Product Integration	-	x	-	-	-	-
Flexible Product Development	-	x	-	-	-	x
System Dynamics Energy Modeling	x	-	x	-	-	-

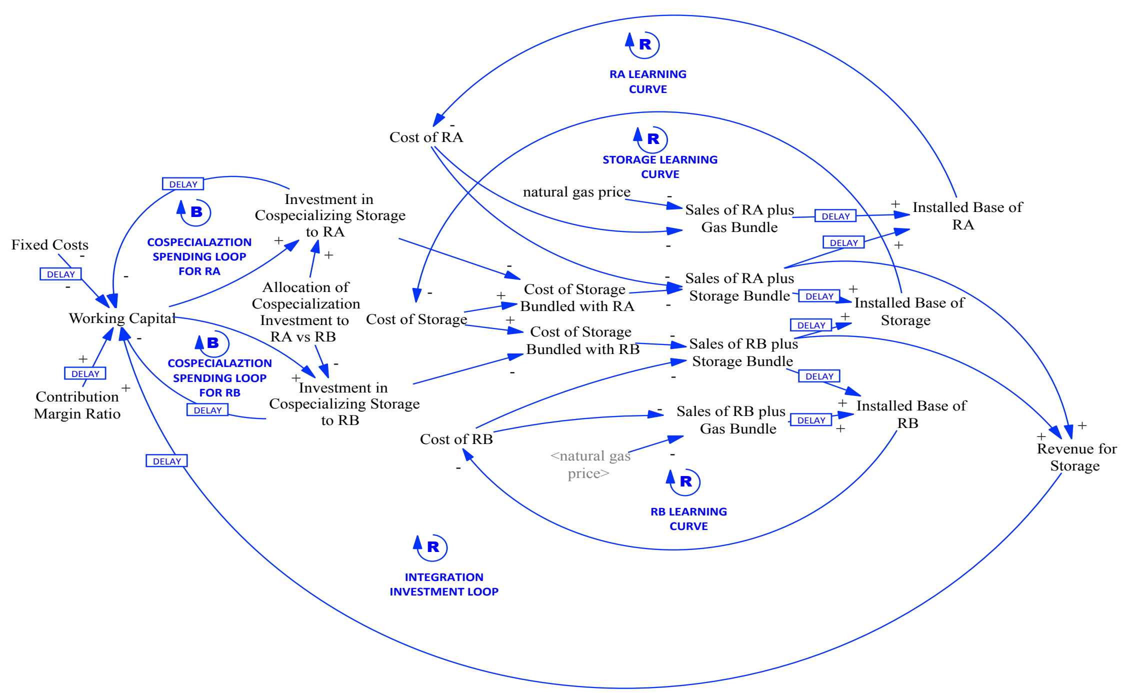
3 The Model

3.1 Startups and Complementary Technologies

We develop a conceptual model to highlight key issues that affect integration investment decisions in the presence of emerging complementary technologies. We ground our analysis in the energy storage industry to provide a concrete example, but will not attempt to capture all of the subtleties of that industry because doing so would add substantial complexity without further illuminating our research questions. For example, we assume that the fraction of the installed base of U.S. power generation held by intermittent renewable generation has reached the level at which each purchase of new, intermittent, renewable power-generation capacity will require a complementary purchase to ensure acceptable power quality (i.e., to reduce the volatility of power output within acceptable parameters). In reality, many geographic areas in the U.S. have not yet experienced that level of penetration. However, in the near term, the industry is expected to reach that level (Taylor 2009). Our model assumes this level of renewable penetration has already been reached because to do otherwise would complicate the model without increasing its power to generate insights. For similar reasons, we include only two complementary technologies in our model. For convenience, we label them "RA" and "RB," and refer to them together as "renewables," "complementary technologies," or just "complements." Most often, we will use wind power and photovoltaic solar power (hereafter just "solar" power) as examples. We model two alternatives that can complement the renewables by sufficiently smoothing out their inherent volatility: natural gas (hereafter "gas") and the startup's storage technology (hereafter, "storage"). Where it helps the exposition, we use batteries as an example of storage. We refer to both gas and storage as "smoothing technologies." In our model, the market of independent power producers (IPPs) that purchases renewable power can choose from four bundles of renewable and smoothing technologies: RA-storage, RA-gas, RB-storage, or RB-gas. These four bundles compete with one another for market share.

Figure 1 illustrates a causal loop diagram of our model. In causal loop diagrams, which present an overview of the dynamic structure of the model, a "+" on an arrow between two variables indicates that the variable's partial derivative (at the head of the arrow) is positive with respect to the variable at the tail. For example, an increase (decrease) in the *Sales of RB plus Storage Bundle* will increase (decrease) the *Revenue for Storage,* all other factors being equal. In contrast, a "–" on an arrow between two variables indicates that the variable's partial derivative (at the head of the arrow) is negative with respect to the variable at the tail. For example, an increase (decrease) in the *Cost of Storage Bundled with RB* will decrease (increase) the *Sales of RB plus Storage Bundle,* all other factors being equal. The delays indicate a delayed response between the two variables, generally caused by the presence of an integration or accumulation of one or more stocks between the two variables. An "R" above a loop's name indicates that the partial derivative of each variable along that loop with respect to itself is positive, albeit with a delay. Hence, these loops are reinforcing cycles. A "B" above a loop's name indicates that the partial derivative of each variable along that loop with respect to itself is negative. These sorts of loops are referred to as "balancing" loops as they tend to balance out over time. We now proceed with a more detailed and mathematical description of each relationship in the model.

Figure 1: Causal Loop Diagram of The Model



First, we assume that learning-by-doing (or the "learning curve") occurs in the production of the two renewable generation technologies and the storage technology, which is typical of immature technologies (Argote 1999), although we note (as does Argote 1999) that some of this learning process is the result of the reinvestment of the contribution margin to reduce technology costs. Accordingly, the cost per kilowatt (kW) purchased in equations (1) and (3a), as levelized over time including in capital, installation, operating and maintenance, and so on (Darling et al.

2011), of each renewable generation technology decreases in the standard power-law fashion as a function of the cumulative installed base for that technology (Argote 1999). The cost of each new unit of storage (in kWh) in (2) and (3b), again levelized over time, also decreases in a similar manner. In contrast, the levelized cost of natural gas, which includes all the costs listed above *plus* fuel cost (Kluza 2009: 42) is that of a mature technology. Given the high commodity price exposure, the gas generation cost is assumed to vary as an AR(1) or "pink noise" process as modeled in (4a) – (4b) to avoid sensitivity to the time step chosen to numerically evaluate the model (for details, see Sterman 2000: 917-920; Anderson and Fiddaman 2010). Thus,

$$Q_i(t) = \int_0^t \left[d_{i,s}(t) + d_{i,g}(t) \right] dt \, , \; i \in \{a,b\} \tag{1}$$

$$Q_s(t) = \int_0^t \left[d_{a,s}(t) + d_{b,s}(t) \right] dt \tag{2}$$

$$c_i(t) = \alpha_i \left[\frac{Q_i(t)}{Q_i(0)} \right]^{-\gamma_i} , \; i \in \{a,b\} \tag{3a}$$

$$c_s(t) = \alpha_s \left[\frac{Q_s(t)}{Q_s(0)} \right]^{-\gamma_s} \tag{3b}$$

$$\frac{dc_g(t)}{dt} = \frac{e(t) - c_g(t)}{\tau_{corr}} \, , \tag{4a}$$

$$e(t) \sim Norm\left(\mu_{Cg}, \sigma_{Cg} \left[\sqrt{2 - \frac{\tau_{dt}}{\tau_{corr}}} \right] \left[\sqrt{\frac{\tau_{corr}}{\tau_{dt}}} \right] \right) \tag{4b}$$

a	is the index for Renewable A.
b	is the index for Renewable B.
s	is the index for storage.
g	is the index for gas.
$d_{i,j}(t)$	is IPP demand at time *t* for the bundle of renewable *i* with smoothing technology *j*.
$Q_i(t)$	is the installed base of renewable technology *i* at time *t*.
$Q_s(t)$	is the installed base of storage at time *t*.
$c_i(t)$	is the cost per unit of renewable technology $i \in \{a,b\}$ at time *t* as levelized over its operational lifetime. Note that this does not include any effects of integration investment.
$C_s(t)$	is the cost per kWh for the storage technology. The cost is levelized over the lifetime and usage intensity of the technology. Note, when storage is bundled with renewable power generation, it is most typically sold in a bundle of 4 kWh of storage for each kW of renewable power capacity (Kluza 2009: 42).
$C_g(t)$	is the cost per kWh from use of gas generation as a smoothing technology, with capital and operating costs levelized over the asset's operational lifetime. Due to the volatility of natural gas prices, the gas generation cost is assumed to vary as an AR(1) or pink noise process with mean μ_{Cg} and standard deviation σ_{Cg}.

$e(t)$ is the white noise input to the pink noise filter; the standard deviation of $e(t)$ is scaled in (4b) so that σ_{C_g} is independent of the time step τ_{dt} used to numerically evaluate the simulation (Anderson and Fiddaman 2010).
τ_{corr} is the correlation time for the AR(1) gas cost process.
α_i is renewable i's initial unit "production" cost.
α_s is storage's initial unit "production" cost.
γ_i is renewable i's learning parameter, $\gamma_i \geq 0$.
γ_s is storage's learning parameter, $\gamma_s \geq 0$.

Note that the learning parameters γ_i, γ_s are related to the learning curve "slope," that is, the percent drop in production cost, in the following manner:

$$\gamma = \ln(\text{learning curve slope}) / \ln(2). \tag{5}$$

3.2 Integration and Cospecialization

Integrating complex technologies is difficult (Iansiti 1995a, 1995b; Parker and Anderson 2002), and entrants in the storage sector are reducing integration costs by cospecializing their products to that of a renewable technology. Some cospecialization may transfer or "spill over" between renewable technologies (Ghemawat and Spence 1985), but for simplicity we model only that portion that does not spill over and assume that the remainder is embedded in the "production" costs as discussed in Sections 3.1 and 3.4. In Section 4, we examine the implications of relaxing this assumption.

We model the effect of the integration investment on cospecialization in (6) by assuming that the cost for the startup's storage technology that is cospecialized for a particular complement is the product of its production cost and a cospecialization cost multiplier $x_{i,s}(t)$ where i indexes either RA or RB. In (7), this multiplier is assumed to exhibit diminishing returns in the cumulative investment $N_i(t)$ and has an upper bound of unity and a lower bound between zero and unity, which is consistent with prior studies on R&D investment (Weill and Olson 1989; Gaimon 1997; Kouvaritakis et al. 2000). Because gas is a mature technology, our model assumes that all potential cospecialization benefits have been realized, so in (8) its cospecialization cost multiplier $x_{i,g}(t)$ is set to unity. Hence, the price of the total bundle of the smoothing technology (either storage or gas) and its complement (either RA or RB) is modeled as shown in (9).

$$N_i(t) = \int_0^t n_i(t)\, dt \text{ where } N_i(0) = 0 \text{ and } i \in \{a,b\} \tag{6}$$

$$x_{i,s}(t) = \exp\left[-\upsilon_i N_i(t)\right]\left(1 - x_{i,\min}\right) + x_{i,\min},\ i \in \{a,b\} \tag{7}$$

$$x_{i,g}(t) = 1,\ i \in \{a,b\} \tag{8}$$

$$p_{i,j}(t) = c_i(t) + x_{i,j}(t)c_j(t),\ i \in \{a,b\},\ j \in \{s,g\} \tag{9}$$

$N_i(t)$ is cumulative integration investment in cospecializing in renewable *i* at time *t* where $N_i(0) = 0$.

$n_i(t)$ is the instantaneous integration investment in cospecializing in renewable *i* at time *t*.

$x_{i,s}(t)$ is the cospecialization cost multiplier for bundling storage and renewable *i* at time *t*.

$x_{i,g}(t)$ is the cospecialization cost multiplier for bundling gas and renewable *i* at time *t*.

$\nu_i\ (t)$ is the cospecialization parameter for renewable *i*, a constant.

$x_{i,min}$ is the minimum cospecialization multiplier and lies between zero and unity.

$p_{i,j}(t)$ is the cost (including integration) per unit of the smoothing technology *j* at time *t* cospecialized to renewable *i*.

Because we do not directly analyze the suppliers' cost structures in these equations but only how they are reflected in bundle prices passed on to the independent power provider (IPP) market, for convenience, the supplier markups in this model are assumed to be impounded into the costs of production and integration for the various technologies. This assumption is reasonable if we assume that the markup is constant between the price at which the market purchases bundles and the actual cost to the various suppliers to provide them. Such a relationship is often found in practice and is commonly assumed in the system dynamics literature (Sterman 2000: 803-813).

3.3 Bundle Cost and Market Adoption

Recall that the IPPs form a market that buys bundles of renewable energy and storage. The rate at which the market purchases each bundle is governed by (10) – (13), which detail the logit choice model that is standard for market models in the system dynamics literature (Sterman et al. 2007) and is derived from the marketing literature (see e.g., Lilien et al. 1992).

$$d_{i,j}(t) = m_{i,j} d_{ipp},\ i \in \{a,b\},\ j \in \{s,g\} \tag{10}$$

$$m_{i,j}(t) = a_{i,j} / \sum_{k,l} a_{k,l},\ i,k \in \{a,b\},\ j,l \in \{s,g\} \tag{11}$$

$$a_{i,j}(t) = \exp\left(-\varepsilon p_{i,j} / p_{ref}\right),\ i \in \{a,b\},\ j \in \{s,g\} \tag{12}$$

$d_{i,j}(t)$ is the demand for the bundle of renewable *i* and smoothing technology *j,*

d_{ipp} is the overall demand for renewables, a constant,

$m_{i,j}(t)$ is the market share of the bundle of renewable *i* and smoothing technology *j,*

$a_{i,j}(t)$ is the market attractiveness of the bundle of renewable i and smoothing technology j,

ε is the sensitivity of market attractiveness to price, and

p_{ref} is a normalizing reference price that enables ε to be a unitless constant.

3.4 Working Capital and Investment in Cospecialization

Figure 1 presents a causal-loop diagram of the full model including the integration investment and working capital structures. We assume that the startup is in the growth/expansion phase and has a sellable, albeit immature, product. There are a number of ways to model R&D investment in cospecialization during this phase. One is to model investment as a constant fraction of the income stream. This is a common practice, particularly in empirical studies, and is also used by Rahmandad (2012) to model investment in long-term capabilities such as R&D. While this formulation captures the decisions of well-established firms reasonably well, it creates irrational behavior in startups, which receive periodic injections of working capital separate from income. Moreover, modeling investment as a function of the income stream does not take into account whether a firm is near bankruptcy, an ever-present danger for startups. Modeling investment as a fraction of revenue is even more prone to both of these problems. To avoid these issues, we adapt the work of Joglekar and Levesque (2009), who suggest that investment in R&D is a constant fraction of working capital. Modeling investment as a constant fraction of working capital requires the creation of a simple balance sheet to track working capital for the storage entrant. Most startups are funded by several rounds of capital injection, which, in principle, can combine both debt and equity financing. However, we make a number of simplifying assumptions to minimize unnecessary complexity in the model because our main purpose is to examine how the startup should make the integration investment decision and not to identify the exact effects of financial structure on the startup. One simplifying assumption is that all financing comes from equity because most high-tech startups are primarily equity financed (Hall 2002, Nolen 2011). The second simplifying assumption is that capital injections are made at equal intervals and in equal amounts. For example, in our base run scenario, which has a decision horizon of 8 years (96 months), cash injections of $10 million each occur at months 0, 32, and 64. We assume also that working capital increases over time as a function of revenue, which is itself a function of the price per unit and unit demand for each of the two renewable-storage bundles as shown in (13). In (9), we explicitly assume that the prices for all technologies in the model are a simple multiple of the variable cost (Sterman 2000: 803, 813). Continuing this assumption, revenue increases working capital in (14) at a rate determined by the contribution margin ratio, which, in this model, also subsumes all ongoing investment that is not explicitly directed toward cospecialization. We also assume in (14) a fixed cost per unit time for administrative burden and similar allied costs. Again, we model investment in cospecialization as a fraction of working capital in (15), but an exogenously determined portion of that investment goes to RA rather than RB.

$$r(t) = \rho \sum_i p_{i,s}(t) d_{i,s}(t)\,,\ i \in \{a, b\} \tag{13}$$

$$\frac{dK(t)}{dt} = \frac{K_{inj}}{M}\delta(t) + \kappa r(t) - f(t) - \sum_i n_i(t) \tag{14}$$

$$n_i(t) = \phi_i \psi(t),\ \text{where} \sum_i \phi_i = 1 \text{ and } i \in \{a, b\} \tag{15}$$

$r_i(t)$ is the revenue for the storage firm, in this case, price * demand.

ρ is a conversion factor between the levelized unit price per kWh and revenue in millions of U.S. dollars (MMUSD).

$K(t)$ is the working capital at time t for the storage entrant (in MMUSD).

K_{inj} is the total injection of working capital in MMUSD to the storage entrant over the entire simulation horizon, which comes from an equity partner.

M is the total number of injections over the simulation horizon.

$\delta(t)$ is an impulse (or Dirac "delta" function) of value unity when $t = \{0, t_f/M, 2t_f/M, \ldots, (M-1)t_f/M\}$ and the startup is not bankrupt (see definition of $t_{bankrupt}$ in Section 3.5). Otherwise $\delta(t) = 0$. (This provides a set of M equally spaced, equally sized injections K_{inj}/M millions of U.S. dollars).

κ is the contribution margin ratio (price – variable cost)/price per unit of storage,

$f(t)$ is the fixed costs at time t for the storage entrant (this is constant over the simulation).

ψ is the fraction of working capital $K(t)$ that is directed per year to investment in cospecialization (e.g., if ψ = 36% per year, then 3% of working capital will be directed to investment in cospecialization each month).

ϕ_i is the fraction of total investment in cospecialization directed to renewable i.

3.5 Objective Function

The objective function of this model is to maximize the net present value (NPV) of the startup firm over the planning horizon.

$$\underset{\psi,\,\phi_a,\,\phi_b}{Max} \int_0^{t_f} \exp(-\theta t)\left\{\frac{dK(t)}{dt} - \frac{\delta(t)K_{inj}}{M}\right\}dt \quad \text{where} \quad t_f = \min\left(t_{horizon}, t_{bankrupt}\right) \qquad (16)$$

θ	is the discount rate.
$t_{horizon}$	is the time horizon for the startup's decisions prior to the liquidity event.
$t_{bankrupt}$	is the time at which working capital *K(t)* first declines to zero, i.e., it becomes insolvent. We equate this with the legal condition of bankruptcy to avoid complicating the model with legal considerations that do not increase our insights. Note that "bankruptcy" may not occur over the decision horizon of the model, in which case $t_{bankrupt}$ is assumed to be greater than $t_{horizon}$.

4 Sensitivity and Policy Testing

In this section, we test the model using the Vensim® simulation package for various sensitivity and policy concerns to examine the effects of integration investment on complementary products. Explicit validation tests for the model are presented in the online appendix as is a table of base case parameter values and their sources.

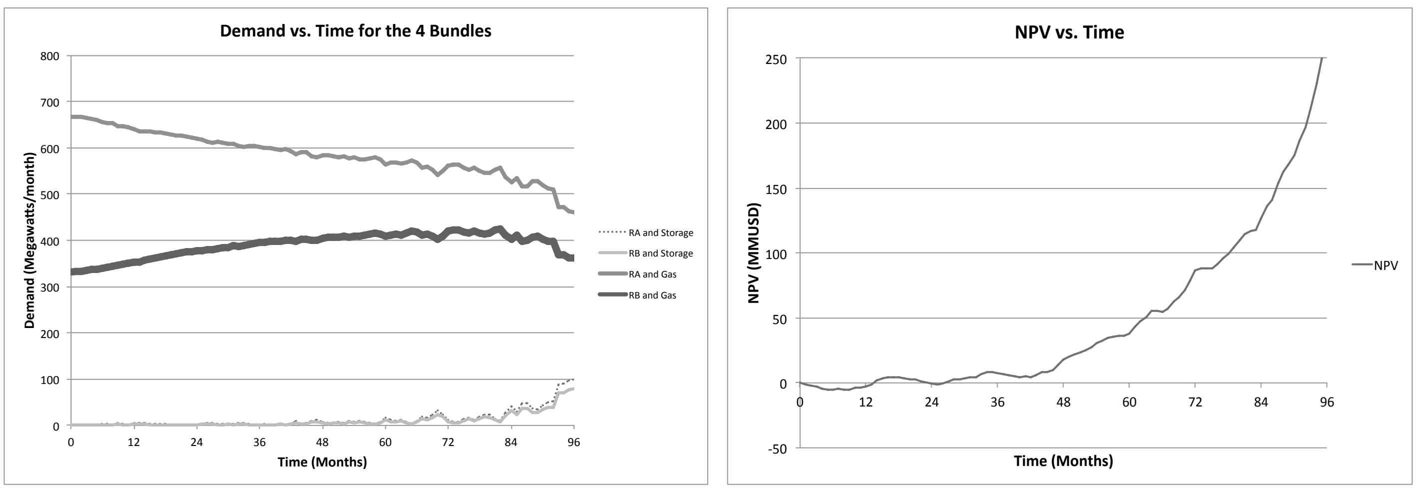
4.1 Base Case Model

This subsection presents results from a deterministic "base case" to illustrate some typical yet important behaviors of the model. In the next subsection we present a Monte Carlo analysis, which provides more robust and general insights into the model under risk.

Demand for each of the four bundles (RA-storage, RB-storage, RA-gas, and RB-gas) is presented for the base case in Figure 2. As an initial basis for comparison, the base case run assumes that, much like wind power versus solar power, RA has a lower initial cost than RB, yet RB's learning curve has a much greater potential for cost reduction. All four bundles are competing for the same market. Integration investment is split evenly between RA and RB. Two trends emerge. Over the simulation's time horizon, demand for the RA- and RB-storage bundles remains small but increases relative to the RA- and RB-gas bundles because, over time, the cost of storage decreases relative to gas. The other trend is that both of RA's bundles are trailing their RB counterparts over time as RB's superior cost reduction opportunities are realized.

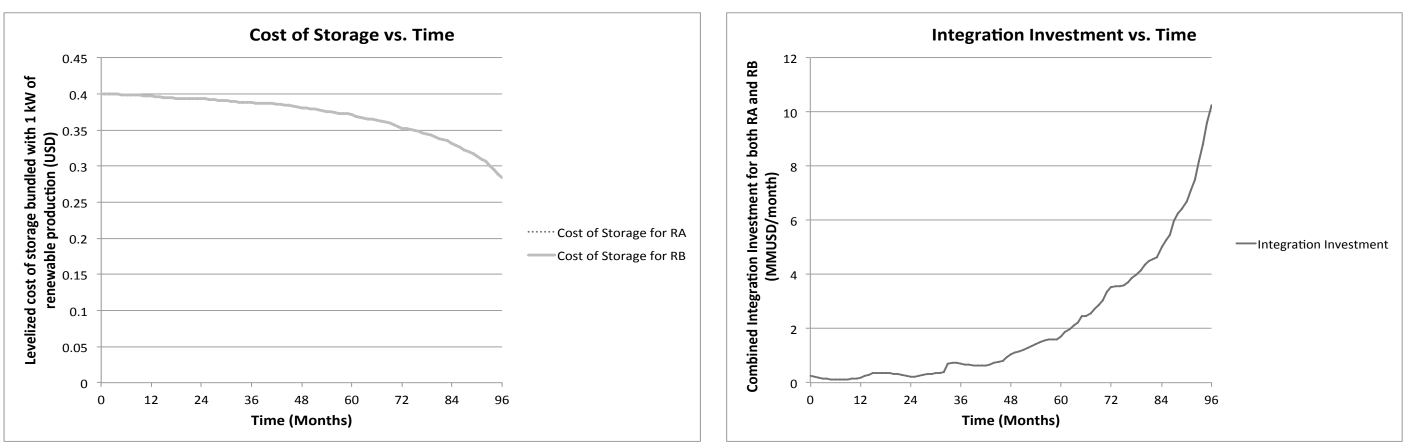
Throughout the simulation, the levelized variable cost of gas (including the amortization of fixed costs, operations, maintenance, etc., as well as fuel) is a stochastic AR(1) or pink-noise process, whose coefficient of variation and correlation times are listed in the online appendix. While the gas price is stochastically “cyclic,” its mean is stationary. In contrast, the price of storage decreases steadily over the simulation timeline because of the startup’s autonomous learning curve and integration investments (Figure 3). (It should be noted that some of this cost decrease from cospecialization could be interpreted as reducing the amount of “rated” megawatts for the renewable lost to volatility, particularly in overvoltage situations.)

Figure 2: Demand (in Megawatts purchased per month) for the Four Capacity Bundles and Overall NPV in the Base Case



Notes: (1) Demand for the RA-storage bundle is slightly larger than demand for the RB-storage bundle. The difference between the two can best be seen at month 96. (2) Each megawatt (MW) of a renewable is bundled with 4 megawatt-hours (MWh) of storage. This is a common assumption in the storage industry (see Kluza 2009: 54). (3) MMUSD = millions of U.S. Dollars.

Figure 3: Cost Structure for Our Base Case Simulation.



Note: The costs are levelized costs of capital expenses, installation, operating & maintenance, etc. (and fuel where appropriate). Also, the cost for storage cospecialized for RA equals that for RB because the integration investment percentage is identical for the two renewables, as are the returns on integration investment.

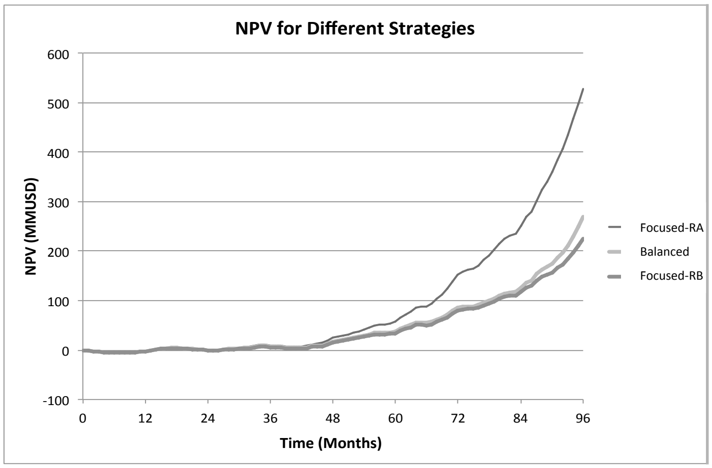
For the base case, the net present value of the startup assumes a 5% per annum discount rate, the approximate U.S. Treasury Bill interest rate over the past decade (U.S. Treasury 2011). The NPV in the base case is shown in Figure 2. Following Tanrisever et al. (Forthcoming), we ignore depreciation and income taxes in our simple financial model; thus we equate cash flow to profit.

4.1.1 Focused vs. Balanced Strategies

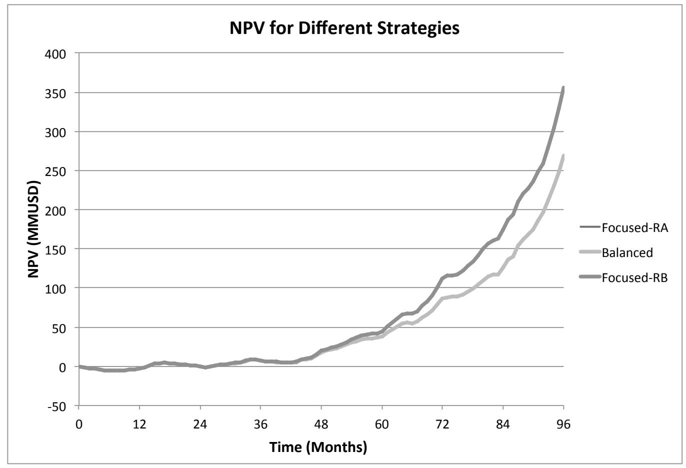
Recall the two research questions with respect to the integration investment problem stated in the introduction. One is the overall level of integration investment the storage startup should commit. The second and more subtle question is: How much of that investment should be allocated to cospecializing in RA rather than RB? To better understand these issues, we change the integration investment allocated to RA (ψ_a) to 100% and change that of RB (ψ_b) to 0%, which we refer to as the "Focused-RA" strategy. We then reverse this allocation, so that RB receives 100% of the cospecialization investment, which we refer to as the "Focused-RB" strategy. In Figure 4a we compare these investment decisions with those of the base case, which uses a "Balanced" strategy that allocates 50% of integration investment to each renewable. The Focused-RA strategy dominates. Thus, a focused strategy can dominate the balanced strategy, if the right complement to cospecialize with is selected. Given the short time horizon of startups, cospecializing with RA (which, like wind power, has relatively low initial costs, but less long-term cost reduction potential) dominates. While it is not shown in Figure 4, if RA had the same initial low cost as RB, but RB had a much greater potential cost reduction through the learning curve, the results would be exactly reversed, with the Focused-RB strategy dominating.

However, would a focused strategy continue to dominate if both renewable technologies were identical in their initial cost and their potential cost reduction (i.e., if both had the same learning curve slopes)? As described in Section 2, the answer is not intuitively obvious. We test this scenario by setting RB's initial cost the same as that of RA's and setting both renewables' learning curve slopes to 80%. Figure 4b shows that the focused strategy still dominates because confining integration investment to cospecializing with just one renewable can better leverage the supply-side externality feedback inherent in the renewables' learning curves than splitting that investment between both renewables. (Note: the NPV for Focused-RA is identical to Focused-RB's and is thus invisible.) Hence, the implication is that a startup's best strategy is to focus its integration investment on cospecializing to one complement, even if the potentials for both complements are identical.

Figure 4: Net Present Value of Wealth Created by Storage Startup for Different Integration Investment Strategies



(a) Base Case Renewable Learning Curve Parameters



(b) Identical Renewable Learning Curve Parameters

Note: In (b), the NPV for Focused-RA is identical to Focused-RB's and is thus invisible.

4.2 Integration Investment Strategies Under Risk

The previous section reveals preliminary findings on the startup's integration investment decision, in particular, that focused strategies can be beneficial even when the two complementary technologies are identical. However, there is great uncertainty about the technological potential for both storage and renewable generation technologies that must be accounted for. Another significant source of uncertainty is fluctuating gas prices. How should uncertainty influence the integration investment decision? To address this, we employ a Monte Carlo simulation to study the behavior of the model described in Section 3 under these uncertainties.

4.2.1 Experimental Design for Monte Carlo Analysis

To examine the effects of technological uncertainty, we consider two strategic decisions. The first is whether to invest 0%, 15%, or 30% of working capital per year in cospecialization. The second decision is how much of that cospecialization investment should be allocated to RA versus RB. For this latter question we specify five possibilities:

Allocation Strategy Number	Percentage of Investment Cospecializing Storage in RA	Percentage of Investment Cospecializing Storage in RB
1	0%	100%
2	25%	75%
3	50%	50%
4	75%	25%
5	100%	0%

This design of experiments results in a study of 3 x 5 = 15 strategies. For each of these 15 financing and investment strategies, we perform a Monte Carlo analysis of 1000 simulation runs. This theoretically yields a total of 15,000 runs, but fortunately, the number of strategies actually simulated can be reduced without loss of generality. In particular, all five allocation strategies yield identical results when 0% investment of working capital in cospecialization is selected. Additionally, if the distributions for the parameters for RA and RB are identical, which is true for most of our Monte Carlo studies; allocation strategies 4 and 5 *are redundant in* their results with allocation strategies 2 and 1 respectively. The learning curve slopes for RA, RB, and storage are drawn from a uniform distribution over the interval of 65% to 95%, with a mean of 80%. The mean and the limits are suggested by Argote (1999: 20). The draws for the learning curve slopes for each of the three technologies during a single run will differ. The initial cost for RB is again set identical to that of RA, so as to maximize the uncertainty over which complement it is preferable *to cospecialize to*. The sample paths of levelized natural gas prices are also allowed to vary over simulation runs, although the mean and coefficient of variation remain constant across simulation runs and have the the same values as in the deterministic case in Section 4.1.

4.2.2 Base Case Monte Carlo Results

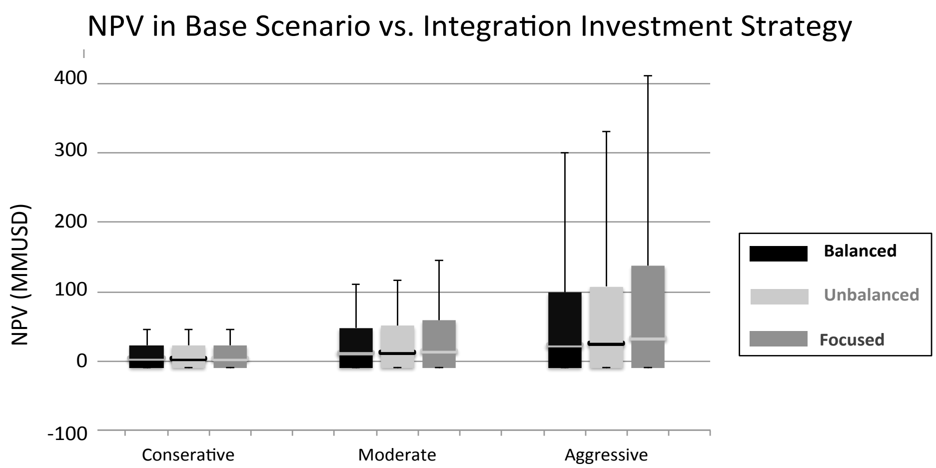
The results of the Monte Carlo simulation are shown in Table 2. These include the average NPV as specified in (16) as well as the standard deviation and coefficient of variation for the NPV, the percent of runs ending in negative NPV (i.e., losing money), the percent of runs ending in a bankruptcy; and the average final market share (in case of bankruptcy, the final market share is assumed to be zero.) Note that the dominant outcome (when there is one) for each integration investment decision is bolded. Some trends are clearly observable under this scenario's parameters. One trend is that startups should select an aggressive, focused strategy with respect to the integration investment in order to maximize NPV. Hence, the focused strategy remains dominant under uncertainty. This is because of the significant skewing of expected NPV created by the supply-side externalities, which is shown by the box and whisker plots for each investment strategy in Figure 5. The implications of this trend are profound. An entrepreneur, at least under this scenario's set of parameters, should not hedge her bets. She should pick a complement to cospecialize in and stick with it, even if, as in this scenario, there is a 50% chance of making the wrong decision.

Table 2: **Comparison of Results of Different Cospecialization Investment Strategies vs. Outcome Parameters**

% Working Capital to Integration Investment	Percent Integration Investment to RA	Percent Integration Investment to RB	Mean NPV	Median NPV	SD NPV	CV NPV	Percent Negative NPV	Percent Bankrupt Runs	Final Market Share
0%	-	-	10.03	2.481	24	2.39	47.40%	**31.50%**	0.42%
15%	0%	100%	43.76	13.43	87.87	2.01	41.50%	35.40%	2.39%
15%	25%	75%	36.22	11.37	73.99	2.04	41.80%	35.50%	1.85%
15%	50%	50%	34.01	11.37	69.36	2.04	42.40%	35.30%	1.67%
15%	75%	25%	36.22	11.37	73.99	2.04	41.80%	35.50%	1.85%
15%	100%	0%	43.76	13.43	87.87	2.01	41.50%	35.40%	2.39%
30%	0%	100%	**116.57**	**32.19**	212.29	1.82	40.50%	38.60%	**7.50%**
30%	25%	75%	93.76	24.37	181.72	1.94	**40.30%**	38.50%	6.83%
30%	50%	50%	85.39	21.34	167.42	1.96	40.60%	38.50%	6.51%
30%	75%	25%	93.76	24.37	181.72	1.94	**40.30%**	38.50%	6.83%
30%	100%	0%	**116.57**	**32.19**	212.29	1.82	40.50%	38.60%	**7.50%**

Note: The "-" for percent cospecialization investment for RA and RB indicates the irrelevance of this decision given the 0% level of working to cospecialization investment. SD stands for standard deviation. CV stands for coefficient of variation (σ/μ).

Figure 5: Box and Whisker Plots Comparing the Results of Various Integration Investment Strategies



Note: "focused," "unbalanced," and "balanced" respectively refer to a "0%/100%", "50%/50%, and "50%/50%" split between investing in cospecializing in RA vs. RB. Because the financial ramifications are symmetric with respect to whether RA or RB is more heavily invested in, only one of the two focused and two unbalanced strategies are displayed. Also, the line in each box and whiskers plot above represents the median, the box the interquartile range (25^{th} to 75^{th} percentile), and the whiskers in the 9^{th} and 91^{st} percentiles. If the distributions were normal, the length of each whisker would equal that of the interquartile box. Finally, note that because of the high number of bankruptcies, the bottom of each interquartile is compressed very close to its associated whisker.

Other trends are also present. For example, it is well known that entrepreneurs often focus more on outcomes other than expected NPV. In particular, oft-mentioned priorities such as autonomy or final market share can trump entrepreneurs' desire for financial success (Naffziger et al. 1994; Shane et al. 2003; Cassar 2007; Swinney et al. 2011). Thus, it is noteworthy that under this set of parameters, while final market share is also optimized by an aggressive, focused strategy, the rate of bankruptcy is not. In this parameterization, the dominant strategy to avoid bankruptcy is the conservative (zero cospecialization) investment strategy, for which the question of focus is irrelevant.

4.2.3 Sensitivity Testing

We next perform a number of additional analyses to test the sensitivity of the model to various factors that (1) are prominent in driving the causal loops in Figure 1, (2) are related to financial measurements, (3) likely to be important, such as spillover. For example, one sensitivity test (shown in Table 3 in the online appendix) increases the time horizon of the model to 120 months. Aggressive integration investment and a focused strategy remain dominant under increased growth, although they are less dominant than in our base case Monte Carlo simulation. Interestingly, however, an aggressive, *balanced* strategy dominates with respect to market share.

For purposes of expositional brevity, Table 3 consolidates the results of the all of the various sensitivity analyses performed (many details of which are in the online appendix) into a list that shows how various factors influence (a) the preference for allocation of cospecialization investment to only one renewable (i.e., a focused versus a balanced strategy) and (b) the preference for more aggressive levels of total cospecialization investment. Table 3 further bins the numerous sensitivity tests by the factors identified in Table 1 (excluding focus, which is an outcome variable). With respect to pursuing a focused versus a balanced integration investment strategy, the data from the sensitivity tests show a consistent preference for a focused strategy with respect to the expected NPV under most scenarios, *despite a 50% chance ex ante that this investment choice may be wrong.* In fact, the cells containing "-" in Table 3 do not indicate that the balanced strategy is preferred by the startup, but only that the *presence* of those factors reduces the advantage of the focused strategy over the balanced strategy. For example, looking at the causal loop in Figure 1, one would expect that increasing the costs of integration would weaken the reinforcing effect of the integration investment loop and raise the point at which the cospecialization investment loops lead to diminishing returns from integration investment. Thus, integration investment is expected to be more beneficial, which it is. (Of course, determining when each loop will dominate is impossible without a simulation, as is typical of systems with multiple nonlinear, delayed feedback loops (Sterman 1994).) One could continue with each of the five factors listed in Table 3, but in the interests of brevity we summarize by noting that any treatment that (1) increases market growth, (2) makes investment in integration more expensive or less efficient, (3) strengthens the supply-side externalities at play in the model, or their uncertainty or asymmetry, (4) effectively compresses the time horizon, or (5) constrains working capital, increases the relative dominance of focused over balanced integration investment strategies.

In general, aggressive investment strategies are favored under most sensitivity tests, but the relative dominance of aggressive over conservative strategies again varies. Moreover, the pattern does not entirely replicate that for focused strategies. For example, if integration is more expensive, the relative dominance of the aggressive strategy decreases with respect to NPV (see Table 3). To understand why this is so, again consider Figure 1. As stated earlier, the cospecialization investment loop that governs integration investment is a reinforcing loop. Hence, initially, additional integration investment increases NPV. At some point, however, additional integration investment faces diminishing returns because of the cospecialization balancing loops. Thus, as the effectiveness of integration investment increases, the benefit to additional integration investment eventually declines, making an aggressive integration investment strategy relatively less profitable than in a scenario of easier integration. Thus, more expensive integration enhances the dominance of a focused integration investment strategy, but reduces that of an aggressive integration strategy. (Note that teasing this out without a simulation model and sensitivity analysis would be hopeless, as Sterman 1994 discusses.)

Table 3: Simulation Sensitivity Analysis of Factors That Favor Investment Strategies in Cospecialization Investment

		Increasing (+) or Decreasing(-) Relative Preference for: Allocate Investment to Only One Complement (Focused Strategy)	Aggressive Cospecialization Investment
Market Growth	Higher Demand Growth	+	-
Integration	More Expensive Integration	+	-
	Less Spillover	+	-
Supply Side Externalities' Strength, Uncertainty & Assymmetry	Greater Market Sensitivity to Price	+	+
	Stronger Storage Learning Curve	+	+
	Stronger Complement Learning Curve	+	+
	Higher Storage Learning Curve Uncertainty	+	+
	Higher Complement Learning Curve Uncertainty	+	+
	Stronger Complement Learning Curve for RB vs. RA	+*	+
	Higher Initial Cost for RB (vs. RA)	+*	+
Time Horizon Compression	Higher Discount Rate	+	+
	Shorter Horizon	+	+
Working Capital Constraints	Higher Fixed Costs	+	+
	Smaller Contribution Margin Ratio	+	-
	Smaller Total Equity Injection	+	-

Note: The (+) or (-) symbols indicate increasing (decreasing) preference for allocation of investment to only one complement (column 1) or for high investment in cospecialization (column 2), all else being equal. This does not mean, for example, that more expensive integration necessarily leads to a conservative investment strategy, only that as integration becomes more expensive, conservative integration investment is relatively more attractive. The "*" indicates that a particular focused investment is directed to the appropriate complement (e.g., if initial cost of RA is higher than RB, then RB will receive the focused integration investment, all other things being equal). Finally, a "stronger" learning curve means that the learning curve slope is smaller. For example, a 70% learning curve is "stronger" than an 80% learning curve because costs drop off by 30% per doubling of cumulative output rather than 20% (Argote 1999).

With respect to aggressiveness, treatments that (1) decrease market demand, (2) make integration less expensive, (3) increase supply-side externality strength, uncertainty, or asymmetry, (4) effectively compress the time horizon, or (5) loosen working capital constraints all generally serve to increase the relative dominance of an aggressive strategy. Finally, it should be noted from Table 3 that market demand, integration, and working capital have opposite effects with respect to favoring focus and aggressiveness, while externalities and time compression have aligned effects.

When considering other outcome metrics such as bankruptcy and market share, the dominant strategy often differs from the results in either column of Table 3. For example, the dominant strategy with respect to bankruptcies is almost always conservative investment, particularly under time compression. This finding is qualitatively in line with Swinney et al.'s findings (2011) that firms that avoid bankruptcies tend to be more conservative in investment than those that do not. With respect to market share, dominant strategies with respect to NPV align more often than not with strategies that maximize market share, but not always (see Table 3 in the online appendix). Instead, three factors in particular favor a bifurcation in strategies, whereby focused strategies favor NPV and balanced strategies favor market share. One factor is "easier" market conditions (e.g., less market sensitivity to price or higher market growth). Another is spillover, because it blurs the distinction between focused and corner strategies. A third factor results from either a longer decision horizon or higher total equity infusion. The second and third factors quickly produce diminishing returns in a focused strategy, which makes a balanced strategy for integration investment more attractive.

5 Limitations and Discussion

Our results reflect the usual limitations of simulation-based mathematical models. For instance, our stylized model is far simpler than reality, which limits generalizability (Barnett 1994). For example, the variability in natural gas prices might not have a clear analogue in other sectors such as the electronics industry. Also, because we rely on simulations rather than analysis, some potential behavior modes may have escaped our investigation. That said, we preferred simulation because an analytically tractable model would have required far more simplification and divergence from reality. Our Monte Carlo sensitivity analyses help to address concerns of generalizability and capture variability in future states of nature. More important, our approach focuses on the interaction of a few reinforcing and balancing loops, and thus highlights behaviors of interest such as the general dominance of aggressive, focused integration strategies. Another limitation is that the nature of our motivating example forces us to use current industry parameters to model a situation that will require several years to fully evolve. For these reasons, the qualitative results and insights of this study are more relevant than the quantitative. Finally, given the importance of natural gas to the renewable energy industry, we model competition only with that one mature entrant and not with other storage startups. On the other hand, one surprising lack of limitation from Section 4 must be mentioned, which is that many of our results apply even in deterministic settings. That is, while uncertainty exaggerates some behaviors, such as the general dominance of focused integration investment, it is often not the root cause of those behaviors. Instead, integration combined with supply-side externalities are the fundamental causes of the behavior highlighted in our model.

This study has several important implications for theory development. First, we have shown that integration investment decisions can make a critical difference for startups' success. Because this result is driven by the presence of complementary technologies, our results provide a two-sided market underpinning for Schilling's (2002) empirical findings. Empirical research is thus needed to extend Schilling's (2002) work to determine exactly what factors lead startups to success in the presence of complementary technologies. As a start, we identified the five factors shown in the sensitivity analysis (Table 3) that influence the impact of complementary technologies. Other important factors could potentially include: (1) how many potential complementary technologies (and whether there is a "standard" to integrate to) are in the emerging complementary market, (2) how many startups are present, and (3) the presence of (potentially multiple) mature competitors. Such studies would be particularly illuminating if they spanned multiple industries with different characteristics such as price sensitivity and market growth. Finally, this paper concentrated on strategies that maximize NPV. While this is appropriate for high-tech industries that are funded by venture capital, to achieve a clearer understanding, we must consider startup industries that are lower tech, bootstrapped, or have some other industry or financial structure. In these cases, it is necessary to better understand decision makers' utility functions (e.g. a preference for market share versus NPV) prior to modeling or empirical research. Finally, the two-sided market literature must be extended as well to consider startups' compressed timing and working capital constraints, which have both been shown in this paper to dramatically affect market outcomes. Additionally, the two-sided market literature must begin to consider the effects of the integration investment strategy, as most research in this area concentrates solely on price subsidies.

Moreover, our specific examination of integration investment also extends the work of Lesveque and colleagues (Levesque 2000; Armstrong and Levesque 2002) on R&D investment. In particular, confirming Archibald et al. (2002) and Tanrisever et al. (Forthcoming), startups must restrict investment due to compressed time horizons and financial capital. These constraints manifest in an emerging complementary industry by driving the startup's preference for focused solutions in integration investment when multiple potential complementary technologies are possible. Our work also contributes to the flexible design literature, demonstrating that working simultaneously on two technological solutions may help mature firms cope with technological uncertainty (Arditti and Levy 1980; Ward et al. 1995; Srinivasan et al. 1997; Krishnan and Bhattacharya 2002; Sommer and Loch 2004; Sommer et al. 2008), but startups may not have that option because of limitations in working capital and compressed timing. This finding broadens the claim made by Tanrisever et al. (Forthcoming) and Swinney et al. (2011) that research with respect to operational decisions for mature firms cannot be applied to startup firms immediately without careful examination of their financial and timing constraints.

6 Conclusion

We began this paper by defining a gap in the literature treating the integration investment decision by startups in industries with complementary technologies as shown in Table 1. We then built a system dynamics model to determine optimal integration investment strategies and explored the effects on this decision of five factors—market growth, integration, supply-side externalities, compressed timing, and working capital constraints. The resultant analysis has the following practical implications: we find that startups ideally should invest in integrating with one clearly superior complementary technology. For example, wind power is currently much cheaper than photovoltaic solar and is likely to remain so over the typical startup decision horizon. This explains why, despite some technological spillover, Xtreme Power, a battery storage startup, directed the bulk of its integration investment toward wind power for its first six years, ignoring integrating with photovoltaic solar (Xtreme Power 2010). However, according to the results of this analysis, even if the "better" complementary renewable had not been so clear, Xtreme Power (and its venture capital backers) would still have done well to focus integration investment on one complementary technology initially, and to switch to another only after commercial success with the first technology had been achieved. Indeed, Xtreme has followed this pattern by beginning only now to invest in integrating to photovoltaic solar. Such insights on focused integration investment would likely extend to other platform industries (e.g., console gaming or office productivity software) with many mature competitors. When mature competitors are not present, however, these insights may not be as applicable. Thus, there is a need for additional research in industries without mature competitors as described earlier.

Few emerging complementary industries directly concern policy makers. However, an industry that does attract the interest of policy makers is the energy storage industry, from which we drew our motivating example. In this case, the preference we find for focused strategies in integration may be problematic for policy. For example, if most storage firms make focused integration investments in wind power rather than in investing in (currently) more expensive technologies (such as photovoltaic solar), this decision trend could result in long-term under-investment in a potentially more efficient technology. Hence, governments may need to intervene because incentives to encourage entrepreneurs to invest in integrating with technologies such as photovoltaic solar may be in the public interest. Because of the robustness of our results, we believe such policy advice may likely also extend to other similar industries, such as smart meters and smart grids, which are also of interest to policy makers.

References

AIM Advisors. 2011. IPO activity - 2010. December 8, 2011. http://biz.yahoo.com/p/industries.html, accessed on December 8, 2011.

Almeida, P., G. Dokko, and L. Rosenkopf. 2003. Startup size and the mechanisms of external learning: Increasing opportunity and decreasing ability? Research Policy, 32 (2), 301-15.

Amit, R., J. Brander, and C. Zott. 1998. Why do venture capital firms exist? Theory and Canadian evidence. Journal of Business Venturing, 13 (6), 441-66.

Anderson, E., and T. Fiddaman. 2010. Pink noise. MetaSD Model Library. 2010. http://models.metasd.com/2010/03/pink-noise/.

Anderson, E.G., Jr., A. Davis-Blake, S. Erzurumlu, N. Joglekar, and G. Parker. 2007. The effects of outsourcing, offshoring, and distributed product development organization on coordinating the NPD process. Pp. 259-90 in *Handbook of new product development management*, edited by C. Loch and S. Kavadias. Oxford, U.K.: Butterworth-Heinemann.

Anderson, E.G., and G.G. Parker. Forthcoming. Integration decisions when outsourcing, offshoring, and distributing knowledge work. Production and Operations Management.

Archibald, T.W., L.C. Thomas, J. Betts, and R.W. Johnston. 2002. Should startup companies be cautious?: Inventory policies which maximise survival probabilities. Management Science, 48 (9), 1161-74.

Arditti, F.D., and H. Levy. 1980. A model of the parallel team strategy in product development. The American Economic Review, 70 (5), 1089-97.

Argote, L. 1999. Organizational learning: Creating, retaining and transferring knowledge. New York: Kluwer.

Armstrong, M.J., and M. Levesque. 2002. Timing and quality decisions for entrepreneurial products. European Journal of Operational Research, 141 (1), 88-106.

Babich, V., and M.J. Sobel. 2004. Pre-IPO operational and financial decisions. Management Science, 50 (7), 935-48.
Bania, N., R.W. Eberts, and M.S. Fogarty. 1993. Universities and the startup of new companies: Can we generalize from Route 128 and silicon valley? The review of economics and statistics, 761-66.
Barnett, A. 1994. Chapter 3 models fail. Pp. 47-66 in *Handbooks in operations research and management science*, edited by M.H.R. S.M. Pollock and A. Barnett: Elsevier.
Boudreau, K., and A. Hagiu. 2008. Platform rules: Multi-sided platforms as regulators. SSRN: http://papers.ssrn.com/abstract=1269966. September 18 2008.
Bruderl, J., P. Preisendorfer, and R. Ziegler. 1992. Survival chances of newly founded business organizations. American sociological review, 57 (April), 227-42.
Cassar, G. 2007. Money, money, money? A longitudinal investigation of entrepreneur career reasons, growth preferences and achieved growth. Entrepreneurship and Regional Development, 19 (1), 89-107.
Chesbrough, H. 2003. Open innovation: The new imperative for creating and profiting from technology. Boston: Harvard Business School Publishing.
Cusumano, M. 2010. The evolution of platform thinking. Communications of the ACM, 53 (1), 32-34.
Darling, S.B., F. You, T. Veselka, and A. Velosa. 2011. Assumptions and the levelized cost of energy for photovoltaics. Energy & Environmental Science 4,3133-39.
Deeds, D.L., D. DeCarolis, and J. Coombs. 2000. Dynamic capabilities and new product development in high technology ventures:: An empirical analysis of new biotechnology firms. Journal of Business Venturing, 15 (3), 211-29.
Eckhardt, J.T., S. Shane, and F. Delmar. 2006. Multistage selection and the financing of new ventures. Management Science, 52 (2), 220-32.
Eisenmann, T., G. Parker, and M. Van Alstyne. 2006. Strategies for two-sided markets. Harvard Business Review, 84 (10).
Eisenmann, T., G. Parker, and M. Van Alstyne. 2009. Opening platforms: How, when and why? in *Platforms, markets and innovation*, edited by A. Gawer. Cheltenham, UK: Edward Elgar.
Eisenmann, T., G. Parker, and M. Van Alstyne. 2011. Platform envelopment. Strategic Management Journal, 32 (12), 16.
Forrester, J.W. 1958. Industrial dynamics: A major breakthrough for decision makers. Harvard Business Review, 36 (4), 37-66.
Gaimon, C. 1997. Planning information technology--knowledge worker systems. Management Science, 43 (9), 1308-28.
—. 2008. The management of technology: A production and operations management perspective. Production and Operations Management, 17 (1), 1-11.
Gans, J.S., and S. Stern. 2000. Incumbency and R&D incentives: Licensing the gale of creative destruction. Journal of Economics & Management Strategy, 9 (4), 485-511.
Gawer, A., and M.A. Cusumano. 2002. Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation. Boston: Harvard Business School Publishing.
Ghemawat, P., and A.M. Spence. 1985. Learning curve spillovers and market performance. Quarterly Journal of Economics, 100 (Issue Supplement), 839-52.
Gompers, P.A. 1995. Optimal investment, monitoring, and the staging of venture capital. Journal of Finance, 1461-89.
Grant, R.M. 1996. Toward a knowledge-based theory of the firm. Strategic Management Journal, 17, 109-22.
Hall, B. 2002. The financing of research and development. NBER: Paper 8773.
Hall, B.H., and J. Lerner. 2009. The financing of R&D and innovation. National Bureau of Economic Research.
Hilmola, O.P., P. Helo, and L. Ojala. 2003. The value of product development lead time in software startup. System Dynamics Review, 19 (1), 75-82.
Iansiti, M. 1995a. Technology development and integration: An empirical study of the interaction between applied science and product development. IEEE Transactions on Engineering Management, 42 (3), 259-69.
—. 1995b. Technology integration: Managing technological evolution in a complex envrironment. Research Policy, 24 (4), 521-42.
Iansiti, M., and R. Levien. 2004. The keystone advantage: What the new dynamics of business ecosystmes mean for strategy, innovation, and sustainability. Boston: Harvard Business School Publishing.
Janney, J.J., and G.G. Dess. 2006. The risk concept for entrepreneurs reconsidered: New challenges to the conventional wisdom. Journal of Business venturing, 21 (3), 385-400.
Joglekar, N.R., and M. Levesque. 2009. Marketing, R&D, and startup valuation. IEEE Transactions on Engineering Management, 56 (2), 229-42.

Kluza, J. 2009. Status of grid scale energy storage and strategies for accelerating cost effective deployment. Massachusetts Institute of Technology: Master's Thesis.
Kogut, B., and U. Zander. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. Organization science, 3 (3), 383-97.
Kouvaritakis, N., A. Soria, and S. Isoard. 2000. Modelling energy technology dynamics: Methodology for adaptive expectations models with learning by doing and learning by searching. International Journal of Global Energy Issues, 14 (1), 104-15.
Krishnan, V., and S. Bhattacharya. 2002. Technology selection and commitment in new product development: The role of uncertainty and design flexibility. Management Science, 48 (3), 313-27.
Krishnan, V., and K.T. Ulrich. 2001. Product development decisions: A review of the literature. Management Science, 47 (1), 1-21.
LaMonica, M. 2010. Giant battery smooths out variable wind power. Cnet News Green Tech. August 4, 2010. http://news.cnet.com/8301-11128_3-20012597-54.html, accessed on September 25, 2010.
Lerner, J. 1995. Venture capitalists and the oversight of private firms. Journal of finance, 301-18.
Levesque, M. 2000. Effects of funding and its return on product quality in new ventures. IEEE Transactions on Engineering Management, 47 (1), 98-105.
Lilien, G.L., P. Kotler, and K.S. Moorthy. 1992. Marketing models. Englewood Cliffs, NJ: Prentice Hall.
Makri, M., M.A. Hitt, and P.J. Lane. 2010. Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. Strategic Management Journal, 31 (6), 602-28.
Mansfield, E., and J.Y. Lee. 1996. The modern university: Contributor to industrial innovation and recipient of industrial R&D support. Research Policy, 25 (7), 1047-58.
Mitchell, V., and B. Nault. 2007. Cooperative planning, uncertainty, and managerial control in concurrent design. Management Science, 53 (3), 375.
Naffziger, D.W., J.S. Hornsby, and D.F. Kuratko. 1994. A proposed research model of entrepreneurial motivation. Entrepreneurship Theory and Practice, 18, 29-29.
Nelson, R.R. 1961. Uncertainty, learning, and the economics of parallel research and development efforts. The review of economics and statistics, 43 (4), 351-64.
Nolen, J. 2011. Personal communication. Austin, TX.
Norton, E., and B.H. Tenenbaum. 1993. Specialization versus diversification as a venture capital investment strategy. Journal of Business venturing, 8 (5), 431-42.
Parker, G., and M. Van Alstyne. 2005. Two-sided network effects: A theory of information product design. Management Science, 51 (10), 1494-504.
Parker, G.G., and E.G. Anderson, Jr. 2002. From buyer to integrator: The transformation of the supply chain manager in the vertically disintegrating frim. Production and Operations Management, 11 (1), 75-91.
Prencipe, A., A. Davies, and M. Hobday (Eds.). 2003. The business of systems integration. Oxford: Oxford University Press.
Rahmandad, H. 2012. Impact of growth opportunities and competition on firm-level capability development trade-offs. Organization science, 23 (1), 138-54.
Ries, E. 2011. The lean startup: How today's entrepreneurs use continuous innovation to create radically successful businesses: Crown Business.
Rochet, J.C., and J. Tirole. 2003. Platform competition in two-sided markets. Journal of the European Economic Association, 1 (4), 990-1029.
Romanelli, E. 1989. Environments and strategies of organization start-up: Effects on early survival. Administrative Science Quarterly, 34 (3).
Rothaermel, F.T. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. Strategic Management Journal, 22 (6-7), 687-99.
Rothaermel, F.T., and D.L. Deeds. 2004. Exploration and exploitation alliances in biotechnology: A system of new product development. Strategic Management Journal, 25 (3), 201-21.
Sandberg, W.R., and C.W. Hofer. 1987. Improving new venture performance: The role of strategy, industry structure, and the entrepreneur. Journal of Business Venturing, 2 (1), 5-28.
Sapienza, H.J., S. Manigart, and W. Vermeir. 1996. Venture capitalist governance and value added in four countries. Journal of Business Venturing, 11 (6), 439-69.
Schilling, M. 1999. Winning the standards race: Building installed base and the availability of complementary goods. European Management Journal, 17 (3), 265-74.
Schilling, M.A. 2002. Technology success and failure in winner-take-all markets: The impact of learning orientation, timing, and network externalities. Academy of Management Journal, 45 (2), 387-98.

—. 2009. Protecting or diffusing a technology platform: Tradeoffs in appropriability, network externalities, and architectural control. Chapter 8 in *Platforms, markets and innovation*, edited by A. Gawer. London: Edward Elgar.
Shan, W., G. Walker, and B. Kogut. 1994. Interfirm cooperation and startup innovation in the biotechnology industry. Strategic Management Journal, 15 (5), 387-94.
Shane, S., E.A. Locke, and C.J. Collins. 2003. Entrepreneurial motivation. Human Resource Management Review, 13 (2), 257-79.
Shane, S.A., and K.T. Ulrich. 2004. Technological innovation, product development, and entrepreneurship in management science. Management Science, 50 (2), 133-44.
Soderblom, A., and J. Wiklund. 2006. Factors determining the performance of early stage high-technology venture capital funds: A review of the academic literature. Stockholm School of Economics.
Sommer, S.C., and C.H. Loch. 2004. Selectionism and learning in projects with complexity and unforeseeable uncertainty. Management Science, 50 (10), 1334-47.
Sommer, S.C., C.H. Loch, and J. Dong. 2008. Managing complexity and unforseeable uncertainty in startup companies: An empirical study. Organization Science, 20 (1), 118-33.
Srinivasan, V., W.S. Lovejoy, and D. Beach. 1997. Integrated product design for marketability and manufacturing. Journal of Marketing Research, 154-63.
Sterman, J.D. 1994. Learning in and about complex systems. System Dynamics Review, 10 (2-3), 291-330.
—. 2000. Business dynamics: Systems thinking and modeling for a complex world. Boston: Irwin/McGraw-Hill.
Sterman, J.D., R. Henderson, E.D. Beinhocker, and L.I. Newman. 2007. Getting big too fast: Strategic dynamics with increasing returns and bounded rationality. Management Science, 53 (4), 683-96.
Struben, J.J.R. 2006. Essays on transition challenges for alternative propulsion vehicles and transportation systems. Massachusetts Institute of Technology: Ph.D. Thesis. 2006.
Struben, J.J.R., and J.D. Sterman. 2007. Transition challenges for alternative fuel vehicles and transportation systems. Massachusetts Institute of Technology: Sloan Working Paper 4587-06. May 2007.
Swinney, R., G.P. Cachon, and S. Netessine. 2011. Capacity investment timing by start-ups and established firms in new markets. Management Science, 57 (4), 763.
Tanrisever, F., S.S. Erzurumlu, and N.R. Joglekar. Forthcoming. Production, process investment and the survival of debt financed startup firms. Production and Operations Management.
Taylor, P. 2009. Companies race to develop utility-scale storage. New York Times. September 28, 2009.
Teece, D.J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing, and public policy. Research Policy, 15 (6), 285-305.
Treasury, U.S. 2011. Daily long-term interest rate data. U.S. Deparment of the Treasury. 2011. http://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=longtermrate, accessed on December 8, 2011.
Tripsas, M. 1997. Unraveling the process of creative destruction: Complementary assets and incumbent survival in the typesetter industry. Strategic Management Journal, 18 (S1), 119-42.
Van de Ven, A.H. 2005. Running in packs to develop knowledge-intensive technologies. MIS Quarterly, 365-77.
von Hippel, E. 2005. Democratizing innovation. Cambridge, MA: MIT Press.
Ward, A., J.K. Liker, J.J. Cristiano, and D.K. Sobek. 1995. The second toyota paradox: How delaying decisions can make better cars faster. Sloan Management Review, 36 (Spring), 43-43.
Weill, P., and M.H. Olson. 1989. Managing investment in information technology: Mini case examples and implications. MIS Quarterly, 13 (1), 3-17.
Xtreme Power. 2010. Technology overview brochure. 2010. http://www.xtremepowerinc.com/technology.php, accessed on August 15, 2010.
Zacharakis, A.L., and G.D. Meyer. 1998. A lack of insight: Do venture capitalists really understand their own decision process? Journal of Business Venturing, 13 (1), 57-76.
—. 2000. The potential of actuarial decision models:: Can they improve the venture capital investment decision? Journal of Business Venturing, 15 (4), 323-46.
Zott, C. 2003. Dynamic capabilities and the emergence of intra-industry differential firm performance: Insights from a simulation study. Strategic Management Journal, 24 (2), 97-125.