

CAPTURING THE STRATEGIC PIVOT: IDENTIFYING THE PERFORMANCE
OUTCOMES OF NEW VENTURE PIVOTS

A DISSERTATION IN
Entrepreneurship and Innovation

Presented to the Faculty of the University
of Missouri-Kansas City in partial fulfillment of
the requirements for the degree

DOCTOR OF PHILOSOPHY

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Kansas City, Missouri
2020

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ABSTRACT

Although pivoting is one of the most recognizable and highly taught subjects in entrepreneurship, relatively little empirical work has been done to establish the causal impact that it has on new venture performance. This is likely due to the methodological challenges that arise when approaching the subject, which include the difficulty of identifying when a pivot has taken place (in real-time, and for a sufficiently large number of ventures that researchers can have confidence in their results); and identifying publicly available performance data for what are in most cases, privately owned firms. To address these issues, I employ a novel research design in which individual pivots are identified using the self-reports of high-growth ventures that participated in seed accelerator programs between 2008 and 2018.

Utilizing pre-recorded interviews and press releases issued at the time of the pivot, I identify both the type of pivot that occurred, and when it was undertaken. Timestamp data from the venture's Twitter feed is then used to identify when the pivot was first announced to the public. Because these reports occur at a time when the ultimate failure or success of the pivot is unknown, they provide an ideal source of information that avoids many of the retrospective and survivor biases that have hindered previous research. By using the change in customer

traction and top management team turnover that occurs in the three months leading up to, and following, a strategic pivot, I determine the success or failure of individual pivots using a sample of approximately 118 early-stage, high-growth firms.

This study makes three main contributions to the literature. First, it develops a more full distribution of the performance outcomes that accompany new venture pivots, and provides scholars with a strong initial prior for determining when pivots are likely to produce successful outcomes. Second, it introduces the concept of traction as a short-term performance measure in the study of early-stage, high-growth firms. Last, this paper connects pivoting's origin in practitioner publications to long standing research in entrepreneurship and innovation, and uses it to highlight the broader relevance of academic research in the field.

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CONTENTS

ABSTRACT.....	iii
TABLES	viii
ILLUSTRATIONS	ix
ACKNOWLEDGEMENTS.....	x
Chapter	
1. INTRODUCTION	1
2. LITERATURE REVIEW	7
2.1 Meaning and Origin	7
2.2 Categories	9
2.3 Pivoting in Prior Academic Research	11
2.3.1 Prior Entrepreneurship Research: Business Model Innovation & Learning from Failure	12
2.3.2 Prior Innovation Research: New Product Development & Learning from Experimentation	15
2.4 Recent Findings	19
2.5 Impact on Customer Traction	23
2.6 Impact on Top Management Teams	26
2.7. Research Questions.....	29
3. RESEARCH DESIGN	30
3.1 Data and Sample	30
3.2 Measures	33
3.3 Methodology	35

3.3.1 Model	37
3.4 Causal Inference and Threats.....	39
3.4.1 Copulas	40
3.4.2 Conditional Ignorability.....	41
4. RESULTS	42
4.1 Customer Traction	42
4.1.1 Robustness Test	44
4.2 TMT Turnover	44
4.2.1 Robustness Test	47
4.3 Supplemental Analysis.....	47
4.4 Summary	50
5. DISCUSSION	51
5.1 Customer Traction as a Measure of New Venture Performance	54
5.2 The Lean Startup in Prior Academic Research.....	55
5.3 Summary	57
Appendix	58
REFERENCES	67
VITA.....	75

TABLES

Table	Page
1. Categorization of Strategic Pivots	58
2. Coding and Interpretation of Variables in Discontinuous Random-Coefficient Growth Models	59
3. Customer Traction: Means, Standard Deviations, and Correlations with Confidence Intervals	60
4. Change in Web Traffic: Reach per Million	61
5. TMT Turnover: Means, Standard Deviations, and Correlations with Confidence Intervals (in Log-Odds)	62
6. Top Management Team Turnover: Departures	63
7. Top Management Team Turnover: Hires	64
8. Change in Time-to-Funding Pre and Post-Pivot (Full Panel)	65

ILLUSTRATIONS

Figure	Page
1. Change in Web Traffic: Posterior Distributions	66

ACKNOWLEDGEMENTS

Special thanks goes to Kate Hodel of KCSOURCELINK for her help in the data collection process, and to members of the committee for their patience and support. This dissertation also makes use of publicly available data from Twitter, Crunchbase, and Amazon's Alexa Web Information Service, without which the paper would not be possible.

CHAPTER 1

INTRODUCTION

When TapIn.tv joined Y Combinator during the accelerator's fifteenth cohort in the summer of 2012, it had already made a name for itself in the field of mobile video streaming by allowing users to broadcast their streams without having to create a personal account (Lawler, 2012; Tan, 2012). Backed by an initial seed investment and clutching a solid foothold in the rapidly growing market of mobile video, TapIn seemed primed to join the ranks of other highly successful startups that had emerged from the industry's first (and at the time, biggest), new venture accelerator (Hochberg, 2016). Less than eight months later, however, the once ascending firm was struggling, and in the process of completing a major strategic pivot to a B2B-focused business model (Kumparak, 2013). Despite benefiting from several advantages that many new ventures lack – including mentoring and financial support from one of the world's largest accelerators – they were forced to close in October, 2013.

TapIn.tv's story is not unique. While pivoting is often spoken of favorably by both scholars and practitioners alike, less frequently mentioned is the likelihood that a large number of these pivots are unsuccessful (Duchesneau & Gartner, 1990; Shepherd et al., 2000). Founding teams that are forced to deviate from their original path by outside events find the process of establishing a viable, prosperous business to be both more difficult and less likely to be successful (Aaker & Day, 1986; Carroll & Delacroix, 1982; Mitchell, 1991; Ries, 2011, p. 108). Even when a change in strategy is undertaken willingly, however, if the team is unclear about the aim of a new product or how customers are supposed to discover it, success is far from certain. Failed attempts to redeploy a firm's resources can occur for a variety of reasons, and doing so

incorrectly can lead to the rapid exhaustion of financial resources and the end of the firm (Cooper et al., 1994).

Despite the surge in scholarly interest on the subject (Crilly, 2018; Hampel et al., 2019; Kirtley & O'Mahony, 2020; McDonald & Gao, 2019; McMullen, 2017; Pillai et al., 2019), relatively little is known about the causal impact that pivoting has on new venture performance (Grimes, 2018). This is likely due to the methodological challenges that arise when approaching the subject, which result in retrospective and survivor biases that eliminate the potential of establishing causal inference. The result has been the emergence of several studies that – however useful in terms of understanding the internal process – provide little in the way of objective data about potential performance outcomes (Bajwa et al., 2017; Jocquet et al., 2015). As a field, scholars have yet to establish which types of pivots are successful, when, or under what circumstances.

In this respect, the primary hurdle to conducting an empirical analysis of pivoting's impact on new venture performance stems from two different but closely related sources: first, the difficulty of establishing that a pivot has taken place from a vantage point outside the company (in real-time, and for a sufficiently large number of firms that researchers can have confidence in the generalizability and statistical power of their results); and second, identifying publicly available performance data for what are in most cases, still privately owned firms. Although many emerging ventures that aspire to high-growth are often encouraged to pivot early in their development (Guinan & Parise, 2017; Jocquet et al., 2015), the occurrence of individual pivots only becomes public knowledge when the firm declares it in an open forum. This creates an additional selection effect, in that researchers are only able to observe those pivots that a firm chooses to make public (Clougherty et al., 2015).

In this study I employ a novel research design that is intended to address the bulk of these challenges. Specifically, I identify the occurrence of individual pivots using the self-reports of high-growth ventures that participated in seed accelerator programs in the United States between 2008 and 2018. Using pre-recorded interviews with company founders, and press releases issued at the time of the pivot, I identify both the type of pivot that occurred and when it was undertaken. Timestamp data from the venture’s Twitter feed is then used to identify the date that the pivot first was first announced to the public. Because these reports occur at a time when the ultimate failure or success of the pivot is unknown, they provide an ideal source of information that avoids many of the retrospective and survivor biases that have hindered previous studies.

Although prior research has often relied on financial indicators as a measure of firm performance – including sales, IPO proceeds, and return-on-assets (Ireland et al., 2005; Mattingly, 2015) – none of these metrics is widely available in the study of early-stage, high-growth ventures. In their place, we utilize two measures to evaluate changes in a firm’s internal and external performance, including the impact that pivoting has on a venture’s traction among potential customers, and the changes it creates in terms of turnover within the top management team (Nuscheler et al., 2019; Yu, 2020). We track these metrics over the 12 weeks leading up to, and following, the pivot’s occurrence, and employ a latent growth curve model to determine the impact of the pivot, while accounting for each firm’s existing trajectory (Hale et al., 2016).

As an observational study that is likely to suffer from endogeneity (specifically, selection effects), I also employ a statistical approach to address bias in the model that does not require the presence of observed instruments (Antonakis et al., 2010). One of a number of latent instrumental variable techniques, copulas create a joint distribution that effectively captures the correlation between an endogenous regressor and the structural error, and makes “inferences on

the model parameters by maximizing the likelihood from the joint distribution” (Park & Gupta, 2012, p. 567). This approach has been found to meet the model assumptions necessary for solving the identification problem (Anderson, 2018; Gui et al., 2019).

This study makes three primary contributions to the literature. First, by validating a measurement model that allows researchers to identify the occurrence of individual pivots at the time they occurred (including those that failed), this study develops a more full distribution of the performance outcomes that accompany new venture pivots. In doing so it aims to provide scholars with a strong initial prior for determining when pivots are likely to produce successful outcomes. Although other latent behaviors in strategic entrepreneurship – including sustained regeneration, strategic renewal, domain redefinition, and business model reconstruction (Covin and Miles, 1999; Kuratko and Audretsch, 2009) – suffer from similar methodological challenges, this study suggests that it is possible to investigate both the inputs and outcomes of strategic pivots on a more regular basis.

Second, this paper introduces the concept of traction as a short-term performance measure in the study of early-stage, high-growth ventures. While traditional measures of firm performance have often relied on metrics such as sales, employee growth, and new venture survival (Ireland et al., 2005; Mattingly, 2015), the emergence of digital technologies has rendered entrepreneurial outcomes “less bounded” (Nambisan, 2016), and calls have gone out for the creation of performance measures that capture changes in a venture’s market share as it develops (Shepherd et al., 2019). Utilizing customer traction as an outcome allows researchers to investigate the short-term changes in performance that occur among early-stage, high-growth ventures in a variety of industries and different stages of development.

Last, this paper connects pivoting's origin in the practitioner works of Steven Blank (2005) and Eric Ries (2011) to long standing research in entrepreneurship and innovation, and uses it to highlight the broader relevance of academic research in the field. While the debate over whether and how entrepreneurship scholars should strive to produce research that is relevant to entrepreneurs remains highly contested (Banks et al., 2016; Wiklund et al., 2019), less widely acknowledged is the impact that such research has already had. By reviewing the foundational texts in each field, this paper highlights how many of the ideas that are central to the now-prevailing approach to new venture development used by practitioners grew out of years of research in the entrepreneurship and innovation literature (Amit & Zott, 2001; Eisenhardt & Tabrizi, 1995; McGrath, 1999; Van de Ven & Polley, 1992).

The remainder of this dissertation is structured as follows. In Chapter 2 I provide an overview of the origins and meaning of the word pivot, followed by a discussion of the specific types of pivots that are included in the term. I then review prior research on the subject, and examine pivoting's overlap with other long-standing concepts in entrepreneurship and innovation. Although the lean startup approach that encompasses pivoting represents a unique concept in strategic entrepreneurship, many of the elements that it contains have deep roots in the literature on entrepreneurship and innovation. I review several of these – including business model innovation (Amit & Zott, 2001; Chesbrough & Rosenbloom, 2002), adaptive and discontinuous processes (Eisenhardt & Tabrizi, 1995; Lynn et al., 1996), and learning by experimentation (Thomke, 1998; Van de Ven & Polley, 1992) – and analyze how each compares and contrasts with the ideas laid out by Blank (2005) and Ries (2011).

Chapter 3 lays out my primary research question, and describes how we might expect pivoting to impact changes in customer traction and top management team composition based on

prior research on market orientation and strategic entrepreneurship (Chandler et al., 2005; Eesley et al., 2014; Kawakami et al., 2012; Nuscheler et al., 2019). I then describe the measures and methodology used to investigate the subject, and provide an overview of Bayesian statistics and the key differences and advantages that distinguish it from the more common frequentist approaches (Kruschke et al., 2012; Zyphur & Oswald, 2015). Last, I examine the possible threats to causal inference that exist in this study, as well as my proposed solution for meeting the conditional ignorability requirement necessary for establishing causal inference (Rubin, 1974, 1978).

CHAPTER 2

LITERATURE REVIEW

2.1 Meaning and Origin

Among early-stage, high-growth ventures, adjusting a firm's strategy to address changes in the surrounding environment is known as 'pivoting.' Based on a firm's previous successes and failures attempting to enter a market, pivoting involves a change in strategy based on the recognition that either the core product or service is struggling to create significant value (Vargo & Lusch, 2004), or the current strategy for gaining customer traction is failing (Maurya, 2016; Ries, 2011; Wisdom et al., 2014; Wood & Moreau, 2006). Crilly (2018) noted that the word 'pivot' was first used in a June 2009 blog post by Eric Ries, who described it as a change in direction prompted by a lack of traction in the marketplace (Ries, 2009). That is, pivoting is said to represent "a change in strategy without a change in vision" (Ries, 2011, p. 108).

Despite the term's original formulation as a strategy concept referring to early-stage ventures with ongoing revenues and developed (if not well established) business models, in recent years it has taken on a second meaning as well. Both in popular culture and among entrepreneurship scholars, pivoting has also been used to refer to nascent entrepreneurs' "willingness to change an idea," based on the receipt of feedback from key stakeholders (Grimes, 2018, p. 5). In this formulation, pivoting refers less to a change in strategy among emerging high-growth ventures, then it does a change in the product ideas of nascent entrepreneurs (Fjeld, 2018; Guinan & Parise, 2017). Ries himself used the term to describe the iterative nature of Blank's (2005) customer development model (CDM), which helped give rise to both pivoting and the broader lean startup approach that encompasses it.

Under the CDM, entrepreneurs begin the process of creating a new venture by evaluating who their customers are, and whether their idea solves a significant enough problem for them to require a solution (Maurya, 2016). Blank (2005) referred to this as the customer discovery phase. When pivots are mentioned in this context it is often because the entrepreneur's idea solves a problem that customers aren't interested in, and they are forced to "pivot" as a result. During the subsequent customer validation and creation stages, however, entrepreneurs work to first establish (and then scale) viable business models around their intended product or service (Ries, 2011). It is at this stage that pivoting is used to refer to a change in strategy based on a new engine of growth.

Although each of these uses are common, in this study I use the term to refer to strategic actions taken at the organizational level (Crilly, 2018), rather than cognitive changes that occur within individual entrepreneurs (Grimes, 2018). It is this usage that forms the dominant approach to academic inquiries (Hampel et al., 2019; Kirtley & O'Mahony, 2020; McDonald & Gao, 2019; Pillai et al., 2019). The benefits of undergoing a strategic pivot, meanwhile, are often described in terms of efficiency. Testing the assumptions that underpin emerging business models is said to give founding teams "the best chance of making course corrections early, and not wasting time and money" (Fjeld, 2018, p. 1). As a strategy, pivoting and other lean methodologies have been shown to decrease costs, lower time to market, and increase overall customer satisfaction and engagement (Guinan & Parise, 2017).

Although both scholars and practitioners have come to view pivoting as an almost "unequivocally good thing" (McMullen, 2017, p. 3), others have begun to question this view. While most pivots are undertaken with the aim of either generating faster growth or ensuring firm survival, the challenges involved in executing a pivot suggest that it is at least as likely to

end in failure as it is in success (Duchesneau & Gartner, 1990; Shepherd et al., 2000). Brush et al. (2015) noted that any “change, or pivot, in key value creating activities, such as distribution, product technology, or market choice, can hasten an early closure.” Likewise, others have noted that the likelihood of establishing a successful business is significantly lower after being forced to change course by outside events (Aaker & Day, 1986; Mitchell, 1991).

While pivoting remains a celebrated concept in entrepreneurial communities (Crilly, 2018; Grimes, 2012) – with some estimates claiming that up to 73 percent of ventures undertake one at some stage in their development (Gruber & Tal, 2017) – the likelihood that a large number of these pivots are unsuccessful, is high.

2.2 Categories

Ries (2011, p. 149) cataloged a series of nine pivots that new ventures should consider when searching for repeatable, scalable business models. Although each is capable of producing significant changes to one or more of the model’s core components (i.e. the product, market, platform, or revenue model) (Bajwa et al., 2017), the choice of which to pursue is determined by the founder’s efforts to validate the primary assumptions that underpin the venture’s business model, rather than the inclinations or opinions of the founders themselves. The results of those efforts indicate which (if any) of the various types of pivots they should enact (Blank, 2013; Guinan & Parise, 2017).

Pivots that involve changes to the venture’s core product include the zoom-in, zoom-out, customer need, platform, and technology pivots (Ries, 2011). The first of these, or zoom-in pivot, occurs when a venture reconfigures a product around what had previously been a single feature. This occurs when the value perceived by customers lies in a very specific aspect of the original product, which then becomes the sole focus of the offering. In contrast, the zoom-out

pivot occurs when what was once a standalone product instead becomes part of a larger whole (typically when the initial product fails to create enough value to exist on its own).

Other product-based pivots involve varying degrees of change to a firm's strategy. For example, technology pivots involve applying the same solution to an existing problem, using new technology. Ries indicated that this is more common in established companies, which seek incremental improvements designed to appeal to their existing customer base (Ries, 2011).

Customer need pivots, meanwhile, can (but don't necessarily) require the development of an entirely new product, while platform pivots involve a shift from a platform to an application (or vice-versa). This can occur when a venture that started by selling a single application to support their platform, instead sees the platform itself emerge as popular third-party development tool.

Still other types of pivots refer to changes in the venture's primary market. Pivots of this type are often more substantial than those that deal with product features, and tend to involve a wider range of factors that lie outside the venture's control. These include the customer segment, engine of growth, and business architecture pivots (Ries, 2011). Customer segment pivots occur when the founding team believes that their product solves a real and significant problem, albeit for a different customer segment than the one they initially intended (Ries, 2011). This type of pivot indicates that the firm has spent months (or longer), building a product that addresses the needs of the wrong customer. Similarly, channel pivots involve a change in how the firm delivers its product or service to their primary consumers.

On the revenue side, engine of growth pivots involve a structural change in the company's customer acquisition strategy. The most common of these approaches include: viral strategies, based on a combination of word-of-mouth and positive spillover effects; "sticky" strategies that rely on maintaining a high customer retention rate; and paid growth, where

revenue is reinvested in customer acquisition (Ries, 2011). A similar type of change is reflected in the business architecture pivot, which results in a shift from pursuing B2B transactions typified by high-margin, low-volume sales, to one that focuses on the needs of individual consumers (or vice-versa). While more straightforward than the engine of growth pivot, a change in the venture's business architecture involves reconfiguring the company's operations around an entirely different type of customer (Ries, 2011).

2.3 Pivoting in Prior Academic Research

Although the lean startup approach that encompasses pivoting represents a unique concept in strategic entrepreneurship, many of the elements that it contains have deep roots in the entrepreneurship and innovation literature.¹ Lean methods are typically characterized by a “scientific” approach to entrepreneurship, which involves: (1) treating assumptions as hypothesis; (2) developing early-stage prototypes or minimum viable products (MVPs); (3) “getting out of the building” to receive customer feedback; and (4) pivoting in response to failed assumptions (Blank, 2005; Grimes, 2018; Ries, 2011). While *The Lean Startup* is notable for combining these elements in a single framework, several of the components refer to an existing body of work that has since become “decoupled from the broader academic literature” (Levinthal & Contigiani, 2018, p. 2).

Perhaps the first to combine these elements in a single construct was Morris, Altman, & Pitt (1999), whose early work on adaptation noted that only a minority of entrepreneurs succeed because they define their idea correctly from the beginning, and that for most success rests on the willingness and ability to adjust to the surrounding environment (Stoica & Schindehutte, 1999).

¹ Other scholars have made a similar connection to pre-existing research in the areas of organizational learning, real options theory and technology evolution. See Levinthal and Contigiani (2018) for summary.

For these firms, the early stages in a business's development requires constant adaptation to the product/service offering, target audience, financial structure, and delivery methods "as the venture evolves from an initial idea or business plan through the early stages of the organizational life cycle" (Stoica & Schindehutte, 1999, p. 4).

Other work on the adaptations that entrepreneurs make in response to feedback from the surrounding environment (as well as the "changes in strategic behavior" that it entails), predates similar observations from Blank (2005) and Ries (2011) by several years, but is largely unknown among practitioners (and academics) (Schindehutte & Morris, 2001, p. 85). Their research is not the only one to predate *The Lean Startup* era, however, and a significant body of work exists in both entrepreneurship and innovation that helped contribute to its emergence. As such, it is worth investigating how the ideas that pivoting and other lean methodologies are built on have been discussed in prior academic research.

2.3.1 Prior Entrepreneurship Research: Business Model Innovation & Learning from Failure

Within entrepreneurship, a number of studies on business model innovation and learning from failure predate similar concepts in the lean startup literature by several years (Blank, 2013). Scholarly research on business model innovation, for instance, has looked at the connection between successful business models and customer value creation – a concept that is widely embraced by followers of the lean startup (Maurya, 2016; Osterwalder et al., 2014; Ries, 2011). Amit and Zott (2001) introduced the idea that business models are the primary element that allows firms to capture the value that they create from the production of goods and services. Looking specifically at how e-businesses approach value creation, they argued that the extent to which ventures are able to maximize efficiency, complementarities, lock-in, and novelty in their products and services, determines the level of value that they create for consumers.

Similar work from Chesbrough and Rosenbloom (2002) investigated the business model's role in capturing the value created by early stage technologies. They argued that the value inherent in a technology remains latent until it is commercialized, and that while business models unlock this hidden value, they also “constrain the subsequent search for new, alternative models for other technologies later on” (Chesbrough & Rosenbloom, 2002, p. 529). A number of practitioner works that follow the lean startup approach stress similar points in their emphasis on customer value creation, arguing that “in order to capture value” in the form of revenue, a venture must first create it for consumers (Olsen, 2015, p. 4; Osterwalder & Pigneur, 2010).

The ability to learn from the process of starting a business, and the failures that result from it, forms another point of comparison with *The Lean Startup*. On the academic side, much of the research on how entrepreneurs learn from failure dates back to McGrath's (1999) early work on the benefits of pursuing high-value opportunities, even when the likelihood of failure is high. McGrath argued that by prioritizing success and the avoidance failure, firms increase the likelihood that those failures that do occur will be both bigger and more expensive than they otherwise would be. In her view, firms with a high intolerance of failure hinder their ability to learn from mistakes, and prevent them from happening again during future projects.

Shepherd (2003) built on this work by examining how the emotions that accompany failure can stand in the way of entrepreneurial learning. He argued that entrepreneurs are only able to learn from failure when they use the information about “why the business failed to revise their existing knowledge of how to manage their own business effectively.” This requires revisiting prior assumptions about “the consequences of previous assessments, decisions, actions, and inactions” (Shepherd, 2003, p. 320). However, he noted that the grief that accompanies these failures can also interfere with entrepreneurs ability to learn from the events that caused it,

believing that in order for entrepreneurs to learn from their previous mistakes they must first undergo the process of recovery.

Similar to McGrath (1999) and Shepherd (2003), lean methodologies encourage entrepreneurs to embrace the idea of failing fast, while continually learning from their experiences (Blank, 2005). Pivoting is said to require entrepreneurs to “keep one foot rooted in what [they’ve] learned so far, while making a fundamental change in strategy in order to seek greater validated learning” (Ries, 2011, p. 154). Despite the importance of learning from past mistakes, however, multiple authors have noted that the fear of failure often prevents startups from pivoting, even when they know a change is necessary (Olsen, 2015; Wasserman, 2012). Ries (2011, p. 161) noted that “when people are forced to change against their better judgement, the process is harder, takes longer, and leads to less decisive outcomes.” Similarly, Maurya (2016, p. 215) argued that although the “fail fast” meme is commonly used among entrepreneurs in startup communities, the “taboo of failure runs so deep that ‘failing fast’ is not always enough to get people to accept failure as a prerequisite to achieving a breakthrough.”

The entrepreneurship literatures’ focus on business model innovation, creating customer value, and learning from failure all feature prominently in the broader works that make up the lean startup approach (Blank, 2005; Ries, 2011). Most notably, the steps dealing with customer discovery and validation are designed to develop business models that deliver value to consumers by iteratively testing the assumptions in the venture’s business model. Those assumptions that fail to survive first contact with consumers are intended to initiate a “learning and discovery” process, in which founders adjust their approach to better meet the needs of their intended customers (Blank, 2005, p. 6). While each of these concepts was present to some extent

in prior research on entrepreneurship, still others from the innovation literature may have played a key role as well.

2.3.2 Prior Innovation Research: New Product Development & Learning from Experimentation

Prior research in the field of innovation indicates a number of areas that may have contributed to the emergence of the *Lean Startup*. Much of the research in this area builds on the innovative practices that were first introduced by U.S. and Japanese corporations in the 1980s and 1990s. Because “several years of intensive investment and effort are often required to develop an innovation to the point where its end results can be determined... a central problem in managing and investing in innovations is determining whether and how to continue a developmental effort in the absence of concrete performance information” (Van de Ven & Polley, 1992, p. 92). In addressing this issue, researchers noticed that successful firms don’t just innovate in terms of the products and services that they offer, but in how they approach the new product development process as well.

Traditionally, new product development (NPD) consisted of three distinct phases that were performed sequentially, including concept development, detailed design, and system-level testing (MacCormack et al., 2001). Importantly, however, customer feedback on the product’s performance wasn’t received until the third phase, when development costs were already nearing their peak (Levinthal & Contigiani, 2018). This problem of how best to design new products at minimal cost was identified as far back as the 1960s, when Nelson (1961) argued that in some cases it was more economical to pursue parallel development efforts, rather than selecting a single design based on the firm’s initial estimates.

In comparing the traditional model of rationally-planned sequential steps to newer experiential models based on improvisation, real-time experience, and flexibility, Eisenhardt and

Tabrizi (1995) found that the latter's use of multiple iterations and extensive testing accelerated the new product development process. More established techniques involving the use of supplier input and computer-aided design were found to be effective only in more mature and well-established industries. Later work by Lynn, Morone, & Paulson (1996) argued that conventional market research in the form of concept testing, customer surveys, and conjoint analysis was ineffective at producing disruptive innovations. Instead, such products emerged through a "probe and learn" approach, in which firms gathered actionable intelligence through iterative product designs and planned market experiments with consumers.

Noting that firms may not have a single "design-test-build" cycle, but an entire series of cycles nested within each other (Simon, 1969), Loch, Terwiesch, & Thomke (2001) developed a model in which the optimal mix of parallel and sequential testing depended on the ratio between the expected testing cost and total development time. This iterative approach to customer development forms a key part of the lean startup method, indicating that many of the techniques involved in pivoting had previously emerged in corporate innovation labs as a way to combat "design grind" or "design fixation." This occurred when engineers and product designers consumed too much time and resources developing elegant solutions while ignoring the needs of actual consumers (Crilly, 2018; Guinan & Parise, 2017; Jansson & Smith, 1991).

Whether and how firms are able to learn from the effectiveness of their new product development efforts became the focus of another branch of research on experimental learning. Initial solutions to the problem of knowing whether or not to proceed with a product's development centered on the adaptive processes of organizational learning (Van de Ven & Polley, 1992). This trial-and-error approach involved planning a series of tests, collecting the outcome data, and adjusting course to achieve the desired result. However, when examining this

model in the context of a biomedical startup, Van de Ven and Polley (1992) rejected it as being too simplistic, and unrepresentative of the competing demands that often get placed on NPD teams in practice. They noted that several organizational processes hinder groups ability to learn from experimentation:

(1) Innovation entrepreneurs were held accountable for achieving over-optimistic plans designed to obtain funding, and this triggered a vicious cycle of impression management and "sugar-coated" administrative reviews. (2) Innovation team members often participated in part-time, temporary and fluid ways... (3) Activities proliferated into complex interdependent paths which masked attention to evaluating the feasibility of the core innovation idea. (4) Setbacks arose frequently, but were not detected as errors that trigger trial-and-error learning.

Each of these processes is familiar to scholars and practitioners of entrepreneurship, even though knowing their potential to occur is rarely enough to prevent them from happening.

In place of the trial-and-error approach, Van de Ven and Polley (1992) proposed a two-action model to explain the occurrence (or not) of organizational learning during different stages of the innovation process. They argued that when investors view an action as successful, they are more willing to delegate decision making authority to the firm. However, when a failure occurs investors are more likely to intervene in the process and struggle with the venture's founders for control of the company. Although both outcomes can lead to organizational learning, the presence of shifting goals, frequent personnel turnover, impression management, and noisy performance data all threaten the ability of founding teams to understand the connection between firm actions and outcomes (Van de Ven & Polley, 1992).

Later work by Thomke (1998) demonstrated how new and improved methods of experimentation could rapidly reduce the total cost and development time involved in creating new products. Using a “design-build-run-analyze” cycle – an extension of Clark and Fujimoto’s (1989) “design-build-test” model – Thomke argued that experiments were capable of being conducted in different modes, using computer simulations and rapid prototyping in place of traditional models. In addition to cost savings, switching between the two could also produce significant gains in terms of efficiency. In a finding that advocates of *The Lean Startup* would appreciate, Thomke (1998, p. 743) argued that such experimentation strategies “can sometimes benefit from getting it wrong the first time,” a strategy that contradicted prior research in new product development.

Miner, Bassoff, and Moorman (2001) made a subsequent distinction between learning from experimentation, and learning from improvisation. In a detailed study of two firms engaged in new product development efforts, the authors noted a number of improvised behavioral processes, physical artifacts, and consumer frameworks that fell outside the organization’s normal new product development routines. These novel (but intentional) activities had significant implications for the organization’s learning potential. In contrast to experimental learning – which involves controlled studies designed to produce a specific form of knowledge – knowledge creation was never the primary goal of improvisation (Miner et al., 2001). Despite the unplanned nature of the firms’ improvised activities, the authors argued that under certain circumstances they could produce a distinct type of short-term learning that “can, but does not necessarily, serve as a ‘trial’ in long-term trial-and-error learning” (Miner et al., 2001, p. 321).

Similar to the academic research on failure, learning from experimentation also forms a core part of the lean startup. Ries (2011, p. 9) argued that the “fundamental activity of a startup is to turn ideas into products, measure how customers respond, and then learn whether to pivot or persevere.” If after several iterations of this “build-measure-learn cycle” it becomes clear that a key element of the product or strategy is flawed, it is incumbent on the entrepreneur to dig deeper into the root causes of the failure, and understand why it occurred (Blank, 2013). As Maurya (2016, p. 215) states, a pivot that is “not grounded in learning is simply a disguised ‘see what sticks’ strategy.” Companies that don’t learn from previous iterations become “stuck in the land of the living dead, neither growing enough nor dying, consuming resources and commitment from employees and other stakeholders but not moving ahead” (Ries, 2011, p. 149).

That much of the theoretical grounding of *The Lean Startup* appears in prior academic research is not to suggest that the founders of that approach owe their success to the insights of others that have so far gone unattributed in the literature. I mention it here only to highlight the diffuse nature of knowledge, and illustrate how the revelations produced by others can come back in new and interesting ways once they have entered the broader public discourse.

2.4 Recent Findings

Despite emerging as a popular concept among entrepreneurs almost a decade ago, empirical research on the subject is only just now starting to appear. In one of the first quantitative studies on new venture pivots, Brush et al. (2015) investigated the factors that caused nascent entrepreneurs to change their business models. Applying an existing survey on organizational change to a group of 295 nascent ventures, the authors found that startups underwent an average of five changes during their development. Contrary to expectations, however, they noted that businesses that were farther along in their development were more

likely to pivot than those that were still at an early-stage (Brush et al., 2015). Although most of the remaining studies that look at pivoting are qualitative, they are nevertheless illustrative of the types of questions that scholars have asked during this initial round of research.

Bajwa et al. (2017) conducted a general survey of the factors that trigger pivots in early-stage technology firms using a review of 55 well-known pivots in 49 different startups, including those from well-known companies like Groupon, PayPal and Yelp. The authors found that most pivots were reactions to external, rather than internal events, and that almost all were customer related. They also detailed 14 major factors that were responsible for triggering these pivots, with common responses including negative customer reactions to the initial product, an inability to survive competition, technology issues, and positive responses from an unforeseen customer segment (Bajwa et al., 2017). Although the study focused on firms that not only survived the pivot but also went on to become wildly successful, it was nevertheless representative of the types of incidents that prompt early-stage software companies to undertake a change in direction.

Approaching the subject from a slightly different angle, Crilly (2018) examined how entrepreneurs balance persistence and flexibility during the design process. Describing the pivot as an example of how to overcome the problems associated with design fixation, Crilly interviewed ten entrepreneurs, investors, and design consultants with the aim of understanding how the process unfolds in a live setting. He found that the level of commitment, expertise, resources, and information that an entrepreneur has access to, all have a direct impact on the likelihood that they will be open to changing an idea (Crilly, 2018). Entrepreneurs whose orientation is focused around the product they are developing, were associated with a general failure to recognize opportunities to pivot. In contrast, entrepreneurs with a market orientation –

or willingness to frame the venture in terms of market demand – were more ready to embrace significant changes in their design.

In a similar study on how entrepreneurs respond to feedback during the early stages of a venture's development, Grimes (2018) investigated how the psychological ownership of ideas can force entrepreneurs to reconsider both their ideas and their identities (sometimes to the detriment of both). While entrepreneurs often seek out the advice of others in order to improve the novelty and usefulness of their emerging products and services, aligning their work with external demands can also jeopardize their sense of self and subjective well-being (Grimes, 2012). "Identity-sharpening feedback practices introduce a tension between creative workers' psychological ownership of their ideas, and socially-informed standards for creative output" (Grimes, 2018, p. 18). In a study of 59 entrepreneurs, he found that founders respond to such feedback by either reaffirming, abstracting, or relinquishing ownership of their idea.

The tension between maintaining an individual identity and meeting the customer demands of *The Lean Startup* has been questioned by other scholars as well, both from a moral lens (McMullen, 2017) and a strategic one (Ladd, 2016). Arguing that the practice of tailoring products to address the needs of potential customers is one that appears susceptible to the "too-much-of-a-good-thing" fallacy, McMullen (2017, p. 3) argued that pivoting is a form of extrinsic motivation that can either undermine or support the intrinsic goals of an entrepreneur. While stating that pivoting is neither inherently good nor inherently bad, he wrote that the act of accommodating customer interests has the potential to "encourage ideas to evolve away from the activities that inspired entrepreneurial entry in the first place" (McMullen, 2017, p. 4), and that such behavior already has a name: selling-out.

Ladd (2016), in turn, challenged the extent to which entrepreneurs should be encouraged to pivot when receiving negative feedback from potential customers. In a study of how 250 teams were evaluated in a pitch to investors following the end of a clean-tech accelerator, he found that while ventures that tested hypotheses performed almost three times better than those that did not, there was no relationship between the number of validated hypotheses and a venture's subsequent success (i.e., "more validation is not better"). Drawing from this, he concluded that one possible reason for the diminishing returns to customer interaction is that too much feedback "might cause the entrepreneurs to change the idea so frequently that they become disheartened," and that "having a strong strategy is more important than conducting a tremendous number of market tests" (Ladd, 2016, p. 2).

Still others have noted what appears to be a "core problem inherent in pivoting" (Nobel, 2011, p. 2): that while firms may need to radically change direction in order to survive, doing so risks alienating the stakeholders that had helped sustain the firm up to that point (Hampel et al., 2019). In a recent paper by McDonald and Gao (2019), the authors explored how founders explain such changes in the wake of fundamental redirections in strategy, and found that by carefully managing expectations during strategic transitions, entrepreneurs could elicit support from key customers, suppliers, and funders. Similarly, Hampel, Tracey, & Weber (2019, p. 1) found that emerging ventures can "remove the affective hostility of stakeholders and rebuild connections with many of them by exposing their struggles, [and] creating a bond focused around shared experiences."

Throughout the recent expansion in scholarly research on the subject, a shift has occurred in how researchers understand the time component surrounding when strategic pivots begin and end. Although Ries (2011) described pivoting as a transitional process leading from one

organizational state to another, initial research on the subject tended to view it more as an event, in which the venture suddenly operated under an entirely new business model. Studies by Kirtley and O'Mahony (2020) and Pillai, Goldfarb, & Kirsch (2019), however, have shifted the focus back to how pivots unfold over time, using longitudinal field studies and historical analysis to document how firms restructure their activities and resources through an accumulated series of individual decisions.

For many founders, the decision to undergo a pivot is a difficult one. Crilly (2018, p. 7), for instance, argued that pivoting should be understood as an attempt by entrepreneurs to balance the conflicting requirements of various stakeholders, forcing them to exhibit both “persistence in the face of skepticism,” and the flexibility to “remain open to new interpretations of what they are doing and what they should be doing.” How that decision affects a venture’s performance in terms of both stability within the top management team and the firm’s ability to acquire new customers, is thus important for understanding how and when pivoting is likely to produce successful outcomes.

2.5 Impact on Customer Traction

When a pivot is undertaken it is done so with the recognition that some core aspect of the venture’s business model is failing to create significant value, and that it must be addressed if the firm is going to survive and grow (Ries, 2011, pp. 61, 77). Ries (2011, p. 164) stated that the “telltale signs of the need to pivot” include discovering that some core element of the product or strategy is flawed, and that either the venture’s value hypothesis (regarding whether the product or service actually delivers value to customers), or growth hypothesis (which tests how customers discover it), is wrong (Ries, 2011, pp. 61, 77).

Although the resulting pivot is intended to establish a more productive growth model (i.e., one that generates greater traction in the marketplace) (Ries, 2011, p. 118), the act itself involves significant changes to the key value creating activities that had sustained the firm up to that point (Brush et al., 2015). When such pivots are successful they can lead to significant increases in customer traction and the rapid success of the firm (Blank, 2013). However, pivots that are based on faulty assumptions, or that occur at a time when the venture has few remaining resources, can result in the failure to achieve significant traction and the subsequent closure of the firm (Duchesneau & Gartner, 1990; Shepherd et al., 2000).

Prior research has found that the type of frequent interaction with customers that is central to the lean startup method has a significant impact on both new product performance (De Luca & Atuahene-Gima, 2007; Joshi & Sharma, 2004; Li & Calantone, 1998), and new venture success (Brettel et al., 2011; Kawakami et al., 2012). However, because nascent ventures are prone to demand fluctuations, resource constraints and limited market presence, shifts in customer traction can be difficult to sustain (Schindehutte & Morris, 2001). While under-adaptation can lead to “unintended costs... lost customers and missed opportunities,” over-adaptation can result in courses of action that fail to generate the necessary payoff (Stoica & Schindehutte, 1999, p. 7).

Because pivoting is almost certain to produce a “significant” effect in terms of changes to a venture’s internal processes and external performance (Brush et al., 2015), a more appropriate question is whether that impact is positive or negative (and under what circumstances) (Hampel et al., 2019). It seems likely that pivoting’s initial impact on customer traction could vary significantly from its impact over time. Several authors have pointed out that pivoting is less an event than a process of redirecting a firm’s activities, resources, and attention as part of a new

strategy (Kirtley & O'Mahony, 2020; Ries, 2011), and how customers respond to that change is likely to evolve as the pivot unfolds.

Specifically, pivoting's initial impact on customer traction is likely to be negative in the first days and weeks following its occurrence. This is true regardless of whether the pivot ends up being a success. It is during this time that the venture has made the decision to move away from its original product or service offering, and to alter its approach to the market in the hopes of establishing a more lucrative customer base (Hampel et al., 2019; McMullen, 2017). Even in cases where the shift involves relatively minor changes to the product features or customer acquisition strategy, the intended target will need at least some time to become familiar with the changes before deciding whether or not to make a purchase (McDonald & Gao, 2019), and during the intervening period the venture's existing customer base is likely to decline.

In other cases where the pivot is driven by shortcomings in the venture's primary value proposition, the resulting changes can require a more substantial shift in firm strategy (Maurya, 2016). Such pivots suggest that the firm does not fully understand its intended market, and that they have spent significant time developing a product that either doesn't address their customer's needs, or that meets the needs of an entirely different group (Ries, 2011). In either case, regardless of whether the pivot involves large structural changes or smaller, more incremental adjustments, the initial impact of the pivot is likely to have a negative impact on customer traction before it has had a chance to take hold.

Whatever pivoting's initial impact, however, the way it affects a venture's ability to attract customers over time is likely to be different. For successful pivots, a change in strategy that helps the firm better address customer needs should have a positive impact on customer interest as the pivot unfolds (Amit & Zott, 2001; Eisenhardt & Tabrizi, 1995). Although

implementing such changes can take time, new ventures benefit from a lack of fixed commitments and organizational controls that make adjusting the firm's internal processes and activities a matter of weeks, rather than months (Schindehutte & Morris, 2001).

For pivots that are unsuccessful, however, either because they are based on faulty assumptions or come too late in a venture's life cycle to be fully implemented (Maurya, 2016; Ries, 2011), the attempted change in strategy is likely to suffer from a lack of resources and direction that cripple the venture's ability to acquire new customers (Hampel et al., 2019; McDonald & Gao, 2019). Whether the venture itself survives or is forced to close as a result of the pivot, the level of customer traction in such firms is likely to decline or approach zero. As a result, in thinking about how a pivot is likely to impact customer traction, we ask:²

Q1: Does the initial impact of a strategic pivot negatively affect a venture's traction among consumers in the week following its occurrence?

Q2: Regardless of its initial impact, do venture's that undergo a strategic pivot experience a positive change in traction over time?

2.6 Impact on Top Management Teams

In addition to producing sometimes significant changes in a venture's value proposition (Brush et al., 2015; Kirtley & O'Mahony, 2020), the decision to undergo a pivot also reflects a necessary (but perhaps unwanted) shift away from the idea that had motivated the founding team to launch the venture in the first place (Grimes, 2018; McMullen, 2017). Just as each stage of development in a nascent firm is accompanied by unique demands that often require a change in leadership (Baron et al., 1999; DeSantola & Gulati, 2017; Kazanjian & Rao, 1999), so too can

² Because we employ a Bayesian estimation approach in this study, our questions are framed in terms of the alternate hypothesis, rather than the null. More information on the distinction between the two is provided below.

the shift in focus that accompanies a strategic pivot lead to turnover among the top management team (Eisenhardt, 2013).

Although a considerable body of work exists on how changes in the top management team affect firm performance, less frequently studied is how changes in a firm's strategy affect the makeup of the top management team (Boeker & Wiltbank, 2005; Eesley et al., 2014). Among the first to investigate this relationship, Chandler, Honig, & Wiklund (2005) argued that TMT turnover is an adaptive mechanism that allows nascent ventures to respond to rapidly changing environments. These shifts in a top management team's composition can occur for both "positive reasons (e.g., founding members have grown the firm beyond their functional abilities or team members have achieved their goals and wish to move on) or negative ones (e.g., certain members are not fulfilling their responsibilities or the start-up is forced to change its strategy)" (Klotz et al., 2014, p. 239).

The factors that motivate leadership changes in nascent firms often fall under the categories of firm growth and strategic change (Boeker & Wiltbank, 2005). While rapid growth can generate excess strain on individual managers and create demand for those with greater administrative abilities, a lack of growth can indicate that existing team members are ineffective, and that new leadership is needed to turn the venture around (McKelvie & Wiklund, 2010; Rubenson & Gupta, 1997). Similarly, a change in strategy can result in a shift away from the product/market mix that contributed to the founders' expertise (Cooper et al., 1994), and push the venture into areas that require a different set of skills in order to be successful (Boeker & Wiltbank, 2005).

As with a change in customer traction, however, pivoting's impact on a top management team's structure is likely to vary as the pivot unfolds. Specifically, early-stage ventures are

likely to see members of the original founding team depart as the company moves away from the vision that first brought them together (Crilly, 2018; Grimes, 2018). While some such moves can occur as the result of changing interests within the team, others are likely to be involuntary withdrawals that take place as a result of declining performance (McKelvie & Wiklund, 2010). Such dismissals have been shown to happen at the behest of both other founders (Boeker & Karichalil, 2002; Schjoedt et al., 2013; Ucbasaran et al., 2003) and investors with a controlling interest in the firm (Huang & Knight, 2017; Lim et al., 2013).

For pivots that are successful, however, the resulting change is likely to be accompanied by additions to the top management team. Because pivoting occurs in early-stage ventures that aspire to high-growth (Blank, 2013; Ries, 2011), a successful pivot should result in attempts to scale the firm, and lead to changes in its internal organization structure as a result (DeTienne, 2010; Jin et al., 2017). Additions to the top management team are then made to both help lead the transition, and to take over some of the new responsibilities in a firm that is preparing for faster growth (Klotz et al., 2014; Serra & Borzillo, 2013). Unlike the initial disruption that is likely to occur when a firm starts to undergo a strategic pivot then, those that survive the transition should experience growth in their top management teams in the months that follow its occurrence.

Q3: Does the decision to undergo a strategic pivot result in the departure of TMT employees?

Q4: Regardless of the initial impact, do venture's that survive a strategic pivot experience growth in their top management teams over time?

2.7. Research Questions

Because prior research suggests that pivoting has a significant impact on a venture's subsequent development (Grimes, 2018; Hampel et al., 2019; Kirtley & O'Mahony, 2020), we have little reason to expect the absence of a relationship between pivoting and new venture performance (i.e. that the effect is mathematically equivalent to zero). As a result, I opted to forgo traditional hypotheses in favor of Bayesian estimation (Kruschke et al., 2012). In contrast to frequentist methods – which can only reject or fail to reject the null – Bayesian allows researchers to quantify the evidence in favor of a specific relationship (that is, to test the alternate hypothesis directly) (Andraszewicz et al., 2014). Under this approach, the relationship between pivoting, customer traction, and top management team turnover is modeled directly, and the underlying effect and uncertainty is reported in the results (Kruschke & Liddell, 2018).

CHAPTER 3

RESEARCH DESIGN

3.1 Data and Sample

Data for the independent variable in this study consists of the self-reported pivots of approximately 118 early-stage, high-growth ventures. These pivots were communicated to the public either: 1) via press release to a large third-party news site such as TechCrunch.com, or 2) in a pre-recorded interview to the seed accelerator program that the venture had previously attended. Seed accelerators are fixed-term, cohort-based programs that include mentorship and educational components, and that provide small seed investments to participating startups in exchange for equity (Cohen & Hochberg, 2014; Fehder & Hochberg, 2014). Because these reports occur at a time when the ultimate failure or success of the pivot is unknown, they provide an ideal source of information that avoids many of the retrospective and survivor biases that have hindered previous studies. In all the final panel includes 51 pivots from firms that were live as of April 2020, 40 from firms that later failed, and 27 from those that later completed successful exits.

Interviews containing the description of individual pivots were retrieved from the websites of the top 30 seed accelerator programs as ranked by MIT's 2017 Seed Accelerator Rankings Project (*Seed Accelerator Rankings Project*, 2017). Programs included in the list are ranked according to the fundraising, valuation, survival, founder satisfaction, and exit status of the ventures that participated in previous cohorts (Hochberg et al., 2017). The final sample includes 35 ventures from Y Combinator and 11 from Techstars, as well as 30 from a number of smaller accelerators and 40 that chose not to attend one. While the interviews reported on these sites frequently include a detailed description of the *what* and *why* of individual pivots, in most

cases they contain only a general reference to *when*. To ascertain this, I used timestamp data provided by the venture's Twitter feed to determine the date that the pivot was first communicated to the public (Antretter et al., 2019; Ko & McKelvie, 2018). Those pivots whose actual date could not be determined were discarded (five in total).

As a secondary source, pivots that were announced to the public via press release were obtained from TechCrunch.com, the leading technology news site for early-stage, high-growth ventures (Yu, 2020). Unlike interviews, which contain only a general reference to *when* the pivot was undertaken (e.g., "we pivoted to a B2B model in the summer of 2014"), press releases represent the first time that a pivot has been announced to the public. As such, timestamp data from the venture's Twitter feed was not required to identify the specific pivot date. Although ideally it would be possible for researchers to identify the exact moment that the venture decided to pivot, without seeing inside the firm the best available alternative is to establish the date that it first became public knowledge.

In addition to identifying when individual pivots first occurred, data on the type of pivot that the firms underwent was also collected as part of our analysis. Because even the most detailed self-report lacks the depth of information necessary to distinguish between various types of pivots (i.e., between a customer segment and channel pivot), I chose to catalog the occurrence of each into one of four broad categories (product, market, platform, and business architecture). This allowed us to capture the type of pivot that occurred without speculating about the subtle differences that exist within each category (Bajwa et al., 2017; Ries, 2011). The final sample includes 23 product pivots, 64 market pivots, 10 platform pivots, 20 business architecture pivots, and 1 engine of growth pivot. Table I contains the operational definition of each, along with its corresponding category.

Using the date that each firm's Twitter account was created as a proxy for the firm's age (being the earliest indication of the founders decision to enter the market), we then calculated summary statistics for the panel (Antretter et al., 2019). In all, the average pivot was undertaken approximately 2.12 years after startup, with a range between 3.3 and 1.04 years at the quartiles. For those firms that went on to either exit or fail, pivots occurred an average of 2.29 years before the terminal event (Shane & Stuart, 2002). Failures were calculated in line with Yu (2020), with ventures coded as being inactive if either: 1) Crunchbase listed the firm as being closed; 2) the venture's website was inactive or could not be found; or 3) the company's Twitter account had not been updated in over a year. In such cases the date of the venture's last Tweet was used to calculate the firm's closure.

Data for the dependent variable in this study comes from two additional sources. For customer traction, changes in the venture's web traffic were collected from Amazon's Alexa Web Information Service ("Alexa") (Hallen et al., 2020). A subsidiary of Amazon, Alexa collects the summary and analytics data of commercial websites using the plugins available for popular internet browsers (Wang & Xu, 2017). Additionally, changes in the top management team were collected as a secondary performance measure using the founder and team information listed on Crunchbase (Cohen et al., 2018; Lyons & Zhang, 2018; Nuscheler et al., 2019), a publicly available database that is owned and operated by TechCrunch. Importantly, because company entries cannot be deleted on the site, there is no survivor bias in the employee and firm history (Ko & McKelvie, 2018; Yu, 2020).

Because the data that is used to identify individual pivots in this study is collected at a time when the ultimate failure or success of the pivot is unknown, it provides an ideal source of information that avoids many of the retrospective and survivor biases that have hindered

previous studies. However, this approach does produce a number of selection effects (discussed below) which cannot be avoided at the design stage. Instead, I employ a statistical approach to addressing endogeneity that does not require the presence of observed instruments (Park & Gupta, 2012). This allows us to establish the conditional ignorability necessary for accurate interpretation of the results (Glynn & Quinn, 2007; Rubin, 1974, 1978).

3.2 Measures

Independent variable – The pivot date. As described above, the dates of individual pivots are identified in two primary ways. First, if a specific date is listed in the press release announcing the pivot, then that date is used as the point when the pivot was first made public. Second, if the pivot was described in an interview with an accelerator but fails to mention a specific date, timestamp data from the venture’s Twitter feed is used to identify when the pivot first became public knowledge (i.e., when the change in product, market, service or platform was first announced on Twitter).

Dependent variable – Customer traction. To capture the change in customer interest that occurs among ventures with widely differing growth models (i.e. manufacturing firms and online exchanges), I examine the change in web traffic (i.e., reach per million) that occurs in the twelve weeks leading up to and following the pivot’s occurrence. Although ideally I would be able to measure the “change in conversion rates, sign-up and trial rates, and customer lifetime value” that occurs over this period (Ries, 2011, p. 119), examining the shift in a venture’s web traffic provides a useful means of gauging the short-term shifts in customer interest that take place following a strategic pivot (Cohen et al., 2018; Yu, 2020).

Page views have been shown to be an important indicator of customer awareness and sales growth (Reijden and Koppius, 2010), as well as providing strong quantitative evidence of

market demand (Greenstein, 2011; Ko & McKelvie, 2018; Weinberg & Mares, 2015). Given the early stage of development of firms in the sample, “creating awareness among (potential) customers is a major objective that usually precedes any other monetary measure” making it an ideal measure of performance for early stage ventures (Nuscheler et al., 2019, p. 129). However, as an outcome it assumes that a customer-facing website is of strategic utility for those firms in the sample, and that an online presence forms at least part of the venture’s customer acquisition strategy.

Dependent variable – TMT turnover. In addition to examining the change in web traffic that accompanies a strategic pivot, changes in the top management team are also analyzed to determine whether the shift in focus that occurs during a pivot results in changes to the firm’s top management team in the six months leading up to (and following) its occurrence. We define the top management team in line with prior research in both entrepreneurship (Nuscheler et al., 2019; Roure & Maidique, 1986) and strategy (Qian et al., 2013), to include the firm’s primary leadership roles in marketing (CMO), engineering (CTO), finance (CFO), operations (COO), and the chief executive (CEO) (Nuscheler et al., 2019, p. 129).

Covariates. Three additional covariates are included in this study, each of which is expected to influence pivoting’s impact on performance. First, we control for the venture’s *stage of development* using the difference between the creation date listed on the firm’s Twitter account, and their reported pivot date. This adjusts for the time elapsed (in weeks) between a venture’s founding and the onset of a pivot. Second, a dummy variable (0/1) is included to indicate the venture’s participation in a *seed accelerator* program. Because seed accelerators contain educational components based on the broader lean startup approach, ventures that take part in an accelerator may be more likely to pivot than other firms that do not (Cohen et al.,

2018; Cohen & Hochberg, 2014). Last, an additional dummy variable (0/1) included to capture those firms that pivot to a B2B model.

3.3 Methodology

To model the impact that pivoting has on customer traction while taking into account each firm's individual growth trajectory, I employ a discontinuous random coefficient growth model (RCGM), using a Bayesian estimation method (Hale et al., 2016; Lang & Bliese, 2009). This approach allows us to model the individual changes in firm performance that take place over time (i.e. within-group effects), and compare them across other early-stage, high-growth firms in the sample (i.e. between-group effects) (Lang & Bliese, 2009, p. 414; Oravecz & Muth, 2018). Because the element of time is particularly important in this study, the use of an RCGM allows us to estimate the frequency of the change that occurs, along with its temporal dependency (i.e., how much change occurs between successive periods) (Gabriel et al., 2017).

To do so, the independent variable in this study (the *pivot date*) was coded in two different ways in order to capture both the immediate impact of the pivot, and the subsequent change in traffic and TMT membership that occurs in the weeks (in the case of traffic) and months (for TMT membership) following its occurrence (see Table 2 for example). Under the first approach, the *pivot event* for each venture was assigned a 0 in each week (month) leading up to the pivot, and a value of 1 for each week (month) thereafter. Similarly, *pivot performance* was also assigned a 0 for each week leading up to the pivot, but was then increased by 1 (i.e. 1, 2, 3, 4, etc.) during each week (month) thereafter. This allows us to capture the linear change in traction and TMT membership that occur as the pivot unfolded (Hale et al., 2016).

Insert Table 2 About Here

Since the dataset used in this study consists of observational data arranged in an imbalanced panel – with hundreds (and in some cases, thousands) of time points nested within individual ventures – a Bayesian approach was selected for its robustness in dealing with small sample studies (Jebb & Woo, 2015) and hierarchical growth models (Feller & Gelman, 2015; Kruschke et al., 2012; León-González & Montolio, 2015). Because frequentist statistics returns to the probability of the data given the null, it relies on randomly generated samples from a fixed-but-unknown population to construct the distribution of parameter estimates (Zyphur & Oswald, 2015). This approach makes frequentist statistics vulnerable to small samples, as the lack of information provided in the data increases the amount of noise in the resulting estimates (Kruschke et al., 2012).

In contrast, Bayesian methods refer to the probability of the hypothesis (i.e. the parameters, or Beta) given the data (Miočević et al., 2018). This excludes reference to any “true” underlying population, and avoids the use of randomly generated samples to estimate the extremeness of the data under the null (Andraszewicz et al., 2014). Instead, Bayesian estimates the probability that a parameter estimate is true given the data that was observed (Jebb & Woo, 2015). This results in a joint posterior distribution indicating “the relative credibility of every combination of parameter values” (Kruschke, 2010, p. 296), rather than a single point estimate with an associated p-value (Kruschke et al., 2012). Under a Bayesian approach, the noise contained in smaller samples is reflected in the credibility interval surrounding the posterior distribution, rather than the parameter estimates themselves.

Bayesian methods are also particularly well-suited to estimating hierarchical models. By pooling firm-specific estimates toward the group mean, extreme individual cases are “shrunk”

toward the group average (Oravecz & Muth, 2018). This mitigates the false alarm rate that occurs in frequentist statistics by minimizing the noise that creates random coincidences in the data (Kruschke & Liddell, 2018).

3.3.1 Model

In general, any model specification that relies on Bayesian inference – be it multilevel, structural equation modeling, or ANOVA – take the following form (Oravecz & Muth, 2018):

$$\text{Posterior} \propto \text{Prior} * \text{Likelihood}^3$$

In this equation, the *prior* represents researchers’ prior knowledge (often, though not always, derived from previous studies) about the likely effect that a predictor has on a particular outcome (Kruschke et al., 2012). The *likelihood*, meanwhile, represents the data that researchers collect as part of the study. These two are then combined to form the *posterior*, in which “prior beliefs meet observed data and become updated” (Jebb & Woo, 2015, p. 96).

Jebb and Woo (2015, p. 94) likened the interpretation of Bayesian statistics to the reasoning process that each of us performs on a daily basis: “We start with some prior beliefs about an aspect of the world (e.g., there is probably some leftover milk in the refrigerator), observe some related information (observing a family member with a large glass of milk), and then update our beliefs accordingly (there might not be any more milk left).” Because the posterior contains the probability distribution of all possible parameter values (Kruschke et al., 2012), the resulting estimate can be expressed in a variety of ways (i.e., “there is a 90% chance that we have at least one cup of milk left,” to “there is only a 2% chance that we have more than half a gallon left in the fridge”).

³ The “ \propto ” symbol indicates “proportional to,” and can be interpreted as an equal sign (Jebb and Woo 2015).

When employing Bayesian estimation, one of researchers' primary responsibilities is to specify a probability distribution that accurately reflects the existing (i.e., "prior") beliefs about a predictor's relationship with a particular outcome (Andraszewicz et al., 2014; Jebb & Woo, 2015). "Prior distributions can be (a) informative priors based on previous findings and theoretical predictions, (b) empirical priors based on observed data, or (c) diffuse, non-informative, or uninformative priors based on no prior knowledge or belief" (Zyphur & Oswald, 2015, p. 395). When existing research indicates a clear relationship with well-known parameter values (between smoking and lung cancer, for example), researchers can weight the prior distribution to place more emphasis on the range of values established in previous studies (Kruschke et al., 2012).

Where no prior research exists, however, or when there is little agreed upon knowledge about a predictor's likely effect, then a weakly informed prior can be used that places more credibility on the "likelihood" (i.e., the recently collected data) when estimating the posterior distribution (Kruschke, 2010; Kruschke et al., 2012). Weakly informed priors aid the posterior's construction by creating a narrower distribution that regularizes parameter estimates away from extreme values, while remaining broad enough (s.d. = 5) to capture outliers (i.e., firms that failed or exited shortly after the pivot) (Kruschke et al., 2012).

Because little is known about pivoting's impact on new venture performance, or whether and under what circumstances it has a positive or negative effect on customer traction and TMT turnover, a weakly informed prior with a mean of zero and standard deviation of five was initially chosen for the model (Zyphur & Oswald, 2015). However, in order to reflect the broad consensus among practitioners that pivoting aids both the development and growth trajectory of

early-stage ventures, I have also included analyses of the results containing a positive mean prior to acknowledge the ‘pro-pivoting’ bias in existing literature (Blank, 2013; Maurya, 2016).

3.4 Causal Inference and Threats

Modeling both the decision to pivot and its corresponding impact on performance raises a number of issues concerning endogeneity. Endogeneity occurs when the effect of x on y cannot be interpreted due to an omitted common cause that renders the coefficient estimates causally uninterpretable (Antonakis et al., 2010). Although endogeneity can occur for a variety of reasons – including selection effects, measurement error, simultaneity, and omitted variable bias (Anderson, 2018) – the primary concern in this study is a combination of selection effects and unmodeled common causes that make it difficult to isolate the effect that individual pivots have on new venture performance. Specifically, two types of selection-effects must be addressed in order to recover the causal inference necessary for accurate interpretation of the results: sample-selection bias and self-selection bias (Clougherty et al., 2015).

Sample-selection bias occurs when a truncated sample prevents researchers from observing a random sample of the population (Anderson, 2018). When a non-randomly selected sample is used to estimate causal relationships, the resulting coefficients are biased as a result of the “dependent variable not being observed for relevant subsamples of the population” (Clougherty et al., 2015, p. 290). In this study, sample-selection bias exists in that we are only able to observe those pivots that a firm chooses to make public through interviews and press releases to third-parties. Firms that underwent additional pivots and chose not to report them, are not included in our analysis.

A second source of endogeneity is present in the self-selection of firms that chose to undertake a pivot. “Managers engage in a variety of strategies, not randomly, but having in mind

their performance implications. Therefore, strategic choices are endogenous to performance” (Rocha et al., 2019, p. 1). In this study, firms make the decision to pivot with the aim of improving their performance. The result is a self-selection bias in which ventures elect to enter the “treatment” (pivot) or “control” (no-pivot) group based on factors that are unobservable to researchers (e.g., personal motivations, cognitive biases, etc.) (Rocha et al., 2019). Because the decision to pivot is not randomly assigned, “untreated” firms do not represent an adequate counterfactual, and causal inference cannot be established as a result (Clougherty et al., 2015).

These biases result in a skewing of the posterior distribution such that the median effect reported in the results will be wrong (Rubin, 1978). In order to meet the conditional ignorability requirement necessary for accurate interpretation of the results, these alternate explanations for pivoting’s impact on performance must be eliminated (Rubin, 1974). This requires us to address each of the above sources of endogeneity to ensure that any resulting coefficient estimates accurately reflect the impact that pivoting has on both customer traction and TMT turnover (Anderson, 2018; Rubin, 2005). To do so, I employ a statistical approach to addressing bias in the model (known as a copula) that does not require the presence of observed instruments (Park & Gupta, 2012).

3.4.1 Copulas

Unlike observed instruments that must be correlated with the endogenous regressor and excluded from the corresponding disturbance term (Anderson, 2018), latent instruments represent a different type of statistical approach to addressing endogeneity that does not require the presence of observed instruments. These approaches go by a variety of different names depending on the model specification, and include the original latent instrumental variable

approach from Ebbes et al. (2005), joint estimation using copulas (Park & Gupta, 2012), the higher moments method (Lewbel, 1997), and heteroskedastic errors (Lewbel, 2012).

Developed in the marketing literature, copulas act as functions that join multivariate distributions together to capture the correlation between an endogenous regressor and the structural error. They work by decomposing the error term into two separate components: one that is correlated with the endogenous regressor, and one that is not (Park & Gupta, 2012). By modeling the joint distribution of the error term and the endogenous regressor in a structural equation, parameter estimates can be correctly identified by maximizing the likelihood of the joint distribution (Park & Gupta, 2012).

3.4.2 Conditional Ignorability

Because the selection effects and unmodeled common causes described above introduce additional variance in the model that could bias parameter estimates unless removed, the use of a copula is necessary to identify the average treatment effect needed for causal inference (Glynn & Quinn, 2007). If successful, this technique will result in parameter estimates that are based on the exogenous portion of the variance attributable to a strategic pivot, and prevent a shift in the posterior distribution caused by sample and self-selection effects contained in the data (Gui et al., 2019).

CHAPTER 4

RESULTS

4.1 Customer Traction

All models were estimated using brms 2.7 in R (v3.4). A discontinuous random coefficient growth model (RCGM) was used in which both the slopes and intercepts were allowed to vary randomly. This allowed us to examine the change in web traffic (in reach per million) that occurs in the twelve weeks leading up to and following a strategic pivot, while also taking into account each firm's individual trajectory leading up to it. Bayesian's use of partial-pooling when constructing the parameter estimates means that all firm-specific estimates are “pulled” toward the group mean in order to minimize the influence of potential outliers (Kruschke and Liddell, 2018).

Insert Table 3 About Here

Because Amazon's Web Information Service only maintains data over a revolving four year period, the sample was limited to pivots that occurred after January 2015. Accounting for missing data in the pre-pivot period left us with a final sample of 46 firm-pivots, containing an average of 102 observations per firm over a six month period (i.e., 12 weeks before and after the pivot). Results for the initial *pivot event* returned a median posterior estimate of -0.21, with a 95% credibility interval (C.I.) between -.57 and .18 (see Table 4 for results). This suggests that for the average venture, a typical pivot results in an immediate drop in web traffic of approximately 210,000 visitors in the week following its occurrence.

Unlike frequentist methods, where a confidence interval that spans zero indicates the presence of a non-significant result, Bayesian has no such interpretation (Jebb & Woo, 2015, p. 111). Rather, because Bayesian returns an entire distribution of possible parameter values in which each point on the curve indicates the probability of a given effect size, a distribution that encompasses zero indicates that the range of credible values suggested by the data is positive in some cases, and negative in others (see Figure 1) (Kruschke et al., 2012). In this case, for instance, while the initial impact of a pivot is likely to be negative for roughly two-thirds of the firms that undertake one (and in some cases, strongly negative), a subset of ventures experience an immediate increase in web traffic in the week following its occurrence.

Insert Table 4 About Here

Looking at the median posterior estimate for *pivot performance*, meanwhile, the reported effect of .04 [95% C.I. 0.0 to .07] suggests that regardless of whether pivoting has an initial impact on customer traction in the first week after it occurs, over time the average venture tends to experience an increase in web traffic of approximately 4,000 visitors per week in each of the 12 weeks following its occurrence. Together, these results suggest that while pivoting is capable of producing immediate changes in customer traction that both benefit and harm early-stage ventures (with varying degrees of probability), over time the average firm tends to benefit from the experience.

Insert Figure 1 About Here

To determine whether these estimates were unduly biased by the presence of either selection effects or an omitted common cause, we applied a copula to a model containing both firm and observation-level fixed-effects, and compared it to the results returned by a naive model in OLS. Estimates for the lower-order terms *pivot event* and *pivot performance* (excluding the influence of time) were reported at 1.56 and .56 under the naïve model, and 1.61 and .60 when applying the copula. This suggests that to the extent there is bias caused by unobserved variance in the model, it did not have a material effect on the estimates.

4.1.1 Robustness Test

In order to reflect the ‘pro-pivoting’ bias that exists in both academic (Andries & Debackere, 2007; Bandera & Thomas, 2019; McMullen, 2017) and practitioner works (Blank, 2013; Maurya, 2016), results of the above models were rerun using a positively informed prior (mean = 1, s.d. = 5) to reflect the belief that pivoting significantly aids both the development and growth trajectory of early-stage ventures. This prior is equivalent to the belief that a typical pivot should result in an increase in web traffic of approximately 1 million page views in the twelve weeks following a pivot’s occurrence.

Updated results for *pivot event* (-.21 [95% C.I. -.60 to .18]) and *pivot performance* (.04 [0.0 to .07]), however, indicate almost no difference in either the median effect size or spread of the distribution. While this is partially due to the relatively small sample size in the study (Kruschke & Liddell, 2018), it nevertheless provides support for the type of relationship suggested by the data.

4.2 TMT Turnover

To model the impact that pivoting has on turnover within the top management team, a zero-inflated binomial model was used in which the slopes and intercepts were allowed to vary

randomly. Because personnel decisions involving the hiring and firing of TMT members in response to strategic change is unlikely to occur on a daily basis, data for the dependent variables was coded to reflect the monthly change in TMT turnover (with separate variables used to capture additions and departures). As such, each firm was coded a 1 for any month in which a TMT member either arrived or departed (and a 0 otherwise), during the three months leading up to and following the pivot's occurrence.

Insert Table 5 About Here

The final panel contained information on the start and stop dates of 637 top management team members for 91 firms, or an average of 7 members per venture. There were twenty-three total departures and thirty-three hires, with CEOs experiencing the largest amount of turnover (six departures and eight hires). Chief Technology Officers were the next most likely to experience a change, with four leaving the TMT and three more coming on board. The only position to experience zero turnover in the sample were CMOs, perhaps suggesting that in the internal battle to assign blame for lags in performance, boards are less likely to fault the venture's marketing efforts than they are with the firm's leadership.

Because the hypotheses were tested using a binomial or logit model, the reported parameter estimates are given in log-odds, with the effect sizes representing the average expected change in log-odds that pivoting has on TMT hires and departures. Since these are difficult to interpret, however, I converted the log-odds to an odds ratio by taking the exponent of the coefficients. The odds ratio represents the odds of a particular outcome occurring given the influence of a predictor (or pivot), relative to the odds of that outcome occurring in its absence.

Somewhat surprisingly, the ratio for *TMT departures* (.61:1) indicates that early-stage ventures are considerably *less* likely to see a member of their top management team leave during a strategic pivot than at other times in a venture's development. This indicates a general lack of support for the alternate hypothesis presented in Q3, and suggests that whatever the uncertainty surrounding a firm's future may be as it undergoes a strategic pivot, the existing leadership in such firms seems committed to seeing it through to the end. Perhaps the knowledge that such changes are an inherent part of the new venture creation process and that few early-stage ventures become highly profitable without them, creates downward pressure on existing team members to leave. Such questions create fruitful avenues for future research.

Insert Table 6 About Here

In contrast, the odds of an early-stage venture adding to its TMT during a pivot are almost twice as high as at other times during its development (1.88:1). This provides support in favor of the hypothesis presented in Q4, and suggests that ventures are more likely to think positively about the pivot and prepare to scale, then they are to wait and see how it turns out. It may be that because these firms are designed to scale, opportunities to do so – however couched in uncertainty – are looked upon as favorable moments for the venture to expand and grow to the level originally sought by the founders and investors.

Insert Table 7 About Here

4.2.1 Robustness Test

As with pivoting's impact on customer traction, however, there is also the possibility that the practitioner bias in favor of pivoting is correct, and that changes in a venture's strategic direction that are based on input from the surrounding environment can significantly aid the growth of early-stage ventures (Kirtley & O'Mahony, 2020; Maurya, 2016). As such, results of the above models were rerun using a positively informed prior, with a tighter distribution around the mean (mean = .2, s.d. = .8).

Updated odds ratios for *TMT departures* (.80:1) and *TMT hires* (1.93:1), reinforce the type of relationship indicated by the initial results. This suggests that early stage ventures that undergo a pivot are both less likely to lose a member of their top management team and more likely to make additions to it than at other stages in the venture's development.

4.3 Supplemental Analysis

In examining pivoting's broader impact on those involved in the new venture creation process, it was suggested that time-to-funding be included as a separate outcome variable in order to examine the impact that pivoting has on investor traction. Emerging research on pivoting has centered on the recognition that while some ventures need to radically change direction in order to survive, doing so risks disrupting their relationships with key stakeholder groups that had sustained the firm up to that point (Hampel et al., 2019; Kirtley & O'Mahony, 2020; McDonald & Gao, 2019). What has yet to be explored, however, is whether the inherent uncertainty of adopting a new business model results in the delay or denial of additional funding.

As such, I collected additional data on the funding rounds of individual ventures from CB Insights and Crunchbase, and used it to analyze whether the inherent uncertainty surrounding new venture pivots increases investors' reluctance to consider additional funding; or

alternatively, whether it suggests a greater depth of market knowledge that encourages further involvement (Gerasymenko et al., 2015; Plummer et al., 2016; Velu, 2015). To model the impact that pivoting has on investor traction I employed a latent growth curve model in which the venture's time-to-funding post-pivot was used as a primary outcome measure (Hale et al., 2016; Shane & Stuart, 2002).

I then deconstructed the panel to isolate just those firms that went on to either exit or fail, and examined whether investors were correct in selecting profitable investments following the announcement of a pivot (Lahr & Mina, 2016). To achieve the conditional ignorability necessary for accurate interpretation of the results, I utilized a generalized method of moments (GMM) technique for addressing endogeneity in multilevel models (Jerry A. Hausman & Taylor, 1981; Kim & Frees, 2007). As a latent instrumental variable approach, generalized method of moments produces consistent parameter estimates by eliminating the correlation between level-1 variables (i.e., funding rounds) and level-2 errors (Gui, 2019).

All models were estimated using *REndo* 2.1 in R (v3.4). I began by fitting a generalized method of moments (GMM) model to the data that returned results for several possible estimators along a robust to efficient continuum (from firm-level fixed effects, to general method of moments and random effects). Results of the Hausman (1978) test indicated a non-significant chi-square ($p = .99$), suggesting that the model did not suffer from omitted variable bias. Rather than proceeding with a random intercept/random slope model, however, I elected to use a mixed-effects GMM that utilizes both the within and between variance of exogenous variables while assuming that any within-firm variance in the model is endogenous (Gui et al., 2019; Kim & Frees, 2007).

After eliminating missing data I was left with a final panel of 98 pivots, including 499 funding rounds from firms that went on to either exit or fail. Firms in the sample went an average of 204 days between funding rounds pre-pivot, and 324 days between rounds post-pivot. Results indicate that for the average firm a typical *pivot event* results in a delay in time-to-funding of 20 days to the first-round post-pivot (with an average time of 374 days). However, the result was not significant ($p = .52$) (see Table 8 for results). In contrast, the time between subsequent rounds (*pivot performance*) increased by an average of 18 days for each round after the venture's initial funding, and was strongly significant ($p < .01$). These models suggest that investors are likely to both shy away from additional investment in the immediate aftermath of a pivot, and to continue conducting normal levels of due diligence once the initial uncertainty surrounding it has disappeared.

Insert Table 8 About Here

After subsetting firms that failed following the pivot's occurrence ($n = 30$, $k = 105$), I then ran additional models to determine whether investors successfully avoided firms with the lowest long-term funding potential. In contrast to the full panel, estimates for the *pivot event* suggested an average acceleration in time-to-funding of 258 days to the first-round post-pivot ($p < .05$). This trend did not improve over time, however, with estimates for *pivot performance* indicating a delay in time-to-funding between subsequent rounds of approximately 134 days ($p < .05$). Together these results suggest that investors chose poorly when evaluating the success of firms that later went on to fail.

Surprisingly, investors showed no willingness to accelerate funding times for those ventures that were eventually acquired following the pivot ($n = 25$, $k = 130$). In fact, parameter estimates for *pivot event* ($p < .01$) suggest a delay in time-to-funding of 162 days, perhaps indicating that ventures that experience a rapid increase in traction may find it beneficial to delay additional investment until better terms are available. Together with the results for *pivot performance* ($p = .8$), this data suggests that even firms with the greatest investment potential receive the same level of due diligence when seeking additional funding.

4.4 Summary

Results of the above models suggest that pivoting's impact on nascent ventures varies considerably among customers, investors, and the venture's top management team. While the change in product features, market segments, or revenue model that accompanies a strategic pivot means that firms are likely to experience a drop in customer interest immediately following its occurrence, the same shift toward customer groups that founders believe receive more value from the venture's offering also makes it likely that firms will experience slow but steady growth in the level of customer traction over time.

Pivoting's impact on investors was more circumspect, however, with delayed funding times accompanying even those firms that went on to have highly profitable exits. Perhaps the most surprising results were that early-stage ventures were noticeably less likely to see a member of their top management team depart during a strategic pivot (and almost twice as likely to add to it), than at other times in a venture's development. While these findings do not represent the final word on the performance impact of new venture pivots, they do provide strong initial evidence of its impact in three key areas, including how the relationship between them looks as it unfolds over time.

CHAPTER 5

DISCUSSION

For several years after pivoting first entered wide scale use in 2011 (Ries, 2011), the underlying assumption that strategic course corrections play a key role in the development of early-stage, high-growth ventures, went largely unchallenged in the literature (Grimes, 2018). Only after several well-known pivots led to high profile failures did scholars begin to ask whether pivoting's outcomes were truly beneficial to each of the firms that pursued them (McMullen, 2017). Subsequent efforts to explore this question have since focused on understanding the process by which nascent ventures decide to pivot (Kirtley & O'Mahony, 2020), and how entrepreneurs communicate strategic change to key stakeholder groups (both successfully and unsuccessfully) (Hampel et al., 2019; McDonald & Gao, 2019).

As of yet relatively little has been done to isolate the causal impact that pivoting on performance (Bandera & Thomas, 2019), and given the methodological challenges that arise when attempting to do so it is unlikely that any one study will succeed in establishing the “true” underlying relationship between them. While it may be tempting to assume that this means having to forgo any attempt at quantitative analysis of the subject, this is not the case. By validating a measurement model that allows researchers to identify the occurrence of individual pivots at the time that they occurred (and including those that failed), this study contributes to a fuller distribution of the performance outcomes that accompany new venture pivots (Bandera & Thomas, 2019).

The results presented here suggest that pivoting is likely to have a negative impact on customer traction immediately following its occurrence, and that this decline is likely a result of the venture moving away from its original value proposition (Brush et al., 2015). Although

insufficient to achieve the level of growth sought by the company's founders, the venture's initial offering (as well as the faith placed in the founding team by early investors) was nevertheless strong enough to carry them through several rounds of funding and see them admitted to one of the world's leading accelerators (Cohen & Hochberg, 2014). Whatever pivoting's initial impact, however, it is also likely that the average venture experiences at least some increase in customer traction in each of the twelve weeks that follow it.

It is possible that this later growth serves as validation for those who espouse pivoting's ability to generate more productive growth models in venture's that aspire to high growth (that is, to justify practitioners' belief in the concept) (Blank, 2013; Maurya, 2016; Ries, 2009). Because pivoting is less an event than it is a process of redirecting a firm's activities, resources, and attention in furtherance of a new strategy (Kirtley & O'Mahony, 2020; Ries, 2011), understanding the time component surrounding how pivots unfold inside and outside the firm is critical to determining how customers are likely to respond to significant changes in a venture's direction (Hampel et al., 2019).

Whether and how these changes affect the composition of a venture's top management team is similarly important for understanding how pivoting affects the internal growth of early-stage ventures. Although considerable work has been done examining how changes in a top management team affect firm performance, less well understood is how changes in a venture's strategy affect the makeup of the top management team (Eesley et al., 2014). Within this research, however, the combination of firm growth and strategic change are often used to explain the majority of all leadership transitions that occur within nascent ventures (Boeker & Wiltbank, 2005; Nuscheler et al., 2019).

Given that pivoting involves the intersection of both (i.e., a strategic change in direction prompted by a lack of traction in the marketplace) (Ries, 2009), it is unclear whether the uncertainty that surrounds strategic pivots encourages firms to either expand their top management teams in preparation for rapid growth, or accommodate the departure of existing members as the venture moves away from its initial idea (Klotz et al., 2014). The findings in this study suggest that, however counterintuitively, early-stage ventures are *less* likely to see a member of their top management team leave during a strategic pivot than at other times in a venture's development.

Instead, our findings indicate that the odds of an early-stage venture adding to its TMT during a strategic pivot are almost twice as high than at any other time in its development. The combination of these two suggests that however uncertain a venture's future may be as it undergoes a strategic pivot, the existing leadership in such firms seems committed to seeing it through to the end. Not only that, but firms also appeared more willing to think positively about the pivot by adding to their top management teams prior to the pivot's completion. This suggests that either the leadership in these ventures lacks the knowledge and experience required to move the firm into a new area, or that they view strategic pivots as opportunities for growth and expansion, act accordingly. Such questions provide ample room for research in the future.

While these results provide only initial evidence – albeit strong – of pivoting's impact on new venture performance, Bayesian is particularly well-suited to addressing these types of questions given its strengths with both small sample studies and its ability to produce results that contribute to the “cumulative and iterative nature of science” (Jebb & Woo, 2015, p. 103; Kruschke et al., 2012). By utilizing a Bayesian approach, the posterior effects observed in this study can be used to set the prior estimate in the next. Over time, this will allow scholars to

determine which types of pivots are successful, when, and under what circumstances (Kirtley & O'Mahony, 2020; Pillai et al., 2019).

5.1 Customer Traction as a Measure of New Venture Performance

When modeling the outcomes that pivoting has early-stage, high-growth ventures, traditional measures of firm performance have utilized a variety of indicators to evaluate the success or failure of a new venture's attempts to enter a marketplace (Ireland et al., 2005; Mattingly, 2015; Wiklund et al., 2019). The most common of these include changes in firm survival (Wennberg et al., 2016), employment (Davis & Shaver, 2012), and sales or profitability (Delmar & Wiklund, 2008). In recent years, however, digital technology has rendered the entrepreneurial process less bound by traditional constraints, instilling a new degree of fluidity into entrepreneurial outcomes and leading to multiple calls for the establishment of new performance metrics that capture the rapidly changing nature of high-growth ventures (Nambisan, 2016; Zaheer et al., 2018).

Among these, Shepherd et al. (2019) identified changes in a venture's market share as a promising metric for future research, writing that such an outcome would be an "indicator of competitive advantage that fits the emphasis on market dominance among new high-tech ventures" (Shepherd et al., 2019, p. 18). While the use of customer traction, or quantitative evidence of market demand (Greenstein, 2011; Weinberg & Mares, 2015), is not the only option for examining a venture's ability to enter a specific market, it does allow researchers to investigate the short-term changes in performance that accompany early-stage, high-growth ventures in different industries and various stages of development.

For example, because manufacturing firms measure growth relative to sales, an increase in performance is one that generates greater traction in terms of higher profitability per customer,

lower cost of customer acquisition, or higher rate of repeat customers (Ries, 2011, p. 116). In contrast, online marketplaces that match individual buyers and sellers have a significantly different growth model (Osterwalder & Pigneur, 2010). Because the success or failure of these firms rests on the network effects created among buyers and sellers, changes in a venture's performance are best captured by "conversion rates, sign-up and trial rates, and customer lifetime value" (Ries, 2011, p. 119).

Although each of these operationalizations presents its own problem in terms of data collection, the emergence of Amazon's Web Information Service allows researchers to measure extremely short-term (i.e., daily) changes in customer interest over an extended period of time (up to four years). This is true for even the smallest ventures, which have long generated considerable interest among researchers, but have also suffered from a dearth of public reporting data that makes evaluating their outcomes difficult for large sample studies (Hallen et al., 2014; Ko & McKelvie, 2018; Nuscheler et al., 2019).

5.2 The Lean Startup in Prior Academic Research

A frequently mentioned concern among entrepreneurship scholars is the widening gap between science and practice, and the perceived irrelevance of many of the field's core findings when it comes to informing the day-to-day operations of business owners and entrepreneurs (Banks et al., 2016; Byrne, 2015; Wiklund et al., 2019). While much of the debate surrounding academic relevance has traditionally centered on whether and how entrepreneurship scholars should strive to produce research that is actively read by practitioners, less frequently mentioned is the way in which entrepreneurship research has already played a significant role in shaping both the educational and operational practices of entrepreneurs (Bortolini, R F et al., 2018; Levinthal & Contigiani, 2018).

Perhaps the clearest example of this is the significant body of work in entrepreneurship and innovation that helped popularize many of the core tenets of the Lean Startup method that encompasses pivoting (Blank, 2005; Ries, 2011). As a framework for helping startups identify who their primary customers are and developing repeatable, scalable business models around them (Blank, 2013), there is a general assumption that the techniques employed by the Lean Startup were developed by practitioners in response to the failure of business schools to understand the process by which entrepreneurs create highly successful ventures (Levinthal & Contigiani, 2018).

This lack of awareness surrounding scholarly contributions to practice has led to growing concerns about the declining relevance of entrepreneurship research (Bansal et al., 2012; Byrne, 2015). One of the aims of this paper is to bring greater attention to the contributions of entrepreneurship researchers by highlighting how many of the ideas that are central to the now-prevailing approach to new venture development used by practitioners grew out of years of research in the entrepreneurship and innovation literature (Amit & Zott, 2001; Eisenhardt & Tabrizi, 1995; McGrath, 1999; Simon, 1969; Van de Ven & Polley, 1992).

That many of the Lean Startup's primary tenants can be traced back to findings in the business model innovation, learning from experimentation, and new product development literatures should be celebrated by academics and practitioners alike (Wiklund et al., 2019). That it is not reflects a lack of understanding not just among entrepreneurs, but by entrepreneurship scholars as well (Bortolini, R F et al., 2018; Levinthal & Contigiani, 2018). Although the debate surrounding the extent to which research should actively seek to inform practice will no doubt continue, that should not prevent academics from emphasizing those areas where research has

already played a significant role in shaping the educational and operational practices of entrepreneurs.

Recognizing that much of the theoretical grounding of the Lean Startup appears in prior academic research is not to suggest that the founders of that approach owe their success to the insights of others that have so far gone unattributed in the literature. It is mentioned here only to highlight the diffuse nature of knowledge, and to illustrate how the revelations produced by others can come back in new ways once they have entered the broader public discourse. By reviewing the foundational texts in each field we hope to demonstrate how in this respect at least, entrepreneurship scholars should not be shy about emphasizing their contributions to practice (Amit & Zott, 2001; Clark & Fujimoto, 1989; Eisenhardt & Tabrizi, 1995).

5.3 Summary

The goal of this dissertation was to provide scholars with a strong initial prior for determining when strategic pivots are likely to produce successful outcomes. In doing so it examined the impact that pivoting has on a firm's ability to attract customers and investors, while adding to and retaining the key members of its top management team. As part of this process this study also made the case for adopting customer traction as a short-term performance measure in the study of early-stage, high-growth ventures. Specifically, utilizing customer traction as an outcome measure allows scholars to examine changes in the market share of ventures in a variety of industries and different stages of development.

Perhaps most importantly, this dissertation also attempted to link the origins of the Lean Startup method to long standing research in entrepreneurship and innovation, in the hope that by doing so the broader relevance of academic research would become more apparent to both scholars and practitioners alike.

Table 1 – Categorization of Strategic Pivots

Category	Pivot Type	Definition
Product	Zoom-in	A single product feature becomes the entire product.
	Zoom-out	An entire product becomes a feature of a larger product.
	Technology	The product offers the same solution with different technology.
Market	Customer need	The new product solves a different customer problem than the original.
	Customer segment	The new product targets a different customer segment.
	Channel	The start-up finds a better way to reach customers.
Platform	Platform	A product becomes a platform or vice versa.
Business Architecture	Business Architecture	The startup switches from B2B sales to B2C (or vice-versa).
Engine of Growth	Engine of Growth	The startup changes its growth strategy to viral, sticky, and paid growth.

Sources: The lean startup, 2011, Eric Ries; and Start-ups must be ready to pivot, 2017, Bajwa et al.

Table 2 – Coding and Interpretation of Variables in Discontinuous
Random-Coefficient Growth Models

Variable	Measurement Occasion												Meaning
	1	2	3	4	5	6	7	8	9	10	11	12	
Linear Growth	0	1	2	3	4	5	6	7	8	9	10	11	Linear growth in firm performance
Pivot Event	0	0	0	0	0	0	1	1	1	1	1	1	Immediate impact due to a pivot's occurrence
Pivot Performance	0	0	0	0	0	0	0	1	2	3	4	5	Linear growth rate after initial event

Table 3 – Customer Traction: Means, Standard Deviations, and Correlations
with Confidence Intervals

Variable	<i>M</i>	<i>SD</i>	1	2	3	4	5
1. reach	10.01	16.35					
2. StartupLag	-3.08	1.81	-.18** [-.25, -.11]				
3. Accelerator	0.46	0.50	-.10** [-.17, -.03]	.01 [-.06, .08]			
4. B2B	0.26	0.44	.31** [.24, .37]	-.20** [-.27, -.13]	-.21** [-.28, -.15]		
5. pivot_performance	2.82	3.70	-.06 [-.13, .01]	.03 [-.04, .10]	.07 [-.01, .14]	-.04 [-.11, .03]	
6. pivot_event	0.52	0.50	-.08* [-.15, -.01]	.04 [-.03, .11]	.06 [-.01, .13]	-.05 [-.12, .02]	.74** [.71, .77]

Table 4 – Change in Web Traffic: Reach per Million

Reach per Million			
<i>Predictors</i>	<i>Estimates</i>	<i>std. Error</i>	<i>CI (95%)</i>
Intercept	6.42	4.16	-1.47 – 14.31
pivot_performance	-0.09	0.33	-0.76 – 0.59
obs_date	-0.47	0.13	-0.72 – -0.21
pivot_event	2.51	2.25	-2.14 – 6.83
StartupLag	-1.54	1.08	-3.66 – 0.51
Accelerator	-1.92	2.97	-7.75 – 4.06
B2B	4.64	3.44	-2.37 – 11.36
pivot_performance.obs_date	0.04	0.02	-0.00 – 0.07
obs_date.pivot_event	-0.21	0.19	-0.57 – 0.18
Random Effects			
σ^2	173.85		
τ_{00}	92.83		
N _{firm_id}	46		
Observations	762		
Marginal R ² / Conditional R ²	0.084 / 0.742		

Table 5 – TMT Turnover: Means, Standard Deviations, and Correlations
with Confidence Intervals (in Log-Odds)

Variable	<i>M</i>	<i>SD</i>	1	2	3	4	5
1. TMT.departures	0.03	0.18					
2. TMT.hires	0.04	0.21	.00 [-.07, .08]				
3. StartupLag	-2.65	1.48	-.06 [-.14, .01]	-.04 [-.11, .04]			
4. Accelerator	0.65	0.48	-.07 [-.14, .01]	.03 [-.05, .11]	.24** [.16, .31]		
5. PivotType	0.18	0.38	-.02 [-.09, .06]	-.08* [-.16, -.00]	-.09* [-.17, -.02]	-.14** [-.22, -.07]	
6. Size	73.67	131.03	.04 [-.04, .11]	.03 [-.05, .11]	-.16** [-.23, -.08]	-.16** [-.23, -.08]	-.09* [-.16, -.01]

Table 6 – Top Management Team Turnover: Departures

TMT Departures			
<i>Predictors</i>	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI (95%)</i>
Intercept	0.89	13.36	-39.32 – 44.72
pivot_process	-0.49	1.18	-5.12 – 2.92
StartupLag	-0.73	1.13	-5.83 – 2.43
Accelerator	-2.22	1.49	-24.30 – 3.81
PivotType	0.04	1.36	-8.38 – 7.51
Size	0.16	0.12	-0.03 – 0.63
Random Effects			
σ^2	0.00		
τ_{00}	0.03		
N _{id}	91		
Observations	637		
Marginal R ² / Conditional R ²	0.011 / 0.020		

Table 7 – Top Management Team Turnover: Hires

TMT Hires			
<i>Predictors</i>	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI (95%)</i>
Intercept	-9.20	12.50	-49.65 – 22.74
pivot_process	0.63	1.08	-2.34 – 5.05
StartupLag	-0.54	1.16	-6.00 – 2.90
Accelerator	0.60	1.46	-5.53 – 10.97
PivotType	-2.29	1.77	-26.80 – 6.76
Size	0.13	0.10	-0.05 – 0.60
Random Effects			
σ^2	0.01		
τ_{00}	0.03		
N _{id}	91		
Observations	637		
Marginal R ² / Conditional R ²	0.021 / 0.041		

Table 8 – Change in Time-to-Funding Pre and Post-Pivot (Full Panel)

Time-to-Funding (Change in Days)				
	Estimate	Std. Error	z-score	Pr(> z)
Intercept	372.14	66.27	5.616	0.000
Pivot event*Obs date	20.19	31.53	0.640	0.522
Pivot performance*Obs date	18.45	7.02	2.629	0.009
Accelerator	-103.89	42.47	-2.446	0.014
Pivot type	-38.61	46.33	-0.833	0.404
Firm size	0.22	0.16	1.401	0.161
Pivot performance	-189.25	46.93	-4.033	0.000
Pivot event	212.78	97.76	2.177	0.030

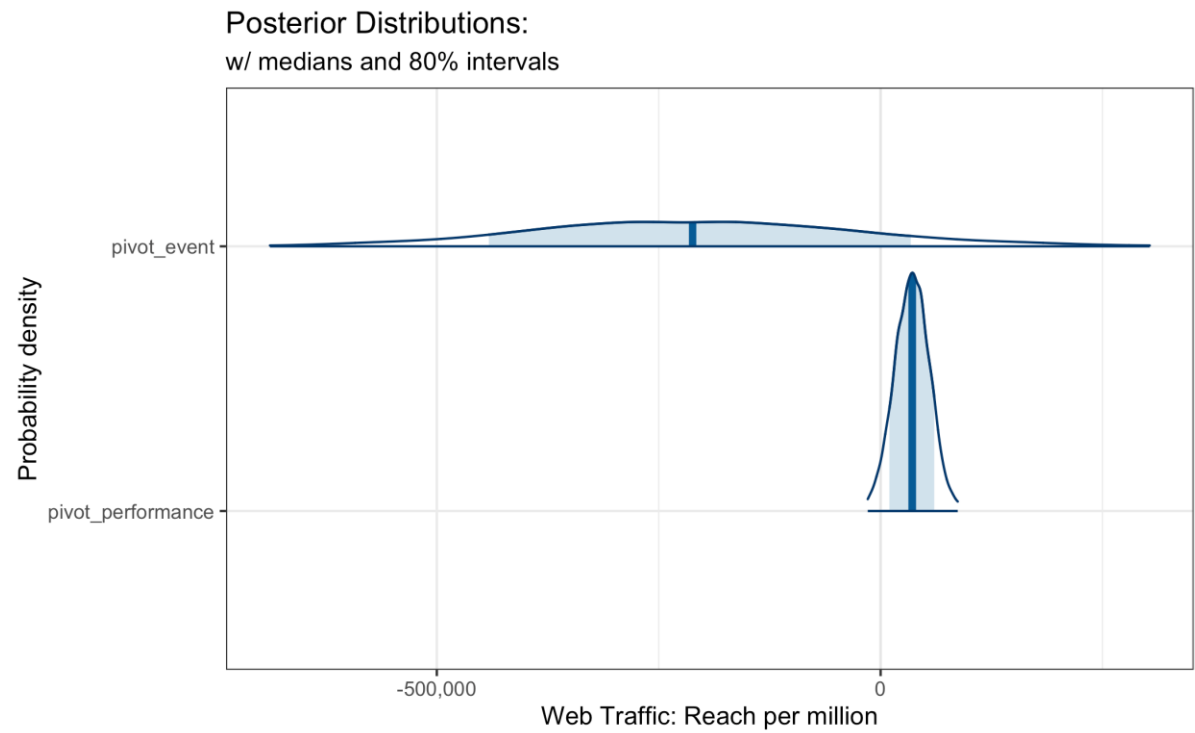


Figure 1 – Change in Web Traffic: Posterior Distributions

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VITA

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After graduating in 2009, Mr. Cottle spent several years running a microenterprise program for immigrants and refugees in Louisville, Kentucky. After leaving in 2012, he became the first director of the Small Business & Entrepreneurship Center at Jefferson Community and Technical College, and subsequently served as a project director and fellow at the National Association for Community College Entrepreneurship from 2013 to 2015.

Upon completion of his degree requirements Mr. Cottle plans to continue pursuing his passion for teaching entrepreneurship, and conducting research that is relevant to both scholars and practitioners.