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THE EFFECT OF AMBIGUITY IN THE PERFORMANCE OF MERGERS AND ACQUISITIONS

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Abstract

Mergers and acquisitions rarely deliver on expectations, yet organizations continue to pursue these strategic decisions. Scholars have researched acquisitions extensively as decisions under risk (Kumar, Dixit, & Francis, 2015) but decision theorists define decisions under risk as decisions where alternatives come with known outcomes and probabilities. In real-world decisions, such as mergers and acquisitions, our knowledge of possible outcomes and their probabilities is rarely complete. Examining acquisitions as decisions under risk may have led researchers to incorrect conclusions or given an incomplete view of these critical strategic choices. In this research, I suggest that mergers and acquisitions are decisions made under ambiguity, or situations where outcomes and probabilities are only partially known (Knight, 1921; Raiffa, 1957; Takemura, 2014). Examining acquisitions as decisions under ambiguity may allow for further understanding of this phenomenon, as well as, how and why so many acquisitions fail. In this study, I conducted an initial qualitative study to identify and confirm sources of ambiguity. Using the information gained from study 1, I examined 140 acquisitions using archival data to study the relationship between ambiguity and acquisition performance. I also examined the role of the size of the acquisition and the decision-maker's experience with acquisitions in this relationship.

Keywords: Decision-making, risk, ambiguity, ambiguity, mergers, and acquisitions

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Chapter 1: Introduction and Contributions

Mergers and Acquisitions often fail to increase a firm's short-term (Asquith, 1983; Dodd, 1980; Jarrell & Poulsen, 1989; Malatesta, 1983) or long-term value (Agrawal, Jaffe, & Mandelker, 1992; Asquith, 1983; Loderer & Martin, 1992) and, in fact, often erode firm value (Chattopadhyay, Glick, & Huber, 2001; Datta, Pinches, & Narayanan, 1992; King, Dalton, Daily, & Covin, 2004; Moeller, Schlingemann, & Stulz, 2003; Seth, Song, & Pettit, 2002). Investors commonly discount the stock of acquirers after an acquisition announcement, which shows their lack of faith (Shleifer & Vishny, 1991), and acquisitions often are resold later at a loss (Porter, 1989). So why do so many acquisitions fail?

Scholars have researched acquisitions extensively as decisions under risk (Kumar et al., 2015). Decisions under risk are described in the field of psychology and risk analysis as the presence of danger or loss (Takemura, 2014), and in decision-making research, decisions under risk are those in which there are a defined set of states (winning or losing), and there is a probability distribution within those states (e.g., 30% chance of loss and 70% chance of gain). In a perfect world, we would have all of the information necessary before deciding between alternatives (Fama, 1970). In real-world decisions, such as acquisitions, our knowledge of possible outcomes and their probabilities is rarely complete. I argue that mergers and acquisitions are decisions under ambiguity. Examining mergers and acquisitions as decisions under ambiguity is more precise in that decision-makers have some information about outcomes and probability (so they are not decisions under ignorance which also fall under uncertainty), but decision-makers do not have all of the information that they might need or wish to have. I test the effects of ambiguity on acquisition performance.

Uncertainty refers to the state in which the possible outcomes or probabilities associated with those outcomes are not completely known (Knight, 1921; Takemura, 2014). Decisions under uncertainty can include decisions under ambiguity, where the decision-maker has some information, and decisions under ignorance, where the decision-maker has no information about potential outcomes and probabilities. In real-world decisions, it is common that we may have some idea of possible outcomes, and perhaps ranges of probabilities but we only have access to limited information, and we do not know what we do not know. In decisions under ambiguity, decision-makers know the condition of the decision (the decision to be made), but do not know all the potential outcomes of the decision or the chance that each may occur. Acquisitions are ambiguous decisions in that managers have access to information about elements and alternatives and may be able to predict some possible outcomes and probabilities but may be faced with information gaps or expert disagreement within the organizational environment.

Milliken (1987) proposed three types of uncertainty differentiated by the type of information that organizations perceive to be lacking: state, effect, and response. State uncertainty is relevant in situations where decision-makers lack information about the nature of the environment where effect uncertainty does not necessarily involve lack of information but instead, the shortage of critical information in how environmental changes will affect them. For example, state uncertainty may be a weather situation where an individual does not know if a hurricane is set to strike their town. In a situation of effect uncertainty, they may know that a hurricane is advancing toward their town, but they are unsure of how it will affect their property. Response uncertainty occurs in situations where there is a perceived lack of information about the response options or the value of each course of action. In the example above, response uncertainty would be uncertainty around the value of responses like evacuation or just needing an umbrella.

Milliken (1987) defined state uncertainty as when managers "perceive the organizational environment, or a particular component of that environment, to be unpredictable…. or how the components of the environment might be changing" (p.136.) Milliken (1987) is describing state uncertainty which could include ambiguity AND ignorance about components in the environment. Mergers and acquisitions fall into the category of decisions under ambiguity because decision-makers have SOME information available to them, so they are not decisions under ignorance. This could be thought of as state ambiguity (fully defined later).

The difference between decisions under ambiguity and decisions under risk is that there is a fundamental difference in the way that people experience decisions under risk compared to most decisions that they face in everyday life (Einhorn & Hogarth, 1986). A classic example of a decision under risk is the disease problem presented by Kahneman and Tversky (1979) where individuals are presented with a decision between two options when faced with a disease outbreak. In this decision, decision-makers can either guarantee that 200 of 600 lives are saved or accept a one-third probability of saving all 600 lives and a two-thirds probability of saving none. In this example of a decision under risk, there are well-defined outcome spaces and probabilities. When assessing decisions in the real world, decision-makers do not have complete information about the potential outcomes from a decision or the probabilities that each outcome will occur. Their decisions may be influenced by beliefs that are loosely held or ill-defined. These beliefs may create biases that influence the process of decision-making but also what information is more salient to the decision. As I discuss later, individuals react very differently when presented with risky decisions than when they are presented with ambiguous decisions where they have some, but all of the information necessary. Ambiguity in decisions can affect, not only how the decision-maker makes choices, but also how they gather information in areas where they sense ambiguity. For these reasons, examining acquisitions as decisions under risk may have led researchers to incorrect conclusions or given an incomplete view of these critical strategic choices. Examining acquisitions as decisions under ambiguity may allow for further understanding of this phenomenon, as well as, how and why so many acquisitions fail.

This research makes three important contributions to the literature. First, this research challenges the viewpoint in management literature that acquisitions are decisions under risk when they are decisions under ambiguity. Much research uses these concepts interchangeably when they are not. For example, March & Shapira (1987) proposed that uncertainty (including ambiguity and ignorance) was just one aspect of risk and that most managers do not typically treat it as important. Asquith (1983) examined the process of mergers and acquisitions by integrating which probabilities in merger information are incorporated into security price movements. Each of these studies and many more assume that, in acquisitions, managers know the possible outcomes and probabilities which assumes that acquisitions are a decision under risk instead of ambiguity. Treating risk and ambiguity as the same construct, treating ambiguity as one aspect of risk, or assuming that ambiguity is unimportant is dangerous because this ignores the processes that individuals use when assessing ambiguity vs. risk, how individuals feel when assessing ambiguity vs. risk, and how those processes and feelings affect decisions. Assuming that in acquisitions all outcomes and probabilities are known also leaves space for a myriad of unanticipated consequences which can lead to a previously unstudied source of failure in acquisitions. This research informs scholarship on decision-making in mergers and acquisitions by examining a unique and important potential source of failure in acquisitions, as well as the effects of different types of ambiguity in acquisition performance. Applying the more accurate lens of ambiguity may better equip scholars and practitioners to identify where ambiguity matters and when it does not in acquisitions.

Second, this research adds to the psychological foundations of strategy. Mergers and acquisitions are massively expensive and critical choices for many organizations, and yet, we still do not know why they fail. Given that we know acquisitions regularly fail to deliver on short or long-term goals and that they may erode firm value (Haleblian, Devers, McNamara, Carpenter, & Davison, 2009), why do organizations continue to pursue these losing propositions? Many scholars have argued that no theoretical framework explains the relationship between acquisitions' antecedents and subsequent performance (Hitt, Harrison, Ireland, & Best, 1998; Hoskisson, Hitt, Johnson, & Moesel, 1993; King et al., 2004; Sirower, 1997). Because acquisitions often fail to achieve performance, firm, or synergy goals, they cannot be justified based on economics alone. Researchers have also turned to behavioral or psychological viewpoints that guide behavior in these crucial organizational decisions the effects of hubris (Hayward & Hambrick, 1997), overconfidence (Malmendier & Tate, 2005), anchoring (Malhotra, Zhu & Reus, 2015), narcissism (Chatterjee & Hambrick, 2011), and identity (Cartwright, 2006) but none of these psychological viewpoints can explain the general failure of acquisitions fully. This research helps fill this critical void by examining previously unidentified and unstudied non-financial sources of failure in mergers and acquisitions.

The third contribution of this research is expanding scholarship in decision theory. Currently, scholars examine decisions under ambiguity in lab-based or application studies that are rooted in simple decisions and choices. In the management literature, research in ambiguity for organizations traditionally has focused on the problems that ambiguity causes and structural solutions to correct it (e.g., Dill, 1958; Duncan, 1972; Lawrence & Lorsch, 1969). Researchers in the management literature primarily have ignored ambiguity since the 1970s in favor of studies in risk and prospect theory that are easier to measure (Milliken, 1987). Given the complexities of today's global environment, scholars and practitioners agree that it is essential to understand the context of ambiguity (Alvarez & Barney, 2005) and create teams that can navigate it (Dibble & Gibson, 2017). To meet these goals, scholars and practitioners require a broader understanding of the effects of ambiguity in management today. Additionally, while there are multiple application papers examining ambiguity, it is vital that we take a theoretical approach in examining the effect of ambiguity in the management literature. This research contributes to the broader body of scholarship decision-making by investigating a real-world decision and the implications of ambiguity on that decision.

Chapter 2: Theory and Literature Review

Theory

Decision-making research: Normative and Descriptive

Behavioral decision theory has two related facets, normative and descriptive. Normative decision theory is focused on prescribing courses of action that conform most closely to the decision-makers' attributes, beliefs, and values (Slovic, Fischhoff, & Lichtenstein, 1977). Descriptive decision theory is the aim of describing these beliefs and values plus how individuals incorporate them into their decisions. Simplified, normative theory research is about how decision-makers "should" make decisions, and descriptive theory research is about how decision-makers "actually" make decisions. Decision-making is studied in essentially all disciplines, e.g., medicine, economics, education, political science, geography, engineering, marketing, management science, and psychology (Slovic et al., 1977; Takemura, 2014). Past descriptive studies have focused on comparisons between normative, or prescribed behavior, and actual behavior but recent research has examined the psychological underpinnings of observed behavior to answer the question "Why do we make the decisions that we do?" This research focuses on descriptive decision theory and the study of how ambiguity affects the real-world decisions of acquisitions. This clarification is necessary because many theories explain behavior in a normative context but fail to predict behavior in a descriptive context.

Categorizing decisions: Certainty, risk, uncertainty, ambiguity, and ignorance

In classical decision theory, decision-making can be categorized into three groups: decisions under certainty, decisions under risk, and decisions under uncertainty (Takemura, 2014). Decisions under uncertainty include decisions under ambiguity and decisions under ignorance. Each of these decision types is based on the characteristics of the knowledge of the decision-making environment or how much decision-makers know before selecting between alternatives (Takemura, 2014). Decision-making under certainty include situations where the result of selecting an alternative is pre-determined. For example, a decision-maker is presented with a choice between $50 in cash or $60 in gift certificates. In this case, the states are known and that they will occur is already known. In decision-making research, decisions under risk include decisions with known probabilities when selecting between two alternatives. A simple example of decisions under risk is the decision to take an umbrella or not. The chance of rain each day can be expressed as a probability and influences whether to take an umbrella that day. Decisions under risk are those in which there are a defined set of states (raining or not raining), and there is a probability or probability distribution within those states (weatherman says there is a 30% chance of rain). The third form of decision-making is decisions under uncertainty. Uncertainty refers to the situation in which the alternatives or probabilities are not known. In relation to the previous example, the decision-maker must decide to take an umbrella or not but, in this case, the decision-maker may not know the probability of rain for the day. Decisions under uncertainty can be subclassified as decisions under ignorance or decisions under ambiguity (Takemura, 2014). Decision-making under ignorance includes cases in which the range of alternatives, possible states, and the range of results are entirely unknown, so the decision-maker has no information available to them. In decisions under ambiguity, the decision-maker has some information available but does not have complete information about all possible outcomes and their associated probabilities (Takemura, 2014). An example of a decision under ignorance is to bet on selecting a red ball from an urn when you do not know what colors are in the urn or what the distribution of those colors is. A decision under ambiguity would be knowing that there are red and black balls in the urn but not knowing the distribution.

One could argue that the overwhelming majority of decisions made by managers are decisions under ambiguity as managers have some information available but rarely have complete information and commonly do not consider the probabilities associated with potential outcomes (Golman & Loewenstein, 2016; Ho, Keller, & Keltyka, 2002). While most studies in acquisitions assume that they are decisions under risk, within these definitions in classical decision theory, acquisitions should be categorized as decisions under ambiguity similar to most managerial decisions.

In organizational research, uncertainty is not split into ambiguity and ignorance but examined as environmental uncertainty and categorized as a state, effect, and response uncertainty (Milliken, 1987). Given the previous example of the decision to take an umbrella, state uncertainty would be a decision to bring an umbrella when an individual does not know if it will rain or not. If the decision-maker is in a region where rain storms come on quickly and are unpredictable, then they will experience state uncertainty. Effect uncertainty will impact a decision-maker who may know there is a 30% chance of rain in their area (so they do not lack all information), but they are unsure if their house will flood or if there will be damage. Response uncertainty would occur when a decision-maker is unsure about the impact of their response to the rain be it with an umbrella, raincoat, rainboots or something more serious such as flood protection or evacuation. In acquisitions, top-level decision-makers must cope with state, effect, and response uncertainty (Thompson, 1967) particularly when they perceive the external environment as unpredictable. Milliken (1987) suggested that strategic choices are most affected by the state of the organizational environment, while effect uncertainty is more specific to sense-making processes in the organization such as identifying threats and opportunities. Decision-makers will experience response uncertainty as they attempt to examine strategic responses. For a comparison, managers may experience effect and response uncertainty when deciding to pursue an acquisition strategy, but once they are engaged in an acquisition process, they will experience state uncertainty. While Milliken's (1987) definitions have been applied in some organizational research, what Milliken fails to do is account for the decisions under ignorance which clarifies the difference between ambiguity and ignorance under the umbrella of uncertainty. Managers may experience ignorance in the state of their environment if a disruptive event happens in their industry but, in general, managers are rarely completely ignorant of the state of their environment. In mergers and acquisitions, managers will experience state ambiguity (a subset of state uncertainty, as defined by Milliken) as they have some information about the state of their environment but not all that is needed. This failure to fully define the difference between decisions under ambiguity and decisions under ignorance has left researchers with little direction about how to account for these constructs in descriptive decision making. The following section explores theories that have been used to predict behavior when faced with uncertainty and specifically ambiguity.

Ambiguity in Theory

In a perfect world, we would have all the information necessary about facts and alternatives open to us before making a decision. The efficient market hypothesis claims that we do (Fama, 1970) but this viewpoint has been widely criticized (Malkiel, 2003) and in real-world decisions, our knowledge is rarely complete. However, there are some degrees of the reliability or unreliability in the information that we collect and use to make our decisions. An important part of decision-making is understanding WHICH degrees of knowledge affect our decision-making. Multiple theories and decision models have been proposed to explain behavior in decisions under ambiguity, including expected utility theory, subjective expected utility theory

(C. F. Camerer & Karjalainen, 1994; Trautmann & van de Kuilen, 2014), the Bayesian approach (Gu, Pung, Zhang, Pung, & Zhang, 2004), traditional prospect theory, and cumulative prospect theory (Wakker, 2010). Below is a brief description of each theory and the challenge of applying these theories to decisions under ambiguity.

Scholars have applied expected utility theory in classic models of decision-making under risk and ambiguity (Von Neumann & Morgenstern, 1947). Expected utility applies when the decision-maker knows the distribution of outcomes before making the decision, for example, the spinning of a roulette wheel. Subjective expected utility (SEU) applies to decisions where the distribution of uncertain outcomes is not known; for example if it will rain tomorrow (Savage, 1951). Individuals know the possible outcomes are raining, or not raining but they may only know a range of probabilities for the chances of rain. Expected utility and subjective expected utility both include assumptions that probabilities are linearly weighted in the utility function that individuals use to evaluate alternatives in a decision (de Lara Resende & Wu, 2010). Savage (1951) suggested that expected utility theory applies to normative decision-making or how decisions “should” be made. He also proposed that individual preferences may guide subjective utility.

According to a Bayesian approach, the decisions-maker's knowledge in a given decision can be represented by a subjective probability measure that is defined by the possible outcomes, or states. This measure can be used to represent the expected utility of each alternative. Basic decision rules say that the decision-maker would pick the alternative with the maximum expected utility. A fundamental assumption of this approach is that a unique probability measure can represent the decision-maker’s knowledge. A consequence of this is that if there are two possible decisions with equal probabilities for each outcome, then the utilities assigned to each decision would be the same. It is possible, however, to find decisions which are identical in all respects relevant to this strict approach but would still motivate different choices. For example, if you have an urn filled with red and black balls, the utility of drawing a red ball is .5, and the utility of drawing a black ball is .5, but the decision-makers favorite color is red. Gärdenfors & Sahlin (1982) proposed a model of decision-making that generalizes the Bayesian decision theory and considers the reliability of probability judgments. They do not define ambiguity explicitly, but they discuss "epistemic reliability.' Epistemic reliability is the amount of relevant information that a decision-maker considers and how it will relate to the distributions of probability in a decision. In their model, decision-makers will calculate the epistemic reliability of each possible probability distribution and then consider only those epistemic reliabilities that meet some threshold of reliable information.

Prospect theory was the first theory that attempted to explain behavior that was not rational (Wakker, 2010) or aligned with one of the previously described rational decision models. Prospect theory proposes that individuals respond to potential gains with risk-averse behavior because they believe they have more to lose than to gain (Bromiley, Miller, & Rau, 2001; Kahneman & Tversky, 1979; Kühberger, 1998). Kahneman and Tversky (1979) identified two phases in the choice process: first, a framing phase plus editing and then an evaluation phase. The framing and editing phase are the preliminary analysis of the problem with the removal of any shared components between choices and then eliminating options. In the second phase, the decision-maker evaluates the framed choices and selects the highest value prospect (Tversky & Kahneman, 1981). A decision frame is "the decision-maker's conception of acts, outcomes, and contingencies associated with a particular choice" (Tversky & Kahneman, 1981, p. 453). Prospect theory was the first theory that provided scholars in decision-making research with a theory that was tractable with empirical validity. While prospect theory allowed for irrational behaviors to be modeled, the original prospect theory sometimes would produce implausible violations of stochastic dominance. Stochastic dominance is a partial order between random variables. For example, gamble A is the obvious choice over gamble B if A gives at least as good a result as B in every state. Stochastic dominance limited the application of prospect theory in theoretical studies.

In 1992, Kahneman and Tversky expanded prospect theory to attempt to address these challenges by incorporating rank dependence. Rank dependence allows for decision-makers to assign weights that are a relative ranking which means that results could be ranked in order of increase in the desirability of results (Tversky & Kahneman, 1992). Cumulative prospect theory can be thought of as a rank-dependent nonlinear expected utility theory (Starmer, 2000). An example of cumulative prospect theory is a single dice game in which we win $2, 4, or 6 if an even number is rolled and must pay $5, 3 or 1 if an odd number is rolled. The potential outcomes are winning $2, $4, or $6 or paying $5, $3, or $1. While all outcomes have equal probability, we can see that winning $6 is the preferable option while having to pay $5 is the least preferable. In addition to rank dependence, Tversky and Kahneman (1992) made other additions to prospect theory that included loss aversion where losses loom larger than gains, nonlinear preferences of diminishing sensitivity where the difference between 99 to 100% is more valuable than the difference between 10 and 11%, and source dependence where willingness to bet depends on the degree and source of ambiguity. Tversky and Kahneman (1992) proposed that these additions to prospect theory naturally would integrate uncertainty, including ambiguity, to model subjective perceptions of uncertainty. There are some challenges to applying cumulative prospect theory to decisions under ambiguity. The first challenge is that this rank-dependent model has drastic and discontinuous changes in weights if ranks change and there are no changes of weights in between (Starmer, 2000). Next, imposing monotonicity (choices must be real numbers with real values) implies that choices are non- transitive. Imposing monotonicity means that if there is an obvious choice of better options and worse options, the dominance is transparent. If outcomes and probabilities are unclear, then it may not be possible to rank and rate all possible outcomes, as is the case with decisions that managers face like mergers and acquisitions. Additionally, cumulative prospect theory assumes that individuals scan and delete options that they do not desire but only if they are detected. In cases of ambiguity, decision-makers may not know what they do not know and may not be able to detect all options creating unforeseeable consequences of their decisions. Also, since prospect theory suggests a two-stage decision process where decision-makers first frame and then edit choices, this assumes the availability of some reference point to compare outcomes. While Kahneman and Tversky have proposed several possibilities for reference points, in the case of acquisitions, there may not be a valid option, and decision-makers must create one. Reference points may be created from past experience, information gathered from others, or perhaps experts but these reference points and can be influenced by personal biases (Baron & Ritov, 1994), industry norms (Kahneman, 1992), frames (Schweitzer, 1995), status quo (Kahneman, Knetsch, & Thaler, 1991), or that individual's goals (Heath, Larrick, & Wu, 1999). This complex process of creating reference points can lead to ambiguity. Even with these challenges, cumulative prospect theory is the only theory that attempts to integrate risk and ambiguity and has delivered empirical support (Wakker, 2010). There is much debate in the psychology and economics literature as to if these challenges are fatal flaws. Some scholars (e.g., Quiggin, 1982) have suggested that transitivity is fundamental to any satisfactory theory. Since this principle is violated in the application of prospect theory in choices in ambiguity, Quiggin (1982) suggests that decisions in ambiguity are not an appropriate application of prospect theory. Many scholars disagree with this viewpoint (Wakker, 2010) and suggest that prospect theory is currently the best model that scholars have available to model an individual's subjective perceptions of probability and predict behavior empirically.

What each of these models fails to describe is the effect of individual choices. Experimental demonstrations of choices reveal patterns that are inconsistent with classic models of decision-making under risk. Ellsberg famously demonstrated ambiguity in a demonstration titled the Ellsberg paradox (Ellsberg, 1961). In these demonstrations, he describes two urns that each contain red and black balls. In the first urn, there are 100 balls with an unknown proportion of red and black balls. In the second urn, there are 50 red and 50 black balls. If you were to place a bet on drawing a red ball and draw that color, you would receive $100 and similarly for black. However, if you bet on the wrong color, the payoff is $0. First, consider betting on the first urn where the proportion of red and black balls is unknown. Most people are indifferent to betting on red or black because the proportion, and therefore probability, of drawing one or the other is unknown. This implies that the subjective probabilities of the two events are equal (.5). When participants are given a chance to select between the first urn (unknown proportion) and the second urn (50/50 proportion), many people prefer to select from urn two. The choice of urn two implies that decision-makers prefer the probability of selecting a certain ball from urn two over selecting a ball from urn when the subjective probability of selecting a certain color ball from each urn is the same. This creates the contradiction that is the Ellsberg paradox. The probability of selecting a red from urn two is perceived as greater than the probability of selecting a red ball from urn one when the probabilities are statistically equal. This pattern is repeated with the black balls as well. Therefore, urn two is seen to have complementary probabilities that sum to more than one (superadditivity), and urn one has complementary probabilities that sum to less than one (subadditivity). The Ellsberg paradox shows that while it may seem awkward to see ambiguity as being more or less certain, there is some observed preference to avoid ambiguity in decisions. It is essential to understand how people perceive this ambiguity in the real world and how it affects their decisions. Empirical evidence has shown that ambiguity affects judgments and choices so it cannot be ignored (S. W. Becker & Brownson, 1964; Curley & Yates, 1985; Gärdenfors & Sahlin, 1982; Yates & Zukowski, 1976).

The Ellsberg experiment shows the failure of expected utility theory when all probabilities are not known (S. W. Becker & Brownson, 1964). Under subjective utility theory, the decision to bet on selecting a red ball from urn one is preferable to selecting a red ball from urn two. With this preference, the subjective probability of drawing a red ball from urn two is lower than .5 implying that the probability from drawing a black ball from urn two is higher than .5 and suggesting that the decision-maker should gamble to select a black ball from urn two. Axioms of subjective expected utility theory exclude behavior where the decision-maker prefers bets from the urn with the known distribution of .5/.5 from the first urn. The choice between urns is an example of the effect of ambiguity on decision-making which is that the probability judgments do not add up to 1 (Einhorn & Hogarth, 1986). In contrast to subjective expected utility (SEU) theory, Ellsberg (1961) showed that people prefer objective over subjective bets. People make decisions differently if there is ambiguity compared with instances where there is no ambiguity.

The Ellsberg paradox also demonstrates that while we have many theories available to describe decision behavior when faced with decisions with ambiguity, decisions makers respond with behavior that does not align with existing theories. His experiments and further empirical analysis have found that individual feelings about ambiguity are not guided by a well-defined process and can extend to the data generating process itself. Applying these findings to the examination of strategic decision-making in the real world, we can see that individuals may respond to the unknown, or ambiguity, differently than they respond to decisions under risk where outcomes and probabilities are known. In acquisitions, decision-makers may attempt to minimize ambiguity or ignore that it exists with the possibility of unforeseen consequences and potential failure.

Outcome ambiguity vs. Probabilistic ambiguity

Ambiguity is conceived as a second-order probability distribution which means there is ambiguity at two levels. One level is outcome ambiguity which means the possible outcomes of a decision are unknown. For example, in the Ellsberg experiment, there is some outcome certainty because we know that the next ball drawn will be either red or black. If we did not know what color the balls were in the urn, like they could be any color imaginable, then we would have complete outcome ignorance. In real-world decisions, like in acquisitions, we may have some idea about outcomes, for example, success or failure of the acquisition, the range of possible profits, potential costs, or integration challenges but ultimately the full range of outcomes is unknown. The second level of ambiguity that makes this construct a second order probability distribution is probabilistic ambiguity. Probabilistic ambiguity means that the probabilities of the outcomes are unknown as well, such as drawing a red ball from urn two where we do not know the probability distribution of the balls in the urn. Einhorn and Hogarth (1986) investigated probabilistic ambiguity by suggesting that decision-makers use an anchor and adjustment process to determine the probabilities of outcomes. Individuals will use anchoring and adjustment will make an initial probability estimate of an outcome, either provided by others or from memory plus experience and then adjust that estimate to reflect the probability of the current decision via a mental stimulation exercise. If a decision-maker has lots of experience or they see very little ambiguity in the probability of the event, they may weigh the initial estimate heavily, and it will serve as a stronger anchor. Where there is much ambiguity about an event, then the decision-maker will put less weight on their first estimate and more weight on the estimate derived from the mental stimulation process. The mental stimulation process could include imagining other possible probabilities above or below the anchor or be affected by an individual's personal attitude toward ambiguity.

There is some debate in the literature as to if outcome ambiguity and probabilistic ambiguity are two separate constructs. One opinion is that outcome ambiguity is a separate construct from probabilistic ambiguity because decision-makers may evaluate a range of outcomes without explicitly considering probabilistic reasoning which means a decision-maker can separate possible outcomes from the probability that those outcomes will happen. Ho, Keller, and Keltyka (2002) support this viewpoint because individual outcomes can have their own range of projected or possible results. Conversely, Camerer and Weber (1992) propose that outcome ambiguity is just an unknown probability distribution of a potential range of possible outcomes. They argue that outcome ambiguity is not a separate construct from ambiguity over probabilities or decision-making under risk. Ellsberg's experiment shows that Camerer and Weber's implication is not correct, though, as decision-makers treat decisions under risk and decisions under ambiguity differently. Multiple studies across many domains (e.g. Hogarth & Kunreuther, 1989; Kuhn & Budescu, 1996; Kunreuther, 1989; Kunreuther et al., 1995; Oliver, 1972) have been conducted and found ambiguity aversion in both loss and gain dimensions as well as in both lab studies and real-world decisions (Ho et al., 2002). While many theories have been applied to explore ambiguity, there is clearly an effect and individual response that we are not capturing with existing theories. This study explores the effects of ambiguity on a real-world decision facing managers today.

Defining Ambiguity

Three approaches have been used to define ambiguity in research. The first approach is used by strict subjectivists that claim there is no such thing as an unknown probability as all probabilities are equally well known and ambiguity is meaningless (de Finetti, 1977). This definition supports the use of measuring decisions as risky and ignoring that ambiguity is a separate construct. Denying the presence of ambiguity may be useful in normative decision-making, but as we have seen in the Ellsberg experiment and from other previous research, ambiguity does affect descriptive decisions or how individuals actually make decisions. The second strategy to define ambiguity as a second order probability distribution of possible values. For example, in the Ellsberg demonstration, the probability of selecting a black ball might be uniformly distributed between zero and one instead of setting is at a value of .5. Since expected utility and subjective expected utility are both a linear function of probabilities then only the expected value should matter, and ambiguity should not. While this approach is common among scholars, we can see that there are some limitations. For example, the ambiguity presented in the Ellsberg demonstrations shows that there is a preference for limiting ambiguity even when presented with two similar choices. The third strategy to define ambiguity is constructing a pragmatic definition that captures the psychological essence of the phenomenon. In this definition, ambiguity is a “class of decisions common in everyday life where at least one of the options is characterized by uncertainty” (Lauriola & Levin, 2001, p. 130).

Early researchers in ambiguity defined it as only missing information and as research became more advanced as the "quality depending on the amount, type, reliability, and unanimity of information" (Ellsberg, 1961, p. 657). Recent research in decision making has defined ambiguity as, "uncertainty about probability, created by missing information that is relevant and should be known" (C. Camerer & Weber, 1992, p. 330; Ellsberg, 1961). Milliken's (1987) definition of state uncertainty where he defined it as when managers "perceive the organizational environment, or a particular component of that environment, to be unpredictable…. or how the components of the environment might be changing" (p. 136) but in her definition, the uncertainty could come from ambiguity or ignorance. Modern research into ambiguity has explored the quality of information further by identifying a deeper definition (C. Camerer & Weber, 1992). Quality of information is influenced by:

1. The probability of information that is relevant and could be known but is not.
2. Source credibility and expert disagreement (Einhorn & Hogarth, 1986). For example, in court cases, jurors must weigh the observations of witnesses, attorneys, and judges to reach a verdict. Missing information about whom to believe creates ambiguity (C. Camerer & Weber, 1992).
3. The weight of evidence (L. J. Cohen, 1977; Keynes, 1921; Shafer, 1976). Standard probabilities express only the implications of the evidence but not the weight that decision-makers give to that evidence. Scholars define the weight of evidence as the amount of available information relative to the amount of information that the decision-maker could conceive (Keynes, 1921). The gap is information that is missing that decision-makers can conceive of but cannot know.

We could combine each these definitions to create a new definition of ambiguity in the state of the environment that specifically applies to organizations:

> State ambiguity (a subset of state uncertainty) is when decision-makers have some, but not all, of the information needed about possible outcomes and probabilities of their decision based on quality of information available depending on the amount, type, reliability, and unanimity leading managers to see the organizational environment, or some feature of that environment, as unpredictable.

The recent definition of ambiguity from the decision-making literature describes qualities of information that lead to ambiguity while the definition from Milliken helps us apply the construct of uncertainty (and the subset of ambiguity) specifically to organizations. The proposed definition applies the construct of state uncertainty by Milliken (1987) and separates that into ambiguity and ignorance. Additionally, this definition addresses the source of ambiguity in terms of the quality of the information available to managers. For example, an organization that is undertaking an acquisition may not know if the government will deregulate the industry that they are entering. There may be some disagreement among experts on deregulation, or they may not know the probability of a price war occurring if deregulation does occur.

Literature Review

There have been three kinds of empirical work on ambiguity. First, are variations of the Ellsberg experiment with different chance devices. Second, there are studies that examine the effects of individual differences in response to decisions under ambiguity. Last, there are applied studies in ambiguity. In this section, I will summarize the categories of studies as well as summarize the findings regarding ambiguity, plus any findings that may apply to the relationship between ambiguity and acquisition performance.

Replications and Extensions of the Ellsberg Experiment

The first empirical study of ambiguity was done in an Ellsberg-type setting and conducted by Becker and Brownson (1964). Ambiguity was studied using urns with red and black balls, but there were ten pairs of urns with differing levels of ambiguity. The researchers found that about half the subjects were ambiguity averse when choosing between two pairs of urns. Study participants typically picked the less ambiguous urn and paid an ambiguity premium, which was a substantial amount, to avoid ambiguity. This means that people may rationalize an unambiguous decision involving possible gains by mentally paying an ambiguity aversion premium to avoid the ambiguity. MacCrimmon (1968) gave 25 executives a series of three Ellsberg problems involving bets on chance or natural events. While almost half exhibited ambiguity aversion again, only 10% exhibited the Ellsberg pattern. Research in ambiguity was extended to examine strict aversion to ambiguity (C. F. Camerer & Karjalainen, 1994; Chen, Katuščák, & Ozdenoren, 2007; Chow & Sarin, 2001; M. Cohen, Jaffray, & Said, 1985; Curley & Yates, 1985; Curley, Yates, & Abrams, 1986; Einhorn & Hogarth, 1986; Lan, 2006; Maffioletti, 1995; Mangelsdorff & Weber, 1994), aversion to partial ambiguity (Yates & Zukowski, 1976), aversion to increasing range of probabilities (S. W. Becker & Brownson, 1964; Curley & Yates, 1985; Dolan & Jones, 2004; Kocher, Lahno, & Trautmann, 2015; Larson Jr, 1980; Yates & Zukowski, 1976), ambiguity preferences at low and high probabilities (Coleman, 2009; Curley & Yates, 1985; Einhorn & Hogarth, 1986; Ghosh & Ray, 1997; Kahn & Sarin, 1988), ambiguity aversion for losses and gains (M. Cohen et al., 1985; Einhorn & Hogarth, 1986; Kahn & Sarin, 1988; Kocher et al., 2015; Ortmann, Prokosheva, Rydval, & Hertwig, 2007; Roca, Hogarth, & Maule, 2006), different types of ambiguity and sources of ambiguity (Rivenbark, 2010), the effects of framing in ambiguous decisions (Bier & Connell, 1994; Kashima & Maher, 1995), including vagueness (Budescu, Kuhn, & Kramer, 2001), how ambiguity aversion influences the framing effect (Osmont, Cassotti, Agogué, Houdé, & Moutier, 2015), positive and negative framing (Davidovich & Yassour, 2009), as well as ambiguity when acting as agents (König-Kersting & Trautmann, 2016), risk premium puzzles (Olsen & Troughton, 2000) and the predictive power of alternative principles of choice under ambiguity (Binmore, Stewart, & Voorhoeve, 2012; Trautmann, Vieider, & Wakker, 2008). These replications and extensions of the Ellsberg paradox are examined predominantly in laboratory studies with strict controls and complete information about the potential outcomes. While these studies do not examine real-world decisions, they do offer some predictions of behavior and conclusions about decisions under ambiguity. First, these studies confirm that, in general, individuals will avoid or attempt to minimize ambiguity in decisions. Most subjects prefer non-ambiguous gambles except at very low probabilities (Einhorn & Hogarth, 1986; Ellsberg, 1961) especially when ambiguity generates "fear" (a small chance of significant loss) people are inclined to be ambiguity averse (Viscusi & Chesson, 1999). Additionally, research has explored some boundary conditions when decision-makers are ambiguity comfortable, prone, or even ambiguity seeking. For example, decision-makers exhibit a preference for ambiguity at low probabilities (Einhorn & Hogarth, 1986) and when ambiguity generates “hope” (offering a chance of avoiding a very likely adverse event) people tend to be ambiguity seeking. Additionally, ambiguity may cause people to be unwilling to act (Curley et al., 1986) or continue to seek information until they feel comfortable enough to act. Ambiguity preference has also been examined extensively in a negative vs. positive domain. Ellsberg initially suggested that and subsequent studies have supported, people are averse to ambiguity when faced with positive rewards. Like prospect theory though, people may prefer ambiguity over certainty in the negative domain. In the negative domain, people prefer ambiguity over clarity serving as a justification against regret (Davidovich & Yassour, 2009). In general, extensions of the Ellsberg experiment are conducted in lab studies, and further research is needed to understand more completely how decision-makers respond to ambiguity in real-world decisions.

Individual Level Antecedents to Ambiguity Preference

Researchers mainly have investigated the individual antecedents of ambiguity preferences as psychological and physiological. Sherman (1974) replicated the Ellsberg pattern and found that intolerance of ambiguity correlated significantly with some intelligence measures which prompted further investigation into the relationship between individual differences and ambiguity. Other psychological and physiological antecedents to ambiguity are the Big 5 personality traits (Lauriola & Levin, 2001), affect (Slovic et al., 1977), testosterone and cortisol levels (Danese, Fernandes, Watson, & Zilioli, 2017), gender differences (Borghans, Heckman, Golsteyn, & Meijers, 2009; Eckel & Grossman, 2008; Schubert, Gysler, Brown, & Brachinger, 2000), perceived level of knowledge about underlying domain of ambiguity (de Lara Resende & Wu, 2010), feeling lucky (B. Pulford & Gill, 2014), optimism and pessimism (Bier & Connell, 1994; B. D. Pulford, 2009), blindness to the benefits of ambiguity (Trautmann & Zeckhauser, 2010), perception of one's own contribution (Di Mauro & Castro, 2011), and confusion (Di Mauro & Castro, 2011; Keren & Willemsen, 2009). The most examined and most robust area of study in ambiguity and individual differences is that of gender. Researchers have identified that women generally require more compensation for the introduction of ambiguity than men, but generally respond more favorably to ambiguity than men do. In high stakes decisions, there is no difference between men and women, and they do not have different preferences for ambiguity. These studies also show that while psychological traits like the Big 5 are associated with risk aversion, there are no identified relationships with ambiguity aversion. In future research, it would be essential to understanding what individual differences relate to ambiguity aversion and if these differences become stronger or disappear in real-world group decisions. Individual differences may be relevant to research in acquisitions as groups made up of individuals make decisions in mergers and acquisitions.

Applied Studies in Ambiguity

Applied studies in ambiguity have adopted some of the findings in lab studies and applied these in a variety of fields including law, crime, medicine, insurance, financial markets, marketing, economics, and entrepreneurship. While it is difficult to provide an exhaustive list of all applied studies in ambiguity, below is a selection of seminal and highly cited papers in each area of study to examine trends in ambiguity research. In the legal field, ambiguity has been examined in terms of the relationship between judge knowledge and ambiguity aversion (Keppe & Weber, 1995) while in the field of crime, ambiguity has been examined in the process of criminal decision-making including perceptions of ambiguity (Loughran, Paternoster, Piquero, & Pogarsky, 2011), and perceived probability of apprehension (Kantorowicz-Reznichenko, 2015). In the field of healthcare, ambiguity has been investigated in treatment options and decisions (Berger, Bleichrodt, & Eeckhoudt, 2013) as well as low take-up of costless genetic tests (Hoy, Peter, & Richter, 2014). Hoy et al. (2014) suggested that individuals perceive ambiguity in how the information in genetic tests will be used and who will have access to that information in the future. These individuals' sense that the information may be used against them and eventually increase the cost of their healthcare. The field of insurance is a natural application for decisions under ambiguity given that insurance is protection again ambiguity (Alary, Gollier, & Treich, 2013; Snow, 2011). Research in financial markets is also a natural extension of the original

Ellsberg experiment. Scholars in this area have found that individuals preferred investing in known ventures such as stocks on the NYSE rather than stocks in lesser-known markets (Ganzach, 2000; Zajonc, 1968), as well as identifying that ambiguity aversion can explain low participation in the stock market despite the potentially high benefits (Easley & O'Hara, 2009). Ambiguity in decision-making has also been investigated in risk-free rate puzzles (Collard, Mukerji, Sheppard, & Tallon, 2011; Gollier, 2011; Ju & Miao, 2012) and stock market participation puzzles (Easley & O'Hara, 2009; Ui, 2010). A fascinating examination of this phenomenon is in economics. Researchers examined ambiguity aversion in models of climate change to motivate rapid emission cuts (Farber, 2011; Millner, Dietz, & Heal, 2013) which served to motivate regulation and policy.

Applied research of ambiguity in management studies is sparse. Management scholars, for the most part, have examined ambiguity as a source of risk and use prospect theory and cumulative prospect theory to predict behavior in ambiguous decisions. Early organizational theories were interested in ambiguity in business (Burns & Stalker, 1961; Lawrence & Lorsch, 1969; Milliken, 1987; Thompson, 1967) and early organizational behavior scholars also found ambiguity an interesting construct. For example, Duncan (1972) and Galbraith (1974) examined perceived ambiguity and its sources, while Downey, Hellriegel, and Slocum Jr (1975) looked at ambiguity and social expectations. Other scholars in organizational behavior explored the effects of ambiguity in individual tasks and roles. Research from entrepreneurship includes studies that link the personal characteristics and risk or ambiguity preferences of entrepreneurs with success of failure (Begley & Boyd, 1987; Schere, 1982; Teoh & Foo, 1997). An example from marketing is an examination of how known brands can reduce ambiguity and risk (Muthukrishnan, Wathieu, & Xu, 2009). In general, management research has focused on problems that ambiguity causes and structural solutions to correct (Dill, 1958; Duncan, 1972; Lawrence & Lorsch, 1969). By the late 1970's research in economics, organizational behavior moved away from ambiguity and began viewing ambiguity as synonymous with or a type of risk possibly because of challenges of measuring ambiguity (Milliken, 1987).

Two observations of applied studies in ambiguity are that, first, they commonly confound the constructs of risk, uncertainty, ambiguity, and ignorance by treating them as the same or as subsets of each other. Second, these studies do not attempt to identify the unique effect of ambiguity. In today's complex global economy, examining decisions in economics, organizational theory, and organizational behavior using risk-based frameworks is overly simplistic and may be limiting our knowledge (Teece & Leih, 2016). Examining real-world decisions as decisions under ambiguity may give us a better understanding of a critical phenomenon, the decision processes used when facing ambiguity, and individual attitudes toward ambiguity. Examining mergers and acquisitions as decisions under ambiguity may help us answer that critical question of why do so many acquisitions fail?

Hypothesis Development

Ambiguity and Acquisition Performance

Inspired by Ellsberg's (1961) experiment with the two urns, the literature shows that ambiguity can account for empirically observed violations of many traditional decision theories such as expected utility theory, subjective utility theory, the Bayesian approach, and prospect theory, and cumulative prospect theory. The Ellsberg experiment shows that individuals generally will be averse to ambiguity and either select a less ambiguous option or attempt to reduce ambiguity when possible. The implication is that if the decision is ambiguous, there may be unforeseen consequences that the decision-maker could not predict.

Outcome ambiguity is more prevalent than probabilistic ambiguity in managers' decision-making and may influence their decisions (Ho et al., 2002). For example, when making decisions, managers may receive an imprecise outcome. Because managers are typically rewarded on outcomes, they are more concerned with outcomes than the probabilities of those outcomes (Ho et al., 2002). It is vital to examine ambiguity framed as outcomes because managers generally do not use precise probability estimates and in fact avoid them when possible (March & Shapira, 1987). In terms of an acquisition, the possible outcomes are the success of the acquisition, failure, or anything in between.

In organizations today, information ambiguity is prevalent (Ho et al., 2002). Managers are commonly exposed to an information gap that adds ambiguity into their decision process (Golman & Loewenstein, 2016). Gumpert (1998) identified that companies typically use benchmark targets, such as revenues or costs, to measure their success causing managers to see outcomes above the benchmark as gains and outcomes below the benchmark as losses. When faced with a possible loss with imprecise probability, managers may try to reach a target despite ambiguity. People likely will consider the ambiguous options with a range of possibilities to be their best option to meet the target (like the "hope" effect) even if a manager identifies two relatively unfavorable options that differ only in whether the probability is precise or a range of probabilities. When performance is above target, decision-makers may focus primarily on avoiding choices that might jeopardize meeting goals or targets (Bell, 1982; Frisch & Baron, 1988). The "fear" effect is more evident in the gain condition than in a loss condition which may lead managers to exhibit ambiguity averse behavior. Recent decision-making literature suggests that the extent of ambiguity in a decision will make the information gap unpleasant and individuals will attempt to close the information gap as much as possible. In mergers and acquisitions, it would be helpful to researchers, and practitioners to understand which types of ambiguity may affect the performance of the acquisition and which information gaps are more important than others.

While ambiguity aversion often occurs at the individual level, I propose that because acquisition decisions typically take place in small teams, such as top management teams or corporate boards (Zhu, 2013) such aversion can also exist at the team level. While teams can combine multiple viewpoints, which may give them the advantage over individuals in decision-making, team members typically do a poor job of pooling evidence because they share little information (Zhu, 2013). Teams commonly resort to a majority opinion (Rutledge, 1993; Valacich, Sarker, Pratt, & Groomer, 2009) and in the decision-making literature, team decisions even may increase ambiguity aversion as observation by peers has been shown to do so (Curley et al., 1986; Muthukrishnan et al., 2009; Trautmann et al., 2008). There are no identified relationships with Big 5 traits and ambiguity, and while there are some differences in ambiguity aversion between men and women, these effects disappear with large stakes or important decisions, such as acquisitions. For these reasons, in this study, I exclude the individual differences of decision-makers in acquisitions and treat the TMT or corporate board as a single decision-making entity.

Very little research exists examining sources of ambiguity in the literature regarding acquisitions. Scholars have examined ambiguity in studies of post-acquisition integration (Datta et al., 1992) or how to manage ambiguity in individuals during the acquisition process (Kramer, Dougherty, & Pierce, 2004; Schweiger & Goulet, 2005). Additionally, studies have examined the inherent ambiguity that accompanies the acquisition of an unlisted startup (J. U. Becker, Clement, & Nöth, 2016). Beyond these, no studies have examined how ambiguity before the acquisition might affect acquisition performance. In the finance literature, there is some examination of financial ambiguity in regard to acquisition (e.g., Erickson, Wang, & Zhang, 2012) and regulatory ambiguity (Desai & Stover, 1985; Nguyen & Phan, 2017). Some research in behavioral finance suggests that investors will overweight and overreact to information that they do have available to them. For example, Black, Guo, Hu, & Vagenas-Nanos (2017) reported that acquiring firms found significantly more gains after announcing private acquisitions than they do in public acquisitions. This suggests that the market sees and reacts positively to the acquisition when investors believe the acquirer has access to some unique, firm-specific information, even if they do not. Last, in the finance literature, some attention has been paid to the increase of acquisitions during merger waves and how reduced monitoring in these acquisitions add ambiguity (Duchin & Schmidt, 2013).

While little research exists on the sources of ambiguity, we may look to the literature on acquisition failures to establish key areas of ambiguity. One such area is technology. Technology acquisitions are seen as an essential path for established firms to increase their technical capabilities (Agarwal & Helfat, 2009; Eisenhardt & Martin, 2000; Santos & Eisenhardt, 2009). Acquisitions are a major feature of many technology firms like Google, Nokia, SAP, and Cisco, and while many firms pursue this strategy, they still receive mixed results (Graebner, Eisenhardt, & Roundy, 2010). Target firms, or firms being acquired, typically have some discretion when determining what to share with acquirers (Coff, 2003; Granstrand & Sjölander, 1990). In high technology sectors, many sellers have their choice of acquiring companies based on the attractiveness of the technology or may sell for idiosyncratic reasons such as disagreement at the top management team or financial pressures (Graebner & Eisenhardt, 2004). When an acquirer chooses to acquire a company based on technology, there may be high levels of ambiguity about the value of the target's resources. A targets' underlying technical capabilities may involve complex knowledge that is difficult to measure (Coff, 2003) and can introduce ambiguity that those capabilities may not bring a competitive advantage to the acquirers and expose them to the possibility that the target's resources are less valuable than expected (Coff, 2003). Additionally, a seller truly may not even understand the value of their firm. With technological resources still under development or embedded in novel products, sellers may not be able to identify or evaluate what their technology may enable (Wu & Knott, 2006). Given these reasons, technology can introduce ambiguity into the process pre-acquisition. Remember that I defined state ambiguity as a subset of state uncertainty where decision-makers have some, but not all, of the information needed about possible outcomes and probabilities of their decision because of based quality of information available depending on the amount, type, reliability, and unanimity leading managers to see the organizational environment, or some feature of that environment, as unpredictable. The quality of information depends on:

1. The probability of information that is relevant and could be known but is not.
2. Source credibility and expert disagreement (Einhorn & Hogarth, 1986). For example, in court cases, jurors must weigh the observations of witnesses, attorneys, and judges to reach a verdict. Missing information about whom to believe creates ambiguity (C. Camerer & Weber, 1992).
3. The weight of evidence (L. J. Cohen, 1977; Keynes, 1921; Shafer, 1976). Standard probabilities express only the implications of the evidence but not the weight that decision-makers give to that evidence. Scholars define the weight of evidence as the amount of available information relative to the amount of

information that the decision-maker could conceive (Keynes, 1921). The gap is information that is missing that decision-makers can conceive of but cannot know.

For the first feature of information is information that could be known but is not. I will call this missing information and suggest that the acquisitions with more missing information will perform more poorly than acquisitions with less missing information.

H1a: The higher the level of missing information about technology the lower the level of acquisition performance.

The second feature of information is expert agreement or the credibility of the source. I will call this the level of reliability of information and propose that acquisitions in technologies with more expert agreement and source credibility will have more reliable information and experience better performance than acquisitions with less reliable information.

H1b: The higher the level of reliability of information about technology the higher the level of acquisition performance.

The third feature of information is the weight of evidence which means that decision-makers with more evidence and fewer information gaps will put a larger weight onto the information that they have. When decision-makers have more information available to them, I propose that the acquisition will perform better.

H1c: The higher the amount of information available about the acquisition the higher the level of acquisition performance.

These three sources of technological ambiguity could each individually impair top-level decision-maker's ability to predict possible outcomes and performance of an acquisition but could also individually be taken as a feature of that specific technological domain. For example, experts in the mobile phone industry may commonly disagree about the direction of the technology. This would not illustrate ambiguity in that specific acquisition but that specific technology. Decision-makers might also perceive ambiguity in an acquisition but not be able to trace that ambiguity to a specific source where they could gather further information. For this reason, I believe that these sources of technological ambiguity will combine to have an effect on acquisition performance. This will represent that more technological ambiguity present before an acquisition will lead to poorer performance.

H1d: The level of technological ambiguity will be negatively related to acquisition performance.

A second motivation for acquisitions is to increase market power by improving customer relationships or expanding into new geographic areas or customer segment (Birkinshaw, Bresman, & Hakanson, 2000; Graebner, 2004). This approach can decrease competition, make it difficult for new rivals to emerge (Santos & Eisenhardt, 2009), or eliminate one or more rivals. Ranft & Lord (2000) found that buyers considering market power or customer knowledge found market power as the primary motivation in 18% of acquisitions. Buyers typically have less information than sellers regarding a target's resources, and other valuable information such as intentions of key individuals or known shortcomings of their organization or resources (Graebner et al., 2010). Some research has been conducted that found conflicting results about the effect of acquisitions with too few or too many similarities with the target. If an acquirer and target have too few similarities, then the buyer may not be familiar enough with the target's resources to implement their strategy effectively (Ahuja & Katila, 2001; Cloodt, Hagedoorn, & Van Kranenburg, 2006; Higgins & Rodriguez, 2006; Kapoor & Lim, 2007). Buyers that acquire firms with complementary resources may be successful by combining a target's technical knowledge with their marketing, manufacturing, or sales (King et al., 2004) but if a target is from too far outside the acquirer's core competency, then they may see negative results (King et al., 2004). Additionally, if the acquirer and target have too much of the same information, there may be redundancies and few opportunities for growth (Graebner et al., 2010). Previous research has identified that industry differences may be a source of failure for acquisitions, but it has not yet been examined as a type of ambiguity. Like hypothesis 1a, information that could be known but is not is called missing information, and I suggest that the acquisitions with more missing information will perform more poorly than acquisitions with less missing information.

H2a: The higher the level of missing information about the target's industry the lower the level of acquisition performance.

Similar to hypothesis 1b, expert agreement or the credibility of the source represents the level of reliability of information. I propose that acquisitions in technologies with more expert agreement and source credibility will have more reliable information and experience better performance than acquisitions with less reliable information.

H2b: The higher the level of reliability of information about the target's industry the higher the level of acquisition performance.

Similar to hypothesis 1c, decision-makers with more evidence and fewer information gaps will put a larger weight onto the information that they do have. When decision-makers have more information available to them, I propose that the acquisition will perform better.

H2c: The higher the amount of information available about the target's industry the higher the level of acquisition performance.

Like ambiguity in technology, the types of ambiguity related to the nature of the industry may each have a unique effect on performance but may also be a feature of that industry. Acquisitions within industries commonly take place in waves (Auster & Sirower, 2002) where decision-makers may overlook missed details and ambiguity in M&A assessments. Combining these types of ambiguity into a single latent variable will help reduce any systematic ambiguity from a single industry that may influence a manager's perception of ambiguity. This will represent that more industry ambiguity present before an acquisition will lead to poorer performance.

H2d: The level of ambiguity in the target's industry will be negatively related to acquisition performance.

Industry and technology are the only two sources of ambiguity that are suggested in the literature today leaving us with potentially unidentified sources of ambiguity in acquisitions. These sources of ambiguity were supported in study 1 and discussed in chapter 3. Additionally, financial ambiguity was identified in study 1 as a source of ambiguity that might have an effect on performance in mergers and acquisitions. Further research is necessary to help identify other, previously non-investigated antecedents.

In the management literature, the dominant financial variable that has been examined in post-acquisition performance is the method of payment (King et al., 2003) including cash, equity, or mixed payments. Finance scholars have largely focused on if acquisitions are wealth creating or wealth reducing events for shareholders and have identified that acquisitions are overwhelmingly positive for target firms but deliver mixed results to investors of acquiring firms (Cartwright and Schoenberg, 2006). Finance scholars tend to focus on the wide variation of post-acquisition performance (Conn et al. 2001) but have not thoroughly investigated the antecedents of M&A performance. Given this lack of examination, I will hypothesize the relationships of financial ambiguity to the post-merger performance like industry and technology. For the first feature of quality of information is information that could be known but is not. I will call this missing information and suggest that the acquisitions with more missing information will perform more poorly than acquisitions with less missing information.

H3a: The higher the level of missing information about the financial situation of the target the lower the level of acquisition performance.

The second feature of information is expert agreement or the credibility of the source. I will call this the level of reliability of information and propose that acquisitions in technologies with more expert agreement and source credibility will have more reliable information and experience better performance than acquisitions with less reliable information.

H3b: The higher the level of reliability of information about the financial situation of the target the higher the level of acquisition performance.

The third feature of information is the weight of evidence which means that decision-makers with more evidence and fewer information gaps will put a larger weight onto the information that they have. When decision-makers have more information available to them, I propose that the acquisition will perform better.

H3c: The higher the amount of information available about the financial situation of the target the higher the level of acquisition performance.

These three sources of financial ambiguity could each individually impair top-level decision-makers' ability to predict possible outcomes and performance of an acquisition but could also individually be taken as a feature of that specific finance domain. Decision-makers might also perceive ambiguity in an acquisition but not be able to trace that ambiguity to a specific source where they could gather further information. For this reason, I believe that these sources of financial ambiguity will combine to have an effect on acquisition performance. This will represent that more financial ambiguity present before an acquisition will lead to poorer performance.

H3d: The overall level of financial ambiguity will be negatively related to acquisition performance.

Stake Effects in Ambiguity and Acquisitions

Beyond basic preferences for ambiguity aversion, Trautmann and van de Kuilen (2014) proposed a more complex pattern of attitudes. For example, the magnitude of the monetary outcomes at stake may affect attitudes towards ambiguity. The issue of stake effects is essential in real-world decisions as managers may encounter a diverse range of outcomes from trivial to extremely high importance as well as a range of probabilities that may or may not be known (Bouchouicha, Martinsson, Medhin, & Vieider, 2017). Laboratory results have found that ambiguity aversion is the dominant finding when examining moderate or low likelihood gains but for low likelihood losses, decision-makers actually prefer ambiguity as they have very little to lose (Coleman, 2009; Curley & Yates, 1985; Einhorn & Hogarth, 1986; Ghosh & Ray, 1997; Hogarth & Kunreuther, 1989; Kahn & Sarin, 1988). Understanding the stake effects involved in decisions under ambiguity may give us insight into how the laboratory results may be generalized.

Because acquisitions require a large amount of resources and potentially have performance implications for the organization, executives view acquisitions as among their most important strategic decisions (Wally & Baum, 1994). Because of this pressure and the visibility of acquisitions, we can assume that managers see acquisitions as decisions with high stakes and would be ambiguity averse or attempt to reduce ambiguity. Larger acquisitions may be more visible and therefore higher stakes, such that decision-makers will have a much lower tolerance for ambiguity in large acquisitions and a higher tolerance for ambiguity in small acquisitions.

H4a: The size of acquisitions will be negatively related to technological ambiguity.

H4b: The size of acquisitions will be negatively related to industry ambiguity.

H4c: The size of acquisitions will be negatively related to financial ambiguity.

Stake effects may explain the relationship between the size of an acquisition and ambiguity, but the size of an acquisition is also an important moderator in acquisition literature (Haleblian et al., 2009). While scholars agree that size is important in acquisitions performance, there is some disagreement about if the effects of size on acquisition performance are positive or negative (Haleblian et al., 2009). Some studies have identified that larger acquisitions can produce positive accounting performance post-acquisition through asset productivity (Healy, Palepu, & Ruback, 1992), enhanced customer attraction, employee productivity, and asset growth (Cornett & Tehranian, 1992). Other scholars have identified competing viewpoints. For example, small acquisitions by small acquirers result in positive gains where large acquisitions by large acquirers result in significant announcement losses (Moeller et al., 2003). Firm size appears to effect returns, but the mixed results leave room to establish boundaries on the effect of size.

As discussed before, ambiguity may provide an opportunity for potentially unidentified sources of failure of an acquisition. In larger acquisitions, ambiguity will be more prevalent and salient so that size will moderate the relationship between ambiguity and acquisition performance.

H5: Size moderates the relationship between ambiguity and performance such that ambiguity in larger acquisitions leads to poorer performance than ambiguity in small acquisitions.

Experience as a moderator of ambiguity and acquisition performance

In examining information ambiguity, decision-makers prefer some sources of ambiguity over others which creates a source preference. For example, an investor may see similar outcomes from two different stock indexes next year but may feel more comfortable or competent in a market with which they are familiar with. Preferring to accept ambiguity in a familiar domain could create an experience bias. De Lara Resende and Wu (2010) identified that decision-makers are actually ambiguity seeking in an area that they feel knowledgeable about while Fox and Tversky (1995) proposed that if an ambiguous choice is in a domain where the decision-maker believes they have the expertise, then they may be more tolerant of ambiguity. The decision-maker may be overly self-confident in their experience or have a “gut feel” about the decision that is influenced by hubris (Hayward & Hambrick, 1997) or overconfidence (Malmendier & Tate, 2005). Managers that have experience in acquisitions may feel that they have enough experience to overcome any unforeseen consequences of ambiguity in the decision-making process.

In the acquisition literature, experience is a crucial contributor to acquisition performance. While this seems intuitive, there are interesting findings regarding the effect. Haleblian and Finkelstein (1999) found that the relationship between acquisition experience and acquisition performance was not linear but U-shaped. Researchers attributed this relationship to the notion that young, inexperienced acquirers may apply experience from recent acquisitions inappropriately, possibly because of hubris (Hayward & Hambrick, 1997), or overconfidence

(Malmendier & Tate, 2005). More experienced acquirers may be able to avoid these missteps. I will examine the moderating role of experience between ambiguity and performance. Past literature can lead to the prediction that experience with acquisitions will make managers more ambiguity tolerant because of overconfidence or home bias (experience bias).

H6a: Experience moderates the relationship between technological ambiguity and acquisition performance such that managers with experience will strengthen the relationship between ambiguity and performance so that the relationship will be more negative.

H6b: Experience moderates the relationship between industry ambiguity and acquisition performance such that managers with recent experience will strengthen the relationship between ambiguity and performance so that the relationship will be more negative.

H6c: Experience moderates the relationship between financial ambiguity and acquisition performance such that managers with recent experience will strengthen the relationship between ambiguity and performance so that the relationship will be more negative.

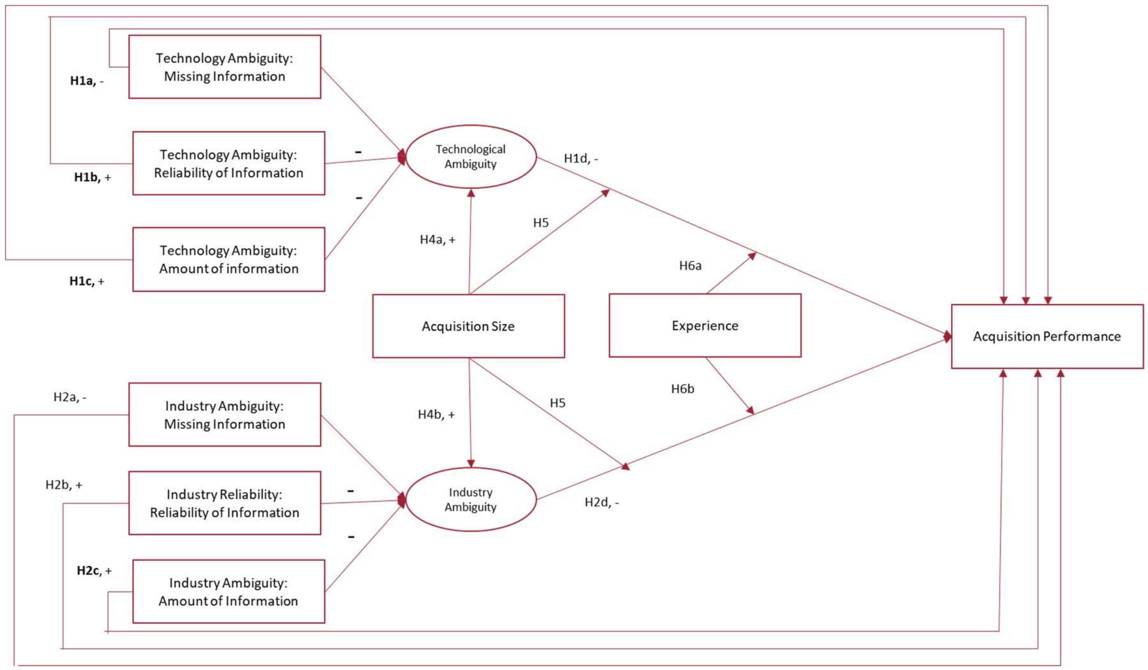

Figure 1: Hypothesized Effects of Technology and Industry Ambiguity in Acquisition Performance

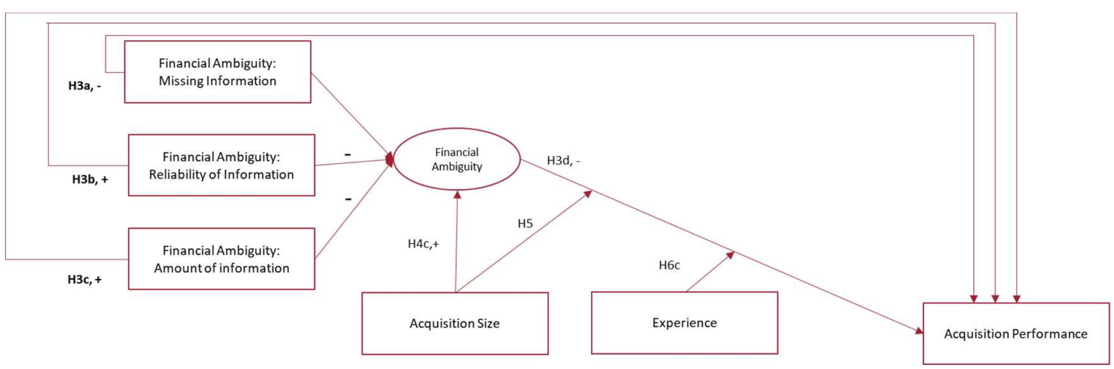

Figure 2: Hypothesized Effects of Financial Ambiguity in Acquisition Performance

Chapter 3: Methods

Because scholars have not studied ambiguity in decision-making in acquisitions, it is challenging to identify sources of ambiguity thoroughly from a theoretical perspective alone. The literature hints at technology and industry as two possible sources of ambiguity, but since scholars have not explored sources of ambiguity in acquisitions thoroughly, additional sources may exist. For this reason, I conducted two studies – an initial qualitative study to explore sources of ambiguity as well as a second quantitative study to test the full hypothesized model.

Study 1

Study 1 was a qualitative case study investigating 12 acquisitions conducted by a single investment firm from 1975 to 2018. The goal of study 1 was to use qualitative analysis to confirm technology and industry as sources of ambiguity in an acquisition as well as identify other sources of ambiguity that have not been predicted by theory or identified in previous research.

Data Collection

The investment firm collected and reported information about each acquisition including announcement and closing dates of each acquisitions, size, industry of target company, industry of acquiring firm, performance of acquisition (up to 5 years), performance of acquirer (up to 5 years), timing of integration of acquisition, length, and depth of due diligence. Additionally, the firm answered each of the following questions about each acquisition.

1. How did you identify the acquisition?

2. What were your sources of information about the acquisition (business owner, accountants, lawyers, colleagues in industry, competitors, industry experts, analysts, press, online sources)?

3. Tell me about any information that you wanted or that would have been helpful, at that time, that you could not get access to.

4. Looking back, what type of information do you wish you had?

5. How long did the due diligence process take?

6. How close was the target company to the acquiring company's core business? How similar were they in sales, business, process, manufacturing process, distribution channels?

7. How and when was the target integrated? How long did it take? How much work was it? What is your perception of the success of the integration?

8. How was the deal financed? Do you feel the financing was right for this deal?

9. What should you have done differently and why?

All data were collected and consolidated into a single spreadsheet.

Study 1 Analysis and Results

The data were analyzed using constant comparative analysis (Dey, 2004; Glaser, 1992; Glaser & Strauss, 2017) with the aid of AtlasTi. Answers to each of the above questions were imported into Atlas.Ti and then read and re-read in an iterative fashion. During readings, potential sources of ambiguity were identified and marked as an "instance of ambiguity." Instances of ambiguity were tagged anywhere where the acquiring firm identified any information that was ambiguous, uncertain, or unknown. Synonyms were also used to identify instances of ambiguity such as inscrutable, murky, mysterious, nebulous, oblique, obscure, opaque, and doubtful. Antonyms were also used when the firm identified areas where they found a lack of clarity, clearness, obviousness, plainness, certainty, confidence, conviction, or trust. The first coder reviewed the text for all acquisitions and identified 27 instances of ambiguity across all 12 acquisitions. A second coder (who was naïve to the hypotheses) was given the directions above and coded 4 of the 12 acquisitions or 30% of the acquisitions. In those acquisition texts, the second coder identified 15 of 18 instances of ambiguity already identified which resulted in a 71.4% level of agreement or a Cohen's Kappa of .73 which is substantial and acceptable agreement (Cohen, 1968).

Next, the instances of ambiguity were then loosely categorized and combined. These categories remained flexible and changeable until late in the analysis process. All categories were checked for negative, opposite, or better categorizations of the data (Bryant & Charmaz, 2007). Once an initial categorization of instances of ambiguity was prepared, an expert panel of 4 tenured Full Professors was consulted to challenge the categorizations or suggest new ones. The major feedback of the panel what that a single category of "due diligence" dominated the results and should be separated into areas of due diligence such as financial, managerial, etc. After the final categorization was complete, it was reviewed and approved by a single expert in strategic decision-making research. Table 1 lists the final categories of ambiguity identified with sample text from the investment firm that represents the type of ambiguity.

Category of Ambiguity	**Example Statement of Ambiguity**
Industry	"Additional information regarding seasonality of the business would have influenced valuation to a small degree." "finished products, applications and customers were not consistent with those of Firm X."
Technology	"seller would not deliver copies of trade secret formulations until the day of closing."
Financial	"analysis of internally-prepared divisional financial statements were (sic) not independently prepared or reviewed." "X had never been audited."
Management	"X was grossly mismanaged."
Operations	"No independent verification of operating results."

Experience	"this was the first major acquisition for Firm X."

Table 1: Sample Instances of Ambiguity

Figure 3 below summarizes the count of instances of ambiguity in each of the categories above:

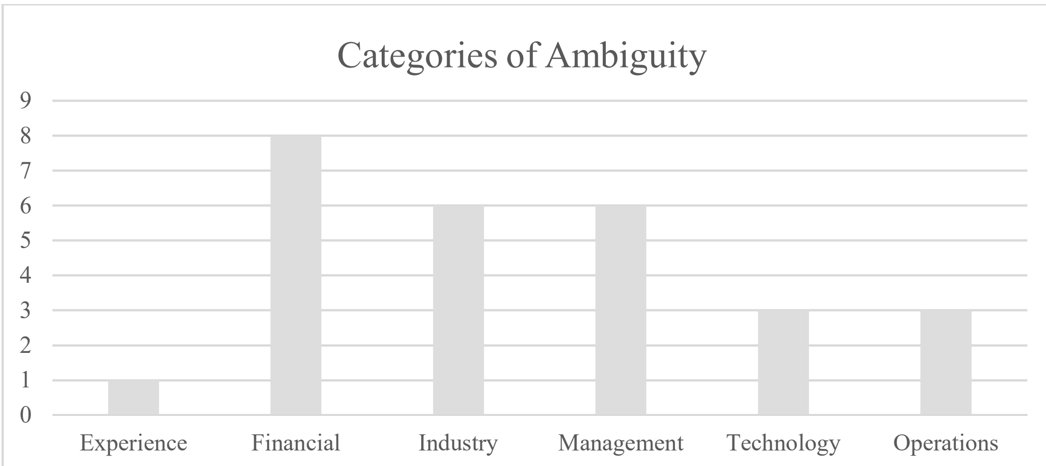

Figure 3: Count of Instances of Ambiguity in each Category

The goal of study 1 was a qualitative analysis a group of acquisitions to find support for technology and industry as sources of ambiguity in an acquisition as well as identify other sources of ambiguity that have not been predicted by theory or identified in previous research. In this case study, I did find support for industry and technology as sources of ambiguity. In this sample of 12 acquisitions, there were 6 instances of ambiguity related to industry and 3 instances related to technology. The largest category of instances of ambiguity was financial ambiguity which had not been previously identified as a source of ambiguity. Acquisitions have been studied extensively from a financial perspective (Haleblian et al., 2009) but have not yet been examined through the lens of ambiguity. These results indicate that from this acquirer's perspective, financial ambiguity is the largest source of ambiguity. For this reason, I added financial ambiguity as a source of ambiguity and formed hypotheses within the framework discussed earlier. These hypotheses are described in chapter 2 and used to develop hypotheses H3a-d, H3c, and H5c.

Within the category financial ambiguity, two themes developed with the case study firm that influenced their perception of ambiguity present in each acquisition. Table 2 presents these themes and sample comments.

Theme in Financial Ambiguity	Example Statement of Theme
Independently verified information	“analysis of internally-prepared divisional financial statements were not independently prepared or reviewed.” “had never been audited.” “No independent verification of operating results.” “Third party professionals were utilized for proof of earnings.”
Length of due diligence	“Very little detailed due diligence was performed” “Detailed diligence was conducted over a period of three months.” “Due diligence was conducted by Firm X management/ownership over a period of approximately seven months.” “Full due diligence and valuation negotiations were conducted over a period of approximately 11 months.”

Table 2: Sample Comments of Financial Ambiguity

This commentary from the acquiring firm indicated that independent analysis of financial results of the target and length of the due diligence process signaled something to the acquirer. This data was used to develop measures for financial ambiguity in study 2.

Study 2

Sample

Study 2 included 140 acquisitions between publicly traded U.S. firms between 1995 and 2015 with payments over $100 Million (Hayward & Hambrick, 1997) using the Securities Data Corporation’s Mergers and Acquisitions database. I chose this sample to include recent years with a wide variety of economic conditions. I selected firms with payments over $100 Million to ensure that the top management team would be involved, and the decision would (most likely) be centralized.

A major limitation of the sample size was analyst coverage which was required to measure expert agreement in Hypotheses H1b, H2b, and H3b. This limited my sample size to only 140 acquisitions over a 21-year period and with an average acquisition size of 4.988 Billion US Dollars. Using analyst commentary limited this sample because not every acquisition was covered by industry, technology, and financial analysts. This requirement may have added bias into the sample by only covering larger acquisitions or acquisitions that may have received more analyst attention.

I conducted a power analysis to ensure that the sample was large enough to detect the hypothesized effects. The hypothesized model predicts relationships between the 3 latent variables (technology, industry, and financial ambiguity) as well as 2 moderators and 1 control variable. Estimating a small effect size and a required significance level of .05, the minimum sample required is 146 acquisitions (Erdfelder, Faul, & Buchner, 1996); therefore this sample does not meet the minimum requirements of a .95. I will consider this in further analysis.

Dependent Variables

Acquisition Performance: Measuring acquisition performance is challenging given that it is a complex theoretical construct and achieving the benefits of measurement precision with generalizability is challenging. Cording, Christmann, and Weigelt (2010) analyzed measurement methods of acquisition performance and identified common measurement methods depending on the intended effect to be measured. They found that an announcement-effect event study was the predominant variable used in studies intending to measure acquirer characteristics. Additionally, research on the performance of acquisitions in management research predominantly used cumulative abnormal returns (CAR) as their measure in announcement-effect event studies (Fama, Fisher, Jensen, & Roll, 1969; Hayward & Hambrick, 1997; Puffer & Weintrop, 1991; Reinganum, 1985). Cumulative abnormal returns are "that part of the return that is unanticipated by a statistical or economic model of anticipated, normal returns" (Reinganum, 1985, p. 51). A positive abnormal return indicates that the security market increased its expectations of future returns from that security. Negative returns indicate that the market lowered its expectations. I measured one-year returns and three-year returns which will measure the cumulative abnormal returns for the period from 30 days before the first takeover announcement to one year and three years post-acquisition.

Independent Variables

Technological ambiguity - Missing information: Given that ambiguity has not been thoroughly studied in acquisitions, there are few established measures for this construct. Therefore, I looked to the operationalize ambiguity using definitions of the quality of information that lead to ambiguity. Missing information is any information relevant to the decision and could be known but is not. Technological complexity can increase the amount of information that is needed to understand the technology fully, and more complexity can introduce the potential for more missing information. Dess and Beard (1984) originally conceived a measure of technical complexity as the percentage of scientists or engineers employed in an industry compared to the total employment. The total number of scientist or engineers and total employment in an industry was retrieved from the Bureau of Labor Statistics per NAICS code for each technology.

Technological Ambiguity - Reliability of information: Reliability of information can be a source of ambiguity when created by expert disagreement. If multiple expert opinions show different viewpoints on a technology, this can cause ambiguity about whom to believe. Analysts and experts typically weigh in on directions of technology. The volume of analyst commentary could indicate the number of opinions expressed about an acquisition and more commentary could introduce ambiguity into the decision-maker's mind about the acquisition. Analyst commentary was identified using the AB/Inform database with the "acquirer" and "target" and then "technology analyst." Analyst commentary typically occurred within 30 days of the acquisition and then decreased. The commentary only increased again if additional information surfaced about the target or acquirer such as lawsuits or investigations. To identify which commentary may specifically introduce ambiguity into the mind of the decision-maker, I only examined the volume of commentary for 30 days after the acquisition announcement to specifically exclude special consideration such as lawsuits or investigations.

Technological ambiguity - Amount of information: Amount of information is the amount of available information relative to the amount of conceivable information (Keynes, 1921). The gap is information that is missing that you can conceive of but cannot know. It is challenging to operationalize a variable that measures something that is not known. For technology, information gaps would be present in the technical intricacy or product complexity. Sharfman and Dean Jr. (1991) suggested product complexity could be measured by the number of distinct product categories within the SIC code. The higher the number of distinct product categories within a SIC code would indicate more complexity and an increase in the amount conceivable amount of information about a technology. Product categories within each SIC code were identified using the standard industrial classification (SIC) code database at siccode.com.

Industry ambiguity - Missing information: Information about an industry that could be known but is not may be attributed to an acquirer's direct experience in that industry. Acquirers who are purchasing a company in the same industry will be familiar with the typical products, clients, and operations of that industry. Acquirers that are acquiring a company in a different industry will have limits on what they can know about that industry before the acquisition and acquirers that are not in the same industry as the target may see industry ambiguity. To estimate the relatedness of acquisitions, I used SIC codes to build an ordinal, 3-point product relatedness scale; 3=acquirer and target have identical 4 digit SIC codes, 2= acquiring firm and target share a 2 digit SIC code, 1= do not share any digits of SIC codes. SIC codes of the target and acquirer were identified using the S&P Capital IQ database.

Industry ambiguity - Reliability of Information: Similar to technology, multiple experts and analysts commonly weigh in on the direction of industries. Multiple expert opinions show different viewpoints, which can cause ambiguity about whom to believe. Analysts and expert typically weight in on directions of an industry Analyst commentary was identified using the AB/Inform database with the “acquirer” and “target” and then “industry analyst.” Analyst commentary typically occurred within 30 days of the acquisition and then decreased. The commentary only increased again if additional information surfaced about the target or acquirer such as lawsuits or investigations. To identify which commentary may specifically introduce ambiguity into the mind of the decision-maker, I only examined the volume of commentary for 30 days after the acquisition announcement to specifically exclude special consideration such as lawsuits or investigations.

Industry ambiguity - The amount of information: Industry turbulence may be a source of ambiguity for acquirers as this could be a source of unplanned change. In economics, a well-established measure exists for industry turbulence defined as the absolute number of all employees within an industry and the increase and decrease of employment over time (Acs &

Audretsch, 1990). Changes in employment over time will provide for the identification of markets that are growing with existing firms and new entrants and those that are shrinking. This information was gathered for the acquisition target via the U.S. Bureau of Labor Statistics which provides annual employment information for industries by SIC code. The total employment for the industry of the target was identified for the year of and the year preceding the acquisition. The percentage of change was calculated, and the absolute value of the change was used to indicate turbulence.

Financial ambiguity - Missing information: Information about the financial situation of a target that could be known but is not may be represented by the financial information that is publicly available about the target prior to the acquisition. Public companies are required to report and publish financial results while private companies have some discretion about what is reported. The availability of externally audited financial information was a major theme from the firm used in the case study for study 1. To represent the potential for financial information that may not be public or published, I used a binary variable where private companies are represented with 0, and public companies were represented with a 1.

Financial ambiguity - Reliability of Information: Like technology and industry, multiple financial experts and analysts commonly weigh in mergers and acquisitions. Multiple expert opinions show different viewpoints, which can cause ambiguity about whom to believe. Financial analyst commentary was identified using the AB/Inform database with the "acquirer" and "target" and then "financial analyst." Analyst commentary typically occurred within 30 days of the acquisition and then decreased. The commentary only increased again if additional information surfaced about the target or acquirer such as lawsuits or investigations. To identify which commentary may specifically introduce ambiguity into the mind of the decision-maker, I only examined the volume of commentary for 30 days after the acquisition announcement to specifically exclude special consideration such as lawsuits or investigations.

Financial ambiguity - The amount of information: Amount of information is the amount of available information relative to the amount of conceivable information (Keynes, 1921). The gap is information that is missing that you can conceive of but cannot know. An existing relationship between the target and acquirer may increase the amount of information the acquirer has about a target. If no previous relationship exists, the length of the due diligence process will influence how much information the acquirer could possibly obtain about the target. The length of due diligence was also a major theme in the case study in study 1 as well. The firm's leader expressed concern over short due diligence periods. For these reasons the length of the relationship between the acquirer and target, either through alliance or due diligence, may influence the weight that they acquirer feels that they may be able to put on the information obtained. The length of the relationship between the acquirer and target was identified through SEC filings on sec.gov.

Moderating Variables

Acquisition Size: The size of acquisitions is a commonly studied contributing, moderating, and controlling variable to acquisition performance (Haleblian et al., 2009) so reliable measures exist. In this study, I measured the absolute size of the acquisition (in Millions of dollars) as well as the relative size of the acquisition. The average acquisition size was $4.988 Billion with a range of $120 Million to $62 Billion. Tests for normality (Kolmogorov-Smirnov and Shapiro-Wilk) were significant but I failed to reject non-normality because of the sample size (Ghasemi & Zahediasl, 2012). The relative size of the acquisition is the revenues of the target organization divided by the revenues of the acquirer in the year preceding the acquisition (Hayward & Hambrick, 1997).

Acquisition Experience: The influence of experience in the context of acquisitions has been studied extensively prompting a full review of the topic (Barkema & Schijven, 2008). Scholars have defined recent experience as having completed acquisitions in the one year before the announcement of the acquisition under investigation (Haleblian, Kim, & Rajagopalan, 2006). Long-term experience can be defined as any period longer than one year. In this study, I measure the experience of the top management teams, but given the turnover of top management teams, I considered the decisions of a stable team. For these reasons, I measured long-term experience as any acquisitions completed in the five years before the announcement of the acquisition under investigation. For each of these variables, I calculated the total number of acquisitions completed by the acquiring firm in the one and five years before the announcement of the acquisition under investigation.

Control Variables

Research on post-acquisition performance is well-trod ground prompting a meta-analysis of variables with significant relationships to acquisition performance. While it is possible to identify many variables that may have a direct effect on acquisition premiums and should be identified for controls in this study, I measured two variables that have not already been included in the model that repeatedly have been identified to influence acquisition performance including conglomerate firms and payment method (King et al., 2004). Additionally, I added the year of acquisition to control for economic differences between years as well as the presence of competing bidders. The use of these four variables as controls will allow me to control for variables that may significantly influence acquisition performance while preserving statistical power.

Conglomerate firms are commonly defined as those that compete in significant unrelated product-market diversification (Rumelt, 1974). A positive impact on performance in acquisitions conducted by conglomerate firms has been found suggesting that there is some integration competence that allows them to create rather than acquire value through M&A activity (Salter & Weinhold, 1978). For this reason, I identified acquisitions conducted by conglomerate firms with a dummy variable of 1 and acquisitions conducted by organizations that are not conglomerates were assigned a 0. Conglomerate firms have been defined as firms that operate in at least two distinct classes measured by four-digit SIC codes (Boguth, Duchin, & Simutin, 2016). Because acquisition performance may vary according to the payment type of the acquisition (Slusky & Caves, 1991), I controlled for the payment method. Dummy variables identified if the acquisition was paid for in all cash, all stock, or a combination. Leveraged buyouts were classified as a combination given that they are commonly financed with a small portion of equity and a large portion of cash (financed by debt). Competing bids on the acquisition have also been found to drive up the price of acquisitions so that I controlled for this with a dummy variable (0=no other bidders, 1=other bidders) (Haunschild, 1994; Slusky & Caves, 1991). Moreover, I controlled for the year of acquisition to account for any systematic differences between the years studied.

Chapter 4: Results

The first step in the analysis of study 2 is to create a correlation table between all variables. Each variable was examined for variance, skewness, kurtosis, and normality as well as any significant relationship between variables. Additionally, this allowed for the identification of which control variables significantly effect acquisition performance, and those variables will be carried forward in the analysis to preserve statistical power. The correlation table is in Table 3a, 3b, and 3c.

		1		2		3		4		5		6	
1	Acquisition Performance: Cumulative Abnormal Returns after 1 Year												
2	Acquisition Performance: Cumulative Abnormal Returns after 3 Years	.738**	0.000										
3	Technical Ambiguity - Missing Information	0.032	0.727	-0.009	0.923								
4	Techancial Ambiguity - Reliability of Information	-0.100	0.268	-0.148	0.107	-0.004	0.963						
5	Technical Ambiguity - Amount of Information	0.031	0.729	-0.071	0.444	-.306**	0.000	-0.040	0.637				
6	Industry Ambiguity - Missing Information	-0.133	0.142	-0.041	0.661	-0.017	0.846	-0.079	0.353	-0.095	0.265		
7	Industry Ambiugity - Reliability of Information	-0.083	0.357	-0.137	0.137	-0.052	0.545	.956**	0.000	-0.030	0.721	-0.065	0.446
8	Industry Ambiguity - Amount of Information	0.063	0.489	0.041	0.659	0.018	0.830	0.023	0.786	0.073	0.392	0.113	0.184
9	Financial Ambiguity - Missing Information	0.062	0.495	0.169	0.066	-0.052	0.548	-.166*	0.050	-0.039	0.643	0.089	0.296
10	Financial Ambiguity - Reliability of Information	-0.086	0.345	-0.144	0.118	-0.051	0.553	.583**	0.000	0.005	0.952	-0.026	0.759
11	Financial Ambiguity - Amount of information	-0.118	0.192	-0.155	0.093	0.042	0.623	-0.136	0.110	0.094	0.270	-0.076	0.372
12	Acquisition Size	0.015	0.872	-0.171	0.064	-0.021	0.805	0.130	0.126	0.112	0.187	-0.139	0.102
13	Acquisition size - Relative	-0.159	0.084	-0.136	0.147	-0.049	0.582	0.058	0.512	0.109	0.218	0.049	0.581
14	Acquisition Experience - 1 year	0.026	0.773	-0.011	0.903	0.044	0.611	0.080	0.350	-0.038	0.657	0.070	0.412
15	Acquisition Experience - 5 Years	0.030	0.744	0.039	0.677	0.016	0.854	0.021	0.806	-0.049	0.564	0.092	0.281
16	Conglomerate Firm	0.014	0.878	0.034	0.712	-0.031	0.720	0.070	0.412	0.004	0.960	-0.048	0.574
17	Payment Method	-0.087	0.337	-0.101	0.272	0.011	0.894	0.009	0.918	0.004	0.961	-0.035	0.685
18	Transaction Year	-0.060	0.506	-.203*	0.027	0.059	0.492	0.149	0.080	0.055	0.517	-0.104	0.222
	**. Correlation is significant at the 0.01 level (2-tailed).												
	*. Correlation is significant at the 0.05 level (2-tailed).												

Table 3a: Correlation Matrix Part 1

		7		8		9		10		11		12	
8	Industry Ambiguity - Amount of Information	0.007	0.939										
9	Financial Ambiguity - Missing Information	-0.150	0.077	-0.039	0.649								
10	Financial Ambiguity - Reliability of Information	.691**	0.000	-0.016	0.848	-0.057	0.500						
11	Financial Ambiguity - Amount of information	-0.124	0.145	-0.071	0.406	-0.045	0.601	-0.029	0.735				
12	Acquisition Size	0.130	0.126	0.084	0.328	-0.133	0.118	0.110	0.196	-0.054	0.527		
13	Acquisition size - Relative	0.027	0.760	.198*	0.024	-0.153	0.082	0.042	0.634	-0.015	0.868	.203*	0.020
14	Acquisition Experience - 1 year	0.067	0.434	0.053	0.538	0.041	0.629	0.018	0.831	-0.128	0.130	0.133	0.116
15	Acquisition Experience - 5 Years	0.028	0.747	-0.009	0.914	0.080	0.345	-0.019	0.825	-0.142	0.094	0.095	0.263
16	Conglomerate Firm	0.002	0.982	-0.035	0.678	0.081	0.341	-0.061	0.477	-0.026	0.758	-0.079	0.351
17	Payment Method	0.012	0.892	-0.034	0.692	0.128	0.133	0.032	0.710	0.051	0.553	-0.075	0.380
18	Transaction Year	0.116	0.173	0.026	0.765	-.530**	0.000	0.062	0.467	0.034	0.689	0.120	0.158
	**. Correlation is significant at the 0.01 level (2-tailed).												
	*. Correlation is significant at the 0.05 level (2-tailed).												

Table 3b: Correlation Matrix Part 2

		13		14		15		16		17	
14	Acquisition Experience - 1 year	-0.007	0.940								
15	Acquisition Experience - 5 Years	-0.023	0.795	.798**	0.000						
16	Conglomerate Firm	-0.058	0.512	0.071	0.402	0.071	0.405				
17	Payment Method	-0.017	0.847	0.028	0.744	-0.012	0.889	-0.044	0.604		
18	Transaction Year	0.138	0.118	-0.086	0.315	-.172*	0.042	-0.002	0.984	-0.134	0.116
	**. Correlation is significant at the 0.01 level (2-tailed).										
	*. Correlation is significant at the 0.05 level (2-tailed).										

Table 3c: Correlation Matrix Part 3

First, I examined the correlations and significance level of the relationships between each type of ambiguity and acquisition performance, and there were no significant relationships without the use of control variables. Next, I examined the effect of the control variables of conglomerate firms, payment methods, and transaction year. The only control variable that had a significant relationship with acquisition performance is the year of acquisition and only with 3-year cumulative abnormal returns (R=-.203, p.027) and not 1-year cumulative abnormal returns. To preserve power, transaction year will be the only control variable carried forward in the analysis and only in relation to 3-year acquisition performance.

To identify if hypotheses H1 a-c, H2 a-c, and H3a-c were supported, I conducted a regression analysis between each type of ambiguity and acquisition performance at 1 and 3 years, while controlling for transaction year in the analysis of 3-year cumulative abnormal returns. The following table presents those results:

Hypothesis	Relationship between type of ambiguity hypothesized and acquisition performance Year 1		Relationship between type of ambiguity hypothesized and acquisition performance Year 3		Summary
	Correlation	Significance	Correlation	Signficance	
H1a: The higher the level of missing information about technology the lower the level of acquisition performance.	0.070	0.492	0.211	0.072	Near Significant Relationship with 3 Year CAR, but in opposite direction of hypothesis
H1b: The higher the level of reliability of information about technology the higher the level of acquisition performance.	0.112	0.634	0.232	0.051	Very near significant relationship with Year 3 CAR as hypothesized
H1c: The higher the amount of information available about the acquisition the higher the level of acquisition performance.	0.070	0.495	0.211	0.033	Significant relationship with Year 3 CAR as hypothesized
H2a: The higher the level of missing information about the industry the lower the level of acquisition performance.	0.113	0.710	-0.218	0.040	Significant relationship with Year 3 CAR as hypothesized
H2b: The higher the level of reliability of information about the industry the higher the level of acquisition performance.	0.099	0.585	0.228	0.045	Significant relationship with Year 3 CAR as hypothesized
H2c: The higher the amount of information available about the industry the higher the level of acquisition performance.	0.083	0.552	0.210	0.025	Significant relationship with Year 3 CAR as hypothesized
H6a: The higher the level of missing information about the financial situation of the target the lower the level of acquisition performance.	0.067	0.775	0.213	0.157	No significant relationship
H6b: The higher the level of reliability of information about the financial situation of the target the higher the level of acquisition performance.	0.099	0.585	0.238	0.038	Significant relationship with Year 3 CAR as hypothesized
H6c: The higher the amount of information available about the financial situation of the target the higher the level of acquisition performance.	0.151	0.590	0.276	0.031	Significant relationship with Year 3 CAR as hypothesized

Table 4: Correlations of Regression Analysis Controlling for Transaction Year

Overall, no types of ambiguity were found to significantly relate to acquisition performance in year 1, but many types of ambiguity were found to have significant relationships with acquisition performance in year 3 when controlling for transaction year. H1c, H2a, H2b, H2c, H3b, and H3c were all supported with a significant relationship between the type of ambiguity and acquisition performance as hypothesized. H3a was not supported, and while H1a was significant, it was not correlated in the direction hypothesized. Since H1a was found to be significant but in the opposite direction hypothesized, I tested this hypothesis for multicollinearity (Technical Ambiguity – Missing Information and Transaction year). The VIF statistic for this relationship was 1.0 which was well below the threshold of 3.0 suggesting that there was no multicollinearity between the two variables (Mansfield & Helms, 1982) and therefore hypothesis 1a was not supported. These are generally very positive results that support the overall hypothesis that ambiguity does influence the performance of mergers and acquisitions.

Next, I examined the effects of nested data as an empirical question (Sharfman & Fernando, 2008) as it is possible that there could be an effect of multiple acquisitions nested within companies, companies within industries, and companies using the same technology. First, I determined what percentage of the acquisitions are nested within companies, industries, or technologies. The 140 unique acquisitions examined in this study were conducted by 125 firms, within 37 industries and 38 unique product categories (NAICS codes). Next, I conducted an analysis of variance with acquisition performance as the dependent variable and SIC codes, companies with multiple acquisitions, and companies with similar technologies as the independent variable.

Nesting Effect Tested	**Significance of Effect**
Nesting of acquisitions within companies	CAR 3 years: $p = .335$
Nesting of acquisitions within industries	CAR 3 years: $p = .955$
Nesting of acquisitions within product categories	CAR 3 years: $p = .498$

Table 5: Nesting Effects

Since there were no significant nesting effects, post-hoc analysis was not required, and nesting effects do not need to be analyzed or parsed out in further analysis.

Hypotheses H1d, H2d, and H3d all predict the relationships between the latent variables for each category of ambiguity (technology, industry, financial). To test these hypotheses, I developed and tested a measurement model using confirmatory factor analysis in AMOS to determine if the observed indicators for ambiguity “hang together” to measure the latent constructs of technological and industry ambiguity. As discussed in the hypothesis development section, several variables were reversed coded such that the relationship between ambiguity and acquisition performance was predicted to be negative. The variables that were reverse coded included technology ambiguity – reliability of information, technology ambiguity – amount of information, industry ambiguity – reliability of information, industry ambiguity – amount of information, financial ambiguity – reliability of information, and financial ambiguity – amount of information. The following figure shows the model:

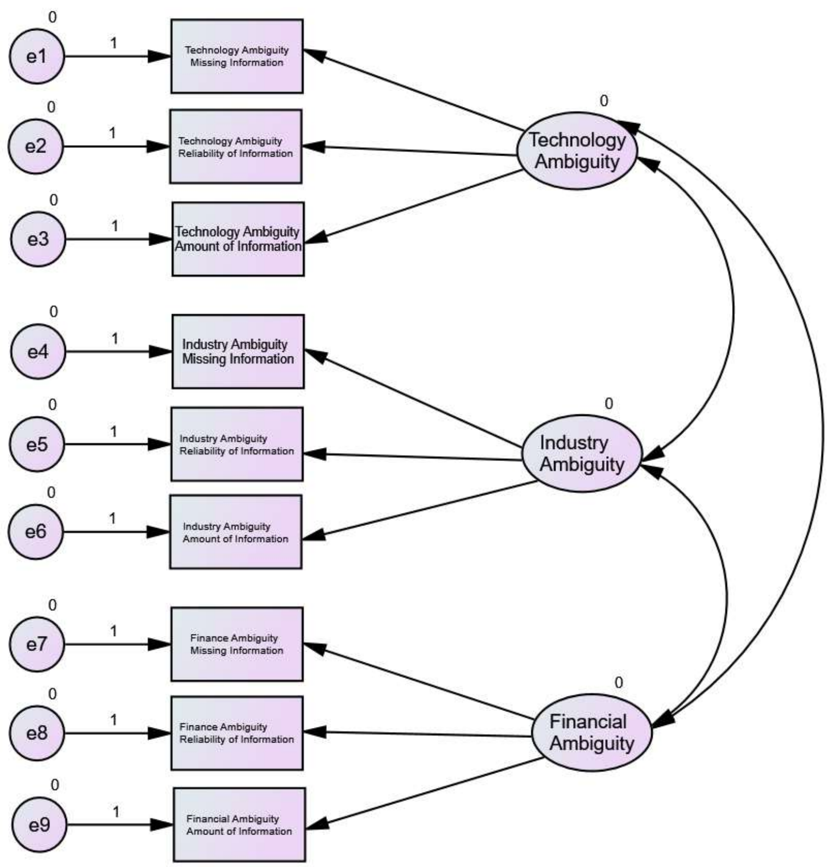

Figure 4: Model for Confirmatory Factor Analysis

Conventional standards for judging model fit were used including the chi-square goodness of fit and RMSEA suggest that this model is not a good fit for the data. (Byrne, 2013). The chi-square was significant (p=.000) suggesting the model was a not good fit for the data. The

RMSEA was .259 with <.05 representing optimal fit. Both statistics suggest that the model is not a good fit for the data. These fit statistics suggest that the individual variables for technology, industry, and financial variables do not "hang together" to create latent variables technology, industry, and financial ambiguity.

To further test the relationships between the individual types of ambiguity, I conducted an confirmatory factor analysis to detect relationships between the individual variables for missing information, reliability of information, and amount of information. The following figure represents the model tested in the exploratory factor analysis.

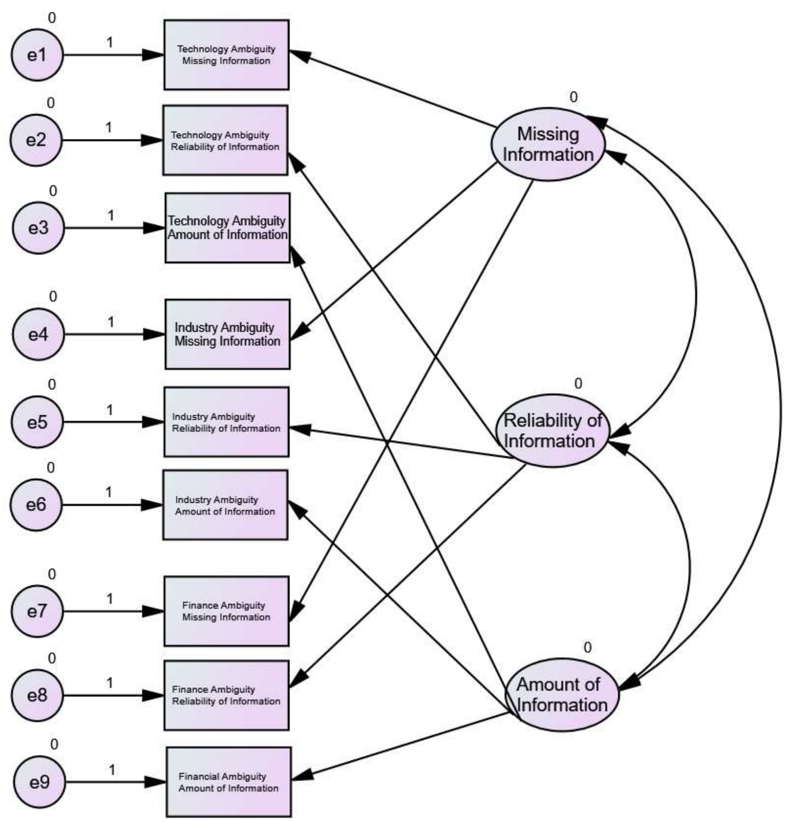

Figure 5: Model for Exploratory Factor Analysis

This model also exhibited a poor fit for the data with a significant chi-square (p=.000) and an RMSEA of .210 which is well above the .05 threshold for a good fit.

Because of the incredibly poor results of the confirmatory and exploratory factor analysis, I did not move forward with testing the relationships between the latent variables of technology, industry, and finance and acquisition performance. I pursued the examination of H4a-c, H5, and H6a-c by measuring the effects of acquisition size and experience with each individual type of ambiguity.

Hypotheses 4a, 4b, and 4c predict that size will have a relationship with ambiguity such that larger acquisitions would have more ambiguity. The correlation table shows that there are no significant relationships between the absolute size of the acquisition or the size of the acquisition relative to the size of the acquirer and each individual type of ambiguity. I examined to see if there may be any control variables that may have a significant relationship with each type of ambiguity and there were none. Overall, the hypotheses that larger acquisitions would have more ambiguity (H4a, H4b, and H4c) was not supported.

Hypothesis 5 predicted that size would moderate the relationship between ambiguity and acquisition performance such that in larger acquisitions, ambiguity would lead to worse performance than in small acquisitions. Table 6 and 7 show the results of this analysis by examining size as a moderator between acquisition performance after 1 and 3 years respectively by examining the absolute size of the acquisitions as well as acquisition size relative to the acquirer. In this analysis, transaction year was used as a control variable as discussed earlier for 3-year cumulative abnormal returns. For parsimony, several variables were reversed coded such that the relationship between ambiguity and acquisition performance was predicted to be negative. The variables that were reverse coded included technology ambiguity – reliability of information, technology ambiguity – amount of information, industry ambiguity – reliability of information, industry ambiguity – amount of information, financial ambiguity – reliability of information, and financial ambiguity – amount of information.

	Acquisition Size		Acquisition Size in Relation with Acquiror	
	R	p	R	p
Technical Ambiguity - Missing Information	0.09	0.082	0.168	0.514
Technical Ambiguity - Reliability of Information	0.119	0.791	0.276	0.06
Technical Ambiguity - Amount of Information	0.097	0.888	0.299	0.03
Industry Ambiguity - Missing Information	0.267	0.48	0.265	0.501
Industry Ambiguity - Reliability of Information	0.115	0.812	0.195	0.352
Industry Ambiguity - Amount of Information	0.101	0.874	0.192	0.363
Financial Ambiguity - Missing Information	0.073	0.958	0.24	0.144
Financial Ambiguity - Reliability of Information	0.117	0.797	0.181	0.427
Financial Ambiguity - Amount of information	0.152	0.606	0.254	0.116

Table 6: Size as a Moderator of Ambiguity and 1 Year Cumulative Abnormal Returns

This analysis shows that size does not appear to moderate the relationship between the individual types of ambiguity and cumulative abnormal returns at 1 year. Only one interaction was a moderator which was the relative size of the acquisition in the relationship between technical ambiguity – amount of information and 1-year cumulative abnormal returns.

The results for the moderating role of size between ambiguity and 3-year cumulative abnormal returns are different and show that the absolute size of the acquisition may have some influence on performance in larger acquisitions (Table 7). While only one of these relationships were significant, many are near significant. Size does show to be a significant moderator in the relationship between Financial Ambiguity – Amount of Information and acquisition performance after three years, but this relationship is near significant with every other type of ambiguity. This may be a feature of this particular sample or perhaps the low sample size. Additionally, I measure the moderating effect of size in the relationship between ambiguity and acquisition performance at 3 years when size was measured relative to the acquirer (acquisition size/annual revenue of acquirer at time of acquisition). With this measure two of these relationships were significant, and many were near significant. Relative size does show to be a significant moderator in the relationship between Technical Ambiguity – Missing information and Financial Ambiguity – Amount of Information with acquisition performance after three years and this relationship is near significant with every other type of ambiguity. This suggests that hypothesis 5 may be partially supported when measured by the absolute size of the acquisition and that acquisition size does moderate the relationship between ambiguity and acquisition performance such that in a larger acquisition, any ambiguity present will have a more negative effect on acquisition performance.

	Acquiror Acquisition Experience 1 Year		Acquisition Size in Relation with Acquiror	
	R	p	R	p
Technical Ambiguity - Missing Information	0.092	0.91	0.157	0.566
Technical Ambiguity - Reliability of Information	0.118	0.796	0.166	0.806
Technical Ambiguity - Amount of Information	0.111	0.827	0.137	0.685
Industry Ambiguity - Missing Information	0.16	0.714	0.305	0.15
Industry Ambiguity - Reliability of Information	0.105	0.859	0.109	0.842
Industry Ambiguity - Amount of Information	0.092	0.911	0.099	0.881
Financial Ambiguity - Missing Information	0.09	0.915	0.116	0.802
Financial Ambiguity - Reliability of Information	0.109	0.836	0.117	0.8
Financial Ambiguity - Amount of information	0.146	0.63	0.143	0.648

Table 7: Size as a Moderator of Ambiguity and 3 Year Cumulative Abnormal Returns

In hypothesis 6, I predicted that experience would moderate the relationship between ambiguity and acquisition performance such that when the acquirer had recent experience in acquisitions, any ambiguity would more negatively impact the performance of the acquisition. In this analysis, transaction year was used as a control variable for 3 year cumulative abnormal returns as discussed earlier and variables that were reverse coded included technology ambiguity – reliability of information, technology ambiguity – amount of information, industry ambiguity – reliability of information, industry ambiguity – amount of information, financial ambiguity – reliability of information, and financial ambiguity – amount of information. Table 8 and 9 show the results of this hypothesis by examining the acquirer's acquisition experience as a moderator between acquisition performance after 1 and 3 years respectively by the acquirer's recent experience 1 year and 5 years before the acquisition.

	Acquiror Acquisition Experience 1 Year		Acquiror Acquisition Experience 5 Years	
	R	p	R	p
Technical Ambiguity - Missing Information	0.092	0.91	0.157	0.566
Technical Ambiguity - Reliability of Information	0.118	0.796	0.166	0.806
Technical Ambiguity - Amount of Information	0.111	0.827	0.137	0.685
Industry Ambiguity - Missing Information	0.16	0.714	0.305	0.15
Industry Ambiguity - Reliability of Information	0.105	0.859	0.109	0.842
Industry Ambiguity - Amount of Information	0.092	0.911	0.099	0.881
Financial Ambiguity - Missing Information	0.09	0.915	0.116	0.802
Financial Ambiguity - Reliability of Information	0.109	0.836	0.117	0.8
Financial Ambiguity - Amount of information	0.146	0.63	0.143	0.648

Table 8: Experience as a Moderator of Ambiguity and 1 Year Cumulative Abnormal Returns

Like the previous analysis in this study, there were no significant results with cumulative abnormal returns in year 1. Experience at 1 and 5 years previous to the acquisition do not moderate any of the relationships between individual ambiguity and 1 year CAR.

When examining cumulative abnormal returns at year 3, the results indicate that very recent acquisition experience (within 1 year) had no moderating effect between ambiguity and acquisition performance, but when examining acquisition experience within 5 years before the acquisition, there is some support of the moderating effect of experience. Experience within 5 years did have a moderating effect between ambiguity and acquisition performance for certain types of ambiguity including Financial Ambiguity – Missing information and Industry Ambiguity – Missing Information and a near significant moderating effect for Technical Ambiguity – Amount of Information and Financial Ambiguity – Amount of Information. These findings indicate that perhaps acquisition experience may have a moderating effect with only certain types of ambiguity and only over the long term.

	Acquiror Acquisition Experience 1 Year		Acquiror Acquisition Experience 5 Years	
	R	p	R	p
Technical Ambiguity - Missing Information	0.203	0.309	0.226	0.201
Technical Ambiguity - Reliability of Information	0.213	0.176	0.23	0.182
Technical Ambiguity - Amount of Information	0.229	0.185	0.263	0.084
Industry Ambiguity - Missing Information	0.246	0.294	0.367	0.049
Industry Ambiguity - Reliability of Information	0.228	0.29	0.227	0.195
Industry Ambiguity - Amount of Information	0.216	0.245	0.221	0.216
Financial Ambiguity - Missing Information	0.252	0.209	0.087	0.043
Financial Ambiguity - Reliability of Information	0.238	0.253	0.236	0.16
Financial Ambiguity - Amount of information	0.262	0.085	0.268	0.073

Table 9: Experience as a Moderator of Ambiguity and 3 Year Cumulative Abnormal Returns

The following table summarized which hypotheses were supported:

Hypothesis	Summary
H1a: The higher the level of missing information about technology the lower the level of acquisition performance.	Not Supported
H1b: The higher the level of reliability of information about technology the higher the level of acquisition performance.	Partially Supported
H1c: The higher the amount of information available about the acquisition the higher the level of acquisition performance.	Supported
H1d: The level of technological ambiguity will be negatively related to acquisition performance.	Not Supported
H2a: The higher the level of missing information about the industry the lower the level of acquisition performance.	Supported
H2b: The higher the level of reliability of information about the industry the higher the level of acquisition performance.	Supported
H2c: The higher the amount of information available about the industry the higher the level of acquisition performance.	Supported
H2d: The level of industry ambiguity will be negatively related to acquisition performance.	Not Supported
H3a: The higher the level of missing information about the financial situation of the target the lower the level of acquisition performance.	Not Supported
H3b: The higher the level of reliability of information about the financial situation of the target the higher the level of acquisition performance.	Supported
H3c: The higher the amount of information available about the financial situation of the target the higher the level of acquisition performance.	Supported
H3d: The level of financial ambiguity will be negatively related to acquisition performance	Not Supported
H4a: The size of acquisitions will be negatively related to technological ambiguity.	Partially Supported
H4b: The size of acquisitions will be negatively related to industry ambiguity.	Partially Supported
H4c: The size of acquisitions will be negatively related to financial ambiguity.	Partially Supported

H5: Size moderates the relationships between ambiguity and performance such that ambiguity in larger acquisitions leads to poorer performance than ambiguity in small acquisitions.	Partially Supported
H6a: Experience moderates the relationship between technological ambiguity and acquisition performance such that managers with experience will strengthen the relationship between ambiguity and performance so that the relationship will be more negative.	Not Supported
H6b: Experience moderates the relationship between industry ambiguity and acquisition performance such that managers with recent experience will strengthen the relationship between ambiguity and performance so that the relationship will be more negative.	Not supported
H6c: Experience moderates the relationship between industry ambiguity and acquisition performance such that managers with recent experience will strengthen the relationship between ambiguity and performance so that the relationship will be more negative.	Partially Supported

Table 10: Summary of Results

Chapter 5: Discussion

The findings of this study support the idea that ambiguity matters in the performance of mergers and acquisitions. Significant relationships were found between year 3 performance and missing information about technology, all three types of industry ambiguity including missing information, reliability of information and amount of information, and missing information about financial ambiguity as well as reliability of information in terms of financial ambiguity. Additionally, the relationship between performance and reliability of information in terms of technology was near significant. While I did not find a direct relationship between the size of the acquisition and ambiguity, I did find partial support for size as a moderator of the relationship between ambiguity and acquisition performance. Additionally, there was uneven support for experience as a moderator of the relationship between ambiguity and performance. In the following section, I will discuss the results in depth and suggest alternative explanations for the results supported by the literature.

The importance of technological ambiguity was supported in study 1 and the hypothesized relationships between types of technology ambiguity and acquisition performance was based on previous research and were supported in study 2. An acquisition target's technology may be complex and difficult to measure (Coff, 2003) which can introduce ambiguity in the acquisition process. Additionally, a seller may not even truly understand the value of the technology they have (Wu & Knott, 2006). Study 1 examined 12 acquisitions, and 3 of those acquisitions included instances of technological ambiguity represented by comments like "seller would not deliver copies of trade secret formulations until the day of closing." Study 2 examined the relationship between different types of ambiguity and performance with mixed results. The hypothesized relationship between missing information about technological ambiguity (H1a) and performance was not supported. It was hypothesized that an increase in missing information would result in lower performance. In this case, missing information was measured as the percentage of scientists and engineers within a technology area. Previous research supported the hypothesis that a higher number of engineers and scientists would imply more technological complexity and therefore ambiguity in that area. The relationship between this variable and performance was near significant but positive such that a higher percentage of engineers and scientists results in better performance as measured by CAR. An explanation for this result could be that acquisitions in areas with a high percentage of engineers and scientists have the resources and expertise available to them to understand better the technology being acquired which would lead to better acquisition performance. Another explanation could be within this sample of large acquisitions (over $100 Million), technology is identified as an area with potential ambiguity, and that ambiguity is thoroughly investigated. However, technical resources may not be able to mitigate all the ambiguity in large and complex product lines. This idea is supported by a significant and positive relationship between the amount of technical information available and performance (H1c). When decisions makers have more information, they weigh that information heavily. When decision-makers have very little information, they put very little weight on the amount of information that they have. In this study amount of information about technology was measured by the number of products within a technology category of the target company in the acquisition. More products in a technology category represented that there was more information that needed to be known about an acquisition target. I hypothesized that a higher amount of information available would result in better performance, therefore, hypothesizing that fewer products in a category would represent a higher amount of information available and better performance. This hypothesis was supported such that buyers that acquired targets with more products in their SIC code had lower performance at year 3 (H1c). The last type of technology ambiguity investigated was reliability of information. I hypothesized that more reliable information would result in better acquisition performance. Reliability of technology information was measured by analyst coverage such that a higher amount of analyst coverage would represent a greater diversity of information and less expert agreement. This lack of expert agreement could represent more ambiguity with the acquirer and lead to poorer acquisition performance. Hypothesis 1b is that less reliability would result in poorer performance so more analyst commentary would lead to poorer performance. This hypothesis was supported (p=.051). In summary, the relationships between the individual types of technological ambiguity and acquisition performance had mixed results. These results suggest that technological ambiguity plays a role in the performance of mergers and acquisitions, but acquirers may be prepared for and mitigate some types. Because acquirers may be aware of this type of ambiguity, they may have or hire experts to mitigate the effect of this type of ambiguity in the performance of mergers and acquisitions.

Industry ambiguity was the second source of ambiguity investigated in this study and found much more consistent support than technology. Industry ambiguity was identified in previous research as a source as ambiguity as buyers commonly have less information than sellers regarding a target's resources, and other valuable information such as intentions of key individuals or known shortcomings of their organization or resources (Graebner et al., 2010). Previous research has identified that industry differences between buyer and target may be a source of failure for acquisitions, but it has not yet been examined as a type of ambiguity. Industry ambiguity was identified in study 1 as a source of ambiguity as 6 instances of industry ambiguity were identified across 12 acquisitions. The investor mentioned industry ambiguity with comments such as “additional information regarding seasonality of the business would have influenced valuation to a small degree” and “finished products, applications, and customers were not consistent with those of Firm X.” In study 2, all three types of industry ambiguity were found to have a significant relationship with acquisition performance. Hypothesis 2a was that missing information about the target would lead to lower acquisition performance. Missing industry information was measured as a similarity between the SIC codes of the target and the acquirer. A higher similarity between the acquirer and target would lead to less ambiguity, and better acquisition performance and less similarity would lead to lower performance because the target may be outside the area of core competency. This hypothesis was supported. Hypothesis 2b suggested that lack of expert agreement could represent more ambiguity with the acquirer and lead to poorer acquisition performance. Reliability of information for industry was measured by industry analyst coverage such that a higher amount of analyst coverage would represent a greater diversity of information and less expert agreement which would result in lower acquisition performance. This hypothesis was supported. Last, the amount of information about the target’s industry was examined. Once again, when decision-makers have more information available to them, they can put more weight on that information. Turbulence in an industry causes doubt in a decision-makers mind about the amount of information needed in an acquisition or how much weight they can put on the information that they have. In this study, that turbulence was measured by changes in employment in the 12 months leading up to the acquisition. A higher absolute value of employment changes would represent more turbulence which represents more ambiguity and would lead to lower acquisition performance. This hypothesis was also supported. Each of the relationships between the types of industry ambiguity and acquisition performance was supported representing that more industry ambiguity leads to poorer performance. Decision-makers may not identify industry as an important source of ambiguity and attempt to mitigate it as much as they may technology. Decision-makers may also feel more confident about acquisitions with industry ambiguity and feel they can overcome it more than ambiguity about technology. Ambiguity about industry may also just be less understood by decision-makers and therefore not identified and reduced before the acquisition. The literature supports this idea as researchers have even found conflicting results about when industry differences between acquirer and target matter and when they do not. Any of these conflicting results would increase ambiguity for acquirers. For example, if an acquirer and target have too few similarities, then the buyer may not be familiar enough with the target’s resources to implement their strategy effectively (Ahuja & Katila, 2001; Cloodt et al., 2006; Higgins & Rodriguez, 2006; Kapoor & Lim, 2007). Buyers that acquire firms with complementary resources may be successful by combining a target's technical knowledge with their marketing, manufacturing, or sales but if a target is from too far outside the acquirer's core competency, then they may see negative results (King et al., 2004). Additionally, if the acquirer and target have too much of the same information, there may be redundancies and few opportunities for growth (Graebner et al., 2010). While this study supports that industry ambiguity does have an effect on performance in mergers and acquisitions, there is clearly more to understand about the relationship between industry ambiguity and acquisition performance.

Financial ambiguity was identified in study 1 and the relationship between financial ambiguity and acquisition performance was somewhat supported in study 2. Financial ambiguity was not identified by previous research, but that is not surprising given that finance scholars have largely focused on the performance of acquisitions and not the antecedents of that performance. Finance scholars have mostly focused on if acquisitions are wealth creating or wealth reducing events for shareholders and have identified that acquisitions or overwhelmingly positive for target firms but deliver mixed results to investors of acquiring firms (Cartwright & Schoenberg, 2006). Finance scholars tend to focus on the wide variation of post-acquisition performance (Conn, Cosh, Guest, & Hughes, 2004) but have not thoroughly investigated the antecedents of M&A performance. Financial ambiguity was the most cited source of ambiguity in study 1 from an investor with a long history of acquisitions. In study 1, eight instances of financial ambiguity were identified across 12 acquisitions. Most of these instances concerned the target's financial statements and if they had not been audited or independently prepared and reviewed. The investor interviewed in this study noted independently verified results as a major source of concern in his decision making. Because the investor in study 1 was so concerned with independently prepared financial statements, I was surprised when hypothesis 3a was not supported. Missing information was identified in study 1 as a critical piece of acquisition performance. In study 2, missing financial information was measured as a binary variable of public or private targets. I hypothesized that missing information would lead to poorer performance and acquisition targets that were private would have less information publicly available that publicly traded firms and less information would lead to poorer performance (H3a). This hypothesis was not supported in this study, but it is possible that this still may be an important area of future study. This study included a sample of large acquisitions of over $100 Million. It is possible that at that size, all firms have independently audited or reviewed financial statements. The average acquisition in study 1 was about $12 Million, and at this size, many target firms had not been audited. It is possible that the size of the acquisitions moderates the effect of this variable in the performance of mergers and acquisitions. While the relationship between missing financial information and performance was not seen in this study, there may be a significant effect in small acquisitions under $100 Million. Like technology and industry ambiguity, reliability of information was examined as expert agreement. Hypothesis 3b suggested that lack of expert agreement could represent more ambiguity with the acquirer and lead to poorer acquisition performance. Reliability of information for financial ambiguity was measured by financial analyst coverage such that a higher amount of analyst coverage would represent a greater diversity of information and less expert agreement which would result in lower acquisition performance. This hypothesis was supported. Another element of financial ambiguity identified in study 1 was the length of due diligence. This was mentioned in some form or another by the investor in every acquisition, and the investor expressed he felt more comfortable with a longer due diligence process. To investigate the effect of length of due diligence in study 2, I hypothesized that a longer relationship, including due diligence, partnership, or alliance, would increase the amount of information that the acquirer had access to and could lead to better acquisition performance (H3c). This hypothesis was supported. Generally, types of financial ambiguity were found to have a significant relationship with acquisition performance. While the relationship between missing financial information and performance was not significant, it is possible that this is because of the measure used or the size of the acquisitions in this study.

In addition to the relationships between types of ambiguity and acquisition performance, I also examined if the types of ambiguity were related and acted as a latent variable. For example, I examined the relationship between missing information about technology, reliability of information about technology, and amount of information available about technology to see if they were related to each other and acted as a latent variable (H1d). I examined the same for industry and financial ambiguity (H2d, H3d). Using confirmatory factor analysis, I investigated if the three types of technology ambiguity were correlated and repeated the process with the three types of industry ambiguity and then financial ambiguity. I also examined if technology, industry, and financial ambiguity were related to each other. The analysis did not support these hypotheses as there were no significant relationships between the types of ambiguity within technology, industry, or finance. A post hoc analysis was conducted to examine if the variables for missing information, reliability of information, and amount of information were related. For example, I tested if there was a relationship between missing information in technology, missing information about industry, and missing information about finance. This analysis also resulted in no significant relationships. An explanation for these results could be that decision-makers can identify ambiguity and treat each type differently. Based on individual differences or experience, certain types of ambiguity may be more important than others to decision-makers and may be assessed and considered differently. It is also possible that decision-makers may see some types of ambiguity as a feature of their environment and consider this type of ambiguity a constant since they would be similar for all acquisitions within that industry or technology area.

Stake effects have featured prominently in the literature as previous studies on ambiguity have identified that the magnitude of the outcome at stake may influence attitudes on ambiguity. (Trautmann and van de Kuilen, 2014). The issue of stake effects is essential in real-world decisions as managers may encounter a diverse range of outcomes from trivial to extremely high as well as a range of probabilities that may or may not be known (Bouchouicha et al., 2017). In this study, I suggested that larger acquisitions may be more visible and therefore higher stakes, such that decision-makers will have a much lower tolerance for ambiguity in large acquisitions and a higher tolerance for ambiguity in small acquisitions. I originally hypothesized a negative relationship between the size of an acquisition and the latent variables for technology (H4a), industry (H4b), and finance (H4c) but since there was no support for these latent constructs, I examined the relationship between size and each individual type of ambiguity. Interestingly enough, there was no relationship between size and ambiguity. Once again, this sample could all be considered high stakes decisions and perhaps there was not a large enough variance is the stakes to show an effect. In addition to a direct relationship between size and ambiguity, I hypothesized that size would moderate the relationship between ambiguity and acquisition performance such that that ambiguity present in larger acquisitions would result in poorer performance (H5). I found some support for the moderating role of the absolute size of the acquisition with significance levels between .013 and .09. Additionally, I examined the moderating role of the relative size of the acquisition (size of acquisition/revenue of acquirer) and found significant or near significant relationships of .006 to .09 for 8 of the 9 relationships specified. While not all of these relationships passed the significance level of .05, this may be a feature of the sample and bears further investigation. It is clear that size has some moderating role between ambiguity and performance of mergers and acquisitions, but these findings are not surprising given the conflicting effect of size that is found in the literature. While scholars agree that size is important in acquisitions performance, there is some disagreement about if the effects of size on acquisition performance are positive or negative (Haleblian et al., 2009). Some studies have identified that larger acquisitions can produce positive accounting performance post-acquisition through asset productivity (Healy et al., 1992), enhanced customer attraction, employee productivity, and asset growth (Cornett & Tehranian, 1992). Other scholars have identified competing viewpoints. For example, small acquisitions by small acquirers result in positive gains where large acquisitions by large acquirers result in significant announcement losses (Moeller et al., 2003). Firm size appears to effect returns, but the mixed results leave room to establish boundaries on the effect of size. Unfortunately, the results of this study do not add clarity to the discussion on the effects of size in the relationship between ambiguity and acquisition performance.

Last, I investigated the effect of experience as a moderator between ambiguity and acquisition performance (H6a-c). I hypothesized this relationship between the latent constructs for each type of ambiguity (technology, industry, financial) but since there was no support for the latent constructs, I examined the moderating role of experience between each individual type of ambiguity and acquisition performance. In the analysis, there was no support for experience as a moderator between ambiguity and performance. This is also unsurprising given the interesting relationships between experience and acquisition performance found in the literature. In the acquisition literature, experience is a crucial contributor to acquisition performance. While this seems intuitive, there are interesting findings regarding the effect. Haleblian and Finkelstein (1999) found that the relationship between acquisition experience and acquisition performance was not linear but U-shaped. Researchers attributed this relationship to the notion that young, inexperienced acquirers may apply experience from recent acquisitions inappropriately, possibly because of hubris (Hayward & Hambrick, 1997), or overconfidence (Malmendier & Tate, 2005). More experienced acquirers may be able to avoid these missteps. In this study, I examined experience within 1 year and 5 years of the acquisition and neither acted a significant moderator in the relationship between ambiguity and acquisition performance. It is possible that experience has a more complex effect in this relationship. Another explanation is that the sample is biased. I examined large acquisitions with analyst coverage which may represent acquirers with homogeneous experience. Additionally, acquisitions at this level may have enough resources to mitigate the bias of their experience as well.

In summary, this research supports that ambiguity does matter in the performance of mergers and acquisitions although we clearly have more to learn about which types of ambiguity matter and under what circumstances. I found that there are significant direct relationships between many types of ambiguity and acquisition performance, but the types of ambiguity did not combine to act as latent variables meaning that ambiguity may not be a latent construct or there is still more work to do in defining and measuring ambiguity. Additionally, I found partial support for size as a moderator of the relationship between ambiguity and acquisition performance, but there was no support for a direct relationship between size and ambiguity. These results contradict the original hypothesis that decision-makers would allow more ambiguity in larger acquisitions but supports the hypothesis that ambiguity in larger acquisitions leads to poorer performance. This suggests a complex relationship between size, performance, and ambiguity in acquisitions. Last, experience did not act as a moderator between ambiguity and performance which could be a feature of this particular sample or suggests that the relationship between experience and performance in acquisitions is complex, which is supported by the literature. These findings create a path forward in investigating the role of ambiguity in the performance of mergers and acquisitions.

Contributions

This research made three important contributions to literature. First, I challenged the viewpoint in management literature that acquisitions are decisions under risk when they are decisions under ambiguity. Mergers and acquisitions have been studied as decisions under risk since the 1970s. Examining these critical strategic decisions as decisions under risk creates the assumption that decision-makers have all of the information necessary about potential outcomes and the probabilities of those outcomes before they make decisions in mergers and acquisitions.

This is not accurate and may have limited what we can learn from examining the antecedents of performance in mergers and acquisitions. In this research, I found support that ambiguity is present in mergers and acquisitions and that, generally, higher levels of ambiguity lead to poorer performance in acquisitions. This means that decisions makers not only face missing information about the merger and acquisition they are approaching, but they must make some judgments about the information available. This changes everything that we know about the strategic decisions of mergers and acquisitions and provides an alternative explanation for why we have been unable to explain the poor performance of mergers and acquisitions to date.

In the last 40 years, mergers and acquisitions have been examined as decisions under risk and researchers have focused their efforts on measuring that risk. Since researchers have not found a financial explanation for failure under risk conditions, they have moved to non-financial sources of failure that included personal responses to risk like overconfidence and hubris. Examining mergers and acquisitions as a decision under ambiguity will also face similar steps. We first need to understand how to measure ambiguity. This study measured industry, technology, and financial sources of ambiguity, but the results show that more work is needed to understand the sources and effects of ambiguity better. Next, we need to understand personal responses to ambiguity including individual responses concerning individual differences, gender, and ambiguity in teams. But the most critical piece of understanding in ambiguity, that is absent from risk research, is how, when, and where do decision-makers evaluate ambiguity. We can assume that ambiguity changes the process of decision making in that decision-makers must make assessments about the information that they have available, but it would be critical to understanding what the decision-making process looks like when ambiguity is considered.

Second, this study adds to research in psychological foundations of strategy. In merger and acquisition research, researchers have turned to behavioral or psychological viewpoints that guide behavior in these crucial organizational decisions only because examining financial sources of failure failed to produce results. Previous studies have examined behavior like hubris and overconfidence in the face of risk, with known outcomes and probabilities, but not when faced with ambiguity, where there is uncertainty about both outcomes and probabilities. This is a failure by researchers as we do not fully understand the cognitive process of decision-making when decision-makers undertake mergers and acquisitions. This research supports ambiguity as a critical feature of decision making in mergers and acquisitions and highlights the need to integrate individual and team responses to ambiguity into M&A research. The concept of ambiguity tolerance has been examined heavily in various branches of psychology (Furnham & Ribchester, 1995) as a personality variable (Budner, 1962) as well as a feature of organizations (Furnham & Gunter, 1993) and national cultures (Hofstede, 1980). Many organizational behaviorists have examined the relationship between ambiguity tolerance and individual level behavioral variables such as promotional preference, role autonomy, and job satisfaction. But while many management scholars in organizational behavior have adopted ambiguity as a critical feature in organizations, ambiguity has not been embraced and investigated in the strategic decision-making research and specifically in the merger and acquisition research. Today, we know very little about how individuals and top management teams respond when they are confronted by an array of unfamiliar, complex, or incongruent clues (Furnham and Ribchester, 1995). This first step in understanding could open doors to integrate psychology and strategy literature further and explore how ambiguity plays a role in strategy decisions, the cognitive issues involved in accounting for ambiguity in strategic decisions, as well as how ambiguity is integrated into organizational learning and memory, and other issues involving the psychology of management decisions.

Last, this research expands scholarship in decision theory by examining ambiguity in the context of a critical, real-world strategic decision. Currently, scholars examine decisions under ambiguity in lab-based or application studies and rooted in simple decisions and choices. This study has expanded the boundary of our understanding of ambiguity into complex, real-world decisions. We know that ambiguity is present and important in strategic decisions, but this study is only the first of many needed to understand how ambiguity may influence organizational decisions fully. First, we must reframe how we look at strategic choices in organizations so that we understand how decision-makers account for ambiguity in real-world decisions. Only examining decisions in a lab and under conditions of complete information has severely limited our understanding of the decision-making process in organizations today and specifically mergers and acquisitions. With the framework used in this paper of ambiguity as a measure of the quality of information, we can examine many choices (from small to large) in organizations to better understand how managers account for ambiguity today and what the most effective way to manage ambiguity in the future.

Future Research

While this study aimed to understand the effect of ambiguity in mergers and acquisitions better, many questions remain to understand how ambiguity effects strategic decisions fully. Most importantly, the effects of ambiguity in decision making are not guided by current theory. Multiple theories and decision models have been proposed to explain behavior in decisions under ambiguity, including expected utility theory, subjective expected utility theory (C. F. Camerer & Karjalainen, 1994; Trautmann & van de Kuilen, 2014), the Bayesian approach (Gu et al., 2004), traditional prospect theory, and cumulative prospect theory (Wakker, 2010) but each of these models fails to predict the effect of individual choices and ambiguity aversion. The Ellsberg paradox discussed earlier, demonstrates that when decision behavior is faced with decisions with ambiguity, they respond with behavior that is not predicted with existing theories. His experiments and further empirical analysis have found that individual feelings about ambiguity are not guided by a well-defined process and can extend to the data generating process itself. Applying these findings to the examination of strategic decision-making in the real world, we can see that individuals may respond to the unknown, or ambiguity, differently than they respond to decisions under risk where outcomes and probabilities are known. We saw the effect of ambiguity in this study, but a theory of ambiguity is required to help us explain this real-world phenomenon.

Second, further research in ambiguity should explore the definition of ambiguity. Modern research in this area has examined ambiguity as the quality of information (Camerer and Weber, 1992). In this study, I proposed that state ambiguity (a subset of state uncertainty) is when decision-makers have some, but not all, of the information needed about possible outcomes and probabilities of their decision based on quality of information available depending on the amount, type, reliability, and unanimity leading managers to see the organizational environment, or some feature of that environment, as unpredictable. In this study, the three ways that quality of information is identified (missing information, reliability of information, and amount of information) appeared to be three distinct constructs and were not related. Further analysis is needed to see if there are other aspects of information that should be measured and if there are distinct constructs within ambiguity and represent quality of information. Additionally, more examination is needed to see if some sources of ambiguity are more salient to decision-makers.

In this study, I examined the effect of mergers and acquisitions as a single example of a complex strategic decision but to fully understand ambiguity, and we should examine it in the context of other strategic decisions. In literature, ambiguity has mainly been examined in laboratory studies or simple replications or extensions of the Ellsberg experiment. This study examined one of the most critical and complex strategic decision-makers make in organizations today. There are many decisions from both simple to complex in organizations that could be examined to understand the effects of ambiguity better.

I also examined ambiguity that is confronted at the firm level and most specifically, how ambiguity effects decisions at the top management team or corporate board (Zhu, 2013) however, ambiguity aversion typically occurs at the individual level. Current research in ambiguity shows that while some individual traits like the Big 5, gender, and culture are associated with risk aversion, there are no identified relationships with ambiguity aversion. In future research, it would be essential to understanding what individual differences relate to ambiguity aversion and if these differences become stronger or disappear in real-world group decisions. Individual differences may be relevant to research in acquisitions as groups made up of individuals make decisions in mergers and acquisitions.

Last, size and experience have featured prominently in previous research in ambiguity although with mixed results. Unfortunately, this study did not clarify these relationships and only added to the confusion around how stakes and experience might influence how ambiguity effects decision making. Perhaps further definition and clarification of the construct of ambiguity would help identify the importance of where, when, and how stakes and experience may influence ambiguity effects and ambiguity aversion.

Limitations

While this study provided some support for the effects of ambiguity in the performance of mergers and acquisitions, there were limitations. A major limitation of this study was sample size. In this sample, analyst coverage which was required to measure expert agreement in Hypotheses H1b, H2b, and H3b. This limited the sample size to only 140 acquisitions over a 21-year period. A power analysis revealed that a sample of 146 acquisitions would be required to detect a small effect size. Not only was the sample below the threshold to detect the hypothesized effects, limiting the sample to acquisitions over $100 Million with analyst commentary may have added bias into the sample as analyst may have commented only on acquisitions with more ambiguity.

Another limitation of this study was the measures used as proxies for the types of ambiguity. While these measures were suggested and supported by previous research, it is possible that these measures did not accurately capture ambiguity. These measures assumed that increased complexity or turbulence introduces ambiguity, but it bears further examination of the relationship and distinction between ambiguity and complexity. These measures should be further explored, developed, and tested.

An additional limitation of this study is the use of cumulative abnormal returns as the measure of performance. Cumulative abnormal returns are a common measure to use when examining the strategic decisions of a firm but many decisions over time contribute to the returns of a firm, and it is possible that other decisions made by a firm that acquires may contribute to cumulative abnormal returns over time.

Implications for practitioners

Ambiguity has long been identified by practitioners as a challenge in decision making, e.g., Dill, 1958; Duncan, 1972; Lawrence & Lorsch, 1969) Given the complexities of today's global environment, scholars and practitioners agree that it is essential to understand the context of ambiguity (Alvarez & Barney, 2005) and create teams that can navigate it (Dibble & Gibson, 2017). In many cases, managers are taught that living with ambiguity is "part of the job" or a condition that must be "lived with." Mergers and acquisitions are massively expensive and critical choices for many organizations that regularly fail to deliver on short or long-term goals and may erode firm value (Haleblian et al., 2009) and these decisions are far too important to discount ambiguity as something that must be "lived with." This research supports the presence of ambiguity in mergers and acquisitions and establishes a relationship with ambiguity and the performance of mergers and acquisitions. So how do managers deal with ambiguity in a time-crunched world? Armed with this research, managers can take steps to actively identify ambiguity in mergers and acquisitions and take steps to reduce that ambiguity when it may negatively influence performance. In the future, researchers can add to the manager's toolkit with more direction about when and where ambiguity is most harmful to organizations.

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