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The Role of Predictions in Acquisition Decision Making: The Strategic Value of AI-Driven Foresight

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Abstract. We examine the role of predictions in acquisition decision making using stock market reactions as a context to formally highlight the foundations and implications of artificial intelligence (AI)–driven foresight. Drawing on behavioral perspectives, we propose that predictions related to market reactions can provide valuable foresight by capturing the wisdom of crowds of market participants and their assessments of value creation. As a result, these predictions, whereas probabilistic in nature, can enhance acquisition decision making in areas such as deal selection and target identification. Furthermore, we argue that predictions and the foresight they provide shape managerial expectations, and when actual market reactions deviate from predictions, they stimulate additional information gathering, which is reflected in processes such as deal completion. We provide evidence supporting these arguments by developing a novel measure of predicted market reactions that extrapolates prior reactions using machine learning models. Our findings highlight the informational value that predictions confer in acquisition decision making and provide formal support for investing in predictive capabilities and AI in such contexts. More broadly, we contribute to a richer understanding of the role of predictions and AI-driven foresight in strategic decision making by demonstrating not just their ex ante value in guiding managerial choices but also their ex post effects in terms of stimulating learning and subsequent information gathering.

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Keywords: artificial intelligence • strategic decision making • acquisitions • strategic foresight • machine learning • market reactions

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1. Introduction

In recent years, the rise of artificial intelligence (AI) has sparked growing interest in the role of predictions and predictive capabilities in strategic decision making. One area of strategic decision making in which predictive capabilities have drawn widespread interest is acquisitions.[1] The increasing prominence of predictive analytics in this realm raises some significant questions, including what role predictions play in acquisition decision making and what informational benefits they confer across various stages of the acquisition process.

In this paper, we develop and test a behaviorally grounded theory of the role of predictions in acquisition decision making with the goal of further understanding the applicability and potential consequences of AI. As strategic choices with long-term implications, acquisitions are characterized by high stakes and substantial uncertainty (Csaszar et al. 2024). Moreover, given the complexity of such decisions and predictions in acquisitions and in strategic decision making more broadly, they remain inherently probabilistic and stochastic in nature rather than deterministic (Tranchero 2024). Hence, it is unclear whether predictions confer meaningful benefits and systematically inform managerial actions despite their potential to fill in "missing information" (Agrawal et al. 2018, p. 24).

To test our behaviorally grounded propositions, we focus on a key performance outcome in acquisitions that has traditionally attracted the attention of diverse stakeholders, namely, stock market reactions to acquisition announcements. In prior research, stock market reactions to mergers and acquisitions (M&A) announcements have been among the most widely studied performance indicators because a significant proportion of announcements elicit negative investor responses. In addition, evidence suggests that managers and financial intermediaries, such as investment banks, have long paid attention to these reactions and have sought to anticipate them as best as possible (Rappaport and Sirower 1999) as they also affect postacquisition dynamics (Luo 2005), such as CEO turnover and employee morale (Lehn and Zhao 2006).

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Given that, in this context, managers have traditionally had strong incentives to predict market reactions and plan their actions, we explore two interrelated themes to address our research questions. First, we examine whether predictions related to market reactions provide foresight (Csaszar 2018, Kapoor and Wilde 2023) that enhances the efficiency and quality of acquisition decision making. For instance, informed by such predictions, managers may choose to pursue targets expected to elicit positive market reactions and avoid those likely to generate negative ones, thereby capturing added value in acquisition transactions. Second, given that predictions are inherently probabilistic and stochastic, we examine whether deviations from predictions matter and carry informational value that influences subsequent decision-making processes. This effect is likely to arise as managers integrate predictions with actual market reactions under uncertainty (Ke et al. 2024). When actual market reactions deviate significantly from predictions (i.e., when prediction errors are observed), these discrepancies generate new information that can shape subsequent decisions. We formalize this idea by proposing that predictions don't just provide ex ante foresight but also that the foresight forms the basis for managerial expectations in forward-looking decision models (Cyert and March 1963). We empirically test these latter effects by focusing on deal completion time, a stage in the acquisition process in which acquirers gather additional information about targets following the announcement but prior to making a full commitment.

To formally test our propositions, we develop a measure of predictions grounded in Brunswik's (1952) lens model (discussed further below; Csaszar 2018). The model suggests that managers are likely to form representations and predictions about market reactions by extrapolating from historical transaction outcomes (Brunswik 1952). To operationalize this idea, we employ machine learning (ML) techniques, which allow us to model such managerial representations without imposing restrictive functional forms. This operationalization is consistent with the assumption that managers make the best use of available information when making predictions and forming expectations (Muth 1961). Specifically, we compiled a data set of 13,237 public and private acquisitions completed by U.S. public acquirers between 1976 and 2022. Next, we trained ML models using 10,590 transactions from 1976 to 2012 to generate predicted market reactions for 2,647 transactions from 2012 to 2022 (i.e., an 80–20 train–test split ratio). We built the ML models using three alternative algorithms and a comprehensive list of 286 input variables (discussed below).

Our study yields several key findings. First, consistent with the theory-based view (Felin and Holweg 2024, Felin et al. 2024), we find that predicted market reactions to actual transactions executed by managers are, on average, higher in value than those associated with a set of random transactions. This result suggests that managers select acquisitions that are received more positively by the market than randomly constructed counterfactual deals, indicating that managers' selection criteria contain information aligned with market reactions. Following this finding, next we demonstrate that, despite their probabilistic nature, predictions by themselves provide meaningful foresight and enhance value creation in acquisitions. Specifically, we show that managers could potentially capture greater value had they forgone acquisitions with negative predicted reactions and pursued only those with positive predicted reactions. Finally, to empirically test that combining predictions with realized outcomes has real consequences, we focus on announced deals that were subsequently completed by acquirers. Here, we find that the greater the absolute difference between predicted and actual market reactions—representing the level of surprise or prediction error—the longer the deal completion time in our test sample of 2,647 transactions. Figure 1 provides a graphical summary of this portion of our empirical framework.

Our study contributes to the literature in several ways. First, we develop and test a theoretically grounded set of propositions about the value of predictions in acquisition decision making. In doing so, we lay the groundwork to address a foundational question for the strategy field: can AI do strategy? Specifically, our analysis offers a way to conceptualize how AI and algorithmic predictive capabilities can inform acquisition decisions and shape their outcomes as these capabilities are deployed at scale (cf. Csaszar et al. 2024). Whereas we elaborate on these implications in our discussion section, it is worth noting that, in various fields, such as finance and law (Kleinberg et al. 2018), rigorous studies have already demonstrated the value of predictions for decision makers such as fund managers and judges. Our goal is analogous in that we aim to develop a deeper theoretical and empirical understanding of predictions as a construct with informational value that can provide strategic foresight. Although the role of predictions itself has been examined in social studies long before the advent of AI (Bubeck et al. 2023, Katz et al. 2024), rigorous, theory-driven analyses remain scarce in strategy research. We seek to address this gap by providing formal evidence of the strategic value of predictions and AI-driven predictive capabilities in acquisition decision making.

Second, we extend understanding of predictions in contexts characterized by "project evaluation with rich data" (Csaszar and Ostler 2020, Choudhary et al. 2023), in which predictions are inherently stochastic and probabilistic rather than deterministic. We examine this dimension by focusing on deviations from predictions,

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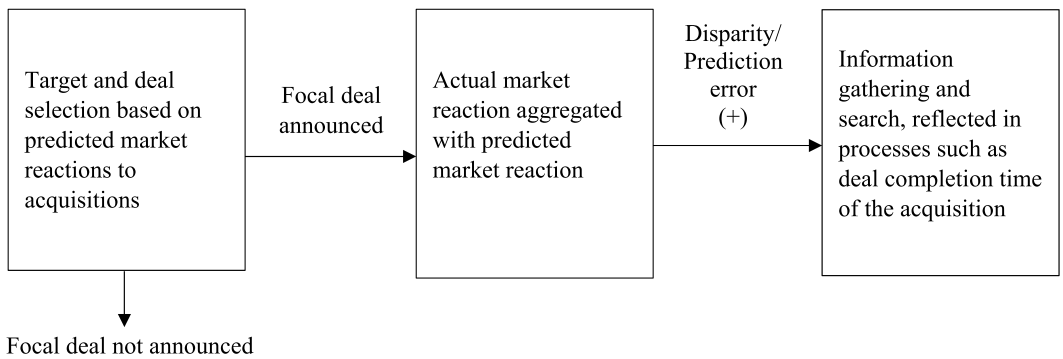
Figure 1. Framework Relating Aggregation Processes to Deal Completion Time



or prediction errors, and their influence on subsequent information-gathering processes, such as deal completion. In doing so, we consider how prior beliefs are integrated into updated beliefs (Ke et al. 2024) by unpacking what follows after actual outcomes and deviations are observed. In this regard, we also advance the behavioral theory tradition rooted in the Carnegie School. Whereas prior research in that tradition emphasizes backward-looking mechanisms, such as performance relative to aspiration levels (Cyert and March 1963, Gavetti and Levinthal 2000), we highlight a complementary, forward-looking mechanism: decision making shaped by outcomes relative to predictions. As predictions increasingly form the basis for managerial expectations, particularly through AI-enabled decision making, they may influence not only how managers interpret actual outcomes but also how they learn and adapt over time through the latter mechanism and the effect of prediction errors.

The rest of the paper proceeds as follows. In the next section, we take a deeper look at why predictions matter and how managers are likely to develop them in the context of acquisitions and market reactions. Following that, we turn to the ex post consequences of predictions and prediction errors as well as their effects on subsequent acquisition processes, such as deal completion. Next, we describe our sample and the models used for the empirical tests, followed by a presentation of the results. We conclude by discussing the broader implications of our findings for improving understanding of the role of AI and predictive capabilities in acquisition decision making.

2. Theory and Hypotheses

2.1. Mental Models and Predictions Related to Market Reactions

The strategy literature has long recognized the central role of predictions in decision making. At a fundamental level, predictions provide foresight in contexts characterized by complexity, uncertainty, and irreversible consequences (Csaszar and Laureiro-Martínez 2018). In such contexts, predictions are likely to be grounded in managers' mental representations of the environment, serving as a basis for formulating and executing various theories of value creation.

These arguments raise an important question: how do managers form predictions in different strategic contexts, including those involving key outcomes, such as market reactions related to acquisitions? To flesh out this aspect, we draw on Brunswik's (1952) lens model (see Csaszar 2018 for details). The Brunswik (1952) model posits that a prediction involves a manager first identifying a set of incoming cues, or x's, relevant to an outcome y. Managers then assign weights, represented by coefficients $\hat{\beta}$'s, to these cues, thereby constructing an internal representation that relates the x's to the outcome y (Hammond et al. 1964). The weighted combination of cues and coefficients produces a predicted value $\hat{y}$, which is subsequently used in decision making. The accuracy of this mental model is reflected in the prediction error: the distance between the observed outcome y and the predicted value $\hat{y}$. Whereas the determinants of prediction errors are theoretically interesting for understanding when managerial mental models are accurate or biased, our initial focus lies on $\hat{y}$ itself, specifically, whether managers' informationally sensitive models and representations produce predictions and $\hat{y}$ s that have value for decision making. In the next section, we turn to the implications of prediction errors for subsequent decision making by discussing their relationship with information gathering and learning processes.

In the context of acquisitions and market reactions, one plausible mental model through which managers may form estimates of $\hat{y}$ (whether explicitly or implicitly) is by drawing on cues and outcomes from prior transactions. This argument aligns with the view that analogical reasoning is central to forming representations and predictions when developing foresight (Gavetti and Menon 2016). In such a predictive model, the x's represent cues, such as acquirer and target characteristics, deal attributes, environmental conditions,

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and so on, whereas the $\widehat{\beta}$'s denote the weights assigned to these cues by managers in producing a predicted market reaction. Prior research suggests that this process—analogical, boundedly rational, and theoretically grounded—also captures the wisdom of crowds in financial markets and reflects investors' assessments of value creation. Specifically, the $\widehat{\beta}$'s, by estimating the weight that the market assigns to each cue, are likely to be correlated with the true importance of that cue for value creation at the time of deal announcement (Csaszar and Laureiro-Martínez 2018). Accordingly, managers can develop and use such internal representations of market reactions to form predictive assessments of value creation for future transactions under consideration.

These arguments, rooted in the notion of semistrong market efficiency, underpin a large body of research examining both the sources of variation in market reactions to acquisition announcements and the consequences of these reactions. For instance, a substantial literature employing event study methodologies investigates how market reactions to acquisition announcements are influenced by various deal fundamentals, keeping with the idea that the weights assigned by the market to these incoming cues (which managers estimate in their internal representations) are meaningful. This research has produced influential insights that form the foundation of our understanding of acquisitions. For example, Chatterjee (1986) and Lubatkin (1987) find that related mergers create greater value than conglomerate mergers as reflected in abnormal stock returns to acquiring firms. Building on this finding, subsequent work, such as Capron and Pistre (2002) and Kim and Finkelstein (2009), explores the role of strategic fit and resource complementarity between acquirers and targets in driving value creation. Another stream, such as Haleblian and Finkelstein (1999), Hayward (2002), Laamanen and Keil (2008), McDonald et al. (2008), Arikan and McGahan (2010), and Kim and Finkelstein (2009), views market reactions as outcomes of organizational learning and experience in acquisitions. Taken together, this research shows that relating market reactions to cues such as resource complementarity and acquirer experience when forming predictions has a valid basis.

Paralleling this line of research, a second stream examines how market reactions as outcomes provide performance feedback for managers (Schijven and Hitt 2012), and this can shape subsequent decision making. This perspective starts with the premise that, although managers possess extensive private information about their firms and potential targets, market investors often hold additional information that is novel or unavailable to managers (Chen et al. 2007). In the context of acquisitions, such information may concern how a transaction could reshape product market conditions or alter the firm's competitive landscape (Chen et al. 2007). Market reactions also provide an external evaluation of a transaction, one that may be less affected by the cognitive biases that frequently influence managerial judgments. Indeed, prior research shows that acquisitions are prone to a wide range of managerial biases (although markets may be biased in their own ways), including hubris and escalating commitment (Jemison and Sitkin 1986, Roll 1986), which market feedback may help mitigate. Furthermore, markets may embed expectations about the future prospects of the target and its industry that managers may not have fully incorporated. Consistent with this performance feedback view, studies find that firms experiencing favorable market reactions to prior acquisitions are more likely to undertake subsequent acquisitions in the near term (Haleblian et al. 2006, Kim et al. 2015) and to assume greater risk (Kumar et al. 2015).

In sum, prior research provides compelling arguments for why managers may benefit from investing effort in predicting market reactions to acquisitions, particularly by drawing on historical transactions and their associated cues. In semistrong markets, such predictions enable managers to anticipate synergies, among others, in a focal transaction and develop foresight with the subsequent realization of actual reactions providing additional performance feedback once observed. More formally, extending Brunswik's (1952) model, let W denote a vector of weights that capture the importance that the manager assigns to each characteristic of the acquisition transaction in the manager's mental representation. The weights W represent the manager's estimates (i.e., $\widehat{\beta}$'s) of the true but unobservable weights that the market assigns to each transaction characteristic (Hammond et al. 1964, Csaszar 2018). Once this representation is developed, W can now be applied to a future transaction under consideration to generate a predicted market reaction, thereby providing managers with an estimate of how the market is likely to respond to a deal. The predicted reaction has value in that it offers managers a forward-looking mechanism and signal that can complement their own private assessments of a target's potential. Formally, these arguments lead to the following testable hypothesis.

Hypothesis 1. *Predictions of market reactions based on historical transactions and their incoming cues confer informational value and foresight and enhance acquisition decision making in ex ante deal selection.*

The above analysis raises two related issues. The first concerns the functional form of W, which contains the estimated coefficients, $\widehat{\beta}$'s that relate incoming cues to market reactions. Because, as researchers, we do not have exact knowledge of W a priori, we may allow the data to speak for themselves. In this regard, machine learning offers a particularly useful approach, enabling

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us to estimate *W* across a sample of acquirers without imposing restrictive functional form assumptions other than that managers will attempt to maximize prediction accuracy by extrapolating from prior reactions. The second issue relates to the interpretation of market reactions. Some studies argue that announcement window reactions should be viewed primarily as indicators of market sentiment at the time rather than as measures of long-term value creation (Zollo and Meier 2008). We agree but emphasize that, even under this interpretation, predicting such reactions remains valuable, because markets often hold information that is distinct from that of managers. Hence, our approach treats predictions of market reactions as one input into the broader acquisition decision-making process along with managers' subjective assessments based on current information, etc.

Whereas the above hypothesis focuses on the informational value and benefits of predictions in conferring foresight, we now turn to the idea that predictions in strategic decision making are inherently probabilistic and subject to error; that is, they inevitably deviate from actual outcomes and are themselves stochastic (Tranchero 2024). This perspective implies that such deviations or prediction errors may themselves carry informational content, an aspect we examine next.

2.2. Predicted Market Reactions and Deviations

To unpack how predictions influence decision making ex post once actual outcomes are observed, we return to the behavioral roots of the Carnegie School. A central insight in this tradition, first advanced by Muth (1961), is that predictions form an important (though not exclusive) basis for managerial expectations about the future. Muth (1961, p. 316) argues that expectations are "informed predictions of future events" derived from relevant theory and the information available within the system as a whole. This argument aligns closely with our above discussion of market reactions, whereby managers can be seen as drawing on both market-wide information and their own specific information to form expectations and predictions about the performance of a prospective transaction.

Building on Muth's (1961) insight, Cyert and March (1963) argue that managerial decisions often stem from deliberate attempts to anticipate future events such that decision making is fundamentally driven by performance expectations. Relatedly, Simon (1947) emphasizes that individuals' behavior is shaped jointly by knowledge, memory, and expectations and that the more purposive an action, the more it depends on the actor's expectations about the future. Extending this reasoning, Gavetti and Levinthal (2000) propose that the type of intelligence that managers use in decision making reflects the joint influence of two decision logics: a backward-looking logic rooted in experiential learning and a forward-looking logic grounded in beliefs and expectations about potential action–outcome linkages.

These arguments yield additional testable implications that deepen our understanding of the role of predictions in decision making under uncertainty. Prior work in the behavioral theory tradition largely emphasizes managerial responses to outcomes relative to historical aspirations. However, the view that predictions provide foresight and serve as a basis for expectations suggests that they can also have ex post consequences as these expectations are carried over into the next phase of decision making when actual outcomes are observed. At this stage, deviations between predicted and actual outcomes, that is, prediction errors, may elicit further behavioral responses as previously formed expectations are violated and an element of surprise arises. The importance of such deviations is also supported by studies in cognitive science that highlight the role of prediction errors in driving learning and adaptive intelligence (Friston 2010). For instance, Sinclair et al. (2021) find that prediction errors prompt the hippocampus to engage in representational updating rather than mere memory preservation, and this tends to occur when observations largely conform to predictions.

Building on these perspectives, in our study, we investigate how deviations from predicted market reactions influence the acquisition decision-making process, particularly when predictions serve as a basis for managerial expectations and foresight. We argue that, when managers announce a transaction and the market reaction conforms to predictions, managers' expectations and beliefs are confirmed, leading to limited follow-on actions. In contrast, when market reactions significantly deviate from predictions, the discrepancy conveys new information, namely, that past patterns may not extrapolate to the present and that the focal transaction may possess unique features relative to historical deals. Under such circumstances, we propose that the magnitude of the deviation from predictions (i.e., the distance between the actual cumulative abnormal return (*CAR*) and predicted *CAR*), prompts more intensive and deliberative managerial responses as decision makers seek to reduce uncertainty and improve acquisition outcomes.

One area in which these deliberative information-gathering processes are likely to manifest is the deal closure phase of an acquisition, that is, the period between the public announcement of an intended transaction when the market first reacts and the formal completion date when the deal becomes legally effective. During this interval, both predicted and actual market reactions remain salient in managers' minds as they assess the market's response to the announcement and compare it with their expectations and predictions. The predeal phase following the announcement

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represents a critical stage in the acquisition process (Welch et al. 2020), serving not only to secure approvals from shareholders and regulatory authorities but also enabling acquiring-firm managers to collect extensive information about the target through due diligence. This due diligence typically involves reviewing the target's financial statements, operational data, and contractual agreements as well as developing integration plans to capture postacquisition synergies. Additionally, managers also evaluate cultural fit during this critical phase (Barney 1988, Makri et al. 2010, Bauer and Matzler 2014, Grimpe and Hussinger 2014, Sears and Hoetker 2014, Bingham et al. 2024). Importantly, acquirers retain the option to withdraw from the deal throughout this phase—albeit at nontrivial cost—if new information reveals heightened risk. Thus, deal completion can be viewed as an information-gathering process that combines the option to acquire additional information with the option to terminate the transaction if there is greater risk perceived. Pavićević and Keil (2021) further suggest that a longer duration of the predeal phase reflects greater procedural rationality as managers engage in more comprehensive information gathering before committing to the acquisition.

In light of these dynamics, we argue that, when actual and predicted market reactions are closely aligned, prior expectations in managers' forward-looking decision models are reinforced as the market reveals minimal new information. In such cases, managers gain confidence in their understanding of the transaction's likely consequences and proceed toward deal completion without extensive additional information gathering. In contrast, when actual market reactions deviate significantly from predictions—contradicting the foresight and expectations on which managers have anchored their decisions—managers are likely to treat this discrepancy as valuable new information. They may then engage in more deliberative reassessments to improve decision quality and acquisition outcomes before making final commitments. Such deviations can occur under two scenarios: when actual market reactions are far worse than predicted (i.e., a negative surprise) or far better than predicted (i.e., a positive surprise).

In the first scenario, when actual market reactions are far worse than predicted, managers may interpret the result as a warning sign that the transaction's potential and associated risks warrant closer scrutiny (Rock 1986). Depending on the magnitude of the discrepancy between actual and predicted reactions, managers may engage in varying degrees of additional information gathering to identify critical factors that were previously overlooked and to reassess the assumptions underlying their evaluations. As a result, larger deviations in the form of negative surprises may induce more extensive due diligence and greater procedural rationality prior to full commitment, leading to a longer deal completion time.

In the second scenario, when actual market reactions are far better than predicted, a risk–return paradox emerges or what Kim et al. (2015) describe as the "momentum versus caution" paradox. On the one hand, favorable market reactions may indicate that investors feel more positively toward the transaction than comparable historical deals. This alignment can reinforce managers' foresight and previously formed expectations, motivating managers to maintain momentum and proceed swiftly toward deal completion. On the other hand, reactions that significantly exceed predictions can also induce caution. As prior research notes, unusually high market valuations relative to management forecasts often signal that shareholders expect exceptional value creation and higher rates of return (Rappaport 1987, Mishina et al. 2010, O'Brien and David 2014, Xu et al. 2019). Consequently, when actual market reactions greatly surpass predictions and previously formed expectations, managers face the challenge of determining whether they can credibly deliver on these elevated expectations (Sirower and Weirens 2022). This may require identifying additional value-creating opportunities, keeping the option to terminate the transaction open. Indeed, evidence shows that managers sometimes withdraw even from deals that initially received favorable market responses (Luo 2005). Kim et al. (2015) also suggest that, in uncertain contexts, in which cause-and-effect relationships and performance outcomes are ambiguous, managers are particularly prone to risk aversion (Kahneman and Tversky 1979), and this can tilt the balance toward caution despite positive market sentiment.

In sum, we propose that predictions and the foresight they provide serve as an important foundation for managerial expectations. Consequently, deviations from these predictions, or prediction errors, are likely to matter and influence subsequent decision-making processes. Such deviations reveal new information in the face of uncertainty, prompting managers to update their expectations and adjust their behavior accordingly (Ke et al. 2024). In the context of acquisitions and market reactions, this suggests that the greater the difference between actual and predicted reactions—whether positive or negative—the more extensive the postannouncement information-gathering and learning processes are likely to be, leading to longer deal completion times. Figure 1 summarizes our framework and motivates the following testable hypothesis, which lays the foundation for unpacking how AI-based predictions can have ex post consequences.

Hypothesis 2. *The larger the absolute disparity between actual and predicted market reactions related to an acquisition announcement, the longer the deal completion time.*

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3. Methods

3.1. Data and Sample

To test our hypotheses regarding the effects of predictions on acquisition decision making, we constructed a sample comprising all completed acquisition transactions by U.S. public acquirers in which the acquirer obtained 100% ownership of the target firm. The data were obtained from the Refinitiv database and span the period from 1976 (the earliest year available) through 2022. We keep only (a) transactions that involve a U.S. public or private target, (b) transactions that are not buybacks, (c) transactions that do not involve financial services acquirers or targets (Standard Industrial Classification (SIC) codes 6000–6999), and (d) transactions that have a deal value of at least $10 million (inflation-adjusted based on 2015 dollars) (Eckbo et al. 2018, Derrien et al. 2023). In addition, we drop instances in which more than one deal is announced by an acquirer on a single day because market reactions to each deal cannot be separately measured. The final sample includes 13,237 acquisition transactions completed by 5,624 unique acquirers. We obtain stock price data from the Center for Research in Security Prices database, firms' annual accounting data from the Compustat database, and monthly macroeconomic data from the Federal Reserve Economic Data database.

3.2. Predictions of Market Reactions

3.2.1. Overview. Following Brunswik's (1952) model and our earlier discussion, we use ML models to construct a measure of predicted market reactions. In essence, ML models serve as empirical analogues for managerial representations or mental models (denoted by the coefficients W) as these decision makers extrapolate from past market reactions to capture the wisdom of crowds of market participants. Theoretically, this approach aligns with Muth's (1961) proposition that predictions formed on the basis of "knowledge in the system as a whole" provide an important foundation for managerial expectations. It is important to note that, in our study, ML functions primarily as a methodological tool that enables us to test the theoretical effects of predictions and illuminate the role of AI systems in strategic decision making although these systems may also employ other predictive technologies besides ML.

To develop our ML models, we split the sample into a training and a testing set using a standard 80–20 train–test split ratio. The training set consists of 10,590 transactions completed between January 1, 1976, and May 18, 2012, whereas the testing set includes 2,647 transactions completed between May 19, 2012, and December 31, 2022. We implement a time series split to ensure that the models are trained only on past transactions and evaluated on subsequent ones, thereby preventing the models from learning from future data and avoiding information leakage (Choudhury et al. 2021).

We consider three alternative ML algorithms, including elastic net, random forest, and gradient-boosted tree, ranked in order of increasing algorithmic complexity. We then select the model with the highest explanatory power in the training set to generate predictions used in testing Hypotheses 1 and 2. This approach assumes that the most informative models best approximate managerial representations as managers attempt to maximize predictive accuracy. As a benchmark, we estimate an ordinary least squares (OLS) regression, which assumes linear relationships among the input cues (the x's in the Brunswik lens model). To enhance out-of-sample performance and capture the information embedded in the data without imposing a priori functional form assumptions, we tune the hyperparameters in the ML models using five-fold cross-validation. The cross-validation procedure also follows a time series split between training and validation subsets, ensuring that predictions are based on past transactions and evaluated on future ones.

3.2.2. Output Variable. The output (or response) variable in our ML models is the market reaction to the acquisition announcement. Following prior acquisition research (Haleblian and Finkelstein 1999, King et al. 2004, Kim et al. 2015, Kumar et al. 2015, Gartenberg and Yiu 2023), we measure market reactions using an event study methodology that calculates the CAR to the acquirer's stock surrounding the announcement date. Specifically, we compute CAR using an event window of (−1, +1) days to take into account potential information leakage prior to the announcement and to capture the adjustment of the stock price immediately thereafter with $t = 0$ representing the announcement date. A short window such as (−1, +1) is appropriate because the majority of price movement typically occurs on the announcement day (Kim et al. 2015) with minor reactions just before and after. We also conducted robustness checks with alternative event windows of (−1, 0), (0, 1), and (0, 2) and found consistent results. Formally, we estimate CAR using the following model:

$$CAR_{i,t} = \sum_{t=-1}^{1}(R_{i,t} - \widehat{R_{i,t}}), \quad (1)$$

where $R_{i,t}$ is the realized stock return of firm i on day t and $\widehat{R_{i,t}}$ is the expected stock return of firm i on day t had the acquisition not been announced. We estimate $\widehat{R_{i,t}}$ using the Fama–French three-factor model over an estimation window of (−250, −50) days relative to the announcement date.

Below, we use this variable to conduct various tests of Hypothesis 1, including comparing its value to actual reactions and considering how it differs across actual and hypothetical reactions. The details of these tests pertaining to predictions and foresight (Hypothesis 1) are

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presented in the results section later and are deferred for now.

3.2.3. Input Variables. To capture the incoming cues (x's) as comprehensively as possible and to approximate managerial representations (W), we use an exhaustive set of 286 input (predictor) variables detailed in Online Appendix A. These variables are grouped into five categories. The first category comprises deal-specific attributes recorded in the Refinitiv database, including the percentage of shares sought by the acquirer, percentage of cash payment, number of bidders, transaction attitude (friendly, hostile, or neutral), and public status of the target (Travlos 1987, Martin 1996, Schwert 2000, Shleifer and Vishny 2003, Moeller et al. 2004, Laamanen et al. 2014). We also capture acquirer–target relatedness through measures of business similarity based on whether the two firms share the same four-digit SIC code (Bennett and Feldman 2017) and geographical proximity between acquirer and target locations (Schildt and Laamanen 2006, Chakrabarti and Mitchell 2016, Bick et al. 2017, Bingham et al. 2024).

The second category of input variables captures the characteristics and accounting performance of the acquirer and the target, constructed from the Compustat database. For acquirers, we account for their size, market capitalization, profitability (return on assets (ROA)), Tobin's Q, leverage ratio, research and development (R&D) intensity, and so on (Grimpe and Hussinger 2014) as well as their industry average performance (e.g., industry average ROA) (Carow et al. 2004, McNamara et al. 2008). For targets, because the accounting performance of private targets is unknown, we only account for their industry average performance based on their SIC code recorded in the Refinitiv database. In addition, we account for the relative size of the acquirer and the target (using industry averages for private targets) (Jarrell and Poulsen 1989, Seth 1990, Loughran and Vijh 1997).

The third category of input variables captures the prior acquisition activities and performance of the acquirer, such as the number of its prior acquisitions, the average announcement returns to its prior acquisitions, and the announcement returns to its most recent acquisitions (Haleblian and Finkelstein 1999, Hayward 2002, Haleblian et al. 2006, Laamanen and Keil 2008, Ellis et al. 2011, Basuil and Datta 2015). These variables account for the effect of historical performance and aspiration levels of experienced acquirers as well as their impact on expectations and predictions. For acquirers without prior transactions, we set these variables to zero (Kim et al. 2015).

The fourth category of input variables captures the activity and performance of recent acquisitions conducted by all the firms in the market prior to a focal acquisition. We include variables such as the number of acquisitions over the six months prior to the focal deal announcement, the average announcement returns of these acquisitions, and the standard deviation of their announcement returns. By including these variables, we account for the effects of merger waves and recent investor sentiment surrounding M&A transactions (Amburgey and Miner 1992, McNamara et al. 2008).

The fifth category of input variables captures the macroeconomic factors prior to the announcement of a focal acquisition (Mitchell and Mulherin 1996), such as the volatility of the stock market and the percentage of acquisition transactions reviewed by the Federal Trade Commission (FTC). All the input variables are winsorized at the 2.5% and 97.5% levels to mitigate the effect of outliers. In addition, the input variables are standardized in the linear elastic net model to mitigate the impact of the scale of the variables on prediction performance.

3.3. Regression Analyses of Deal Completion Time

Building on our ML-based measure of predicted market reactions, we next test Hypothesis 2 by examining how deviations between predicted and actual reactions affect subsequent stages of decision making as reflected in deal completion time. The regression analyses use the 2,647 transactions in the ML testing set for which we obtained *Predicted CAR* values from the trained ML models.

3.3.1. Dependent Variable. The dependent variable in our regression analyses is deal completion time during the closure phase of an acquisition transaction (*Deal Completion Time*). We measure it as the logarithm of one plus the number of days between the public announcement date of an intended transaction and its completion date, using data from the Refinitiv database. In our testing sample, the average deal completion time is 59 days. Transactions involving private targets take an average of 42 days to complete, whereas those involving public targets take an average of 128 days. These statistics are broadly consistent with previous studies with some variations because of the sampling criteria (see Dikova et al. 2010, Chahine et al. 2018).

3.3.2. Independent Variable and Control Variables. When testing for Hypothesis 2 for a given transaction in the test set, we measure the distance between the actual and predicted market reactions (*CAR-Predicted CAR Disparity*) by the absolute difference between the actual *CAR* and the *Predicted CAR* generated by the trained ML model. This value represents the prediction error or surprise associated with the transaction, encompassing both positive and negative deviations.

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In terms of control variables, we follow prior literature and control for a number of variables that may be associated with deal completion time. First, at the transaction level, we control for deal attributes including public status of the target (dummy), percentage of stock payment (in decimal), relative deal size (deal size over acquirer assets) (Luo 2005, Paul 2007, Dikova et al. 2010, Muehlfeld et al. 2012, Kim et al. 2015, Luypaert and Maeseneire 2015, Li et al. 2017), and acquirer-target relatedness. These factors can influence the complexity of a transaction and the likelihood of acquisition success, thereby affecting deal completion time independent of prediction errors. In terms of acquirer–target relatedness, we control for both their (a) business similarity, which is a dummy variable that is one if the acquirer and the target have the same four-digit SIC code and zero otherwise, and (b) geographical proximity measured by the distance between the states of their headquarters (logarithm of thousand miles) recorded in the Refinitiv database.

Second, we control for regulatory scrutiny and preannouncement due diligence time. To control for the influence of regulatory review on deal completion time, we construct two variables: (a) a merger enforcement action indicator (*FTC Enforcement*), which is a dummy variable that is one if the focal transaction is reviewed by the FTC and zero otherwise, and (b) the number of transactions reviewed by the FTC over the past 90 days prior to the focal acquisition announcement (*FTC Transactions Reviewed* in logarithm). Both measures are constructed based on the public information on the FTC website (https://www.ftc.gov/policy-notices/open-government/data-sets). To control for the impact of preannouncement due diligence on deal completion time, we construct the variable *Pre-Announcement Days*, measured by the logarithm of one plus the number of days between the date when the target publicly announces its search for buyers and the announcement date of the focal transaction by the acquirer. The date when the target starts looking for an acquirer is recorded in Refinitiv.

Third, at the acquiring firm level, we control for the acquirer's accounting performance and prior acquisition experience. We control for major performance measures of the acquirer, including its profitability (ROA), Tobin's Q, and leverage ratio (i.e., debt-to-equity ratio) (Li et al. 2017, Chahine et al. 2018). To account for the possibility that managers learn from prior acquisitions to improve the efficiency of the current decision, we control for the acquirer's prior acquisition experience (Muehlfeld et al. 2012, Bick et al. 2017), measured by the logarithm of one plus the total number of previous transactions conducted by the acquirer. Additionally, we control for the historical average performance of the acquirer's prior acquisitions measured by CAR (Kim et al. 2015). Finally, we control for the impact of M&A waves on the completion of current transactions (Heath and Mitchell 2023), measured by the logarithm of one plus the total number of transactions conducted by all firms (not limited to the focal firm) in the past 90 days prior to the announcement of the focal transaction.

We specify the following OLS regression model to test our Hypothesis 2:

$$\begin{aligned} &\textit{Deal Completion Time} \\ &\quad = \alpha + \beta \times abs\,(\textit{CAR} - \textit{Predicted CAR}) + \textit{Controls} \\ &\qquad + \textit{Industry FE} + \textit{Firm FE}. \end{aligned} \tag{2}$$

4. Results

4.1. Predictions and Foresight

Table 1 reports the in-sample and out-of-sample performance of the ML models used to generate our prediction measure, including elastic net, random forest, and gradient-boosted tree algorithms. The table also compares these models with the benchmark OLS model. Among these models, the random forest model yields the highest R^2 in both the training set and test set, indicating superior predictive performance. As expected, the OLS model performs the worst in the test set, exhibiting a negative adjusted R^2, consistent with its tendency to overfit when applied to complex, high-dimensional data.

It is noteworthy that the R^2 achieved by the random forest model in the test set is comparable in magnitude to those reported in prior studies demonstrating the value of prediction-driven foresight in other settings. For instance, Gu et al. (2020) report an R^2 of 4.8% when predicting stock returns, and Bali et al. (2023) report an R^2 of 2.26% when predicting option returns. These levels of explanatory power reflect the inherent complexity and uncertainty of predicting market-related outcomes. Importantly, both studies show that portfolio managers can capture substantial value and outperform benchmarks even at these levels of explanatory power. In our analysis, we obtain comparable R^2 levels when predicting abnormal reactions, variables that are themselves residuals from market models. As such, our R^2 estimates are consistent with those observed in numerous event studies employing abnormal returns as dependent variables in cross-sectional regressions.

Because the random forest model yields the highest R^2 and best captures the information embedded in the system as a whole, we use the coefficients generated by this model as a proxy for managerial representations used to generate predictions. Following the model choice, we also calculate the importance of each input variable in predicting market reactions. Although this is not the primary focus of our study, ML models can serve exploratory purposes by identifying salient

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Table 1. Prediction Performance of ML Models

Model		Mean absolute error	Mean squared error	R^2
OLS (benchmark)	Train	0.049	0.005	0.079
	Test	0.075	0.010	−1.215
Elastic net	Train	0.050	0.005	0.029
	Test	0.046	0.005	0.013
Random forest	Train	0.033	0.002	0.547
	Test	0.046	0.004	0.041
Gradient-boosted tree	Train	0.043	0.004	0.268
	Test	0.046	0.005	0.009

Notes. ML models are trained using time series fivefold cross-validation. The elastic net model uses a penalty term of 0.05 and an L1 ratio of 0.05. The random forest model uses a maximum depth of 20, a minimum of 10 samples per leaf, a minimum of five samples to split a node, and 300 trees. The gradient-boosted tree model uses a learning rate of 0.001, a maximum depth of 20, a minimum of 10 samples per leaf, a minimum of five samples to split a node, and 300 boosting stages. The input variables are standardized in the linear elastic net model. The OLS model has a negative value of R^2 (= 1 − residual sum of squares/total sum of squares) in out-of-sample performance (rather than a positive value) because, when evaluating the performance of the model that was trained on the training set, there is no guarantee that the differences between the actual and predicted values of CAR in the testing set (i.e., residual sum of squares) will be smaller than the variation of CAR within the testing set itself (i.e., total sum of squares). A negative R^2 indicates that the OLS model generalizes poorly to the testing set.

patterns in the data through post hoc analyses (Choudhury et al. 2021). This investigation further supports the construct validity of using the random forest predictions to proxy for managerial representations and foresight. Hence, for the interested reader, in Table 2, we present the 10 most important predictors of market reactions based on (a) impurity-based importance scores from the training set and (b) permutation-based importance scores from the training or testing set. Across all metrics, relative deal size (deal size over acquirer assets), target public status, and percentage of stock payment emerge as the top three predictors. Other important variables include acquirer characteristics (e.g., firm size), industry conditions of both acquirer and target, and the performance of recent acquisitions in the market. Additional analyses and visualizations, including an example decision tree from the random forest model, are reported in Online Appendix B. Overall, these results are consistent with prior research and reinforce the notion that predictions derived from ML models meaningfully capture the impact of key informational cues, thereby providing the foundation for our subsequent econometric analyses.

In terms of the actual CARs, in our sample, the average market returns to acquisition announcements across all transactions is 0.787% with a standard deviation of 0.070 after being winsorized at the 2.5% and 97.5% levels. For 3,507 acquisitions of public targets, the average announcement return is −0.777% with a standard deviation of 0.070 (significantly different from zero at the 0.1% level, p = 0.000); for 9,730 acquisitions of private targets, the average announcement return is 1.351% with a standard deviation of 0.069 (significantly different from zero at the 0.1% level, p = 0.000). The average announcement return is 0.683% with a

Table 2. Ten Most Important Input Variables in Random Forest Model

	Impurity-based importance (training)	Permutation-based importance (training)	Permutation-based importance (testing)
1st	Relative deal size	Relative deal size	Relative deal size
2nd	Target public status	Target public status	Target public status
3rd	Percentage of stock payment	Percentage of stock payment	Percentage of stock payment
4th	Acquirer net assets	Acquirer net assets	Acquirer industry return
5th	Value of common stock	Initial offer price	Acquirer net assets
6th	Acquirer earnings before interest and taxes	Acquirer firm size	Same industry indicator
7th	Initial offer price	Acquirer industry return	Offer price premium
8th	Acquirer industry return	Acquirer market capitalization	Acquirer earnings before interest and taxes
9th	S&P 500 return	Acquirer earnings before interest and taxes	Last-three-month average announcement returns
10th	Target industry return	Value of common stock	Acquirer R&D intensity

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standard deviation of 0.070 in the training set, and it is 1.200% with a standard deviation of 0.068 in our testing set. These summary statistics conform well with prior research on acquisitions.

In terms of predicted values, the average predicted CAR in the training set is 0.714% with a standard deviation of 0.026, and it is 0.664% with a standard deviation of 0.015 in the testing set. In the testing set, the actual and predicted CAR differ significantly at the 5% level. This discrepancy arises because the actual CAR includes extreme values with a minimum value of −14.866% and a maximum value of 20.394% (winsorized at the 2.5% and 97.5% levels). In contrast, the ML predictions are inherently less extreme with a minimum of −3.01% and a maximum of 4.32% (winsorized at the 2.5% and 97.5% levels).

With this background, next, we turn to testing Hypothesis 1 that predictions can provide important foresight and facilitate acquisition decision making in areas such as deal selection. As a preliminary step, we adopt various binomial tests that are used widely in the M&A literature. In these tests, we examine to what extent predicted reactions correspond with actual market reactions surrounding the announcement of the deal in terms of value creation or destruction and the direction of the reaction. As reported in Table 3, in the test set of 2,647 transactions, the ML measure of predictions had the same sign as the actual CAR in 1,530 cases (344 plus 1,186, equivalent to 57.8%). We compare this incidence with a chance scenario that implies a 50–50 chance of a positive or negative CAR (i.e., an expected accuracy rate of 50%). The binomial test shows that the incidence of 57.8% is greater than 50% at the $p < 0.000$ level. In the second binomial test, we compare this incidence with the observed likelihood of a positive CAR in the training set. In our training set of 10,590 transactions, 5,487 transactions (51.81%) received a positive CAR. Assuming that the likelihood of receiving a positive CAR in the training period persists into the testing period, the expected likelihood of a positive CAR in the test set would then be 51.81%. The second binomial test showed that the incidence of 1,530 cases (57.80%) is greater than 51.81% at the $p < 0.000$ level as well.

Next, in analyses reported in Table 4, we conduct a further test in which we regress actual market reactions on predicted market reactions after controlling for a host of variables at the acquirer, target, and transaction levels. Results indicate that predicted reactions were positively associated with actual reactions. The coefficient of predicted reactions when regressed on actual reactions was close to one ($\beta = 0.71$, $p < 0.001$), further indicating that predictions can provide important foresight into actual market reactions ahead of a transaction. Specifically, the coefficient is not statistically different from one at the 5% significance level ($p = 0.087$), suggesting that the predicted reactions developed from historical reactions are, on average, close to the magnitude of the actual reactions. These results provide initial support for Hypothesis 1.

Next, we further build evidence in support of Hypothesis 1 by directly examining managerial decision making in the M&A market. Here, we tested whether predicted reactions to actual transactions that were executed by managers were, on average, higher than the predicted reactions related to a set of hypothetical transactions comprising random acquirer–target pairs. The

Table 3. Number of Transactions with Positive/Negative Predicted and Actual CAR

	Negative *CAR*	Positive *CAR*	Total
Negative *Predicted CAR*	344	339	683
Positive *Predicted CAR*	778	1,186	1,964
Total	1,122	1,525	2,647

Table 4. OLS Regression Analysis of the Association Between Predicted Market Reactions and Actual Market Reactions

Variables	Model 1
Predicted CAR	0.707***
	(0.171)
Public Target	0.003
	(0.005)
Percentage of Stock Payment	−0.008
	(0.008)
Deal Value to Acquirer Assets	0.007^{+}
	(0.004)
Same Industry	0.000
	(0.005)
Geographical Distance	−0.001
	(0.001)
FTC Enforcement	−0.001
	(0.013)
FTC Transactions Reviewed	0.013^{+}
	(0.007)
Pre-Announcement Days	−0.001
	(0.002)
Acquirer ROA	0.002
	(0.021)
Acquirer Tobin's Q	0.001
	(0.002)
Acquirer Leverage Ratio	0.003
	(0.002)
Acquirer Acquisition Experience	0.009*
	(0.005)
Acquirer Historical Average CAR	−1.215***
	(0.064)
M&A Wave	0.005
	(0.008)
Constant	0.082
	(0.076)
Observations	2,647
Adjusted R^2	0.493

Notes. Dependent variable is *CAR*. $N = 2{,}647$. Models are estimated with firm, industry, and year fixed effects. Standard errors are reported in parentheses.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.10$.

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rationale behind this test is that, as managers implement specific theories of value creation, these theories should lead to performance improvements on average as opposed to random deals in which there is no such theory of value creation in place.

To conduct the test, we constructed hypothetical transactions by matching an acquirer with alternative targets that appear in our ML testing set. Next, we generate predictions of market reactions to these hypothetical transactions using our random forest model to obtain the measure of "predicted market reactions to an alternative transaction." We construct hypothetical transactions using two approaches: (a) by randomly selecting five alternative targets in the testing set and (b) by selecting five targets in the testing set with the highest similarity to the actual target based on the cosine similarity of 30 variables in our ML models that capture firm and industry characteristics (e.g., public status, industry average performance). We restrict the target pool to our testing set (versus using the entire population of U.S. public and private firms for target selection) because these firms are at risk of being acquired during our window. We also match an acquirer with more than one potential target to obtain a more robust estimation of predicted market reactions to alternative transactions. After identifying the alternative transactions, we predict market reactions to these transactions using the trained random forest model. As deal-specific attributes (e.g., deal size, percentage of stock payment) are unknown in hypothetical transactions, we set these variables to their median value in the testing set.

According to the paired *t*-test presented in Table 5, the average predicted market returns to actual transactions (0.662%) is significantly higher than the average predicted market returns to hypothetical transactions based on either random selection of the alternative targets (0.559%, $p < 0.001$) or selection of the most similar targets (0.594%, $p < 0.05$). The differences are meaningful, and even when compared with hypothetical targets that are similar to the focal target, the ML model predicted returns are significantly higher by about 0.068%. Taken together, the results in Table 5 provide continued evidence that, on average, predictions formed based on historical transactions can provide useful information and foresight to managers and can be a meaningful input in deal selection.

As a final piece of evidence to support the informational benefits of predictions and Hypothesis 1, we estimate the value created when deals that were predicted to have positive performance are followed through, whereas deals with predicted negative performance were foregone. This test differs from the tests reported in Table 5 in that it considers the possible outcomes if managers were to act solely based on predictions such as those generated by AI systems even if their own assessments were inconsistent with predictions. Table 6 shows that the total market returns to all the 2,647 transactions in the ML testing set is $67,486.00 million. However, if managers proceed with transactions with only positive predicted market reactions based on information gathered from historical transactions, they can prevent a total loss of $13,458.00 million, leading to an increased total dollar-value market return of $80,944.01 million in the M&A market over the 10-year period. Indeed, as Table 6 shows, if managers had only executed transactions with predicted positive returns, the average value per transaction generated would be positive at $41.21 million. These latter results normatively imply that predictions are a useful input into decision making even though they are probabilistic in nature and that managers not considering predictions at all in decision making can have negative consequences for decision quality. Taken together, the results in Tables 4–6 offer evidence that predictions provide valuable foresight and can improve the quality of decision making ex ante in areas such as deal selection.

4.2. Prediction Errors/Deviations and Deal Completion Time

Next, we conduct regression analyses to test Hypothesis 2. The sample includes 2,647 transactions in the ML testing set, in which we have both measures of actual market reactions (*CAR*) and predicted market reactions (*Predicted CAR*) generated by the trained ML models. Table 7 reports that the absolute disparity between actual and predicted market reactions (*CAR-Predicted CAR Disparity*), which is the distance between y and $\hat{y}$ in the Brunswik lens model, has a correlation of 0.25 with actual market reactions (*CAR*) and a correlation of

Table 5. Predicted Market Reactions of Actual vs. Alternative Transactions

Predicted CAR	Mean, %	Standard deviation
Actual transactions (1)	0.662	0.015
Alternative transactions with a random target selected (2)	0.559	0.006
Difference (1–2)	0.104***	(*p*-value 0.001)
Alternative transactions with a similar target selected (3)	0.594	0.007
Difference (1–3)	0.068*	(*p*-value 0.029)

Notes. $N = 2{,}647$. For each actual transaction, five alternative transactions are constructed.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.10$.

Table 6. Dollar Value Returns to Transactions with Positive and Negative Predicted CAR

Dollar value market returns (million)	*N*	Mean	Total returns
All transactions	2,647	$25.50	$67,486.00
Transactions with positive *Predicted CAR*	1,964	$41.21	$80,944.01
Transactions with negative *Predicted CAR*	683	−$19.70	−$13,458.00

Note. Dollar value market returns are calculated as the product of CAR and the acquirer's market value prior to the acquisition announcement, adjusted to 2015 dollars.

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0.14 with predicted market reactions (*Predicted CAR*). Neither correlation is high, indicating that the three variables can be included as regressors simultaneously in our model.

As a first step in our investigation of Hypothesis 2, we regress the deviation and prediction error (i.e., *CAR-Predicted CAR Disparity*) on various acquirer and deal characteristics that appear as controls in our regression. Online Appendix C presents the results. As reported, market reactions continue to be informative relative to predictions when the target is public, when the deal size is large, and when the preannouncement due diligence period is longer. These variables had a positive and significant impact on the *Disparity* dependent variable. Additionally, the disparity is lower when acquirer leverage is higher and when acquirer historical average CAR is higher, indicating that predictions correspond more closely with actual reactions under these conditions.

Table 8, Model 1, presents the main results of our hypothesis test with *CAR-Predicted CAR Disparity* as the independent variable, whereas Models 2–4 provide results with various controls added. The models show that, even after controlling for the above factors, in which actual reactions may contain unique information, *CAR-Predicted CAR Disparity* was associated with longer deal completion time. These results highlight that predictions play a role in acquisition decision making ex post by influencing subsequent information-gathering processes. We argue that this effect arises as expectations and foresight are contradicted in forward-looking models and as added information is revealed to managers by stock market participants in semistrong markets. Conceptually, when there are large deviations, the market may be signaling that the focal transaction is relatively unique compared with historical transactions with similar observable cues. This new information, in turn, may prompt acquiring firm managers to reconsider their assessments of a focal transaction in their aggregation processes, thereby leading to a longer deal completion time.

We conduct several additional checks to assess the robustness of our results with respect to Hypothesis 2. First, we used the predicted CAR from alternative train–test split ratios, including an 85–15 ratio and a 75–25 ratio (compared with the 80–20 ratio used in the main results). Second, we tested the impact of the disparity between actual and predicted CAR on deal completion time using *Deal Completion Time Above Median (dummy)* as the dependent variable. We did this because deal completion is reported as zero in some cases in our data set, and we assume that, in these instances, deal completion was at the lower end of the range of reported values of the full sample. In these analyses (unreported), we find that the coefficient of *CAR-Predicted CAR Disparity* is significantly positive, consistent with the results in Table 8. Next, in addition to the impact of *CAR-Predicted CAR Disparity*, we examine the impact of negative surprises specifically on deal completion time. We consider two alternative conditions of negative surprises: (a) the predicted CAR is positive, but the actual CAR is negative (778 cases), and (b) both predicted CAR and actual CAR are negative, but the actual CAR is lower than the predicted CAR (293 cases). We define the independent variable *Negative Surprise* as one if the acquirer encounters the above two scenarios (a total of 1,071 cases) and zero otherwise. In both tests (unreported), we find that negative market reaction surprises were positively associated with a longer deal completion time. Apart from these analyses, we conducted spline regressions to test whether there was a difference in effects between predictions that deviated positively and negatively from actual market reactions and found no differences. As noted above, even when actual reactions greatly exceed predicted reactions, the prediction error and surprise may lead to more intensive due diligence because, now, the burden is on managers to deliver on these higher expected returns.

Finally, we conducted additional regression analyses to examine whether disparity with predicted CAR impacts deal withdrawal. For this test, we constructed a sample of 2,724 transactions, consisting of 2,647 completed transactions in the ML testing set that were used in the main regression analyses as well as 77 transactions in which the acquirer was seeking 100% of ownership after the transaction but decided to withdraw the deal after its public announcement. This sample shows a withdrawal ratio of 2.84%, which is considerably lower than the 8.1% withdrawal rate reported in Luo's (2005) sample for deals involving public acquirers and public targets, which includes foothold acquisitions typically more prone to reversals. In these analyses (unreported), we find that both higher CAR and higher predicted CAR were individually associated with

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Table 7. Summary Statistics of Variables Used in Regression Analysis

	Variable	Mean	Standard deviation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	*Deal Completion Time*	2.720	2.043																	
2	*CAR*	0.012	0.067	0.00																
3	*Predicted CAR*	0.007	0.015	−0.12	0.22															
4	*CAR-Predicted CAR Disparity*	0.046	0.046	0.13	0.25	0.14														
5	*Public Target*	0.204	0.403	0.47	−0.09	−0.54	0.05													
6	*Percentage of Stock Payment*	0.175	0.324	0.37	0.00	−0.07	0.21	0.25												
7	*Deal Value to Acquirer Assets*	0.713	1.145	0.28	0.09	0.28	0.26	0.08	0.43											
8	*Same Industry*	0.227	0.419	0.23	0.02	−0.20	0.06	0.40	0.09	0.09										
9	*Geographical Distance*	5.409	2.811	−0.05	0.01	0.10	−0.05	−0.08	−0.12	−0.01	−0.05									
10	*FTC Enforcement*	0.036	0.185	0.06	0.00	−0.12	−0.03	0.12	−0.05	−0.04	0.09	0.02								
11	*FTC Transactions Reviewed*	6.302	0.253	0.01	0.01	0.00	−0.01	−0.01	0.01	−0.02	0.00	0.00	0.00							
12	*Preannouncement Days*	0.190	0.762	0.21	−0.03	−0.15	0.03	0.23	0.08	0.09	0.12	−0.01	0.08	0.01						
13	*Acquirer ROA*	0.014	0.159	0.03	−0.03	−0.03	−0.16	0.07	−0.16	−0.05	0.18	−0.07	0.11	0.06	0.05					
14	*Acquirer Tobin's Q*	2.502	1.430	0.00	−0.05	−0.09	0.07	−0.05	0.04	0.12	0.02	0.04	0.04	0.01	0.02	−0.19				
15	*Acquirer Leverage Ratio*	0.850	1.077	0.09	0.00	−0.08	−0.04	0.09	−0.02	−0.02	−0.04	−0.05	−0.05	0.00	0.04	0.02	−0.09			
16	*Acquirer Acquisition Experience*	0.933	0.892	−0.04	−0.08	−0.27	−0.24	0.12	−0.27	−0.27	0.08	−0.04	0.01	0.02	0.06	0.23	−0.06	0.02		
17	*Acquirer Historical Average CAR*	0.006	0.031	−0.08	0.00	0.10	0.00	−0.08	−0.06	−0.02	0.04	0.02	0.16	0.01	−0.03	0.01	−0.01	−0.06	0.07	
18	*M&A Wave*	4.140	0.236	−0.02	0.03	0.05	0.00	−0.06	0.03	0.04	−0.02	0.03	−0.04	−0.01	−0.03	−0.04	0.05	−0.02	−0.05	0.02

Notes. $N = 2{,}647$. Variables 2–18 are winsorized at the 2.5% and 97.5% levels.

lower deal withdrawal, indicating that the latter variable has important informational value in terms of predicting withdrawal. However, the deviation between the actual and predicted CAR variables did not have a significant effect. One reason could be that, apart from sampling differences, deal cancellation also captures the probability of a deal not receiving regulatory approval (Luo 2005, Zhang and Tong 2021). Hence, it differs from the information-gathering efforts that are reflected in deal completion time, which is our main outcome of interest. In sum, across various specifications, we find support for Hypothesis 2, indicating that predictions and deviations thereof are consequential in subsequent stages of acquisition decision making.

5. Discussion and Conclusion

5.1. Overview

We investigated the role of predictions in acquisition decision making using a set of propositions grounded in behavioral decision-making theory. As interest in predictive analytics continues to grow, particularly with the rapid diffusion of AI, it is increasingly important for strategy scholars to develop a better understanding of how predictions shape strategic decision processes. Strategic decisions such as M&As are characterized by a high degree of complexity and uncertainty, implying that predictions in these contexts are inherently stochastic and probabilistic rather than deterministic. This recognition highlights the need to investigate the role of predictions in both ex ante terms before decisions are made and in ex post terms when actual outcomes are observed and deviate from predictions.

In response to these imperatives, we advance two main arguments. First, we propose that predictions can provide meaningful foresight in strategic decision making even though they are inherently probabilistic, especially as they capture meaningful relationships between outcomes and incoming cues as depicted in Brunswik's (1952) model. Second, we argue that, once actual outcomes are observed, deviations from predictions, or prediction errors, play a critical role in shaping subsequent information-gathering and decision-making processes. This argument rests on the notion that, as predictions offer foresight, they also become a central (though not exclusive) basis for managerial expectations in forward-looking decision models. As a consequence, when prediction errors arise, managers may be motivated to engage in uncertainty reduction and adaptive learning to improve decision quality, updating their beliefs and representations of the decision environment (Ke et al. 2024).

We tested these arguments in the context of acquisitions and stock market reactions, an area in which managers have long been known to pay close attention to market responses and to anticipate them as best as

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Table 8. OLS Regression Analysis of Effect of Predicted Market Reactions on Deal Completion Time

Variables	Model 1	Model 2	Model 3	Model 4
CAR-Predicted CAR Disparity	4.230***	3.957***	3.938***	3.755**
	(1.149)	(1.159)	(1.141)	(1.151)
CAR		1.498+		1.058
		(0.873)		(0.872)
Predicted CAR			21.331***	20.629***
			(4.831)	(4.864)
Public Target	1.674***	1.686***	1.946***	1.946***
	(0.142)	(0.142)	(0.153)	(0.153)
Percentage of Stock Payment	0.332	0.358+	0.584**	0.594**
	(0.215)	(0.216)	(0.221)	(0.221)
Deal Value to Acquirer Assets	0.580***	0.569***	0.506***	0.501***
	(0.113)	(0.113)	(0.113)	(0.113)
Same Industry	0.169	0.166	0.156	0.155
	(0.132)	(0.132)	(0.131)	(0.131)
Geographical Distance	0.010	0.010	0.008	0.009
	(0.018)	(0.018)	(0.018)	(0.018)
FTC Enforcement	−0.425	−0.421	−0.386	−0.385
	(0.376)	(0.376)	(0.373)	(0.373)
FTC Transactions Reviewed	−0.097	−0.115	−0.079	−0.093
	(0.189)	(0.189)	(0.187)	(0.187)
Preannouncement Days	0.022	0.025	0.044	0.046
	(0.060)	(0.060)	(0.060)	(0.060)
Acquirer ROA	0.643	0.636	0.563	0.561
	(0.597)	(0.597)	(0.592)	(0.592)
Acquirer Tobin's Q	−0.010	−0.010	0.002	0.002
	(0.065)	(0.065)	(0.064)	(0.064)
Acquirer Leverage Ratio	0.133*	0.127*	0.143*	0.139*
	(0.063)	(0.063)	(0.063)	(0.063)
Acquirer Acquisition Experience	0.046	0.034	0.074	0.065
	(0.131)	(0.131)	(0.130)	(0.131)
Acquirer Historical Average CAR	−3.372+	−1.573	−2.820	−1.567
	(1.835)	(2.112)	(1.824)	(2.096)
M&A Wave	−0.123	−0.130	−0.110	−0.116
	(0.237)	(0.237)	(0.235)	(0.235)
Constant	2.759	2.640	2.061	2.001
	(2.174)	(2.174)	(2.162)	(2.162)
Adjusted R^2	0.555	0.556	0.563	0.563

Notes. Dependent variable is *Deal Completion Time*. $N = 2{,}647$. Models are estimated with firm, industry, and year fixed effects. Standard errors are reported in parentheses.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.10$.

possible (Rappaport 1987, Rappaport and Sirower 1999). Against this backdrop, we propose that as managers form predictions about market reactions based on historical transactions and the associated incoming cues, they can gain valuable foresight to guide subsequent decision making in areas such as deal selection. We further argue that this effect arises because such predictions capture, at least in part, the wisdom of stock market participants and, hence, that the managerial representations underlying these predictions can meaningfully inform decision making.

We empirically tested our hypotheses by developing a measure of predictions using ML models grounded in the premise that managers are likely to form predictions and mental representations by making the best use of information in incoming cues and past outcomes. Our results show that predictions not only confer value and inform decision making ex ante in areas such as deal selection but that prediction errors also have meaningful ex post consequences. Specifically, larger deviations between predicted and actual reactions are associated with longer deal completion times, reflecting more extensive information gathering and deliberation by managers.

5.2. Implications for AI and Prediction Capabilities

Our analyses allow us to derive a set of implications and to envision in a more theoretically grounded manner how AI and prediction capabilities are likely to shape acquisition decision making.

Our first implication, normatively speaking, is that AI and predictive capabilities are indeed both relevant and potentially valuable in enhancing acquisition decision making. As shown in Tables 4–6, predictions were

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consistently associated with value creation across various analyses. Thus, in response to the question—can AI do strategy—our findings suggest that AI systems capable of capturing mechanisms such as the wisdom of crowds of market participants can serve as a useful and distinct input into managerial decision making thereby complementing rather than replacing managers' private assessments. This implication is important because, whereas the value of predictions has been demonstrated in various professional domains, such as image recognition in clinical diagnosis, algorithmic trading in finance, and predictive modeling in legal contexts, comparable evidence has yet to accumulate in the strategy field. Establishing such evidence is all the more critical given that strategic decision making often departs from the assumptions of the traditional Bayesian framework because of incomplete information about initial probability distributions (Ke et al. 2024).

In practical terms, our study suggests that investing in AI capabilities in contexts such as acquisitions can help alleviate bounded rationality and provide valuable information at relatively low marginal costs (although developing such capabilities may require substantial asset investment and entail high initial fixed costs). These systems, despite producing probabilistic outputs, can serve as valuable components of human–machine ensembles (Choudhary et al. 2023), thereby augmenting managerial judgment rather than replacing it. In principle, managers and other M&A participants, such as investment banks and private equity firms, can develop such systems and interactively query them to identify potential acquisition targets that are likely to create or destroy value. Such recommendations can expand the opportunity set by revealing promising targets that might not have been previously considered by managers given AI's ability to surface opportunities beyond existing knowledge frontiers (Dell'Acqua et al. 2023). When deployed at scale, these predictive capabilities can, thus, enhance the overall efficiency of M&A markets and create added value for shareholders.

However, several important caveats warrant attention. First, merely inputting a random or unstructured set of potential targets into an AI system without an underlying theory of value creation is unlikely to yield meaningful or interpretable recommendations (Felin et al. 2024). Hence, the set of candidate targets must be fundamentally theory-driven even if managers occasionally explore targets beyond conventional boundaries. In other words, implicit or explicit theories of value creation should guide both the generation and interpretation of predictions from AI systems. Doing so would enable managers not only to make more informed decisions ex ante (such as bidding for the right targets and offering appropriate premiums; Reuer et al. 2012), but also to interpret ex post deviations between predicted and actual outcomes meaningfully and to take adaptive actions accordingly.

Moreover, because predictions are inherently probabilistic and AI systems often operate as black boxes (Ke et al. 2024), managerial judgment and private assessments remain indispensable in determining which targets should ultimately be pursued. We, therefore, expect that managers may occasionally acquire targets with predicted negative reactions as predictions will not and should not fully dominate decision making (Ke et al. 2024). However, such choices warrant careful scrutiny given the evidence presented in Table 8. Conversely, it is entirely possible that managers will forgo targets with predicted positive reactions because of the absence of a coherent theory of value creation, underscoring again the centrality of human judgment. Thus, AI-driven predictions in strategic contexts such as acquisitions are unlikely to replace managerial decision making in the way that predictive systems dominate in domains such as autonomous driving or clinical diagnosis. Instead, our findings support the view that complementarity—rather than substitution—will primarily characterize the relationship between human decision makers and AI in strategy contexts such as M&A with each contributing distinct strengths to the decision process.

The continued importance of managerial judgment, combined with the probabilistic nature of predictions, also suggests that AI capabilities will not eliminate information advantages or asymmetries to the point that all targets are valued equivalently by potential acquirers in the M&A market. As our analysis shows, predicted market reactions are sensitive to both acquirer and target characteristics and depend on the specific combination in the dyad. Even if prediction technologies become widely available and dispersed, such systems could merely reveal which targets are potentially attractive to various players based on observables, including competitors. Nevertheless, the substantial role of managerial assessments and information about private synergies (Barney 1986) implies that unique and valuable opportunities will persist. Competitors are unlikely to fully bid away these opportunities, leading to continued heterogeneity in acquirers' willingness to pay and deal premiums. Put differently, our findings suggest that the diffusion of prediction technologies will not lead to complete convergence in valuation or to the erosion of competitive advantage in the M&A market (Barney and Reeves 2024). Because predictions are probabilistic and managerial knowledge and theories of value creation remain essential, substantial scope will continue to exist for realizing performance benefits through acquisitions even in an era of AI-enabled prediction.

Beyond target selection and foresight, our analysis implies that, because deviations from predictions and

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prediction errors carry informational value, strategic decision making in an AI-driven world must explicitly consider how actual outcomes are systematically aggregated with predictions. From a practical standpoint, this means that managers must act upon deviations robustly, fully leveraging the information they contain. As noted earlier, a rich body of work in cognitive science demonstrates that prediction errors drive learning and adaptation, and our study extends this insight to the strategy domain. In this regard, the continuing challenge lies in the black box nature of AI-generated predictions. As managers update their beliefs (Ke et al. 2024), they must interpret what these deviations reveal with the support of other constituents including investment banks and advisors.

More broadly, our analysis underscores that prediction errors are likely to play a pivotal role in strategic decision making, a role that will only become increasingly salient as AI systems become more integrated into managerial practice. As we argue, this forward-looking mechanism differs from the traditional emphasis in the strategy literature on backward-looking models that center on deviations from aspirations. Whereas economic and behavioral theories have long emphasized the role of forward-looking mechanisms and expectations in decision making (Muth 1961, Cyert and March 1963), we anticipate the growing adoption of AI systems to render this expectation-based channel even more influential. Our findings, therefore, call for strategy scholars to explicitly incorporate this forward-looking dimension into future research on learning and adaptation.

5.3. Future Directions

Whereas our paper focuses on market reactions, future studies could similarly leverage ML models to examine the effects of other types of predictions relevant to acquisition decision making. For instance, in the context of acquisitions, additional y hats or $\widehat{y}$'s (Mullainathan and Spiess 2017) with potential informational consequences include predicted acquisition premiums and predicted likelihoods of regulatory approval. Predictions regarding these variables could provide complementary forms of foresight, such as expectations related to asset prices or potential frictions during the postannouncement phase. Exploring how such predictions influence target selection, value creation, and postacquisition dynamics represents a promising avenue for future research.

Second, future studies could differentiate among various types of acquisitions in the M&A market, such as platform acquisitions (Wang et al. 2024) for which predictions may incorporate variables such as network effects, user complementarities, and ecosystem positioning. Applying predictive models to these contexts could help unpack the unique factors that shape foresight in multisided settings, in which value creation depends on interactions across participants rather than bilateral synergies alone. This line of inquiry is particularly relevant as platform acquisitions continue to grow in strategic importance and prevalence within the M&A landscape (Chen et al. 2022).

Third, whereas we focus on predictions generated by extrapolating from past market reactions, future research could explore whether predictions derived from alternative AI technologies, such as large language models, can similarly provide valuable foresight. These tools leverage vast amounts of publicly available information to generate predictions and are widely accessible to managers and other decision makers (Olenick and Zemsky 2023, Boussioux et al. 2024). Future studies could, therefore, examine aggregation processes that combine predictions from multiple sources, including ML-based and generative AI-based models, and assess how these hybrid systems influence managerial decision making.

Fourth, future research could delve deeper into the underlying causes of prediction errors. Whereas we offer initial evidence on the consequences of prediction errors (Hypothesis 2 and Table 8), a useful next step would be to investigate why and when such errors arise. Doing so could shed light on areas in which current theories of market reactions remain incomplete and identify hidden patterns or contingencies in the data that prior work overlooks. Additionally, understanding the sources of prediction errors could further refine both behavioral models of decision making and the design of AI systems used in strategic analysis.

Fifth, whereas our large sample econometric analyses captured the effects of predictions on decision making at an aggregate level, future research could complement these findings with field-based evidence and qualitative insights. Engaging directly with managers, investment bankers, and other M&A practitioners can offer a richer understanding of how predictions are formed and integrated with private assessments and how managerial beliefs and representations are updated in practice.

Finally, whereas our study examines the role of predictions in acquisition decision making, future research could extend this framework to other strategic contexts, such as divestitures, alliances, and investment decisions within multibusiness firms in the face of various frictions (Kumar 2013, Cabral et al. 2020). In these settings as well, predictions may provide valuable foresight that shapes strategic choices, conferring performance benefits.

In sum, there is a wide scope for examining the role of predictions, not only in acquisitions but in strategic decision making more broadly. The rapid growth of interest in AI and predictive capabilities provides additional impetus for such inquiries. We hope that future

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research will build on the behavioral foundations we develop to deepen our understanding of how predictive technologies and AI shape managerial foresight and strategic decision making.

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Endnote
[1] Recent reports in the popular press and professional outlets (e.g., "How Mergers and Acquisitions Can be Transformed using Artificial Intelligence," M&A Worldwide, 2022; "Transforming Mergers and Acquisitions through Artificial Intelligence," Linder, 2022) suggest that managers are increasingly exploring the use of predictive analytics powered by AI and high-dimensional data. These capabilities are seen as particularly valuable in several stages of the acquisition process, including identifying potential targets and selecting deals, anticipating financial returns and synergies, and applying data-driven insights to support due diligence and postmerger integration.

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