**Working Paper**

**Hitting a Curveball: Strategic Factor Markets, Uncertainty, and Performance.**

**Abstract:**

Strategic factor markets allow firms to obtain competitive advantages through having superior information and more accurate expectations about the value of resources compared to rivals. Interestingly, this theoretical statement has yet to find consistent empirical support. Using a comprehensive proprietary dataset, we analyze factor markets under different forms of uncertainty—specifically, strategic factor market and resource uncertainty. Our findings parallel previous empirical work in showing that superior information does not always lead to more accurate expectations; however, this relationship is contingent on both types of uncertainty. Furthermore, we uncover the existence of firm-specific strategic factor market capabilities. We demonstrate that uncertainty and firm-specific capabilities are necessary, but not sufficient, for obtaining competitive advantages through strategic factor market exchanges. Our findings help explain prior mixed empirical results while demonstrating the importance of uncertainty and firm-specific capabilities in strategic factor market decision-making.

**Keywords**: Strategic factor markets; resource uncertainty; SFM uncertainty; firm-specific capabilities.

*“We have a crystal ball. I take my instinct and what I have learned, and it allows me to project,*

*it allows me to dream.”*

– American League Regional Scouting Supervisor

Strategic factor markets are “where firms buy and sell the resources necessary to implement their strategies” (Barney, 1986, p. 1232). Firms can obtain a competitive advantage in strategic factor markets by having superior information compared to other firms (Barney, 1986; Makadok & Barney, 2001). According to this perspective, superior information helps firms set more accurate expectations regarding a resource’s value, which lets firms select resources that lead to competitive advantage. However, prior empirical research has not supported this idea (Maritan & Peteraf, 2011). In fact, scholars have found that managers do not use information asymmetries to their advantage, and therefore, the core strategic factor market theoretical relationship between information and performance is tenuous (Poppo & Weigelt, 2000). This finding questions the first principles of strategic factor market theory and conflicts with recent conceptual work (Felin et al., 2016; Leiblein et al., 2017; Schmidt & Keil, 2013).

The resource-based view posits that firms can obtain competitive advantages from having more accurate expectations than other firms, but empirical work has not established this relationship (Poppo & Weigelt, 2000). Our research question therefore asks why this paradox occurs and what mechanisms can explain it. While the prior empirical strategic factor market literature examines strategic actions, factor market characteristics, and resource attributes in high-certainty strategic factor markets (Allen et al., 2022; Kim et al., 2015; Knott, 2003), we included original strategic factor market constructs to investigate this paradox. We replicated the prior empirical null results; however, after including both uncertainty and firm-specific capabilities in our theoretical model, we found support for the first principles of strategic factor market theory (Barney, 1986). We showed that uncertainty and firm-specific capabilities are necessary for competitive advantage but not sufficient by themselves (Coff & Kryscynski, 2011). Our results were further strengthened after incorporating alternative mechanisms such as complementarity, market position, and price (Adegbesan, 2009; Schmidt & Keil, 2013).

To help answer our research question, we instituted an empirical approach that allowed us to examine strategic factor markets in fine-grained detail and address the common criticisms of RBV empirical work (Arend, 2006; Kraaijenbrink et al., 2010). Sports data has proven crucial to management studies, as it allows for measurable performance metrics and resource-level analysis (e.g., Bond & Poskanzer, 2023; Bradley & Aguinis, 2023; Shamsie & Mannor, 2013). To accomplish our task, we turned to Major League Baseball (Day et al., 2012; Fonti et al., 2022; Poppo & Weigelt, 2000). Our empirical approach enabled us to consider the original theoretical arguments more faithfully than prior studies have. We found results similar to those of previous scholars (Poppo & Weigelt, 2000), but we also incorporated uncertainty and firm-specific capabilities into our model to expand prior theory. When including these constructs that are present in the initial resource-based view conceptualizations, we found empirical support for strategic factor market theory. Our dataset also allowed us to overcome several problems previously encountered in RBV research. First, the resource’s value is easily measurable and calculable, overcoming concerns about the resource black box (Arend, 2006; Wolfe et al., 2005). Second, transactions between organizations are observable and contain complete information while separating the resource’s value from firm performance (Priem & Butler, 2001). Finally, our context allowed us to account for endogeneity through a difference-in-differences model.

Our study makes three significant contributions to the strategic factor market literature. First, we explain why the prior results do not align with strategic factor market theory (Felin et al., 2016; Leiblein, 2011; Ross, 2012). In doing so, we unpack the multidimensional nature of uncertainty and highlight the importance of both strategic factor market and resource uncertainty in determining performance. Second, we provide robust empirical support for the foundational ideas of strategic factor markets with solid links to the theoretical constructs and appropriate endogeneity checks. Last, we emphasize the role of firm-specific capabilities within strategic factor markets by showing how they affect performance and interact with uncertainty (Coff & Kryscynski, 2011; Denrell et al., 2003; Karim & Capron, 2016). Overall, by considering various types of uncertainty and the firm’s capabilities, our research bridges a gap in the existing literature and offers support for the fundamental concepts of strategic factor market theory.

**THEORETICAL BACKGROUND**

**Strategic Factor Markets**

Strategic factor markets (henceforth “SFMs”) are the markets behind the markets where firms go to purchase resources (Barney, 1986). The approach of utilizing SFMs differs from capability building, wherein firms develop their resources internally (Makadok, 2001). Firms can utilize SFMs to gain competitive advantages in product markets (Barney, 1989). Competitive advantage can be achieved by being luckier than other firms, having greater resource complementarity, or having a superior market position (Adegbesan, 2009; Barney, 1986; Schmidt & Keil, 2013). Arguably, however, the most crucial way firms can gain competitive advantages in SFMs is by having more accurate expectations.

Firms gain more accurate expectations through, in part, having better information than their competitors regarding the value of resources. Accurate expectations allow firms to avoid purchasing overpriced resources and thus suffering from the winner’s curse while helping them identify resources with lower resource prices than their actual future value (Barney, 1986, p. 1233–1234).

[Insert Figure 1 about here]

“Significant variation exists in markets for resources,” asserts Leiblein (2011, p. 913), suggesting that SFMs rely on the characteristics of the market and its factors. There is a duality between the product and resource markets, as performance in one will affect the other (Anand & Singh, 1997). Factors such as size, market concentration, and market efficiency influence resource selection (Leiblein, 2011; Ross, 2012). Not all SFMs are the same, and to treat them as such in research might lead to misspecified results. Thus, an important takeaway from this research stream is that both the nature of the SFM and its resources matter. However, the importance of the market is questionable, given the lack of empirical support for even the most essential SFM tenets regarding information and performance (Poppo & Weigelt, 2000).

**Prior Strategic Factor Market Empirical Literature**

Few studies have been able to test SFM theory empirically, and the SFM empirical literature has brought mixed findings on whether information can help firms set more accurate expectations (Maritan & Peteraf, 2011; Poppo & Weigelt, 2000). Nevertheless, some researchers have tried to study how SFMs influence strategic actions and performance.

*Strategic Actions*

A few papers have examined how SFMs affect the firm’s strategic actions. Most of these papers have examined how rivals react to resource selection, a topic beyond the scope of this paper. However, one did explore how a resource’s attributes influence the firm’s decision to maintain or divest a resource.

Two papers have examined how SFM characteristics affect strategic actions. Adegbesan and Higgins (2011) studied how scarcity, complementarity, and bargaining ability in SFMs influence the pie-splitting control rights of factor alliance deals. Gianiodis et al. (2019) used the context of the biotechnology industry to examine the likelihood of legal lawsuits arising. Their areas of interest primarily involved relations between two firms, such as the existence of licensing or a joint venture, and firm attributes, such as the patent count of the firm. Allen et al. (2022) shifted away from previous work by examining how the focal resource and other resource attributes affect a firm’s likelihood of divesting from a resource.

In all of these papers, the dependent variable specifically pertained to the likelihood of a firm’s strategic action. They all found that both SFM and resource characteristics influence a firm’s decision-making. However, they did not examine how these factors influence firm performance, the crux of the SFM relationship shown in Figure 1. While they generally provide tangential support for SFM theory, they did not directly study the mechanisms that lead to more accurate expectations.

*Performance Outcomes: SFM Characteristics*

We now shift to studies that explore firm performance to analyze why previous scholars have yet to find direct support for the first principles of SFM theory. In particular, two papers study how SFM characteristics affect performance.

Kim et al. (2015) examined the effect of SFMs on accounting returns by studying market characteristics such as resource-poor or rich countries. Their independent variables, which were at the market level, included SFM quality characteristics, and they aimed to determine why SFMs “matter in exploring rationales for geographic diversification” (Kim et al., 2015, p. 518). Knott (2003) took a different approach, studying the returns that franchises received depending on their franchisee’s policies and the business owner’s willingness to follow them. She focused on the awareness of business routines and the franchisee’s relationship with the franchiser rather than resource-picking capabilities.

These two papers support the idea that SFM characteristics affect performance. They both found that firms engaging in resource picking in countries with more favorable economies, or that follow specific procedures, can obtain a competitive advantage over their rivals that do not. These papers, though, studied attributes of firms and markets and their subsequent effect on SFM performance rather than the underlying theoretical relationship between information, more accurate expectations, and performance. Therefore, while this empirical work “may include some arguments from SFM theory, there have been very few empirical studies of SFM operation,” assert Maritan and Peteraf (2011, p. 1377).

*Performance Outcomes: Resource Attributes*

One paper has directly tested whether information leads to competitive advantages in SFMs and found no results. In it, Poppo and Weigelt (2000) investigated the value of information in SFMs. They examined success at the firm level and incorporated resource attributes into their analysis:

In their study, they used baseball organization data to determine whether some organizations perform better than others when purchasing major league-level free agents. Their paper mentions how “managers can exploit uncertainty about a factor’s true value to generate returns” (Poppo & Weigelt, 2000, p. 585). However, they do not return to this idea either theoretically or empirically. According to their research, teams that purchase free agents do not perform better than others and firms do not utilize better information to obtain more accurate expectations. The authors suggest that many of the mechanisms proposed by Barney (1986) may not work as the theory suggests.

Prior researchers have not considered two critical theoretical elements that may explain previous unsupportive findings: uncertainty and firm-specific capabilities. As strategic factor markets are highly dependent on their uncertainty level (Felin et al., 2016; Leiblein et al., 2017), empirical studies must consider this factor or risk finding misleading results. The resource-based view also differs from traditional economic approaches in studying firm-specific capabilities (Mahoney & McGahan, 2007); however, prior empirical strategic factor market research curiously omits this factor.

We now turn to how these gaps in the literature might affect the relationship between information and expectations. We break uncertainty into two levels—SFM uncertainty and resource uncertainty—to examine how they affect the likelihood that firms can obtain more accurate expectations. Then, we look at how firm-specific capabilities affect these relationships.

**HYPOTHESES**

*“Everyone likes information; do not get me wrong, but you have got to make a decision. More information creates more doubt. I do not like doubt.”*

– National League Scouting Director

As discussed above, prior theoretical and empirical research did not consider the effects of uncertainty and firm-specific capabilities on firms’ ability to gain an accuracy advantage. In this section, we will disentangle the two components of uncertainty—SFM and resource uncertainty—and then examine how important firm-specific capabilities are for accurate expectations. Finally, we will theorize about how resource uncertainty and firm-specific capabilities interact and the subsequent implications for expectation-setting.

**SFM Uncertainty**

Uncertainty focuses on the relationship between an action and its outcome. Specifically, uncertainty “implies imperfect knowledge about the causal relationships between means and ends” as Garud and Van de Ven (1992, p. 93) explain. The first principles of the resource-based view acknowledge uncertainty’s critical role in securing competitive advantage (Lippman & Rumelt, 1982; Peteraf, 1993; Wernerfelt, 1984). For SFMs, uncertainty is a knowledge problem that firms can solve with more information. As firms accrue and assimilate more information, their understanding of the causal link between resources and performance sharpens, positioning them to anticipate abnormal returns more effectively (Arend, 2006; Capron & Pistre, 2002). In other words, firms with more information should be able to obtain greater accuracy advantages in strategic factor markets with greater uncertainty.

Market structure matters for how firms succeed in SFMs (Felin et al., 2016). Market uncertainty entails uncertainty that “cannot be controlled and is independent of what happens at the firm level” and “consists of factors that are common to the entire economy” (Beckman et al., 2004, p. 262). Market uncertainty influences firms’ ability to gain more accurate expectations than others in SFMs.

SFM uncertainty affects all firms’ knowledge of causal relationships between resources and performance. When markets become less uncertain or grow rigid and cease expanding, the patterns and causal links between data and eventual SFM performance become known (Oster, 1999). Greater market certainty creates barriers to acquiring a competitive advantage over rival firms through more accurate expectations (Peteraf, 1993). This process occurs when all firms in an industry understand the causal relationships between resources and performance, which prevents any particular firm from gaining an informational advantage over competitors in SFMs (Barney, 1986; Makadok & Barney, 2001). One of the most significant factors affecting SFM uncertainty is the age of the market (Oster, 1999).

SFM uncertainty changes over time. Initially, traders do not know which types of resources lead to competitive advantage. By investing in information gathering, some traders learn about these causal links and become informed traders. Informed traders will have a competitive advantage over uninformed traders. As time passes, the uninformed become knowledgeable through herding or imitation, diminishing the advantage of the informed (Grossman & Stiglitz, 1980; Huber et al., 2011). This process is conceptually different from resource uncertainty, as the new resources that enter the SFM still have the same amount of intrinsic uncertainty as the prior resources used to have when they entered the SFM (Beckman et al., 2004; Brealey & Myers, 2003).

When we examine the previous SFM conceptual equation, we can see that while specific market characteristics are included in earlier models, the concept of SFM uncertainty has not been explored. However, SFM uncertainty can help explain previous mixed findings:

Therefore, we propose that over time, strategic factor markets become less uncertain, thus negatively affecting resource-picking success:

**Hypothesis 1:** *The greater the strategic factor market uncertainty, the higher the likelihood of resource picking leading to accuracy advantages.*

**Resource Uncertainty**

In our context, an SFM’s degree of certainty depends partly on the knowledge needed to determine if the resource causally leads to superior performance (Barney, 1986; Townsend et al., 2018). In prior SFM literature, most works examined resources whose value is known with a high degree of certainty. Knott (2003) studied franchises offered for sale, while Poppo and Weigelt (2000) looked at baseball free agents only at the MLB level, which is the highest level. These papers advanced SFM theory but only focused on SFMs with low resource uncertainty. However, the degree of resource uncertainty is critical to performance (Felin et al., 2016).

When a resource has more uncertainty, it allows firms to discover the causal relationship between resources and performance and create private information available only to their firm (Makadok & Barney, 2001). Therefore, SFMs with high degrees of resource uncertainty should provide more opportunities for firms to obtain accuracy advantages—which could be one reason why firms invest more in researching resources when those resources have high uncertainty (Makadok & Barney, 2001). Only SFMs with high degrees of resource uncertainty allow firms to benefit from more accurate expectations.

It is essential to distinguish between the two levels of uncertainty: SFM and resource uncertainty. While we have described them theoretically in this and the previous section, an example can help differentiate the two types of uncertainty. In the case of pharmaceuticals, resource uncertainty would be tied to the resource itself. For example, it might involve whether a particular drug compound will lead to its intended solution (Gianiodis et al., 2019). However, SFM uncertainty exists as well in pharmaceuticals. SFM uncertainty has decreased due to more readily available public information about all existing drugs due to increased regulation and the internet (Oster, 1999). In the case of Major League Baseball, resource uncertainty is intrinsic to the player, while SFM uncertainty is the general causal relationship common between all players and performance. Therefore, although resource uncertainty and SFM uncertainty increase the potential value of accurate expectations, they are conceptually different.

While Poppo and Weigelt (2000) correctly showed that information does not lead to more accurate expectations in highly certain SFMs, this does not apply to all resources. Regarding resources with high uncertainty, firms can achieve more accurate expectations, giving them an accuracy advantage. Returning to our model, we can see that resource uncertainty should also affect SFM expectations and can help explain the divergence between Poppo and Weigelt (2000) and Barney (1986):

Thus, we make the following hypothesis:

**Hypothesis 2:** *The greater the resource uncertainty in the strategic factor market, the higher the likelihood that resource picking will lead to accuracy advantages.*

**Firm-Specific Resource-Picking Capabilities**

*“The younger they are in A-ball, we believe we can do this or adjust that to change them. When they get older, they are what they are.”*

– American League Director of Player Development

Prior research suggests uncertainty is insufficient to provide firms with a competitive advantage in strategic factor markets (Peteraf, 1993). If uncertainty were a sufficient condition, then any firm could find a market with uncertain resources, buy relevant factors, and gain an accuracy advantage over those firms that did not select resources (Barney, 1986, 1989; Dierickx & Cool, 1989).

Instead, a firm-specific resource-picking capability may allow some firms to gain an accuracy advantage over other firms in SFMs (Coff & Kryscynski, 2011; Denrell et al., 2003). This capability stems from a firm’s ability to gather, process, or interpret information better than other firms (Makadok & Barney, 2001). While information homogeneity is an issue in resource picking compared to capability building (Denrell et al., 2003), some firms may have more private information than others or a better ability to utilize private information, thus allowing them to overcome the Grossman-Stiglitz paradox (Grossman & Stiglitz, 1980). This capability is like the “managerial skill” discussed in the theoretical literature (Barney, 1989, p. 1513).

Most theoretical and empirical SFM studies treat each firm as being the same (Makadok & Barney, 2001; Maritan & Peteraf, 2011). However, a core tenet of the management field holds that firm-specific capabilities matter (Coff & Kryscynski, 2011; Mahoney & McGahan, 2007; Nag et al., 2007). SFM theory has incorporated these insights in part by examining the complementarities between market resources and the current asset base of a firm (Adegbesan, 2009; Lippman & Rumelt, 2003). Recently, other scholars have incorporated the firm’s market position (Schmidt & Keil, 2013) as well as the potential product market/factor market rivalries between firms (Gianiodis et al., 2019). However, to our knowledge, the empirical work has not shown that some firms have superior information-processing capabilities regarding resource picking.

The idea that firms are heterogeneous is well-noted in the resource-based view (Peteraf, 1993), but it has yet to be thoroughly analyzed or tested in the context of SFMs. We believe there is a firm-specific resource-picking capability that will allow some firms to perform better than others (Makadok & Barney, 2001). This relationship should prove true even when controlling for both complementarity and market position. Thus, a firm-specific capability should help firms achieve a competitive advantage in SFMs above and beyond uncertainty. Incorporating firm-specific capabilities, rather than just firm attributes, helps round out the main effects in our theoretical model:

Therefore, we hypothesize as follows:

**Hypothesis 3:** *The greater the firm’s capabilities in the strategic factor market, the higher the likelihood of resource picking leading to accuracy advantages.*

**The Intersection of Resource Uncertainty and Firm-Specific Capabilities**

Resource uncertainty and firm capabilities affect firms’ SFM performance (Barney, 1986). Thus far, we have predicted that firms can achieve more accurate expectations only in cases of high resource uncertainty compared to other firms. At the same time, certain firms have higher resource-picking capabilities than others. However, what will happen at the intersections of each quadrant? We use a stylized example from our context—Major League Baseball—to describe our predictions.

[Insert Figure 2 about here]

First, when resources have little uncertainty and firms have low capability (Quadrant I), the firm typically has poor resource-picking ability. The intersection of highly certain resources and poor-performing firms will lead the purchasing firm to buy resources that will disappoint over time (Amit & Schoemaker, 1993; Barney, 1986; Poppo & Weigelt, 2000). An excellent recent example of this phenomenon is the San Francisco Giants’ trading for former MVP Andrew McCutchen. The San Francisco Giants were at a low point capability-wise when they traded for McCutchen—a decorated major-league player with a long track record. Unfortunately for the Giants, McCutchen performed below expectations despite a hefty price and was traded again elsewhere after a few months.

We expect low returns on highly certain resources even when the firm has a high capability (Quadrant II), because the seller has had significant time to evaluate the resource and the other firms on the market are very aware of the resource’s value. Nevertheless, high-capability firms often purchase highly certain resources (Barney, 1988). One example is when the New York Yankees essentially purchased the reigning Most Valuable Player—Giancarlo Stanton—in 2018. However, despite the Yankees’ strengths as an organization with one of the best minor league systems at the time, Giancarlo Stanton’s performance fell short of expectations.

Being situated in the other oft-diagonal (Quadrant III), where there is great resource uncertainty and poor performance, should also lead to low competitive advantage. In this case, low-capability firms cannot achieve more accurate expectations than other firms. Therefore, despite the possibility of resource selection that allows for high returns, poor-performing firms are unable to find these deals (Amit & Schoemaker, 1993). The Miami Marlins’ trading of Christian Yelich for Lewis Brinson and others in 2018 serves as one example. The Miami Marlins, who had historically failed to identify talent, traded a young major league player for a bevy of prospects, led by top-rated prospect Lewis Brinson. Despite high hopes and expectations, Lewis could not find consistent success and has left the major leagues. This illustrative example shows why uncertainty by itself is not sufficient.

Finally, in Quadrant IV, we see the case of high-capability firms picking uncertain resources. Famous success stories abound in this quadrant, from Shoeless Joe Jackson in 1910 to John Smoltz in 1987 to Jeff Bagwell in 1990. We see one recent case in the Houston Astros’ trading for Yordan Alvarez in 2016. “Air Yordan,” as he has been called since, was a 19-year-old prospect from Cuba who was thought to be good but not great. The Houston Astros, one of the best-performing teams in the major leagues and in terms of resource picking, discovered him in the Los Angeles Dodgers’ farm system and traded a relatively insignificant reliever for him. Since then, he has been a two-time All-Star and was third in MVP voting in 2022. The rich can get richer not necessarily from being able to buy resources, as the Yankees have found out consistently, but rather, by having accurate expectations on resources with high uncertainty, much like the Houston Astros have (Barney, 1986; Felin et al., 2016; Leiblein et al., 2017).

In summary, we believe that only in Quadrant IV—cases of high resource uncertainty with high firm capabilities—can firms consistently obtain accuracy advantages over competitors. Both uncertainty and high capabilities are necessary but not sufficient by themselves for firms to turn accurate expectations into better SFM purchases and subsequent competitive advantage.

**Hypothesis 4:** *Only in cases of great resource uncertainty and high firm capability do firms have a higher likelihood of resource picking leading to accuracy advantages.*

**METHODOLOGY**

**Context**

Scholars have seldom empirically tested SFM theory due to practical limitations. Researchers often cannot measure resources, especially objectively, that tie a specific resource to a specific outcome (Kraaijenbrink et al., 2010). Resources are not often directly related to firm performance (Arend, 2006). Therefore, even if resources in SFMs are measurable, the link between the resource and performance remains tenuous. SFM boundaries prove difficult to tie down, and firms often hide when and why they obtained a resource. Studies on SFM theory must overcome all these obstacles, which has limited direct SFM research to date (Maritan & Peteraf, 2011). We turn to North American professional baseball to solve this problem.

Management and SFM scholars have often utilized sports data to test predictions regarding firm performance (Allen et al., 2022; Day et al., 2012; Kim & Makadok, 2021; Kim & Makadok, 2022). Baseball data offers many avenues for addressing the problems with RBV research. First, the value of resources is measurable and calculable in baseball, as players have statistics on their performance (Wolfe et al., 2005). Since contracts are long-term and usually last through the minor league and the first few major league seasons, the resources are also straightforwardly tied to firms for extended periods. Firm transactions are observable and contain complete information, allowing researchers to track resource picking over time. Finally, baseball data enables us to look at different aspects of resource uncertainty, as players typically go through the minor league levels before reaching the major league level. In addition to our OLS regressions, this setting provides an ideal context for a difference-in-differences model.

Our difference-in-differences model uses the designated-hitter rule of 1973. From 1888 to 1972, all players both played in the field and were in the batting order, including the pitcher, who was typically the team’s weakest hitter. In 1973, the American League surprisingly voted for a designated hitter to bat instead of the pitcher, while the National League voted against this change. This rule change created a situation where specific resources were now more valuable for American League teams, as they could find space in their lineup for a designated hitter. However, teams were unsure of how to use this rule change, including for their minor league system (Newhan, 1973). This dilemma created a unique natural experiment through which to test an uncertain situation for hypothesis 2.

**Data**

First, to contextualize our research, we initially engaged in discussions with former and current high-ranking employees of Major League Baseball. Through semi-structured interviews, we gathered insights from a diverse range of sources, including scouts, player development directors, and former general managers. We focused on the influence of uncertainty and firm capabilities on resource picking and attaining competitive advantage. Furthermore, we solicited examples illustrating the dynamics of information flow within their organizations and explored potential limitations to the volume of information that proves beneficial for resource selection. Following these interviews, we proceeded with our empirical analysis.

We collected archival data for Major League Baseball organizations and their minor league subsidiaries from 1890 to 2018. We obtained the data used in our analyses from the following sources: Player performance data, team performance data, and player salaries came from Baseball-Reference.com, while information about player trades, ballpark locations, and team managers was obtained from Retrosheet (www.retrosheet.org) and corroborated with data from the Chadwick Baseball Bureau (www.chadwick-bureau.com). We augmented this data with a hand-collected dataset on scouts. We then worked with the Society for American Baseball Research (www.sabr.org) to obtain proprietary data about minor league player salaries from minor league contracts. We also gathered public data about player bonuses from Baseball America (www.baseballamerica.com). Metropolitan statistical areas data (U.S.) and census metropolitan areas data (Canada) were obtained from the U.S. Census Bureau (www.census.gov) and Statistics Canada (www.statcan.gc.ca), respectively. Finally, while we found similar results with a broader sample, we limited our final dataset to data from 1949 to 2018 due to changes in the minor league system in the early 1950s.

One of the most critical aspects of our data is that we look at all levels of resource management in baseball, from A to MLB. Players typically progress from the A level to AA, then AAA, then finally MLB. The players at the A level tend to be younger, have shorter track records, and have greater uncertainty about their performance (Sullivan, 1991). Most prior research on baseball organizations published in business journals has only looked at the MLB level, with a few exceptions (e.g., Schwab, 2007). A key benefit of our dataset is that it allows us to examine all the resources in an organization, not just the most certain ones. This feature of our data is vital for RBV research, as the resource’s uncertainty is paramount to how much information the focal firm and competitors have regarding the resource (Makadok & Barney, 2001).

**Dependent Variable**

Our primary dependent variable is *on-base plus slugging*, commonly known as *OPS*. In RBV research, it is crucial to differentiate between the resource’s value and the firm’s performance metric (Priem & Butler, 2001). *OPS* accomplishes this and serves as one of the most popular metrics for judging a player’s performance (Marr & Thau, 2014). *OPS* offers value to management studies because the player’s performance is exogenous to firm-based decisions, unlike other commonly used metrics such as *WAR* and *runs scored*. The *OPS* equation is straightforward, combining the likelihood of a player getting on base with the impact of the player at bat. In baseball, the players on offense try to score runs by running around the bases. Therefore, players need to get on base (“on-base percentage”) and move themselves and others around the bases (“slugging percentage”). These are the two crucial elements of a player’s offensive output, and they are critical to the team’s performance. The equation is as follows:

where *H* stands for “hits”; *BB*, for “walks”; *HBP*, for “hit by pitch”; *AB*, for total “at-bats”; *SF*, for “sacrifice flies”; and *TB*, for “total bases.”

Previous studies have used other metrics to calculate performance in baseball organizations, such as runs scored (Poppo & Weigelt, 2000) and adjusted batting runs (Bloom, 1999). While these serve as valuable metrics, they are either obscure or use statistics that are not widely available throughout recorded baseball history. We chose *OPS* because it offers us the greatest operationalization of our data, and the baseball statistics community confirms its relevance to both player and team performance (Albert, 2010). Similarly, the fact that our statistic was exogenous to firm-based decision-making made us feel comfortable in this choice. We ran our models using alternative dependent variables with similar results and significance.

**Independent Variables**

*SFM transaction*. In Major League Baseball, organizations can either engage in capability building by developing their players within their organization or engage in resource picking by acquiring players from other organizations. Capability building can be represented through drafting and holding onto players throughout their careers. For resource picking, measured by our *SFM transaction* variable, we stayed true to the theoretical and prior empirical literature by examining players acquired by a team in that particular year from another organization (Barney, 1986; Poppo & Weigelt, 2000). To represent transactions, we combined five different actions a Major League Baseball team might take to acquire a resource in an SFM.

We looked at free agent pickups, trades between teams, outright purchases of players, waived players, and players obtained in the Rule 5 draft. Each approach leads a team to acquire a resource from another team, either at cost or for free. Therefore, theoretically, these approaches should move teams in a similar direction because they all represent resource picking. To verify this conjecture, we tested the homogeneity of slope coefficients across these categories using the delta test (Pesaran & Yamagata, 2008). We failed to reject the null hypothesis that the slope coefficients are homogenous across categories (Δ = 1.42, p = 0.156). Therefore, we combined all five actions into a single *SFM transaction* dummy variable for the sake of ease. Each player received a “1” if involved in an SFM transaction in that given baseball financial year and a “0” otherwise.[[1]](#footnote-1)

*Year*. We employed the *year* variable as a proxy for SFM uncertainty to examine how decreasing SFM uncertainty over time moderates the performance effect of resource picking in SFMs. Uncertainty in factor markets decreases over time as information about the resources and firms becomes more available (Oster, 1999). Our dataset spans the years 1949 to 2018.

*Level.* Here, we measured the level at which the player is playing each year. Following minor league reclassification in 1963, we categorized players into four levels: A, AA, AAA, and MLB. A is the lowest level, followed by AA, AAA, and MLB, which is the highest level in North American professional baseball. As our data is at the *year-team-player-level* unit of analysis, we assigned each entry to one of these four levels.

*Minor league*. This variable is similar to *level* but lumps all three minor leagues (A, AA, AAA) into a single dummy variable. While we included all individual levels in our *level* variable to show that the resource-picking advantage holds for all minor leagues for hypotheses 1 to 3, we used this dichotomous *minor league* variable when testing hypothesis 4 to present interpretable results for a three-way interaction model.

*Firm resource-picking capability.* This variable captures the firm’s resource-picking capability. Following the approach of Kim and Makadok (2021), we captured residuals from a regression that calculates the improvement in the *OPS* of players acquired by teams through resource picking, minus the idiosyncratic individual effects of those players. Then, we calculated a three-year moving average of the captured OPS residuals aggregated at the affiliation and year level to smooth out short-term fluctuations and trends. This rolling average gives us a comprehensive view of the firm’s resource-picking capability by year.

**Control Variables**

We controlled for individual and team factors. Our most crucial individual control is *lagged OPS*, representing the player’s performance in the previous year (Bloom, 1999). This variable is necessary because different players have different abilities.[[2]](#footnote-2) We also controlled for the player’s *age*, as older players often perform better than younger players at similar levels (Marr & Thau, 2014). At the same time, we included *age squared*, as the relationship between player performance and age is known to follow an inverted U shape (Marr & Thau, 2014). Additionally, we included the player’s *salary* and *bonus* information to control for the resource cost. Finally, we controlled for a player’s *complementarity* with the team, using an approach found in the empirical literature (Krishnan et al., 1997; Schweiger et al., 2019) by focusing on a player’s congruence with team strategy based on five factors: walks, hits, home runs, stolen bases, and total bases.[[3]](#footnote-3)

We introduced team controls into our model as well. For all variables, we tracked the organization, meaning that if a team switched cities (e.g., the Washington Senators moved to Minnesota in 1961), we continued tracking it as the same organization. First, we controlled for *scouts*, who act as information gatherers in baseball, as they travel worldwide to find and evaluate players on various teams. Then, we added *employees*, who support the team and can represent the firm’s size. We included the *win percentage* for the current year and *lagged win percentage* for the previous year of the MLB parent organization, as the aspiration level of the parent organization may affect its resource-picking goals (Hahl, 2016; Hill et al., 2017). We included the MLB parent organization’s offensive aspiration level using the *MLB runs* and *lagged MLB runs*, which represent the offensive performance of the organization and its needs (Bloom, 1999). We added the control variables *attendance* and *lagged attendance*, representing the organization’s financial performance (Schwab, 2007). We also operationalized a market’s size and economic potential by including the *population* of the MLB city based on metropolitan statistical area and census metropolitan area data (Hill et al., 2017; Shamsie & Mannor, 2013). Lastly, we included the *market position* of the teams to control for the standing and influence of the teams in the baseball industry.

**Model Specifications**

First, we used ordinary least squares (OLS) regression with organizational affiliation and year fixed effects, and our unit of analysis was at the player level. The affiliation fixed effects controlled for time-invariant differences in players’ performance due to unobserved factors that differ across organizations, and the time fixed effects controlled for common time trends affecting all organizations. While we used OLS to test most of our hypotheses, we also utilized a difference-in-differences model to control for a possible endogeneity issue in testing hypothesis 2, as described later.

We used the following equation to test the hypothesized moderation effects of (1) SFM uncertainty in hypothesis 1, measured by year; (2) resource uncertainty in hypothesis 2, measured by level; (3) firm-specific capabilities in hypothesis 3, measured by the residuals; and (4) the three-way interaction across SFM transaction, resource uncertainty (level) and firm-specific capabilities (residuals), as follows:



To test the causality of our arguments, we utilized a difference-in-differences approach. Our difference-in-differences model tested hypothesis 2 based on the designated-hitter rule that surprised firms in the American League in 1973. In our model, the designated-hitter rule constituted the external shock; players in the American League were the treatment group, and those in the National League served as the control group. We used the following two-way fixed-effects model:

In this model, we limited the number of control variables. While the results are similar to those with the complete set of control variables, difference-in-differences models perform better when they are parsimonious (Atanasov & Black, 2016). Including control variables in difference-in-differences models proves especially challenging when the external shock can affect the control variables independently, which is the case for most of our control variables. Therefore, we chose a model where only the most consequential and independent control variable—*lagged OPS*—was included.

Before we observed this treatment effect, we tested the parallel trend assumption to ensure that in the absence of the designated-hitter rule, the difference between the National League and American League would have remained stable over time (Angrist & Pischke, 2008; Mora & Reggio, 2015). We found support for our model specification and report these findings in the results section.

**RESULTS**

Before presenting the results for the tests of our hypotheses, we will discuss potential multicollinearity and the correlation coefficients across the independent and control variables. Table 1 provides the summary statistics and the correlation matrix for the variables used in our analysis. The correlations between a few variables appear high, primarily between those recorded for the focal year and the previous year, such as *OPS, win percentage, MLB runs,* and *attendance*, as expected. *Age* has a moderate positive correlation with *salary*, which is expected given that players improve their performance and visibility over time, which improves their chances of receiving higher salaries. The variables *win percentage*, *MLB runs*, and *attendance,* as well as their lagged values, are also moderately correlated with one another, which is not surprising because a team’s success, as indicated by win percentage and runs scored, often leads to increased fan engagement and higher attendance due to fan expectations and media coverage. However, our models do not have a concerning multicollinearity problem, as the mean VIF in our base model is 3.39 (well below the widely accepted threshold of 10), with the highest value being 8 (Neter et al., 1985).

[Insert Table 1 about here]

We report the results for only the control variables in Model 1 of Table 2. *Age, level* (all minor leagues)*, lagged OPS,* *MLB runs*, *salary,* and *bonus* are all positive and significant. As apparent from the negative coefficient of *age squared*, *age* has a curvilinear effect on performance. This result is not surprising, given that a player’s performance first increases and then decreases after a certain peak (Schulz et al., 1994). Interestingly, *attendance* is negatively correlated with *OPS*. This finding could be due to the draft system present in Major League Baseball, which provides poor-performing teams that typically have low attendance with top entry-level talent.

Hypothesis 1 predicts that greater SFM uncertainty will increase the likelihood that resource picking will lead to an accuracy advantage. We argue that the SFM uncertainty decreases over time because it becomes harder to gain abnormal profit when decision rules are known and public information is high. We analyze the interaction between *SFM transaction* and *year* to test this hypothesis. Model 2 of Table 2 presents our findings. As indicated in the table, the coefficient of the interaction term is negative and significant (β = -0.0009, SE = 0.0003, p = 0.004; 95% CI -0.0012 to -0.003), supporting our prediction that SFM uncertainty positively moderates the effect of resource picking on setting more accurate expectations.

[Insert Table 2 about here]

To test hypothesis 2, which argues that resource uncertainty positively moderates the effect of SFM transactions on accuracy advantages, we utilized both a split-sample approach and an interaction model. We used a split-sample approach primarily to validate the results of Poppo and Weigelt’s (2000) study, which found that resource picking negatively affects performance in the highest league, and to test the effect of resource uncertainty at other levels. If our expectation is correct, we should see the SFM transaction effect varying depending on the degree of certainty of the available resources, such that resource picking leads to an accuracy advantage only with high resource uncertainty.

Therefore, in our split-sample model, we analyzed the main effects of resource picking across different uncertainty levels (i.e., different leagues). Our results, detailed in Table 3, affirm that resource picking negatively and significantly affects performance at the MLB level (β = -0.011, SE = 0.0003, p = 0.004; CI -0.018 to -0.004). In contrast, it positively and significantly affects performance at the AAA, AA, and A levels (level AAA: β = 0.023, SE = 0.0038, p < 0.000, 95% CI 0.015 to 0.030; level AA: β = 0.026, SE = 0.0055, p < 0.000, 95% CI 0.015 to 0.038; level A: β = 0.036, SE = 0.0071, p < 0.000, 95% CI 0.022 to 0.051), reinforcing the notion that uncertainty is essential for successful resource selection.

[Insert Table 3 about here]

We now move to the interaction model, where we introduced the interaction term between *SFM transaction* and *level* and further analyzed hypothesis 2, as shown in Table 2, Model 3. Here we also examined the potential change in the relationship between resource picking and accurate expectations, depending on the player’s level. We expected positive coefficients for the interaction terms between SFM transactions and all minor league levels, while holding MLB-level players as the reference group. As predicted, we observed that compared to those at MLB level, *SFM transaction*’s interactions with players at AAA, AA, and A are positive and significant (level AAA: β = 0.034, SE = 0.005, p = 0.000, 95% CI 0.023 to 0.046; level AA: β = 0.046, SE = 0.007, p = 0.000, 95% CI 0.032 to 0.060; level A: β = 0.091, SE = 0.010, p = 0.000, 95% CI 0.070 to 0.112 for level A), supporting our hypothesis. Therefore, while we observed that resource picking does not always lead to superior performance, it does so with high resource uncertainty.

To examine the causality proposed in hypothesis 2, we employed a difference-in-differences model. This analysis hinged on two primary variables: *Designated hitter treated* and *Designated hitter after treatment.* The former is a binary dummy variable indicating whether a team has ever implemented the designated hitter rule, coded as 1 if yes, 0 otherwise. The latter variable also takes on binary values, with 1 denoting the years from 1973 onward, signaling the period post-adoption of the designated hitter rule, and 0 representing earlier years.

First, we analyzed the parallel trends assumption through a visual exploration (Atanasov & Black, 2016). Figure 3 presents the mean performances of treatment (American League) and control (National League) groups separately before and after the treatment. The graph reveals that the American League’s and National League’s mean *OPS* performance exhibited parallel trends before 1973. We also ran an empirical test based on Mora and Reggio’s (2015) approach for added robustness. We failed to reject the assumption that the treatment and control groups are similar before the treatment date, as our p-value was above 0.10. Additionally, there is no reason to suspect that a spillover effect occurred prior to this shock, as the rule divergence surprised players and teams (McKelvey, 2004). Therefore, we can reasonably assume that the critical assumptions hold for the difference-in-differences analysis.

[Insert Figure 3 about here]

For this difference-in-differences analysis, we looked at a period that brought greater uncertainty for one league than for the other. To observe the effect of this policy change, we started by limiting the data to only the resources chosen in factor markets between 1963 and 1983, 10 years before the shock and 10 years after. While we also tested our models with different ranges that showed similar results, a 10-year range is ideal for the empirical context, as each league needed to spend a few years adjusting and developing players accordingly. We report the results of our difference-in-differences regression in Model 4 of Table 2. As predicted, the interaction term coefficient between the *designated hitter treated* and the *designated hitter after treatment* is positive and significant (β = 0.032, SE = 0.013, p = 0.011; 95% CI 0.007 to 0.057), supporting hypothesis 2.

To test hypothesis 3, which proposes that the effect of resource-picking on an accuracy advantage is contingent upon the resource-picking capability of a firm, we introduced an interaction term between *SFM transaction* and *firm resource-picking capability* to our model. As Model 5 of Table 2 shows, the coefficient of the interaction is positive and significant (β = 0.735, SE = 0.044, p < 0.001; 95% CI 0.644 to 0.826), supporting hypothesis 3.

Finally, hypothesis 4 argues that both resource uncertainty and firm-specific capabilities are individually necessary, but not sufficient, for consistently gaining an accuracy advantage. We performed two regression analyses to test the role of resource-picking capabilities of firms with uncertain resources: a three-way interaction model with *SFM transaction, minor league,* and *firm resource-picking capability,* and a split-sample approach with *firm resource-picking capability* and *minor league.* Regarding the former model, we expected to see a positive coefficient for the three-way interaction. After introducing these variables independently in Model 6, we tested the interaction terms in Model 7, Table 2. As indicated in the table, the coefficient of the three-way interaction is positive and significant (β = 0.304, SE = 0.104, p = 0.007; 95% CI 0.091 to 0.516), supporting hypothesis 4.

Second, we employed a split-sample model that classified the sample into four groups: major league with low capability (Quadrant I: Table 4, Model 1), major league with high capability (Quadrant II: Table 4, Model 2), minor league with low capability (Quadrant III: Table 4, Model 3), and minor league with high capability (Quadrant IV: Table 4, Model 4). We anticipated observing a significant and positive coefficient for *SFM transaction* solely in the fourth quadrant, which would reflect the acquisition of minor league players by firms with high resource-picking capabilities. The results in Table 4 affirm this expectation: The *SFM transaction* coefficient is negative and significant for the first quadrant, which pertains to major league players and low-capability firms (β = -0.024, SE = 0.004, p < 0.000; 95% CI -0.032 to 0.015). Conversely, the coefficients are statistically insignificant for the second and third quadrants, which reflect major league players with high-capability firms and minor league players with low-capability firms, respectively (β = -0.002, SE = 0.005, p = 0.657, 95% CI -0.012 to 0.008; β = -0.006, SE = 0.005, p = 0.237, 95% CI -0.015 to 0.004, respectively). Lastly, the coefficient is positive and significant for the fourth quadrant, which concerns minor league players acquired by high-capability firms (β = 0.042, SE = 0.005, p < 0.000; 95% CI 0.033 to 0.052). These findings substantiate our hypothesis that firms are more likely to achieve accurate expectations in resource-picking when facing significant resource uncertainty and possessing high resource-picking capabilities.

[Insert Table 4 about here]

**Alternative Mechanism Analysis**

The strategy literature has identified other constructs that affect SFM performance outside of information. First, existing resource complementarity can lead some firms to perform better with a particular resource than others (Adegbesan, 2009; Lippman & Rumelt, 2003; Wernerfelt, 2011). Complementarity occurs when a firm’s existing resources positively interact with a resource in the SFM in such a way that “the combinations lead to the creation of a ‘surplus’ over and above the sum of the amounts of value they could create independently” (Adegbesan, 2009, p. 463). Second, the expected market position of the firm can also influence SFM performance (Schmidt & Keil, 2013). Scholars have broken down expected market performance into three categories: the customer’s willingness to pay, the expected market price, and the expected firm opportunity cost (Schmidt & Keil, 2013).

Complementarity and market position[[4]](#footnote-4) should influence SFM performance; however, they should not affect the firm’s accuracy of expectations. Until now, we have studied how resource uncertainty, SFM uncertainty, and the firm-specific capabilities of an organization determine accuracy advantages. These elements directly affect the ability of a firm to set accurate expectations, as they help influence how sure a firm is about a resource’s value. Complementarity and market position, on the other hand, affect SFM performance by determining whether the resource is more valuable in a specific firm than in another. Nevertheless, due to the importance of these characteristics in SFMs, we controlled for the effect of complementarity and market position in all of our models. As indicated in the models in Table 2, our hypotheses were supported after controlling for complementarity and market position, providing evidence for the importance of uncertainty and firm-specific capabilities on the accuracy of expectations.

**Robustness Tests**

We performed several robustness checks to analyze the sensitivity of our findings, and we report our results in the online appendices. First, we investigated an additional uncertainty variable construct to further support hypothesis 2 by testing the moderating role of *age* on the relationship between resource picking and an accuracy advantage. A player’s strengths, weaknesses, and performance become more certain the longer they play, we found. A very high correlation exists between a player’s age and the number of years he has played baseball, since most players start playing around the same age (Fair, 2008; Schultz et al., 1994). This relationship was further verified throughout our conversations with scouts and general managers, as they repeatedly stated that both the level of play and the age of the player are operationalizations of resource uncertainty.

Therefore, we measured resource uncertainty by a player’s age and added this variable as an interaction term instead of using their league (as we did in the primary analysis). Our result in Model 1 of Online Appendix 1 shows that the effect of uncertainty in moderating the relationship between SFM transactions and an accuracy advantage remained robust, as the interaction term coefficient was negative and significant. This finding supports the idea that resource uncertainty affects a firm’s ability to set more accurate expectations.

Second, we reran our main models after adding *management change* as a control variable to ensure that team general manager changes would not affect our results (Peeters et al., 2020). The new regressions did not significantly affect our models’ coefficients and confidence levels, as evidenced by models 2 through 6 in Online Appendix 1. This result helps support our hypotheses, showing that what drives our results is genuinely resource picking moderated by resource uncertainty, SFM uncertainty, and firm-specific capabilities rather than organizational change.

We also found additional validation based on how we formed our measure of *SFM transactions*. When we combined all five types of SFM transactions in a single measure, we saw support for both those transactions with a seller pricing mechanism (i.e., trades, purchases) and those without a pricing mechanism (i.e., waivers, free agents, rule 5 draft).[[5]](#footnote-5) The fact that multiple types of SFM transactions bore a similar pattern compared to capability building demonstrates that the type of transaction does not influence the usefulness of our main mechanisms.

Finally, we tested the robustness of our findings by accounting for the player fixed effects. We did not integrate player fixed effects in our primary analyses because most players do not undergo multiple SFM transactions during their careers. However, we included individual fixed effects in our supplemental analysis, as it can help control for unobservable individual differences among players that may affect their performance, reducing the risk of omitted variable bias. Despite the limitations in observations created by the player fixed effects in the model, the results align with our hypotheses, except for the interaction between *level A* and *SFM transaction*, which became insignificant. We suspect the latter finding emerged due to a lack of variation or sample size by which to detect statistically significant effects over time when controlling for player-specific factors. Results are reported in Online Appendix 2. As the table shows, the moderating role of the other two levels remains positive and significant. When all minor leagues are combined to create a binary variable, its interaction with *SFM transaction* is also significant.[[6]](#footnote-6)

**DISCUSSION AND CONCLUSIONS**

In this paper, we disentangle different facets of uncertainty and show why prior research has found mixed results regarding the value of information. In other words, we highlight the mechanism of uncertainty by showing that only when firms can use private information to their advantage can they achieve more accurate expectations. Additionally, we find that as markets become less uncertain, they become more rigid, and the ability of firms to form more accurate expectations than others decreases. Finally, we show the importance of firm-specific capabilities in SFMs while demonstrating that this is a necessary, but not sufficient, condition for firms to achieve an accuracy advantage from resource picking.

One interesting finding was that there are firm-specific characteristics that affect SFMs outside of complementarity (Adegbesan, 2009; Lippman & Rumelt, 2003) and market position (Schmidt & Keil, 2013). These and factor market rivalry (Gianiodis et al., 2019) have dominated the recent literature on SFMs. However, except for some prior theoretical work (Makadok & Barney, 2001), scholars have not studied the influence of firm heterogeneity in information gathering, processing, and action outside of work on high-certainty SFMs (Poppo & Weigelt, 2000). We focus on the effect of firm-specific capability rather than firm-specific attributes as we recenter attention on the strategist. By studying the “managerial skill” that Barney (1989) refers to, we hope to reinvigorate focus on low-church RBV (Gavetti & Levinthal, 2004), whereby further research into the cognitive biases and microfoundations of the strategist in SFMs could identify new potential areas of competitive advantage (Amit & Schoemaker, 1993; Felin et al., 2021; Foss, 2011).

Our theorizing is also supported by the literature on financial intermediation (Chant, 1992; Hodula et al., 2023). While our research offers a perspective on how information, uncertainty, and firm-specific capabilities affect SFMs, it can also speak to the financial literature on how information aggregation affects pricing (Grossman & Stiglitz, 1980). Specifically, our work helps answer the Grossman-Stiglitz paradox—why firms would pay for information if the market aggregates it completely—in SFMs by detailing the delicate balance between uncertainty and accuracy advantages. We therefore offer a fresh perspective that not only reconciles existing inconsistencies but also advances our understanding of the mechanisms underlying resource selection in uncertain environments (Maritan & Peteraf, 2011).

Our work speaks to the research on strategic factor market efficiency as well (Felin et al., 2016; Leiblein, 2011; Ross, 2012). SFM efficiency “directly affects the opportunity for a bidder to benefit in the market for strategic factors” (Leiblein, 2011, p. 913) and is tied to prior concepts of market efficiency in the finance literature (Ross, 2012). Previous scholars have noted the number of buyers, the number of sellers, and the availability of data as critical influencers of market efficiency (Leiblein, 2011; Ross, 2012). We specifically consider time and SFM uncertainty, which are essential attributes of SFM efficiency, and how they affect the likelihood of setting more accurate expectations. While other scholars have examined SFM efficiency theoretically, we believe we are the first to test SFM efficiency empirically. We encourage other researchers to further examine the intricate role of information efficiency in accuracy advantages.

Overall, we have identified three primary contributions of our study to the SFM and strategic management literature. Our first contribution entails how uncertainty affects expectation accuracy and, thus, performance. Prior SFM works have mainly focused on resource markets with low degrees of uncertainty (Maritan & Peteraf, 2011). That has led to the counterintuitive finding that investing in acquiring private information does not lead to more accurate expectations and, subsequently, advantages (Poppo & Weigelt, 2000). While our study corroborates these findings, it also reveals that they only capture part of the bigger picture. By accounting for the difference between low- and high-uncertainty resources and markets, we reconcile an apparent inconsistency in the SFM literature and add further support to the central tenets of the SFM theory. We also do so in a quantitatively rigorous way, leading to our next contribution.

Second, we bolster the resource-based view by providing robust empirical support for our findings. We show that prior analyses that considered only the highest levels of information availability are incomplete. We therefore offer new avenues for empirical SFM research that may shed more light on the theory’s importance and prevalence. SFMs have proven notoriously difficult to research, as firms aim to hide both what they pay and purchase in SFMs (Arend, 2006; Priem & Butler, 2001). This opacity has led to a relative dearth of empirical SFM studies compared to the theory’s importance and prevalence (Barney et al., 2001). We introduce a context that allows us to test core SFM assumptions through an innovative look at multiple types of resources, and we encourage future researchers to develop similar empirical tests for SFMs, as there remains much to discover.

Third, we uncover a boundary condition for the importance of firm-specific capabilities in SFMs. Previous research has explored the circumstances under which firms will or will not attempt to gain information (Makadok & Barney, 2001; Maritan & Florence, 2008). Additionally, other studies have considered firm-specific attributes such as complementarity (Adegbesan, 2009; Lippman & Rumelt, 2003) or market position (Schmidt & Keil, 2013). However, to our knowledge, this is the first study that explicitly examines the influence of firm-specific capabilities on the accuracy of expectations. We find that while resource-picking capabilities offer benefits, their utility only matters in cases of high uncertainty. Therefore, future research should not look at firm-specific capabilities or the market condition in isolation for SFM research, but rather, in conjunction.

We offer recommendations to managers as well. SFMs, which are the markets before the markets, help determine an organization’s future (Barney, 1986). Resource market purchases are standard in the real world, ranging from players in professional baseball (Poppo & Weigelt, 2000) to patents in technology sectors (Gianiodis et al., 2019). Managers must pay attention to the types of uncertainty that exist within SFMs and how they affect their ability to set expectations (Felin et al., 2016; Leiblein, 2011). We also suggest that managers build up their firm-specific capabilities regarding resource picking. By identifying the causal relationship between a resource and performance, a firm can obtain a competitive advantage through purchasing resources. Utilizing such analysis, firms could better position themselves in the resource and product markets.

Our study also has limitations, leading to important future research areas. While we examine many aspects of SFMs with appropriate endogeneity controls, we acknowledge this is a one-industry study. Further research could look at multiple industries within the same SFM to add to the inter-industry SFM competition literature (Gianiodis et al., 2019). While our dataset aptly fits the context of our study and provides a unique way to test theoretical RBV constructs, we recommend examining other contexts when and if creative datasets become available.

Overall, further work is needed to support the foundational SFM ideas. We show the influence of resource uncertainty, SFM uncertainty, and firm-specific capabilities on SFM performance, which helps solidify the link between information and performance. Our study adds to the existing theory by illustrating when and where these links work. We show that uncertainty and firm-specific capabilities are necessary, but not sufficient, conditions for firms to obtain more accurate expectations than others. We hope our extension of the SFM literature spurs further research into how firms can utilize SFMs to obtain competitive advantages.

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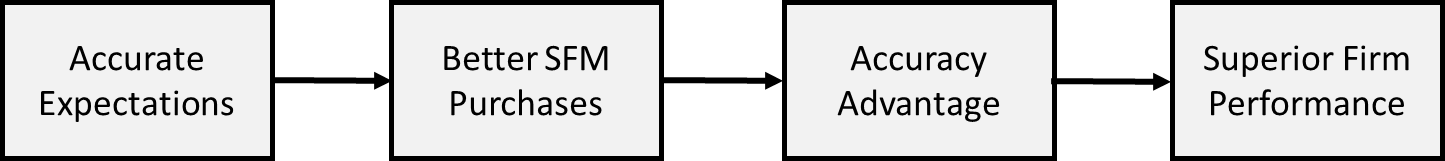
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**Figure 1:** Strategic Factor Market Process Map

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**Figure 2:** Predictions for the Intersection of Resource Uncertainty and Firm Capabilities



**Figure 3:** Parallel Trends—Designated Hitter

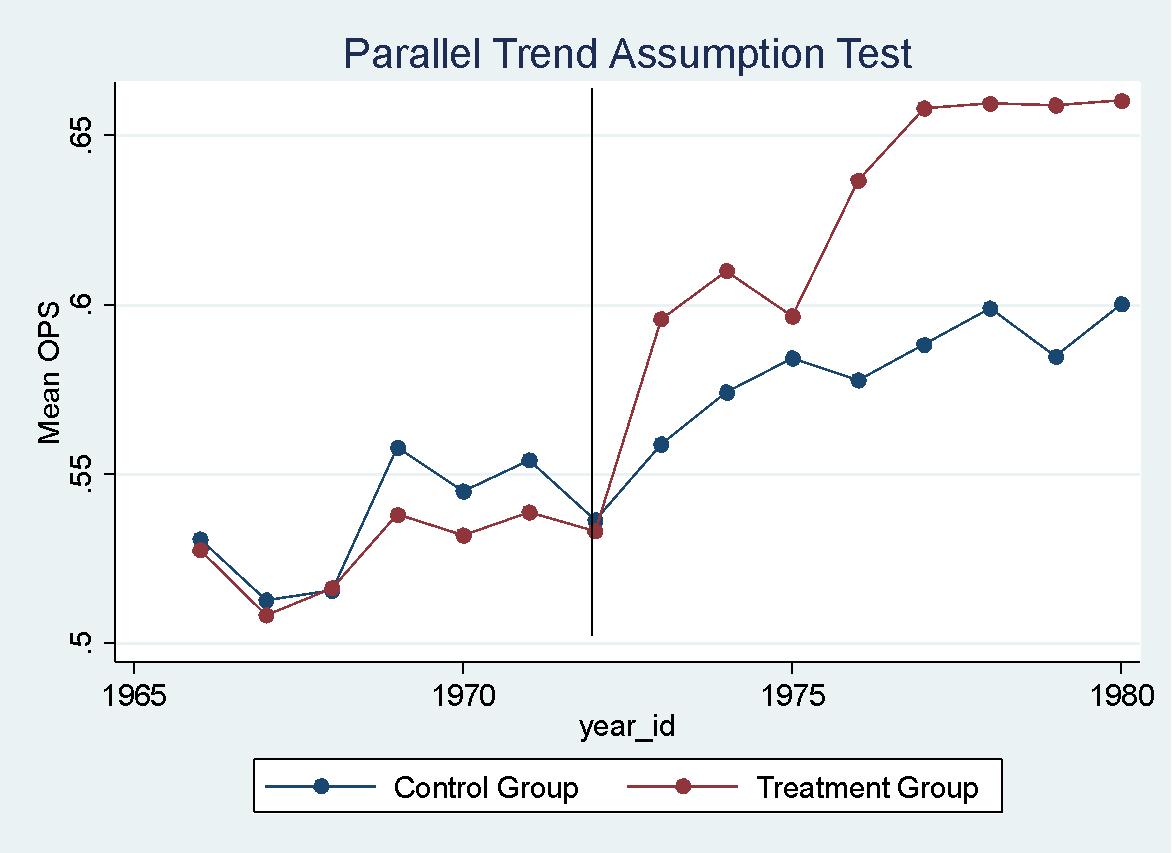


Table 1: Matrix of correlations

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variables | Mean | Std.Dev. | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) |
| **(1) OPS** | .598 | .297 | 1.000 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| **(2) Age** | 24.677 | 4.172 | -0.025 | 1.000 | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| **(3) Lagged OPS** | .624 | .266 | 0.378 | -0.062 | 1.000 | - | - | - | - | - | - | - | - | - | - | - | - | - | - |
| **(4) Scouts** | 5.789 | 5.316 | 0.008 | 0.049 | 0.030 | 1.000 | - | - | - | - | - | - | - | - | - | - | - | - | - |
| **(5) Employees** | 51.063 | 24.058 | -0.010 | 0.015 | -0.002 | 0.344 | 1.000 | - | - | - | - | - | - | - | - | - | - | - | - |
| **(6) Win Percentage** | .501 | .072 | 0.016 | 0.020 | 0.010 | 0.058 | -0.001 | 1.000 | - | - | - | - | - | - | - | - | - | - | - |
| **(7) MLB Runs** | 707.718 | 96.241 | 0.049 | 0.060 | 0.049 | 0.123 | -0.001 | 0.457 | 1.000 | - | - | - | - | - | - | - | - | - | - |
| **(8) Attendance** | 1.973 | .828 | -0.005 | 0.073 | -0.001 | 0.310 | 0.122 | 0.467 | 0.394 | 1.000 | - | - | - | - | - | - | - | - | - |
| **(9) Lagged Win Percentage** | .501 | .072 | 0.007 | 0.032 | 0.016 | 0.034 | 0.019 | 0.457 | 0.221 | 0.447 | 1.000 | - | - | - | - | - | - | - | - |
| **(10) Lagged MLB Runs** | 707.476 | 96.963 | 0.043 | 0.070 | 0.055 | 0.144 | 0.015 | 0.237 | 0.480 | 0.348 | 0.438 | 1.000 | - | - | - | - | - | - | - |
| **(11) Lagged Attendance** | 1.962 | .828 | -0.007 | 0.072 | -0.000 | 0.321 | 0.145 | 0.283 | 0.208 | 0.878 | 0.443 | 0.388 | 1.000 | - | - | - | - | - | - |
| **(12) Population (in millions)** | 4.066 | 3.650 | 0.014 | 0.009 | 0.023 | 0.164 | -0.017 | 0.150 | 0.042 | 0.299 | 0.151 | 0.041 | 0.292 | 1.000 | - | - | - | - | - |
| **(13) Salary (in thousands)** | 290.280 | 1505.700 | 0.012 | 0.407 | -0.009 | 0.118 | 0.050 | 0.050 | 0.044 | 0.117 | 0.060 | 0.053 | 0.118 | 0.051 | 1.000 | - | - | - | - |
| **(14) Bonus (in thousands)** | 215.822 | 652.349 | 0.036 | -0.003 | 0.015 | 0.194 | 0.090 | -0.007 | 0.008 | 0.061 | -0.007 | 0.017 | 0.064 | -0.009 | 0.244 | 1.000 | - | - | - |
| **(15) Complementarity** | .321 | .289 | -0.252 | 0.139 | -0.378 | 0.018 | 0.020 | 0.001 | -0.010 | 0.029 | -0.003 | -0.013 | 0.026 | -0.007 | 0.079 | 0.028 | 1.000 | - | - |
| **(16) Market Position** | 3.498 | 1.915 | -0.013 | -0.036 | -0.010 | -0.113 | -0.031 | -0.851 | -0.417 | -0.455 | -0.382 | -0.233 | -0.295 | -0.128 | -0.062 | -0.028 | -0.011 | 1.000 | - |
| **(17) Firm RP Capability** | .08 | 0.45 | 0.036 | 0.012 | -0.004 | -0.057 | -0.050 | 0.121 | 0.244 | 0.066 | 0.011 | 0.067 | 0.042 | 0.045 | -0.025 | -0.059 | 0.003 | -0.104 | 1.000 |

Table 2: Main Regressions

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) |  | (3) | | (4) | | (5) | | (6) | (7) | |
|  | OPS | OPS |  | OPS | | OPS | | OPS | | OPS | OPS | |
|  | (Controls) | (H1) |  | (H2) | | (H2-DiD) | | (H3) | | (H4 Controls) | (H4) | |
| Age | 0.0191\*\*\* | 0.0189\*\*\* |  | 0.0169\*\*\* | | - | | 0.0190\*\*\* | | 0.0136\*\*\* | 0.0112\*\*\* | |
|  | (0.00256) | (0.00267) |  | (0.00257) | | - | | (0.00258) | | (0.00250) | (0.00254) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Age Squared | -0.000288\*\*\* | -0.000282\*\*\* |  | -0.000247\*\*\* | | - | | -0.00029\*\*\* | | -0.00020\*\*\* | -0.00016\*\*\* | |
|  | (0.0000471) | (0.0000490) |  | (0.0000470) | | - | | (0.0000475) | | (0.0000468) | (0.0000479) | |
|  |  |  |  |  | |  | |  | |  |  | |
| SFM Transaction | 0.00985\*\*\* | 1.906\*\*\* |  | -0.0209\*\*\* | | - | | -0.0539\*\*\* | | 0.00918\*\*\* | -0.0682\*\*\* | |
|  | (0.00185) | (0.535) |  | (0.00314) | | - | | (0.00449) | | (0.00217) | (0.00759) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Level AAA | 0.0638\*\*\* | 0.0650\*\*\* |  | 0.0535\*\*\* | | - | | 0.0646\*\*\* | | - | - | |
|  | (0.00495) | (0.00499) |  | (0.00463) | | - | | (0.00496) | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| Level AA | 0.0618\*\*\* | 0.0629\*\*\* |  | 0.0508\*\*\* | | - | | 0.0625\*\*\* | | - | - | |
|  | (0.00379) | (0.00388) |  | (0.00370) | | - | | (0.00381) | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| Level A | 0.0748\*\*\* | 0.0752\*\*\* |  | 0.0627\*\*\* | | - | | 0.0753\*\*\* | | - | - | |
|  | (0.00483) | (0.00489) |  | (0.00477) | | - | | (0.00486) | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| Lagged OPS | 0.349\*\*\* | 0.349\*\*\* |  | 0.348\*\*\* | | 0.466\*\*\* | | 0.349\*\*\* | | 0.350\*\*\* | 0.350\*\*\* | |
|  | (0.00730) | (0.00728) |  | (0.00720) | | (0.0136) | | (0.00736) | | (0.00719) | (0.00722) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Scouts | 0.0000468 | -0.000192 |  | 0.0000307 | | - | | -0.0000237 | | -0.0000128 | -0.0000158 | |
|  | (0.000401) | (0.000423) |  | (0.000404) | | - | | (0.000404) | | (0.000409) | (0.000409) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Employees | -0.0000129 | -0.0000241 |  | -0.0000152 | | - | | -0.0000133 | | -0.0000186 | -0.0000201 | |
|  | (0.0000464) | (0.0000505) |  | (0.0000461) | | - | | (0.0000425) | | (0.0000433) | (0.0000425) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Win Percentage | 0.0300 | -0.0101 |  | 0.0288 | | - | | 0.0194 | | 0.0225 | 0.0179 | |
|  | (0.0248) | (0.0300) |  | (0.0248) | | - | | (0.0237) | | (0.0240) | (0.0238) | |
|  |  |  |  |  | |  | |  | |  |  | |
| MLB Runs | 0.000053\*\*\* | 0.000065\*\*\* |  | 0.000053\*\*\* | | - | | 0.0000378\*\* | | 0.0000410\*\* | 0.0000386\*\* | |
|  | (0.0000186) | (0.0000144) |  | (0.0000187) | | - | | (0.0000182) | | (0.0000182) | (0.0000182) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Attendance | -0.00694\* | -0.00548 |  | -0.00690\* | | - | | -0.00506 | | -0.00584\* | -0.00526 | |
|  | (0.00350) | (0.00345) |  | (0.00352) | | - | | (0.00314) | | (0.00327) | (0.00313) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Lagged Win | -0.0123 | -0.0264 |  | -0.0131 | | - | | -0.0114 | | -0.0127 | -0.0117 | |
| Percentage | (0.0164) | (0.0185) |  | (0.0165) | | - | | (0.0153) | | (0.0152) | (0.0152) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Lagged MLB Runs | 0.00000549 | 0.0000258\*\* |  | 0.00000442 | | - | | 0.0000110 | | 0.0000116 | 0.0000105 | |
|  | (0.0000185) | (0.0000120) |  | (0.0000188) | | - | | (0.0000180) | | (0.0000180) | (0.0000182) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Lagged Attendance | 0.00123 | 0.000460 |  | 0.00133 | | - | | -0.0000638 | | 0.000496 | 0.000123 | |
|  | (0.00253) | (0.00265) |  | (0.00255) | | - | | (0.00244) | | (0.00254) | (0.00243) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Population | -2.85e-10 | 9.86e-10 |  | -2.51e-10 | | - | | 1.42e-10 | | -6.15e-11 | -9.70e-12 | |
|  | (2.54e-09) | (2.44e-09) |  | (2.54e-09) | | - | | (2.48e-09) | | (2.49e-09) | (2.45e-09) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Salary | 5.32e-09\*\*\* | 5.39e-09\*\*\* |  | 5.19e-09\*\*\* | | - | | 5.34e-09\*\*\* | | 5.50e-09\*\*\* | 5.47e-09\*\*\* | |
|  | (7.36e-10) | (7.40e-10) |  | (7.41e-10) | | - | | (7.27e-10) | | (7.58e-10) | (7.56e-10) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Bonus | 1.77e-08\*\*\* | 1.76e-08\*\*\* |  | 1.70e-08\*\*\* | | - | | 1.78e-08\*\*\* | | 1.67e-08\*\*\* | 1.62e-08\*\*\* | |
|  | (1.71e-09) | (1.70e-09) |  | (1.72e-09) | | - | | (1.73e-09) | | (1.55e-09) | (1.60e-09) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Complementarity | -0.270\*\*\* | -0.270\*\*\* |  | -0.271\*\*\* | | - | | -0.270\*\*\* | | -0.271\*\*\* | -0.271\*\*\* | |
|  | (0.0117) | (0.0119) |  | (0.0117) | | - | | (0.0118) | | (0.0118) | (0.0119) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Market Position | -0.000212 | -0.00168 |  | -0.000232 | | - | | -0.000258 | | -0.000309 | -0.000317 | |
|  | (0.00121) | (0.00148) |  | (0.00121) | | - | | (0.00121) | | (0.00121) | (0.00122) | |
| Table 2 (Continued) |  |  |  |  | |  | |  | |  |  | |
|  | (1) | (2) |  | (3) | | (4) | | (5) | | (6) | (7) | |
|  | OPS | OPS |  | OPS | | OPS | | OPS | | OPS | OPS | |
|  | (Controls) | (H1) |  | (H2) | | (H2-DiD) | | (H3) | | (H4 Controls) | (H4) | |
| Year | - | -0.000656\*\*\* |  | - | - | | - | | - | | - |
|  | - | (0.000197) |  | - | - | | - | | - | | - |
|  |  |  |  |  |  | |  | |  | |  |
| SFM Transaction \* | - | -0.000947\*\*\* |  | - | - | | - | | - | | - |
| Year | - | (0.000267) |  | - | - | | - | | - | | - |
|  |  |  |  |  |  | |  | |  | |  |
| SFM Transaction \* | - | - |  | 0.0340\*\*\* | | - | | - | | - | - | |
| Level AAA | - | - |  | (0.00529) | | - | | - | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| SFM Transaction \* | - | - |  | 0.0460\*\*\* | | - | | - | | - | - | |
| Level AA | - | - |  | (0.00690) | | - | | - | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| SFM Transaction \* | - | - |  | 0.0915\*\*\* | | - | | - | | - | - | |
| Level A | - | - |  | (0.0102) | | - | | - | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| Designated Hitter | - | - |  | - | | 0.058\*\*\* | | - | | - | - | |
| (DH) After | - | - |  | - | | (0.0214) | | - | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| DH Treated | - | - |  | - | | -0.0159 | | - | | - | - | |
|  | - | - |  | - | | (0.0324) | | - | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| DH After X | - | - |  | - | | 0.0323\*\* | | - | | - | - | |
| DH Treated | - | - |  | - | | (0.0127) | | - | | - | - | |
|  |  |  |  |  | |  | |  | |  |  | |
| Firm Resource | - | - |  | - | | - | | 0.0289 | | 0.117\*\*\* | 0.0411 | |
| Picking (RP) Capa. | - | - |  | - | | - | | (0.0255) | | (0.0276) | (0.0549) | |
|  |  |  |  |  | |  | |  | |  |  | |
| SFM Transaction \* | - | - |  | - | | - | | 0.735\*\*\* | | - | 0.544\*\*\* | |
| Firm RP Capability | - | - |  | - | | - | | (0.0445) | | - | (0.0727) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Minor League | - | - |  | - | | - | | - | | 0.0650\*\*\* | 0.0553\*\*\* | |
|  | - | - |  | - | | - | | - | | (0.00390) | (0.00620) | |
|  |  |  |  |  | |  | |  | |  |  | |
| SFM Transaction\* | - | - |  | - | | - | | - | | - | 0.0166 | |
| Minor League | - | - |  | - | | - | | - | | - | (0.0106) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Minor League\* | - | - |  | - | | - | | - | | - | -0.0168 | |
| Firm RP Capability | - | - |  | - | | - | | - | | - | (0.0583) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Triple Interaction | - | - |  | - | | - | | - | | - | 0.304\*\*\* | |
| (ML X RP X SFM) | - | - |  | - | | - | | - | | - | (0.104) | |
|  |  |  |  |  | |  | |  | |  |  | |
| Year FE | Included | Not included |  | Included | | Included | | Included | | Included | Included | |
| Affiliation FE | Included | Included |  | Included | | Included | | Included | | Included | Included | |
|  |  |  |  |  | |  | |  | |  |  | |
| Constant | 0.110\*\* | 1.407\*\*\* |  | 0.153\*\*\* | | 0.234\*\*\* | | 0.117\*\* | | 0.189\*\*\* | 0.242\*\*\* | |
|  | (0.0499) | (0.371) |  | (0.0499) | | (0.0214) | | (0.0499) | | (0.0489) | (0.0488) | |
| Observations | 91727 | 91727 |  | 91727 | | 6350 | | 91727 | | 91727 | 91727 | |
| *R*2 | 0.245 | 0.242 |  | 0.246 | | 0.208 | | 0.247 | | 0.245 | 0.247 | |
| Adjusted *R*2 | 0.244 | 0.242 |  | 0.245 | | 0.202 | | 0.246 | | 0.244 | 0.246 | |

Robust standard errors in parentheses, clustered by affiliation (\* *p* < 0.10, \*\* *p* < 0.05, \*\*\* *p* < 0.01).

Table 3: Split Sample by Levels

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | OPS (MLB) | OPS (AAA) | OPS (AA) | OPS (A) |
| Age | 0.0125\* | 0.00240 | -0.0208\* | 0.0126\* |
|  | (0.00621) | (0.00872) | (0.0103) | (0.00672) |
|  |  |  |  |  |
| Age Squared | -0.000216\*\* | -0.0000344 | 0.000423\*\* | -0.0000870 |
|  | (0.000103) | (0.000154) | (0.000205) | (0.000144) |
|  |  |  |  |  |
| SFM Transaction | -0.0113\*\*\* | 0.0225\*\*\* | 0.0264\*\*\* | 0.0365\*\*\* |
|  | (0.00349) | (0.00381) | (0.00555) | (0.00720) |
|  |  |  |  |  |
| Lagged OPS | 0.232\*\*\* | 0.351\*\*\* | 0.318\*\*\* | 0.290\*\*\* |
|  | (0.0136) | (0.0152) | (0.0187) | (0.0134) |
|  |  |  |  |  |
| Scouts | 0.00136\*\*\* | -0.000648 | 0.000772 | -0.000449 |
|  | (0.000429) | (0.000706) | (0.000886) | (0.000373) |
|  |  |  |  |  |
| Employees | -0.000116 | -0.000150 | 0.00000275 | 0.0000942\*\* |
|  | (0.0000779) | (0.000131) | (0.0000924) | (0.0000397) |
|  |  |  |  |  |
| Win Percentage | -0.0610 | 0.0762 | 0.100 | -0.00667 |
|  | (0.0494) | (0.0622) | (0.0753) | (0.0354) |
|  |  |  |  |  |
| MLB Runs | 0.000330\*\*\* | 0.0000318 | -0.0000470 | -0.00000294 |
|  | (0.0000328) | (0.0000388) | (0.0000565) | (0.0000215) |
|  |  |  |  |  |
| Attendance | 0.00603 | -0.0179\*\* | -0.0110\* | 0.000893 |
|  | (0.00557) | (0.00808) | (0.00634) | (0.00461) |
|  |  |  |  |  |
| Lagged Win Percentage | 0.0334 | -0.0210 | 0.0151 | -0.0424\* |
|  | (0.0295) | (0.0296) | (0.0354) | (0.0237) |
|  |  |  |  |  |
| Lagged MLB Runs | -0.0000286 | -0.0000198 | 0.0000431 | 0.0000380 |
|  | (0.0000283) | (0.0000313) | (0.0000463) | (0.0000229) |
|  |  |  |  |  |
| Lagged Attendance | -0.00469 | 0.00626 | -0.00401 | 0.00268 |
|  | (0.00466) | (0.00662) | (0.00521) | (0.00386) |
|  |  |  |  |  |
| Population | -2.99e-09 | 9.26e-09\* | -5.32e-09 | -2.86e-09 |
|  | (3.53e-09) | (4.83e-09) | (6.03e-09) | (4.65e-09) |
|  |  |  |  |  |
| Salary | 5.23e-09\*\*\* | 1.34e-08\*\*\* | 9.42e-09\*\* | 6.20e-10 |
|  | (8.08e-10) | (2.47e-09) | (4.23e-09) | (3.00e-09) |
|  |  |  |  |  |
| Bonus | 3.35e-09\*\* | 1.68e-08\*\*\* | 1.66e-08\*\*\* | 3.49e-08\*\*\* |
|  | (1.23e-09) | (2.84e-09) | (2.53e-09) | (4.06e-09) |
|  |  |  |  |  |
| Complementarity | -0.577\*\*\* | -0.272\*\*\* | -0.253\*\*\* | -0.106\*\*\* |
|  | (0.0208) | (0.0245) | (0.0272) | (0.0187) |
|  |  |  |  |  |
| Market Position | -0.000621 | -0.000537 | 0.00205 | -0.00111 |
|  | (0.00210) | (0.00232) | (0.00230) | (0.00170) |
|  |  |  |  |  |
| Year FE | Included | Included | Included | Included |
| Affiliation FE | Included | Included | Included | Included |
|  |  |  |  |  |
| Constant | 0.301\*\*\* | 0.414\*\*\* | 0.747\*\*\* | 0.273\*\*\* |
|  | (0.0999) | (0.131) | (0.127) | (0.0958) |
| Observations | 15055 | 23783 | 19046 | 33843 |
| *R*2 | 0.532 | 0.233 | 0.213 | 0.107 |
| Adjusted *R*2 | 0.530 | 0.231 | 0.211 | 0.105 |

Robust standard errors in parentheses, clustered by affiliation (\* *p* < 0.10, \*\* *p* < 0.05, \*\*\* *p* < 0.01).

Table 4: Split Sample by Firm Resource-Picking Capability and Level

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | OPS  (Major League  Low Capability) | OPS  (Major League  High Capability) | OPS  (Minor League  Low Capability) | OPS  (Minor League  High Capability) |
| Age | 0.0205\*\* | 0.00622 | 0.00161 | 0.0174\*\*\* |
|  | (0.00833) | (0.0111) | (0.00536) | (0.00434) |
|  |  |  |  |  |
| Age Squared | -0.000366\*\* | -0.0000968 | -0.000000846 | -0.000286\*\*\* |
|  | (0.000136) | (0.000183) | (0.000101) | (0.0000872) |
|  |  |  |  |  |
| SFM Transaction | -0.0240\*\*\* | -0.00213 | -0.00555 | 0.0422\*\*\* |
|  | (0.00416) | (0.00475) | (0.00460) | (0.00465) |
|  |  |  |  |  |
| Lagged OPS | 0.220\*\*\* | 0.237\*\*\* | 0.332\*\*\* | 0.358\*\*\* |
|  | (0.0219) | (0.0190) | (0.0110) | (0.0132) |
|  |  |  |  |  |
| Scouts | 0.00189\*\* | 0.00156\*\* | -0.0000377 | -0.000783 |
|  | (0.000896) | (0.000731) | (0.000597) | (0.000580) |
|  |  |  |  |  |
| Employees | 0.0000136 | -0.000144 | -0.0000802 | 0.000180\* |
|  | (0.0000748) | (0.000123) | (0.0000495) | (0.0000919) |
|  |  |  |  |  |
| Win Percentage | -0.00542 | -0.124\* | 0.0192 | 0.0550 |
|  | (0.0766) | (0.0704) | (0.0314) | (0.0467) |
|  |  |  |  |  |
| MLB Runs | 0.000307\*\*\* | 0.000341\*\*\* | -0.0000344 | 0.0000223 |
|  | (0.0000386) | (0.0000523) | (0.0000245) | (0.0000286) |
|  |  |  |  |  |
| Attendance | 0.00874 | 0.00903 | -0.00459 | -0.00932\*\* |
|  | (0.00978) | (0.00752) | (0.00537) | (0.00447) |
|  |  |  |  |  |
| Lagged Win Percentage | 0.0615 | 0.0354 | -0.0121 | -0.0406 |
|  | (0.0420) | (0.0368) | (0.0234) | (0.0280) |
|  |  |  |  |  |
| Lagged MLB Runs | -0.0000489 | -0.0000369 | 0.0000260 | 0.0000121 |
|  | (0.0000468) | (0.0000439) | (0.0000261) | (0.0000294) |
|  |  |  |  |  |
| Lagged Attendance | -0.0111 | -0.00735 | 0.00264 | 0.000658 |
|  | (0.00729) | (0.00666) | (0.00520) | (0.00353) |
|  |  |  |  |  |
| Population | -7.11e-09\* | -5.23e-10 | -3.94e-09 | 7.29e-09 |
|  | (3.88e-09) | (7.72e-09) | (2.55e-09) | (4.44e-09) |
|  |  |  |  |  |
| Salary | 4.69e-09\*\*\* | 6.01e-09\*\*\* | 7.80e-09\*\*\* | 1.34e-08\*\*\* |
|  | (9.97e-10) | (1.21e-09) | (2.23e-09) | (2.55e-09) |
|  |  |  |  |  |
| Bonus | 9.35e-10 | 6.11e-09\*\* | 2.32e-08\*\*\* | 2.02e-08\*\*\* |
|  | (1.89e-09) | (2.24e-09) | (3.29e-09) | (2.70e-09) |
|  |  |  |  |  |
| Complementarity | -0.618\*\*\* | -0.549\*\*\* | -0.232\*\*\* | -0.211\*\*\* |
|  | (0.0306) | (0.0272) | (0.0166) | (0.0211) |
|  |  |  |  |  |
| Market Position | 0.00183 | -0.00277 | -0.00185 | 0.00132 |
|  | (0.00266) | (0.00322) | (0.00119) | (0.00195) |
|  |  |  |  |  |
| Year FE | Included | Included | Included | Included |
| Affiliation FE | Included | Included | Included | Included |
|  |  |  |  |  |
| Constant | 0.212 | 0.406\*\* | 0.490\*\*\* | 0.169\*\* |
|  | (0.129) | (0.173) | (0.0850) | (0.0795) |
| Observations | 6642 | 8413 | 35166 | 41506 |
| *R*2 | 0.582 | 0.498 | 0.190 | 0.193 |
| Adjusted *R*2 | 0.578 | 0.494 | 0.189 | 0.192 |

Standard errors in parentheses(\* *p* < 0.10, \*\* *p* < 0.05, \*\*\* *p* < 0.01).

**Online Appendices**

**to**

**Hitting a Curveball: Strategic Factor Markets, Uncertainty, and Performance.**

Online Appendix 1. Age of Resource Uncertainty and Management Change Controls Added.

Online Appendix 2. Player Fixed Effects Added.

Online Appendix 1: Age as Resource Uncertainty (M1) and Management Change Controls Added (M2–M6).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | (1) | (2) |  | (3) | (4) | (5) | (6) |
|  | OPS | OPS (H1) |  | OPS (H2) | OPS (H3) | OPS | OPS (H4) |
| Age Squared | -0.0000609 | -0.000310\*\*\* |  | -0.000262\*\*\* | -0.00030\*\*\* | -0.00019\*\*\* | -0.000148\*\* |
|  | (0.0000478) | (0.0000506) |  | (0.0000494) | (0.0000511) | (0.0000549) | (0.0000555) |
|  |  |  |  |  |  |  |  |
| Level AAA | 0.0680\*\*\* | 0.0662\*\*\* |  | 0.0555\*\*\* | 0.0666\*\*\* | - | - |
|  | (0.00471) | (0.00510) |  | (0.00472) | (0.00504) | - | - |
|  |  |  |  |  |  |  |  |
| Level AA | 0.0669\*\*\* | 0.0656\*\*\* |  | 0.0542\*\*\* | 0.0659\*\*\* | - | - |
|  | (0.00355) | (0.00397) |  | (0.00386) | (0.00394) | - | - |
|  |  |  |  |  |  |  |  |
| Level A | 0.0811\*\*\* | 0.0805\*\*\* |  | 0.0682\*\*\* | 0.0809\*\*\* | - | - |
|  | (0.00411) | (0.00510) |  | (0.00500) | (0.00506) | - | - |
|  |  |  |  |  |  |  |  |
| SFM Transaction | 0.0830\*\*\* | 1.900\*\*\* |  | -0.0196\*\*\* | -0.0560\*\*\* | 0.00887\*\*\* | -0.0627\*\*\* |
|  | (0.0165) | (0.628) |  | (0.00319) | (0.00509) | (0.00221) | (0.00786) |
|  |  |  |  |  |  |  |  |
| Age | 0.00934\*\*\* | 0.0206\*\*\* |  | 0.0178\*\*\* | 0.0201\*\*\* | 0.0131\*\*\* | 0.0107\*\*\* |
|  | (0.00259) | (0.00273) |  | (0.00267) | (0.00275) | (0.00298) | (0.00300) |
|  |  |  |  |  |  |  |  |
| SFM Transaction \* Age | -0.00298\*\*\* | - |  | - | - | - | - |
|  | (0.000575) | - |  | - | - | - | - |
|  |  |  |  |  |  |  |  |
| Lagged OPS | 0.341\*\*\* | 0.354\*\*\* |  | 0.354\*\*\* | 0.355\*\*\* | 0.356\*\*\* | 0.356\*\*\* |
|  | (0.00632) | (0.00823) |  | (0.00804) | (0.00827) | (0.00804) | (0.00806) |
|  |  |  |  |  |  |  |  |
| Scouts | -0.0000613 | -0.000394 |  | 0.0000150 | -0.0000418 | -0.0000272 | -0.0000259 |
|  | (0.000403) | (0.000435) |  | (0.000412) | (0.000412) | (0.000413) | (0.000416) |
|  |  |  |  |  |  |  |  |
| Employees | 0.00000296 | 0.0000320 |  | 0.00000932 | 0.0000152 | 0.0000111 | 0.00000593 |
|  | (0.0000473) | (0.0000590) |  | (0.0000532) | (0.0000475) | (0.0000476) | (0.0000482) |
|  |  |  |  |  |  |  |  |
| Win Percentage | 0.0428 | -0.0144 |  | 0.0325 | 0.0236 | 0.0280 | 0.0225 |
|  | (0.0264) | (0.0334) |  | (0.0245) | (0.0238) | (0.0240) | (0.0239) |
|  |  |  |  |  |  |  |  |
| MLB Runs | 0.0000598\*\*\* | 0.0000729\*\*\* |  | 0.0000470\*\* | 0.0000295 | 0.0000313 | 0.0000312 |
|  | (0.0000194) | (0.0000174) |  | (0.0000212) | (0.0000208) | (0.0000207) | (0.0000209) |
|  |  |  |  |  |  |  |  |
| Attendance | -0.00711\*\* | -0.00703\* |  | -0.00891\*\* | -0.00688\*\* | -0.00763\*\* | -0.00705\*\* |
|  | (0.00316) | (0.00371) |  | (0.00334) | (0.00296) | (0.00307) | (0.00294) |
|  |  |  |  |  |  |  |  |
| Lagged Win Percentage | -0.0121 | -0.0408\*\* |  | -0.00839 | -0.00629 | -0.00734 | -0.00607 |
|  | (0.0166) | (0.0193) |  | (0.0172) | (0.0160) | (0.0157) | (0.0159) |
|  |  |  |  |  |  |  |  |
| Lagged MLB Runs | -0.00000320 | 0.0000396\*\*\* |  | 0.000000177 | 0.00000736 | 0.00000771 | 0.00000653 |
|  | (0.0000216) | (0.0000115) |  | (0.0000174) | (0.0000166) | (0.0000166) | (0.0000167) |
|  |  |  |  |  |  |  |  |
| Lagged Attendance | 0.00248 | 0.00237 |  | 0.00280 | 0.00132 | 0.00188 | 0.00145 |
|  | (0.00244) | (0.00297) |  | (0.00266) | (0.00261) | (0.00266) | (0.00258) |
|  |  |  |  |  |  |  |  |
| Population | 3.18e-10 | 4.37e-09 |  | 1.52e-09 | 2.13e-09 | 1.80e-09 | 1.78e-09 |
|  | (2.56e-09) | (3.17e-09) |  | (3.47e-09) | (3.22e-09) | (3.17e-09) | (3.28e-09) |
|  |  |  |  |  |  |  |  |
| Bonus | 2.01e-08\*\*\* | 1.77e-08\*\*\* |  | 1.71e-08\*\*\* | 1.79e-08\*\*\* | 1.66e-08\*\*\* | 1.61e-08\*\*\* |
|  | (1.68e-09) | (1.71e-09) |  | (1.73e-09) | (1.75e-09) | (1.54e-09) | (1.59e-09) |
|  |  |  |  |  |  |  |  |
| Complementarity | -0.278\*\*\* | -0.265\*\*\* |  | -0.266\*\*\* | -0.265\*\*\* | -0.266\*\*\* | -0.267\*\*\* |
|  | (0.0116) | (0.0122) |  | (0.0121) | (0.0121) | (0.0122) | (0.0123) |
|  |  |  |  |  |  |  |  |
| Market Position | -0.000236 | -0.00176 |  | -0.000284 | -0.000220 | -0.000217 | -0.000267 |
|  | (0.00126) | (0.00156) |  | (0.00125) | (0.00125) | (0.00126) | (0.00126) |
|  |  |  |  |  |  |  |  |
|  | (1) | (2) |  | (3) | (4) | (5) | (6) |
|  | OPS | OPS (H1) |  | OPS (H2) | OPS (H3) | OPS | OPS (H4) |
| Year | - | -0.000643\*\*\* |  | - | - | - | - |
|  | - | (0.000229) |  | - | - | - | - |
|  |  |  |  |  |  |  |  |
| SFM | - | - |  | 0.0324\*\*\* | - | - | - |
| Transaction \* Level AAA | - | - |  | (0.00512) | - | - | - |
|  |  |  |  |  |  |  |  |
| SFM | - | - |  | 0.0439\*\*\* | - | - | - |
| Transaction \* Level AA | - | - |  | (0.00694) | - | - | - |
|  |  |  |  |  |  |  |  |
| SFM | - | - |  | 0.0899\*\*\* | - | - | - |
| Transaction \* Level A | - | - |  | (0.0107) | - | - | - |
|  |  |  |  |  |  |  |  |
| Salary | - | 5.46e-09\*\*\* |  | 5.34e-09\*\*\* | 5.49e-09\*\*\* | 5.72e-09\*\*\* | 5.69e-09\*\*\* |
|  | - | (7.52e-10) |  | (7.56e-10) | (7.42e-10) | (7.75e-10) | (7.72e-10) |
|  |  |  |  |  |  |  |  |
| Management Change | - | -0.00374 |  | -0.000594 | -0.000388 | -0.000429 | -0.000228 |
|  | - | (0.00289) |  | (0.00252) | (0.00242) | (0.00243) | (0.00241) |
|  |  |  |  |  |  |  |  |
| SFM Transaction\* Year | - | -0.000943\*\*\* |  | - | - | - | - |
|  | - | (0.000314) |  | - | - | - | - |
|  |  |  |  |  |  |  |  |
| Firm Resource-Picking | - | - |  | - | 0.0394 | 0.145\*\*\* | 0.105 |
| (RP) Capability | - | - |  | - | (0.0316) | (0.0319) | (0.0626) |
|  |  |  |  |  |  |  |  |
| SFM Transaction \* | - | - |  | - | 0.756\*\*\* | - | 0.497\*\*\* |
| Firm RP Capability | - | - |  | - | (0.0481) | - | (0.0767) |
|  |  |  |  |  |  |  |  |
| Minor League | - | - |  | - | - | 0.0680\*\*\* | 0.0643\*\*\* |
|  | - | - |  | - | - | (0.00388) | (0.00721) |
|  |  |  |  |  |  |  |  |
| SFM Transaction \* | - | - |  | - | - | - | 0.00622 |
| Minor League | - | - |  | - | - | - | (0.0112) |
|  |  |  |  |  |  |  |  |
| Minor League \* | - | - |  | - | - | - | -0.0814 |
| Firm RP Capability | - | - |  | - | - | - | (0.0708) |
|  |  |  |  |  |  |  |  |
| Triple Interaction | - | - |  | - | - | - | 0.393\*\*\* |
| (ML X RP X SFM) | - | - |  | - | - | - | (0.115) |
|  |  |  |  |  |  |  |  |
| Year FE | Included | Not included |  | Included | Included | Included | Included |
| Affiliation FE | Included | Included |  | Included | Included | Included | Included |
|  |  |  |  |  |  |  |  |
| Constant | 0.203\*\*\* | 1.327\*\*\* |  | 0.109\*\* | 0.0677 | 0.164\*\*\* | 0.213\*\*\* |
|  | (0.0526) | (0.426) |  | (0.0466) | (0.0482) | (0.0523) | (0.0516) |
| Observations | 100099 | 82872 |  | 82872 | 82872 | 82872 | 82872 |
| *R*2 | 0.251 | 0.242 |  | 0.246 | 0.247 | 0.244 | 0.247 |
| Adjusted *R*2 | 0.251 | 0.242 |  | 0.245 | 0.246 | 0.244 | 0.246 |

Robust standard errors in parentheses, clustered by affiliation (\* *p* < 0.10, \*\* *p* < 0.05, \*\*\* *p* < 0.01).

Online Appendix 2: Player Fixed Effects Added.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | (1) |  | (2) | (3) | (3) | (5) |
|  | OPS (H1) |  | OPS (H2) | OPS (H3) | OPS | OPS (H4) |
| Age | 0.0608\*\*\* |  | 0.0669\*\*\* | 0.0671\*\*\* | 0.0430\*\*\* | 0.0409\*\*\* |
|  | (0.00635) |  | (0.00629) | (0.00624) | (0.00603) | (0.00609) |
|  |  |  |  |  |  |  |
| Age Squared | -0.00111\*\*\* |  | -0.00120\*\*\* | -0.00120\*\*\* | -0.000750\*\*\* | -0.000717\*\*\* |
|  | (0.0000602) |  | (0.0000604) | (0.0000595) | (0.0000522) | (0.0000530) |
|  |  |  |  |  |  |  |
| SFM Transaction | 1.429\*\*\* |  | -0.0156\*\*\* | -0.0508\*\*\* | -0.00447\* | -0.0374\*\*\* |
|  | (0.464) |  | (0.00380) | (0.00570) | (0.00256) | (0.00901) |
|  |  |  |  |  |  |  |
| Level AAA | 0.0839\*\*\* |  | 0.0802\*\*\* | 0.0852\*\*\* | - | - |
|  | (0.00325) |  | (0.00353) | (0.00323) | - | - |
|  |  |  |  |  |  |  |
| Level AA | 0.102\*\*\* |  | 0.0984\*\*\* | 0.103\*\*\* | - | - |
|  | (0.00384) |  | (0.00397) | (0.00382) | - | - |
|  |  |  |  |  |  |  |
| Level A | 0.148\*\*\* |  | 0.145\*\*\* | 0.149\*\*\* | - | - |
|  | (0.00456) |  | (0.00465) | (0.00455) | - | - |
|  |  |  |  |  |  |  |
| Lagged OPS | -0.0917\*\*\* |  | -0.0996\*\*\* | -0.0978\*\*\* | -0.102\*\*\* | -0.101\*\*\* |
|  | (0.00833) |  | (0.00835) | (0.00838) | (0.00833) | (0.00837) |
|  |  |  |  |  |  |  |
| Win Percentage | -0.0426\* |  | 0.0188 | 0.0137 | 0.0210 | 0.0189 |
|  | (0.0230) |  | (0.0242) | (0.0241) | (0.0241) | (0.0240) |
|  |  |  |  |  |  |  |
| MLB Runs | 0.0000941\*\*\* |  | 0.0000532\*\*\* | 0.0000334\*\* | 0.0000349\*\* | 0.0000332\*\* |
|  | (0.0000108) |  | (0.0000149) | (0.0000151) | (0.0000151) | (0.0000151) |
|  |  |  |  |  |  |  |
| Attendance | -0.00315 |  | -0.00248 | -0.00112 | -0.00141 | -0.00134 |
|  | (0.00262) |  | (0.00295) | (0.00295) | (0.00295) | (0.00295) |
|  |  |  |  |  |  |  |
| Lagged Win Percentage | -0.0517\*\*\* |  | -0.0196 | -0.0132 | -0.0120 | -0.00966 |
|  | (0.0142) |  | (0.0160) | (0.0160) | (0.0160) | (0.0160) |
|  |  |  |  |  |  |  |
| Lagged MLB Runs | 0.0000608\*\*\* |  | 0.00000812 | 0.0000124 | 0.0000142 | 0.0000120 |
|  | (0.0000104) |  | (0.0000154) | (0.0000154) | (0.0000154) | (0.0000154) |
|  |  |  |  |  |  |  |
| Lagged Attendance | 0.00417\* |  | 0.00389 | 0.00206 | 0.00247 | 0.00217 |
|  | (0.00242) |  | (0.00270) | (0.00270) | (0.00270) | (0.00270) |
|  |  |  |  |  |  |  |
| Population | -3.68e-11 |  | -4.00e-11 | -9.05e-11 | -1.20e-10 | -1.30e-10 |
|  | (3.55e-10) |  | (3.52e-10) | (3.51e-10) | (3.50e-10) | (3.50e-10) |
|  |  |  |  |  |  |  |
| Complementarity | -0.112\*\*\* |  | -0.112\*\*\* | -0.113\*\*\* | -0.112\*\*\* | -0.112\*\*\* |
|  | (0.0104) |  | (0.0104) | (0.0104) | (0.0105) | (0.0105) |
|  |  |  |  |  |  |  |
| Market Position | -0.00149 |  | 0.000486 | 0.000545 | 0.000677 | 0.000646 |
|  | (0.000909) |  | (0.000932) | (0.000930) | (0.000931) | (0.000930) |
|  |  |  |  |  |  |  |
| Year | -0.000955 |  | - | - | - | - |
|  | (0.00618) |  | - | - | - | - |
|  |  |  |  |  |  |  |
| SFM Transaction \* Year | -0.000718\*\*\* |  | - | - | - | - |
|  | (0.000232) |  | - | - | - | - |
| SFM Transaction \* Level AAA | - |  | 0.0156\*\*\* | - | - | - |
|  | - |  | (0.00502) | - | - | - |
|  |  |  |  |  |  |  |
| SFM Transaction \* Level AA | - |  | 0.0221\*\*\* | - | - | - |
|  | - |  | (0.00759) | - | - | - |
|  |  |  |  |  |  |  |
| SFM Transaction \* Level A | - |  | -0.00296 | - | - | - |
|  | - |  | (0.0103) | - | - | - |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
|  | (1) |  | (2) | (3) | (3) | (5) |
|  | OPS (H1) |  | OPS (H2) | OPS (H3) | OPS | OPS (H4) |
| Firm Resource-Picking Capability | - |  | - | 0.0844\*\*\* | 0.165\*\*\* | 0.0654 |
| (RP) | - |  | - | (0.0217) | (0.0209) | (0.0494) |
|  |  |  |  |  |  |  |
| SFM Transaction \* Capability | - |  | - | 0.510\*\*\* | - | 0.273\*\*\* |
|  | - |  | - | (0.0580) | - | (0.0921) |
|  |  |  |  |  |  |  |
| Minor League | - |  | - | - | 0.0921\*\*\* | 0.0856\*\*\* |
|  | - |  | - | - | (0.00316) | (0.00577) |
|  |  |  |  |  |  |  |
| SFM Transaction \* Minor League | - |  | - | - | - | -0.0173 |
|  | - |  | - | - | - | (0.0111) |
|  |  |  |  |  |  |  |
| Minor League \* | - |  | - | - | - | 0.0248 |
| Firm RP Capability | - |  | - | - | - | (0.0531) |
|  |  |  |  |  |  |  |
| Minor League \* | - |  | - | - | - | 0.362\*\*\* |
| Firm RP Capability | - |  | - | - | - | (0.115) |
|  |  |  |  |  |  |  |
| Scouts | 0.0000389 |  | 0.000247 | 0.0000942 | 0.000188 | 0.000138 |
|  | (0.000275) |  | (0.000279) | (0.000278) | (0.000280) | (0.000279) |
|  |  |  |  |  |  |  |
| Employees | -0.00000441 |  | 0.0000405 | 0.0000503 | 0.0000357 | 0.0000380 |
|  | (0.0000532) |  | (0.0000535) | (0.0000534) | (0.0000535) | (0.0000534) |
|  |  |  |  |  |  |  |
| Salary | 1.39e-09\* |  | 2.71e-09\*\*\* | 2.46e-09\*\*\* | 4.27e-09\*\*\* | 4.15e-09\*\*\* |
|  | (7.30e-10) |  | (7.30e-10) | (7.27e-10) | (7.17e-10) | (7.20e-10) |
|  |  |  |  |  |  |  |
| Year FE | Not included |  | Included | Included | Included | Included |
| Affiliation FE | Not included |  | Not included | Not included | Not included | Not included |
| Player FE | Included |  | Included | Included | Included | Included |
|  |  |  |  |  |  |  |
| Constant | 1.681 |  | -0.253\*\*\* | -0.254\*\*\* | 0.140\*\*\* | 0.179\*\*\* |
|  | (12.22) |  | (0.0498) | (0.0487) | (0.0414) | (0.0429) |
| Observations | 91727 |  | 91727 | 91727 | 91727 | 91727 |
| *R*2 | 0.049 |  | 0.057 | 0.059 | 0.050 | 0.051 |
| Adjusted *R*2 | 0.049 |  | 0.056 | 0.058 | 0.049 | 0.051 |

Robust standard errors in parentheses, clustered by player (\* *p* < 0.10, \*\* *p* < 0.05, \*\*\* *p* < 0.01).

1. Our results remained consistent even in non-reciprocal transactions, such as waived players, Rule 5 draft acquisitions, and free agent pickups. We do not anticipate purchase price affecting expectation-setting from a theoretical perspective, and our findings confirm that uncertainty and firm capabilities play a significant role in all types of resource picking. [↑](#footnote-ref-1)
2. The omission of fielding as a control variable could raise a concern. Due to year-based data limitations, we could not include it in all our regressions. Nevertheless, we conducted a regression with fielding to assess our results’ robustness, and they remained consistent. The output table can be provided upon request. [↑](#footnote-ref-2)
3. We also examined another aspect of complementarity—synergy with the existing resource base—with similar results. [↑](#footnote-ref-3)
4. We included components for each aspect of market position. We operationalized the customer’s willingness to pay through attendance and population size, which are good revenue proxies (Hill et al., 2017; Schwab, 2007; Shamsie & Mannor, 2013). We included both salary and signing bonus information for players at all levels to account for the pricing mechanism. Finally, we used Baseball America’s organizational talent rankings to proxy the expected firm opportunity cost. [↑](#footnote-ref-4)
5. Results are available upon request. [↑](#footnote-ref-5)
6. Results are available upon request. [↑](#footnote-ref-6)