Essays on value creation and appropriation in human-capital-intensive firms

by

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Dedication

To my parents and brothers

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Table of Contents

List of Figures

List of Tables

Abstract

Essays on value creation and appropriation in human-capital-intensive firms

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Pranav Garg

Chair: Sendil K. Ethiraj

Human-capital-intensive firms contribute an increasing share of economic activity in developed countries. This dissertation builds on the idea that individuals have some unique attributes that influence value creation and value appropriation in human-capital-intensive firms. First, an individual is not a passive input and can exercise discretion. The extent of discretion for individuals leads to performance heterogeneity across firms and hence differences in value created by firms. Second, an individual can renegotiate her contract ex-post. An individual's ability to renegotiate her contract affects the share of value appropriated by the firm vis-à-vis its employees. This dissertation deepens our theoretical understanding of these two unique attributes of human capital by exploring questions related to value creation and appropriation in human-capital-intensive firms.

The dissertation comprises two studies. The first study focuses on value creation by theorizing about the micro-foundations of product creation. It asks the question: How do the micro-motives of employees explain their product creation behavior? The study argues that in firms that rely primarily on individuals' capabilities to create value, we can

view product creation as an outcome of the micro-motives of employees who compete for promotions and wage increases in the firm's internal labor market. The study focuses on the explicit incentives and career concerns of employees to theorize about their product creation behavior. It tests the empirical implications using data from the U.S. mutual fund industry from 1992 to 2010.

The second study theorizes about value appropriation by building on the micro-foundations of team production. It asks the question: How does the organization of production affect the division of surplus between the firm owner and labor? The study argues that reciprocal interdependence among employees can create complementarity in human-capital-intensive activity. Division of the returns from complementarity depends on whether interdependence among employees is symmetric or asymmetric. The study also suggests that complementarity is amenable to design and identifies management practices that generate complementarity. The study tests the hypotheses using data from the U.S. National Basketball Association from 1991 to 2007.

The dissertation highlights how the incentives of employees and the organization of production have unique implications in human-capital-intensive activity.

Chapter 1: Introduction

"Nothing is more fundamental in setting our research agenda and informing our research methods than our view of the nature of the human beings whose behavior we are studying."

— Simon (1985: 303)

Less than two decades ago, the organizational worker embodying skills and knowledge was a silent subject in popular books that envisaged the post-industrial era (Drucker, 1993).[1] In a short span of time, however, this worker has become conspicuous as human-capital-intensive firms contribute an increasing share of economic activity in developed countries (Rossi-Hansberg and Wright, 2007). In the U.S. for instance, employment and revenue in the professional, scientific, and technical services sector (NAICS: 54) have respectively grown at a compound annual rate of 4.2% and 8.0% from 1997 to 2007.[2] The increasing prominence of human capital has significant implications. On the one hand, practitioners must grapple with newer challenges of managing firms wherein they have limited control over their most critical asset. On the other hand, scholars have more opportunities to ask novel questions in human-capital-intensive contexts and extend existing knowledge in various theoretical streams.

[1] "Organizational worker" refers to an operating-level employee as distinct from a senior executive in the firm.

[2] Calculations based on U.S. Economic Census data from 1997 and 2007 (Source: www.census.gov). As an approximate comparison, U.S. GDP increased at a compound annual rate of 5.4% over the same period (Source: World Bank Statistics). NAICS stands for North American Industry Classification System.

Scholarly interest in human capital in the context of business firms spans several decades (Becker, 1964; Alchian and Demsetz, 1972; Williamson, Wachter, and Harris, 1975; Zucker, Darby, and Brewer, 1998). Within the broad domain of research on human capital, strategy research on human-capital-intensive firms has grown in the last fifteen years (Coff, 1997; Anand, Galetovic, and Stein, 2007; von Nordenflycht, 2011). Joining this research stream, this dissertation suggests that critical to advancing knowledge in existing theoretical perspectives is one's view about the organizational worker in influencing organizational actions and outcomes. Prominent perspectives within strategy such as the resource-based view (Wernerfelt, 1984; Barney, 1991) and activity systems in firms (Porter, 1991, 1996) have treated the firm as a unitary entity. In doing so, these perspectives have implicitly assumed a passive role for the organizational worker. For reasons discussed below, this assumption has limited appeal in human-capital-intensive firms such as consulting firms, asset management companies, sports franchises, and law firms. Such firms rely primarily on individuals' capabilities to create value. Since individuals are the main input in the production function, the tools of production are knowledge and skills embodied by individuals.

Thus, aside from their increasing prominence in economic activity, human-capital-intensive firms merit further attention due to some unique attributes of an individual. First, an individual is not a passive input and can exercise discretion (Coff, 1997; Wright, Dunford, and Snell, 2001). For instance, s/he can choose the effort level or depart from the firm. Second, an individual can renegotiate her contract ex-post (Coff, 1999). Moreover, a human-capital-intensive firm cannot use its ownership of physical capital to exert control over employees (Grossman and Hart, 1986). Section 1.1 of this chapter discusses these characteristics in detail.

The unique characteristics of an individual have implications for value creation and appropriation in human-capital-intensive firms. Value creation and appropriation are central topics in strategy research (Rumelt, Schendel, and Teece, 1991). Indeed, scholars have presented theoretical arguments about value creation and appropriation in the context of human-capital-intensive activity (Coff, 1999). These topics deserve further theoretical and empirical inquiry in human-capital-intensive firms because the unique characteristics of an individual can prompt novel tradeoffs and questions. Hence, studying human-capital-intensive firms is not merely an exercise in applying existing theories and frameworks to a new context.

This dissertation comprises two studies on value creation and appropriation in human-capital-intensive firms. The following section of this chapter elaborates the motivation to study human-capital-intensive firms. The subsequent section offers a synopsis of each study by discussing the theoretical motivation, research question, and key hypotheses. An outline of the research design follows. The last section discusses the contributions of the dissertation.

1.1 Motivation: Why study human-capital-intensive firms?

The dissertation uses an input-based definition for a human-capital-intensive firm—any firm in which individuals are the main input in the production function. An individual as the primary input in production can create several benefits for a firm. First, a firm can increase the specificity of an individual's human capital through specialized training (Becker, 1964). Firm-specific human capital increases a firm's competitive advantage by reducing an individual's external options (Parsons, 1972; Coff and Kryscynski, 2011). Second, if key employees don't leave, a firm can limit imitation of its processes because interactions among individuals are socially complex (Barney, 1991). Third, a firm can sustain its competitive advantage because the tacit knowledge of individuals makes it difficult for rivals to ascertain the relation between complex interactions and firm performance (Lippman and Rumelt, 1982). Finally, a firm may be more flexible in organizing work involving only individuals. This flexibility increases a firm's adaptability to unexpected changes in its external environment.

Conversely, an individual as the primary input in production can also create costs for a firm because s/he has some unique attributes vis-à-vis physical capital. First, an individual is not a passive input. S/he possesses free will and can exercise discretion (Coff, 1997; Wright *et al.*, 2001). An individual can choose her effort level or even depart from the firm (Alchian and Demsetz, 1972; MacDonald and Ryall, 2004). The extent of discretion for individuals leads to performance heterogeneity across firms and hence differences in the value created by firms. For example, in the absence of an incentive-alignment mechanism like a partnership, firms may find it difficult to reign in excessive risk-taking by employees (Wiseman and Gomez-Mejia, 1998). Similarly, the unexpected departure of employees can adversely affect value creation (Aime *et al.*, 2010) due to depletion of human capital (Wezel, Cattani, and Pennings, 2006), loss of social capital in the form of external ties (Broschak, 2004), and disruption of routines (Shaw *et al.*, 2005). In fact, scholars have observed that the concept of an "organizational man" seeking lifelong employment in a firm has given way to the notion of a "free agent" (Holtom *et* *al.*, 2008: 264). Given the centrality of individuals in human-capital-intensive firms, such firms can ill-afford to subordinate or ignore individuals' preferences.

Second, an individual can renegotiate her contract ex-post. An individual's ability to renegotiate her contract affects the share of value appropriated by the firm vis-à-vis its employees (Coff, 1999). The ability of an individual to renegotiate her contract magnifies the challenges for human-capital-intensive firms. Such firms have no ownership over their most critical input. In addition, given the negligible importance of physical capital, these firms cannot use their ownership of physical capital to exert control over employees (Grossman and Hart, 1986). Consequently, human-capital-intensive firms cannot hedge against the uncertainty due to employee's ability to renegotiate her contract as effectively as they can hedge against uncertainty in the use of physical capital.

Building on the unique attributes of an individual, Chapter 2 focuses on value creation in human-capital-intensive firms by theorizing about the product creation behavior of employees. The chapter focuses on the explicit incentives and career concerns of employees to theorize about their product creation behavior. While Chapter 2 focuses on value creation, Chapter 3 theorizes about value appropriation. The chapter offers a structure-based explanation for the division of value between the firm owner and employees in human-capital-intensive firms.

1.2 Dissertation outline

This section provides a brief overview of the studies discussed in Chapters 2 and 3. Each overview discusses the motivation, research question, and hypotheses in each study.

1.2.1 The micro-foundations of product creation

Chapter 2 focuses on value creation by exploring the micro-foundations of product creation. To explain product creation, prior research in strategy has provided insightful quantitative evidence for firm-level antecedents (Katila and Ahuja, 2002; Eggers, 2012) and rich qualitative evidence for the influential role of operating-level employees (Burgelman, 1983; Ethiraj, Ramasubbu, and Krishnan, 2012; Kapoor and Adner, forthcoming). Forthcoming research also provides quantitative evidence for venture creation both inside and outside firms by individuals (Kacperczyk, forthcoming). Focusing on the individual as the unit of analysis is becoming an important research enterprise, especially in the context of human-capital-intensive firms (Groysberg and Lee, 2009).

The study in Chapter 2 joins this enterprise by relating the micro-motives of employees to their product creation behavior. A deeper understanding of this relation is especially important in knowledge-intensive industries that rely primarily on individuals' capabilities to create value. In such industries, firms offer considerable autonomy to employees (Felin, Zenger, and Tomsik, 2009). When the locus of expertise rests with employees having considerable autonomy, their behavior can have important consequences for firms. This study asks the question: *How do the micro-motives of employees explain their product creation behavior?*

The study focuses on firms that operate in multiple product categories in an industry. It builds on the idea that similar to the competition among firms in the product market, a parallel competitive market exists inside the firm wherein employees compete with each other for promotions and wage increases in the internal labor market of the firm. Inter-firm competition in the product market and intra-firm competition among employees are interlinked. In a given period, the forces of inter-firm competition and consumer demand determine a performance-based rank order of a firm's products in an industry category. Insofar as employees manage these products, the rank order of a firm's products in the industry category simultaneously creates a rank order among employees in the corresponding category of the firm.

I argue that the rank order among employees in the focal category of the firm can have two effects. First, high performers ("leaders") in the category have an incentive to consolidate their leadership position vis-à-vis the low performers ("laggards"). Creating more products in the same category allows leaders to leverage their reputation and generate additional demand due to a spillover effect, provided some degree of differentiation between the existing and new product(s) precludes cannibalization. Second, conditional on performance revelation in a given period, laggards have a greater incentive to differentiate themselves from leaders rather than compete head-to-head with them in the subsequent period. This is because an individual's performance relative to similar others within a category of the firm is the basis for promotions and wage increases. Competing in a different category with no leader allows laggards to steer away from direct competition with leaders in the focal category. In this manner, laggards can redefine their reference group for performance comparison and also get a chance to become leaders in their new category.

Building on the preceding arguments, the first hypothesis suggests that relative to laggards, leaders in a category in the firm create more products in the same category. In contrast, the second hypothesis predicts that relative to leaders, laggards in the focal category create more products in different categories with no leader in the firm in the prior year. Chapter 2 discusses the logic for the hypotheses in more detail.

1.2.2 The division of gains from complementarities

While Chapter 2 focuses on value creation, Chapter 3 focuses on value appropriation. It examines the organizational antecedents of the division of firm surplus between the firm owner and labor by building on the micro-foundations of team production.[3] Team production can lead to an inseparability problem when it is difficult to discern an individual's contribution to the team's output (Alchian and Demsetz, 1972). The inseparability problem creates a tradeoff for the division of firm surplus between the firm owner and labor. On the one hand, human-capital-intensive activity shifts bargaining power toward labor. On the other hand, team production reduces labor's bargaining power if it impedes accurate measurement of individuals' contributions. Hence, the study builds on the idea that the organization of production affects the relative bargaining powers of the firm owner and labor. The research question is: *How does the organization of production affect the division of surplus between the firm owner and labor in human-capital-intensive activity?*

The study argues that reciprocal interdependence among team members creates the potential for complementarity that, in turn, translates into higher firm surplus. Division of this surplus is subject to bargaining between the firm owner and labor. Assuming team members do not bargain collectively, higher complementarity increases the firm owner's share of surplus, if interdependence among team members is symmetric. If, however, some high-performing individuals ("stars") contribute disproportionately to

[3] Though Chapter 3 does not explicitly theorize about individual-level incentives, the empirical specifications in this chapter control for individual-level incentives.

generating the surplus, interdependence is asymmetric. In this case, as complementarity increases, stars can appropriate a greater proportion (relative to non-stars) of labor's share of firm surplus.

Further, the study suggests that complementarity is amenable to managerial design. It identifies three levers that generate complementarity—the nature of interaction among team members, relative dominance of team members, and team composition. It argues that greater interaction among team members and higher recruitment of team-oriented individuals are associated with higher complementarity, while dominant team members are associated with lower complementarity. Chapter 3 discusses the hypotheses in detail.

1.3 Research design

The hypotheses in Chapters 2 and 3 are tested using econometric analysis on archival data. With advances in econometric techniques and availability of fine-grained data at the individual level, opportunity is rife for a concerted effort to measure intra-firm constructs and delve into the black box of the firm (Shaw, 2009; Bloom, Sadun, and Van Reenen, 2010). The methodological approach in this dissertation is a step in this direction.

Chapter 2 uses data from the U.S. mutual fund industry. The mutual fund industry is an appropriate context for at least three reasons. First, individuals are the key drivers of firm performance and product creation in the industry (Rao and Drazin, 2002; Lounsbury and Leblebici, 2004). Second, the industry has an established practice of benchmarking fund performance on an industry-wide basis (Sharpe, 1998). Third, mutual fund families offering funds across multiple categories have become the dominant organizational form in the industry (Gaspar, Massa, and Matos, 2006). This organizational form allows researchers to study various aspects of managerial behavior and careers in such firms.

The primary data source to test the hypotheses is the Center for Research in Security Prices (CRSP) Survivorship-Bias Free Mutual Fund Database for the period 1992–2010. In addition, I also use data from several other sources to identify mergers and acquisitions, and changes in firm names in the industry. Chapter 2 provides a detailed description of the data, variables, and empirical specifications. To gain a better understanding of product creation in mutual fund companies, I supplement the quantitative analysis with qualitative data. I conducted semi-structured interviews with more than twenty former and current employees of U.S. mutual fund companies. Collectively, their experience spanned portfolio management, research, risk management, compliance, and client relations/servicing.

Chapter 3 uses data from the National Basketball Association, a professional sports league in the U.S. Sport is an appropriate context because the organization of work in sports franchises mirrors the organization of work in other business contexts (Keidel, 1987; Wolfe *et al.*, 2005). Prior research has used basketball as a context for empirical analysis in both management (Pfeffer and Davis-Blake, 1986; Staw and Hoang, 1995; Berman, Down, and Hill, 2002) and economics (Price and Wolfers, 2010).

The data set in Chapter 3 is compiled using statistics from several web-based and text-based sources. The data set includes statistics at the game, player, and firm levels. Such fine-grained data helped devise measures for several intra-firm constructs. For example, game-level performance data for players and franchises helped generate a measure of *complementarity* at the team level using the Cobb-Douglas production function. Similarly, data on player wages and firm operating profits helped create a measure for an *employee's share of firm surplus*. Chapter 3 includes a detailed description of the data sources, variables, and model specifications.

Chapter 2: The micro-foundations of product creation

2.1 Introduction

A firm's portfolio of products is a strategic lever for the firm to differentiate itself in the product market and gain competitive advantage. Given the strategic importance of a product portfolio for firms, scholars have sought to understand the antecedents of product creation. We can divide research in strategy on the antecedents of product creation into two broad streams. One stream has focused on the firm-level antecedents. For example, the related perspectives of organizational search and organizational learning have examined antecedents such as search depth and scope (Katila and Ahuja, 2002) and the type and timing of a firm's experience (Eggers, 2012). Another stream has delved into the black box of the firm to highlight the role of operating-level employees. In this line of research, scholars have provided qualitative evidence on the influential role of lower and middle managers in shaping investment decisions (Bower, 1970) and in creating ventures and products (Burgelman, 1983). Recent research also provides quantitative evidence for venture creation both inside and outside firms by employees (Kacperczyk, forthcoming).

Prior research has provided insightful quantitative evidence on firm-level antecedents and rich qualitative evidence on the significant role of operating-level employees to explain product creation. Focusing on the individual as the unit of analysis is becoming an important research enterprise, especially in the context of human-capital-intensive firms (Groysberg, Lee, and Nanda, 2008a; Groysberg and Lee, 2009). This study embraces and extends this enterprise by relating the micro-motives of employees to their product creation behavior. A deeper understanding of this relation is especially important in knowledge-intensive industries that rely primarily on individuals' capabilities to create value. In such industries, firms offer considerable autonomy to employees (Felin *et al.*, 2009). When the locus of expertise rests with employees having considerable autonomy, their behavior can have important consequences for firms. This study offers theoretical arguments for product creation at the level of employees and asks the question: *How do the micro-motives of employees explain their product creation behavior?*

To relate the micro-motives of employees to their product creation behavior, this study focuses on firms that span multiple product categories in an industry. The study builds on the idea that similar to the competition among firms in the product market, a parallel competitive market exists inside the firm wherein employees compete with each other for promotions and wage increases in the internal labor market of the firm. For example, scholars have noted that "internal competitive processes pit individuals in the organization against each other in competition for scarce organizational resources and opportunities" (March, 1991: 81). Inter-firm competition in the product market and intra-firm competition among employees are interlinked. In a given period, the forces of inter-firm competition and consumer demand determine a performance-based rank order of a firm's products in an industry category. Insofar as employees manage these products, the rank order of a firm's products in the industry category simultaneously creates a rank order among employees in the corresponding category of the firm.

I argue that the rank order among employees in the firm's focal category can have two effects. First, high performers ("leaders") in the category have an incentive to consolidate their leadership position vis-à-vis the low performers (“laggards”). Creating more products in the same category allows leaders to leverage their reputation and generate additional demand due to a spillover effect, provided some degree of differentiation between the existing and new product(s) precludes cannibalization. The preceding logic leads to the first hypotheses that relative to laggards, leaders in a category of the firm create more products in the same category.

Second, conditional on performance revelation in a given period, laggards have a greater incentive to differentiate themselves from leaders rather than compete head-to-head with them in the subsequent period. This is because an individual’s performance relative to similar others within a firm’s category is the basis for promotions and wage increases. Competing in a different category with no leader allows laggards to steer away from direct competition with leaders in the focal category. In this manner, laggards can redefine their reference group for performance comparison and also get a chance to become leaders in their new category. This logic leads to the second hypothesis that relative to leaders, laggards in a firm’s category create more products in different categories with no leader in the firm in the prior year.

I tested the two hypotheses in the context of the U.S. mutual fund industry. The mutual fund industry is an appropriate context for at least three reasons. First, individuals are the key drivers of firm performance and product creation in the industry (Rao and Drazin, 2002; Lounsbury and Leblebici, 2004). Second, the industry has an established practice of benchmarking fund performance on an industry-wide basis (Sharpe, 1998). Third, mutual fund families offering funds across multiple categories have become the dominant organizational form in the industry (Gaspar *et al.*, 2006). This organizational form allows researchers to study various aspects of managerial behavior and careers in such firms.

I used archival data from the Center for Research in Security Prices (CRSP) Survivorship-Bias Free Mutual Fund Database for the period 1992–2010 to test the hypotheses. To gain a better understanding of product creation in mutual fund companies, I supplemented the quantitative analysis with qualitative data. I conducted semi-structured interviews with more than twenty former and current employees of U.S. mutual fund companies. Collectively, their experience spanned functions such as portfolio management, research, risk management, compliance, and client relations/servicing. The interviews ranged from twenty minutes to one hour. For reasons of confidentiality, I do not identify the names of the interviewees and the mutual fund companies.

The rest of this chapter is organized as follows. In the next section, I briefly review the literature relevant to the study. The subsequent section presents the theory and derives testable implications in the context of the mutual fund industry. Thereafter, I describe the empirical methodology. I discuss the results in the penultimate section. The last section concludes by discussing the contributions, implications, and limitations of the study.

2.2 Literature review

The literature review briefly surveys research on the antecedents of product creation and on incentives in firms. I argue that while prior research on the antecedents of product creation provides useful insights, we need to delve further into the black box of the firm to deepen our understanding of product creation by focusing on individuals as the unit of analysis. In some industries, firms rely mainly on the capabilities of individuals to create value (Henderson and Mitchell, 1997). Theorizing about the antecedents of product creation using individuals as the unit of analysis is especially pertinent in such contexts. In making the case for focusing on individuals as the unit of analysis, I also discuss the relevance of the predominantly economics-based research on explicit incentives and career concerns of employees for understanding product creation.

2.2.1 Antecedents of product creation

In strategy research on the antecedents of product creation in firms, one stream of work has focused on the firm-level antecedents. Within this body of work, one set of studies has adopted the organizational learning lens to study product creation. Using the exploration-exploitation framework (March, 1991), scholars have examined the conditions under which firms draw on existing technological and customer-related competences or develop new competences to create products (Danneels, 2002). Others have analyzed how the interplay between intra- and inter-organizational learning processes affects new product development (Holmqvist, 2004). Another set of studies have adopted the theoretically-related search perspective to explain product creation. Scholars have argued that firms create new products by searching for knowledge both inside and outside their industry either as members of a community of collaborators (Wade, 1996) or as competitors (Katila and Chen, 2008). This set of studies has enhanced our understanding of product creation by highlighting firm-level antecedents such as the age of a firm’s own knowledge and competitor’s knowledge (Katila, 2002), search scope and depth (Katila and Ahuja, 2002), and search timing relative to competitors (Katila and Chen, 2008).

Complementing research on the firm-level antecedents, another stream of research has delved inside the firm to explain product creation. Within this research stream, one group of studies has acknowledged the important role of top management teams and key personnel (Brown and Eisenhardt, 1995; Shane and Ulrich, 2004). For example, scholars have studied the role of "gatekeepers" who straddle the firm's boundaries and create an information bridge between insiders and outsiders (Allen, 1970). Others have examined the effect of the degree of integration between cross-functional teams or departments on new product outcomes (Dougherty, 1990; Ayers, Dahlstrom, and Skinner, 1997).

Another body of work that has looked inside the firm has emphasized the role of operating-level employees. For instance, Bower (1970) provided qualitative evidence about the influence of operating-level employees on resource allocation and investment decisions inside a firm. Likewise, Burgelman (1983) advanced our understanding of strategic change by proposing a process model of internal venture creation in a firm wherein lower and middle managers play a significant role. Recent research also provides qualitative evidence on the important role of managers and engineers in the introduction of incremental innovations (Ethiraj *et al.*, 2012) and new product generations (Kapoor and Adner, forthcoming).

Yet another set of studies have sought to unpack the construct of organizational capabilities and used a qualitative approach to highlight the role of operating-level employees in product creation. For instance, Tripsas and Gavetti (2000) analyze how managerial cognition aids the development of technological capabilities, and ultimately commercialization of products. In a study of product development processes over a 15-year period, Salvato (2009) reports that ordinary but intentional interventions by employees to improve core processes shape a firm's product development capability over time. He argues, however, that in the capabilities perspective, individual agents have been "placed in the background" (Salvato, 2009: 384). Taylor (2010) investigates the influence of intra-firm political competition among project groups in the adoption of new technologies. He finds that project groups adopt the new technologies of other project groups in their own next generation of new products.

The preceding discussion highlights that extant research has provided insightful quantitative evidence about firm-level antecedents and rich qualitative evidence about the influential role of operating-level employees in creating ventures and products in firms. Focusing on the individual as the unit of analysis is an important research enterprise, especially in human-capital-intensive firms (Groysberg *et al.*, 2008a; Groysberg and Lee, 2009). This study embraces and extends this enterprise by focusing on the relation between the micro-motives of employees and their product creation behavior inside firms. A deeper understanding of this relation is important especially in industries that rely primarily on individuals' capabilities to create value.

Even in such contexts, existing explanations for product creation have focused mostly on more aggregate levels of analysis. For example, in the context of the asset management industry, institutional theory scholars have argued that creation and spread of new products were influenced by the professionalization of managers (Lounsbury and Leblebici, 2004) and by norms within the profession (Jonsson and Regner, 2009). Other scholars focusing on product creation have examined the effect of firm-level antecedents such as recruiting strategies (Rao and Drazin, 2002), and the type and timing of a firm's prior experience (Eggers, 2012). A recent paper, however, focuses on individuals as the unit of analysis and provides empirical evidence about the effect of firm age and firm size on employee intrapreneurship i.e., venture creation inside an existing firm versus employee entrepreneurship i.e., venture creation in a new firm (Kacperczyk, forthcoming).[4] Especially in such contexts, focusing on individuals as the unit of analysis is a worthy enterprise as summarized by Joseph Stiglitz's remark that "The financial sector is rife with incentives (at both the organizational and individual levels) for excessive risk-taking and short-sighted behavior" (Economist, 2010). In this regard, the economics research on the provision of incentives in firms is relevant.

2.2.2 Incentives in firms

This part of the literature review briefly surveys research on the complementary perspectives of explicit incentives and career concerns of employees. Indeed, recent research argues that both compensation-based incentives and career concerns affect managerial behavior (Hu *et al.*, 2011).

Research on incentives in firms is primarily rooted in economics. Early research on incentives was closely related to that on the economics of internal organization (Arrow, 1974; Spence, 1975). Subsequently, this research became the basis for theoretical models in organizational economics and empirical research in personnel economics. An exhaustive survey of these vast literatures is beyond the scope of this review. It suffices to say that both the theoretical and empirical literatures suggest that employees respond to the design of incentive contracts in firms (Oyer and Schaefer,

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[4] Similar to Kacperczyk (forthcoming), this study also focuses on fund creation by managers in the mutual fund industry. The two studies, however, differ in at least a couple of ways. First, Kacperczyk (forthcoming) theorizes about fund creation within and outside a firm's boundaries. In contrast, this study theorizes about fund creation within a firm's boundaries. Second, in theorizing about fund creation behavior of portfolio managers, Kacperczyk (forthcoming) analyzes the role of bureaucratization and internal opportunities. The current study focuses on the incentives and career concerns of portfolio managers to theorize about their fund creation behavior.

2011). The following discussion relates research on the design of incentive contracts in firms to product creation by individuals.

To understand how the design of incentive contracts in firms can motivate product creation by individuals, we can use the classic tradeoff for a firm between providing incentives and insurance to employees (Ross, 1973; Stiglitz, 1975; Mirrlees, 1976). On the one hand, a fixed salary contract provides a risk-averse employee full insurance but no incentive to exert extra effort to increase output. On the other hand, a purely output-based incentive contract provides full incentive and title to the output but no insurance to the employee. The actual incentive contract in firms attempts to balance incentives and risk. If an employee's compensation contract comprises a variable component linked to her/his product's performance relative to a benchmark, s/he will have an incentive to create multiple products to diversify individual risk, subject to resource and individual constraints.

Second, prior research argues that the design of incentive contracts can also lead to distortionary behavior by employees (Kerr, 1975). This argument finds support in theoretical models on the use of piece rates versus fixed salary (Freixas, Guesnerie, and Tirole, 1985; Lazear, 1986b) and on multitasking by employees (Holmstrom and Milgrom, 1991; Baker, 1992). Empirical research also shows evidence of distortionary employee behavior in response to the design of incentive contracts (Oyer, 1998; Larkin, 2007). While such behavior can arise in both single-business and multi-business firms, the design of incentives in multi-business or multi-divisional firms can, per se, create a wedge between actions that are optimal from the firm's perspective and from a division or individual's perspective (March and Simon, 1958). For example, if firm-created incentives reward performance in a local market, managers will increase product variety in the local market and not account for the firm-level costs of their actions (Thomas, 2011). In sum, the design of incentive contracts in firms is an important determinant of employee product creation.

Scholars have, however, observed that “incentive contracts are not the only source of incentives” (Gibbons, 2005: 2). For example, in addition to explicit incentive contracts, one type of non-contract-based incentive for employees emanates from their career concerns (Fama, 1980; Holmstrom, 1999). The career concerns perspective suggests that labor markets—both internal and external to the firm—use an employee’s current performance as a signal to learn about her underlying ability. From an individual’s perspective, the incentive-creating mechanism is sequential learning by the current and potential employers about her ability. Learning about an individual’s ability determines her future wages, promotion, and employment opportunities (Gibbons and Murphy, 1992). Hence, the relation between current performance and future outcomes influences an individual’s behavior in the current period. Scholars have also related the career concerns of employees with operational autonomy to their choice of task difficulty since this choice influences the information contained in the eventual outcome about underlying ability (Siemsen, 2008). Siemsen shows via a formal model that more able employees may choose moderately difficult tasks to signal their ability, while less able employees may choose more difficult tasks to mask their lack of ability. Complementing the formal models, empirical research shows that career concerns motivate younger employees to herd and follow more conservative strategies (Chevalier and Ellison, 1999). Recent research in innovation finds that individual motives such as job security have a negative relation to the patents applications filed by scientists and engineers in basic/applied research (Sauermann and Cohen, 2010).

Building on the prior review, I argue that a useful lens to gain a deeper understanding of product creation is by relating it to the explicit incentives and career concerns of employees who compete for promotions and wage increases in the firm's internal labor market. Indeed, scholars have observed that "internal competitive processes pit individuals in the organization against each other in competition for scarce organizational resources and opportunities" (March, 1991: 81). Focusing on the explicit incentives and career concerns of employees to theorize about their product creation behavior is especially pertinent when the locus of expertise to create value for the firm rests predominantly with operating-level employees. When the locus of expertise rests with employees, their behavior can have important consequences for firms.

2.3 Theory and hypotheses

One context in which operating-level employees significantly influence value creation for the firm is the mutual fund industry. This section uses the mutual fund industry as a context to develop theoretical arguments for the product creation behavior of operating-level employees and derive testable implications. I begin by discussing the organizational structure and nature of decision making in a representative mutual fund firm. Next, I discuss the characteristics of the product market in the mutual fund industry. Subsequently, I relate the consequences of inter-firm competition in the product market to the behavior of portfolio managers inside a mutual fund firm and derive testable implications.

2.3.1 The organization of mutual fund firms

The mutual fund industry is a human-capital-intensive sector. In this industry, managerial skills play a crucial role and portfolio managers are responsible for a fund's performance (Rao and Drazin, 2002). John Bogle, the former CEO of The Vanguard Group, has described human beings as the "prime instrument" for executing a firm's strategy (Bogle, 2011: 21). The dominant organizational form in the industry is firms that offer funds across multiple categories (Gaspar *et al.*, 2006). A category is a product market segment wherein funds offered by various firms share a common investment objective (described in more detail below). By the late 1980s, mutual fund firms spanning multiple categories managed 97% of the industry's assets (Lounsbury and Leblebici, 2004). In fact, scholars have likened such firms to any other diversified firm (Siggelkow, 2003). Figure 1 is a simple visual representation of such firms.

Within the firm, funds map to different categories in the industry. Hence, funds with a common investment objective are part of the same category in the firm. As an example, consider a category called "Large Growth" in the firm. This category comprises funds that invest in companies with high market capitalization and offer investors capital appreciation in the portfolio of stocks. Though all funds in the category share this common objective, they differ in some respects from each other. One fund invests all its capital in large companies. Another fund invests at least 80% of its capital in large companies. Yet another fund invests at least 80% of its capital only in blue chip companies (i.e., companies whose stock is included in the S&P 500 or Dow Jones Index). Another category in the firm could be a sector-specific category called "Healthcare". In this category, individual funds focus on pharmaceutical firms, biotechnology firms, and firms delivering healthcare services, respectively. These examples suggest that while funds within a category are similar since they have a common investment objective, they are not replicas of each other as they differ along some dimension(s). From an investor's perspective, a common investment objective implies that funds within a firm's category are more substitutable compared to funds across categories. Put differently, horizontal differentiation among funds within a category is relatively less than that among funds across categories.

Given this structure of categories within the firm, the study focuses on fund creation by an individual portfolio manager who takes independent actions to maximize the performance of her/his fund in a category. Thus, even though both teams and individuals create funds in a typical mutual fund firm, this study abstracts from team-created funds in the theoretical arguments. I exclude team-created funds due to the lack of performance data on individual members of a team. Focusing on solo-created funds allows mapping the performance of a fund to an individual portfolio manager.

With regard to operational decision making in the firm, prior research suggests that firms relying primarily on individuals' capabilities to create value offer substantial autonomy to employees (Felin *et al.*, 2009). In such firms, the production process utilizes the tacit knowledge of employees that, in turn, leads to greater autonomy for them in operational decisions. Along these lines, operational decision-making is decentralized in mutual fund companies; there is little coordination across portfolio managers of different funds (Chen *et al.*, 2004).[5] Even though portfolio managers are subject to oversight through internal mechanisms like the board of directors and external mechanisms like regulations, they enjoy significant discretion in their actions to manage a fund i.e., buy

[5] This is also mandated by regulation

and sell stocks in the portfolio. Based on empirical analysis of the control restrictions on fund management in mutual fund firms, scholars have concluded that "fund managers in general have become less constrained in more recent years" (Almazan *et al.*, 2004: 319).

With regard to the fund creation process, the study suggests that even though a corporate-level team gives final approval for creating a fund, operating-level employees present proposals to the corporate level for such initiatives. Hence, even though portfolio managers may not be the final decision makers, they have significant influence on the corporate level in the decision to create a fund. Qualitative evidence from research on mutual fund firms confirms the influential role of operating-level managers in the fund creation process (Kacperczyk, forthcoming). A manager I interviewed offered the following perspective about the influence of the operational team (comprising investment managers, financial advisors, and marketing professionals) on the top management or investment committee in the ultimate decision to create a new fund:

> "The top management is focused on business strategy, do we have talent, leadership, and things like that rather than thinking about let's make a Latin American healthcare small cap fund. The way that process worked in terms of approval was that it was very much a bottom-up process at [firm name]. The review and approval was very systematized—big company, lots of those ideas coming through, so you had a certain checklists and it had to go through all the different departments. And it was matrixed in a way that a pretty thin report lands on that committee's desk for approval."

2.3.2 Product market competition among firms

In the product market, firms compete with the objective that their funds in a particular category outperform similar funds of rival firms. This inter-firm competition manifests in the industry practice of benchmarking funds based on their industry-wide relative performance. This practice may have its roots in the transformation of the industry's core logic. Since the 1930s, the industry was characterized by a *regulatory logic* that focused on long-term investing and wealth preservation; by the mid-1980s, the regulatory logic gave way to a *market logic* (Lounsbury, 2002). Inherent in the market logic was greater professionalization of the occupation and competition based on short-term performance. Portfolio managers began to be glamorized like rock stars (Griffeth, 1995). Commenting on the practice of celebrating managers as stars in mutual fund firms, a portfolio manager said:

> "At a firm like [firm name] where they have twenty funds that will be very similar, I guess there is more of a push to be a significant outperformer because you need to not only outperform funds at other firms but you also need to outperform the other funds internally because you are competing internally as well as externally."

The forces of inter-firm competition and consumer demand determine a performance-based rank order of all funds in a particular industry category. There are two facets to this rank order. First, there is an industry-level rank order of all funds offered by various firms in the category. Second, there is a firm-level rank order of funds offered by a firm in the category. The latter rank order is equivalent to the rank order of funds in a firm's category since each category in the firm maps to a unique category in the industry.

2.3.3 Behavior of portfolio managers inside the firm

Given the boundary condition that a fund is managed by an individual portfolio manager, a fund's performance can be ascribed to a portfolio manager. A key idea of this study is that due to this one-to-one mapping of a fund to a portfolio manager, the firm-level rank order of funds in a category also creates a rank order among portfolio managers in the corresponding category of the firm. For a portfolio manager who manages multiple funds, her average performance across her portfolio of funds is the basis of performance comparison with other managers.[6] The rank order so generated enables the firm to benchmark a portfolio manager's performance against that of other managers in the firm's category. A person recounted her/his experience at a mutual fund firm:

> "Not only are you judged on performance but you are paid on performance. For instance, there were two very similar products on the growth team [at the firm I worked]. […] They [the respective portfolio managers of the two products] acknowledged that it was somewhat awkward because they were competing for the same flow of funds. It was very clear that one [of the two funds] was doing better than the other. One of the portfolio managers mentioned every week or so that he was afraid he was going to lose his job. His performance was worse and he was going to see a drop in his flow of funds."

The above quote highlights that performance benchmarking among portfolio managers has important economic consequences for them in the firm's internal labor market.[7] Prior research in other human-capital-intensive contexts suggests that high-performing employees get disproportionately higher pay (Chacar and Hesterly, 2008). Further, an employee's relative performance signals her ability and determines the pace of her career progress over time (Baker and Holmstrom, 1995). A small percentage of high-performing employees go on a 'fast track' compared to others in the firm (Rosenbaum, 1984; Willbur, 1987; Cannings, 1988). In addition, empirical research

[6] It is, however, also possible that variance in performance across funds in a manager's portfolio may induce different behaviors with respect to fund creation. For example, two portfolio managers who manage three funds each would behave differently if one has two high-performing funds while the other has one high-performing fund. Likewise, the behavior of portfolio managers may differ if among a portfolio manager's three funds, the high-performing one is a major fund (e.g., by size) while for another portfolio manager, two minor funds are high-performing. Theorizing about and empirically testing the effect of variance in the performance of funds in a manager's portfolio on her fund creation behavior may be an interesting avenue to explore in future research.

[7] While this study discusses the consequences of an employee's relative performance in a firm's internal labor market, high performers also stand to gain in the external labor market. Scholars have argued that high performers can generate more job offers with rival firms (Lazear, 1986a) and have a higher likelihood of starting their own firm (Perry, 1992).

shows that early-career promotions have a momentum effect—an early first promotion also leads to a faster second promotion (Baker, Gibbs, and Holmstrom, 1994a). In sum, superior relative performance leads to promotion and compensation-related gains for portfolio managers, both at a point in time and over time.[8]

Related to the economic consequences of performance benchmarking, portfolio managers are more likely to compare themselves with peers inside than outside the firm. This view finds support in the assertion that "individuals within a firm seldom view those outside the firm as salient referents and vice versa" (Nickerson and Zenger, 2008: 1439). Several explanations support this assertion—first, more common characteristics among employees in the same firm, presumably due to the firm's common recruiting criteria; second, a shared sense of identity among employees of the same firm (Kogut and Zander, 1992); and third, greater physical proximity and social interaction among them (Nickerson and Zenger, 2008). An employee of a mutual fund company said the following:

> "We have two portfolios that focus specifically on [sector] investing. And those two portfolio managers are aware probably every minute of every day how their fund is performing relative to the benchmark. But they are also highly aware of each other's performance and all their investing activities—their trades, we get trading notifications."

The greater attention to peers inside the firm means that the rank order of managers in a category in the firm has a relatively greater impact on a portfolio manager's behavior compared to the industry-wide rank order of managers in the

[8] In addition to the economic consequences for portfolio managers, the practice of benchmarking funds also entails significant consequences for other major stakeholders in the industry. For investors, the practice simplifies the task of choosing among a variety of funds (Jaffe, 1995; Sharpe, 1998). For fund companies, the practice affects their growth and survival since investors allocate capital across and within fund companies based on the performance of funds (Sirri and Tufano, 1998; Nanda, Wang, and Zheng, 2004).

category. The rank order of portfolio managers in a firm's category creates a winner among them. For ease of notation, I henceforth term winners as "leaders" and other portfolio managers as "laggards". The emergence of leaders and laggards gives managers feedback about their performance, both relative to their own prior performance and the performance of similar others. This performance feedback influences the aspiration levels of managers and triggers actions (Greve, 2003).[9] The ensuing discussion focuses on the actions of leaders and laggards, conditional on observing a rank order within a category of the firm. One action that the generation of a rank order influences is the propensity of leaders and laggards to create new funds. Shedding light on the dynamics inside firms, a portfolio manager spoke about how awareness of peers' actions inside the firm affects one's own actions:

> "From a portfolio manager's perspective, we are certainly aware of what the other portfolio managers and analysts are doing, and what they are thinking. […] But you want to add your own secret sauce. That's where you come into differentiating your product vis-à-vis some of the others in-house and even vis-à-vis some of your competitors at different firms."

Behavior of leaders: Incentives

Conditional on observing the rank order, leaders in a category in the firm may not have an incentive to change the status quo in the next period. In fact, they may even seek to consolidate their leadership position in the category vis-à-vis laggards. One way for leaders to consolidate their position is to create new funds in the same category. The following arguments can explain this behavior. First, leaders can leverage their reputation and create demand for new funds due to a spillover effect, provided some degree of

[9] Research on learning from performance feedback builds on work in the behavioral theory of the firm (Cyert and March, 1963), prospect theory (Kahneman and Tversky, 1979), and goal setting (Locke and Latham, 1990).

differentiation among the old and new funds precludes cannibalization. Based on empirical analysis, scholars have concluded that "star performance results in greater cash inflow to the fund" (Nanda *et al.*, 2004: 667). This condition implies that leaders have an incentive to create extensions adjacent to their current fund(s) to increase assets under management and hence personal compensation (which is a function of assets under management).[10] A portfolio manager confirmed the value of leveraging reputation:

> "If you are a leader [in a category], think about it—there is a halo effect for you to launch another fund. If you like this fund, you are going to love this new fund in the same space. And it's managed by the same manager."

Second, individual-level learning about one's own competence or expertise can also explain fund creation in the same category. Superior relative performance reinforces an individual's belief in her current actions (Levinthal and March, 1993). Thus, creating funds in the same category is equivalent to leveraging the skills that led to superior relative performance in the prior period. Referring to the value of knowledge and expertise, a portfolio manager said:

> "You are much more comfortable probably launching a second fund within an asset type that you know rather than launching a new fund."

Collectively, these motivations suggest that relative to laggards, leaders in a category in the firm will create more funds in the same category in the subsequent period. The preceding discussion leads to the following hypothesis:

Hypothesis 1: Relative to laggards, leaders in a category in the firm create more funds in the *same* category.

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[10] Research in the context of the hedge fund industry suggests that managers can increase their compensation in the short run by creating new funds (de Figueiredo and Rawley, 2011).

Behavior of laggards: Career concerns

Conditional on observing the rank order, laggards in a category can compete head-to-head with leaders. Head-to-head competition with leaders, however, presents several challenges for laggards. First, performance can influence resource allocation—research in the context of higher education suggests that prior performance is one basis for allocating budgets to and within universities (Williams, 1997; Layzell, 1998; Liefner, 2003). Interpreted in the context of this study, laggards are likely to find it relatively more difficult to obtain resources for fund creation and related activities in the firm compared to leaders. Second, prior research argues that "expectations about future outcomes in situations of uncertainty are likely to be created by observing past outcomes" (Dirks, 2000: 1005). Hence, by repeatedly being in the lower end of the distribution, laggards run the risk of being identified and branded as low performers. Third, and relatedly, lower relative performance can have adverse implications with regard to compensation and promotions in the firm's internal labor market (Baker and Holmstrom, 1995). In sum, conditional on observing the rank order, competing head-to-head with leaders in the same category may not be optimal for laggards.

When head-to-head competition is not the optimal choice, laggards can choose an alternative strategy of distancing themselves from leaders. Prior research shows through laboratory studies that when individuals are evaluated on the same criterion, low performers distance themselves from similar others after results are revealed (Pleban and Tesser, 1981; Tesser, 1988). For laggards, distancing themselves from leaders reduces the relevance of the dimension on which the firm evaluates both leaders and laggards.

Therefore, distancing alters the evaluation criterion for laggards within the firm in the subsequent period.

The foregoing logic implies that conditional on observing the rank order of managers in a category in the firm, laggards have a relatively greater incentive to avert direct competition with leaders than compete head-to-head with them in the subsequent period. Laggards can avoid direct competition with leaders by differentiating themselves. A portfolio manager at another firm said the following when asked about the motivations of portfolio managers to create a fund in a different category:

> "Maybe if you have been an also-ran, it's better to go try a new space and try to be a leader in that space. I always thought about it this way—I am going to guess that there are over a hundred analysts that follow Intel. If I am with [company name] in [city name], and I am the hundred-and-first guy to come out with a 28 cents a share for next quarter for Intel, what difference does that make? Why wouldn't I pick some other company that is only followed by three or four analysts, and maybe add my value there."

Consistent with the above view, another interviewee said the following:

> "They might not be managing the same funds but you might have manager A and B working in the same boundary or space [category]. A was just killing it and B was not doing so well. That reputation builds in and B keeps getting held under the performance of manager A. So from an individual growth perspective, they might want to break the perception that they are sub-part of this pairing and do something new. I think a lot of that comes down to individual aspirations."

By competing in a different category with no leader in the firm, laggards can redefine their reference group for performance comparison in the firm's internal labor market and also get a chance to become leaders in their new category. The increased ex-ante likelihood of becoming a leader means that it is relatively more beneficial for laggards to compete in a different category since relative performance within a category is the basis for promotions and compensation-related gains. Hence, relative to leaders, laggards in a category will create more funds in different categories with no leader in the firm in the prior year. The preceding discussion leads to the following hypothesis:

Hypothesis 2: Relative to leaders, laggards in a category in the firm create more funds in *different* categories with no leader in the firm in the prior year.

In sum, we can view fund creation by portfolio managers in a mutual fund firm as a sequential process. In a given period, inter-firm competition and consumer demand lead to a performance-based rank order of funds in an industry category. Since it is assumed that a fund is managed by an individual portfolio manager, the rank order of funds in an industry category simultaneously creates a rank order of portfolio managers in the corresponding category of a firm. Conditional on observing the rank order, leaders in a category in the firm have an incentive to maintain the status quo and may even seek to consolidate their leadership position vis-à-vis laggards in the subsequent period. Consequently, compared to laggards, leaders may create more funds in the same category to capitalize on their superior relative performance. In contrast, career concerns motivate laggards in the category to differentiate themselves from leaders and redefine their reference group for performance comparison. One way to redefine the reference group and alter the basis of performance comparison is to compete and create funds in a different category with no leader in the firm. Thus, compared to leaders, laggards may create more funds in different categories with no leader in the firm in the prior year. These arguments sum up how the incentives and career concerns of portfolio managers can explain their fund creation behavior in a firm’s category. Figure 2 illustrates a portfolio manager’s decision tree that forms the basis for testing the two hypotheses.

2.4 Research design and methodology

2.4.1 Sample and data

The primary source of data for the study was the Center for Research in Security Prices (CRSP) Survivorship-Bias Free Mutual Fund Database. The CRSP database is widely used for academic research on the mutual fund industry in management (Eggers, 2012; Kacperczyk, forthcoming), finance (Kacperczyk, Sialm, and Zheng, 2008; Massa, Reuter, and Zitzewitz, 2010), and economics (Chen *et al.*, 2004; Hortacsu and Syverson, 2004).

The sample for this study included only equity funds. I did not include bond and money market funds since doing so would have reduced comparability of managers across the different segments of the industry. Within equity funds, prior research makes further distinctions. For instance, some studies have focused on U.S. equity funds i.e., those that invest in U.S. companies only and excluded equity funds that invest in non-U.S. companies (Huang, Sialm, and Zhang, 2011). Other studies have focused only on equity funds in large segments (Growth, Growth and Income, and Small Company Growth) and excluded equity funds in other segments (Kempf and Ruenzi, 2008). Such distinctions were not necessary for this study. To create the sample of equity funds for this study, I followed the classifications for equity funds used in prior studies (Kempf and Ruenzi, 2008; Huang *et al.*, 2011; Eggers, 2012). Some types of equity funds were common to the samples in the respective studies. Hence, using multiple studies to define the set of equity funds ensured that I did not exclude a certain type of equity fund based on some exclusion criteria such as geography, sector, or size that a particular study may have used in its sample.

While CRSP provides data from 1961 onward, scholars have highlighted problems in the data prior to 1984. For instance, from 1962 to 1983, about 15% of the funds report only annual returns (and not monthly returns), and the average annual return for these funds is 5.29% lower compared to funds that report monthly returns (Fama and French, 2010). Consequently, in analyses that use funds reporting monthly returns, there can be a selection bias when using data from 1962 to 1983 (Fama and French, 2010). This issue is relevant to this study since I calculate a fund's annual performance based on its monthly returns (see below). Further, even if one uses data only on monthly returns, the differences in alpha (a measure of risk-adjusted return) between the CRSP and Morningstar databases are highest before 1984, and are greater for small funds than for large funds (Elton, Gruber, and Blake, 2001). Given that returns of a typical fund when adjusted for risk and other factors are small, small differences in alpha can lead to erroneous conclusions.

With regard to the objective of this study, there were additional limitations in the data prior to 1992. Critical to the analyses in this study was identifying the firm that owned a particular fund and mapping a fund to a category based on its investment objective. The CRSP database maps funds to categories using different sets of objective codes for different periods of time. These include the Wiesenberger objective codes (prior to 1993), Strategic Insight (SI) objective codes (1993 to 1998), and Lipper objective codes (1999 onward). Prior to 1992, however, there is a relatively higher proportion of missing data both for firm names and for objective codes. First, firm names were missing for more than 10% of the data in each year from 1984 to 1988; the proportion of missing firm names was close to zero from 1992. Second, the Wiesenberger objective codes were missing for more than 10% of the annual data prior to 1993. In contrast, the Strategic Insight codes and Lipper objective codes were missing for less than 2% of the data.[11] In view of these issues, the sample period for the study was 1992 to 2010. To classify equity funds into categories, I used the SI objective codes for 1992–1997 and the Lipper objective codes for 1998–2010. The sample comprised 60 unique fund categories based on SI codes and 50 unique fund categories based on Lipper codes.

I employed some additional steps to make the data more precise for the purpose of this study. Since this study focuses on managerial behavior in a firm's internal labor market, it was important to account for changes in the names of mutual fund companies, and for mergers and acquisitions (M&A) among firms. Not identifying changes in firm names would imply that a manager moved to another firm when s/he actually did not, hence overstating the rate of turnover across firms. Similarly, when a firm acquires or merges with another firm, managers of the two firms become part of the internal labor market of one firm. Not identifying an M&A event would imply that managers of the two firms continue to be part of two separate internal labor markets, when in fact, they work in one firm after the M&A event. The CRSP database does not account for changes in firm names and M&A events in some instances. For example, if a firm changed its name, the database continues to show both the old and new names. Similarly, the database continues to report a firm's name even after it has been acquired by or merged with another firm.

[11] I extrapolated the SI objective codes from 1993 to 1992 because of a high proportion of missing Wiesenberger codes in 1992 (52% of the data) and 1993 (84% of the data). Similarly, I extrapolated the Lipper objective codes from 1999 to 1998 because of a high proportion of missing SI objective codes in 1998 (26% of the data) and 1999 (50% of the data). The Lipper objective codes were missing for about 5% of the data in 1998. However the year 1998 is not included in the regression sample for reasons stated later.

I gathered data on both changes in firm names and M&A events from various sources such as the websites of mutual fund companies, US Securities and Exchange Commission, *BusinessWeek*, *The New York Times*, and *Hoovers* among others. In all, I identified 28 name changes and 164 M&A events from 1992 to 2010. For example, if a firm changed its name in 1999, I updated the data by replacing the firm's old name with its new name for the period prior to 1999. Likewise, if a firm acquired (or merged with) another firm in 2004 but the acquired firm still showed as an independent entity in the database after 2004, I updated the acquired firm's name with that of the acquiring firm from 2004 onward. In addition, I standardized the names of firms since the database reports several variants of a firm's name in many cases.[12] I also standardized the different variants of a portfolio manager's name in the sample. The final sample comprised 22,650 manager-years. In the regression analysis, I excluded 1992 because all independent variables were lagged by one year. I also excluded 1998 since a change from SI codes to Lipper codes would have overestimated the funds created in a different category.

2.4.2 Variables and model specification

Dependent and independent variables

To test the hypotheses, the *unit of analysis* was the portfolio manager-firm-category-year. The *dependent variable* was $Newfunds_{ijkt}$, the number of funds created by portfolio manager i in firm j in category k in year t. I defined fund creation as an instance of a portfolio manager starting one or more funds in the firm and not merely taking over the management of an existing fund from a colleague in the firm. Hence, the dependent

[12] For example, there were eight versions of one firm's name: "Morgan Stanley Asset Management Inc.", "Morgan Stanley Asset Mgmt Inc", "Morgan Stanley Inv Advisors", "Morgan Stanley Investment Advisors Inc", "Morgan Stanley Investment Advisors Inc.", "Morgan Stanley Inv Mgmt", "Morgan Stanley Investment Management Inc", and "Morgan Stanley Investment Mgmt Inc".

variable was positive when a manager created one or more funds in a category in the firm in a particular year and zero if s/he did not create a fund or started managing an existing fund.

The main *independent variable* was $Leader_{ik(t-1)}$, a dummy variable for whether portfolio manager *i* was a leader (1) or a laggard (0) in category *k* in year *t-1* in the industry. Defining leaders and laggards at the category-industry level allowed me to get variation to test Hypothesis 2, i.e., relative to leaders, laggards create more funds in different categories with no leader in the firm in the prior year. Using a firm-level definition of a leader would have implied that every firm had a leader in each category, thereby providing no variation to test Hypothesis 2.[13]

I identified leaders and laggards based on the annual returns (performance) of their funds. I chose annual performance as the basis of comparison since scholars have argued that "annual performance determines the status of managers among investors" (Rao and Drazin, 2002: 497). Furthermore, interviews with industry experts suggested that annual performance is also an important factor in determining a portfolio manager's performance bonus. Following Gavazza (2011), I calculated a fund's annual return as $\prod_{m=1}^{12}(1 + r_m)$ where r_m denotes a fund's monthly return as reported in the CRSP database. A leader was a portfolio manager whose fund's annual return was among the top 10% of all funds in a given year at the category-industry level; the balance 90% were laggards.

For portfolio managers who managed multiple funds in a year, I calculated an average score based on the performance of all her/his funds in the category. A leader was

[13] In the empirical specifications, I control for a portfolio manager's performance relative to peers at the firm-category-year level.

defined as someone with an average score of 0.5 or greater. For example, suppose someone managed five funds in a category in a given year. Of these, three funds were in the top 10% at the industry-category level while two funds were not. The average score for this manager would be (3*1 + 2*0)/5 = 0.6. Hence, this manager would be a leader at the category-industry level in a given year. At the firm-category-year level, the breakdown of the number of funds managed by portfolio managers was the following: 48.42% (one fund), 15.20% (two funds), 12.41% (three funds), 11.70% (four funds), 5.40% (five funds), and the balance 6.87% (six funds or more).

Further, the basis for choosing the 10% cut-off for annual fund performance to define a leader was Morningstar's popular fund rating system that influences investor behavior (Sharpe, 1998). On a scale of 1 to 5, Morningstar assigns a 5-star rating to the top 10% funds.[14] In general, an increase in the Morningstar rating of a fund has a substantive effect on capital inflow into the fund (Bergstresser and Poterba, 2002). While firms have an incentive to publicize their 5-star (top 10%) and 4-star funds (next 22.5%) to broaden their set of attractive funds, investors respond asymmetrically to these two sets of funds. Prior research finds that the existence of a five-star-rated fund in a fund family leads to greater inflow of investor capital into both the specific fund and the larger fund family (Nanda *et al.*, 2004). Furthermore, an increase in rating from four to five stars has a disproportionate effect on capital inflow into a fund—in the six months after the upgrade from four to five stars, actual capital inflow is 25% above the average expected capital inflow into the fund (Del Guercio and Tkac, 2008). The second reason for choosing the 10% cutoff was that inherent in the notion of a leader (or star) is the

[14] The percentage distribution of funds within a category in Morningstar's rating system is as follows: five stars (10%), four stars (22.5%), three stars (35%), two stars (22.5%), and one star (10%).

assumption of small numbers (Rosen, 1981). These arguments notwithstanding, I did sensitivity analysis for the definition of leaders and laggards and report the results in the robustness section.

Control variables

I included the following control variables in the specification (See Table 1 for the description of control variables). At the category-industry level, I controlled for the effect of imitation across firms by including the *number of funds at the category-industry level*. To control for a category's attractiveness in the industry, I included a variable for *category growth in the industry* (calculated as growth in total net assets). At the category-firm level, I controlled for the effect of crowding within a firm by including the *number of funds at the category-firm level*. I also included *category growth in the firm* (calculated as growth in total net assets) to control for a category's attractiveness in the firm. I constructed these variables using CRSP data.

At the firm level, I used CRSP data to control for the *number of categories* (a proxy for firm scope), *firm performance* (calculated as the weighted average of the annual returns of all funds using a fund's net assets as weights), *firm size* (calculated as total net assets), and *firm cash flow*. I calculated firm cash flow as the firm's current year net assets minus the product of the firm's preceding year net assets and firm return during the year, and divided this difference by the firm's preceding year net assets (Kacperczyk, forthcoming). I also controlled for *firm age* (in years) by collecting data from the Directory of Corporate Affiliations (DCA) and the websites of mutual fund companies, *BusinessWeek*, and the US Securities and Exchange Commission.[15]

[15] I thank Minyuan Zhao for sharing the Directory of Corporate Affiliations data.

At the portfolio manager level, I included a proxy for a *manager's remuneration*. I calculated this variable as the product of a fund's expense ratio and fund net assets, and summed it across all funds of a portfolio manager. This calculation assumed that a portfolio manager's remuneration is positively correlated with the expense ratio and size of her/his funds. Nevertheless, this is an approximate measure and subject to limitations. It was, however, the best available proxy since it is difficult to obtain precise and comprehensive data about the terms of a portfolio manager's incentive contract from CRSP and other sources. Further, I controlled for a *manager's existing funds in the firm* and a *manager's firm-specific tenure* (calculated as the number of years that a manager has worked in a firm).

To predict the excess zeroes in the dependent variable, I included two variables in the logit part of the zero-inflated negative binomial model (see next sub-section). First, I included a *manager's performance in the firm-category* (relative to peers). A manager's relative performance in the firm-category would be related to her/his ability to garner resources in the firm and thus influence the likelihood of creating an additional fund. Second, I included a *manager's existing funds in the firm*. By setting a capacity constraint on a manager's span of control, a manager's existing funds would influence her/his ability to create an additional fund. Finally, to control for time-related effects and unobserved firm heterogeneity, I included year and firm fixed effects as appropriate.

Model specification

Since the dependent variable was a non-negative integer, the appropriate model to test the hypotheses was a count model. In the set of count models, the Poisson model necessitates equality of the conditional mean and variance, which was violated in the data. The negative binomial (NB) model does not necessitate the (conditional) mean–variance equality. But portfolio managers need not necessarily create funds in every year, thereby resulting in an excess proportion of zeroes in the dependent variable. The excess proportion of zeroes suggested using the zero-inflated negative binomial (ZINB) model.

To select the appropriate model, I compared the fit of various count models—Poisson, Zero-inflated Poisson (ZIP), NB, and ZINB—using the *countfit* command in Stata (Long and Freese, 2006). The command uses the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and additional tests to compare the fit of the four models. Using the specification in Table 12, I estimated the number of funds created by a portfolio manager without distinguishing between same and different categories. Results based on the *countfit* command supported using the ZINB model. Figure 3 shows the difference between the observed and predicted probabilities of each count across four models—Poisson, NB, ZIP, and ZINB.[16] Among these models, the Poisson and ZIP models showed the maximum deviation between the predicted and observed probabilities for the counts of 0 and 1. Values of goodness-of-fit measures such as AIC and BIC (in addition to other statistics) also suggested that the ZINB model was preferred.[17] Collectively, these tests confirmed the ZINB model as the preferred model among the four count models.

[16] I thank Shawna Smith (Indiana University and Instructor, Categorical Data Analysis, Inter-University Consortium for Political and Social Research, 2012, University of Michigan) for helpful discussions about comparing count models in Stata.

[17] If the absolute difference in the BIC values of two models exceeds ten, then the model with the lower BIC value is strongly preferred (Raftery, 1995). This condition was true for the different pairs of models compared.

Based on the above results, I tested the hypotheses using the ZINB model. For a portfolio manager *i*, the specification for the number of funds created in category *d* in firm *j* in year *t* was:

$$\text{Regime 1: } E(\text{Newfunds}_{ijdt}) = \eta_{i(t\text{-}1)} \exp\left(\alpha_0 + \alpha_1 \text{Leader}_{ik(t\text{-}1)} + \beta\varphi_{kj(t\text{-}1)} + \gamma\xi_{j(t\text{-}1)} + \theta\omega_{k(t\text{-}1)} + \vartheta_t + \mu_j\right) \quad \ldots(1)$$

$$\text{Regime 2: } E(\text{Newfunds}_{ijdt}) = 0 \quad \ldots(2)$$

$$\text{Prob(Regime 1)} = \exp\left(\delta_0 + \delta_1\eta_{i(t-1)}\right)/[1 + \exp\left(\delta_0 + \delta_1\eta_{i(t-1)}\right)] \quad \ldots(3)$$

To test the hypotheses, I used the same specification—once each for funds created in the same category in year *t* and for funds created in different categories in year *t* with no leader in the firm in year *t-1*. For funds created in the same category, d = k in specification 1. The dependent variable was the number of funds created by a portfolio manager in year *t* in the same category that s/he operated in year *t-1*, regardless of whether s/he created a fund in that category in year *t-1*. The dependent variable was positive for managers who created at least one fund in the same category and zero otherwise (for managers who stayed in the same category but did not create a fund, and managers who moved to different categories with no leader in the firm in the prior year). Hypothesis 1 predicts that relative to laggards, leaders in year *t-1* create more funds in the same category in year *t*. Hence, for d = k, the expected sign for α_1 was positive.

For funds created in different categories in year *t* with no leader in the firm in year *t-1*, d ≠ k in specification 1. The dependent variable was the number of funds created by a portfolio manager in year *t* in a category with no leader in the firm in year *t-1* and distinct from the category that s/he operated in year *t-1*. The dependent variable was positive for managers who created at least one fund in a different category with no leader in the firm in the prior year and zero otherwise (for managers who moved to a different category with no leader in the firm in the prior year but did not create a fund, and managers who stayed in the same category). Hypothesis 2 predicts that relative to leaders, laggards in a category in year *t-1* create more funds in year *t* in different categories with no leader in the firm in year *t-1*. Hence, for $d \neq k$, the expected sign for α_1 was negative.

In specification 1, $\varphi_{kj(t-1)}$, $\xi_{j(t-1)}$, and $\omega_{k(t-1)}$ are the vectors of control variables lagged by one year at the category-firm, firm, and category-industry levels respectively; ϑ_t and μ_j are vectors of year fixed effects and firm fixed effects, respectively. Scholars have used dummy variables as fixed effects in the ZINB model in prior research in management (Henisz and Macher, 2004; Fosfuri, 2006; Zhao, 2006), economics (Keller and Levinson, 2002; Kahn, 2005; Nesta and Saviotti, 2005), sociology (King, Messner, and Baller, 2009), and political science (Moore and Shellman, 2004). Since the level of analysis is the manager-firm-category-year, the length of each panel is finite. The use of dummy variables can lead to an incidental parameters problem due to which the maximum-likelihood estimates of the coefficients of interest (i.e., α, β, γ, and θ) may not be consistent (Neyman and Scott, 1948; Lancaster, 2000). In the specific case of count models, Hausman, Hall, and Griliches (1984) have discussed the incidental parameters for the conditional fixed-effects negative binomial model.[18] To date, however, there seems to be no formal theoretical proof for the existence (or the lack) of an incidental parameters problem for the ZINB model. Nonetheless, this study acknowledges the potential for an incidental parameters problem.

[18] In more recent work, Allison and Waterman (2002) and Greene (2007) have shown that the conditional fixed-effects model due to Hausman, Hall, and Griliches (1984) is not a true fixed-effects model since it builds the effect into the variance, and not the mean, of the random variable.

To account for serial correlation in a portfolio manager's behavior over time and heteroskedasticity across managers, I used robust standard errors clustered at the portfolio manager level. In specifications 1 and 3, η represents the vector of two lagged variables used to explain the excess zeroes in the dependent variable. As discussed earlier, these variables are a portfolio manager's performance in the firm-category (relative to peers) and her/his existing funds in the firm.

It is possible that conditional on performance revelation in a given year, a firm may ask a laggard to leave in the subsequent year or s/he may do so voluntarily. Likewise, another firm may poach a leader or s/he may leave voluntarily to join another firm. Therefore, in studying the fund creation behavior of portfolio managers over time, it is important to address the issue of managerial turnover after performance revelation. I tried to address this issue by coding fund creation in a given year at the level of the manager–firm dyad, and not just at the manager level. Thus, I have analyzed fund creation behavior for portfolio managers who did not leave the firm, conditional on performance revelation. But this methodology raises the potential for a selection bias as certain individuals (leaders and/or laggards) are asked or decide to leave a firm, while others do not. A more precise or appropriate way of accounting for managerial turnover in studying a manager's fund creation behavior remains an agenda for continuing work.

After coding fund creation, the breakdown of the 22,650 observations at the manager–firm–year level in the sample was as follows: 15,796 observations for fund creation in the same category, 1,472 (533 + 939) for fund creation in different categories with no leader in the firm in the prior year, and 161 observations for fund creation in different categories with a leader in the firm in the prior year. Of the 1,472 observations, 939 observations in year 1998 were excluded for reasons stated earlier. The balance 5,221 observations were the missing first year's observation in the panel of each unique manager–firm dyad (See Table 2 for a detailed description).

In the regression sample, the number of unique portfolio managers was 3,373 with a 6.14% turnover rate between firms. Further, the number of funds created in the same category was 1,814 (265 by leaders and 1,549 by laggards). The number of funds created in different categories with no leader in the firm in the prior year was 134 (8 by leaders and 126 by laggards). For the omitted case (not included in the regression analysis), the number of funds created in different categories with a leader in the firm in the prior year was 64 (10 by leaders and 54 by laggards). Hence, the proportion of funds created in the three cases was: 90.16% (Hypothesis 1), 6.66% (Hypothesis 2), and 3.18% (omitted case). See Table 3 for details.

2.5 Results

2.5.1 Descriptive statistics

Table 4 presents the descriptive statistics and correlation matrix of the variables used to estimate the number of funds created by a portfolio manager in the same category and different categories with no leader in the firm in the prior year. To avoid a sample selection bias, I used the same sample of portfolio managers to test the two hypotheses. Given the same sample, the descriptive statistics are the same for all variables except for the different dependent variables for the two hypotheses. Hence, the correlations of the two dependent variables with the set of independent variables differ.

Focusing on the main independent variable of interest in Table 4, there is a positive correlation between the dummy variable for a leader and the number of funds created in the same category. In contrast, there is a negative correlation between the dummy variable for a leader and the number of funds created in different categories with no leader in the firm in the prior year. The descriptive statistics suggest significant differences across managers in remuneration and relative performance at the category-firm level, and across firms in category growth, funds within a category, overall size, and cash flow.

Additional tables provide more descriptive statistics. Table 5, Table 6, and Table 7 show the relation between the number of funds created (for H1 and H2 separately) and three manager-level variables—deciles of remuneration, firm-specific tenure, and relative performance in a firm-category, respectively. Table 8 and Table 9 show the relation between the number of funds created (for H1 and H2 separately) and the number of existing funds of a portfolio manager.[19] Table 10 shows the relation between the number of funds created (for H1 and H2 separately) and four firm-level variables—number of categories, firm performance, firm size, and firm cash flow.

2.5.2 Main results

Table 11 presents results of the t-tests for the mean number of funds created by leaders and laggards in the same category (Hypothesis 1) and in different categories with no leader in the firm in the prior year (Hypothesis 2). The data in Table 11 are only for individuals who create funds i.e., for whom the dependent variable is positive. It does not include individuals who do not create a fund i.e., for whom the dependent variable is

[19] In supplementary regression analysis, I restricted the sample to portfolio managers who manage only one fund. However, the models did not converge, perhaps due to the low incidence of funds created by portfolio managers who manage only one fund, as shown in Table 8 for H1 and in Table 9 for H2.

zero. Based on Table 11, Figure 4 shows the differences in the mean number of funds created by leaders and laggards in the two cases.

In regression analysis, the specification for Hypothesis 2 did not converge without rescaling some of the variables. To make the specifications converge, I used log transformations of some variables like category growth in the industry, category growth in the firm, and firm size that had a high range of values. The first two of these variables can take negative values and it is not possible to create log transformations of negative values. Therefore, before creating the log-transformed variable, I added a constant to the particular variable to ensure that its range was positive. I also winsorized a manager's relative performance in the firm-category and a firm's cash flow at 1% and 99% to attenuate the effect of outliers.

Using the ZINB model, Table 12 presents regression results for the relative behaviors of leaders and laggards with regard to the number of funds created. Models 1–4 present results for the number of funds created in the same category. Model 1 includes variables at the category-industry level; Model 2 includes variables at the firm and category-firm levels in addition. Further, Model 3 includes the manager-level variables as well.

Model 2 suggests evidence for imitation across firms—portfolio managers create more funds in a category that has a higher number of funds in the industry. In contrast, there is evidence for the negative effect of crowding at the category-firm level. Portfolio managers create fewer funds in a category with more funds in the firm. Further, managers create more funds in older firms as confirmed by the positive and significant coefficient estimate for firm age. In Model 3, portfolio managers with higher firm-specific tenure create fewer funds, which seemed contrary to intuition. This result, however, is consistent with the idea that individuals become conservative after sequential learning about competence, independent of the nature of the reward function (see Prendergast and Stole, 1996 for a formal model). Interviews with industry insiders confirmed the intuition that while longer-tenured managers may have the ability to create more funds in a firm, they may not necessarily have the willingness to do so having sequentially learned about an investment strategy that works for them.

To explain the excess zeroes for funds created in the same category, the coefficient estimate for a manager's existing number of funds is negative and significant in Models 1–3. This result suggests that for every additional fund managed by a portfolio manager, the odds of no fund creation decrease. In contrast, the coefficient estimate for a manager's relative performance in the firm-category is positive and significant in Models 1–3. This result suggests that the odds of a zero (i.e., no fund created) increase with relative performance in the firm-category, which seems counterintuitive. One possible explanation for this result is that higher performers in a firm-category do not want to change the status quo, presumably because they have found an investment strategy that reaps rewards.

In Model 3, the coefficient estimate for a manager's relative performance in the firm-category is negative in the NB part of the ZINB model. This seemed counterintuitive i.e., managers with higher performance in the firm-category create fewer funds. To analyze further, I split a manager's relative performance into five quintiles. I further divided the highest quintile (80-100%) into two deciles (80-90% and 90-100%). In results not reported, the bottom quintile (0-20%) is negative and significant. The second and third quintiles drop out from the specification since they are all zero values. The fourth quintile (60-80%) and ninth decile (80-90%) are negative but non-significant. The highest decile (90-100%) is positive but non-significant. Thus, it seems that the positive relation between the number of funds created and a manager's relative performance in the firm-category is only true for the highest decile (though it is non-significant). This result is consistent with the positive and significant coefficient estimate for the leader dummy (defined as the top 10% performers in the industry-category).

Model 4 presents the full model for funds created in the same category. The results for the control variables in Model 4 are broadly similar to those in Models 1–3. In Model 4, the coefficient estimate for the leader dummy is positive and significant ($\hat{\alpha}_1 = 0.482$; $p < 0.01$). This estimate implies that being a leader increases the expected number of funds created by a factor of 1.619 [i.e., exp(0.482)], holding all other variables constant. Stated differently, being a leader increases the expected number of funds created by 61.9%, holding all other variables constant (Long and Freese, 2006). This result supports Hypothesis 1 that relative to laggards, leaders in a category create more funds in the same category in the subsequent year, all else equal.

Further, in light of the positive coefficient for a manager's performance in the firm-category in the logit part of the ZINB model, the positive coefficient for the leader dummy in the NB part of the ZINB model warrants explanation. It implies that the expected number of funds created is higher for managers who are leaders at the category-industry level. One interpretation of this positive coefficient is that those who decide to create a fund(s) i.e., cross the threshold of zero, are also high performers in the category-industry, and they create relatively more funds than laggards.

Models 5–8 present results for Hypothesis 2. It predicts that relative to leaders, laggards in a category create more funds in different categories with no leader in the firm in the prior year. Model 5 includes control variables at the category-industry level; Model 6 includes control variables at the firm and category-firm levels in addition. Further, Model 7 includes the manager-level variables as well. To predict the excess zeroes in the dependent variable, a manager's performance is positive but non-significant in Model 7. In addition, though the coefficient estimate of a manager's existing funds is negative, it is not significant in Model 7.

Model 8 presents the full model including the dummy variable for a leader. In Model 8, the coefficient estimate for the leader dummy is negative ($\widehat{\alpha}_1$ = -0.069) as predicted but not significant. Thus, Hypothesis 2 is not supported, though preliminary data in Table 11 showed a negative correlation between the leader dummy and number of funds created in different categories with no leader in the firm in the prior year. The lack of statistical significance in the model may, in part, be explained by the low incidence of fund creation in different categories with no leader in the firm in the prior year.

One possible explanation for the low incidence of fund creation for Hypothesis 2 could be that there may be sufficient monitoring at the upper echelons of the firm that limits the incidence of such activity at the individual level. Thus, while the operational team comprising investment and sales professionals may influence the fund creation process in mutual fund companies, it need not imply unconstrained freedom to create funds.

Another possible explanation for the low incidence may be related to the nature of skills required by a portfolio manager to move to different categories and manage existing funds or create new ones. It is plausible that over time, managers develop skills that are specific to some sector (media, pharmaceutical, or real estate), type of company (large cap, mid cap, or small cap), or geographical area (Latin America, Asia, or Europe). In creating a new fund, a large majority of portfolio managers would leverage their existing skill set and knowledge. Only a small fraction may have the incentive to switch to managing/starting funds in a category that requires a different set of skills. In the data, I find a low negative correlation between the fraction of managers who move to different categories with no leader and a manager's firm-specific tenure. Over time, managers may discover an investment style that leads to higher relative performance. Thus, longer-tenured managers not only show lower propensity to moving to different categories with no leader in the firm but conditional on moving, they also create fewer funds in different categories (as confirmed in the regression analyses also).

2.5.3 Robustness tests

Using the ZINB model, I also assessed the sensitivity of the results to the inclusion of additional variables in the specification. The results are presented in Table 13. First, I checked for whether a manager's firm-specific tenure has a curvilinear relation with the number of funds created. I included the mean-deviated squared term of a manager's firm-specific tenure to mitigate concerns of multicollinearity with the linear term. The results for the leader dummy for Hypotheses 1 and 2 (Models 1 and 2, respectively) are similar to those in Table 12. Further, a manager's firm-specific tenure is negative and significant in both Models 1 and 2. Finally, the squared term of a manager's firm-specific tenure is non-significant in both models. One explanation for the lack of evidence of a curvilinear relationship could be the low average firm-specific tenure of a manager (less than five years) in the sample.

Second, I created three interaction terms by multiplying the dummy variable for a leader with a manager's remuneration, firm-specific tenure, and existing funds, respectively and conducted three additional tests. To mitigate concerns of multicollinearity, I used the mean-deviated values of the three variables in the interaction terms. The results are presented in Models 3–8 in Table 13. The results for Hypotheses 1 and 2 are similar to those in Table 12. The coefficient estimate for the leader dummy is positive and significant ($p < 0.01$ in Models 3, 5, and 7) for Hypothesis 1. In contrast, the coefficient estimate for the leader dummy is negative but not significant for Hypothesis 2 (Models 4, 6, and 8). Results for the three variables—manager's remuneration, firm-specific tenure, and existing funds—that are interacted with the dummy variable for a leader are broadly similar to those in Table 12. The three interaction terms are not significant for both Hypothesis 1 (Models 3, 5, and 7) and Hypothesis 2 (Models 4, 6, and 8), respectively.

Third, while the existing specification includes control variables such as number of existing funds and category growth at both the category-firm and category-industry levels, I included two additional variables to control for the size of a category at these two levels. Given that a category's size is highly correlated with the number of funds in it, I included the rank of a category by size at the category-firm and category-industry levels. The results for the two hypotheses are similar to those in Table 12. The coefficient estimate for the leader dummy is positive and significant ($p < 0.01$) for Hypothesis 1 (Model 9); it is negative and non-significant for Hypothesis 2 (Model 10). Further, the coefficient estimates for the rank of a category in both a firm and in an industry are not significant in both Models 9 and Model 10.

I also checked for the sensitivity of the results to alternative definitions of a leader and laggard. The results are presented in Table 14. First, I used three different definitions of a leader—a manager whose performance is among the top 5%, top 15%, and top 20% in a year at the category-industry level. The results for Hypothesis 1 are robust to the alternative definitions of a leader in all three cases (Models 1, 3, and 5). For Hypothesis 2, however, the coefficient estimate is not significant for the top 5% (Model 2). The models did not converge for Hypothesis 2 using the definition of a leader as the top 15% and top 20%. The non-convergence of these models may be driven by including the manager's relative performance in the firm-category in the NB part of the ZINB model. The same models converge when this variable is not included in the NB part of the ZINB model, and in these cases, the coefficient estimate for the leader dummy is positive and non-significant. Second, I used an alternative definition of laggards as those in the 0-70% range (Models 7 and 8). I retained the definition of a leader as a manager whose performance is among the top 10% of all funds in a year at the category-industry level. As before, the coefficient estimate for a leader is positive and significant for Hypothesis 1 ($p < 0.01$). For Hypothesis 2, it is negative but not significant.

To assess the sensitivity of the results to the regression model used, I estimated the specifications in Table 12 using the negative binomial (NB) model instead of the zero-inflated negative binomial (ZINB) model. I used two different NB models. First, I used the conditional fixed-effects NB model per Hausman, Hall, and Griliches (1984). Table 15 presents the results. Hypothesis 1 is supported since the coefficient estimate for the leader dummy is positive and significant ($\widehat{\alpha}_1$ = 0.465; $p < 0.01$) in Model 4. Hypothesis 2, however, is not supported since the coefficient for the leader dummy is positive ($\widehat{\alpha}_1$ = 0.100) but non-significant in Model 8. In addition, I also used the unconditional fixed-effects NB model for the following reasons. Allison and Waterman (2002) and Greene (2007) have argued that the conditional fixed-effects NB model due to Hausman, Hall, and Griliches (1984) and implemented in Stata and other statistical packages is not a true fixed-effects model since it builds the effect into the variance, and not the mean, of the random variable. Further, Allison and Waterman (2002) show via simulation that the unconditional fixed-effects NB model avoids the incidental parameter problem (a theoretical proof is awaited), though it produces lower standard errors that can be corrected. Likewise, Greene (2007) also calls for a theoretical inquiry about the potential of the incidental parameters problem in the unconditional model. In view of these observations, Table 16 presents the results using the unconditional fixed-effects NB model. Hypothesis 1 is supported since the coefficient estimate for the leader dummy is positive and significant ($\widehat{\alpha}_1$ = 0.458; $p < 0.01$) in Model 4. Hypothesis 2, however, is not supported since the coefficient for the leader dummy is negative ($\widehat{\alpha}_1$ = -0.100) but non-significant in Model 8.

2.6 Discussion and conclusion

This study theorizes about the product creation behavior of individuals who compete for promotions and compensation-related gains in the firm's internal labor market. It classifies individuals into leaders and laggards (based on their relative performance) and derives testable implications about their subsequent product creation behavior. The first hypothesis suggests that due to the incentives of individuals, leaders in a category create more products relative to laggards in the same category. In contrast, the second hypothesis predicts that to differentiate themselves from leaders, laggards create more products relative to leaders in different categories with no leader in the firm in the prior year. Differentiation can help laggards alter their reference group for relative performance comparison and also gives them a chance to become leaders in their new category. Empirical analyses for fund creation in the U.S. mutual fund industry support Hypothesis 1 but not Hypothesis 2.

The intended contribution of the study is to theorize about the micro-foundations of product creation in firms by relating it to the explicit incentives and career concerns of employees. Prior research has offered insightful quantitative evidence on firm-level antecedents and rich qualitative evidence on the significant role of operating-level employees to explain product creation. Forthcoming research also provides quantitative evidence for venture creation both inside and outside firms by individuals (Kacperczyk, forthcoming). This study embraces and extends this enterprise by suggesting that we can view product creation in firms as an outcome of the micro-motives of employees who compete for promotions and wage increases in the firm's internal labor market. By exploring the micro-foundations of product creation, the study also joins research that focuses on the important role of individuals, especially in human-capital-intensive firms (Groysberg *et al.*, 2008a; Groysberg and Lee, 2009). Indeed, scholars from diverse perspectives within strategy have called for focusing on individuals as important determinants of performance heterogeneity across firms (Bartlett and Ghoshal, 2002; Gavetti, Levinthal, and Ocasio, 2007; Teece, 2007; Abell, Felin, and Foss, 2008).

One of the benefits of studying individual-level behavior may be that it can explain firm-level outcomes. For example, individual-level behavior may explain firm scope. Though agency theory highlights managerial motivations, it has largely focused on corporate managers who diversify for power, status, and compensation (Jensen and Meckling, 1976). Economics research on diversification has emphasized market power and excess capacity in resources as motivations for firms to diversify (Montgomery, 1994). Management research on strategic change has studied the influence of operating employees on firm scope by proposing a process model of internal corporate venturing (Burgelman, 1983). Burgelman's study briefly alludes to career-related gains as a motive for proposing internal ventures. This study builds on it to suggest arguments for how these motives translate into individual-level actions. It argues that in order to progress in the firm's internal labor market, employees may seek to differentiate themselves from each other by creating new-to-the-firm products or categories. Viewed in this manner, the behavior of operating-level employees can influence firm scope. The incidence of such behavior in the regression sample for this study is such that individuals create about 6.7% of the funds in different categories with no leader in the prior year.

The study has the following limitations. First, a boundary condition of the arguments is that each product is created by an individual manager. Hence, the study abstracts from team-based creation of products. In reality, however, both individuals and teams create products in firms. In part, data constraints guided the choice to focus solely on individuals. From the available data, it is difficult to tease out an individual's contribution to a team's performance. Focusing on individuals ensures a clear mapping between their performance and subsequent actions. With more fine-grained data about the performance of individuals in teams, future research can incorporate team-based product creation in both the theory and empirical analyses.

Second, the analyses does not account for the precise terms of the incentive contracts of portfolio managers. While it includes a proxy for managerial remuneration, it is an imperfect measure. This perhaps also explains the consistently non-significant coefficient estimate for this variable across several specifications. Obtaining comprehensive data on incentive contracts would have helped account for the relation between the precise terms of incentive contracts and managerial behavior. The lack of precise data on incentive contracts, however, characterizes the bulk of the prior research in the mutual fund industry. For example, Chevalier and Ellison (1997) note that it is rare to observe performance evaluation schemes. Even studies that have accessed proprietary data on incentive contracts have reported availability for a maximum of only 108 funds in a year (Elton, Gruber, and Blake, 2003). Future research would benefit from detailed data on the incentive contracts of portfolio managers. For instance, it would be useful to obtain such data from a large mutual fund company to examine various aspects of managerial behavior, akin to single-firm studies on the internal economics of firms (Baker *et al.*, 1994a; Baker, Gibbs, and Holmstrom, 1994b).

Third, the study uses a limited set of firm-level variables to explain product creation. Presumably, heterogeneity across firms in terms of the degree of decentralization, the organization of research teams, and other management practices would also be important factors that influence an individual’s product creation behavior. Future endeavors could collect data on such variables to offer a more nuanced understanding of product creation in the mutual fund industry. Recent research offers suggestions for using surveys to collect such data (Bloom and Van Reenen, 2010).

In conclusion, this study is an attempt to explore the micro-foundations of product creation in firms that rely primarily on the expertise of individuals to create value. To do so, the study relates the micro-motives of employees who compete for promotions and wage increases in the firm's internal labor market to their product creation behavior inside firms. Focusing on the individual level is a promising avenue to offer a more nuanced understanding of the dynamics inside firms.

Chapter 3: The division of gains from complementarities

3.1 Introduction

The industrial revolution triggered enduring interest in the division of firm surplus among the agents of production. Emphasizing the role of market competition, John Stuart Mill recognized that each input will appropriate the value that it contributes to economic activity (Mill, 1848). Mill, however, also pointed out that unskilled labor is at the mercy of competitive forces, and may not receive even its marginal product when scarce land and capital are more critical to production (Mill, 1848: Book IV, Chapter 7). This was an early recognition that the wage-bargaining process disadvantages labor because labor is abundant and substitutable. This bargaining problem endures in the 21st century, albeit with the opposite effect: it is not easy to substitute skilled human capital employed in knowledge-based work. Under these conditions, labor's bargaining power increases (Miller and Shamsie, 1996; Groysberg *et al.*, 2008a) and so does its potential to appropriate firm surplus (Hansmann, 1996).

Team production can mitigate labor's bargaining power in human-capital-intensive activity. Alchian and Demsetz (1972) argue that team production presents an inseparability problem when it is difficult to discern individual contributions to team output. This inseparability problem creates friction in the mobility of labor between firms and shifts bargaining power to firm owners. It also uncovers an interesting tension with respect to the division of surplus in human-capital-intensive activity. On the one hand, economic activity involving skilled human capital shifts bargaining power toward labor. On the other hand, team-based production impedes accurate measurement of individuals' contributions. In other words, the *organization* of production in human-capital-intensive activity can affect the relative bargaining power of firm owners and labor.

This study explores the impact of organization design on wage bargaining by examining the micro-foundations of team production. It builds on the premise that team production does not always create an inseparability problem. For instance, while baseball and basketball both involve team production, baseball is an aggregate of individual efforts and basketball is not (Wolfe *et al.*, 2005). Thus, the *organization* of team-based production affects the degree to which one can measure individual contributions to the team. An important determinant of the measurability of individual contributions is the extent of interdependence among team members. Anecdotal evidence from law (Hillman, 2002-2003), investment banking (Groysberg, Sant, and Abrahams, 2008b), and baseball (Scully, 1994; Chacar and Hesterly, 2008) suggests that low interdependence makes it easier to measure individual contributions, thus allowing individuals to appropriate more of the firm surplus (Gilson and Mnookin, 1985). In contrast, it is more difficult to measure individual contributions in teams with high interdependence, thereby constraining an individual's ability to appropriate firm surplus.

The study distinguishes between team production based on *pooled* interdependence and *reciprocal* interdependence (Thompson, 1967). While pooled interdependence involves coordination by standardizing procedures, reciprocal interdependence involves coordination by mutual adjustment among team members (March and Simon, 1958). Reciprocal interdependence enables team output to be greater than the sum of individuals' outputs due to complementarity among them. The division of the incremental output will be contingent on the nature of team interdependence. If interdependence among team members is symmetric, a team member's external options will be no better than the status quo, because no other firm will gain by hiring her. In these cases, firm owners will appropriate a greater share of the surplus as complementarity increases. If, however, one or more individuals ("stars") contribute disproportionately to a team's incremental surplus, interdependence among team members is asymmetric and the star can leverage external options to increase her bargaining power. As a result, as complementarity increases, stars can appropriate a greater share (relative to non-stars) of labor's share of surplus.

A corollary question is whether complementarity is amenable to design. The study argues that creating complementarity is endogenous to organizing and hence a strategic choice for firm owners. Drawing on the prior literature in team learning (Edmondson, Dillon, and Roloff, 2007), the study identifies three managerial levers that create complementarity—the nature of *interaction* among team members, the relative *dominance* of team members, and the *composition* of a team.

3.2 Theory and hypotheses

3.2.1 Team production in human-capital-intensive activity

Teams are ubiquitous in human-capital-intensive activity (e.g., in movie production, sports, drug development, consulting, investment banking, and academia, among others). Theoretical interest in team production goes back to Alchian and Demsetz (1972). They define team production using three identifying characteristics: (1) several types of resources are used, (2) the output or product is not a simple sum of the separable inputs, and (3) not all resources belong to one person. Consider a research team developing a flu vaccine, for instance. Running experiments, collecting data, and creating samples may require some division of labor, but the vaccine itself is an indivisible output.

Millhiser, Coen, and Solow (2011) offer a simple model of a team. In their model, team output is a function of both individual outputs and peer effects. Peer effects are the contributions each individual makes to the output of fellow team members. Without peer effects, a team's output is simply a sum of individual outputs. Using simple notation, let Y be the output of a team of size N, y_i be the output of individual i, x_i be her input, and x_j be the vector of inputs of all other team members. Team output Y can be decomposed as follows:

$$\mathrm{Y} = \sum_{\mathrm{i}} \mathrm{y_i} + \sum_{\mathrm{i}} \sum_{\mathrm{j}=1}^{\mathrm{N}-1} \frac{\partial^2 \mathrm{y_i}}{\partial \mathrm{x_i}\, \partial \mathrm{x_j}}$$

For a team with peer effects, $\sum_{\mathrm{i}} \sum_{\mathrm{j}=1}^{\mathrm{N}-1} \frac{\partial^2 \mathrm{y_i}}{\partial \mathrm{x_i}\, \partial \mathrm{x_j}} \neq 0$, and hence $\mathrm{Y} \neq \mathrm{y_i} + \mathrm{y_j}$.

For a team without peer effects, $\sum_{\mathrm{i}} \sum_{\mathrm{j}=1}^{\mathrm{N}-1} \frac{\partial^2 \mathrm{y_i}}{\partial \mathrm{x_i}\, \partial \mathrm{x_j}} = 0$, and hence $\mathrm{Y} = \mathrm{y_i} + \mathrm{y_j}$.

In terms of Thompson's (1967) typology of task interdependence in firms, teams without peer effects are teams with pooled interdependence. One example of pooled interdependence is a baseball team, whose output is an aggregation of individual contributions, as described by Frei and Campbell (2006: 2):

> "Though baseball is a team sport, success is a function of the discrete achievements of individual players…the individual player's actions and the resulting impact on the game can be readily observed and recorded."

Peer effects arise from reciprocal interdependence—when each team member contributes to the output of other team members—as described in Thompson's (1967) framework. Peer effects may be positive or negative. For instance, Tziner and Eden (1985) found that some military tank crews performed *below* the level predicted by the sum of their individual skills. In other cases, peer effects are positive, creating team output that is *greater* than the sum of individual contributions. For instance, Lewis (2009) describes teamwork in the Houston Rockets basketball team:

> "The five players on any basketball team are far more than the sum of their parts; the Rockets devote a lot of energy to untangling subtle interactions among the team's elements…How many points a player scores, for example, is no true indication of how much he has helped his team."

Similarly, prior empirical work has found that interdependence among a bundle of firm policies creates complementarities that lead to performance gains at the team level (Ichniowski, Shaw, and Prennushi, 1997).

The nature of a team's interdependence will ultimately impact bargaining between the firm owner and labor. With pooled interdependence, as in baseball, there is little scope to generate complementarity, so $Y = y_i + y_j$. Moreover, the team's output is separable into discrete contributions from individual members. This implies that an individual's remuneration will closely match the marginal product. If the individual's remuneration is substantially lower than the marginal product, competitive labor market forces would bid up her wages to match the marginal product.

With reciprocal interdependence, however, teams may create complementarities that increase team output above the sum of its individual inputs i.e., $Y > y_i + y_j$; the incremental output $Y - (y_i + y_j)$ is the returns to complementarity. Peer effects make it difficult to separate the returns to complementarity into individual contributions and this difficulty has significant implications for the division of firm surplus. The next section discusses how the firm owner and labor divide the returns to complementarity generated by reciprocal interdependence.

3.2.2 Division of returns to complementarity

Thus far, the study has exploited heterogeneity in the organization of teams to argue that team production under reciprocal interdependence can create complementarity. The returns from complementarity are subject to bargaining between the firm owner and labor. On the one hand, the firm owner has some bargaining power over interdependent team members. Peer effects could make individual outputs firm-specific, implying that the individual's next best alternative may be inferior to the status quo (Idson and Kahane, 2004). On the other hand, interdependence among team members implies that replacing individuals is not costless for the firm owner. If training a new individual could be costly and potentially disrupt team dynamics (Tziner and Eden, 1985), the owner's next best alternative may be inferior to the status quo, as well. Hence, the outcome of bargaining for surplus created by complementarity is contingent.

Bargaining between the firm owner and labor occurs in the shadow of an external labor market, i.e., it depends on the nature of outside options available to labor (MacDonald and Ryall, 2004). Thus, to understand the effect of complementarity on the division of surplus, it is useful to understand the bargaining power of labor through a comparative analysis (Moulin, 1995). A specific contingency—whether interdependence among team members is symmetric—affects the outside options of labor and consequently its bargaining power vis-à-vis the firm owner. Also, examining the nature of interdependence in teams allows incorporating the effect of human capital differences among individuals within teams.

Symmetric interdependence among team members

Consider a firm in which team members generate complementarity based on *symmetric* interdependence, so that each member contributes to other members' output to the same degree. Because no individual makes a disproportionate contribution to the output of fellow team members, no individual accounts for the bulk of the gains from complementarity. Symmetric interdependence exists when $\frac{\partial^2 y_i}{\partial x_i \, \partial x_j} = \frac{\partial^2 y_k}{\partial x_k \, \partial x_j} \; \forall \, j = 1 \text{ to } N - 1$.

Labor market alternatives available to individual team members will determine how the firm owner and labor divide the returns to complementarity under symmetric interdependence. First, given symmetric interdependence, an individual gains no advantage by moving to a similar firm with no interdependence. In a similar firm, albeit with no interdependence, the upper bound of wages for the individual is the marginal product because of the principle of feasibility (see MacDonald and Ryall, 2004). This implies that to retain the individual, a firm owner needs to offer just a small amount more than a comparable firm without interdependence (see Anand *et al.*, 2007 for a formal proof of the result). If the individual already receives a wage equal to the value of the marginal product, plus a nominal portion of the returns from complementarity, the individual does not gain by moving to a similar firm with no interdependence.

Would the individual be better off moving to a firm with symmetric interdependence? An individual can generate a higher wage offer only if she can increase the firm surplus. There are two circumstances under which this might occur. First, an individual can increase firm surplus if her individual output exceeds that of the person replaced, all else equal. Her higher wage would be a function of her individual performance. Because the study focuses on the division of surplus due to complementarity, this mechanism is beyond the scope of the theory (though controlled for empirically). Second, an individual can increase firm surplus if the value of her peer effect is greater than the peer effect of the person replaced, such that she has a disproportionate impact on complementarity. However, a single team member with a disproportionate impact on complementarity violates the symmetric interdependence case.

In sum, an individual in a team with symmetric interdependence will not be able to use the labor market to bid up her wages. Under symmetric interdependence, the equilibrium wage of an individual will be just fractionally greater than the corresponding wage of an individual in a team with no interdependence. The individual will be unable to generate a higher wage unless she can disproportionately increase complementarity, which is not possible under symmetric interdependence. The preceding discussion leads to the following hypothesis:

Hypothesis 1a: As complementarity increases, an employee's share of firm surplus decreases.

Asymmetric interdependence among team members

Under *asymmetric* interdependence, one or more team members contribute disproportionately to generating complementarity. Asymmetric interdependence exists when $\frac{\partial^2 y_i}{\partial x_i \, \partial x_j} \neq \frac{\partial^2 y_k}{\partial x_k \, \partial x_j} \; \forall \; j = 1 \text{ to } N-1$.

For instance, Azoulay, Zivin, and Wang (2010) show that the unexpected death of an academic star results in a stable 5% to 8% decline in the publication productivity of the individual's co-authors. Prior research suggests that stars, who asymmetrically enhance their colleagues' productivity, can appropriate much of the returns to complementarity (see Rosen, 1981). The intuition is as follows: If a firm offers the star a wage equal to the individual's marginal product when much of the complementarity comprises the person's contribution, the individual will seek to generate a superior outside offer. Because stars' contributions are less firm-specific than contributions from non-stars, stars can generate complementarity and increase the output of most firms in which they work (Miller and Shamsie, 1996). The optimal decision for a competing firm owner would be to bid up the star's wage by sharing a portion of the complementarity surplus. Competing offers will force a star's initial employer to bid up the star's wage close to the sum of the individual's marginal product plus a portion of firm surplus. Thus, stars will appropriate a greater share of the returns to complementarity than non-stars in the focal firm. This reasoning helps explain why star actors, athletes, and scientists command a wage significantly higher than the average (Rosen, 1981).

An example illustrates the nature of bargaining given asymmetric interdependence among team members. In the early 1990s, IMG served as an agent for golf star Greg Norman. In 1993, Norman terminated his contract with IMG. "'Greg was tired of being used as leverage,' says Williams, referring to the practice of telling an advertiser that if it wanted Norman, it would have to sign another IMG client as well," (Kiersh, 1994: 89). Explaining his decision to terminate his contract with IMG, Norman said, "Even Joe Soap from down the street could have made me a lot of money. Quite honestly, I was the hottest property in golf. Since I left IMG my income has increased" (McDonnell, 1998: 7). In sum, when stars generate much of the complementarity due to asymmetric interdependence among team members, they will appropriate a greater share of the surplus than non-stars. The preceding discussion leads to the following hypothesis:

Hypothesis 1b: The greater the complementarity, the greater the share of firm surplus appropriated by stars relative to non-stars.

3.2.3 Sources of complementarity

Research in the human resource management and organizational economics literatures shows that management practices influence productivity and financial performance at the team and firm levels (Huselid, 1995; Ichniowski *et al.*, 1997; Cappelli and Neumark, 2001; Bloom and Van Reenen, 2007). The broader implication is that differences in management practices across firms reflect underlying differences in the quality of management across firms. With this body of research as the motivation, the study asks how management practices can foster complementarity in teams. Before that, a discussion of why reciprocal interdependence engenders complementarity follows.

Reciprocal interdependence, by definition, introduces contingencies into team task performance. For an individual, there is uncertainty in the choice of actions because individual actions (and outcomes) depend on the actions (and outcomes) of other team members. Ongoing mutual adjustment ensures close coordination of and synchronization among team members (March and Simon, 1958; Thompson, 1967). Thus, it is useful to examine the processes that facilitate coordination by mutual adjustment.

Prior research documents two major processes that facilitate coordination by mutual adjustment. First, the source of coordination is located and managed among team members (Rico *et al.*, 2008). This allows members to learn from and adapt to one another, facilitating the emergence of fine-grained and contingent behaviors (Kogut and Zander, 1996). For instance, in a study comparing the organization of work in a Saturn manufacturing facility to organization in other automotive facilities, researchers found significant differences in team performance (Shaiken, Lopez, and Mankita, 1997). The more traditional form of organization involved the union and the firm negotiating and setting rules and standards of behaviors at the firm level. At the Saturn plant, however, the union was involved in the day-to-day adaptation among teams of workers. Consequently, teams in the Saturn plant could make ongoing adaptations rapidly and adhere to higher quality standards without escalating every decision to negotiation between management and the union. The value of local coordination in managing interdependence is documented in other settings as well (Adler, 1992; Ichniowski *et al.*, 1997).

The second process that facilitates coordination by mutual adjustment involves the division of labor. Prior literature highlights the productivity benefits of specialization and a clear division of labor (Becker and Murphy, 1992). High levels of specialization in teams, however, may impede the development of understanding and a common language (Cohen and Levinthal, 1990). In the absence of a common language, coordination must rely on standardization and scripted programs (March and Simon, 1958). Using scripted programs reduces the potential for complementarity because it is difficult to predict individual actions under reciprocal interdependence. In contrast, overlapping task roles allow team members to appreciate and anticipate each others' behaviors. Anticipation fosters the creation and maintenance of tacit knowledge, which helps team members execute complex repertoires of behavior and improvise successfully when unpredictable contingencies arise (Miner, Bassoff, and Moorman, 2001). Thus, a fluid division of labor, with flexibility in assuming task roles, facilitates coordination by mutual adjustment. For instance, Beaulieu and Zimmerman (2005: 9) highlight the value of a fluid division of labor in the New England Patriots franchise (in the U.S. National Football League):

> "Bill Belichick and the Patriots were known around the league for the complexity of both their offensive and defensive plays. Learning these plays took a substantial amount of time with the playbook and extensive practice. In addition, the Patriots' game required players to make frequent adjustments, in response to the actions and formations of the opposing team, in real time as the play unfolded. This modus operandi could be a competitive advantage for the Patriots since it had the potential to disrupt and distract players on the other team."

The net effect of coordination by mutual adjustment is the emergence of a collective mind among team members (Weick and Roberts, 1993). Developing a collective mind spans a complex social process in which team members come to share a common goal and subordinate their own interests for the collective good of the team.

Can managers influence the degree of interdependence among teams? One perspective in prior research views interdependence as a property that firms inherit rather than choose (Rivkin, 2000). In other words, interdependence may be a result of accretive, path-dependent processes or mandated by technological constraints. While this characterization of interdependence is valid, this study argues that *how* the interdependence is managed is critical to whether it translates into complementarity (Tziner and Eden, 1985; Ethiraj, Levinthal, and Roy, 2008). Managing interdependence is clearly within the scope of managerial choices.

Drawing on the literature on team learning, the study argues that firm owners can create complementarity by actively constructing and managing interdependence among team members. Edmondson et al. (2007) provide evidence of a link between team characteristics and the development of shared learning. They emphasize the importance of team stability, knowledge sharing, team interaction, and team composition. Thus, following Edmondson et al. (2007), the study conjectures that complementarity is a function of at least three managerial choices: team interaction, team member dominance, and team composition. Because of the emphasis on the organizational factors that create complementarity, the study does not explicitly theorize about other important factors like individual incentives. It does, however, control for individual incentives in the empirical analyses.

Team interaction

While team-member interdependence is necessary, it is not sufficient to achieve complementarity. Team members may be inept at managing their interdependence. The ensuing negative peer effects would result in team output being less than the sum of individual outputs. Such dysfunctional team outcomes are widely documented in the literature (Tziner and Eden, 1985; Keyton, 1999; Felps, Mitchell, and Byington, 2006; Amason and Mooney, 2008). One explanation for dysfunctional team outcomes is sporadic interaction among team members, which hinders the development of shared knowledge and communication.

Coordination in the presence of high interdependence involves frequent and continuous micro-interactions among individuals for long periods of time (Okhuysen and Eisenhardt, 2002). Huckman and Pisano (2006) show that the team-specificity of performance among cardiac surgeons is rooted in greater familiarity between team members. Familiarity facilitates the creation of shared knowledge and understanding of each others' roles and tasks. Moreover, the history-dependent process involved in sustaining shared knowledge and communication implies that the addition or removal of an individual has significant consequences for the retention and perpetuation of a collective mind.

Teams that achieve continuity and longevity foster a co-specialization of skills among team members (Adler, 1990). This co-specialization is fostered in three ways. First, team members can learn from each other via observation and longevity, which helps improve observational learning (Nadler, Thompson, and Van Boven, 2003). Second, stable relationships among team members facilitate improvisation by creating a shared history of experimentation (Moorman and Miner, 1998). Finally, people in teams with stable interaction patterns gain knowledge of each other's capabilities (Edmondson *et al.*, 2007).

In sum, greater interaction among team members encourages development of shared knowledge and communication which, in turn, increases complementarity. The preceding discussion leads to the following hypothesis:

Hypothesis 2: The greater the interaction in the team, the higher the complementarity.

Team member dominance

An individual's disproportionate influence within a team has implications for complementarity. The prevailing evidence suggests a dominant team member can undermine team effectiveness in myriad ways. First, the theory of proportional representation suggests that less influential individuals underperform in the presence of highly influential individuals because, not only do the views of the former get stifled, but they also suffer from low confidence and self-esteem—a phenomenon labeled tokenism (Kanter, 1977). Second, recognition of disproportionate dependence on one person can affect team interaction and performance. In a study of R&D teams, Cohen and Zhou (1991) found that imbalances in expertise fostered a hub-and-spoke communication pattern rather than a multilateral one. Such a hub-and-spoke model of communication undermines the development of a collective mind (Weick and Roberts, 1993).

In addition, perceptions of equity are important drivers of individual motivation. Adams (Adams, 1963) argued that when individuals perceive that the ratio of their outcomes to inputs is less than that of their peers, it leads to perceptions of inequity. Such perceptions have implications for motivation and effort on the job. Scholars have advanced similar ideas in the context of group behavior. In a famous study of government bureaucracy, Blau (1955) found that agents consulted frequently with agents possessing equal expertise and rarely with agents possessing greater expertise. Agents consulted highly experienced agents much less frequently because they anticipated fewer opportunities to reciprocate. In contrast, they consulted with agents of similar expertise more frequently because a more equitable social exchange was possible. Blau’s study suggests that trust formation and communication are likely to decline in a team comprised of members with unequal influence. Based on these arguments, increases in the relative dominance of an individual should adversely affect complementarity. The preceding discussion leads to the following hypothesis:

Hypothesis 3: The greater the dominance of any single team member, the lower the complementarity.

Team composition

Prior research suggests that team composition affects the emergence and stability of norms that, in turn, influence work processes and outcomes (Gibson and Vermeulen, 2003). To understand the effect of team composition on complementarity, the relevant question is: What kinds of individual differences affect behavioral adaptation in reciprocally interdependent teams? Prior research suggests at least three components: demographic attributes, psychological characteristics, and the work context (Harrison *et al.*, 2002). Research also confirms that prior experience or socialization provides a composite and integrated view of how individuals might respond and adapt to working in interdependent teams (Katz, 1982). Hence, the sorting process for fostering complementarity should identify team-oriented individuals. The output of team-oriented individuals is likely to be team-specific because they are more likely to learn from and adapt to the demands of a new team (Wageman and Gordon, 2005). A team orientation involves developing shared cognition with fellow team members. It includes having the requisite task-specific knowledge (i.e., knowing who knows what) and team-member-specific knowledge (i.e., knowing and anticipating how a team member will behave in a range of circumstances) (Cannon-Bowers and Salas, 2001). Whereas the former draws on the shared expertise of the team in performing the task, the latter reduces the behavioral uncertainty of predicting team members' individual actions.

Team composition is an outcome of a two-way process whereby individuals join or leave a firm. This implies that complementarity will increase when firms recruit team-oriented individuals and decrease when firms lose team-oriented individuals. The preceding discussion leads to the following hypothesis:

Hypothesis 4: The more team-oriented individuals a firm recruits (loses), the higher (lower) the complementarity.

3.3 Research design and methodology

3.3.1 Research context: U.S. National Basketball Association

The context for the study is the U.S. National Basketball Association (NBA). Scholars have argued that sport is a fertile empirical ground for researchers to gain a deeper understanding of organizations as the world of sport mirrors the world of work (Keidel, 1987; Wolfe *et al.*, 2005). Whereas baseball helps understand the autonomy of organizational parts, basketball exhibits voluntary cooperation among the parts (Wolfe *et al.*, 2005: 184). Further, there is a long tradition in management and economics to use basketball as a research context (Pfeffer and Davis-Blake, 1986; Harder, 1992; Staw and Hoang, 1995; Berman *et al.*, 2002; Price and Wolfers, 2010).

Beyond this broader rationale, the NBA is an appropriate context to test the hypotheses for at least five reasons. First, NBA franchises are human-capital-intensive since players are the primary input in a team's output and hence their wages constitute the bulk of the franchise expenditures (See Figure 5). Second, to measure complementarity, it is necessary that the firm's output is based on reciprocal interdependence among individuals. In the NBA, a team's game performance is a function of the collective effort of players. Third, fine-grained performance data for players allows measurement of each player's contribution to a team's output (Kahn, 2000; Oliver, 2004). Fourth, ownership is separate from labor for all franchises because a clause in the NBA collective bargaining agreement (CBA) prohibits players from owning a stake in a team (see Article 29, Section 8 of the 2005 CBA). Thus, ownership form is constant across firms. Finally, to examine the division of surplus between the firm owner and labor, accurate data on either the returns to the firm owner or to labor are needed. There is fairly accurate data on team revenues, team operating profits, and player wages available for the NBA.

There can, however, be one important criticism of using the NBA as a context for this study. There is a longstanding debate about the objective of franchise owners in professional sports leagues (Rottenberg, 1956). While some scholars argue that franchise owners pursue higher profits, others assert that they chase a higher win percentage (Vrooman, 2000). If owners are not interested in higher profits, the NBA is an inappropriate context to test the hypotheses. The limited empirical evidence suggests that owners do pursue higher profits (Ferguson *et al.*, 1991; Romer, 2006). The following newspaper quote highlights the perils of ignoring team profitability for both the franchise and their host cities. Paul Allen, the Microsoft co-founder, owns the Portland Trailblazers franchise:

> "Allen has not only watched his Ogden Arena Company go bankrupt, but was forced to hand over to Rose Garden creditors, the…revenue sources that normally go to the team. Allen claimed he was losing hundreds of millions of dollars and threatened to leave the city unless Portland officials bail him out (Weiner, 2006)."

The debate on pursuing profits versus wins assumes a tradeoff between the two objectives i.e., a franchise owner may achieve a higher win percentage by paying higher wages to players. Figure 5 suggests no systematic correlation between win percentage and player wages in the sample. The data support the view that there is no tradeoff between pursuing higher profits and a higher win percentage, particularly via player wages as an underlying mechanism.

Using data on player wages to capture share of surplus is problematic if the wage-setting process is endogenous. There are several concerns in this regard. First, periodically, the NBA Players' Association negotiates the terms and conditions related to wages (including contracts, revenue distribution, players' trades etc.) with the franchise owners under the CBA.[20] The NBA eliminated the reserve clause and introduced free agency in 1980 due to the activism of the players' union and the threat of anti-trust lawsuits (Scott, Long, and Somppi, 1985). Consequently, an NBA player could become a free agent once his first contract expired. Free agency led to an explosion in player wages and a redistribution of surplus from franchise owners to players. Because the sample begins in 1991, the introduction of free agency in the NBA does not affect the analyses.

Second, concurrent with the introduction of free agency, the NBA instituted a player salary cap and floor, indexed to the league's gross revenues. Thus, the absolute values of both the salary cap and salary floor vary year-on-year. On the one hand, a salary floor guarantees a certain percentage of the league's revenues to the players. On the other hand, a salary cap ensures that the players do not appropriate the entire surplus (as theory would predict) and make the franchises unprofitable. Despite the sharp increase in the salary cap from $12.5 million (1991-92) to $55.6 million (2007-08) (Source: NBA.com), the NBA does not follow a hard salary cap. Franchises can exceed their salary caps under

[20] For the period under study, the CBA was renegotiated prior to the 1995-96, 1998-99 and 2005-2006 seasons. Most notably, a lockout by franchise owners delayed the start of the 1998-99 season by about three months, thereby curtailing the regular season to 50 games instead of the usual 82 games. Dummy variables are included corresponding to the four phases: 1991-1994, 1995-1997, 1998-2004 and 2005-2007.

a variety of exceptions. The existence of a soft salary cap allows variance across teams in the extent to which labor appropriates the firm surplus.[21]

In sum, elimination of the reserve clause had a markedly different impact on players' wages in baseball and basketball respectively. The reserve clause enabled firm owners to exploit monopsony profits by tying players to teams for the duration of their sporting careers. Hence, there was a significant gap between a player's marginal revenue product (MRP) and his wage prior to the 1970s (Scully, 1974). With elimination of the reserve clause in baseball, much of the gap disappeared in the 1990s due to competitive labor market forces (Scully, 1994; Chacar and Hesterly, 2008). This evidence confirms that baseball is indeed a nominal team sport. In contrast, despite elimination of the reserve clause in basketball, a significant positive gap between a player's MRP and wage remains (Scott *et al.*, 1985; Idson and Kahane, 2004). While this gap is smaller for free agents, it is positive on average. Further, the gap varies both by team and by player (Idson and Kahane, 2004). This evidence presents a puzzle as to why competitive labor market forces have not eliminated the gap between a player's MRP and wage in basketball, unlike in baseball. While the gap may differ across players due to differences in their bargaining power, understanding the gap across teams requires a firm-level explanation. This study argues that complementarity can explain at least some of the gap between a player's MRP and wage at the team level.

[21] Due to a soft salary cap, the NBA instituted a luxury tax in 1999 that became effective from the 2002-2003 season. The luxury tax—paid by teams that exceed the salary cap—is a mechanism to control excessive spending by franchises on player wages.

3.3.2 Sample and data

The sample comprised data for the period 1991 to 2007. The data were from websites used in prior academic research on the NBA. In cases where the data were from websites not previously cited, a random sample was cross-checked from the annual *Sporting News Official NBA Registers*. Data on players' wages are from *Forbes*, Patricia Bender's website, and other publicly available sources.[22] These data were matched to the players' annual statistics such as value above replacement, defensive rating, points, assists, and blocks among others from www.basketball-reference.com and www.dougstats.com (See Table 17 for the description of control variables). Any record for which there were no performance statistics for a player, either due to injury or retirement, was deleted. The usable sample comprised 7355 player-years from 1991 to 2007. Because of lags on several independent variables, the first year of data (1991) was lost resulting in a final regression sample of 6866 player-years.

To calculate the measure of complementarity, game-level player performance and attendance data were used from www.databasebasketball.com, www.espn.com, www.jonstats.com, and www.nba.com. The data for stadium capacity were from the *Official NBA Guide* and www.nbahoopsonline.com. To make the data comparable across teams, the analyses were limited to regular season games and excluded playoff games. To ensure that the inclusion of marginal players did not bias the results, a record was deleted if a player played less than five minutes in the game (about 10% of total game time of 48

[22] Patricia Bender and Doug Steele are freelancers who have collected NBA data from various newspaper and media sources. The data on their websites (http://www.eskimo.com/~pbender/index.html and http://www.dougstats.com) are used in other academic papers on basketball (see e.g., Berri and Jewell, 2004; Eschker, Perez, and Siegler, 2004).

minutes). Such observations accounted for about 5% of the sample. The final sample to calculate complementarity comprised 19,498 regular season games from 1991 to 2007.

Nominations received by players for various awards capture star effects (see Table 17). Lexis-Nexis provided data on the votes received by players for nomination to the annual all-star game. The Associated Press news wires and the NBA, Sports Illustrated, and ESPN websites provided data on a player's contract status every year (e.g., whether he was an unrestricted free agent, a restricted free agent, or under contract with a team).

Teams recruit players in two ways—select rookies from the annual NBA draft or trade existing players. The list of drafted rookies was compiled from www.nbadraft.net. Data on a rookie's assists for three years prior to his draft and his status (high school, college, or international) at the time of the draft were from the *Sporting News Official NBA Register*. The list of players traded among the teams was generated from the game-level data discussed above. From the annual statistics of players, the prior record of assists for two categories of traded players—players in-traded and players lost/released—was compiled.

Data were collected on each NBA franchise and its home city from 1991 to 2007. Data on a team's operating profits were from www.rodneyfort.com (compiled from *Financial World* and *Forbes* magazines). The regular season win percentages of teams and coach records came from www.basketball-reference.com. A proxy for a team's potential market size was the population data from the US Census Bureau at the Metropolitan Statistical Area level within a radius of 50 miles from the team's home city.

Data for the fan cost index (the cost of a game for a family of four) were from Rodney Fort's website and Team Marketing Report.

3.3.3 Variables and model specification

Generating the complementarity measure

Davis and Thomas (1993) use the closest analog of the measure required for this study. In deriving their measure that they call synergy, the authors emphasize two gaps in prior work. First, complementarity is often captured using the potential for realization (e.g., a firm operating in two related industries) and not the actual realization. Second, complementarity is simply measured as the presence or the lack of it (i.e., from 0 to +∞). To present a real tradeoff, there should also be the possibility of negative complementarity (i.e., complementarity should extend from -∞ to +∞). In fixing these gaps, they measure complementarity as the interaction between specific intermediate inputs. The measure in this study is qualitatively similar.

The measure of complementarity uses a production function equation for basketball (Zak, Huang, and Siegfried, 1979) based on the Cobb-Douglas specification. This specification affords the contribution of each input to be team-specific. (Appendix 1 provides a derivation of the production function for basketball as a special case of the Cobb-Douglas specification). For each game in the game-level sample, the logarithmic ratio of the focal team's points to the opponent team's points was estimated as a function of the logarithm of the performance of individual players of the focal team and several control variables. More formally, at the game level,

$$\mathrm{R_{ig}} = \ln\left[\frac{\mathrm{P_{ig}}}{\mathrm{P_{jg}}}\right] - \sum_{p=1}^{k} \widehat{\alpha_p} \ln \mathrm{X_{ipg}} - \hat{\beta}\mathrm{Z_{ig}} - \hat{\gamma}\mathrm{A_{ig}} - \hat{\delta}\mathrm{Z_{ig}} * \mathrm{A_{ig}} - \hat{\theta}\mathrm{NA_{ig}} \ldots\ldots\ldots\ldots\ldots (1)$$

where R_{ig} was residuals for team i in game g, P_{ig} and P_{jg} were the points scored by teams i and j respectively in game g, X_{ipg} was the performance of player p of team i in game g, Z_{ig} was a binary variable equal to one if game g was a home game for team i (Mizruchi, 1985), A_{ig} was the ratio of attendance to stadium capacity, and NA_{ig} was a binary variable for missing attendance data.

In equation 1 above, two measures of player performance X_{ipg} were used to generate two different sets of residuals at the game level. The first performance measure, the *Hoops Grading Statistic (HGS)*, is a composite measure that aggregates field goals, blocks, free throws, assists, steals, offensive rebounds, defensive rebounds, turnovers, and field goals missed by each player.[23] This measure has been used by basketball statisticians (Barra, 2001) and in recent academic research (Stiroh, 2007). See Table 18 for coefficient estimates of α_p, β, γ, δ, and θ to derive the HGS-based residuals. The second measure of individual performance, labeled *Harderstat*, has also been used in academic research on basketball (Harder, 1992).[24]

Using game-level residuals R_{ig}, complementarity at the team-year level was calculated as,

$$\mathrm{TC_{it}} = \left(\sum_{g=1}^{G} \mathrm{R_{ig}}\right) \Big/ \mathrm{G} \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

[23] HGS = [FGM*1.4 + Blk*1.4 + FTM + Ast + Stl + Orb*0.85 + Drb*0.5 - TO*0.8 - FGmiss*0.6]*48 / Min where FGM: Field Goals Made; Blk: Blocks; FTM: Free Throws Made; Ast: Assists; Stl: Steals; Orb: Offensive Rebounds; Drb: Defensive Rebounds; TO: Turnovers; FGmiss: Field Goals Missed; Min: Minutes played. Field goals include three-point shots. All statistics are at the game level.

[24] Harderstat = [Reb + Ast + Blk + Stl + (FGM – FGA) + (FTM – FTA)] / Min where Reb: Total Rebounds; Ast: Assists; Blk: Blocks; Stl: Steals; FGM: Field Goals Made; FGA: Field Goals Attempted; FTM: Free Throws Made; FTA: Free Throws Attempted; Min: Minutes played. Field goals include three-point shots. All statistics are at the game level.

where TC_{it} was the annual complementarity value for team *i* averaged over *G* regular season games in year *t*. This procedure to calculate complementarity assumed that the variance in team performance unexplained by individual players was a reasonable proxy for complementarity.[25]

There are, however, concerns about using residuals to measure complementarity. First, it is debatable whether residuals capture complementarity or some other unobservable team attributes (Appendix 1 discusses the confounds). If complementarity is even modestly correlated with the residual, the approach was empirically sound, provided other variables that might be correlated with both complementarity and a player's share of firm surplus were controlled for. Second, one might argue that complementarity is reflected in improved individual performance statistics. It is certainly a theoretical possibility but one that biased our results to non-significance. To the extent that complementarity was already captured in individual performance, the measure of complementarity was conservative.

The external validity of the measure of complementarity was assessed in two ways. First, by explaining the origins of complementarity through regression analysis, one can examine whether theoretically grounded managerial actions help or hinder the development of complementarity. Second, an alternative measure of complementarity based on off-court +/- statistics for each player from the 2002-03 season (when the data are first available) was used. The correlation between the measure of complementarity

[25] To control for unobserved heterogeneity among players, the game-level regressions were also estimated by including player fixed effects. In results not reported, the player fixed effects were non-significant suggesting that relevant aspects of individual player performance our captured in the composite individual player performance measures.

based on off-court +/- statistics and the residual-based measure of complementarity provided evidence of convergent validity.

Finally, using residuals to measure unobservable constructs like complementarity is not without precedent. In economics, firm productivity and aggregate productivity has been measured using residuals (Solow, 1957; Griliches, 1996). In finance, residuals measure firm-specific risk in capital asset pricing models (Campbell *et al.*, 2001). In sociology and organization theory, residuals are used to measure early promotion in careers (Burt, Hogarth, and Michaud, 2000), resource-partitioning (Swaminathan, 2001), technological change (Schilling and Steensma, 2001), and compensation practices (Gerhart and Milkovich, 1990). In sum, these efforts to control for relevant inputs, assess external validity, and reliance on prior literature helped alleviate concerns about the measure for complementarity.

Estimating an employee's share of firm surplus

Hypotheses 1a and 1b examine the effect of complementarity on a player's share of firm surplus. The unit of analysis is the individual. The specification for a player's share of firm surplus using the (team) fixed effects estimator was as follows:

$$\ln\left[\frac{P_{pit}}{1-P_{pit}}\right] = \alpha TC_{i(t-1)} + \beta S_{i(t-1)} + \gamma[TC * S]_{i(t-1)} + \eta X_{i(t-1)} + \xi Z_{it} + \lambda_t + \mu_i + \varepsilon_{it} \ldots\ldots\ldots (3)$$

In equation 3, the dependent variable was the logit transformation of P_{pit}, the share of player p in the surplus of firm i in year t. A player's share of the firm surplus was the ratio of his wage to the firm surplus, i.e., the sum of team wages and operating profit. The main independent variable of interest was $TC_{i(t-1)}$, the lagged measure of complementarity. $S_{i(t-1)}$ was the binary variable for all-star player, $X_{i(t-1)}$ was a vector of lagged player-level controls, Z_{it} was a vector of team-level controls, λ_t were time dummies, and μ_i were team fixed effects. Table 17 describes the control variables. The expected sign on the coefficient estimate of complementarity (α) was negative for Hypothesis 1a and positive for its interaction with the measure for a star player (γ) for Hypothesis 1b.

Explaining the origins of complementarity

The unit of analysis is the firm. To explain the origins of complementarity TC_{it}, the specification used was:

$$\mathrm{TC_{it}} = \alpha \mathrm{TmI_{it}} + \beta \mathrm{TmF_{it}} + \gamma \mathrm{PD_{it}} + \delta \mathrm{AsR_{it}} + \varphi \mathrm{AsL_{it}} + \rho \mathrm{AsD_{it}} + \omega \mathrm{Z_{it}} + \lambda_t + \varepsilon_{it} \ldots\ldots\ldots (4)$$

Equation 4 included two measures of team interaction to test Hypothesis 2. The first measure TmI_{it} was team interaction following prior research (Berri, Schmidt, and Brook, 2004). This measure was a proxy for *on-court interactions* among players. For players returning to a team's roster in year *t*, the average of the total minutes played in years *t*-1 and *t* by each returning player was calculated. The sum of the average minutes of all returning players was divided by the team's roster size in year t. If M_{it} and $M_{i(t-1)}$ were the minutes played by a returning player *i* in years *t* and *t-1* respectively, and k_t was the team's roster size in year *t*, team interaction was calculated as $\left[\sum_i \left(\frac{M_{it}+M_{i(t-1)}}{2}\right)\right]/k_t$ (where $i = 0$ to n; n $\leq k$). Consider a team in year *t* with a roster size of 10 players including two returning players. Further, let the two players play for 200 and 150 minutes in year *t-1* and for 300 and 300 minutes in year *t*, respectively. The team interaction score for the team in year *t* was 47.5.

TmF_{it} was team familiarity, the second measure of team interaction. Team familiarity captures the average amount of shared experience amongst pairs of team members (Reagans, Argote, and Brooks, 2005; Huckman, Staats, and Upton, 2009). Thus, team familiarity was a proxy for *off-court interactions* among players. Team familiarity was calculated as $\sum_{i=1}^{N} \sum_{j=1}^{N} RK_{ij} / N(N-1)/2$, where N was the roster size and RK_{ij} was the number of games in which player i and j played in year t. This measure was divided by a team's regular season games to capture average team familiarity per game. Consistent with Hypothesis 2, the expected signs on the coefficient estimates for both team interaction (α) and team familiarity (β) were positive.

To test Hypothesis 3, PD_{it} captured player dominance. It was measured by adapting the CEO centrality measure in the executive compensation literature (Bebchuk, Cremers, and Peyer, 2007). The measure of player dominance at the team-year level was the ratio of the minutes of the player with the maximum playing time to the aggregate minutes of the five players with the most playing time in the team. Higher values of this measure reflect one player's dominance over the others. Lower scores reflect equality among players on the team. Consistent with Hypothesis 3, the expected sign on the coefficient estimate for player dominance (γ) was negative.

To test Hypothesis 4, the team orientation of players was captured through AsD_{it}, the assist measure for drafted players, AsR_{it}, the assist measure for recruited players, and AsL_{it}, the assist measure for lost/released players.[26] These three team-level measures were based on the average of individual values in a team. For players selected through the annual NBA draft, the last three years of their collegiate or international league records

[26] The assists measure used to explain complementarity (equation 4) was distinct from the assists score in the regressions used to derive the measure of complementarity (equation 1). In equation 1, the residuals were extracted after removing the effect of player performance (which included his assist score in that year). So complementarity was net of player assist performance. In contrast, the assist measure used to capture team orientation in equation 4 was the lagged two-year average of the assists score of the players who were traded in any particular year.

on assists were used. No data on a player's assists record were available if he was drafted straight from high school. Likewise, for players recruited and released/lost through inter-team trades, the two-year average of their NBA record on assists was used.

Assists is a good proxy for team orientation because an assist occurs when a player's pass results in points for the team. The use of assists as a measure of team orientation is also supported in prior empirical work (Staw and Hoang, 1995). Players with a better record of assists performance are likely to be more team oriented. It is possible, however, that the assists score of a player is high due to his position in the team. For instance, the role of point guards in a team is to create plays for the entire team which naturally increases his assists score. The specification included the number of point guards recruited in a particular year to control for this possibility. Consistent with Hypothesis 4, the expected sign on the coefficient estimate for drafted players (ρ) was positive. For the traded players, the expected sign on the coefficient estimates for recruited players (δ) was positive and for players lost/released (φ) was negative.

Z_{it} was a vector of team-level controls and λ_t were time-specific dummies. Table 17 describes the control variables in detail. To account for panel heteroskedasticity, equation 4 was estimated using both generalized least squares (GLS) and (team) fixed effects regressions.

3.4 Results

3.4.1 Descriptive statistics

Table 19 presents the descriptive statistics and correlation matrix of the variables used to estimate a player's share of firm surplus. The player's share of firm surplus is negatively related to complementarity. The positive correlation between player performance, indicators of star status, and the player's share of firm surplus confirms the face validity of a human-capital-intensive context.

Additional tables provide more descriptive statistics about the data. The regression analyses estimates a player's share of surplus as a function of complementarity calculated as a residual from the relation between a firm's output and players' performances. To learn more about the sources of variation in player's annual wage and a player's share of surplus, Table 20 shows the correlations of these two measures with various measures of a player's performance. The correlations are positive and significant at the 5% level. Figure 6 shows the scatter plots for a player's share of surplus and four different performance measures—value above replacement, player efficiency rating, Hoops Grading Statistic (HGS), and Harderstat. Table 21 presents a player's mean annual wage and mean share of firm surplus for five quintiles of player characteristics—value above replacement, player efficiency rating, defensive rating, and league experience. Table 22 presents the differences between stars and non-stars for various measures including annual wage, share of surplus, performance measures, and contract status. A star is defined as a player chosen for the all-star game in a particular year. The results are in the expected direction—stars command significantly higher wages and show higher performance along various dimensions.

Table 23 presents the descriptive statistics and correlation matrix of the variables used to explain complementarity. Team familiarity, team interaction, and assists of in-traded players are positively associated with complementarity. Player dominance, assists of lost/released players, and assists of drafted players are negatively correlated with complementarity.

3.4.2 Main results

Central to the theoretical argument is the premise that complementarity increases firm surplus. The study tests this premise by estimating firm surplus (team wages plus operating profits in millions of 1984 dollars) as a function of the one-year lagged value of complementarity (HGS-based measure), after controlling for city-level characteristics and year effects in (team) fixed effects regressions. The coefficient estimate on complementarity is positive and significant (66.70; $p < 0.01$). This result confirms that complementarity increases the firm surplus available to be split between the firm owner and labor. For the estimated sample, a one standard deviation increase in complementarity is associated with a $2.85 million (constant dollars) increase in firm surplus, other things held constant.

Estimating a player's share of firm surplus

Table 24 presents the results of fixed effects regression models to assess the effect of complementarity on a player's share of firm surplus. Model 1 includes the team- and city-level control variables. Model 2 includes the lagged variables for player-level effects. A player's performance relative to others (i.e., value above replacement) is positively and significantly related to his share of firm surplus. There is a positive relationship between the number of all-star votes received and the share of firm surplus.[27] The coefficient estimate for a player's defensive rating is negative and significant. Because defensive rating is the points allowed by a player per 100 possessions, higher values of defensive rating imply lower defensive ability. Thus, consistent with intuition, the negative

[27] The negative coefficient estimate for the all-star dummy is counter-intuitive. We surmise that this negative sign is due to its high correlation with all-star votes ($r = 0.70$; $p < 0.001$) and value above replacement ($r = 0.63$; $p < 0.001$).

coefficient on defensive rating suggests that players with a lower defensive rating score (i.e., better defensive ability) earn a greater share of firm surplus. A team's prior success (a proxy for a desirable work environment) measured by the number of times a team made it to the playoffs in the last three years is negative and significant. This result suggests that players may be willing to accept a wage discount for the opportunity to be in a successful team. Finally, there are significant, albeit diminishing returns to experience.

Model 4 presents the full model to estimate a player's share of firm surplus. After controlling for player-, team- and city-level characteristics, there is strong support for H1a that complementarity is negatively related to a player's share of firm surplus. One standard deviation increase in complementarity is associated with a 15.36% reduction in a player's share of firm surplus for the estimated sample, other things held constant. The interaction term of complementarity and the all-star dummy is positive as predicted but not statistically significant. Thus, there is no support for H1b. There are two possible explanations for the non-significant result. The first explanation is that stars do not contribute to creating complementarity. To examine this possibility, the incidence of stars in teams exhibiting high complementarity is plotted. The fourth quartile of complementarity contains a large cluster of stars (304 out of the total of 852 players who received all-star votes). This eliminates the first explanation. The second explanation is that stars are unable to capture the returns to complementarity. Given that the coefficient on the interaction term is positive, one would be cautious about making the latter conclusion. Indeed, the joint test of complementarity and the interaction term is negative and significant. Thus, it is likely that stars appropriate returns from complementarity, though the precision of the estimate in the data is not sufficient to attain statistical significance for the interaction term.

Explaining the origins of complementarity

Table 25 presents the results of models that explain complementarity. In both the GLS and fixed effects regressions using only the control variables (models 1 and 2 respectively), team roster size is negative and significant. Larger teams not only reduce the average number of minutes played by each player but also increase the number of players with whom shared knowledge and communication routines have to be developed, thereby reducing complementarity. Coach experience is positively related to complementarity. *A priori*, the expectation was that the presence of stars would reduce complementarity because of their incentives to invest in their individual skills rather than in building the team's shared knowledge. This expectation, however, does not bear out because a team's number of all-star votes is positively related to complementarity. But the number of unrestricted free agents (i.e., players with short-term incentives) is negatively related to complementarity.

Models 3 and 4 present results of the full models for GLS and fixed effects regressions, respectively. Consistent with H2, team interaction is positively and significantly related to complementarity in both models 3 and 4. A 1% increase in team interaction is related to a 0.0007 unit increase in complementarity (115% of its mean) in the GLS model and a 0.00086 unit increase in complementarity (144% of its mean) in the fixed effects model, other things held constant. With respect to team familiarity, while its effect is positive, it is marginally significant in the GLS regression but significant in the fixed effects regression. Further, the effect of team familiarity is lower in magnitude compared to the effect of team interaction. A 1% increase in team familiarity is related to a 0.00043 unit increase in complementarity (72% of its mean) in the GLS model and a 0.00049 unit increase in complementarity (82% of its mean) in the fixed effects model.

There is support for H3 that the greater the minutes played by one player as a proportion of the top five players' minutes, the lower the complementarity. While the effect of a player's dominance is highly significant in the GLS regression (model 3), it is only marginally significant in the fixed effects regression (model 4). These results suggest that influential players are a stable feature of teams as opposed to varying over time within a team.

Consistent with H4, the recruitment of team-oriented players is positively related to complementarity while the loss of team-oriented players is negatively related to complementarity. The estimate for in-traded players is highly significant in both the cross-section (model 3) and over time (model 4). In model 3, a 1% increase in the team orientation of in-traded players is related to a 0.00012 unit increase in complementarity (20% of its mean), other things held constant. Likewise, in model 4, a 1% increase in the team orientation of in-traded players is related to a 0.00013 unit increase in complementarity (22% of its mean). The corresponding coefficient estimate for players lost/released through trades is also significant. In the cross-section (model 3), a 1% increase in team orientation of lost players is related to a 0.00009 unit decrease in complementarity (15% of its mean). Likewise, over time (model 4), a 1% increase in team orientation of lost players reduces complementarity by 0.00012 units (20% of its mean). The coefficient estimate for the team orientation of drafted players, however, is not significant in either the cross-section or over time, presumably because drafted players get very little playing time in their first year. In the estimation sample, a drafted player gets an average of 15 minutes of playing time per game in his rookie year relative to the league average of 21 minutes per player.

3.4.3 Robustness tests

Results for the four hypotheses were also generated using the alternative Harderstat-based measure of complementarity. See Table 26 for coefficient estimates of α_p, β, γ, δ, and θ to derive the Harderstat-based measure of complementarity. Table 27 and Table 28 present the results for the four hypotheses. These results are qualitatively similar to those using the HGS-based measure of complementarity.

The study includes two robustness tests for the measure of complementarity. First, a concern with a residual-based measure of complementarity is that it may measure other unobservable aspects of team performance. To address this concern, an alternative measure of complementarity is used. Beginning with the 2002-03 season, the NBA collected +/- statistics. These +/- statistics are of two types: one reflects the effect of a player on his team's performance when he is on-court while the second reflects the player's effect on his team's performance when he is off-court. The study posits that the individual off-court +/- statistics is a close analog of a player's indirect contribution to his team because the performance difference of a team when a player is off-court reflects his peer effect on his team members. Averaging the off-court +/- statistics across all players for a team in a year yields an estimate of complementarity. The complementarity measure based on off-court +/- statistics is positively correlated with the residual-based measure of complementarity ($r = 0.89$; $p < 0.001$). This result alleviates some of concerns about the residual-based measure of complementarity. In addition, the specification for a player's share of firm surplus for the period 2002 to 2007 is re-estimated using the measure of complementarity based on the off-court +/- statistics. Though not reported, the results using this alternative measure are qualitatively similar to those reported in Table 24. The results provide support that the residual-based measure of complementarity captures the same underlying construct as the measure of complementarity based on the off-court +/- statistics.

Another concern is that there may be measurement error inherent in residuals. To address this concern, the HGS and Harderstat-based measures for complementarity (TC_{it}) are converted into their respective z-values. In results not reported, the estimate for complementarity is negative and highly significant. Similar to the main results in Table 24, the interaction term between complementarity and the all-star dummy is positive, though non-significant. The results for estimating complementarity using its z-values are largely similar to the main results in Table 25 except that while team familiarity is positive, it is non-significant. The two robustness tests provide support that the results are robust to alternative ways of measuring complementarity.

To estimate a player's share of firm surplus, two alternative regression models for fractional dependent variables, i.e., the generalized linear model (Hausman and Leonard, 1997) and the generalized estimating equation (Papke and Wooldridge, 2008) are used. The dependent variable is the ratio of a player's wage divided by the sum of team wages and operating profit. The results—presented in model 1 (generalized linear model) and model 2 (generalized estimating equation) of Table 29—are qualitatively similar to the main results in Table 24.

To check whether the results to estimate a player's share of firm surplus are robust to alternative measures of player performance, player efficiency rating (PER) is used instead of value above replacement. PER is also a relative measure of player performance because the league-average PER is always 15. The results—reported in model 3 of Table 29—are consistent with the main results in Table 24.

Another concern with estimating a player's share of firm surplus is using a player's past record of assists as a proxy for his team orientation. Since assists is a measurable performance statistics, it could be a marketable skill in the context of the theory. Consequently, a player can use this skill to capture a greater share of the surplus. To address this issue, the player's assists record is removed from his HGS performance measure. A player's share of surplus is re-estimated by including the modified HGS performance measure and assists as separate regressors. In results not reported, the coefficient estimate on assists is statistically different from zero ($p < 0.001$). The result suggests that assists as a skill indeed has marketable value though it does not alter the sign or significance of the main hypotheses.

One concern with explaining complementarity is the reverse causality between complementarity and team interaction in H2. This concern is addressed by using the square of the mean-deviated value of team interaction as its instrument and estimate a 2SLS regression (Lewbel, 1997). The results from the second stage, presented in model 1 of Table 30, show that both team interaction and team familiarity are still positive, though the latter is only marginally significant.

Another concern with explaining complementarity is that player assists is not a proxy for a player's team orientation but a product of team strategy driven, in part, by the coach. The complementarity equation is re-estimated by substituting a coach's league experience with his team-specific experience to explain complementarity (models 2 and 3 in Table 30). The coefficient estimate is positive and significant in both the GLS and fixed effects models. This implies that a coach's team-specific experience is influential in increasing complementarity, presumably due to greater familiarity with and knowledge of the players and the franchise's staff.

Further, a player's assist percentage is used instead of the absolute value of assists as an alternative measure of team orientation. Assist percentage is an estimate of the percentage of field goals that a player assisted with. The results in models 4 and 5 of Table 30 are largely similar to the main results. The exceptions are that the assist percentage of lost/released players is non-significant in both the cross-section and over time; player dominance is non-significant over time. In sum, the robustness tests yield results broadly convergent with the main analyses.

The empirical analyses focused only on a player's propensity to appropriate firm surplus. These analyses are extended to explore the relation between complementarity and a player's ability to depart from a team. Using a Cox proportional hazard specification, the hazard of a player's departure from a franchise is estimated as a function of complementarity and other control variables. The coefficient estimate of complementarity is negative and significant (See Table 31). One standard deviation change in complementarity reduces the likelihood of departure by 2.4%. The Kaplan-Meier survival plots from the raw data for player departure confirm this result (See Figure 7). Teams with higher complementarity (relative to the median complementarity in a year) have a higher percentage of players who did not depart from the team, especially year five onward when players are free from their initial contract.

Finally, the game-level residuals that are the basis of the complementarity measure were also generated using the constant elasticity of substitution (CES) production function. In fact, the Cobb-Douglas production function used in the study is a special case of the CES production function with unit elasticity of substitution among the inputs. Hoff (2004) presents a linear approximation of the CES production function for *n* inputs by building on prior research for two inputs (Kmenta, 1967). Appendix 1 presents the linear approximation of the general CES function adapted to this study. Based on this approximation, game-level residuals using HGS and Harderstat measures of player performance were generated. Like before, these residuals were used to calculate the HGS-based and Harderstat-based measures of complementarity at the team-year level. Using these two measures of complementarity, Table 32 and Table 33 present the results for a player's share of surplus and for explaining complementarity, respectively. These results are qualitatively similar to those using the Cobb-Douglas production function.

3.5 Discussion and conclusion

This study examines the organizational factors that affect the division of surplus between a firm owner and labor in human-capital-intensive activity. It argues that reciprocal interdependence among team members fosters complementarity, creating an incremental surplus. Dividing this surplus is subject to bargaining between the firm owner and labor. The empirical analyses support the principal hypothesis that an increase in complementarity is associated with a reduction in players' share of firm surplus. The findings show that recruiting team-oriented players increases complementarity, as does greater team interaction. In contrast, an increase in the dominance of a single team member reduces complementarity.

The results offer two contributions. First, in contrast to the canonical view, the study views interdependence as an instrument of active management (Burton and Obel, 1980). The historical view of organizations as production entities mandated administrative efficiency to reduce uncertainty for sub-units. Interdependence was anathema for efficient administrative coordination (Simon, 1962). In human-capital-intensive activity, however, reducing interdependence has two significant consequences: (1) It gives bargaining power to individuals and undermines returns to firm owners because, unlike physical capital, labor can renegotiate the terms of trade *ex-post*; and (2) It requires specialization and well-defined roles for individuals. Specialization facilitates competitive imitation and allows individuals to appropriate firm surplus through the labor market. By suggesting that reciprocal interdependence can create complementarity in human-capital-intensive contexts, the study points out that costs do not always outweigh benefits in interdependent systems.

Second, the study suggests that firms can foster complementarity, contributing to literature on the organizational factors that affect the division of surplus between firm owners and labor. Much of the literature in organizational economics examines the relation between different ownership forms and surplus division (Alchian and Demsetz, 1972). The study departs from this tradition by using a human-capital-intensive context where the ownership form is uniform (i.e., all firms adopt a separation of ownership and control), which violates the predictions of normative theory. Rather than predicting ownership type based on the extent of complementarity, the study suggests that complementarity affects the division of surplus between the firm owner and labor. Further, it departs from prior literature in not treating complementarity as an exogenous property of the task (e.g., Anand *et al.*, 2007). Moreover, the study develops a theory outlining the organizational mechanisms that generate variance in complementarity in the same task across different teams.

The study prompts two questions: One, if complementarity increases the owner's share of firm surplus, then why don't all owners pursue interdependent teams? There are several candidate explanations. First, gains from complementarities may be transient due to the fragility of interdependence. In the context of this study, a manager of an NBA team ascribed the fragility of interdependence to reasons such as the movement, fitness, and retirement of players. Second, as the theory and analyses demonstrate, designing teams to generate complementarity is complex and some teams may be better at it than others. Capability differences among teams may explain the variance in their pursuit of complementarities. Third, the returns to complementarities may be decreasing in interdependence, i.e., the fifth team-oriented team member may be worth less than the fourth. And if teams are heterogeneous as per the second explanation, the point at which diminishing returns to interdependence set in may vary across teams as well. Finally, interdependence has other tradeoffs that are not examined in this paper (Simon, 1962). It can slow innovation, impede adaptation, and increase the hazards of mortality in large organizations (Levinthal, 1997; Ethiraj *et al.*, 2012). These risks are true in human-capital-intensive contexts, as well. Some firms may tradeoff the gains from complementarity against the increased complexity that higher interdependence poses. Thus, evaluating the consequences of interdependence for organizational performance and survival requires a more comprehensive examination of the underlying tradeoffs. Surplus division is just one of the several implications of interdependence for organizations.

Two, why would an individual help to create complementarity when it decreases his own bargaining power? The answer to this puzzle is found in the theoretical framework. The study argues that, as complementarity increases, stars in human-capital-intensive activity appropriate a higher share of the surplus than non-stars. It is possible that non-stars exert effort to foster complementarity because they also hope to become stars and appropriate the surplus in the future. This parallels the tendency of low-ranking drug dealers to accept low wages in spite of greater risks to their lives (Levitt and Venkatesh, 2000).

The theory and findings developed here extend to a wide swath of human-capital-intensive contexts—including accounting services, legal services, consulting services, and investment banking—*provided three important boundary conditions are met*. First, labor must account for the bulk of inputs. Second, the activity must be team-based to create the potential for complementarity. Finally, individual performance must be measurable to create the potential for appropriation. If these three conditions are met, firm owners can foster complementarity and increase their surplus share.

The above implications notwithstanding, the study has limitations. First, it focuses only on team interaction, individual dominance, and team composition as levers for creating complementarity. They are but a small slice of the myriad organizational choices in human-capital-intensive activity. It is important to consider other choices like training systems that lead to development of shared knowledge. Second, complementarity is a residual-based measure from a production function equation. While it is not a perfect measure, it best reflects complementarity within the limitations of the available data. This study is a modest attempt to theorize about the challenges of managing human-capital-intensive activity. Much work remains to be done before we develop a comprehensive understanding of the choices and tradeoffs involved in managing human-capital-intensive activity.

Chapter 4: Conclusion

The dissertation focuses on value creation and appropriation in human-capital-intensive firms by highlighting the role of operating-level employees. This dissertation builds on the idea that some unique attributes of individuals have implications for value creation and value appropriation in human-capital-intensive firms. First, an individual is not a passive input and can exercise discretion. The extent of discretion for individuals leads to performance heterogeneity across firms and hence differences in the value created by firms. Second, an individual can renegotiate her contract ex-post. Moreover, a human-capital-intensive firm cannot use its ownership of physical capital to exert control over employees. An individual’s ability to renegotiate her contract affects the share of value appropriated by the firm vis-à-vis its employees. This dissertation seeks to deepen our theoretical understanding of these two unique attributes of human capital by exploring questions related to value creation and appropriation in human-capital-intensive firms.

Chapter 2 focused on value creation in human-capital-intensive firms by theorizing about the micro-foundations of product creation. The chapter presented arguments that related incentive provision and career concerns of employees to product creation. While Chapter 2 focused on value creation, Chapter 3 theorized about value appropriation. It examined the organizational antecedents of the division of firm surplus between the firm owner and labor by building on the micro-foundations of team production in human-capital-intensive firms.

The rest of this chapter is organized as follows. Section 4.1 discusses the theoretical contributions of the dissertation. The subsequent section sheds light on some managerial implications. The last section discusses some avenues for future research.

4.1 Theoretical contributions

The dissertation joins the research stream that theorizes about the antecedents of product creation. It theorizes about the antecedents of product creation in the context of firms that rely primarily on individuals' capabilities to create value. Prior research on the origins of product creation provides insightful quantitative evidence for firm-level antecedents and rich qualitative evidence about the influential role of operating-level employees. For example, Burgelman (1983) proposed a process model of internal corporate venturing and briefly alluded to career-related gains as a motivation for proposing internal ventures. More recently, Kacperczyk (forthcoming) has empirically examined internal and external venture creation by employees. The dissertation joins this research stream by proposing that we can view product creation as an outcome of the micro-motives of employees who compete for promotions and wage increases in the firm's internal labor market. The theoretical arguments relate the explicit incentives and career concerns of employees to their product creation behavior.

Second, the dissertation offers a novel perspective on the division of value between the firm owner and labor in human-capital-intensive firms. Research in organizational economics has studied value appropriation by relating it to different ownership forms (Alchian and Demsetz, 1972). Holding the ownership form constant, the dissertation introduces organizational mechanisms to research on value appropriation. It suggests that differences in the organization of production can lead to different levels of complementarity among employees and affect the share of firm surplus that the firm owner appropriates vis-à-vis employees. In offering this perspective, the dissertation also aligns with prior work that highlights the benefits of highly interdependent systems. Prior research argues for benefits beyond a firm's boundary—greater interdependence among a firm's practices makes it more difficult for rivals to imitate them (Rivkin, 2000). This dissertation makes a case for benefits within the firm's boundary—higher interdependence among employees leads to greater complementarity that, in turn, increases the firm owner's share of firm surplus.

Third, the dissertation joins the research enterprise that highlights the influential role of individuals in firms. The classics in management focused on the internal processes of firms and highlighted the important role of individuals in shaping firms' actions (Barnard, 1938; Simon, 1947; March and Simon, 1958; Chandler, 1962; Cyert and March, 1963; Bower, 1970). More recent research provides theoretical arguments and empirical evidence for the critical role that operating-level employees play in affecting firm value (Groysberg *et al.*, 2008a), firm revenue (Mollick, 2012), and internal venture creation (Kacperczyk, forthcoming). By attempting to understand the role of individuals in affecting value creation and appropriation, this dissertation joins this research enterprise. In doing so, it also heeds to the call to look inside the black box of the firm (Rumelt *et al.*, 1991) and to focus on individuals as important determinants of firm behavior and outcomes (Bartlett and Ghoshal, 2002; Gavetti *et al.*, 2007; Teece, 2007; Abell *et al.*, 2008).

4.2 Managerial implications

The dissertation has implications for the management of human-capital-intensive firms. In theorizing about the antecedents of product creation, the dissertation argues that to progress in the firm's internal labor market, employees may seek to differentiate themselves from each other by creating new-to-the-firm products or categories. Viewed in this manner, the performance of individuals not only determines a firm's performance in the current period but can also influence the firm's scope in future by shaping the behavior of other employees within the firm. Though the incidence of such behavior is low per the data, managers of human-capital-intensive firms need to be aware of such firm-level implications of employee actions, especially since these firms rely primarily on individuals' capabilities to create value.

The dissertation also highlights that explicit incentives may be a necessary but not sufficient mechanism to influence employee behavior. Even in the presence of a particular incentive contract, additional considerations such as the desire for career progress in the firm's internal labor market may motivate employee actions. Employees can seek to compete in different categories to steer away from direct competition with high performers in the focal category and get a chance to become high performers in the new category. The low occurrence of this phenomenon in the data notwithstanding, managers of human-capital-intensive firms should view explicit incentives as an important but one of several considerations that guide employee behavior.

In theorizing about the relation between the organization of production and division of surplus, the dissertation suggests that complementarity need not be an exogenous property of an organizational system as assumed in prior research (e.g., Anand *et al.*, 2007). Firms can use management practices as levers to create different levels of interdependence and hence foster different levels of complementarity among employees. Indeed, research in the human resource management and organizational economics literatures shows that management practices influence productivity and financial performance at the team and firm levels (Huselid, 1995; Ichniowski *et al.*, 1997; Cappelli and Neumark, 2001; Bloom and Van Reenen, 2007). The dissertation identifies some management practices that can affect the level of complementarity in the firm. These include first, recruiting practices that influence the kind of people selected into or disengaged from the firm, and second, the creation of routines that influence the nature of interactions and development of shared understanding among employees. These two are a subset of a potentially large set of practices that a firm's management can use to foster complementarity among employees.

4.3 Avenues for future research

The dissertation offers directions for future work in the context of human-capital-intensive firms. First, the dissertation theorizes about value creation and value appropriation independent of each other. For a firm, however, the decision to choose a particular strategy is based on the joint consideration of the value it seeks to create and the share it expects to capture (Brandenburger and Nalebuff, 1996). The ability of employees, especially high performers, to renegotiate the terms of trade ex-post offers interesting possibilities to jointly theorize about value creation and appropriation in human-capital-intensive firms. For instance, future work can attempt to study the conditions under which human-capital-intensive firms may face a tradeoff between value creation and appropriation. Such an inquiry can have implications for the choices that human-capital-intensive firms make with respect to organization design and workforce composition.

Second, while the study on value creation offered incentive-based arguments, the study on value appropriation theorized mostly about structure-related mechanisms. An interesting avenue for future research in human-capital-intensive firms would be to understand the effect of the interplay between structure and incentive mechanisms on value creation. Empirical inquiry in this direction has been limited by the paucity of precise and comprehensive internal data from firms. In recent years, however, there has been an increasing trend toward conducting experiments in firms (Bandiera, Barankay, and Rasul, 2011). Using the experimental methodology, future research could analyze how the interplay between structure and incentives affects value creation by teams in human-capital-intensive firms. Such an effort can help illuminate the conditions under which structure and incentive mechanisms are either substitutes or complements in affecting value creation by teams.

To conclude, the dissertation focuses on value creation and appropriation in the context of human-capital-intensive firms. In doing so, it also joins the theoretical and empirical research enterprise that looks inside the black box of the firm and focuses on the important role of individuals. Assuming that human-capital-intensive activity will continue to contribute an increasing share of global economic output in future, the landscape of human-capital-intensive firms is a fertile ground to seek interesting questions.

Figures

Figure 1. Illustrative case of three firms operating in the industry

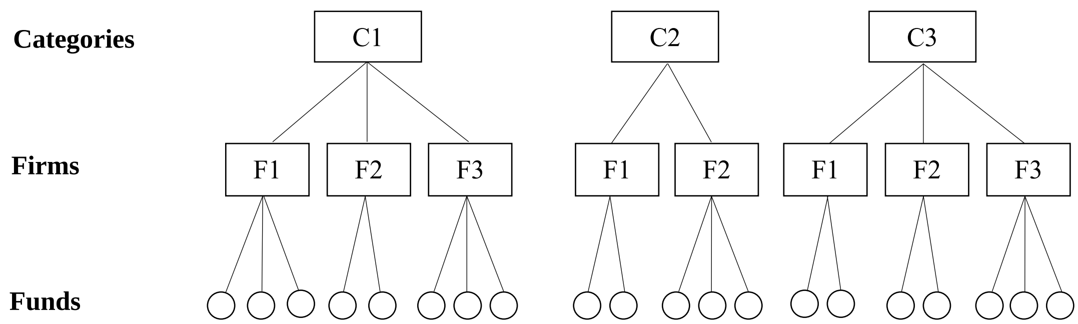
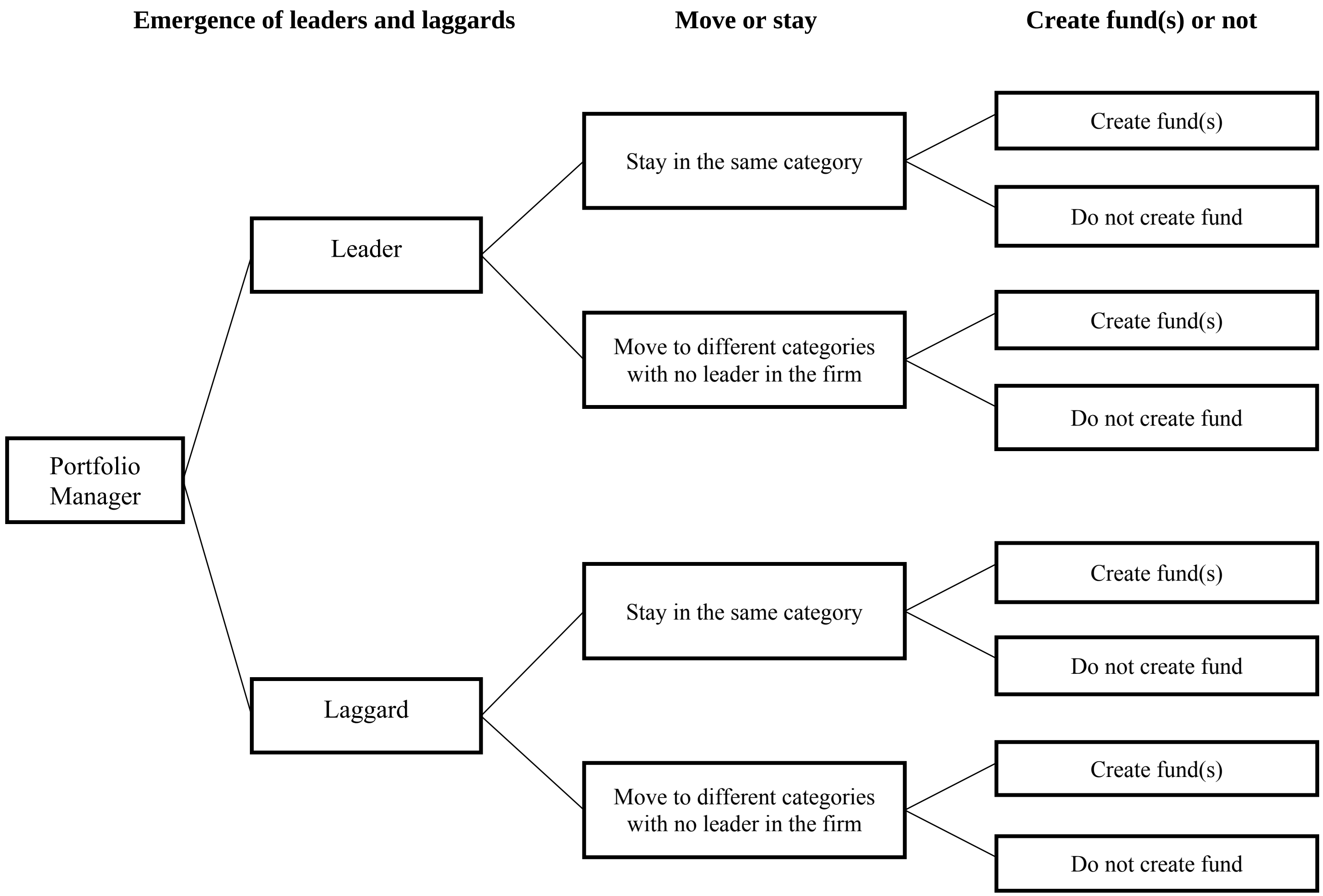
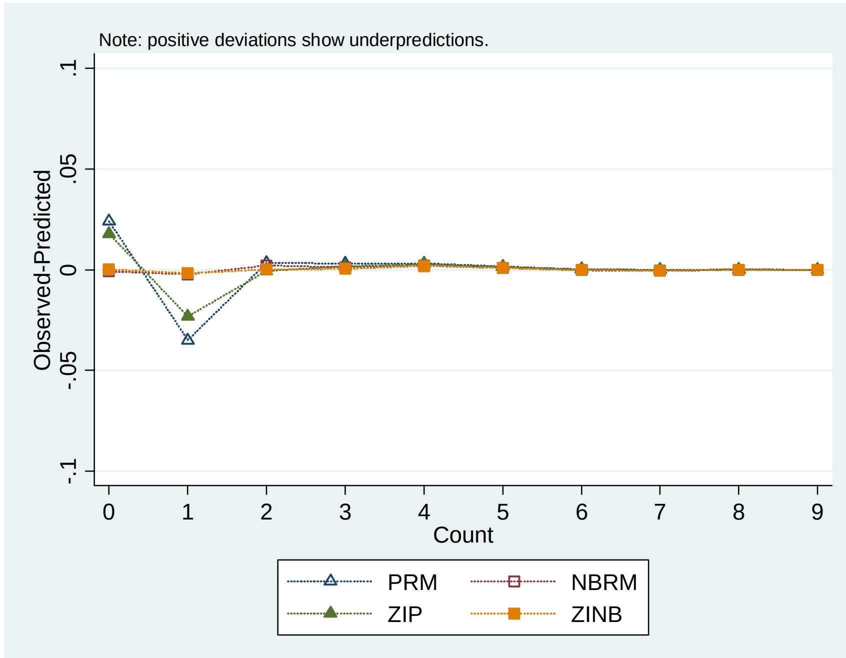


Figure 2. Visual representation of a portfolio manager's decision tree



Note: The scenario of "Do not create fund" refers to managing an existing fund. The above figure omits the third case of portfolio managers who do or do not create funds in different categories with a leader in the firm in the prior year.

Figure 3. Observed and predicted probabilities for four count models

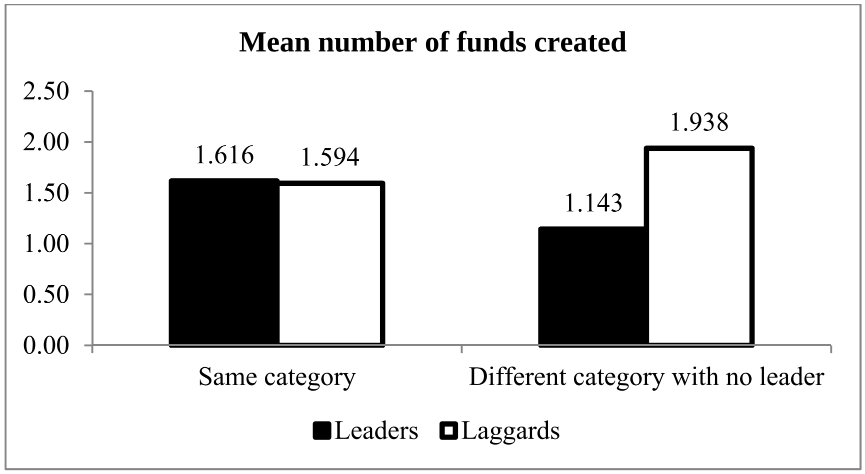


Notes:
1. Positive deviations show under-predictions from the observed probability of a count
2. PRM–Poisson model; NBRM–Negative Binomial model; ZIP–Zero-Inflated Poisson model; ZINB–Zero-Inflated Negative Binomial model

Tests and Fit Statistics: ZINB is the preferred model

```
PRM            BIC=-1.468e+05  AIC=     0.678  Prefer  Over  Evidence
-------------------------------------------------------------------------
  vs NBRM      BIC=-1.480e+05  dif=  1177.720  NBRM    PRM   Very strong
               AIC=     0.605  dif=     0.073  NBRM    PRM
               LRX2= 1187.421  prob=    0.000  NBRM    PRM   p=0.000
-------------------------------------------------------------------------
  vs ZIP       BIC=-1.483e+05  dif=  1476.836  ZIP     PRM   Very strong
               AIC=     0.586  dif=     0.092  ZIP     PRM
               Vuong=  18.666  prob=    0.000  ZIP     PRM   p=0.000
-------------------------------------------------------------------------
  vs ZINB      BIC=-1.488e+05  dif=  2051.754  ZINB    PRM   Very strong
               AIC=     0.550  dif=     0.128  ZINB    PRM
-------------------------------------------------------------------------
NBRM           BIC=-1.480e+05  AIC=     0.605  Prefer  Over  Evidence
-------------------------------------------------------------------------
  vs ZIP       BIC=-1.483e+05  dif=   299.115  ZIP     NBRM  Very strong
               AIC=     0.586  dif=     0.019  ZIP     NBRM
-------------------------------------------------------------------------
  vs ZINB      BIC=-1.488e+05  dif=   874.033  ZINB    NBRM  Very strong
               AIC=     0.550  dif=     0.055  ZINB    NBRM
               Vuong=  18.094  prob=    0.000  ZINB    NBRM  p=0.000
-------------------------------------------------------------------------
ZIP            BIC=-1.483e+05  AIC=     0.586  Prefer  Over  Evidence
-------------------------------------------------------------------------
  vs ZINB      BIC=-1.488e+05  dif=   574.918  ZINB    ZIP   Very strong
               AIC=     0.550  dif=     0.036  ZINB    ZIP
               LRX2=  584.619  prob=    0.000  ZINB    ZIP   p=0.000
-------------------------------------------------------------------------
```

Figure 4. Mean number of funds created by leaders and laggards



Note: Figure based on data in Table 11

Figure 5. Franchise wage bill and win percentage ratios 1991–2007

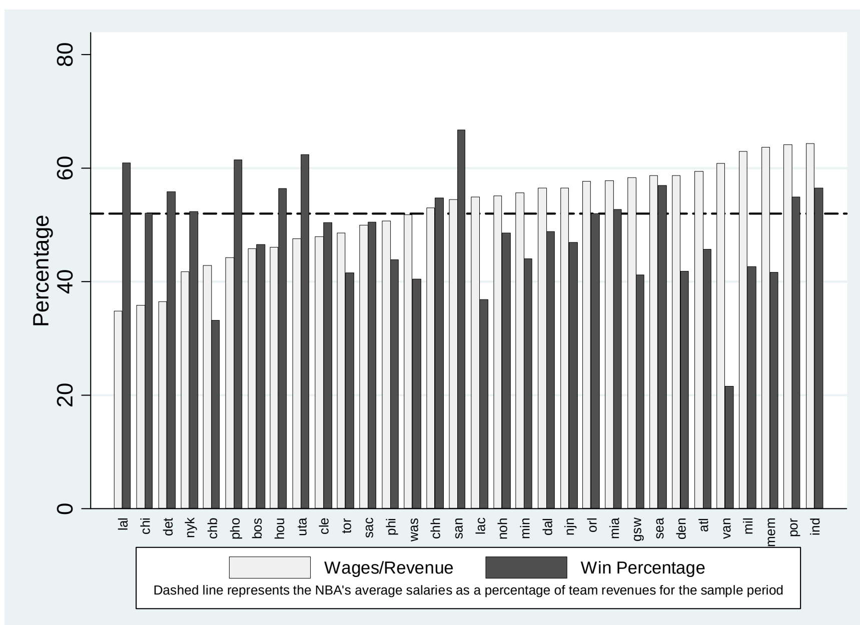
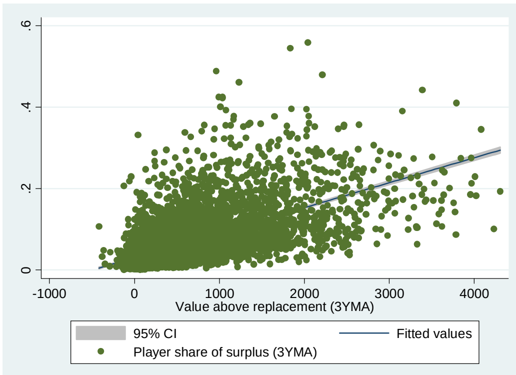
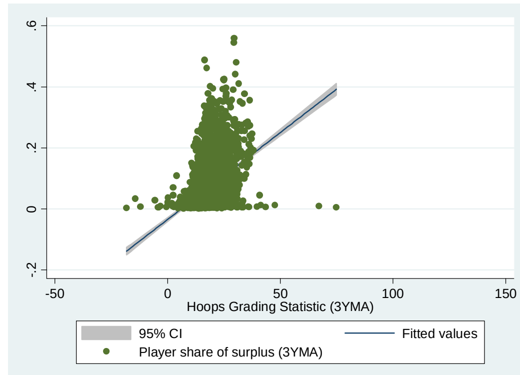


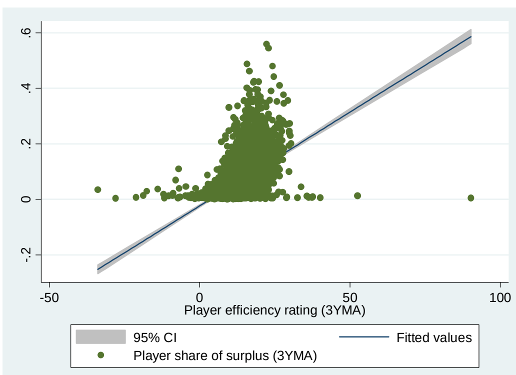
Figure 6. Scatter plots for player's share of surplus and performance measures



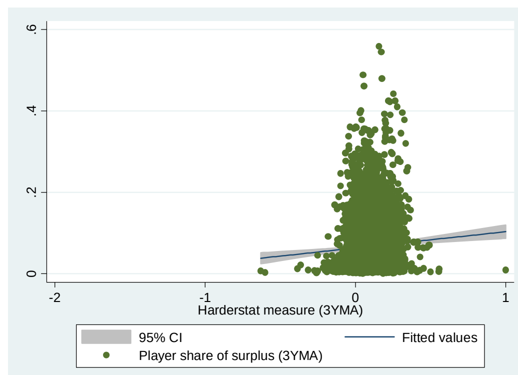
Value above replacement



Hoops Grading Statistic



Player efficiency rating

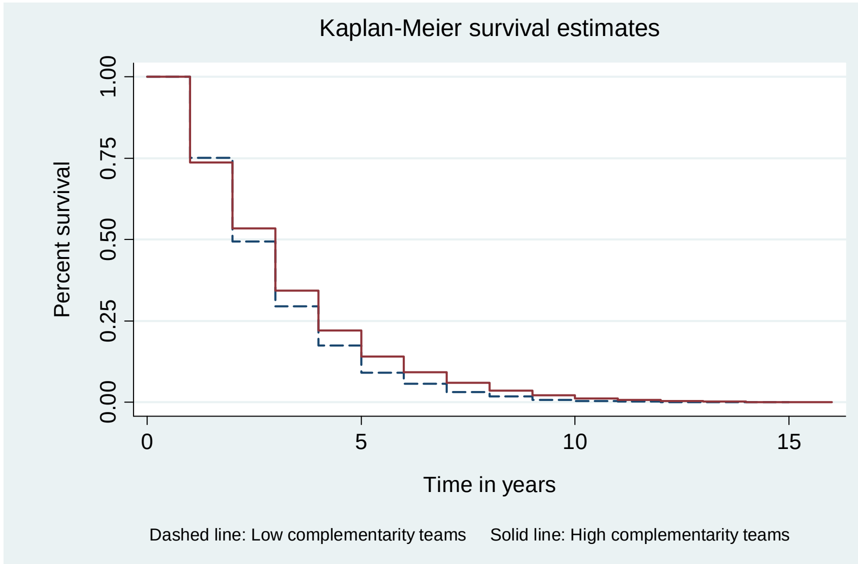


Harderstat

Notes:

1. A player's share of firm surplus and performance measures are three-year moving averages
2. Player performance measures are lagged by one year relative to share of firm surplus

Figure 7. Hazard of a player's departure from a franchise



Tables

Table 1. Description of control variables used in Chapter 2

Level	Variables	Notes
Individual level	Manager’s remuneration (t-1)	Proxy for manager’s incentives
	Manager’s firm-specific tenure (t-1)	Manager’s experience in years in the firm
	Manager’s existing funds (t-1)	Number of funds of a manager in the firm
	Manager’s performance in firm-category relative to peers (t-1)	Manager’s performance within the firm
Category-firm level	Funds in the category in the firm (t-1)	Effect of crowding in a firm’s category
	Category growth in the firm [(t-1) – (t-2)]	Proxy for category attractiveness in the firm
Firm level	Number of categories in the firm (t-1)	Proxy for firm scope
	Firm performance (t-1)	Weighted average of performance of funds (weighted by fund size)
	Firm size (t-1)	Assets under management at the firm level
	Firm age (t-1)	Firm age in years
	Firm cash flow [(t-1) – (t-2)]	Change in assets under management, accounting for firm returns
Category-industry level	Funds in the category in the industry (t-1)	Effect of imitation in an industry category
	Category growth in the industry [(t-1) – (t-2)]	Proxy for category attractiveness in the industry

Table 2. Leaders and laggards who create at least one fund or no fund

		Leaders	Laggards	Total
Same category (H1)	Create at least one fund	164	972	**1,136**
		(8.26%)	(6.78%)	(6.96%)
	Do not create fund	1,745	12,915	**14,660**
		(87.87%)	(90.04%)	(89.78%)
	Total	**1,909**	**13,887**	**15,796**
		(96.12%)	(96.82%)	(96.74%)
Different categories with no leader in the firm in the prior year (H2)	Create at least one fund	7	65	**72**
		(0.35%)	(0.45%)	(0.44%)
	Do not create fund	70	391	**461**
		(3.53%)	(2.73%)	(2.82%)
	Total	**77**	**456**	**533**
		(3.88%)	(3.18%)	(3.26%)
Regression sample	Create at least one fund	171	1,037	**1,208**
		(8.61%)	(7.23%)	(7.40%)
	Do not create fund	1,815	13,306	**15,121**
		(91.39%)	(92.77%)	(92.60%)
	Total	**1,986**	**14,343**	**16,329**
		(100%)	(100%)	(100%)
Different categories with leader in the firm in the prior year (Omitted case)	Create at least one fund	4	24	**28**
	Do not create fund	23	110	**133**
	Total	**27**	**134**	**161**

Notes:

1. Data are at the portfolio manager–firm–category–year level
2. 939 observations in year 1998 are excluded from the regression analyses for Hypothesis 2 since a change from Strategic Insight codes to Lipper codes in 1998 would overestimate the funds created in a different category.
3. The above table does not include 5,221 observations which are the missing first observations in the panel of each unique firm–manager dyad.
4. The case of “Different categories with leader in the prior year” is omitted from the regression analysis
5. Total sample: 15,796 (H1) + 533 (H2) + 939 (excluded observations from 1998) + 161 (omitted case) + 5,221 (missing first observations in each unique firm–manager dyad) = 22,650
6. Percentages represent leaders and laggards who create at least one fund and do not create a fund as a proportion of the total number of observations (16,329) in the regression sample, respectively.

Table 3. Number of funds created by leaders and laggards

Number of funds created	By Leaders	By Laggards	Total
Funds created in the same category (H1)	265 [164] (93.64%)	1,549 [972] (89.59%)	**1,814** [1,136] (90.16%)
Funds created in different categories with no leader in the firm in the prior year (H2)	8 [7] (2.83%)	126 [65] (7.29%)	**134** [72] (6.66%)
Funds created in different categories with leader in the prior year (Omitted case)	10 [4] (3.53%)	54 [24] (3.12%)	**64** [28] (3.18%)
Total	**283** [175]	**1,729** [1,061]	**2,012** [1,236]

Notes:

1. For each cell in the above table, the first number is the total number of funds created by leaders or laggards in the sample (after excluding the year 1998). The second number in square brackets is the number of individuals (leaders or laggards) who create at least one fund. This number is obtained from the corresponding cell in Table 2. The third number in parentheses represents the proportion of funds created by leaders or laggards in the three cases.
2. The mean number of funds per leader or laggard (presented in Table 11) is calculated by dividing the number of funds by the number of individuals in each cell. For example, the mean number of funds is 1.616 [265/164] for leaders and 1.594 [1549/972] for laggards in the case of funds created in the same category.

Table 4. Descriptive statistics and correlation matrix of variables (Chapter 2)

	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Funds created in the same category	0.111	0.506	0	15	1																
2	Funds created in a different category with no leader	0.008	0.150	0	6	-0.012	1															
3	Dummy for leader	0.122	0.327	0	1	0.016	-0.010	1														
4	Manager's remuneration	9.591	32.797	0	838.99	0.046	-0.004	0.017	1													
5	Manager's firm-specific tenure	4.337	3.475	1	18	-0.034	-0.025	0.007	0.256	1												
6	Manager's existing funds	2.568	2.137	1	25	0.300	0.036	-0.044	0.170	0.079	1											
7	Manager's performance in firm-category	0.016	0.095	-0.226	0.534	-0.102	-0.035	0.115	0.029	-0.020	-0.017	1										
8	Funds in the category in the firm	9	16	0	160	0.035	-0.001	-0.009	0.258	0.142	0.388	0.062	1									
9	Category growth in the firm	0.816	0.463	0	11.604	0.031	-0.010	0.110	-0.002	-0.094	-0.003	0.008	-0.025	1								
10	Number of categories in the firm	12	9	1	45	0.056	0.018	-0.018	0.279	0.068	0.327	0.054	0.483	-0.016	1							
11	Firm performance	1.086	0.223	0	3.450	0.017	0.004	0.148	0.026	-0.026	-0.043	0.034	-0.058	0.245	-0.024	1						
12	Firm size	8.232	3.018	0	13.786	0.080	0.021	-0.024	0.283	0.095	0.364	0.064	0.435	0.010	0.860	0.047	1					
13	Firm age	40	28	1	86	0.068	0.013	-0.040	0.144	0.085	0.294	0.026	0.275	-0.017	0.403	-0.020	0.468	1				
14	Firm cash flow	-0.683	1.404	-1.473	10.796	-0.008	-0.009	0.035	-0.034	-0.125	-0.023	-0.011	-0.032	0.329	-0.042	0.077	-0.055	-0.059	1			
15	Funds in the category in the industry	947	924	0	3758	-0.002	-0.017	-0.002	0.084	0.254	0.119	0.016	0.442	-0.060	-0.055	-0.120	-0.058	0.016	-0.034	1		
16	Category growth in the industry	0.125	0.401	-1.528	7.493	0.028	0.006	0.032	0.003	-0.062	-0.053	0.026	-0.078	0.218	-0.048	0.455	-0.017	-0.019	0.056	-0.153	1	
17	Year	2002	4.911	1993	2010	-0.018	-0.027	0.000	0.084	0.441	0.264	-0.067	0.299	-0.051	0.232	-0.124	0.226	0.151	-0.064	0.478	-0.150	1

Notes:

1. Number of observations: 16,329
2. Correlations greater than 0.016 are statistically significant at the 0.05 level or lower
3. Values reported for variables 9, 12, and 16 are logarithmic transformations

Table 5. Fund creation and remuneration of portfolio managers

Deciles of remuneration	Total new funds			Mean new funds		
	Total	Same cat	Diff cat	Total	Same cat	Diff cat
1	212	192	20	0.129	0.117	0.012
2	312	280	32	0.191	0.172	0.020
3	189	182	7	0.116	0.112	0.004
4	196	181	15	0.120	0.111	0.009
5	150	137	13	0.065	0.059	0.006
6	88	87	1	0.042	0.041	0.000
7	33	32	1	0.070	0.068	0.002
8	161	151	10	0.099	0.093	0.006
9	250	235	15	0.153	0.144	0.009
10	357	337	20	0.220	0.207	0.012
Sample	**1948**	**1814**	**134**	**0.119**	**0.111**	**0.008**

Notes:
1. "Same cat" means fund creation in the same category (H1)
2. "Diff cat" means fund creation in different categories with no leader in the firm in the prior year (H2)
3. "Total" is the sum of "Same cat" and "Diff cat" in the regression sample
4. Portfolio manager's remuneration is lagged by one year

Table 6. Fund creation and firm-specific tenure of portfolio managers

Firm-specific tenure	Total new funds			Mean new funds		
	Total	Same cat	Diff cat	Total	Same cat	Diff cat
1	516	467	49	0.148	0.134	0.014
2	431	400	31	0.146	0.135	0.010
3	229	208	21	0.101	0.092	0.009
4	188	179	9	0.110	0.104	0.005
5	164	158	6	0.121	0.117	0.004
6	95	84	11	0.107	0.094	0.012
7	83	80	3	0.093	0.089	0.003
8	61	60	1	0.089	0.088	0.001
9	61	61	0	0.114	0.114	0.000
10	34	34	0	0.084	0.084	0.000
11	24	23	1	0.079	0.075	0.003
12	23	22	1	0.099	0.094	0.004
13	13	12	1	0.077	0.071	0.006
14	10	10	0	0.075	0.075	0.000
15	5	5	0	0.050	0.050	0.000
16	9	9	0	0.113	0.113	0.000
17	1	1	0	0.015	0.015	0.000
18	1	1	0	0.020	0.020	0.000
Sample	**1948**	**1814**	**134**	**0.119**	**0.111**	**0.008**

Notes:
1. "Same cat" means fund creation in the same category (H1)
2. "Diff cat" means fund creation in different categories with no leader in the firm in the prior year (H2)
3. "Total" is the sum of "Same cat" and "Diff cat" in the regression sample
4. Portfolio manager's firm-specific tenure is lagged by one year

Table 7. Fund creation and performance of portfolio managers in firm-category

Year	Relative performance	Total new funds Total	Total new funds Same cat	Total new funds Diff cat	Mean new funds Total	Mean new funds Same cat	Mean new funds Diff cat
1993	Below med	11	8	3	0.204	0.148	0.056
	Above med	75	52	23	0.143	0.099	0.044
1994	Below med	18	18	0	0.220	0.220	0.000
	Above med	101	90	11	0.169	0.150	0.018
1995	Below med	10	10	0	0.094	0.094	0.000
	Above med	49	45	4	0.068	0.062	0.006
1996	Below med	36	36	0	0.371	0.371	0.000
	Above med	98	93	5	0.135	0.128	0.007
1997	Below med	33	28	5	0.351	0.298	0.053
	Above med	83	76	7	0.115	0.105	0.010
1999	Below med	23	23	0	0.177	0.177	0.000
	Above med	116	109	7	0.125	0.117	0.008
2000	Below med	52	51	1	0.349	0.342	0.007
	Above med	141	133	8	0.139	0.131	0.008
2001	Below med	36	31	5	0.229	0.197	0.032
	Above med	97	88	9	0.101	0.092	0.009
2002	Below med	39	38	1	0.231	0.225	0.006
	Above med	92	87	5	0.094	0.089	0.005
2003	Below med	28	28	0	0.161	0.161	0.000
	Above med	81	79	2	0.086	0.084	0.002
2004	Below med	18	18	0	0.110	0.110	0.000
	Above med	42	41	1	0.046	0.045	0.001
2005	Below med	46	41	5	0.271	0.241	0.029
	Above med	70	69	1	0.080	0.079	0.001
2006	Below med	33	33	0	0.193	0.193	0.000
	Above med	62	53	9	0.074	0.063	0.011
2007	Below med	51	45	6	0.319	0.281	0.038
	Above med	98	97	1	0.119	0.117	0.001
2008	Below med	68	68	0	0.425	0.425	0.000
	Above med	66	62	4	0.080	0.075	0.005
2009	Below med	50	47	3	0.305	0.287	0.018
	Above med	49	49	0	0.059	0.059	0.000
2010	Below med	33	27	6	0.241	0.197	0.044
	Above med	43	41	2	0.055	0.053	0.003
	Below med	**585**	**550**	**35**	**0.250**	**0.235**	**0.015**
	Above med	**1363**	**1264**	**99**	**0.097**	**0.090**	**0.007**
	Sample	**1948**	**1814**	**134**	**0.119**	**0.111**	**0.008**

Notes:
1. "Same cat" means fund creation in the same category (H1)
2. "Diff cat" means fund creation in different categories with no leader in the firm in the prior year (H2)
3. "Total" is the sum of "Same cat" and "Diff cat" in the regression sample
4. Portfolio manager's performance is relative to peers at the firm-category-year level; lagged by one year
5. "Above med" means relative performance in firm-category is above median; "Below med" means relative performance in firm-category is below median

Table 8. Fund creation and existing funds of portfolio managers (H1)

	New funds in same category (H1)																
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**Total**
Existing funds																	
1	7455	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7462
2	2232	239	5	0	0	0	0	0	0	0	0	0	0	0	0	0	2476
3	1843	144	62	2	0	0	0	0	0	0	0	0	0	0	0	0	2051
4	1764	150	50	23	3	0	0	0	0	0	0	0	0	0	0	0	1990
5	830	110	22	10	24	0	0	0	0	0	0	0	0	0	0	0	996
6	524	54	14	14	3	11	0	0	0	0	0	0	0	0	0	0	620
7	181	23	10	7	4	4	0	0	0	0	0	0	0	0	0	0	229
8	136	14	11	5	12	0	0	0	0	0	0	0	0	0	0	0	178
9	67	11	4	6	4	2	0	0	0	0	0	0	0	0	0	0	94
10	64	13	9	2	1	4	2	0	0	0	0	0	0	0	0	0	95
11	34	4	7	1	2	5	0	0	0	0	0	0	0	0	0	0	53
12	20	2	0	1	0	1	1	0	1	0	0	0	0	0	0	0	26
13	13	1	1	2	2	0	0	0	0	0	1	0	0	0	0	0	20
14	4	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	9
15	6	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	7
16	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
17	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
18	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	6	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	7
25	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6
Observations	**15193**	**774**	**196**	**75**	**56**	**28**	**3**	**0**	**2**	**0**	**1**	**0**	**0**	**0**	**0**	**1**	**16329**
New funds	**0**	**774**	**392**	**225**	**224**	**140**	**18**	**0**	**16**	**0**	**10**	**0**	**0**	**0**	**0**	**15**	**1814**

Table 9. Fund creation and existing funds of portfolio managers (H2)

	New funds in different categories with no leader (H2)							
	0	**1**	**2**	**3**	**4**	**5**	**6**	**Total**
Existing funds								
1	7449	13	0	0	0	0	0	7462
2	2459	15	2	0	0	0	0	2476
3	2035	4	9	3	0	0	0	2051
4	1980	2	2	0	6	0	0	1990
5	992	3	1	0	0	0	0	996
6	615	2	0	1	0	0	2	620
7	224	2	1	1	0	1	0	229
8	176	0	1	0	0	1	0	178
9	94	0	0	0	0	0	0	94
10	95	0	0	0	0	0	0	95
11	53	0	0	0	0	0	0	53
12	26	0	0	0	0	0	0	26
13	20	0	0	0	0	0	0	20
14	9	0	0	0	0	0	0	9
15	7	0	0	0	0	0	0	7
16	2	0	0	0	0	0	0	2
17	5	0	0	0	0	0	0	5
18	2	0	0	0	0	0	0	2
19	1	0	0	0	0	0	0	1
20	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0
24	7	0	0	0	0	0	0	7
25	6	0	0	0	0	0	0	6
Observations	**16257**	**41**	**16**	**5**	**6**	**2**	**2**	**16329**
New funds	**0**	**41**	**32**	**15**	**24**	**10**	**12**	**134**

Note: Portfolio manager’s existing funds lagged by one year

Table 10. Fund creation and quintiles of firm-level variables

	Number of categories			Firm performance			Firm size			Firm cash flow		
Quintiles	**Total**	**Same cat**	**Diff cat**	**Total**	**Same cat**	**Diff cat**	**Total**	**Same cat**	**Diff cat**	**Total**	**Same cat**	**Diff cat**
1	147	135	12	376	357	19	108	99	9	302	286	16
2	322	316	6	373	333	40	257	249	8	492	455	37
3	511	478	33	389	365	24	492	465	27	408	361	47
4	551	506	45	481	448	33	628	587	41	441	419	22
5	417	379	38	329	311	18	463	414	49	305	293	12
Sample	**1948**	**1814**	**134**	**1948**	**1814**	**134**	**1948**	**1814**	**134**	**1948**	**1814**	**134**

Notes:
1. “Same cat” means fund creation in the same category (H1)
2. “Diff cat” means fund creation in different categories with no leader in the firm in the prior year (H2)
3. “Total” is the sum of “Same cat” and “Diff cat” in the regressions sample
4. All firm variables lagged by one year
5. Quintile 5 represents the highest value for each firm-level variable

Table 11. T-tests for number of funds created by leaders and laggards

	Funds created in the same category (H1)		Funds created in different categories with no leader in the firm (H2)	
	Mean number of funds	**Number of individuals**	**Mean number of funds**	**Number of individuals**
Leaders	1.616	164	1.143	7
Laggards	1.594	972	1.938	65
Total observations		1,136		72
Difference in means (Leaders – Laggards)	0.022		-0.795	
p-value (two-tailed)	0.819		0.123	

Note: The data in the above table are only for individuals who create funds i.e., for whom the dependent variable is positive. It does not include individuals who do not create a fund at all i.e., for whom the dependent variable is zero. When the latter individuals are included, the mean number of funds created by leaders and laggards in the same category are 0.139 (1,909 leaders) and 0.112 (13,887 laggards), respectively. The p-value (two-tailed test) for the difference in means is 0.03. Likewise, the mean number of funds created by leaders and laggards in different categories with no leader in the firm are 0.104 (77 leaders) and 0.276 (456 laggards), respectively. The p-value (two-tailed test) for the difference in means is 0.078.

Table 12. Fund creation by leaders relative to laggards (ZINB model)

Dependent variable: Funds created	Same category				Different category			
Zero-inflated negative binomial model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Leader				0.482**				-0.069
				(0.095)				(0.514)
Manager's remuneration			0.002*	0.002*			0.003	0.003
			(0.001)	(0.001)			(0.006)	(0.006)
Manager's firm-specific tenure			-0.048**	-0.048**			-0.277**	-0.277*
			(0.013)	(0.013)			(0.104)	(0.134)
Manager's existing funds			0.319**	0.322**			0.283*	0.277+
			(0.036)	(0.036)			(0.142)	(0.162)
Manager's performance in firm-category			-3.694**	-3.796**			-6.712*	-6.651*
			(0.542)	(0.549)			(3.067)	(3.257)
Funds in the category in the firm		-1.125**	-1.198**	-1.218**		1.298	3.536	3.546
		(0.333)	(0.367)	(0.369)		(2.583)	(2.683)	(3.165)
Category growth in the firm		0.209*	0.096	0.076		-1.127	-1.331	-1.325
		(0.101)	(0.074)	(0.070)		(2.730)	(1.654)	(1.772)
Number of categories in the firm		-0.002	-0.026*	-0.026*		-0.097	-0.148+	-0.150
		(0.012)	(0.013)	(0.013)		(0.110)	(0.076)	(0.107)
Firm performance		0.559+	0.604+	0.328		0.606	1.300	1.321
		(0.329)	(0.338)	(0.334)		(4.242)	(2.698)	(3.040)
Firm size		0.048	0.050	0.057+		0.318	0.312*	0.314*
		(0.034)	(0.033)	(0.033)		(0.323)	(0.123)	(0.148)
Firm age		0.005*	0.004*	0.004*		0.007	0.012	0.012
		(0.002)	(0.002)	(0.002)		(0.008)	(0.009)	(0.009)
Firm cash flow		-0.017	-0.016	-0.015		-2.121	-1.407	-1.406
		(0.026)	(0.026)	(0.026)		(3.293)	(1.013)	(1.102)
Funds in the category in the industry	0.012*	0.025**	0.011+	0.011+	-0.011	-0.056	-0.105*	-0.106+
	(0.005)	(0.007)	(0.006)	(0.006)	(0.015)	(0.121)	(0.043)	(0.061)
Category growth in the industry	0.336*	0.311*	0.227*	0.213*	1.031	0.100	1.380**	1.368*
	(0.152)	(0.145)	(0.096)	(0.093)	(0.779)	(3.584)	(0.473)	(0.560)
Constant	-0.400**	-1.631**	-3.443**	-3.224**	-3.329**	-4.605	-4.209	-4.208
	(0.155)	(0.474)	(0.576)	(0.571)	(0.768)	(7.999)	(3.268)	(3.454)
Inflate								
Manager's performance in firm-category	5.384**	5.388**	3.660**	3.738**	5.691	6.798*	4.122	4.141
	(1.324)	(1.307)	(1.147)	(1.162)	(5.787)	(3.241)	(2.926)	(3.168)
Manager's existing funds	-5.512**	-5.493**	-5.937**	-5.889**	-2.112	-0.074+	-0.026	-0.027
	(0.443)	(0.444)	(0.483)	(0.476)	(2.195)	(0.045)	(0.063)	(0.077)
Constant	10.591**	10.544**	10.791**	10.748**	3.636+	4.266**	3.864**	3.872**
	(0.797)	(0.797)	(0.797)	(0.795)	(1.956)	(1.084)	(0.466)	(0.570)
Observations	16329	16329	16329	16329	16329	16329	16329	16329
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-4414.93	-4398.77	-4167.44	-4155.70	-479.47	-475.59	-460.82	-460.81

Notes:

1. Robust standard errors clustered at the portfolio manager level in parentheses
2. All independent variables lagged by one year
3. + p<0.10, * p<0.05, ** p<0.01 (all tests are two-tailed)

Table 13. Alternative functional specifications (ZINB Model)

Dependent variable: Funds created Zero-inflated negative binomial model	Same cat 1	Diff cat 2	Same cat 3	Diff cat 4	Same cat 5	Diff cat 6	Same cat 7	Diff cat 8	Same cat 9	Diff cat 10
Leader	0.484**	-0.071	0.478**	-0.051	0.473**	-0.148	0.492**	-0.072	0.481**	-0.188
	(0.095)	(0.473)	(0.096)	(0.506)	(0.097)	(0.635)	(0.105)	(0.480)	(0.095)	(0.680)
Manager's remuneration	0.001+	0.003	0.001	0.003	0.002+	0.003	0.002*	0.003	0.002*	0.005
	(0.001)	(0.005)	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.006)	(0.001)	(0.009)
Manager's firm-specific tenure	-0.053**	-0.258*	-0.047**	-0.278**	-0.049**	-0.280**	-0.048**	-0.275**	-0.047**	-0.356
	(0.016)	(0.111)	(0.013)	(0.107)	(0.013)	(0.104)	(0.013)	(0.096)	(0.013)	(0.310)
Manager's existing funds	0.322**	0.292+	0.322**	0.279+	0.322**	0.274+	0.322**	0.285+	0.322**	0.241
	(0.036)	(0.174)	(0.036)	(0.166)	(0.036)	(0.154)	(0.036)	(0.162)	(0.036)	(0.244)
Manager's performance in firm-category	-3.796**	-6.691*	-3.793**	-6.631*	-3.785**	-6.678*	-3.796**	-6.606*	-3.798**	-6.180*
	(0.549)	(3.243)	(0.549)	(3.311)	(0.548)	(3.302)	(0.549)	(3.255)	(0.550)	(2.709)
Manager's firm-specific tenure (squared)	0.003	-0.008								
	(0.003)	(0.020)								
Leader*Manager's remuneration			0.001	-0.003						
			(0.001)	(0.010)						
Leader*Firm-specific tenure					0.023	0.065				
					(0.037)	(0.270)				
Leader*Manager's existing funds							-0.012	-0.147		
							(0.067)	(0.317)		
Funds in the category in the firm	-1.222**	3.694	-1.225**	3.596	-1.226**	3.457	-1.215**	3.567	-1.175**	3.628
	(0.368)	(2.883)	(0.370)	(2.888)	(0.370)	(2.714)	(0.371)	(2.771)	(0.381)	(3.228)
Category growth in the firm	0.077	-1.318	0.077	-1.297	0.077	-1.347	0.076	-1.310	0.079	-1.264
	(0.070)	(1.651)	(0.070)	(1.647)	(0.070)	(1.731)	(0.070)	(1.615)	(0.070)	(1.383)
Category rank in the firm									-0.005	-0.034
									(0.012)	(0.072)
Number of categories in the firm	-0.026*	-0.145+	-0.026*	-0.150+	-0.026*	-0.150+	-0.026*	-0.148+	-0.026*	-0.197
	(0.013)	(0.084)	(0.013)	(0.089)	(0.013)	(0.088)	(0.013)	(0.083)	(0.013)	(0.206)
Firm performance	0.325	1.277	0.328	1.335	0.328	1.336	0.324	1.333	0.330	2.191
	(0.335)	(2.628)	(0.334)	(2.757)	(0.334)	(2.735)	(0.334)	(2.636)	(0.334)	(5.156)
Firm size	0.057+	0.307*	0.057+	0.313*	0.058+	0.315*	0.057+	0.311*	0.057+	0.399
	(0.033)	(0.125)	(0.033)	(0.134)	(0.033)	(0.129)	(0.033)	(0.139)	(0.033)	(0.247)
Firm age	0.004*	0.012	0.004*	0.012	0.004*	0.012	0.004*	0.012	0.004*	0.013
	(0.002)	(0.008)	(0.002)	(0.009)	(0.002)	(0.009)	(0.002)	(0.008)	(0.002)	(0.008)
Firm cash flow	-0.015	-1.387	-0.015	-1.418	-0.015	-1.384	-0.015	-1.416	-0.015	-1.452
	(0.026)	(0.973)	(0.026)	(1.036)	(0.026)	(0.992)	(0.026)	(0.951)	(0.026)	(1.007)
Funds in the category in the industry	0.011+	-0.106*	0.011+	-0.107*	0.011+	-0.104*	0.011+	-0.105*	0.012+	-0.127+
	(0.006)	(0.043)	(0.006)	(0.046)	(0.006)	(0.048)	(0.006)	(0.043)	(0.007)	(0.071)
Category growth in the industry	0.213*	1.329**	0.213*	1.360**	0.212*	1.373**	0.213*	1.354**	0.217*	1.613*
	(0.092)	(0.490)	(0.093)	(0.497)	(0.092)	(0.491)	(0.093)	(0.460)	(0.095)	(0.681)
Category rank in the industry									0.001	0.019
									(0.006)	(0.028)
Constant	-1.454**	-4.128	-3.225**	-4.231	-3.213**	-4.205	-3.220**	-4.244	-3.241**	-4.968
	(0.444)	(2.611)	(0.571)	(3.326)	(0.572)	(3.301)	(0.572)	(3.247)	(0.576)	(5.362)
Inflate										
Manager's performance in firm-category	3.738**	4.125	3.738**	4.159	3.743**	4.093	3.741**	4.156	3.736**	4.688
	(1.161)	(2.932)	(1.161)	(2.987)	(1.163)	(3.049)	(1.162)	(2.948)	(1.161)	(3.239)
Manager's existing funds	-5.892**	-0.023	-5.889**	-0.027	-5.887**	-0.028	-5.888**	-0.027	-5.892**	-0.053
	(0.478)	(0.069)	(0.477)	(0.071)	(0.476)	(0.068)	(0.476)	(0.064)	(0.477)	(0.126)
Constant	10.748**	3.850**	10.748**	3.876**	10.746**	3.866**	10.747**	3.868**	10.753**	4.081**
	(0.796)	(0.477)	(0.795)	(0.519)	(0.795)	(0.526)	(0.795)	(0.417)	(0.796)	(0.816)
Observations	16329	16329	16329	16329	16329	16329	16329	16329	16329	16329
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-4155.36	-460.75	-4155.66	-460.79	-4155.53	-460.78	-4155.69	-460.78	-4155.57	-461.55

Notes:
1. Robust standard errors clustered at the portfolio manager level in parentheses
2. All independent variables lagged by one year
3. + $p<0.10$, * $p<0.05$, ** $p<0.01$ (all tests are two-tailed)

Table 14. Alternative definitions of leaders and laggards (ZINB Model)

	Alternative definitions of a leader						Alternative definition of a laggard	
Dependent variable: Funds created	**Top 5% vs 0-95%**		**Top 15% vs 0-85%**		**Top 20% vs 0-80%**		**Top 10% vs 0-70%**	
Zero-inflated negative binomial model	**Same cat**	**Diff cat**	**Same cat**	**Diff cat**	**Same cat**	**Diff cat**	**Same cat**	**Diff cat**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Leader	0.566**	-1.553	0.511**	No	0.463**	No	0.526**	-0.025
	(0.125)	(1.410)	(0.079)	convergence	(0.074)	convergence	(0.098)	(1.258)
Manager's remuneration	0.002*	0.000	0.002*		0.002*		0.001+	0.005+
	(0.001)	(0.006)	(0.001)		(0.001)		(0.001)	(0.003)
Manager's firm-specific tenure	-0.048**	-0.146**	-0.047**		-0.048**		-0.048**	-0.287+
	(0.013)	(0.039)	(0.013)		(0.013)		(0.015)	(0.174)
Manager's existing funds	0.326**	0.183**	0.329**		0.327**		0.320**	-0.242
	(0.036)	(0.069)	(0.037)		(0.037)		(0.034)	(0.260)
Manager's performance in firm-category	-3.623**	-6.578**	-3.621**		-3.681**		-3.987**	-8.364
	(0.508)	(2.080)	(0.511)		(0.510)		(0.585)	(7.762)
Funds in the category in the firm	-1.185**	-0.019	-1.189**		-1.176**		-1.279**	2.355
	(0.368)	(1.050)	(0.369)		(0.367)		(0.394)	(3.098)
Category growth in the firm	0.073	-3.088+	0.056		0.058		0.075	-5.407
	(0.071)	(1.737)	(0.064)		(0.064)		(0.074)	(7.754)
Number of categories in the firm	-0.026*	-0.033	-0.027*		-0.026*		-0.027+	-0.176
	(0.013)	(0.049)	(0.013)		(0.013)		(0.014)	(0.220)
Firm performance	0.385	0.489	0.304		0.264		0.192	1.866
	(0.326)	(1.448)	(0.328)		(0.326)		(0.378)	(8.263)
Firm size	0.058+	0.175	0.060+		0.058+		0.054	0.290
	(0.033)	(0.132)	(0.033)		(0.033)		(0.037)	(0.242)
Firm age	0.004*	0.010	0.004*		0.004*		0.004+	0.013
	(0.002)	(0.007)	(0.002)		(0.002)		(0.002)	(0.012)
Firm cash flow	-0.013	-0.044	-0.014		-0.016		0.003	-1.062
	(0.026)	(0.066)	(0.025)		(0.025)		(0.035)	(1.352)
Funds in the category in the industry	0.011+	-0.018	0.011+		0.011+		0.012+	-0.136
	(0.006)	(0.020)	(0.006)		(0.006)		(0.007)	(0.099)
Category growth in the industry	0.241*	0.846	0.211*		0.212*		0.204*	-0.496
	(0.096)	(0.664)	(0.095)		(0.095)		(0.088)	(0.975)
Constant	-1.523**	-4.095*	-3.228**		-1.467**		-1.234*	-4.108
	(0.433)	(1.757)	(0.564)		(0.431)		(0.484)	(5.889)
Inf								
Manager's performance in firm-category	3.464**	5.231	3.513**		3.485**		3.938**	5.044
	(1.085)	(8.396)	(1.098)		(1.100)		(1.380)	(6.077)
Manager's existing funds	-5.963**	-16.717	-5.909**		-5.897**		-5.695**	-0.244
	(0.492)	(16.026)	(0.483)		(0.481)		(0.503)	(0.159)
Constant	10.807**	17.770	10.758**		10.744**		10.493**	4.560**
	(0.803)	(16.212)	(0.799)		(0.799)		(0.846)	(1.065)
Observations	16360	16360	16262		16233		12807	12807
Year fixed effects	Yes	Yes	Yes		Yes		Yes	Yes
Firm fixed effects	Yes	Yes	Yes		Yes		Yes	Yes
Log likelihood	-4154.56	-530.32	-4135.51		-4134.95		-3215.07	-302.14

Notes:
1. Robust standard errors clustered at the portfolio manager level in parentheses
2. All independent variables lagged by one year
3. + p<0.10, * p<0.05, ** p<0.01 (all tests are two-tailed)

Table 15. Fund creation by leaders relative to laggards (Conditional fixed-effects NB model)

Dependent variable: Funds created	Same category				Different category			
Negative binomial model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Leader				0.465**				0.100
				(0.087)				(0.409)
Manager's remuneration			0.003**	0.003**			0.003	0.003
			(0.001)	(0.001)			(0.003)	(0.003)
Manager's firm-specific tenure			-0.051**	-0.052**			-0.062	-0.062
			(0.011)	(0.011)			(0.053)	(0.053)
Manager's existing funds			0.229**	0.231**			0.172**	0.172**
			(0.009)	(0.009)			(0.060)	(0.060)
Manager's performance in firm-category			-6.084**	-6.340**			-7.568**	-7.604**
			(0.420)	(0.418)			(1.758)	(1.761)
Funds in the category in the firm		0.148	-0.896**	-0.880**		-1.808	-2.743	-2.742
		(0.247)	(0.289)	(0.288)		(1.520)	(1.733)	(1.733)
Category growth in the firm		0.113	0.096	0.073		-3.341	-3.594	-3.648
		(0.070)	(0.067)	(0.068)		(2.603)	(2.706)	(2.726)
Number of categories in the firm		-0.042**	-0.037**	-0.035**		-0.021	-0.026	-0.026
		(0.009)	(0.009)	(0.009)		(0.034)	(0.034)	(0.034)
Firm performance		0.329	0.357	0.050		-1.031	-1.068	-1.115
		(0.286)	(0.286)	(0.296)		(1.489)	(1.533)	(1.539)
Firm size		0.220**	0.216**	0.217**		0.261*	0.265*	0.265*
		(0.026)	(0.026)	(0.026)		(0.117)	(0.117)	(0.117)
Firm age		0.004**	0.004**	0.005**		0.003	0.004	0.004
		(0.001)	(0.001)	(0.001)		(0.006)	(0.006)	(0.006)
Firm cash flow		0.001	-0.010	-0.011		-0.331	-0.348	-0.348
		(0.023)	(0.023)	(0.023)		(0.353)	(0.353)	(0.353)
Funds in the category in the industry	0.003	0.005	0.014**	0.014**	-0.021	0.001	-0.001	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.019)	(0.024)	(0.024)	(0.024)
Category growth in the industry	0.177	0.186	0.181	0.183	0.200	0.362	0.359	0.360
	(0.125)	(0.125)	(0.124)	(0.124)	(0.383)	(0.377)	(0.383)	(0.383)
Constant	-1.992**	-3.740**	-4.545**	-4.250**	-3.555**	-4.702**	-4.470*	-6.078**
	(0.150)	(0.366)	(0.458)	(0.465)	(0.337)	(1.707)	(1.750)	(2.216)
Observations	16329	16329	16329	16329	16329	16329	16329	16329
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-5020.18	-4954.79	-4621.05	-4608.05	-438.94	-430.97	-414.59	-414.56

Notes:
1. Standard errors in parentheses
2. All independent variables lagged by one year
3. + $p<0.10$, * $p<0.05$, ** $p<0.01$ (all tests are two-tailed)

Table 16. Fund creation by leaders relative to laggards (Unconditional fixed-effects NB model)

Dependent variable: Funds created	Same category				Different category			
Negative binomial model	1	2	3	4	5	6	7	8
Leader				0.458**				-0.100
				(0.096)				(0.492)
Manager's remuneration			0.002*	0.002*			0.004	0.004
			(0.001)	(0.001)			(0.004)	(0.004)
Manager's firm-specific tenure			-0.071**	-0.071**			-0.145**	-0.145**
			(0.014)	(0.014)			(0.040)	(0.040)
Manager's existing funds			0.540**	0.542**			0.296**	0.295**
			(0.035)	(0.035)			(0.087)	(0.086)
Manager's performance in firm-category			-4.018**	-4.136**			-9.230*	-9.184*
			(0.547)	(0.554)			(4.198)	(4.232)
Funds in the category in the firm		-0.345	-0.849*	-0.864*		-0.734	-1.252	-1.247
		(0.313)	(0.366)	(0.367)		(1.036)	(1.436)	(1.436)
Category growth in the firm		0.247*	0.075	0.047		-2.085	-2.719	-2.704
		(0.116)	(0.077)	(0.073)		(1.475)	(2.042)	(2.057)
Number of categories in the firm		-0.007	-0.037**	-0.037**		-0.063	-0.053	-0.053
		(0.012)	(0.013)	(0.013)		(0.050)	(0.050)	(0.051)
Firm performance		0.312	0.355	0.075		-0.069	-0.023	0.009
		(0.357)	(0.361)	(0.361)		(1.628)	(1.490)	(1.477)
Firm size		0.226**	0.226**	0.231**		0.287**	0.237*	0.238*
		(0.032)	(0.031)	(0.030)		(0.111)	(0.111)	(0.112)
Firm age		0.006**	0.004*	0.004*		0.007	0.008	0.007
		(0.002)	(0.002)	(0.002)		(0.007)	(0.008)	(0.007)
Firm cash flow		0.002	-0.001	0.000		-0.423*	-0.357*	-0.356*
		(0.028)	(0.027)	(0.028)		(0.200)	(0.175)	(0.174)
Funds in the category in the industry	0.010+	0.019**	0.004	0.004	-0.010	-0.002	-0.022	-0.022
	(0.005)	(0.007)	(0.006)	(0.006)	(0.015)	(0.021)	(0.021)	(0.021)
Category growth in the industry	0.158	0.173	0.119	0.114	0.727	0.919	0.797	0.793
	(0.105)	(0.106)	(0.087)	(0.087)	(0.588)	(0.605)	(0.660)	(0.655)
Constant	-2.163**	-4.130**	-4.781**	-4.544**	-4.507**	-6.311**	-7.070**	-7.100**
	(0.145)	(0.468)	(0.571)	(0.569)	(0.546)	(1.973)	(1.961)	(1.947)
Observations	16329	16329	16329	16329	16329	16329	16329	16329
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-5139.06	-5065.09	-4628.56	-4618.15	-495.84	-490.96	-471.45	-471.43

Notes:
1. Robust standard errors clustered at the portfolio manager level in parentheses
2. All independent variables lagged by one year
3. + p<0.10, * p<0.05, ** p<0.01 (all tests are two-tailed)

Table 17. Description of control variables used in Chapter 3

Level	Variables	Measurement Details	Notes
Individual level	Player efficiency rating (PER)	A measure of per-minute production of a player	A player's performance effect on wage; standardized such that league average is 15; lagged by one year
	Value above replacement (VAR)	[(PER – 9)/15]*Minutes played	A player's value above the league replacement level (9) taking playing time into consideration; lagged by one year
	Defensive rating	Points allowed by a player per 100 possessions	Player's defensive record effect on wage; lagged by one year
	Experience	Player experience in the NBA in years	Effect of experience on wage; lagged by one year
	All-star votes	Votes received by a player for all-star team	Star effect on wage; lagged by one year
	All-star dummy	Binary variable: Equals one if a player was selected for the all-star game	Star effect on wage; lagged by one year
	Most valuable player nomination	Binary variable: Equals one if a player was nominated for the award	Star effect on wage; lagged by one year
	Best defensive player nomination	Binary variable: Equals one if a player was nominated for the award	Star effect on wage; lagged by one year
	Most improved player nomination	Binary variable: Equals one if a player was nominated for the award	Star effect on wage; lagged by one year
	Best sixth man nomination	Binary variable: Equals one if a player was nominated for the award	Star effect on wage; lagged by one year
	Unrestricted free agent	Binary variable: Equals one if a player was an unrestricted free agent	Effect of short-term incentives on wage; lagged by one year
	Rookie	Binary variable: Equals one if a player was a newcomer in the year	Newcomer effect on wage; lagged by one year
	Player still on drafting team	Binary variable: Equals one if a player is still with the team that drafted him	Effect of being with first team on wage; lagged by one year
Firm level	Number of times a team in playoffs	Count variable: Equals the number of times a team made it to playoffs in last three years	Effect of team success on wage (with success being a proxy for a fun working environment); lagged by one year
	Coach win percentage	Coach's regular season win percentage	Proxy for coach quality; two-year moving average
	Unrestricted free agents on team	Number of unrestricted free agents in a team	Effect of short-term incentives of players on complementarity; lagged by one year
	Roster size	Number of players on a team in a year	Effect of team size on complementarity
	Team all-star votes	All-star votes summed to team-year level	Star effect on complementarity
	Coach experience	Coach NBA experience in years	Coach effect on complementarity
	Point guards recruited	Count variable	Number of point guards recruited by a team in a year; lagged by one year

	Players still on drafting team	Number of players in the team still with the team that drafted them	Effect of players being with first team on complementarity; lagged by one year
	International players drafted	Binary variable: Equals one if a team drafted at least one international player	Whether a team recruited an international player in the NBA draft in a year
	High school players drafted	Binary variable: Equals one if a team drafted at least one high school player	Whether a team recruited a high school student in the NBA draft in a year
	No player in-traded	Binary variable: Equals one if a team did not in-trade a player	Whether a team did not recruit any player through inter-team trades in a year
	No player lost	Binary variable: Equals one if a team did not lose/release a player	Whether a team did not lose any player through inter-team trades in a year
	No player drafted	Binary variable: Equals one if a team did not draft a player	Whether a team did not recruit a player in the NBA draft in a year
City level	MSA population	Metropolitan statistical area population in a 50 mile radius of team's host city	Effect of potential market size of a team's host city on wage
	Fan cost index	Average cost of attending a game	Effects of cost of living on wage
	Phase dummies	Four phase dummies corresponding to three CBA renegotiations in the sample period	Effects of the different CBAs on wage

Table 18. Estimating complementarity at the game level using HGS measure of player performance

Dependent variable: Team points/Opponent points	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Player 1 performance	0.148***	0.130***	0.143***	0.145***	0.131***	0.163***	0.174***	0.185***	0.130***	0.152***	0.177***	0.162***	0.166***	0.172***	0.127***	0.169***	0.163***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)	(0.019)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
Player 2 performance	0.132***	0.123***	0.141***	0.152***	0.161***	0.148***	0.134***	0.149***	0.144***	0.162***	0.175***	0.170***	0.129***	0.158***	0.130***	0.164***	0.157***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.019)	(0.014)	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.014)
Player 3 performance	0.163***	0.146***	0.145***	0.141***	0.142***	0.186***	0.165***	0.141***	0.156***	0.154***	0.188***	0.167***	0.143***	0.164***	0.144***	0.167***	0.162***
	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.018)	(0.015)	(0.015)	(0.016)	(0.016)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Player 4 performance	0.125***	0.112***	0.156***	0.141***	0.138***	0.132***	0.149***	0.177***	0.148***	0.168***	0.167***	0.188***	0.163***	0.147***	0.138***	0.145***	0.149***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.019)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)
Player 5 performance	0.129***	0.144***	0.171***	0.128***	0.161***	0.165***	0.152***	0.194***	0.167***	0.140***	0.175***	0.149***	0.176***	0.136***	0.148***	0.161***	0.145***
	(0.013)	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)	(0.014)	(0.019)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Player 6 performance	0.136***	0.153***	0.159***	0.163***	0.138***	0.161***	0.146***	0.157***	0.167***	0.157***	0.190***	0.157***	0.138***	0.153***	0.155***	0.159***	0.175***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.015)	(0.015)	(0.019)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Player 7 performance	0.150***	0.151***	0.111***	0.177***	0.156***	0.152***	0.191***	0.149***	0.151***	0.146***	0.185***	0.141***	0.130***	0.156***	0.148***	0.154***	0.144***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)	(0.019)	(0.014)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
Player 8 performance	0.121***	0.136***	0.135***	0.094***	0.143***	0.094***	0.134***	0.135***	0.163***	0.172***	0.144***	0.138***	0.154***	0.174***	0.119***	0.128***	0.128***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.019)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)
Player 9 performance	0.075***	0.115***	0.101***	0.087***	0.095***	0.075***	0.094***	0.112***	0.104***	0.116***	0.137***	0.090***	0.101***	0.107***	0.062***	0.099***	0.094***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.013)	(0.018)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)
Player 10 performance	0.022*	0.007	0.015	0.008	0.026*	0.022	0.023*	0.072***	0.064***	0.050***	0.058***	0.073***	0.042***	0.063***	0.035**	0.020	0.037***
	(0.012)	(0.011)	(0.012)	(0.013)	(0.013)	(0.015)	(0.013)	(0.018)	(0.013)	(0.015)	(0.014)	(0.015)	(0.015)	(0.013)	(0.014)	(0.013)	(0.013)
Binary variable: Home team	0.055***	0.047***	0.049***	0.040***	0.041***	0.035***	0.040***	0.049***	0.048***	0.041***	0.047***	0.055***	0.053***	0.047***	0.048***	0.041***	0.045***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)
Ratio of attendance to stadium capacity	-0.023	-0.031	-0.057***	-0.097***	-0.105***	-0.084***	-0.130***	-0.062**	-0.104***	-0.100***	-0.059***	-0.081***	-0.052*	-0.122***	-0.069**	-0.108***	-0.098***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)	(0.020)	(0.029)	(0.023)	(0.024)	(0.020)	(0.021)	(0.027)	(0.026)	(0.032)	(0.029)	(0.022)
Home * Ratio of attendance to stadium capacity	-0.044	-0.027	0.055	0.051	0.075**	0.011	0.091***	0.035	0.091**	0.020	-0.025	-0.002	0.001	0.059	-0.054	0.070	0.022
	(0.035)	(0.036)	(0.038)	(0.039)	(0.035)	(0.030)	(0.034)	(0.051)	(0.038)	(0.040)	(0.023)	(0.029)	(0.042)	(0.042)	(0.050)	(0.047)	(0.039)
Binary variable: Attendance not available	0.021	-0.033	0.000	0.000	-0.050	-0.070***	-0.099**	0.000	0.000	0.012	-0.055***	-0.075***	-0.043	0.000	0.000	-0.155***	-0.076
	(0.072)	(0.074)	(0.000)	(0.000)	(0.035)	(0.025)	(0.046)	(0.000)	(0.000)	(0.082)	(0.020)	(0.024)	(0.081)	(0.000)	(0.000)	(0.059)	(0.058)
Constant	-5.081***	-5.135***	-5.352***	-5.137***	-5.346***	-5.379***	-5.597***	-6.082***	-5.757***	-5.833***	-6.624***	-5.929***	-5.563***	-5.870***	-5.013***	-5.655***	-5.620***
	(0.176)	(0.179)	(0.176)	(0.188)	(0.195)	(0.200)	(0.189)	(0.269)	(0.197)	(0.215)	(0.209)	(0.214)	(0.209)	(0.204)	(0.194)	(0.193)	(0.188)
Observations	2214	2214	2208	2214	2378	2354	2368	1446	2378	2350	2340	2330	2366	2456	2460	2460	2460
Number of teams	27	27	27	27	29	29	29	29	29	29	29	29	29	30	30	30	30
R-squared	0.36	0.36	0.38	0.33	0.31	0.30	0.35	0.34	0.35	0.30	0.36	0.33	0.32	0.32	0.30	0.33	0.34
F-value	88.93	86.74	101.80	81.88	74.76	70.97	89.65	55.22	96.05	71.20	93.89	80.26	77.79	88.98	78.91	85.93	90.51
Team fixed effect	11.07	13.32	14.83	12.02	15.34	18.62	15.68	7.88	10.93	11.07	8.39	10.87	9.20	12.02	9.01	9.94	15.02

Notes:

1. Dependent variable and individual player performance variables are in logarithmic value (per the Cobb-Douglas production function)
2. Standard errors in parentheses
3. + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (all tests are two-tailed)

Table 19. Descriptive statistics and correlation matrix of variables to estimate a player's share of firm surplus using HGS-based measure of complementarity

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	Log[Player share of surplus/(1-Player share of surplus)]	-3.336	1.293	-9.493	5.466	1																							
2	Complementarity	0.000	0.043	-0.110	0.106	-0.061	1																						
3	All-star dummy	0.055	0.228	0	1	0.281	0.143	1																					
4	Value above replacement	0.505	0.697	-0.738	4.689	0.556	0.122	0.633	1																				
5	All-star votes	0.006	0.024	0	0.256	0.305	0.147	0.702	0.618	1																			
6	Defensive rating	0.089	0.039	0	0.120	0.353	0.036	0.088	0.301	0.098	1																		
7	Experience	3.851	3.263	0	16	0.423	0.154	0.132	0.284	0.181	0.490	1																	
8	Experience squared	25.478	35.965	0	256	0.311	0.145	0.092	0.184	0.154	0.287	0.941	1																
9	Most valuable player nomination	0.038	0.192	0	1	0.237	0.144	0.652	0.579	0.581	0.067	0.114	0.081	1															
10	Best defensive player nomination	0.027	0.161	0	1	0.173	0.100	0.279	0.306	0.331	0.049	0.141	0.127	0.274	1														
11	Most improved player nomination	0.040	0.197	0	1	0.124	0.020	0.129	0.291	0.093	0.083	0.031	-0.013	0.109	0.127	1													
12	Best sixth man nomination	0.021	0.144	0	1	0.068	0.047	-0.026	0.095	-0.024	0.059	0.091	0.073	-0.013	-0.012	0.124	1												
13	Unrestricted free agent	0.178	0.383	0	1	-0.106	0.059	-0.047	-0.069	-0.049	0.195	0.264	0.224	-0.035	-0.008	0.001	0.006	1											
14	Rookie	0.090	0.287	0	1	-0.044	-0.026	-0.018	-0.034	-0.020	0.137	-0.063	-0.077	-0.018	-0.014	0.031	0.000	-0.001	1										
15	Player still on drafting team	0.303	0.460	0	1	-0.010	-0.059	0.025	0.070	0.046	0.283	-0.294	-0.304	0.010	0.033	0.073	-0.002	-0.107	0.217	1									
16	Team's prior success	1.644	1.184	0	3	-0.048	0.700	0.119	0.100	0.123	0.017	0.105	0.094	0.114	0.080	-0.009	0.044	0.048	-0.026	-0.063	1								
17	(2YMA) Coach regular season win percentage	0.443	0.227	0	0.860	-0.002	0.461	0.085	0.088	0.097	0.042	0.094	0.084	0.103	0.050	0.000	0.031	0.014	0.000	-0.021	0.392	1							
18	(Log) MSA population	15.582	0.792	14.014	17.162	-0.038	-0.093	-0.009	-0.018	0.003	0.008	0.011	0.013	-0.026	-0.009	-0.001	-0.009	-0.028	0.007	0.013	-0.140	-0.033	1						
19	Fan cost index	238.987	63.196	117.800	469.600	-0.049	0.278	0.031	0.028	0.083	0.005	0.247	0.262	0.033	0.074	0.059	0.054	0.065	0.055	0.050	0.223	0.160	0.324	1					
20	CBA - 1 (1991-1994)	0.175	0.380	0	1	-0.027	-0.005	0.021	0.010	-0.033	-0.001	-0.261	-0.253	0.004	-0.069	-0.089	-0.060	-0.099	-0.073	-0.086	0.044	0.009	-0.018	-0.503	1				
21	CBA - 2 (1995-1997)	0.186	0.389	0	1	-0.063	-0.005	0.015	0.011	0.028	0.022	-0.064	-0.113	0.006	-0.030	-0.034	-0.021	-0.007	-0.037	-0.007	0.014	0.019	-0.023	-0.255	-0.220	1			
22	CBA - 3 (1998-2004)	0.442	0.497	0	1	0.072	0.000	-0.026	-0.026	-0.047	-0.015	0.173	0.180	0.006	0.006	0.034	0.018	0.117	-0.005	0.023	-0.029	-0.039	0.014	0.349	-0.409	-0.426	1		
23	CBA - 4 (2005-2007)	0.197	0.398	0	1	-0.003	0.009	-0.002	0.012	0.063	-0.002	0.095	0.127	-0.017	0.087	0.075	0.054	-0.045	0.112	0.060	-0.019	0.022	0.023	0.294	-0.228	-0.237	-0.441	1	
24	Year	2000	4.588	1992	2007	0.018	0.010	-0.013	0.002	0.051	-0.010	0.256	0.292	-0.015	0.098	0.118	0.082	0.038	0.126	0.102	-0.051	0.002	0.035	0.586	-0.667	-0.379	0.259	0.684	1

Notes:

1. Number of observations: 6866
2. Correlations greater than 0.024 are significant at 0.05 level or lower
3. Player share of surplus = Player wage / [(Team annual wage + team operating income)]
4. Variables 2-16 are lagged by one year; variables 4-6 are rescaled; variables 3 and 9-15 are binary
5. Abbreviations: 2YMA - Two year moving average; MSA - Metropolitan statistical area; CBA - Collective bargaining agreement

Table 20. Correlations of player's annual wage and share of firm surplus with player performance measures

Player performance measures	Player's annual wage	Player's share of surplus
Value above replacement	0.670	0.621
Player efficiency rating	0.501	0.477
Hoops Grading Statistic	0.417	0.413
Harderstat measure	0.057	0.058
All-star votes	0.518	0.378
All-star dummy	0.414	0.337
Defensive rating	0.234	0.247
Most valuable player nomination	0.350	0.300
Best defensive player nomination	0.294	0.212
Most improved player nomination	0.084	0.059
Best sixth man nomination	0.050	0.024

Notes:
1. First four performance measures, annual wage, and share of firm surplus are three-year moving averages to overcome idiosyncrasies in a single year's data
2. All player performance measures lagged by one year
3. All correlations significant at 5% level

Table 21. Player’s annual wage, share of firm surplus, and quintiles of player measures

Quintiles	Player's annual wage (mean)				Player's share of firm surplus (mean)			
	VAR	PER	DRTG	EXP	VAR	PER	DRTG	EXP
1	0.583	0.484	1.031	0.523	0.023	0.020	0.037	0.023
2	0.747	0.932	2.061	1.002	0.029	0.036	0.071	0.045
3	1.204	1.301	1.708	1.816	0.045	0.049	0.064	0.072
4	1.880	1.910	1.522	2.595	0.071	0.070	0.058	0.089
5	3.543	3.312	1.552	3.171	0.125	0.118	0.062	0.095

Notes:
1. Player's annual wage in millions of constant dollars, indexed to 1984
2. Player's share of firm surplus = Player annual wage/(Team annual wage + team operating income)
3. VAR: Value Above Replacement; PER: Player Efficiency Rating; DRTG: Defensive Rating; EXP: Experience in years
4. Quintile 5 represents the highest value for each variable (VAR, PER, DRTG, and EXP)
5. All four variables (VAR, PER, DRTG, and EXP) lagged by one year
6. Higher values of defensive rating imply lower defensive ability

Table 22. Comparing stars and non-stars

	Observations	Player's annual wage	Player's share of firm surplus	VAR	PER	Harderstat	HGS	All-star votes	Defensive rating	MVP nomination	Unrestricted free agent
Star	376	4.710	0.163	2343.962	21.572	0.113	25.672	788854	102.995	0.553	0.104
Non-star	6055	1.322	0.056	415.706	12.132	0.102	16.554	27568	105.492	0.006	0.228
Difference in means		3.388	0.107	1928.256	9.440	0.011	9.117	761286	-2.497	0.548	-0.124
t-statistic		38.92	27.84	66.11	33.28	1.85	31.41	78.82	5.28	73.38	5.65

Notes:
1. Dummy variable for a star lagged by one year; Above data excludes 1998 since there was no all-star game in that year
2. Player's annual wage in millions of constant dollars, indexed to 1984
3. Player's share of firm surplus = Player annual wage/(Team annual wage + team operating income)
4. VAR: Value Above Replacement; PER: Player Efficiency Rating; HGS: Hoops Grading Statistic; MVP nomination: Most Valuable Player nomination
5. Higher values of defensive rating imply lower defensive ability

Table 23. Descriptive statistics and correlation matrix of variables to explain complementarity using HGS-based measure of complementarity

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Complementarity	0.001	0.043	-0.110	0.106	1																				
2	Team interaction	0.624	0.135	0.166	1.017	0.391	1																			
3	Team familiarity	0.331	0.062	0.168	0.570	0.142	0.170	1																		
4	Player dominance	0.218	0.013	0.186	0.274	-0.136	-0.152	-0.015	1																	
5	Assists of in-traded players	0.855	0.298	0	2.065	0.126	-0.075	0.035	0.018	1																
6	Assists of lost players	0.931	0.317	0	2.061	-0.051	0.163	-0.027	-0.043	0.162	1															
7	Assists of drafted players	0.992	0.440	0	2.041	-0.057	-0.044	0.015	-0.052	-0.008	-0.057	1														
8	Unrestricted free agents on team	1.518	0.440	0	2.485	-0.012	-0.217	-0.152	-0.010	-0.001	-0.045	0.059	1													
9	Roster size	2.708	0.097	2.303	2.996	-0.220	-0.464	-0.122	0.053	-0.147	-0.017	-0.103	0.099	1												
10	Team all-star votes	3.898	1.624	0	6.339	0.557	0.262	0.028	-0.051	0.096	-0.055	-0.016	0.057	-0.125	1											
11	Coach experience	1.920	0.773	0.693	3.466	0.266	0.160	0.008	-0.032	0.104	0.052	-0.016	0.023	-0.102	0.215	1										
12	Number of point guards in-traded	3.315	1.225	1	9	-0.015	0.006	-0.243	-0.053	0.046	-0.034	-0.025	-0.076	-0.010	-0.038	0.036	1									
13	Players still on drafting team	4.569	1.986	0	11	-0.233	-0.213	-0.048	0.062	-0.062	-0.104	-0.068	-0.082	0.292	-0.181	-0.038	0.091	1								
14	International players drafted	0.249	0.433	0	1	0.052	-0.014	-0.076	0.040	-0.032	-0.024	-0.089	-0.017	0.090	0.032	0.027	-0.016	0.118	1							
15	High school players drafted	0.088	0.283	0	1	-0.073	-0.096	-0.052	0.049	0.011	-0.013	-0.267	-0.007	0.057	-0.111	-0.063	0.021	0.048	-0.035	1						
16	No player in-traded	0.004	0.066	0	1	0.021	0.076	-0.053	-0.013	-0.191	0.020	0.036	0.093	-0.072	0.039	0.001	-0.044	-0.036	-0.038	-0.021	1					
17	No player lost	0.004	0.066	0	1	0.083	0.062	0.043	-0.089	0.050	-0.195	-0.012	-0.011	-0.027	0.060	0.055	0.091	-0.002	0.038	-0.021	-0.004	1				
18	No player drafted	0.046	0.210	0	1	0.079	0.074	0.053	0.070	0.044	0.047	-0.496	-0.025	-0.017	0.031	0.021	0.055	-0.016	-0.127	-0.068	-0.015	-0.015	1			
19	MSA population	15.581	0.796	14.014	17.162	-0.108	-0.047	-0.057	0.055	0.029	0.031	0.017	-0.033	0.016	-0.023	0.052	-0.022	0.051	0.019	-0.081	-0.042	-0.004	0.002	1		
20	Fan cost index	5.443	0.260	4.769	6.152	0.211	0.009	-0.055	0.121	0.061	-0.011	-0.108	-0.035	0.030	0.175	0.112	0.132	0.199	0.184	0.051	0.014	0.074	0.076	0.297	1	
21	Year	2000	4.606	1992	2007	-0.004	-0.053	-0.174	0.044	-0.003	0.020	-0.087	-0.145	0.090	0.040	0.071	0.337	0.373	0.287	0.134	-0.024	0.063	0.044	0.038	0.635	1

Notes:
1. Number of observations: 457
2. Correlations greater than 0.093 are statistically significant at 0.05 level or lower
3. Variables 2-11, 19, and 20 are expressed in natural logarithms and variables 14-18 are binary

Table 24. Estimating a player's share of firm surplus using HGS-based measure of complementarity

Dependent variable: log [P/(1-P)] P defined in notes to the table		1	2	3	4
Complementarity	(H1a)			-3.076*** (0.414)	-3.097*** (0.418)
Complementarity * All-star dummy	(H1b)				0.505 (1.366)
All-star dummy			-0.272*** (0.076)	-0.259*** (0.076)	-0.266*** (0.078)
Value above replacement			0.835*** (0.025)	0.833*** (0.025)	0.833*** (0.025)
All-star votes			2.228** (0.704)	2.188** (0.701)	2.164** (0.704)
Defensive rating			-3.019*** (0.532)	-3.151*** (0.531)	-3.151*** (0.531)
Experience			0.399*** (0.017)	0.404*** (0.017)	0.404*** (0.017)
Experience squared			-0.021*** (0.001)	-0.021*** (0.001)	-0.021*** (0.001)
Most valuable player nomination			-0.415*** (0.079)	-0.395*** (0.079)	-0.401*** (0.080)
Best defensive player nomination			0.088 (0.073)	0.097 (0.073)	0.096 (0.073)
Most improved player nomination			-0.207*** (0.059)	-0.194*** (0.058)	-0.193*** (0.058)
Best sixth man nomination			-0.020 (0.076)	-0.016 (0.076)	-0.016 (0.076)
Unrestricted free agent			-0.620*** (0.030)	-0.619*** (0.030)	-0.619*** (0.030)
Rookie			-0.058 (0.039)	-0.060 (0.039)	-0.060 (0.039)
Player still on drafting team			0.268*** (0.034)	0.275*** (0.033)	0.276*** (0.033)
Team's prior success		-0.019 (0.017)	-0.069*** (0.012)	-0.012 (0.014)	-0.012 (0.014)
Coach regular season win percent		0.298*** (0.078)	0.053 (0.055)	0.158** (0.057)	0.158** (0.057)
MSA population		-0.596 (0.418)	-0.654* (0.296)	-0.435 (0.296)	-0.439 (0.297)
Fan cost index		-0.003*** (0.001)	-0.004*** (0.000)	-0.004*** (0.000)	-0.004*** (0.000)
Constant		6.326 (6.484)	6.807 (4.590)	3.203 (4.597)	3.268 (4.601)
Number of observations		6866	6866	6866	6866
R-squared		0.034	0.518	0.521	0.521
Log likelihood		-11261	-8877	-8849	-8849
Regression F-value		12.60	228.1	224.6	218.0
Team fixed effect F-value		7.324	13.21	11.95	11.94

Notes:
1. P = Player wage / [(Team annual wage + team operating income)]
2. Team's prior success: Number of times it reached playoffs in the last three years
3. All models include fixed effects for teams, years, and phases corresponding to CBAs
4. Standard errors in parentheses
5. + p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001 (all tests are two-tailed)

Table 25. Explaining complementarity using HGS-based measure of complementarity

Dependent variable: Complementarity		1 GLS	2 FE	3 GLS	4 FE
Team interaction	(H2)			0.070***	0.086***
				(0.013)	(0.019)
Team familiarity	(H2)			0.043+	0.049*
				(0.022)	(0.023)
Player dominance	(H3)			-0.322**	-0.263+
				(0.107)	(0.154)
Assists of in-traded players	(H4)			0.012**	0.013**
				(0.004)	(0.005)
Assists of lost players	(H4)			-0.009*	-0.012*
				(0.004)	(0.006)
Assists of drafted players	(H4)			-0.001	0.000
				(0.004)	(0.005)
Unrestricted free agents on team		-0.009*	-0.011*	-0.006+	-0.007
		(0.004)	(0.004)	(0.003)	(0.004)
Roster size		-0.038*	-0.050**	0.004	0.002
		(0.015)	(0.015)	(0.016)	(0.017)
Team all-star votes		0.012***	0.010***	0.011***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)
Coach experience		0.006***	0.008*	0.005**	0.007*
		(0.002)	(0.003)	(0.002)	(0.003)
Number of point guards in-traded		0.001	0.001	0.002	0.001
		(0.001)	(0.002)	(0.001)	(0.002)
Players still on drafting team		-0.002**	-0.001	-0.002**	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
International players drafted		0.003	0.005	0.003	0.005
		(0.003)	(0.004)	(0.003)	(0.004)
High school players drafted		-0.005	-0.004	-0.003	-0.003
		(0.005)	(0.006)	(0.005)	(0.007)
No player in-traded		-0.006	-0.004	-0.003	-0.001
		(0.020)	(0.007)	(0.022)	(0.016)
No player lost		0.009	0.011	-0.014	-0.012
		(0.022)	(0.008)	(0.023)	(0.011)
No player drafted		0.003	0.005	0.001	0.002
		(0.007)	(0.010)	(0.008)	(0.011)
MSA population		-0.011***	0.046	-0.009***	0.043
		(0.002)	(0.071)	(0.002)	(0.059)
Fan cost index		0.058***	0.033	0.051***	0.032+
		(0.008)	(0.022)	(0.008)	(0.018)
Constant		-0.066	-0.791	-0.167**	-0.878
		(0.055)	(1.130)	(0.064)	(0.988)
Number of observations		457	457	457	457
R-squared		-	0.32	-	0.40
Team fixed effects		-	Yes	-	Yes
Log likelihood		-	964.0	-	992.7
Wald chi square		469.0		555.9	-

Notes:
1. All models include year fixed effects
2. Standard errors in parentheses (clustered by team in models 2 and 4)
3. + p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001 (all tests are two-tailed)

Table 26. Estimating complementarity at the game level using Harderstat measure of player performance

Dependent variable: Team points/Opponent points	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Player 1 performance	0.647***	0.493***	0.681***	0.759***	0.693***	0.705***	0.794***	0.846***	0.700***	0.707***	0.828***	0.897***	0.796***	0.816***	0.751***	0.799***	0.911***
	(0.056)	(0.061)	(0.058)	(0.063)	(0.066)	(0.067)	(0.068)	(0.086)	(0.064)	(0.070)	(0.067)	(0.071)	(0.066)	(0.065)	(0.066)	(0.064)	(0.062)
Player 2 performance	0.658***	0.568***	0.696***	0.740***	0.745***	0.801***	0.786***	0.777***	0.659***	0.754***	0.932***	0.820***	0.763***	0.730***	0.793***	0.825***	0.848***
	(0.058)	(0.058)	(0.057)	(0.062)	(0.062)	(0.068)	(0.066)	(0.090)	(0.062)	(0.070)	(0.071)	(0.066)	(0.067)	(0.064)	(0.065)	(0.064)	(0.064)
Player 3 performance	0.690***	0.756***	0.766***	0.729***	0.671***	0.809***	0.776***	0.836***	0.771***	0.756***	0.862***	0.874***	0.762***	0.777***	0.761***	0.773***	0.767***
	(0.060)	(0.060)	(0.059)	(0.063)	(0.063)	(0.067)	(0.064)	(0.085)	(0.064)	(0.069)	(0.069)	(0.071)	(0.068)	(0.064)	(0.065)	(0.065)	(0.064)
Player 4 performance	0.626***	0.548***	0.719***	0.730***	0.804***	0.624***	0.740***	0.711***	0.738***	0.826***	0.804***	0.767***	0.826***	0.796***	0.694***	0.864***	0.712***
	(0.058)	(0.058)	(0.061)	(0.063)	(0.062)	(0.070)	(0.065)	(0.086)	(0.064)	(0.067)	(0.069)	(0.070)	(0.068)	(0.065)	(0.064)	(0.063)	(0.064)
Player 5 performance	0.500***	0.674***	0.765***	0.653***	0.635***	0.774***	0.741***	0.861***	0.743***	0.777***	0.934***	0.855***	0.872***	0.854***	0.879***	0.752***	0.805***
	(0.056)	(0.059)	(0.059)	(0.063)	(0.064)	(0.068)	(0.067)	(0.086)	(0.062)	(0.071)	(0.068)	(0.069)	(0.068)	(0.063)	(0.067)	(0.064)	(0.063)
Player 6 performance	0.638***	0.744***	0.759***	0.670***	0.665***	0.827***	0.755***	0.790***	0.743***	0.776***	0.797***	0.705***	0.690***	0.811***	0.727***	0.659***	0.862***
	(0.056)	(0.060)	(0.058)	(0.061)	(0.063)	(0.067)	(0.064)	(0.086)	(0.064)	(0.070)	(0.068)	(0.070)	(0.066)	(0.064)	(0.063)	(0.065)	(0.064)
Player 7 performance	0.612***	0.799***	0.684***	0.786***	0.748***	0.712***	0.786***	0.775***	0.811***	0.850***	0.811***	0.751***	0.802***	0.749***	0.755***	0.789***	0.781***
	(0.056)	(0.060)	(0.059)	(0.062)	(0.065)	(0.068)	(0.065)	(0.085)	(0.064)	(0.069)	(0.070)	(0.068)	(0.070)	(0.065)	(0.063)	(0.065)	(0.063)
Player 8 performance	0.548***	0.644***	0.702***	0.641***	0.753***	0.608***	0.872***	0.739***	0.871***	0.841***	0.922***	0.796***	0.734***	0.811***	0.698***	0.754***	0.723***
	(0.058)	(0.061)	(0.061)	(0.062)	(0.065)	(0.068)	(0.066)	(0.089)	(0.065)	(0.069)	(0.071)	(0.070)	(0.069)	(0.066)	(0.064)	(0.063)	(0.064)
Player 9 performance	0.474***	0.680***	0.735***	0.597***	0.746***	0.571***	0.762***	1.009***	0.748***	0.821***	0.857***	0.679***	0.739***	0.707***	0.709***	0.758***	0.731***
	(0.061)	(0.061)	(0.060)	(0.065)	(0.068)	(0.076)	(0.069)	(0.091)	(0.067)	(0.077)	(0.074)	(0.074)	(0.071)	(0.068)	(0.073)	(0.072)	(0.067)
Player 10 performance	0.563***	0.667***	0.500***	0.650***	0.586***	0.648***	0.552***	0.814***	0.853***	0.654***	0.968***	0.878***	0.818***	0.918***	0.765***	0.712***	0.596***
	(0.078)	(0.077)	(0.075)	(0.081)	(0.088)	(0.092)	(0.089)	(0.109)	(0.082)	(0.090)	(0.097)	(0.095)	(0.093)	(0.085)	(0.092)	(0.091)	(0.089)
Binary variable: Home team	0.060***	0.049***	0.052***	0.038***	0.041***	0.036***	0.037***	0.045***	0.044***	0.041***	0.045***	0.050***	0.052***	0.044***	0.051***	0.045***	0.051***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Ratio of attendance to stadium capacity	-0.026	-0.045**	-0.028	-0.084***	-0.088***	-0.099***	-0.137***	-0.088***	-0.119***	-0.109***	-0.064***	-0.091***	-0.057**	-0.109***	-0.066**	-0.098***	-0.111***
	(0.021)	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)	(0.020)	(0.029)	(0.023)	(0.024)	(0.020)	(0.021)	(0.027)	(0.026)	(0.031)	(0.029)	(0.022)
Home * Ratio of attendance to stadium capacity	-0.036	0.005	0.010	0.050	0.049	0.009	0.107***	0.070	0.082**	0.044	0.005	-0.005	0.002	0.079*	-0.045	0.066	0.054
	(0.035)	(0.035)	(0.038)	(0.038)	(0.035)	(0.030)	(0.034)	(0.050)	(0.038)	(0.039)	(0.023)	(0.029)	(0.042)	(0.042)	(0.049)	(0.047)	(0.039)
Binary variable: Attendance not available	-0.020	-0.071	0.000	0.000	-0.053	-0.086***	-0.106**	0.000	0.000	-0.022	-0.038*	-0.091***	-0.021	0.000	0.000	-0.057	-0.069
	(0.073)	(0.074)	(0.000)	(0.000)	(0.035)	(0.025)	(0.047)	(0.000)	(0.000)	(0.081)	(0.020)	(0.024)	(0.080)	(0.000)	(0.000)	(0.059)	(0.057)
Constant	-9.718***	-10.700***	-11.427***	-11.279***	-11.418***	-11.459***	-12.189***	-13.192***	-12.334***	-12.536***	-14.124***	-12.976***	-12.648***	-12.866***	-12.189***	-12.412***	-12.495***
	(0.350)	(0.359)	(0.354)	(0.378)	(0.390)	(0.424)	(0.407)	(0.552)	(0.395)	(0.440)	(0.436)	(0.449)	(0.441)	(0.422)	(0.414)	(0.414)	(0.410)
Observations	2214	2214	2208	2214	2378	2354	2368	1446	2378	2350	2340	2330	2366	2456	2460	2460	2460
Number of teams	27	27	27	27	29	29	29	29	29	29	29	29	29	30	30	30	30
R-square	0.35	0.36	0.40	0.35	0.33	0.29	0.35	0.35	0.37	0.32	0.37	0.34	0.33	0.34	0.34	0.33	0.35
F-value	84.30	89.09	109.6	89.25	82.74	68.36	88.23	58.08	104.3	75.90	96.44	85.67	83.09	94.13	94.06	84.67	93.52
Team fixed effect	10.91	13.08	14.44	11.54	12.88	15.92	14.98	6.946	11.27	10.97	9.355	12.63	7.753	10.78	8.265	7.719	14.83

Notes:

1. Dependent variable and individual player performance variables are in logarithmic value (per the Cobb-Douglas production function)
2. Standard errors in parentheses
3. + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (all tests are two-tailed)

Table 27. Estimating a player's share of firm surplus using Harderstat-based measure of complementarity

Dependent variable: log [P/(1-P)] P defined in notes to the table		1	2	3	4
Complementarity	(H1a)			-2.916***	-2.946***
				(0.406)	(0.410)
Complementarity * All-star dummy	(H1b)				0.723
					(1.411)
All-star dummy			-0.272***	-0.262***	-0.273***
			(0.076)	(0.076)	(0.078)
Value above replacement			0.835***	0.835***	0.835***
			(0.025)	(0.025)	(0.025)
All-star votes			2.228**	2.142**	2.129**
			(0.704)	(0.702)	(0.702)
Defensive rating			-3.019***	-3.097***	-3.098***
			(0.532)	(0.531)	(0.531)
Experience			0.399***	0.402***	0.402***
			(0.017)	(0.017)	(0.017)
Experience squared			-0.021***	-0.021***	-0.021***
			(0.001)	(0.001)	(0.001)
Most valuable player nomination			-0.415***	-0.392***	-0.402***
			(0.079)	(0.079)	(0.081)
Best defensive player nomination			0.088	0.099	0.098
			(0.073)	(0.073)	(0.073)
Most improved player nomination			-0.207***	-0.194***	-0.194***
			(0.059)	(0.058)	(0.058)
Best sixth man nomination			-0.020	-0.013	-0.013
			(0.076)	(0.076)	(0.076)
Unrestricted free agent			-0.620***	-0.617***	-0.618***
			(0.030)	(0.030)	(0.030)
Rookie			-0.058	-0.061	-0.061
			(0.039)	(0.039)	(0.039)
Player still on drafting team			0.268***	0.273***	0.274***
			(0.034)	(0.033)	(0.033)
Team's prior success		-0.019	-0.069***	-0.014	-0.014
		(0.017)	(0.012)	(0.014)	(0.014)
Coach regular season win percent		0.298***	0.053	0.144*	0.144*
		(0.078)	(0.055)	(0.056)	(0.056)
MSA population		-0.596	-0.654*	-0.473	-0.479
		(0.418)	(0.296)	(0.296)	(0.296)
Fan cost index		-0.003***	-0.004***	-0.004***	-0.004***
		(0.001)	(0.000)	(0.000)	(0.000)
Constant		6.326	6.807	3.827	3.922
		(6.484)	(4.590)	(4.592)	(4.596)
Number of observations		6866	6866	6866	6866
R-squared		0.034	0.518	0.521	0.521
Log likelihood		-11261	-8877	-8851	-8851
Regression F-value		12.60	228.1	224.4	217.8
Team fixed effect F-value		7.324	13.21	12.62	12.61

Notes:
1. P = Player wage / [(Team annual wage + team operating income)]
2. Team's prior success: Number of times it reached playoffs in the last three years
3. All models include fixed effects for teams, years, and phases corresponding to CBAs
4. Standard errors in parentheses
5. + p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001 (all tests are two-tailed)

Table 28. Explaining complementarity using Harderstat-based measure of complementarity

Dependent variable: Complementarity		1 GLS	2 FE	3 GLS	4 FE
Team interaction	(H2)			0.083***	0.092***
				(0.012)	(0.017)
Team familiarity	(H2)			0.046*	0.053+
				(0.022)	(0.028)
Player dominance	(H3)			-0.345***	-0.310*
				(0.103)	(0.140)
Assists of in-traded players	(H4)			0.013**	0.013**
				(0.004)	(0.004)
Assists of lost players	(H4)			-0.012**	-0.013*
				(0.004)	(0.005)
Assists of drafted players	(H4)			0.002	0.002
				(0.003)	(0.004)
Unrestricted free agents on team		-0.007*	-0.011*	-0.005	-0.007
		(0.004)	(0.004)	(0.003)	(0.004)
Roster size		-0.051***	-0.066***	-0.002	-0.011
		(0.015)	(0.013)	(0.015)	(0.014)
Team all-star votes		0.010***	0.009***	0.009***	0.007***
		(0.001)	(0.001)	(0.001)	(0.001)
Coach experience		0.008***	0.010**	0.006***	0.008**
		(0.002)	(0.003)	(0.002)	(0.003)
Number of point guards in-traded		-0.001	0.000	0.001	0.001
		(0.001)	(0.002)	(0.001)	(0.001)
Players still on drafting team		-0.002**	-0.001	-0.002**	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
International players drafted		0.002	0.005	0.004	0.006
		(0.003)	(0.004)	(0.003)	(0.004)
High school players drafted		-0.001	-0.004	0.003	-0.002
		(0.005)	(0.006)	(0.005)	(0.006)
No player in-traded		-0.010	0.004	-0.007	0.006
		(0.019)	(0.007)	(0.020)	(0.009)
No player lost		0.025	0.011	-0.003	-0.014
		(0.022)	(0.013)	(0.022)	(0.010)
No player drafted		0.008	0.009	0.008	0.008
		(0.006)	(0.009)	(0.007)	(0.010)
MSA population		-0.011***	0.022	-0.009***	0.018
		(0.002)	(0.067)	(0.002)	(0.053)
Fan cost index		0.044***	0.024	0.039***	0.023
		(0.008)	(0.022)	(0.007)	(0.019)
Constant		0.036	-0.317	-0.094	-0.393
		(0.055)	(1.080)	(0.061)	(0.882)
Number of observations		457	457	457	457
R-squared		-	0.31	-	0.40
Team fixed effects		-	Yes	-	Yes
Log likelihood		-	962.5	-	995.9
Wald chi square		381.1		524.0	-

Notes:
1. All models include year fixed effects
2. Standard errors in parentheses (clustered by team in models 2 and 4)
3. + p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001 (all tests are two-tailed)

Table 29. Robustness tests for estimating a player's share of firm surplus using HGS-based measure of complementarity

Dependent variable		1 P	2 P	3 log[P/(1-P)]
Complementarity	(H1a)	-3.585***	-1.690+	-3.269***
		(1.044)	(0.940)	(0.436)
Complementarity * All-star dummy	(H1b)	1.381	0.276	0.094
		(1.571)	(2.326)	(1.423)
All-star dummy		-0.143+	-0.068	0.182*
		(0.076)	(0.136)	(0.079)
Value above replacement		0.597***	0.303***	
		(0.025)	(0.049)	
Player efficiency rating				58.983***
				(2.644)
All-star votes		2.140**	1.101	5.628***
		(0.741)	(1.196)	(0.719)
Defensive rating		-3.437***	-2.026	-7.994***
		(0.673)	(1.297)	(0.600)
Experience		0.375***	0.177***	0.462***
		(0.021)	(0.039)	(0.017)
Experience squared		-0.019***	-0.009***	-0.025***
		(0.002)	(0.003)	(0.001)
Most valuable player nomination		-0.236*	-0.125	0.017
		(0.100)	(0.141)	(0.082)
Best defensive player nomination		0.110	0.048	0.222**
		(0.072)	(0.126)	(0.075)
Most improved player nomination		-0.129*	-0.070	0.140*
		(0.054)	(0.112)	(0.059)
Best sixth man nomination		-0.093+	-0.064	0.088
		(0.050)	(0.154)	(0.079)
Unrestricted free agent		-0.460***	-0.223**	-0.716***
		(0.047)	(0.070)	(0.031)
Rookie		-0.072	-0.030	-0.095*
		(0.049)	(0.091)	(0.040)
Player still on drafting team		0.197***	0.099	0.311***
		(0.039)	(0.072)	(0.035)
Team's prior success		0.015	0.004	-0.014
		(0.030)	(0.032)	(0.015)
Coach regular season win percent		0.146	0.071	0.147*
		(0.118)	(0.127)	(0.059)
MSA population		-0.112	-0.011	-0.433
		(0.870)	(0.092)	(0.309)
Fan cost index		-0.004***	-0.002+	-0.003***
		(0.001)	(0.001)	(0.000)
Constant		-1.445	-1.461	3.246
		(13.176)	(1.409)	(4.794)
Number of observations		6866	6866	6866
R-squared		-	-	0.48
Regression F-value		-	-	185.0
Team fixed effect F-value		-	-	11.6

Notes:
1. P = Player wage / [(Team annual wage + team operating income)]
2. Team's prior success: Number of times it reached playoffs in the last three years
3. Model 1 uses the generalized linear model; Model 2 uses the generalized estimating equation; Model 3 uses player efficiency rating instead of VAR in a fixed effects model
4. All models include fixed effects for years and phases corresponding to CBAs
5. Models 1 and 3 include team fixed effects
6. Standard errors in parentheses
7. + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (all tests are two-tailed)

Table 30. Robustness tests for explaining complementarity using HGS-based measure of complementarity

Dependent variable: Complementarity		1 IV	2 GLS	3 FE	4 GLS	5 FE
Team interaction	(H2)	0.090*	0.071***	0.085***	0.065***	0.082***
		(0.040)	(0.013)	(0.018)	(0.013)	(0.018)
Team familiarity	(H2)	0.049+	0.040+	0.047*	0.045*	0.052*
		(0.027)	(0.022)	(0.021)	(0.022)	(0.024)
Player dominance	(H3)	-0.259*	-0.352**	-0.287+	-0.317**	-0.254
		(0.128)	(0.107)	(0.149)	(0.107)	(0.156)
Assists of in-traded players	(H4)	0.013*	0.014**	0.016***		
		(0.006)	(0.004)	(0.004)		
Assist percentage of in-traded players	(H4)				0.006+	0.007*
					(0.003)	(0.003)
Assists of lost players	(H4)	-0.013*	-0.009*	-0.012+		
		(0.006)	(0.004)	(0.006)		
Assist percentage of lost players	(H4)				-0.003	-0.005
					(0.003)	(0.004)
Assists of drafted players	(H4)	0.000	0.000	0.000	-0.001	0.000
		(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Unrestricted free agents on team		-0.006	-0.006+	-0.007+	-0.005	-0.006
		(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Roster size		0.004	0.005	0.005	-0.002	-0.004
		(0.027)	(0.016)	(0.016)	(0.016)	(0.017)
Team all-star votes		0.009***	0.011***	0.008***	0.011***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Coach experience		0.007**			0.005**	0.007*
		(0.002)			(0.002)	(0.003)
Coach team-specific experience			0.007**	0.012*		
			(0.003)	(0.006)		
Number of point guards in-traded		0.001	0.001	0.001	0.002	0.001
		(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Players still on drafting team		-0.001	-0.002**	-0.001	-0.002*	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
International players drafted		0.005	0.003	0.005	0.003	0.005
		(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
High school players drafted		-0.003	-0.003	-0.004	-0.003	-0.003
		(0.006)	(0.005)	(0.007)	(0.005)	(0.007)
No player in-traded		-0.001	-0.006	-0.002	-0.001	0.003
		(0.023)	(0.022)	(0.017)	(0.023)	(0.015)
No player lost		-0.012	-0.013	-0.012	-0.012	-0.012
		(0.023)	(0.024)	(0.010)	(0.024)	(0.015)
No player drafted		0.002	0.003	0.003	0.000	0.002
		(0.009)	(0.008)	(0.010)	(0.008)	(0.011)
MSA population		0.043	-0.008***	0.033	-0.009***	0.037
		(0.040)	(0.002)	(0.062)	(0.002)	(0.059)
Fan cost index		0.032*	0.050***	0.028	0.052***	0.031
		(0.013)	(0.008)	(0.018)	(0.008)	(0.019)
Constant		-0.897	-0.167**	-0.717	-0.154*	-0.769
		(0.642)	(0.064)	(1.022)	(0.064)	(0.978)
Number of observations		457	457	457	457	457
R-squared		-	-	0.41	-	0.39
Team fixed effects		Yes	-	Yes	-	Yes
Log likelihood		-	-	994.2	-	989.8
Wald Chi Square		232.5	569.1	-	545.1	-

Notes:
1. All models include year fixed effects
2. Standard errors in parentheses (clustered by team in models 3 and 5)
3. + p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001 (all tests are two-tailed)

Table 31. Hazard of a player's departure from a franchise

Dependent variable: Player's departure from a team Model: Cox proportional hazard	1	2	3	4
Complementarity (Harderstat-based)				-0.833*
				(0.338)
Complementarity (HGS-based)			-0.790*	
			(0.330)	
Cumulative number of teams changed		0.332***	0.331***	0.331***
		(0.030)	(0.030)	(0.030)
(Log) Player annual salary (constant dollars)		0.126***	0.124***	0.123***
		(0.018)	(0.017)	(0.017)
Unrestricted free agent		0.276***	0.277***	0.277***
		(0.031)	(0.031)	(0.031)
All-star votes		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
Value above replacement		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
Defensive rating		0.003	0.002	0.002
		(0.002)	(0.002)	(0.002)
Experience		-0.126***	-0.122***	-0.122***
		(0.018)	(0.018)	(0.018)
Most valuable player nomination		-0.603**	-0.589**	-0.587**
		(0.207)	(0.207)	(0.207)
Best defensive player nomination		-0.253	-0.241	-0.240
		(0.180)	(0.177)	(0.177)
Most improved player nomination		-0.369**	-0.370**	-0.368**
		(0.119)	(0.119)	(0.119)
Best sixth man nomination		-0.195	-0.182	-0.180
		(0.138)	(0.138)	(0.138)
Rookie		0.017	0.016	0.016
		(0.042)	(0.042)	(0.042)
Team's prior success	-0.041***	-0.038***	-0.035***	-0.035***
	(0.010)	(0.011)	(0.011)	(0.011)
Coach experience	0.005**	0.006***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
CBA - 2	0.062	0.042	0.034	0.032
	(0.080)	(0.080)	(0.080)	(0.080)
CBA - 3	-0.013	-0.114	-0.128	-0.128
	(0.082)	(0.086)	(0.086)	(0.086)
CBA - 4	-0.160+	-0.162+	-0.169+	-0.170+
	(0.090)	(0.087)	(0.087)	(0.087)
Observations	5825	5825	5825	5825
Year fixed effects	Yes	Yes	Yes	Yes
Log likelihood	-10792	-10713	-10712	-10712
Regression F-value	115.9	414.2	419.9	420.0

Notes:
1. Coefficient estimates reported above are not hazard ratios
2. Team's prior success: Number of times it reached playoffs in the last three years
3. Standard errors in parentheses
4. + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (all tests are two-tailed)

Table 32. Estimating a player's share of firm surplus using CES production function to calculate game-level complementarity

Dependent variable: log [P/(1-P)] P defined in notes to the table		HGS measure of complementarity 1	2	3	4	Harderstat measure of complementarity 5	6	7	8
Complementarity	(H1a)			-3.116***	-3.138***			-2.793***	-2.818***
				(0.431)	(0.435)			(0.406)	(0.410)
Complementarity * All-star dummy	(H1b)				0.530				0.609
					(1.441)				(1.418)
All-star dummy			-0.272***	-0.260***	-0.267***		-0.272***	-0.262***	-0.271***
			(0.076)	(0.076)	(0.078)		(0.076)	(0.076)	(0.078)
Value above replacement			0.835***	0.833***	0.833***		0.835***	0.835***	0.835***
			(0.025)	(0.025)	(0.025)		(0.025)	(0.025)	(0.025)
All-star votes			2.228**	2.193**	2.169**		2.228**	2.142**	2.131**
			(0.704)	(0.701)	(0.705)		(0.704)	(0.702)	(0.702)
Defensive rating			-3.019***	-3.170***	-3.169***		-3.019***	-3.103***	-3.105***
			(0.532)	(0.531)	(0.531)		(0.532)	(0.531)	(0.531)
Experience			0.399***	0.404***	0.404***		0.399***	0.402***	0.402***
			(0.017)	(0.017)	(0.017)		(0.017)	(0.017)	(0.017)
Experience squared			-0.021***	-0.021***	-0.021***		-0.021***	-0.021***	-0.021***
			(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
Most valuable player nomination			-0.415***	-0.399***	-0.404***		-0.415***	-0.394***	-0.402***
			(0.079)	(0.079)	(0.080)		(0.079)	(0.079)	(0.081)
Best defensive player nomination			0.088	0.099	0.098		0.088	0.098	0.097
			(0.073)	(0.073)	(0.073)		(0.073)	(0.073)	(0.073)
Most improved player nomination			-0.207***	-0.195***	-0.194***		-0.207***	-0.195***	-0.194***
			(0.059)	(0.058)	(0.058)		(0.059)	(0.058)	(0.058)
Best sixth man nomination			-0.020	-0.016	-0.015		-0.020	-0.013	-0.013
			(0.076)	(0.076)	(0.076)		(0.076)	(0.076)	(0.076)
Unrestricted free agent			-0.620***	-0.619***	-0.619***		-0.620***	-0.618***	-0.618***
			(0.030)	(0.030)	(0.030)		(0.030)	(0.030)	(0.030)
Rookie			-0.058	-0.060	-0.060		-0.058	-0.061	-0.061
			(0.039)	(0.039)	(0.039)		(0.039)	(0.039)	(0.039)
Player still on drafting team			0.268***	0.277***	0.277***		0.268***	0.274***	0.274***
			(0.034)	(0.033)	(0.034)		(0.034)	(0.033)	(0.034)
Team's prior success		-0.019	-0.069***	-0.016	-0.016	-0.019	-0.069***	-0.017	-0.017
		(0.017)	(0.012)	(0.014)	(0.014)	(0.017)	(0.012)	(0.014)	(0.014)
Coach regular season win percent		0.298***	0.053	0.153**	0.153**	0.298***	0.053	0.139*	0.139*
		(0.078)	(0.055)	(0.057)	(0.057)	(0.078)	(0.055)	(0.056)	(0.056)
MSA population		-0.596	-0.654*	-0.440	-0.444	-0.596	-0.654*	-0.486	-0.491+
		(0.418)	(0.296)	(0.297)	(0.297)	(0.418)	(0.296)	(0.296)	(0.296)
Fan cost index		-0.003***	-0.004***	-0.004***	-0.004***	-0.003***	-0.004***	-0.004***	-0.004***
		(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Constant		6.326	6.807	3.298	3.359	6.326	6.807	4.033	4.109
		(6.484)	(4.590)	(4.598)	(4.602)	(6.484)	(4.590)	(4.592)	(4.596)
Number of observations		6866	6866	6866	6866	6866	6866	6866	6866
R-squared		0.034	0.518	0.521	0.521	0.034	0.518	0.521	0.521
Log likelihood		-11261	-8877	-8851	-8851	-11261	-8877	-8853	-8853
Regression F-value		12.60	228.1	224.4	217.8	12.60	228.1	224.1	217.5
Team fixed effect F-value		7.324	13.21	12.51	12.50	7.324	13.21	12.71	12.70

Notes:
1. P = Player wage / [(Team annual wage + team operating income)]
2. Team's prior success: Number of times it reached playoffs in the last three years
3. All models include fixed effects for teams, years, and phases corresponding to CBAs
4. Standard errors in parentheses
5. + p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001 (all tests are two-tailed)

Table 33. Explaining complementarity using CES production function to calculate game-level complementarity

	HGS measure of complementarity				Harderstat measure of complementarity			
Dependent variable: Complementarity	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	GLS	**FE**	**GLS**	**FE**	**GLS**	**FE**	**GLS**	**FE**
Team interaction			0.062***	0.080***			0.083***	0.090***
			(0.012)	(0.018)			(0.012)	(0.017)
Team familiarity			0.043*	0.050*			0.046*	0.052+
			(0.022)	(0.023)			(0.022)	(0.028)
Player dominance			-0.300**	-0.227			-0.362***	-0.309*
			(0.104)	(0.141)			(0.102)	(0.141)
Assists of in-traded players			0.010*	0.011*			0.013**	0.014**
			(0.004)	(0.005)			(0.004)	(0.004)
Assists of lost players			-0.009*	-0.012*			-0.012**	-0.013*
			(0.004)	(0.006)			(0.004)	(0.005)
Assists of drafted players			-0.001	-0.001			0.002	0.002
			(0.004)	(0.004)			(0.003)	(0.004)
Unrestricted free agents on team	-0.008*	-0.010*	-0.005	-0.006	-0.007*	-0.012*	-0.005	-0.007+
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Roster size	-0.037**	-0.049**	-0.001	-0.002	-0.051***	-0.066***	-0.002	-0.012
	(0.014)	(0.014)	(0.015)	(0.016)	(0.015)	(0.013)	(0.015)	(0.014)
Team all-star votes	0.011***	0.010***	0.010***	0.008***	0.010***	0.009***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Coach experience	0.005**	0.007*	0.004*	0.006+	0.008***	0.009**	0.006***	0.008*
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Number of point guards in-traded	0.001	0.001	0.002	0.002	-0.001	0.000	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Players still on drafting team	-0.002**	-0.001	-0.002*	-0.001	-0.002**	-0.001	-0.002**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
International players drafted	0.003	0.005	0.003	0.005	0.002	0.005	0.003	0.006
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
High school players drafted	-0.004	-0.005	-0.004	-0.005	-0.001	-0.003	0.003	-0.002
	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)
No player in-traded	-0.007	-0.005	-0.004	-0.003	-0.014	-0.000	-0.011	0.002
	(0.020)	(0.008)	(0.021)	(0.016)	(0.020)	(0.007)	(0.020)	(0.011)
No player lost	0.003	0.008	-0.020	-0.014	0.024	0.010	-0.004	-0.015
	(0.021)	(0.009)	(0.022)	(0.013)	(0.022)	(0.014)	(0.022)	(0.010)
No player drafted	0.001	0.001	-0.002	-0.003	0.007	0.009	0.007	0.007
	(0.006)	(0.009)	(0.007)	(0.010)	(0.006)	(0.009)	(0.007)	(0.010)
MSA population	-0.010***	0.043	-0.008***	0.040	-0.010***	0.020	-0.009***	0.015
	(0.002)	(0.067)	(0.002)	(0.058)	(0.002)	(0.068)	(0.002)	(0.054)
Fan cost index	0.053***	0.028	0.047***	0.027	0.045***	0.023	0.040***	0.022
	(0.008)	(0.020)	(0.008)	(0.017)	(0.008)	(0.022)	(0.007)	(0.019)
Constant	-0.059	-0.707	-0.140*	-0.793	0.029	-0.278	-0.099	-0.348
	(0.053)	(1.079)	(0.061)	(0.961)	(0.055)	(1.092)	(0.060)	(0.899)
Number of observations	457	457	457	457	457	457	457	457
R-squared	-	0.300	-	0.378	-	0.307	-	0.400
Team fixed effects	-	Yes	-	Yes	-	Yes	-	Yes
Log likelihood	-	983.4	-	1010	-	964.3	-	997.2
Wald chi square	407.0	-	482.3	-	382.4	-	529.8	-

Notes:
1. All models include year fixed effects
2. Standard errors in parentheses (clustered by team in models 2, 4, 6, and 8)
3. + $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (all tests are two-tailed)

Appendix

Appendix 1: Estimating complementarity for basketball from the Cobb-Douglas production function and general CES production function

Consider a standard Cobb-Douglas production function describing the production of output Y using two inputs, labor (L) and capital (K). Thus,

$$Y = AL^{\alpha}K^{\beta} \quad \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where A is total factor productivity, α the elasticity of output to changes in labor, and β the elasticity of output to changes in capital. Several features of the model emerge from equation (1):

1. The multiplicative term indicates that labor and capital are both needed for output. However, both labor and capital are infinitely substitutable.
2. The values of α and β capture returns to scale in inputs. If $\alpha + \beta = 1$, the production function exhibits constant returns to scale, i.e., a unit change in inputs (labor and capital) results in a unit change in output.
3. Total factor productivity (TFP) = $A = Y/L^{\alpha}K^{\beta}$. Thus, A captures the joint productivity of inputs.

The logarithmic form of the Cobb-Douglas function makes it empirically tractable. We have

$$\ln(Y) = \ln(A) + \alpha\ln(L) + \beta\ln(K) \quad \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Equation (2) shows that by regressing observed output Y on observed inputs L and K, the coefficients α and β capture the marginal product of a unit of labor and capital respectively, and the residual A captures total factor productivity, an unobservable.

There are several important assumptions underlying equation (2):

1. The inputs have no quadratic effects on output, i.e., substituting labor for capital and vice versa has no impact on output. However, it is possible that both labor and capital may have nonlinear effects on output.
2. The inputs have no interaction effects, i.e., different combinations of labor and capital have no output effects. In other words $\partial^2Y/\partial L\partial K = 0$.
3. There are no other relevant inputs related to labor and capital that are omitted from equation (2).

If the above three assumptions are met, we would expect that regressing output on labor and capital will yield an almost perfect regression R-square. In other words, the quantity of inputs and the relationship among them will perfectly predict output. However, if any of the above assumptions is violated, it would be tantamount to omitted variables that would be captured in the residual term, A. Thus, in equation (2), the residual can reflect the combination of one or more of the following effects: (1) inputs have nonlinear effects, (2) inputs have interaction effects or complementarities, or (3) relevant inputs are omitted.

In sum, in the Cobb –Douglas specification, if it is possible to rule out the possibility of omitted variables, and nonlinear effects of inputs, the residual is an empirical estimate of the complementarity among inputs.

Translating the canonical discussion of the Cobb-Douglas specification into the basketball context, consider team output to be a win or a loss captured as a ratio of points for (PF) and points against (PA). The only input here is labor or the players. Thus, the output function is:

$$\frac{\mathrm{PF}}{\mathrm{PA}} = \mathrm{AL}_{\mathrm{k}}^{\propto_{\mathrm{k}}}$$

where k is the number of players. The logarithmic form is:

$$\ln\left(\frac{\mathrm{PF}}{\mathrm{PA}}\right) = \ln(\mathrm{A}) + \sum_{\mathrm{k}} \propto_{\mathrm{k}} \ln(\mathrm{L}_{\mathrm{k}})$$

If the assumptions of the Cobb-Douglas production function hold, then A = 0 and the coefficients α_k reflect the marginal product of labor. In the case of basketball, it is possible to rule out nonlinear effects of players because players are indivisible and only five players can remain on court at any time. However, it is possible that the amount of time that a player remains on court can have nonlinear effects on team output because of factors such as fatigue. If we control for time on court, such nonlinear effects are accounted for. Similarly, since labor is the predominant input to a team's output, the concern of omitted inputs is minimal. Other variables such as the home environment (that influences player motivation) and spectator attendance may have important effects on a team's output. If we can control for such effects, then the residual should only contain the interaction effects between the players. Thus, we use the residual from the Cobb-Douglas specification of the basketball production function as a proxy for complementarity among players at the game level.

Following Hoff (2004), the linear approximation of the *n*-input general CES production function for the specific case of this study would be:

$$\ln\left(\frac{\mathrm{PF}}{\mathrm{PA}}\right) = \ln(\mathrm{A}) + \sum_{\mathrm{k}} \propto_{\mathrm{k}} \ln(\mathrm{L}_{\mathrm{k}}) + \sum_{\mathrm{k}} \sum_{\mathrm{j}} \alpha_{\mathrm{kj}} \ln(\mathrm{L}_{\mathrm{k}}) \ln(\mathrm{L}_{\mathrm{j}}) \text{ where k, j} = 1 \text{ to n}$$

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