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WHAT DO MANAGERS DO? AN ECONOMIST'S PERSPECTIVE

Alan M. Benson  
Kathryn L. Shaw

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**ABSTRACT**

Economic activity, when sufficiently ambitious, requires motivating and coordinating individuals to work toward a common goal. These aims are the purview of managers. What, however, do managers actually do? We outline three defining principles of economic research on managers and relate them to the set of skills reported by managers on LinkedIn. We highlight “managers of people” and “managers of projects” as a useful distinction for categorizing theoretical, empirical, and descriptive accounts of managers. In light of our three principles, we review research on how managers can create value—namely, by hiring, retaining, training, monitoring, evaluating, allocating, and supervising. We propose that managers apply these skills in different proportions depending on the production technology in which they are embedded and that research on managers should seek to produce generalizable insights by exploring managers’ contributions in different contexts.

Alan M. Benson  
University of Minnesota  
Carlson School of Management  
321 19th Ave S, 3-300  
Minneapolis, MN 55409  
bensona@umn.edu

Kathryn L. Shaw  
Graduate School of Business  
Stanford University  
Stanford, CA 94305-5015  
and NBER  
kathryns@stanford.edu

# What Do Managers Do? An Economist's Perspective\*

Alan Benson                      Kathryn Shaw  
University of Minnesota      Stanford University

## Abstract

Economic activity, when sufficiently ambitious, requires motivating and coordinating individuals to work toward a common goal. These aims are the purview of managers. What, however, do managers actually do? We outline three defining principles of economic research on managers and relate them to the set of skills reported by managers on LinkedIn. We highlight “managers of people” and “managers of projects” as a useful distinction for categorizing theoretical, empirical, and descriptive accounts of managers. In light of our three principles, we review research on how managers can create value— namely, by hiring, retaining, training, monitoring, evaluating, allocating, and supervising. We propose that managers apply these skills in different proportions depending on the production technology in which they are embedded and that research on managers should seek to produce generalizable insights by exploring managers’ contributions in different contexts.

JEL Classifications: M5: Personnel economics; M1: Business administration; M2: Business economics; J24: Human capital, skills, occupational choice, productivity; D23: Organizational behavior, transaction costs, property rights; L23: Organization of production

Keywords: Managers, people management, personnel economics, organizational economics, hiring, motivation, training, performance evaluation, monitoring, supervision, incentives, promotions, human resource management

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# 1 INTRODUCTION

What do managers do? As economists, we pursue this question by probing how managers add value for their firms. Our inquiry is disciplined by the common set of principles that also underlie other areas of applied microeconomics, tailored to study the multitude of managers' activities. It is an exciting time in our field. Companies are awash in detailed and standardized personnel data, offering fallow ground for researchers to cultivate our understanding of how managers hire, train, and direct workers in service of the firm's objectives. Our article is for those researchers and for anyone interested in the major themes, the specific topics, and the current state of economic research on managers.

Our goal is to provide a foundation for thinking about managers and our view of how recent work is situated upon it. We begin by defining our economic perspective of managers in terms of three fundamental principles: what managers do depends on the production technology, managers' skill sets, and their incentives. These points pervade the papers in the research literature.

Our primary unifying observation that technological patterns give rise to "managers of people" and "managers of projects." In settings where work is generally done by independently working individual contributors with either strong performance metrics or strong dedication to work, managers more closely resemble "people managers" who primarily take responsibility for hiring, retaining, and training their subordinates. In settings where work is carried out primarily by highly interdependent work units, managers more closely resemble "project managers" who do the work of monitoring, planning, and coordinating the activities of their team. In practice, most managers do elements of both, but we argue that this axis proves useful for understanding both the theoretical and empirical literature on managers, as well as real-world descriptions of what managers do.

Our designation that there are two types of managers – people managers and project managers – comes from our assessment of theoretical and empirical literature, a case study, and a descriptive analysis of the near-universe of manager's professional profiles on LinkedIn. These are laid out in Sections 4 through 6 below.

What managers do is create value for their firms, and we build upon our foundation above to review the evidence, in Section 7, on the specific ways managers create value. We focus on six activities: hiring, retaining, training, motivating, evaluating, and allocating workers. Our survey of these topics reflects our three principles: Managers operate in different technological environments, apply different skills, and respond to personal incentives. Across these activities, we present available evidence on how managers vary in their respective ability, and how delegating authority to managers may enable them to leverage local information but also invite opportunism and bias.

Our final four sections bring together the implications of the review. Section 9 takes the elements of what managers do and relates them back to our people managers/project managers distinction. Section 11 considers managers as leaders and expert contributors embedded in teams. Section 12 reviews the empirical methods used to study managers. Section 8 provides our view of what we know from the economic literature on managers, what we do not know, and some thoughts on artificial intelligence.

Our chief thesis is that this new collection of empirical work is building a more complete picture of how managers create value for their organizations and, in some cases, where value is lost. Before reviewing this empirical work, we posit that there are people managers and project managers, forming a foundation for thinking about the value of managers. Ultimately, researchers' lessons gleaned from many settings may be extended not only to the immediate challenges facing firms, but also to emerging questions such as how new technologies will shape what managers do in the future.

## 2 AN ECONOMIC PERSPECTIVE OF MANAGERS

In our view, the economic perspective on managers builds upon a common set of starting principles. These principles underlie a broad spectrum of work in applied economics but hold special relevance for economists who study managers.

1. *Technology determines the activities of workers and managers.* Technologies are chosen by firms as they maximize profits to produce a sustainable competitive advantage. Mid-level managers take the firm's technology as given, including the major human resource management practices of the firm.
2. *Each manager's skills are distinctively different, as each manager possesses a cluster of skills relevant to their work area's technology.* The firm determines the larger production technology, and thus managers' skills would vary by firm or industry or work group. In addition, in the short run, managers may exert discretion over how work is carried out, who is selected to do tasks, and how to motivate workers. All together, this involves the application of many managerial skills, spanning the technology of firms and the methods a manager chooses for her work group, creating many unique skill combinations for managers.
3. *Managers are guided by their own self-interest.* Just as managers manage self-interested workers, principals manage self-interested managers. Managers then respond to monetary or nonmonetary incentives, but their interests are not presumed to be equivalent to the firm's. Principals set policies to encourage managers to apply their local information productively.

Other factors will also determine the manager’s goals and the specifics of the models that researchers apply.

Thus, the writer of every research paper should answer the following questions: what is the specific technology that determines the activities of workers and managers; what skill set does the manager need; and how is the manager guided by their own self-interest or incentives? The writer needs these answers before he begins his analysis, viewing them as inputs into modelling what managers do as they create value for firms.

Readers should find that researchers addressed the three principles to motivate the details they put into their research. This feeds into the theoretical models and methods researchers apply. Because much current empirical research is done within one firm, we use our discipline’s principles to underlie theory, produce generalizable claims, and inoculate the literature against becoming a collection of anecdotes (Lazear, 2012; Hoffman and Stanton, 2024).

As a practical matter, empirical research has advanced one in-depth investigation at a time, in an effort to reveal what market-level data cannot (what Ichniowski and Shaw (2013), refer to as “insider econometrics”). Using data from “inside” firms, one study might test whether supervisors with better interpersonal skills are better at motivating workers, and another may test whether managers are biased in whom they hire and promote. Understanding the environment – technology, skills, and managerial incentives – is the starting point for answering questions within firms.

### 3 TECHNOLOGY GIVES RISE TO TWO TYPES OF MANAGERS

Economics provides at least one very strong theoretical reason to believe that managers create value: the existence of firms and managers themselves. As noted by Gibbons and Waldman (1999), firms exist because they outcompete markets in some instances, presumably where managerial fiat is more efficient than market prices. Without a market inside firms, individual workers or groups of workers must be held responsible for achieving the organization’s goals.

We posit that there are two types of technology are key to uncovering what managers do: Technology Type 1, individual work, and Technology Type 2, group work. These two types form the *locus of accountability* within the firm from which to consider the accountability of workers and of managers. The locus of accountability is the place where technology is situated or work occurs such that the roles of managers and workers follow from it.

The first technology, Technology Type 1, is individual work done in a wide range of settings. This can be is a setting with easily measurable individual output, that is useful for tying pay to performance, as would occur in work with commission. Or it can be a setting in which individuals gain great personal utility from

their work, as might software workers. *The locus of accountability lies primarily with the worker.* As a result, managers are largely responsible for hiring and training workers, but not necessarily for directing or monitoring them because those objectives can be fulfilled by tying pay or employment to the workers' measurable performance outcomes. *We define the type of managers here to be "people managers."*

The second technology, Technology Type 2, is group work also done with a breadth of technologies. This can be a setting in which production is carried out by a group of workers, who may be interdependent team members working toward some single collective deliverable. *The locus of accountability lies with the manager and the team as a whole.* As a result, managers are responsible for monitoring group projects, allocating the interdependent work of group members, and the production planning. These managers may directly supervise work on projects or production lines. It is very difficult to provide workers with the right individual incentives, so the broader set of coordinating and monitoring activities that must be performed by the manager of their group. *We define the type of managers here to be "project managers."*

This general theme of accountability, which has been situated on standardized theoretical foundations since at least [Alchian and Demsetz \(1972\)](#); [Holmström \(1979, 1982\)](#), calls attention to the importance of the underlying technology in determining what managers do. Where accountability lies generally depends on whether production is interdependent, coordinated, and measured at a group level. In the long run, these features are determined by the prevailing production technology; recall Principle 1 that technology shapes the activities of workers and managers.

Overall, the scope of possible activities that managers might perform is immense, and our review highlights the potentially common tasks of hiring, retaining, training, motivating, evaluating, and allocating. However, not all managers do all these things; recall Principle 2 that managers' skills reflect technology. Rather, the manager's responsibility over these tasks is a product of the firm's and senior managers' decision to delegate authority over these tasks. Typically, first-line managers have little formal authority, in that final decisions that are highly consequential for their subordinates must be at least rubber-stamped by bosses. However, in the nomenclature of [Aghion and Tirole \(1997\)](#), in some cases, front-line managers possess tremendous real authority over employment decisions because the benefits to the firm of leveraging the managers' local knowledge outweigh the costs of monitoring and decisions to discipline the pursuit of their own imperfectly aligned interests (Principle 3). In environments where subordinates work independently, where individual performance is well measured, and where concerns such as quality or reputation do not spill over to the group, real authority over how to perform the work can be further delegated to subordinates, and managers have little need to direct them.<sup>1</sup> In environments where work is

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<sup>1</sup> this case, workers can be paid an incentive in lieu of monitoring if their output is contractible (e.g., [Bandiera et al. \(2021\)](#)) or, more commonly, a salary with monitoring (as in, for example [Shapiro and Stiglitz \(1984\)](#)).

interdependent and outcomes are uncertain, keeping real authority with managers allows them to respond swiftly to issues, direct workers, and make adjustments based on incoming information.<sup>2</sup> As we will argue, differences in the locus of accountability and its attendant implications give rise to the distinction between people managers and project managers that we see in our vignette study, in LinkedIn professional profiles, and in the settings evaluated in the empirical literature.

## 4 DIFFERENT MANAGERS APPLY DIFFERENT SKILLS

A managers' productivity can be thought of as a function of the production technology, the managers' ability or skill, and their motivation—the determining factor is whether they enhance the productivity of their subordinates either individually or as a group. More simply, the manager's success, then, depends on whether she has the right skill mix and incentives to deliver what the firm needs from her at that time.

A first perspective is to show that some managers can produce highly productive workers, and some cannot. [Lazear et al. \(2015\)](#) use panel data on managers and workers, in technology-based jobs that measure worker productivity as they do fairly routine tasks. Their result is that managers have a very large impact on workers' productivity. Some managers are able to elicit high productivity from workers, such that their workers are in the 90th percentile of the productivity distribution. Other managers produce workers who are at the 10th percentile of worker productivity. Workers are doing the same job at each point in time, but some work much faster. How big is the difference across managers? Compare those managers have workers in the 90th-percentile, to those managers with workers in the 10th percentile. That means that the worker productivity for the top managers is equal to adding one more worker's output to a team of nine workers. Some managers are very highly skilled and some are not. The econometric results suggest that the best managers are motivating the workers.

In another paper whose goals is to estimate manager effects, [Metcalfe et al. \(2023\)](#) exploit homogeneity in work technology across in two large retailers to conclude that a substantial share of the variation in performance across stores is owed to variation in manager quality. They find that who makes a good manager is hard to predict on the basis of the relatively limited set of observable manager characteristics, though the authors find that managers who perform well in terms of labor productivity also appear to be good managers on other metrics.

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<sup>2</sup> In some settings, the locus of accountability can also be higher than the manager, meaning that the manager's decisions also affect the larger organization. When limited liability constraints or measurement issues limit the use of incentives to solve moral hazard problems, managers are presumably subject to greater oversight and possess less real authority even if this impairs their application of local knowledge. [Aghion et al. \(2021\)](#) provide a recent review on the tradeoffs firms make when deciding whether to delegate decisions to lower-level managers. We are most concerned with lower-level managers making shop-floor decisions and so see accountability at higher levels as also leading managers to resemble project managers in terms of what they do.



Overall, high performing managers could have different personal traits, or appropriate skills, or appropriate human capital. For economists, the focus is on his skills or human capital is always important.

To imagine the range of human capital that managers have across the many possible jobs, the study of managers needs theoretical conceptions of human capital needed across jobs. Several approaches, such as the task-specific human capital framework (Gibbons and Waldman, 2004) or the skills-weights approach (Lazear, 2009) do this. Lazear conceives of human capital as multidimensional, and posits that a firm's specific needs are some weighted combination of technologically general skills. For instance, for the chair of a history department, skills in research and teaching history will be important, as would budgeting and managing personnel. These skills are individually generalizable to different jobs, but a managerially talented history professor would have skills particularly valued in that one role.

Pushing Lazear's (2009) idea that firms may value skills in certain combinations, a single job in an organization has its own unique skill combination, and thus many managers have very distinct skill combinations. This is an important way to think about managers' value to the firm, going beyond the black box of firm-specific skills.

#### 4.1 Managers in settings with individual worker performance

In individual work settings of Technology Type 1, the managers are *people managers* in that they manage individuals and rely on the managerial skills of value in different work settings to do so. Researchers find conflict between what worker skills produce current success and the skills he will need when promoted to be a manager.

One incarnation of this idea is the "Peter principle": the notion that organizations weight the worker's past job performance in sales when making promotion to manager decisions, even though the skills for the manager are very different from those as a sales worker. Benson et al. 2019 use data on sales workers from 131 firms, to find that firms prioritize prior sales performance in promotion decisions at the expense of other indicators, such as collaboration between salesworkers, which better predicts success in management. This tension arises because organizations use promotions for two purposes: promotion is both an incentive for hard work to get promoted, and promotion is for the workers who have the right skills needed for the new match to be manager. For instance, as Baker et al. 1988 note, "in many cases, the best performer at one level in the hierarchy is not the best candidate for the job one level up—the best salesman is rarely the best manager." Similarly, Weidmann et al. 2024 find that managers selected on measurable indicators of economic decision-making and fluid intelligence outperform managers who are randomly selected, self-selected, or selected based on task skill. Using data on executives, Kaplan et al. 2012 find that personality traits predict managerial success, though Weidmann et al.'s 2024 study of mid-level managers

finds that personality traits are less predictive of success than managerial skills themselves. In Section 8.5, we return to the larger set of studies that have assessed performance evaluations as a tool for identifying high-potential workers.

Other researchers have estimated the economic significance of people skills as one required skill for managers. Deming and Kahn 2018 find substantial variation in the mix of skill requirements for professionals and managers across firms and corroborate the importance of social skills for advancement. Hoffman and Tadelis 2021 find that survey-measured people management skills are correlated with managerial productivity, at least along the dimension of retaining subordinates.

#### 4.2 Managers in settings with group or team performance

In group-based work settings of Technology Type 2, the managers are *project managers* and their workers seek to collaborate to achieve collective goals. The value of project managers cannot be measured by the sum product of individual workers. Here, too, the literature makes clear that there is extensive variation in managers' skills and productivity. Much of this literature was born from the now well-established observation that there are large and persistent productivity differences across similar enterprises, where managers are managing establishments (e.g., Bloom and Reenen (2007); Syverson (2004, 2011); Hsieh and Klenow (2009); Ichniowski et al. (1997)).

Are these persistent productivity differences attributable to heterogeneity in the quality of managers or of the establishments? Several recent papers establish that managers improve productivity and shy why using clever modelling. Fenizia 2022 examines this question using data from managerial rotations among Italian civil servants. She finds that a one standard deviation increase in managerial talent increases office productivity by 10%, partly through hiring and selective attrition. Giorcelli 2019 exploits an unexpected budget cut in a US federal program that provided managerial skills training to Italian managers in the 1950s. She finds that firms with treated managers enjoyed long-term increases in productivity. Using detailed survey data from German manufacturing firms, Bender et al. 2018 find that manager human capital explains substantial variation in the relationship between firm practices and productivity, suggesting that better managers both are more likely to adopt better practices and are better managers themselves.

In the context of garment production lines, where work is highly interdependent, Adhvaryu et al. 2023a find that manager quality varies widely and that skills related to the preservation of managerial attention and control are especially strong predictors of productivity across production line. Metcalfe et al. (2023) exploit homogeneity in practices in two large retailers to conclude that a substantial share of the variation in performance across stores is owed to variation in manager quality. They find that who makes a good manager is hard to predict on the basis of the relatively limited set of observable manager characteristics, though the authors find that managers who perform well in terms of labor productivity also appear to be

good managers on other metrics. [Bertrand and Schoar \(2003\)](#), using matched firm–manager data, find that substantial variation in firms’ practices and performance can be explained by the effects of individual managers.

#### 4.3 Comparing people managers and project managers

In sum, close followers of the research on managers will recognize clear differences in the characterization of managers’ jobs across settings: there are people managers when subordinates have their own productivity measures; there are project managers when subordinates work in a group. Studies of the performance of people managers who supervise individuals, largely interpret people managers’ skills as related to their jobs of hiring, training, motivating, allocating, and evaluating workers. Studies of the performance of project managers typically measure managerial productivity as a function of the management practices that the manager uses and at the level of the group unit that she manages.

This split in the literature reflects the empirical reality that there are fundamental differences in managerial methods across settings of individual work versus group work. The case study presented next in Section 5 reinforces this conclusion. Data analysis from LinkedIn presented in Section 6 shows the clusters of managers’ self-identified skill sets.

## 5 EXAMPLES OF PEOPLE MANAGERS AND PROJECT MANAGERS IN A LARGE BANK

To provide a concrete example of our distinction between people managers and project managers, we present a case study of the managers in the wealth management and risk management divisions of a large North American bank. Table 1 compares the major differences between these two divisions, thus providing a basic description of job duties, organizational structure, worker incentive pay, and manager incentive pay, computed from records of managers in these two divisions, spanning 2013–2017 with about 80,000 total workers per year.

Workers in the wealth management division, are called wealth advisors because they work with clients to allocate their wealth to stocks and mutual funds, and the customers pay fees for assets under management and for making stock trades. Once the wealth advisors in this division pass a probationary period, they are paid heavily in commissions, bonuses, and profit sharing. New wealth advisors receive a

temporary guaranteed base pay, and some support staff also receive base pay.<sup>3</sup> As Table 1 shows, individual workers' incentive pay averages 47.9% of their total pay.

The risk management division assesses risks in all segments of the business, developing and implementing plans related to measuring, assessing, and mitigating risk, and overseeing the bank's compliance with defined standards. Risk management employees work as a team, averaging 4.39 team members, with one acting as team leader or manager. Workers' annual bonuses average only 4.2% of their income.

The managers in the two divisions also have very different ratios of incentive pay. Managers in the wealth management division have incentive pay averaging 24% of total pay, which is largely determined by the assets being managed by their subordinates. Managers in the risk management division have very low levels of incentive pay, and these come largely in the form of bonuses from the bank. Managers in risk management are part of a team for which there are no direct incentives for compliance, and those in wealth management have their pay aligned with that of their subordinates. The managers in these two settings also perform very different duties. In the wealth management division, managers are initially responsible for hiring, developing, and coaching advisors, and otherwise directly supervising support staff. Once hired and trained, wealth advisors have relatively high autonomy, and their managers have little need to engage in monitoring.<sup>4</sup>

Because managers in this wealth management setting are relatively hands off, the organizational structure is relatively flat, and managers oversee an average of 11.89 workers. In risk management, managers are responsible for project-level deliverables, including identifying, assessing, managing, and mitigating the bank's financial and operational risks. This involves working alongside their subordinates, directing them in the performance of duties, monitoring and reviewing their work products, and learning how to evaluate and coordinate their group's activities in the course of direct participation and observation. This intensive involvement with their groups yields relatively small teams; the average manager in risk management oversees an average of only 4.39 workers.

We use the terms "people managers" and "project managers" to designate the differences between managers while also recognizing that managers of each type have much in common. The empirical literature on managers largely considers either managers of people or projects, so this typology could help orient our settings relative to other work. Research papers on people managers may or may not generalize to papers on project managers, and vice versa. Indeed, the managers in the wealth management and risk

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<sup>3</sup> Support staff, in this case, can be thought of as closely monitored and "paid for performance" in they retain their base compensation

<sup>4</sup> Prendergast 2002 also makes this observation when he notes that workers with a high degree of autonomy are also those who tend to earn the largest share of their pay in the form of incentives.

management divisions that we examine here differ in almost every aspect that is typically studied: They have different numbers of subordinates and different pay schemes, do different things, and apply different types of skills. To improve our understanding of managers of these two types, future researchers will need to analyze systematic differences between managers doing different activities instead of carefully restricting their samples to confirm they are homogeneous.

Table 1: People/project manager typology within a large bank

	Wealth Management	Risk Management
Type	People managers	Project managers
Common job description terms	<i>Hiring, termination, and performance reviews of direct reports; onboarding; reporting; leadership; coaching; directly and indirectly supervising; performance measurement; driving enablement priorities; employee engagement; communication</i>	<i>Defining and implementing a risk framework; development of recovery plan; developing stress-testing statements; ensuring regulatory compliance model; oversight; quality assurance; ensuring consistency; advising senior management</i>
Structure	11.89 subordinates per manager	4.39 subordinates per manager
Subordinate pay	47.9% incentive pay (100% for wealth advisors)	4.2% incentive pay
Manager pay	24.0% incentive pay	7.5% incentive pay

Notes: Common job description terms come from our review of job descriptions and job advertisements. Structure reports the average number of subordinates reporting to first-line managers in the corresponding division. Subordinate pay is the average share of incentive pay (including individual and group-level commissions and bonuses) for workers and managers.

## 5 THE BIG PICTURE: A VIEW FROM LINKEDIN

Newly available data from personal profiles on LinkedIn can be used to group managers according to the types of jobs that they do.

## 5.1 The Data from LinkedIn

Since Adam Smith described the pin factory, economists who study the workplace have drawn inspiration from their observations on the ground ((Ichniowski et al., 1997; Lazear, 2012; Hoffman and Stanton, 2024). How can we generalize these settings?

To characterize what managers do and the skills they apply, we use profiles from the professional networking site LinkedIn to describe managers' skills and analyze how managers are connected.<sup>5</sup> These data offer several features that make them uniquely well suited for our purposes. First, the 38 million global managers who self-report approximately 1,500 types of professional skills provide an unusually comprehensive characterization of management.<sup>6</sup> Second, individual users typically select multiple skills (an average of 5 per user), allowing us to analyze clusters of commonly co-occurring skills. These two features allow us to describe not only the specific skills that managers frequently cite but also the skill sets that individual managers cite together. The skills that managers report do not necessarily correspond to what managers do to create value, but we use them as an approximation.

Table 2: Top skill elements within management skill clusters

Rank	People Management	Project Management
1	Management	Project management
2	Leadership	Strategic planning
3	Training	Team leadership
4	Team building	Negotiation
5	Human resources	Project planning
6	Performance management	Business strategy
7	Employee relations	Strategy
8	Employee training	Budgets
9	Hiring and onboarding	Product development
10	Employee engagement	Business planning

<sup>5</sup> The data set used in this paper is from Revelio Labs, which has scraped and cleaned the LinkedIn data. LinkedIn prompts users to list skills, noting, "We recommend adding your top 5 [skills] used in this role. They'll also appear in your Skills section." Users may select skills suggested by the platform or type in their own entries. In the latter case, standardized skills are suggested based on the word stem. The data provider then collects the standardized and manually input skills into a set of "mapped skills" intended to encompass different ways of describing the same skill

<sup>6</sup> We define managers as workers at the fourth level of Revelio Labs' seven-level seniority typology, where the levels are entry, junior, associate, manager, director, executive, and senior executive. Revelio codes these levels by taking the average of three scores: one based on job title, company, and history; a second based on job history; and a third based on age. Although users can insert skills manually, a few design features aid in standardizing the codes; for instance, the site allows single-click entry of standardized skills commonly held by users with the same role, standardized skills populate the search box as the user begins typing, and users are reminded that the skills they select are used by recruiters. The analysis draws upon the set of 1,500 standardized mapped skills. Skill clusters are mapped by Revelio through a mix of k-means clustering with 75 clusters and some supervised curation to yield a hierarchical skills typology.

Notes: The table combines hiring and onboarding into one skill and the project management and strategic planning skill clusters into one cluster labeled project management.

Table 2 reports managers' ten most common skills within two clusters of the most frequently cited skills among managers in the LinkedIn data.<sup>7</sup> The first column reports skills within what we label the people management skill cluster for managing individual contributors. These managers' activities include hiring, training, employee engagement (motivation), and performance management (retention and evaluation). The second column reports skills in what we label the project management cluster. These managers are needed to set goal, allocate tasks, and coordinate group efforts toward a collective objective.

The skills listed on LinkedIn are similar to, though more detailed than, other popular characterizations of what managers do. Perhaps the most widely used resource for quantitatively characterizing job attributes is O\*NET, from the US Department of Labor.<sup>8</sup> The O\*NET skills typology spans 35 skills. The O\*NET skills related to dealing with personnel resources ("selecting and managing the best workers for a job") and instructing ("teaching people how to do something") are most aligned with people management skills. Coordination ("changing what is done based on other people's actions"), systems evaluation ("measuring how well a system is working and how to improve it"), and time management ("managing your time and the time of other people") are also skills commonly listed among managers and align with our conceptualization of project managers. The skill of monitoring ("keeping track of how well people and/or groups are doing in order to make improvements") applies to both people and project managers, as O\*NET combines individual and group monitoring. Other common skills among managers listed in O\*NET relate to people and communication skills that are likely inputs into skills such as coordinating and managing workers.

## 5.2 People Managers and Project Managers in LinkedIn

The LinkedIn data tell us that the people and project management skill sets are among the most common and central among managers' skills overall, even as the component skills are applied in different domains.

To illustrate this, we graph Revelio's 75 skill clusters as nodes, where the weight of the edges is determined by the share of workers who report at least one skill from both clusters. We algorithmically

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<sup>7</sup> The largest skill cluster among managers is the cluster that begins with strategic planning, followed by people management, Microsoft Office, and project management. For expositional clarity, the table combines strategic planning with project management skills and omits the Microsoft Office skill cluster (which extends to other office productivity software).

<sup>8</sup> O\*NET has two chief disadvantages compared with LinkedIn. First, its 35 skills are far more coarse than those in LinkedIn. Second, O\*NET has occupation-level characteristics, and so does not allow for analysis of how these skills are commonly connected within individuals.

situate these nodes on the graph to minimize the distance between node connections, subject to a constraint that generates space for display purposes, and label the nodes with the most common single skill in the node's skill set.<sup>9</sup> Figure 1 displays the graph.

Our first claim is that both people management skills (in red) and project management skills (in blue) occupy central places in the overall skills network. The people management node has the greatest eigenvector centrality (1.0), and the two project management nodes are just behind in second and fourth place in eigenvector centrality terms (0.999 for strategic planning and 0.971 for project management).<sup>10</sup> The eigenvector centrality values fall sharply for skill nodes after the first seven, with the subsequent nodes beginning to represent domain expertise rather than business expertise. The centrality of these skills speaks to the general theme that there is a central set of management skills. A list of the top-40 most common skill clusters, their embedded skills, their centrality, and their counts is in the appendix.

Our second claim is that the people management and project management skill sets are each connected to different sets of skills. We argue that this divergence signifies differences in where people vs. project skills are relatively valued.<sup>11</sup> The people management cluster has 41 skill clusters that are more strongly connected to it than to any other cluster. One of the largest

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<sup>9</sup> We minimize the distance between well-connected nodes using the ForceAtlas algorithm. For display purposes (e.g., to prevent nodes from overlapping or being shown far from center of the graph), we then apply the Fruchterman–Reingold algorithm. For clarity, we relabel the people management node.

<sup>10</sup> Eigenvector centrality measures connectedness to other nodes, particularly other highly central nodes. The third most central node includes office productivity software, which we exclude from our discussion for conceptual reasons.

<sup>11</sup> For instance, consider the process improvement node, which is located centrally and slightly offset from the 11 o'clock position. This node (which also includes program management and cross-functional team leadership) is closer to the project management node than the people management node because managers are more likely to co-list process improvement skills with project management skills. Process improvement is also relatively central because it is more general purpose than the nodes on the periphery. For example, many profiles list at least one element from the project management cluster and the aerospace cluster (in the outer periphery, at 7 o'clock). Like other peripheral skills, the probability of aerospace skills being cited conditional on project management being cited is low, but the probability of project management being cited conditional on aerospace having been cited is high. Because managers who list a project management skill also list skills in other domains, the clustering algorithm does not associate project management per se with aerospace: Aerospace is only one of the many clusters to which project managers are connected—and not a particularly large one. In contrast, project management is the second most



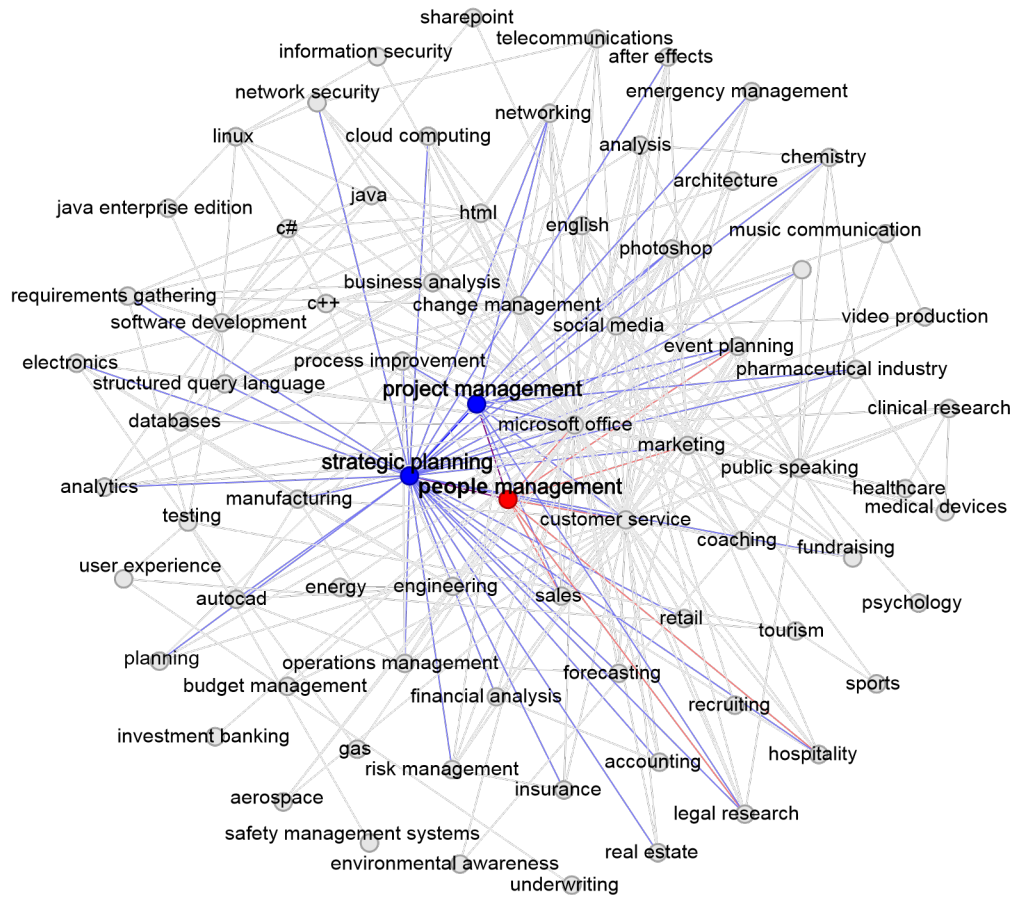


Figure 1  
LinkedIn skill clusters and their connectedness among managers

Figure 1 shows Revelio's 75 clusters of the skills listed on 38.3 million manager profiles on LinkedIn, labeled with the node's most common skill element. The graph situates the nodes to minimize the distance between strongly connected nodes (i.e., those for which many profiles list one or more skills from both nodes). The graph displays the edge between nodes  $i$  and  $j$  if  $j$  is the node most connected to  $i$  or has at least 50% as many connections as the most connected node.

among these is other general management skills. The largest functional cluster is sales/business development/account management, followed by marketing/marketing strategy/customer relationship management. Notably, sales and marketing are arguably the areas where results are most easily measured at the level of the individual contributor. Other functions most commonly listed with people management skills are those for which individual performance is relatively measurable. This suggests that people managers spend their time assisting their direct reports in becoming more productive for the firm. Managers on LinkedIn frequently list people skills and general management skills rather than strictly technical or "hard" skills.

frequently cited connection among managers who list aerospace skills: The most frequently cited connection is process improvement, which again is also tightly coupled with project management.

Nine skill clusters are more strongly connected to project management than to any other skill cluster; the most pronounced of these are safety management systems/mining/occupational health (the second most co-listed cluster is cited 22.8% less often), engineering/project engineering/commissioning (20%), and testing/automation/electrical engineering (19.8%). The five largest skill clusters that most commonly co-list project management are all in engineering or energy. Several construction skills are so tightly connected to project management that they occupy the same cluster. Other clusters that neighbor project management more closely than people management include clusters related to engineering, safety, security, and operations: activities that largely involve coordinating people toward the completion of large collective projects and for which the failure of one individual may be both difficult to detect and collectively consequential.

We summarize our findings from this analysis as follows: (1) both the people and project management skill clusters are central and tightly connected to many other skill sets; (2) people and project management skills both occupy distinct skill clusters; (3) the people management cluster is most tightly connected to skills for which performance is more easily measured at the level of the manager’s direct reports; and finally, (4) the project management cluster is most tightly connected to skills around managing interdependent processes, skills applied to settings where performance would intuitively be more easily measured at group or project level, and skills applied to settings where the organizational externalities for individual failure appear greatest.

The previous sections have laid the foundation for our review of the literature. Table 3 integrates the pieces into one table.

Table 3: What do managers do, as a function of their skill set and technology

	Manage Type follows from Technology type	
Worker Technology	Tech Type 1: individual work	Tech Type 2: project work
Manager Skill Type	People Managers	Project Managers
What do managers do? Activities	Hire, train, mentor	Evaluate, allocate, monitor

In sum, technology determines the activities of workers and managers; each manager’s skills are distinctively different, as each manager possesses a cluster of skills relevant to their work area’s technology; and managers are guided by their own self-interest as they undertake the activities best suited for them.

We now zoom in on the evidence regarding the specific activities that managers carry out and how they create value. The principal's pursuit of profit maximization involves hiring and motivating managers to perform a set of activities that are productive in their particular environment. Project managers can enhance productivity by managing the production technology— for example, by properly allocating people or monitoring the production line to troubleshoot problems. People managers can enhance productivity by hiring or training better workers or monitoring workers or motivating them to put in more effort. The literature on both types of managers teaches us that managers can be interpreted as self-interested economic agents. The empirical literature on managers then typically estimates managers' activities in any of the dimensions mentioned above, though the exact dimension studied by each paper typically depends largely on what is important and measurable in the specific research setting.

We intentionally focus on the most recent empirical papers on each topic.<sup>12</sup> Our aim in doing so is to convey the current state of the literature. Interested parties can refer to the cited papers for further context.

### 6.1 Hiring

Building a successful organization begins with hiring the right people. With the decline of firms' centralized recruiting departments, this important function has fallen on direct managers reliant on private signals, such as interviews or prior familiarity (Behrenz, 2001). Many factors have led to this transition: the decline of internal career pathways in favor of external recruiting, the phasing-out of internal recruiting functions relying on formal job analysis, and the advent of new technologies that place more control over hiring with direct managers themselves (Cowgill, 2024; Cappelli, 2019).

Research on managers and hiring is converging on a set of insights, which we believe are the following. First, there appears to be only circumstantial evidence, at best, that some managers are inherently better at cold-screening workers. Second, the evidence suggests that the primary channel whereby some managers perform better at hiring is by acquiring information about workers through either personal observation or referrals rather than screening. Third, though this private information may be valuable, relying on managers to provide private information invites bias. Fourth, the private information gleaned by

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<sup>12</sup> We found relatively few theoretical papers explicitly concerned with some dimension of managerial skill. Most theoretical papers on some managerial activity typically take the environment as exogenous and managers as homogeneous. Heterogeneity in managers' ability may be a relatively trivial extension of a model in which managers observe workers' ability, match quality, or effort with varying levels of noise. One recent exception is Dessein and Santos (2021), who explicitly seek to model multidimensional skill heterogeneity across managers and how differences in managers' skills may lead to large differences in how they respond to their environment.

managers might be substitutable with other sources of information, such as testing, leading to new questions as to how managers should be involved in hiring decisions. We delve into the literature that forms the basis of our view.

We first consider the possibility that some managers create value for their firms because they receive especially precise signals of applicants' quality. Economic evidence on this topic is conspicuously scarce, but an extensive literature in organizational psychology largely rejects that some managers have a special ability to screen candidates and instead extols formal testing and structured interviews for their superior predictive validity and reliability. Consistent with this evidence, Hoffman et al. (2018), using data from an anonymous job testing provider of low-skilled service sector workers seeking employment, such as call center workers, find that strictly relying on a testing algorithm in simple hiring decisions would yield better results than managers applying discretion, even when the managers can observe the recommendations of the hiring algorithm. Other evidence comes from Mocanu (2022), who analyzes detailed hiring process data from the period when Brazil implemented a reform that required civil servants to be screened through impartial hiring practices. Although she finds that the introduction of formal testing enhanced the quality of hires, she also finds that the elimination of subjective screening tools resulted in worse hires.

Most economic evidence has not tested whether individual managers are better screeners but rather on the less data-intensive question of whether managers with certain characteristics make them better screeners. For instance, we hold out hope that academic economists are better at screening other academic economists, even in the absence of direct evidence. Phelps (1972) considers this possibility in the context of screening discrimination, whereby managers receive better signals of worker quality within familiar groups. Screening discrimination, along with taste-based discrimination and complementary productivity, may explain the empirical observation that managers tend to hire workers of their own race, even within establishments. Benson et al. (2024b) use department-level hiring of commissioned salespeople within retail stores and find that managers tend to hire within their same race. They also construct a test of the three mechanisms above using the mean and variance of sales productivity by the racial concordance of the hiring manager, finding evidence of each across different racial pairs. Giuliano et al. (2009), also using data from retail stores, find that managers are more likely to hire people of their same race, even within location. In a pair of audit studies, Cowgill (2024) test for both supply-side and demand-side taste-based discrimination. They show that hiring discrimination among workers is about twice as great as discrimination among managers. Miller and Schmutte (2021) find that firm founders are more likely to hire from their same race, though the effect dissipates as firms grow, presumably as the firm becomes less reliant on the founder for hiring decisions. If managers are better at screening same-type workers, then this would have equilibrium implications for sorting; for instance, firms could enter a virtuous cycle of hiring, promoting, and screening more productive workers (Board et al., 2023).

Notwithstanding the limited evidence that some managers are better at screening, we now have more established evidence that managers may leverage private information regarding individual workers' quality through prior personal or professional experience rather than interviews. However, delegating hiring decisions to managers to benefit from their private information on prior experience can invite bias without sufficient incentives to use their prior experience with workers to screen for productivity. For instance, [Bandiera et al. \(2009\)](#), in an experiment on a strawberry farm where managers selected their field workers on a day-to-day basis, find that incentive pay for managers led them to choose better-quality workers to supervise rather than their friends. [Hedegaard and Tyran \(2018\)](#), in a lab experiment, estimate the "price for prejudice," or the incentive pay that managers were willing to forgo to avoid hiring people from a highly productive ethnic minority. In a field experiment that manipulated hiring authority in Chinese stores, [Wu and Liu \(2020\)](#) find that delegating hiring authority to managers yielded better hiring outcomes in stores where managers had stronger incentives. Notably, in each of these settings, the hiring managers were able to glean productivity information by directly observing workers performing the precise task. The possibility that managers make better hires by observing past performance is mirrored by firms' widespread use of internships, through which supervising managers presumably learn about workers' abilities through training ([Autor et al., 2003](#)). Finally, the lesson that past performance in a similar role is a strong indicator of performance in future similar roles is mirrored in the referrals literature, as is the lesson that weak incentives to provide good information can instead yield biased information.

Delegating hiring decisions to managers may also invite bias not only given the likelihood that they are prone to hiring from their own endogenous social networks but also if they favor certain groups ([Jackson, 2021](#)). [Kuhn and Shen \(2013\)](#), in an analysis of Chinese job boards where employers can list an explicit gender preference, find extensive variation in gender bias within firms, which they attribute to managers' idiosyncratic preferences over gender, height, age, and beauty rather than skills. [Shukla \(2022\)](#), analyzing hiring at US and European multinationals recruiting at an elite Indian university, find that members of disadvantaged castes have similar rates of advancement through the hiring process up until the final round interviews, where managers screen candidates on subjective characteristics such as cultural fit. [Cullen and Perez-Truglia \(2023\)](#) find that women lack access to professional social networks, and others (e.g., [Currarini et al. \(2016\)](#)) document racially homophilous social ties, which may partly explain why managers tend to hire from their same group.

Managers may also become biased if they update their beliefs about different groups based on their own experience on the job. In principle, the promise of formal recruiting procedures is that screening criteria may be statistically validated across many more data points than would be available to managers who update their beliefs solely on the basis of personal experience. Early evidence that managers update

beliefs on the fly has come from online labor markets. In these, hirers appear to experiment by selecting workers based on different credentials and then endogenously hiring where they find the most success (Leung, 2018; Kokkodis and Ransbotham, 2023). Such a practice poses the risk of managers having idiosyncratically bad experiences hiring people from minority groups and thereafter avoid hiring from those groups, leading them to be caught on an equilibrium path where they do not hire minorities Lepage (forthcoming). Along these lines, Benson and Lepage (2023), using data from a large retailer, find that individual managers who have a bad experience hiring a Black worker are unlikely to hire a Black worker in subsequent hiring events.

Taken together, the evidence makes clear that managers may come to possess valuable information on job candidates' quality through observation and that this information may be elicited if managers are provided incentives sufficient to overcome their personal biases. Overall, the evidence suggests that the information benefits of referrals dominate the potential costs of favoritism, particularly when incentives for providing high-quality referrals are sufficiently strong (Bandiera et al., 2007; Hedegaard and Tyran, 2018; Wu and Liu, 2020).

## 6.2 Retention

Managers can also create value by retaining workers. Worker turnover imposes a wide range of potential costs on employers: the cost of the turnover itself, the cost of hiring and training a replacement worker, and the potential forgone income from replacing a high-quality match with a random draw. Turnover is also disruptive for work groups and those who remain.

Conceptually, we can refer to fundamental principles of Section 3 to understand managers' role in retention. In some settings, retention is particularly important because the firm invests heavily in selecting, training, and incorporating workers into semi-autonomous and interdependent teams, and turnover constitutes a greater loss in the firm's investment (Milgrom and Roberts, 1995; Ichniowski et al., 1997). In cases where firms emphasize low costs in hiring, training, and individual production, retention is less important. As illustrated by cases such as Costco and Walmart, different strategies can translate to wide differences in management practices, compensation patterns, and retention patterns even within the same industry (Emanuel and Harrington, 2020; Acemoglu, 2001; Osterman, 2018).

Perhaps the strongest evidence linking people skills and retention is provided by Hoffman and Tadelis (2021). Using data from a large high-tech firm, they find that survey-measured people management skills are highly correlated with greater subordinate retention: Replacing a manager at the 10th percentile in measured people skills with one at the 90th percentile corresponds to a 60% reduction in overall turnover and declines in turnover among workers estimated to be high

performers.

We can also think about the manager's decision to direct effort toward retention as part of the manager's multitasking problem. [Friebel et al. \(2022\)](#) consider a field experiment at a large retailer with nearly 193 shops. They prompted managers to direct attention to employee retention. Though retention improved at treated stores, other measures of store performance did not, suggesting that the reallocation of effort may have come at the cost of other activities, such as spending time with customers.

Managers may also affect the retention of subordinates of certain groups through the classical channels described in the discrimination literature. For instance, [Benson et al. \(2024a\)](#) find that retention is greater when there is concordance between manager and worker race. Theoretically, this could be explained by relative taste-based bias, by same-race hires being more productive, or by same-race hires being initially better screened. Data on hiring on the mean and variance of the sales productivity distributions conditional on a worker's being hired by a same-race manager offer evidence—albeit of varying proportion depending on the racial pairing—for all three explanations. Similarly, [Alan et al. \(2023\)](#) find that female turnover is lower under female managers, which they attribute to female managers' efforts to invest in social and professional relationships with other women and to improvements in workplace climate.

### 6.3 Training and Mentoring

Economic research also establishes that managers vary in the extent to which they build their workers' human capital. The topics are large, including managers' mentoring and training, peer learning, and information sharing all fall under this category.

[Sandvik et al. \(2020\)](#) provide one of the most comprehensive recent field studies of how managers create value through training. They examine sales agents whose productivity may be tracked by revenue per call. Managers are responsible for improving sales agents' performance through formal training, probationary screening, and ongoing feedback. Importantly, managers can encourage worker development by managing workplace knowledge flows, including by setting up policies that encourage peer learning from the best performers.

Managers also provide value through direct mentoring. Perhaps counterintuitively, much of the new evidence suggests that mentoring should be mandatory, regular, and broad based, rather than a product of self-selection or targeting. [Sandvik et al. \(2023\)](#) implement a clever experiment to test the causal impact of mentoring on workers who opt into mentoring vs. those assigned to receive mandatory mentoring. Interestingly, they find that mentoring had a stronger impact on the workers for whom participation was mandatory, suggesting that the workers who opted in had more to gain from mentoring than those who opted out. In a separate field experiment in Chinese retail stores,

Wu and Liu (2021) compare experimentally randomized mentoring to mentoring targeted at workers believed to be at the greatest risk of attrition. They, too, find the sharpest reductions in turnover among the set randomly assigned to receive mentorship.

The optimal allocation of managerial effort toward training also appears to depend on the institutional context. Using data from a Colombian government agency, Espinosa and Stanton (2023) find that centralized training of workers makes them require less attention from managers, allowing managers to focus on other activities. Similarly, using data from a garment factory, Adhvaryu et al. (2023b) find that providing soft-skills training to front-line workers enhances productivity among coworkers, particularly where workers have greater autonomy relative to managers. A much broader literature on high-performance work systems and self-managed teams finds that selectively hiring, training, incentivizing, and providing autonomy to semi-autonomous teams is a substitute for close managerial supervision and top-down control (Ichniowski et al., 1997; MacDuffie, 1995).

#### 6.4 Motivating

The literature on managers has also examined their ability to motivate or otherwise magnify the productivity of a given set of subordinates. Several recent empirical papers on this topic estimate managers' motivational effects by estimating subordinate productivity with two-way fixed effects for managers and workers, an approach that allows researchers to recover a "manager value added" effect that controls for static differences across workers and settings. For instance, Lazear et al. (2015), described above in Section 3, estimate a two-way fixed effect model in the context of supervisors of workers doing routine tasks. They find that the difference in productivity under a 90th-percentile manager and a 10th-percentile manager is equivalent to the productivity from an additional worker. Benson et al. (2019) estimate manager value added from the manager fixed effects in a regression with salesperson productivity. They find large differences in the productivity of sales workers under different managers: A worker under a 75th-percentile manager has nearly five times the sales of one under a 25th-percentile manager, approximately half the raw sales gap between workers at these quartiles. Weidmann et al. (2024) estimate manager effects on motivation by exploiting experimental high-frequency random assignment of managers to teams.

One natural hypothesis is that motivation and ability are complements, in which case firms should hire and assign the most motivational managers to the most talented subordinates (Tervio, 2008; Gabaix and Landier, 2008). However, what little evidence exists on this topic generally provides little support. Studies in garment production (Adhvaryu et al., 2020), retail stores (Metcalfe et al., 2023), software development teams (Cowgill, 2024), and fruit picking (Bandiera et al., 2009) have found negative assortative matching. Benson et al. (2019) find that the best-performing salespeople tend to be assigned to the best-performing



teams when promoted, though these promotions were associated with performance declines. [Bandiera et al. \(2009\)](#) find positive assortative matching after managers are provided stronger incentives. Though the theoretical literature reasons that positive assortative matching both is efficient and can explain the skewed pay among top managers, the empirical literature on lower-level managers has struggled to find clear evidence that this generally characterizes allocations within firms.

People are motivated by considerations other than money, and managers may be able to enhance or detract from their subordinates' willingness to allocate effort. [Hermalin \(1998\)](#), for instance, theorizes that leaders can signal important causes by "leading by example," eliciting the voluntary participation of followers. In this vein, organizations may select prosocial rather than profit-driven managers considering their motivational effects on subordinates [Kajackaite and Sliwka \(2020\)](#). Workers may also be demotivated if they have a poorly matched boss. [Glover et al. \(2017\)](#) finds that the productivity of minority cashiers (who were not paid for performance) declined during shifts in which they were assigned to work under a manager found to be biased by an implicit association test.

## 6.5 Evaluating and Monitoring

In 1911, Frederick Winslow Taylor provided one of the earliest conceptions of a manager: namely, as a monitor who merely confirms that workers are performing their specified duties in the "one-best way." Some of the ideas of scientific management now echo in contemporary management models in which managers ensure that workers are meeting at least minimal performance standards as a condition of continued employment (e.g., [Shapiro and Stiglitz \(1984\)](#)).

The high level of behavioral control under Taylorism is now generally eschewed in favor of providing workers with greater autonomy, enablement, and incentives for reaching prespecified outcomes, except in situations where a manager's monitoring and supervision is required to check moral hazard. Much of what economists refer to as monitoring also falls under what practitioners refer to as performance management, highlighting contemporary organizations' emphasis on using evaluations for the dual purpose of evaluation and professional development (identifying and training high-ability workers). In other words, managers' collected knowledge about workers is valuable beyond its role in deterring would-be cheaters and shirkers.

The evaluative purpose of performance management is important because so much of what most workers do is difficult to fully capture through objective performance metrics and therefore it is difficult to conceive of workhorse models of employer decisions (e.g., employer learning, incentive pay, promotion rules, or separations for unsatisfactory performance) in the absence of input from managers. The theoretical groundwork for evaluations comes from the idea that, in the course of supervision, managers

accumulate the information required to substitute for indicators of worker performance that are difficult to measure (Holmström and Milgrom, 1991; Baker et al., 1988). In many settings, it is easy to measure the quantity of what a worker produces but not the worker's quality, cooperativeness, idea generation, or other productive behaviors. If the latter are observable to the manager, then, in principle, the firm can address moral hazard problems by asking the manager to subjectively assess the worker on these dimensions (MacLeod, 2003).

The practical implementation of performance evaluations and how they translate to pay, separations, and promotions also closely aligns with classical economic theory. In the case of merit raises, organizations typically refer to a "merit matrix" that considers two factors: an individual's pay relative to the market median for that job (the compa ratio) and how her performance compares to the expected performance for a job. The largest raises go to individuals with a low compa ratio and high evaluations, which presumably helps pay catch up to the worker's marginal product. Some practices, such as Microsoft's awarding of bonuses for past performance, raises for present skills, and promotions and stock options for future potential ratings, seek to align compensation with the timing with which performance brings value to the firm (Bartlett and Wozny, 2000).

Performance evaluations also lay the groundwork for separations. Jack Welch, CEO of General Electric, famously introduced his "vitality curve" evaluations, which required that some share of a manager's subordinates receive the lowest scores. Serial poor scores resulted in termination. Similarly, modern organizations place low-rated workers on performance-improvement plans (PIPs), which are typically an antecedent to separation. This use of evaluations reflects the practical enactment of economic theories of termination for shirking, poor ability, or a poor match (e.g., Shapiro and Stiglitz (1984); Altonji and Pierret (2001); Jovanovic (1979)).

Last, managers' performance evaluations are increasingly supplanting tenure-based rules in promotion decisions. In general, organizations limit pay raises to set ranges because of concerns over horizontal inequity (e.g., Baker et al. (1994); Breza et al. (2018); Cullen et al. (2022)). In these cases, advancing in pay requires being promoted to a job with a higher salary (Lazear and Rosen, 1981). This situation poses a dilemma: Should organizations promote based on past performance to apply promotions as an incentive, or should they promote based on future potential to achieve the best match? As noted in Section 3.2, workers and managers apply different skills in different settings, implying that these two promotion strategies are not always aligned, giving rise to the Peter principle (Benson et al., 2019; Weidmann et al., 2024).

A burgeoning literature examines how organizations trade off bias and local information when asking managers to report on difficult-to-verify, subjective traits such as employee potential. The evidence

suggests that ratings of employee potential are correlated with observed and unobserved manager characteristics and are biased against women but also are informative about future performance net of observed past performance. Studies have also consistently found that ratings of employee potential are highly correlated with the rated workers' future careers ([Adhvaryu et al., 2022a](#); [Frederikson et al., 2017](#); [Benson et al., 2024b](#); [Minni, 2023](#); [Moers, 2006](#); [Künneke, 2024](#)).

One class of bias that can affect such ratings relates to one of our core principles—namely, that managers respond to incentives. For instance, [Bol \(2011\)](#) finds suggestive evidence that managers compress and inflate ratings to avoid conflict with subordinates. [Haegele \(2022\)](#) notes that managers have an incentive to obfuscate the presence of high-performing subordinates to lower the risk of the high performers being moved off their team. [Benson et al. \(2024b\)](#) find that managers give higher ratings of potential to workers who are more likely to turn over, suggesting they may use high ratings, and the likelihood of promotion, as a retention tool.

Another class of bias results in preferential treatment for one group. For instance, women are stereotypically perceived as less likely to be leaders, which may translate into lower ratings of their potential ([Eagly and Karau, 2002](#); [Benson et al., 2024b](#)). Managers may find it easier to assign women low ratings if, on average, women are less likely to advocate for themselves or negotiate for higher ratings ([Babcock and Laschever, 2009](#); [Biasi and Sarsons, 2022](#); [Caldwell et al., 2023](#); [Roussille, 2024](#)). Bias in evaluations can translate into gender differences in pay, even in highly regimented systems such as the US federal government, particularly where evaluations have a subjective component [Fortin et al. \(2023\)](#).

The second major purpose of the performance management process is development. The developmental purpose of evaluations is one way to conceive of training, as discussed in the prior section. However, economic research on this objective of evaluations is scant relative to the attention that it receives in practice. [Adhvaryu et al. \(2022b\)](#) offer a notable exception. They find that the implementation of performance management technology at a quick-service restaurant chain enabled faster, data-driven feedback for managers, complementing their training efforts and relieving operational bottlenecks. They further find that the productivity gains dissipated among managers who neglected to refresh workers' skills, corroborating that better performance management technology and its skillful application by management had complementary effects on subordinates' human capital.

## 6.6 Allocating

The allocation of workers across firms has long been a major topic in labor economics. Canonical models consider the case that firms view only public signals of a worker's ability, such as her education.

Employer learning and job matching models then consider the case that firms learn about ability or match quality by observing workers on the job (e.g., [Altonji and Pierret \(2001\)](#); [Jovanovic \(1979\)](#)). Personnel economists have thought about allocation in much the same way, except they note that much “firm learning” accrues specifically to the manager. Delegating decisions to managers enables them to apply their local knowledge, but it also invites bias ([Aghion and Tirole, 1997](#)). Notwithstanding the costs of delegation, the period from the 1940s to the present day has seen managers taking on greater responsibility over hiring and allocation decisions, largely because of the decline of the predictable career pathways and seniority-based promotion rules that characterized internal labor markets ([Cappelli, 2001](#)).

Recent years have seen a blossoming of field evidence that corroborates that managers can enhance firm productivity through better matching of internal workers to jobs. Using data featuring manager job rotations at a large multinational company, [Minni \(2023\)](#) finds that good managers, defined as those revealed to be good by quick subsequent promotion, more actively move their subordinates both laterally and vertically and enhance their productivity and future advancement. [Adhvaryu et al. \(2022c\)](#), using data from an Indian garment plant, find that the most attentive managers enhance productivity by reassigning workers in response to particulate matter pollution. [Cowgill \(2024\)](#) compare manager-dictated matches with counterfactual internal matching arrangements in terms of match quality and workers’ preferences. Their study highlights the dilemma of balancing the firm’s and worker’s preferences in task assignments, along with the potential application of mechanism design to solve job allocation problems. In their setting of enterprise software teams, they find that managers’ matches are better on both margins than random assignments, though managers’ matches generally underperform algorithm-proposed matches in terms of quality.

These settings are notable because the managers in them are provided career incentives to develop their subordinates. However, studies of other settings have found that managers’ pursuit of their own interests can be costly for the firm. Examples include talent hoarding [Haegele \(2022\)](#), whereby managers misreport performance to avoid losing star performers; discrimination against workers in task assignment based on race or gender (e.g., [Hjort \(2014\)](#); [Babcock et al. \(2017\)](#)); and strategic relocation of workers to solidify one’s political power ([Xu et al., 2023](#)). [De Janvry et al. \(2023\)](#), in a study of Chinese civil servants, find that workers engage in significant influence activities, including reallocating their efforts around evaluators’ preferred projects.

## 7 MANAGERS OF PEOPLE AND MANAGERS OF PROJECTS

Sections 3 through 6 provided a theoretical, empirical, and descriptive account that motivated our delineation of people and project managers, and Section 8 outlined the empirical literature on six

managerial activities. This section places managers' activities back within the framework of people and project managers, taking stock of what managers do.

We view the activities of hiring, retaining, and training as being key among people managers. Many of the empirical studies of Section 6 refer to settings where workers have clear individual performance metrics and/or other personal incentives to perform their non-interdependent jobs well. Theoretically, this liberates the manager from certain duties, such as intensively monitoring the worker. These empirical models of individual worker performance also fit our analysis of managerial skills: When the technology of the job provides individuals with incentives, managers are left with the jobs of hiring and training—that is, they are people managers.

We view the activities of monitoring (particularly team monitoring) and allocating as being more heavily weighted toward project managers. When productivity is measured at the level of the project or group, the organization shifts accountability to the manager, who is primarily concerned with activities that ensure the success of the group. Because workers in these settings typically work alongside each other and with each other, they also learn each others' abilities and have a strong sense of the overall production technologies. In many of these settings, teams are afforded a relatively high degree of incentives and autonomy to fix their own problems, and managers may participate directly in production ([MacDuffie, 1995](#)). Task interdependence enables workers to engage in peer monitoring ([Knez and Simester, 2001](#)), and organizations may supplement reviews from managers with reviews from peers (as in the case of 360-degree reviews). We view these activities as more characteristic of line supervisors, shift supervisors, team leaders, and managers in other settings where their tasks primarily involve overseeing a specific process.

Because the empirical literature on managers typically goes deeply into one setting, the process of conveying the facts of that setting and relating those to a firm's or manager's objective function remains largely a matter of the researcher's judgment, based on her knowledge of the literature and the facts on the ground. Often, protecting confidentiality for the firm limits the researcher in providing detail. However, if the author or reader situates the firm as one run by people managers or by project managers, the purpose of the managers is made clearer.

## 8 MANAGERS AS TEAM LEADERS

Over time, technological shifts have rewarded social skills rather than manual skills, and have seen a shift toward teams ([Weidmann and Deming, 2021](#)). There is variety in the types of teamwork, so what roles do managers play? Papers on teams are often focused on the factors surrounding the team's performance and do not have information on the team leaders or managers. For example, in their study

of steel mills, [Boning et al. \(2007\)](#) find that team incentives were most effective when coupled with practices that encouraged workers to implement their ideas.

To see the evolution of teams and the role of managers, we propose two team types. First, in the case of problem-solving teams, managers set goals but are not part of the process of achieving them. Implicit in this arrangement is that management has a clear idea of what must be done but not a clear idea of how to do it and the knowledge of how to do it lies with a set of workers. In problem-solving teams, workers are pulled off their main jobs to work together to solve a problem that the firm now faces (e.g., [Lazear \(1999\)](#)). Such teams originally arose in car production in Japan in the 1980s and then were replicated in the US to enhance US competitiveness ([MacDuffie, 1995](#); [Ichniowski et al., 1997](#)).

Problem-solving teams are widely used today, particularly in environments where the production technology implies clear team goals. In principle, teams are vulnerable to the free-rider problem, whereby the benefits of a worker's private effort are diluted by the group ([Alchian and Demsetz, 1972](#); [Holmström, 1982](#)). Notwithstanding this concern, most empirical studies have found that group incentives can increase productivity through mechanisms such as peer learning ([Hamilton et al., 2003](#)), peer pressure ([Friebel et al., 2017](#)), and the devising of creative solutions to complex problems ([Boning et al., 2007](#)).

A second team structure is semi-autonomous work teams, which are very common where work is interdependent. Unlike project management teams led by a single manager, these teams have considerable autonomy over how to perform their job, and the role of the manager can be substituted by incentives. The usual collective action and moral hazard problems may be solved by giving workers input into their team's composition ([Bandiera et al., 2013](#)), by peer monitoring ([Friebel et al., 2017](#)), or by selecting and assigning teams and bosses based upon shared values ([Prendergast, 2007](#); [Espinosa and Delfino, 2024](#)). [Englmaier et al. \(2024\)](#) find that the simple act of suggesting that a team select a leader reduces coordination costs and improves the probability that the team completes a task. Other studies have found that semi-autonomous team production is most effective when workers are hired for their teamwork and problem-solving skills, they are cross-trained across interdependent jobs, and they are provided the autonomy and incentives to do their job well ([Osterman, 1994](#); [MacDuffie, 1995](#); [Ichniowski et al., 1997](#)). The rise of semi-autonomous teams may also help explain the rising value of social skills ([Hamilton et al., 2003](#)).

In sum, the role of the manager in team settings could be much diminished relative to that in project settings, where she guides or directly oversees the project. Managers in team settings are more similar to people managers, as we have defined them, because the worker's incentives in teams arise intrinsically and in the individual worker in a piece-rate setting from the ability to observe individual output. In both cases, the manager hires, fires, trains, and allocates.

## 9 EMPIRICAL METHODS

The empirical literature reviewed in Section 6 features a wide range of empirical methods. How do the empirical methods being used to study managers serve our ultimate goal of understanding what managers do and how they provide value?

Much of the empirical economic research on managers can be classified as “insider econometrics” ([Ichniowski and Shaw, 2003](#)). Though insider econometrics was originally conceived as a tool for studying management practices rather than managers themselves, applications of this approach to the two topics have many similarities. Such studies typically estimate a productivity regression as a function of managers, identify what managers do that raises productivity and where those activities are most valued, model who becomes a manager, and use field research and interviews throughout the research process.

These studies generally use observational data and identification methods applied in other areas of economics. For instance, they may exploit the random assignment of workers to managers, use a regression discontinuity that leads a worker to be recommended by an algorithm, or use establishment-level senior manager turnover as an instrument for internal promotions.

Another class of research in this stream uses field experiments. The chief benefit of field experiments is that they combine the validity of field settings and provide greater assurance that the treatment (e.g., the mentor to whom a worker is assigned) is not endogenous. In principle, preregistration inoculates such research against practices such as p-hacking and hypothesizing after results are known (HARKing). Field experiments also have disadvantages, however: In addition to the great difficulty of running them on managers, field experiments may be subject to contamination between the treated and control groups ([Levitt and List, 2009](#)).

Laboratory experiments have also grown in popularity and now figure prominently in research on managers. Recent studies have found that classic findings from the field, such as lower callback rates for Black job applicants, can be reproduced in the lab (e.g., [Kessler et al. \(2019\)](#)). This gives rise to the possibility that lab experiments will allow researchers to reproduce field evidence in a more controlled setting and with more complete data.

[Hoffman and Stanton \(2024\)](#), in their review of personnel economics, characterize the personnel economist as “an explorer,” noting that the field has organically expanded to capture new questions and accept new types of evidence. Regardless of the methods used, it is important that researchers provide an argument for what it is about their setting that informs their theoretical and empirical treatment of their subject.

Throughout this review article, we have argued that research on managers exhibits a common set of principles: Technology determines the activities of workers and managers; each manager's skills are distinctively different, as each manager possesses a cluster of skills relevant to their work area's technology; managers are guided by their own self-interest.

We have also argued that the theoretical and empirical literature has provided a foundation for what we now see in the descriptive data: there are people managers and product managers and the activities they undertake to maximize their unit's performance are different.

### 10.1 What Do We Know?

Research on managers has made clear that managers help explain enormous variation in the productivity of firms. Better managers could be better in many dimensions: They may be better at recruiting, retaining, training, motivating, allocating, or evaluating. Much of the work on hiring and evaluating has pinned down the importance of leveraging managers' observations and experience with workers. Incidentally, this mirrors a characteristic premise of the employer learning literature: namely, that firms do not really observe match quality or ability until the worker is on the job. The empirical literature on managers corroborates this assumption but also reminds us that this knowledge often resides with the manager and not the firm.

Evidently, inducing managers to act in the best interests of the firm is not straightforward. Studies are replete with examples of how managers' decisions reflect some combination of the incentives provided to them by the firm and their own considerations. Removing subjective assessments and the exercise of discretion by managers may reduce bias but also comes at the cost of the firm's ability to make well-informed decisions.

### 10.2 What Do We Not Know?

In our view, the chief questions for the literature on managers relate to theory building and generalizability. Intuitively, a well-executed study that examines one production technology is likely to generalize to settings in precisely the same industry, occupation, country, and so on. However, extrapolating from a specific research setting to general principles requires well-established theories.

As [Ichniowski and Shaw \(2013\)](#) describe:

The data may come from one firm or from several companies within one industry, but the theoretical model generating the hypotheses is not specific to the single industry context. This means that



ultimately the broader goal of the insider study is to test a more general economic principle that will enhance our understanding of the theory of the firm.

Research on managers generally tries to hold the production technology constant, articulate how managers create value in that setting, and then analyze how managers make decisions in response to firm policies or incentives. Research comparing managers who operate under different production technologies is more challenging to write, but it would help studies of specific settings situate themselves for the purposes of establishing external validity and replicating results at scale (Hoffman and Stanton, 2024). Our review offers people and project managers as one such example, and we hope that Section 5's vignette analysis of the bank and the analysis of skills listed on professional profiles suggest that such distinctions exist and warrant further study.

A second key question that comes up throughout our review is whether firms can ever drop their reliance on managers as a source of subjective information or make it incentive compatible for managers to report truthfully. The studies discussed in Section 6 make clear that managers possess valuable local knowledge but that delegating to managers invites bias. Technology has rapidly increased the scope and scale of firms' data collection on workers, potentially facilitating firms' ability to monitor managers' decisions or even substitute such decision-making using algorithms. In principle, technology may also facilitate the implementation of prediction markets as a means of aggregating knowledge and incentivizing accurate forecasts, as has been demonstrated in firms like Ford and Google (Cowgill and Zitzewitz, 2015; Gillen et al., 2017). Future work can examine whether better data, tools, and technology will allow firms to make better decisions without relying on potentially biased managers.

A third key question is where managers come from and how better managers can be identified. Recent studies have found that performance in non-managerial roles remains a poor predictor of managerial performance (Baker et al., 1988; Benson et al., 2019; Weidmann et al., 2024), and several other researchers find that great managers might not be discovered or developed because of a lack of exposure to opportunities (Minni, 2023), talent hoarding (Haegele, 2022), or the fact that the risk of promotion is borne by the firm but success is observed by the broader market and so the benefits cannot be fully recouped by the firm (Terviö, 2009; Waldman, 1984). Several other works specifically highlight challenges in identifying and developing female leaders, including women's assignment to non-promotable tasks (Babcock et al., 2017), bias in evaluations of worker potential (Benson et al., 2024b), volition to lead (Azmat et al., 2024; Haegele, 2024), backlash from subordinates (Chakraborty and Serra, 2024), and gender differences in attributions of credit for group work (Sarsons et al., 2021). Research has only just begun to understand the costs of failing to identify talented leaders.

### 10.3 Artificial Intelligence

Managers are facing many technological changes, but perhaps the most important technical change is the rapid adoption of artificial intelligence (AI).

Research on AI's impact on managers is very nascent. However, as a starting point, we can consider AI through the lens of skill-biased technical change (for a more complete review, see [Acemoglu and Restrepo \(2018\)](#)). For instance, [Autor et al. \(2003\)](#) find that computerization was largely a substitute for routine manual and cognitive tasks, such as repetitive assembly and record-keeping, and made workers more productive in the performance of non-routine cognitive tasks.

The most recent evidence on the effects of AI suggest it can either substitute for routine tasks or it can augment non-routine tasks that managers do, which would not be true of the technological changes of the past. For instance, [Brynjolfsson et al. \(2023\)](#) analyze the productivity effects of AI in an experiment in a call center, which does have non-routine work. In their experiment, half of the employees were given generative AI to help them better answer questions that come in. The authors find that the AI was particularly effective at improving the productivity of novice and low-performing employees. In a similar study, [Noy and Zhang \(2023\)](#) use an online experiment to test the value of ChatGPT in improving a professional writing assignment. The average worker required 40% less time and experienced 18% higher quality, but the largest benefits accrued to experimental subjects who performed poorly without the aid of ChatGPT. Their findings demonstrate ChatGPT's capabilities in professional writing and communication and its ability to raise the performance of less-skilled workers to nearly the same level as highly skilled workers', at least in these tasks.

Turning to traditional machine learning (ML), we observe that many studies across several domains have found ML algorithms outperform humans across a variety of well-defined tasks. The goal of ML is to make predictions better than humans', and ML tools are already widely used in the hiring process. For instance, [Sajjadi et al. \(2019\)](#) use machine learning to analyze the content of cover letters for 16,071 applicants for teaching jobs in a large school district. They find that hired applicants whose cover letters emphasized a passion for teaching had more favorable outcomes for schools, in the form of teacher retention, expert evaluations of teaching effectiveness, and student test score improvement.

Generative AI, in particular, holds significant potential to perform a much wider variety of tasks. Large language models such as ChatGPT are explicitly trained on a vast array of data to perform general purpose tasks. In contrast to the computerization of the 1970s and 1980s, these tools appear to be proliferating as a substitute for non-routine cognitive tasks, such as those performed by managers and highly skilled professionals ([Autor, 2022](#); [Acemoglu, 2001](#); [The White House, 2022](#)). Notwithstanding these applications,

we believe it is unlikely that AI technologies will substitute for managers in the way computers substituted for record clerks or cotton-milling technology substituted for the Luddites. That is, after a firm relies more on AI, it remains true that managers must exercise judgment in highly unstructured and complex environments, which remains a great challenge for AI [Agrawal et al. \(2018\)](#). Second, existing evidence points to the importance of people skills in managing people and working in teams (e.g., [Deming and Kahn \(2018\)](#); [Hoffman et al. \(2018\)](#)). AI tools can still be of great assistance to managers. Even in unstructured environments, they can help devise creative solutions to consider or help managers communicate with subordinates.

Therefore, like the technological changes of the past, AI can raise productivity and also raise output quality. AI will impact managers' jobs both because it impacts what their subordinates do and because it will substitute or complement various aspects of what managers themselves do. We believe that AI will ultimately help managers make better, more informed choices and allow them to shift their attention to activities that are not substitutable with AI. That means that AI augments the work of managers, and only substitutes for the repetitive tasks that lowers their quality of their output.

## 11 CONCLUDING REMARKS

It is an exciting time to be studying managers. To this point, our understanding of managers has been informed by on-the-ground observation, theoretical models, and a multitude of close empirical studies on various aspects of what managers do to create value for their firms. Researchers are now blessed with unprecedented access not only to firms but also to data sources that feature rich, standardized information on managers across firms. We anticipate that the literature on managers will grow by dint of the creativity that researchers bring to their study. This research has the promise to speak to key questions on how managers, organizations, and markets will mediate the economic transactions of the future.

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