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Michael Gibbs, Alec Levenson and Cindy Zoghi

ABSTRACT

In this chapter we study job design. Do organizations plan precisely how the job is to be done ex ante, or ask workers to determine the process as they go? We first model this decision and predict complementarity among these following job attributes: multitasking, discretion, skills, and interdependence of tasks. We argue that characteristics of the firm and industry (e.g., product and technology, organizational change) can explain observed patterns and trends in job design. We then use novel data on these job attributes to examine these issues. As predicted, job designs tend to be "coherent" across these attributes within the same job.

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Job designs also tend to follow similar patterns across jobs in the same firm, and especially in the same establishment: when one job is optimized ex ante, others are more likely to be also. There is evidence that firms segregate different types of job designs across different establishments. At the industry level, both computer usage and R&D spending are related to job design decisions.

1. INTRODUCTION

Job design is a fundamental issue in organization design. Which tasks should be put together in the same job, what skills and training are needed, what decisions the employee is allowed to make, with whom the employee works, and related questions are crucial for efficiency and innovation. These issues have long been a focus of social psychology, which has a large literature on effects of job "enrichment" on intrinsic motivation. By contrast, job design has been underemphasized in economics, with some notable exceptions such as Adam Smith's (1776) discussion of specialization.

Empirical evidence suggests that there are patterns and trends in job design. For example, the management research literature and evidence from large organizations (Cohen & Bailey, 1997; Lawler, Mohrman, & Benson, 2001) suggest a trend in recent decades toward teams and human resource practices associated with job "enrichment," i.e., multitasking instead of specialization, and greater employee discretion. In addition, this job design approach seems to be positively associated with organizational change (Milgrom & Roberts, 1990, 1995; Caroli & Van Reenen, 2001). Finally, a substantial literature argues that organizational change in recent years has been skill-biased, leading to increasing returns to skills and a greater emphasis on higher-skilled workers in firms that have undergone change (Autor, Katz, & Krueger, 1998; Bresnahan, Brynjolfsson, & Hitt, 2002; Autor, Levy, & Murnane, 2003; Zoghi & Pabilonia, 2004).

In this chapter we present an economic analysis of job design. First, we present a simple model of inter-task learning that can provide an explanation of trends toward broader job design and greater worker discretion, and the association of job design attributes with organizational change. The model is based on a straightforward idea: combining interdependent tasks in a job may enable the worker to learn process improvements. If this effect dominates gains from specialization, then multitasking leads to greater productivity. Learning should be greater for high-skill workers who are given discretion. Thus, interdependence may lead to multitask jobs, and greater discretion and skills. We then argue that job design should be related to characteristics of the firm's environment – its product, industry, and technology – yielding economy-wide patterns of job design within firms, and within establishments in the same firm.

The predictions about economy-wide patterns of firm characteristics and job design are relatively new to both the economic and social psychology literatures on job design. The empirical literatures have previously ignored such patterns because the existing data are not drawn from representative national samples. Lacking data with which to test such predictions, the theoretical literatures similarly have not explored them in depth. One exception from the theoretical literature is Morita (2001), which focuses only on specificity of human capital and not other aspects of job design. Thus a contribution of the chapter is the job design predictions at an economy-wide level.

The second part of the chapter analyzes a unique dataset that provides the first nationally representative view of the distribution of job design characteristics. The Bureau of Labor Statistics (BLS) National Compensation Survey (NCS) measures job design attributes, including multitasking, discretion, skills, and interdependence. As predicted, we find that all four are strongly positively correlated. At the job level, there is a strong tendency toward "coherent" job design, meaning that jobs tend to be high, medium, or low on all four attributes, relative to the occupation median for each attribute. At the establishment level, there is a tendency for firms to choose either a "modern" approach (many jobs high on all design dimensions) or a "classical" approach (many jobs low on all dimensions). This is consistent with our arguments that job design approaches vary with the firm's product and market characteristics. At the firm level, there is a tendency to push job design toward extremes, choosing modern design in some establishments and classical design in others. This is consistent with multi-establishment firms using establishments to isolate modern and classical jobs from each other to maximize the benefits of job design. At the industry level, both R&D spending and computer usage are associated with modern job design.

2. A SIMPLE MODEL OF MULTITASKING, INTERDEPENDENCE, AND DISCRETION

We now present a simple model of job design based on Lindbeck and Snower (2000) and Gibbs and Levenson (2002). We augment the Lindbeck and Snower approach by considering employee discretion. Our first results are similar to the previous literature (Milgrom & Roberts, 1990; Holmstrom & Milgrom, 1991, 1994; Morita, 2001; Dessein & Santos, 2006) in providing an argument for complementarity of specific job design components. We then discuss implications for the distribution of job design characteristics within establishments compared to the firm as a whole, and at the economy-wide level. After the model, we discuss several related empirical predictions suggested by our approach. The model and other predictions are developed explicitly with the goal of generating testable predictions for the dataset used in this chapter.

Consider a setting where a firm has to allocate production between two workers. It has the choice of specializing jobs, or of using multitasking (where workers work independently from each other, producing the entire product or service themselves). In the case of multitasking, it also has the choice of deciding how workers should allocate their time between tasks, or giving them discretion to decide this for themselves. Our analysis is intended to shed light on factors that might tip the balance of job design toward specialization or multitasking, and toward centralization or decentralization. For this reason, we do not model some related issues. In particular, our analysis understates the advantages of specialization, because we force the ratio of specialized workers to be one-to-one. Allowing firms to deploy different ratios of workers to each task, or to have some multitask and some specialized workers, would improve the firm's ability to exploit differences in productivity across the two tasks. Similarly, we do not model agency problems ensuing from worker discretion. That is partly because we do not have good incentive variables in our dataset, and also because our focus is on how the job design itself affects productivity independent of any incentive effects.

Consider a firm with two workers, each with one unit of time to perform assigned tasks. There are two possible methods of production. In one, both workers multitask, producing the entire product via a Cobb–Douglas production function, and total firm output is the sum of individual worker outputs. In the other, both workers specialize, and work from their tasks is combined within the Cobb–Douglas production function to get total output. The production function is $Q = X_1 \times X_2^{\alpha}$. Their marginal product of effort on a task equals s.

Thus, if the workers specialize and their work is combined, output is $Q = s^{1+\alpha}$. As in Becker and Murphy (1992), assume a constant coordination cost C if workers specialize, but none if they multitask:

$$Q_{\text{specialized}} = s^{1+\alpha} - C \tag{1}$$

Now consider the opposite case, where workers spend some time on each task. The key idea in this chapter is *inter-task learning*: in performing one task, the worker may improve output on the other. For example, a worker who performs both tasks should better understand what to emphasize in performing each task, so that the outputs from both tasks fit together better, leading to lower costs or better quality. Exposing a worker to a broader set of tasks also may lead to more innovation and creativity. Using the familiar example of academia, most universities are organized to combine teaching and research, because in most cases working on one improves work on the other. Similarly, interdisciplinary research is often encouraged because it tends to lead to more creative new research topics.

Define τ as the fraction of time that a multitasking worker spends on task 1, with $1-\tau$ for task 2. To capture inter-task learning, which is only relevant for multitasking workers, the extent that output improves on a task is proportional to time spent on the other task:

$$X_1 = s\tau + k(1-\tau); \quad X_2 = s(1-\tau) + k\tau$$

where $k =$ the degree of inter-task learning. There are thus two competing effects on worker productivity. One is the standard gains from specialization s, which applies to all workers; the other is the gains from inter-task learning k, which applies only to multitasking workers. We do not assume that one effect is larger than the other. Output for a single multitasking worker i is:

$$Q_i = (s\tau + k(1-\tau))(s(1-\tau) + k\tau)^{\alpha}$$

τ is chosen by the firm to optimize Q_i:

$$\tau^* = \frac{s - \alpha k}{(1+\alpha)(s-k)}; \quad 1 - \tau^* = \frac{s\alpha - k}{(1+\alpha)(s-k)} \tag{2}$$

Given the allocation of time between the two tasks, individual worker output is given by substituting τ^* and $1-\tau^*$ into Q_i above. Total output is twice this for two multitasking, independent workers:

$$Q_{\text{multitask}} = 2\alpha^{\alpha}\left(\frac{s+k}{1+\alpha}\right)^{1+\alpha} \tag{3}$$

For example, if $k = 0$ and $\alpha = 1$, then $Q_{\text{multitask}} = 1/2 \times s^2$, and $Q_{\text{specialized}} = s^2 - C$, which is greater than $Q_{\text{multitask}}$ as long as C is not too large. The greater the coordination costs, the more likely is multitasking to be optimal rather than specialization. In Eq. (2), for multitasking with $\tau \in (0,1)$, α cannot be too different from 1 in either direction.

Similarly, comparing Eqs. (1) and (3), as α diverges from 1 in either direction, specialization is more likely to be the best design. Thus we should see multitasking only if comparative advantage is not too strong. The effects of higher marginal product s are also ambiguous, since higher s increases output for both specialized and multitask jobs.

In the appendix, we show that there is always some range of parameter values for which multitasking is more efficient than specialization. Holding s and α fixed, the larger is the opportunity for inter-task learning k, the more likely is this to be the case.

2.1. Multitasking and Interdependence

An immediate result of Eqs. (1) and (3) is that multitask jobs are more likely to be optimal; the more important is inter-task learning:

$$\frac{\partial Q_{\text{multitask}}}{\partial k} > 0, \quad \text{while} \quad \frac{\partial Q_{\text{specialized}}}{\partial k} = 0 \tag{4}$$

In this view, a primary cause of multitasking – which reduces traditional gains from specialization – is that it allows the worker to learn about production and make continuous improvements. The degree of specialization is limited not just by coordination costs (Becker & Murphy, 1992), but also by inter-task learning opportunities.[1] For workers to learn on the job, multitasking is important because task interdependencies are an important source of inefficiencies in production, and one that is exacerbated by specialization. Thus, complex production processes (greater task interdependence) are more likely to use multitask jobs.

Our approach stands in contrast to Morita (2001), who addresses the conditions under which an economy will have an equilibrium with jobs that emphasize continuous process improvement, training, and specific human capital versus an equilibrium with jobs that have general human capital, less training, and little to no continuous process improvement. In Morita's model, workers learn how to perform specialized tasks that have a return only to the firm currently employing them – hence the accumulation of firm-specific human capital. A key issue Morita sought to address was lower turnover (and greater training) in Japan versus the United States. In our model, in contrast, learning how to perform multitask jobs does not lead to the accumulation of firm-specific capital. Moreover, our predictions do not lead to an equilibrium in which all jobs in an economy are either specialized or not specialized, as is the case for Morita's model.

The role of task interdependence in this model is similar to what Milgrom and Roberts (1990) call complementarities among elements of the firm's strategy. In their formulation, complementarities mean that the marginal returns to adopting one element are increasing in the level of the other elements. In their case, they examine aspects such as technology adoption, marketing, and engineering. In their model, if there are complementarities among these, then it makes economic sense for the firm to make coordinated changes among all of them at the same time. For example, introducing computer-aided design technology makes it cheaper for the firm to adapt a broader product line and to update its products more frequently, which is reinforced by an engineering approach that designs production processes more quickly using cross-functional teams, and by a marketing approach that emphasizes lower prices, faster delivery, and smaller batch sizes (more customized product lines). The main difference between Milgrom and Roberts (1990) and our model is the focus: Milgrom and Roberts focus on technology changes and organization design; we focus on job design.

Holmstrom and Milgrom (1991, 1994) more directly consider job design: the firm's decision is over whether to hire the person directly as a regular employee or as an independent contractor. Hiring as a regular employee means greater supervision and less discretion than hiring as an independent contractor. In our approach, as detailed in the next section, discretion and supervision are central to the firm's decision-making process. However, instead of deciding over a relationship as regular employee versus independent contractor (representing two polar opposites of discretion and supervision), in our approach the firm selects different amounts of discretion and supervision for a range of "regular employee" jobs.

2.2. Multitasking and Discretion

Another important job design characteristic is the degree of discretion (decentralization) given to an employee (Ortega, 2004; Zoghi, 2002). When there is learning in a multitask job, discretion allows the worker to test new methods of production to solve problems and implement improvements (Jensen & Wruck, 1994). In our model, a simple way to capture this idea is that discretion allows the worker to adjust the allocation of time τ depending on circumstances. For example, suppose the production environment k (or s, k/s, or α) is stochastic, and ex ante the firm knows the distribution of k but not its specific value. If workers perform both tasks, they observe the state of the world before choosing their allocation of time, allowing them to observe in real time the relative value of focusing on one task or devoting time to both. If they are specialized, they do not possess this knowledge because they do not perform the second task, and regardless have no time allocation decision to make. If workers are given discretion, they can choose τ based on this knowledge, though at some agency cost D.[2] Otherwise, the firm chooses τ without this knowledge. Using the worker's knowledge can improve output.

$$E[Q_{\text{multitask|discretion}}] \geq E[Q_{\text{multitask|centralization}}] \qquad (5)$$

For proof of Eq. (5), see Appendix B. Moreover, discretion will tend to be more valuable in more uncertain production environments. From Eq. (3), Q is convex in s, k, s/k, and α. Therefore, expected output will be higher when variance in any of these parameters can be exploited by the worker. Unfortunately, solving for the optimal time allocation τ^* when production is stochastic does not yield closed form solutions, even for simple cases (e.g., binary k or α). However, combining these ideas and the case in Eq. (4) above, a reasonable prediction to test with our data is that discretion should be complementary with multitasking, especially in more uncertain environments.

We do not model incentives. Giving a worker discretion creates agency costs. The firm would presumably respond by implementing an incentive scheme to better align incentives. Thus, the benefits of discretion would in practice be net of agency costs. In datasets similar to ours but including information on incentives, it would be interesting to study whether incentives are more likely to be used, and are stronger, the greater is the use of discretion, multitasking, and interdependence.

Putting these two arguments together, the model predicts complementarity among multitasking, interdependence, and discretion. It also predicts complementarity among specialization, lack of interdependence, and centralization. This suggests two patterns of job design. The first we will call "classical" job design: specialized jobs with little discretion. The second we will call "modern" job design because it matches the apparent trend: "job enrichment" as described in the behavioral literature, using multitasking and more worker discretion. Both types of jobs should be observed in the economy (or industry, or firm). The extent to which we expect to see one or the other depends on the importance of gains from specialization versus inter-task learning. We expect to see "classical" jobs more where interdependence is lower, and "modern" jobs more where interdependence is higher.

Our model shares some similarities with Lindbeck and Snower (2000). In both cases, multitask learning provides the foundation upon which implications for specialization and job design are derived. Lindbeck and Snower (2000), however, consider the roles of technological change that promotes task complementarities (similar in spirit to Milgrom & Roberts', 1990 complementarities), changes in worker preferences for multitask work, and advances in human capital that makes workers better able to multitask; they do not consider other aspects of job design such as discretion. By addressing discretion and the degree of supervision, we indicate potential additional insights into firms' job design choices.

Our model also shares some similarities with Dessein and Santos (2006), which was developed contemporaneously. Dessein and Santos (2006) address the relationships among specialization, discretion, the ease of communication between employees about tasks and their outcomes, and uncertainty in the economic environment. Their goal, similar to ours, is to provide a model that can explain organizations' decisions to create modern versus classical jobs. Their emphasis on uncertainty provides similar predictions as our focus on product complexity, however, with important differences: their approach is better suited for exploring how the external economic environment influences firms' job design decisions; our approach focuses more on how product characteristics influence job design decisions. Moreover, they do not address the role of skills, which we do in the next section.

2.3. The Role of Skills

Skills play a central role in labor economics research, so it is of interest to consider their role in this context. There are two general off-setting effects. The first is that gains from specialization may be complementary to skills. For example, specialization may increase returns on investments in skills in two ways (see Murphy, 1986). First, specialization of training may lower training costs if there are fixed costs to learning new topics. Second, focused work may lead to economies of scale in skill acquisition on the job. For these reasons, we might see more highly skilled workers in more specialized jobs.

A countervailing effect is that skills may facilitate on-the-job learning. If more highly skilled workers are better able to learn on the job, then skills will be complementary to discretion. Returns to skills would be higher in more complex work environments, where the scope for inter-task learning is higher. This effect is suggested by the literature on skill-biased technical change. Much of that literature (Autor et al., 1998, 2003; Goldin & Katz, 1998) has focused on the relationship between technology change and wages, but job design considerations are also important (Autor, Levy, & Murnane, 2002). If certain types of technological change complement problem-solving or abstract-thinking skills (Levy & Murnane, 2005), they may increase the strength of inter-task learning.

Which effect dominates is an empirical question. If skills are more complementary to specialization, then we should see more highly skilled workers given narrow jobs with low discretion – to became masters of their specialized trades. If skills are more complementary to discretion and multitasking, then we should see more highly skilled workers given more enriched jobs.

As a prelude to the empirical work below, it is worth noting that by "skills" we mean the ability to perform the tasks that are needed for a job. Because tasks differ in the skills needed to execute them, we do not assume that what defines "highly skilled" for one set of jobs or for an occupation is the same as what defines skills in another set of jobs or occupation. In particular, we are concerned about skills that are more specific than can be described by total years of schooling, general degree attainment (i.e., high school graduate versus undergraduate degree versus graduate degree), and total years of labor market experience. Though not exactly the same, previous measures of occupation-specific experience (Shaw, 1987; Neal, 1999) are the closest analogy from the existing literature to our concept of the skills needed to perform specific job tasks. As the discussion below details, the job-based data we analyze contain a more precise measure of task- and job-relevant skills than standard employee-based datasets.

2.4. *The Role of Product and Process Characteristics*

Our argument is that a primary reason for multitasking is to facilitate continuous improvement by workers as they perform their jobs. An alternative way for the firm to choose effective production methods is to invest in ex ante optimization. In fact, an important influence on the early job design literature and practice is industrial engineering, a formal method for ex ante optimization pioneered by Frederick Taylor ("Taylorism") and others in the early 20th century. Ex ante optimization should tip the balance away from multitasking and toward specialization, since it implies that there will be less scope for workers to learn improvements on the job.

This helps provide additional predictions about patterns of job design within establishments, firms, and industries.

Consider ex ante optimization of production methods as an investment by the firm. Our model might be extended to allow the firm to invest in ex ante process improvements at some cost. This would increase s and/or α, but reduce opportunities k for workers to make continuous improvements. A greater investment in better methods should therefore induce more use of classical job design. The expected return on investments in ex ante optimization depends on the degree to which it uncovers methods close to the optimum, and the extent to which the efficiency gains are expected to be reaped in the future. These depend on the complexity, predictability, and stability of the firm's product and environment.

First consider product or process complexity. Greater complexity (e.g., more parts; modules in a software program; broader product line) should imply greater cost to ex ante perfection of production methods. The cost of optimizing the manufacture of a tin can (less than half a dozen parts) is substantially lower than optimizing the manufacture of a diesel engine (2,000 or more parts). Moreover, in the diesel engine, the parts have to work together well – there is high interdependency. Such interdependencies tend to be the kind of situations where ex ante optimization is more difficult, quality problems arise, etc.

A second important characteristic of the product or process is the extent to which it is unpredictable. Consider management consulting. Each client engagement is typically different from the last. Some processes and methods can be reapplied, but new methods or applications often need to be developed. Moreover, judgment as to what methods to apply may be required. To the extent that situations arise over and over, the consulting firm may be able to develop standard methods and provide employees with a menu of choices from which to select. However, if any of the work is idiosyncratic and unforeseeable, some optimization will have to occur in real time.

A third important product or process characteristic is stability. This plays out both backward and forward in time. The longer a product has been produced with few or no changes, the more is known about how to make it efficiently, and the lower is the potential for inter-task learning. The longer the firm expects to make the same product in the future, the greater the expected returns on ex ante optimization, leading to greater investments in ex ante optimization.

These factors (complexity, predictability, and stability) influence the return on investments in ex ante optimization of methods, and therefore optimal job design. If the return is small, the firm will invest less in ex ante optimization, and there are greater possibilities for employees to engage in continuous improvement. Continuous improvement is more likely to be successful with a modern approach to job design, and vice versa. Therefore, for groups of workers producing products or using processes that have similar complexity, predictability, and stability, job design should be similar. The more similar these factors for two workers, the more would we expect their job designs to be similar to each other in terms of multitasking or specialization; discretion or decentralization; and degree of skills. This should even apply across jobs that are in different occupations.

This leads to several useful empirical predictions. First, firms should tend toward choosing a similar job design approach (on the spectrum from classical to modern job design) for all jobs within the same firm. This is consistent with Milgrom and Roberts' (1990) complementarities model and with research on the effects of adoption and use of "high performance work systems" on productivity and profitability of organizations (Appelbaum & Batt, 1994; Cappelli & Neumark, 2001; Ichniowski & Shaw, 1995; Ichniowski, Shaw, & Prennushi, 1997; MacDuffie, 1995). Many of these studies find that while the adoption of a single policy does not affect measurable outcomes, there are complementarities between policies that can have real effects.

The complementarities should even apply to workers in different occupations. For example, if a firm gives its production workers greater discretion and more tasks than is typical, we predict that the same firm is more likely to also give its secretaries greater discretion and more tasks. Thus we expect a clustering of high levels of multitasking, discretion, skills, and interdependence within some firms, medium levels at other firms, and low levels at still other firms. In social psychology, Porter, Lawler, and Hackman (1975) make a similar conjecture, which they do not test. Note though that high, medium, and low are relative terms. The prediction is about multitasking, etc. *relative to their occupational norms.*

Note that we do not conclude that modern jobs are optimal for all establishments. If a firm employs multiple strategies across its product line, segmenting the strategies by establishment may be a preferred way of accomplishing its objectives. For example, consider a large firm with a diversified product line spanning both high and low margin products, such as General Electric (GE). GE separates into different divisions (and establishments) the design, engineering, marketing, and production of light bulbs versus jet engines. Though the benefits of modern job design may accrue to both types of production, they should exhibit a greater rate of return in jet engines where the degree of complexity is much greater than it is

for light bulbs. Thus an optimal job design strategy may include adopting different degrees of modern job design across establishments making different products or servicing different customer segments.

Such patterns should be stronger within establishments than within firms as a whole, given differences in the degree of product diversification across firms. At a naïve level, product attributes are likely to be more similar within than across establishments because of product diversity within firms. Less naïvely, establishments are groupings of employees *chosen by the firm.* Because workers are grouped together by choice, it is more likely that the products, customers, technology, etc. that they work with are the same as their colleagues' in the same establishment, compared to employees randomly chosen from the same firm but different establishments. Moreover, if workers are put together at a site when their work is highly interdependent, establishments can in a sense be viewed as teams. If their work is interdependent, then it is even more likely that product and technology attributes will affect them similarly.

Finally, this general prediction should also apply, though more weakly, within industries. Within an industry, products and processes should be more similar than in the economy as a whole. This implies that the returns to investments in ex ante optimization should vary by industry, and there should be patterns of ex ante optimization or continuous improvement across industries. Therefore, industries should show some tendency toward greater use of modern or classical job design approaches.

This logic might also help explain a recent trend toward "modern" jobs (Caroli & Van Reenen, 2001). The past few decades have exhibited rapid change, due to modern manufacturing and flexible production methods, information technology and technological change, shorter product cycles, and increasing emphasis on customization and complex product lines (Milgrom & Roberts, 1990, 1995). All reduce the returns from investing in industrial engineering, and increase the returns to continuous improvement. In a changing environment, there is greater scope for workers to develop improvements and aid implementation of change, because old methods are less likely to be optimal. We now turn to a description of the data that we employ to test these ideas.

3. DATA

Our empirical analyses use a novel dataset that contains information on job design from a nationally representative sample of establishments in the

United States. The NCS is a restricted-use dataset collected by the BLS. It covers the nonagricultural, nonfederal sectors of the US economy. Our data are from 1999. The data were collected by field economists who visited sampled establishments and randomly selected 5–20 workers from the site's personnel records, depending on establishment size. Through interviews with human resources representatives, detailed information about the jobs those workers hold was obtained.

The data include information on occupation and union status of each job, industry, whether the establishment is privately owned or public (state or local government), earnings, and an indicator for use of incentive pay.[3] No demographic information about the worker is collected. The most unusual feature of the dataset is the "leveling factors," which are intended to measure various job design attributes consistently across occupations. These factors are based on the federal government's Factor Evaluation System, which is used to set federal pay scales.[4] There are 10 different leveling factors, or job design attributes, of which we use 5 in this chapter[5]: knowledge; supervision received; guidelines; complexity; and scope & effect. Here we provide a brief synopsis of each and how they correspond to the concepts from our theoretical discussion. All are measured on Likert scales with ranges varying from 1–3 to 1–9.

1. *Knowledge:* This measures the nature and extent of applied information that the workers are required to possess to do acceptable work – this is quite similar to the general notion of human capital, though it differs substantially from the typical operationalization used by labor economists (measuring education/years of schooling and years of general labor market experience). Values of 1–2 roughly correspond to skills required to do simple, routine, or repetitive tasks; 3 is the level of skills required to do standard clerical assignments, resolve recurring problems, or operate and adjust varied equipment for purposes such as performing standardized tests or operations; 4 is at the level of an apprenticeship or someone who can perform nonstandard procedural assignments and resolve a wide range of problems; 5 is at the level of a college graduate who has mastered the basic principles, concepts and methodology of a professional or administrative occupation, and/or who can solve unusually complex problems; and so on. Thus, larger values imply greater knowledge. This factor corresponds quite well to our *skills* job design attribute.
2. *Supervision received:* This measures the nature and extent of supervision and instruction required by the supervisor, the extent of modification and participation permitted by the employee, and the degree of review of completed work. Larger values correspond to *less* supervision. Values of 1–2 indicate substantial supervisory control with minimal employee input; 3 implies some autonomy for the employee to handle problems and deviations; 4–5 indicate that general objectives are set by the supervisor while the worker has more responsibility for implementation and there is little review of the completed job. This factor corresponds to some dimensions of *discretion* in our discussion above. We use it, along with the next factor, to proxy for that concept.
3. *Guidelines:* Measures how specific and applicable the guidelines are for completing the work, and the extent of judgment needed to apply them. As with supervision received, larger numbers correspond to *less* use of Guidelines. Values of 1–2 signify that detailed guidelines are available that are applicable in most situations that are likely to arise; 3 indicates that, while guidelines are available, the worker must judge whether they are applicable, and how to adapt them; 4–5 indicate that few guidelines are available or applicable to completing this job. Thus, we interpret both supervision received and guidelines as indicators of our concept of *discretion.*[6]
4. *Complexity:* Complexity measures two things: the extent to which the job has multiple dimensions, in terms of the nature, number, variety, and intricacy of tasks or processes; and the extent to which the job has unpredictability, due to the need to assess unusual circumstances, variations in approach, and the presence of incomplete or conflicting data. The former is closer to what we mean by multitasking as the opposite of specialization, though unpredictability also suggests variation in tasks. Moreover, complexity is positively associated with interrelationships between tasks. In our discussion of job enrichment, we argued that an important reason for multitasking is to design jobs so that employees see complex interactions between the most complementary tasks. Thus, the NCS Complexity corresponds reasonably well to our concept of *multitasking*.
5. *Scope and effect:* Scope and effect measures the extent to which the employee's work has impacts on activities and persons in (and beyond) the organization, for example by affecting the design of systems, the operation of other organizations, the development of programs or missions. As scope and effect gets larger, the impacts get larger. This measures the interdependence of a job with other processes and jobs in and beyond the organization, rather than interdependence between tasks within the same job. However, it seems likely that greater interdependence between jobs will be positively correlated with greater

interdependence between tasks within jobs, indicating that overall interdependence is higher. We interpret this as a proxy for *interdependence*.[7]

4. RESULTS

4.1. Bivariate Relationships between Job Characteristics

Table 1 shows the Spearman's rank-order correlations among the five factors. The correlations are high, consistent with our prediction that there should be positive relationships among multitasking, discretion, and interdependence. Table 2 replicates the bivariate relationships from Table 1 using ordered logits, predicting multitasking as a function of either discretion (measured by either guidelines or supervision), skills, or interdependence; guidelines as a function of supervision, skills, or interdependence; supervision as a function of skills or interdependence; and skills as a function of interdependence. Each cell represents a separate regression, with the row naming the dependent variable and the column naming the independent variable. The first number in each cell shows the estimated ordered logit coefficient.

Each model includes controls for both union and nonprofit status. The top panel is for the entire sample. The middle and bottom panels have only non-managers and only managers, respectively. Table A1 repeats the ordered logits adding first a set of indicators for the establishment's primary

Table 1. Correlations between Job Design Attributes.

	Discretion		Skills	Interdependence
	Guidelines	Supervision		
Multitasking	0.8475	0.8505	0.8341	0.8485
Discretion				
Guidelines		0.8450	0.8234	0.8701
Supervision received			0.8274	0.8404
Skills				0.8176

Spearman's rank-order correlations between job design attributes. Because sample sizes are so large and significance levels are so high, those statistics are not shown in the tables. Overall sample size = 137,181; there are 15,349 firms, and 19,791 establishments.

Table 2. Unrestricted Relationships between Pairs of Job Design Attributes.

	Discretion		Skills	Interdependence
	Guidelines	Supervision		
(a) Full sample				
Multitasking	4.491	3.881	1.777	4.033
	(0.4759)	(0.4848)	(0.4218)	(0.4776)
Discretion				
Guidelines		3.395	1.470	3.756
		(0.4886)	(0.3916)	(0.5247)
Supervision			1.714	3.517
			(0.4308)	(0.4702)
Skills				2.952
				(0.3024)
(b) Non-managers only				
Multitasking	4.541	3.907	1.894	3.949
	(0.4538)	(0.4638)	(0.4120)	(0.4504)
Discretion				
Guidelines		3.901	1.566	3.684
		(0.4613)	(0.3887)	(0.5004)
Supervision			1.806	3.473
			(0.4201)	(0.4467)
Skills				3.039
				(0.2957)
(c) Managers only				
Multitasking	4.290	3.901	3.455	4.182
	(0.4283)	(0.4264)	(0.4147)	(0.4772)
Discretion				
Guidelines		4.568	2.774	4.016
		(0.4534)	(0.3255)	(0.5321)
Supervision			2.793	3.439
			(0.3605)	(0.4415)
Skills				3.028
				(0.3903)

Relationships between factors are coefficients from ordered logits; each cell represents a separate logit. Rows are dependent variables; columns are independent variables. Pseudo-R^2 are in parentheses. Additional controls included in each regression: union status and nonprofit status.

industry and then the job's primary occupation. Because of large sample sizes, all the coefficients have high levels of statistical significance, so standard errors are not included. A more informative statistic is the pseudo-R^2 (in parentheses below each coefficient): $1-(LL_{\text{Full model}}/LL_{\text{Constant only}})$, where LL is the log-likelihood. The pseudo-R^2 shows the extent to which the variance in the dependent variable is "explained" by the model.

In all the models in the top panel of Table 2 for the full sample, the Pseudo-R^2 indicates a strong relationship between the factors. Close to half the variance in multitasking is explained by either of the discretion variables and by interdependence. Not surprisingly, there is also a strong positive relationship between the two measures of discretion. More than half the variance in guidelines is explained by interdependence. Overall, Table 2 presents strong evidence consistent with the prediction that job designs will tend to be "coherent" with respect to multitasking, discretion, and interdependence: these three characteristics are all positively associated with each other.

The relationships between skills and multitasking, skills and discretion, and skills and interdependence are also positive, but are not as strong. These suggest that, on balance, skills favor inter-task learning and continuous improvement rather than specialization. This is consistent with the evidence on skill-biased technological change and increasing returns to skill investments in recent decades. Rapid technological change reduces the incentive for firms to invest in ex ante optimization, and increases the opportunities for workers to make continuous improvements. That implies a trend toward multitasking and discretion. Our evidence suggests that these work even better if the worker has greater skills.

In addition to the results for the full sample at the top of Table 2, the results for the non-managerial and managerial samples are reported in the middle and bottom of the table. The first point of note is that the basic patterns are the same: strong positive correlations among all job design characteristics. Second, the correlations among skills and each of multitasking, guidelines, or supervision are much stronger within the managerial sample than within the non-managerial sample. This suggests that problem-solving skills are more valuable in managerial jobs.

That the evidence supports the theory for both the managerial and non-managerial samples, and the relationships are stronger when controlling for occupations, are particularly noteworthy in light of previous empirical evidence. The examples studied most often come from manufacturing, and are closely tied into the discussion in recent years of the impact of human resource practices on productivity and profitability (Huselid, 1995; MacDuffie, 1995; Ichniowski et al., 1997; Cappelli & Neumark, 2001). The disproportionate focus on manufacturing is understandable given the intellectual heritage and framework established by Taylor (1923), and the ease of measuring productivity in manufacturing. But the theory does not

require a manufacturing setting, as the more recent research on service environments demonstrates (Batt, 2002; Batt & Moynihan, 2002).[8] Yet despite the gains that have been made at the case study level, to date there has been no systematic data available to test these predictions economy-wide. Table 2 provides the first such evidence.

4.2. Multivariate Relationships between Job Characteristics

The results in Tables 2 and A1 provide evidence that pairs of job design attributes – including skills – are complementary. A stronger test focuses on the extent to which they cluster together as a group so that job designs are "coherent" at the job level – all dimensions high, all medium, or all low – which we test in Table 3. At the top of Table 3 are the distributions of each dimension relative to the median in the entire sample.[9] Because we expect that occupations segregate jobs into groups that are already similar on each job design dimension, we want to focus on the extent to which a job is low, medium, or high relative to the occupational norm. Consequently, in the second panel of Table 3 we center the values for each job around the median for each 3-digit occupation. Comparing the patterns in the top two panels of Table 3, the much higher concentration at the median in the second panel shows that occupations group together jobs that are similar along each design dimension.

To construct a multidimensional measure to test whether job design dimensions group together as all high, all low, or all medium along all four dimensions, we first use the rankings in the middle panel of Table 3 to assign a value of 1 (below the occupational median = L), 2 (at the occupational median = M), or 3 (above the occupational median = H) to each job for each dimension. We then sum these values for each job to create an index that ranges from 4 (LLLL) to 12 (HHHH) for each job. There are 81 possible combinations of the four characteristics, and 9 possible sums. The bottom panel of Table 3 shows the percentage of jobs with all low values, all high, all medium, as well as all other possible sums. The value of 8 is broken into two groups: jobs that have all medium (MMMM) for all four dimensions, and those that have an index value of 8 via some other combination of values (e.g., LHMM, MLMH, HMML, etc.). The first column contains the actual distribution of the index values in the sample, with the standard error of each percentage in parentheses under the mean. The second column has the probability that that index should occur if the

Table 3. Distribution of Leveling Factors.

	L (<Median)	M (Median)	H (>Median)
Distribution relative to median value in the economy			
Skills	0.362	0.199	0.439
Guidelines	0.333	0.361	0.306
Multitasking	0.193	0.351	0.456
Interdependence	0.309	0.345	0.346
Distribution relative to median value within 3-digit occupation			
Skills	0.251	0.540	0.209
Guidelines	0.190	0.610	0.200
Multitasking	0.194	0.603	0.203
Interdependence	0.185	0.619	0.196

Index Relative to Median	Fraction of All Jobs (SE)	Pr(Characteristics Randomly Assigned from Empirical Distribution)	Actual/Predicted
Index (Σ) of skills, guidelines, multitasking, and interdependence (using distribution relative to median value within 3-digit occupation)			
4 (= LLLL)	0.0541 (0.0006)	0.0017	31.6
5	0.0697 (0.0007)	0.0202	3.4
6	0.1109 (0.0009)	0.0957	1.2
7	0.1488 (0.0010)	0.2320	0.6
8 (= MMMM)	0.2502 (0.0012)	0.1230	2.0
All other values of index = 8 except MMMM	0.0151 (0.0003)	0.1856	0.1
9	0.1268 (0.0009)	0.2278	0.6
10	0.0796 (0.0007)	0.0929	0.9
11	0.0823 (0.0007)	0.0196	4.2
12 (= HHHH)	0.0626 (0.0007)	0.0017	37.6

values in the middle panel of the table were randomly distributed across all jobs. The third column has the ratio of the actual to predicted values.

The strong test of the extent to which firms choose between classical and modern job designs across jobs is provided by comparing the percentage of

jobs with all low or all high values to the expected percentage if job characteristics were randomly assigned based on their univariate frequency distributions from the middle panel of Table 3. For example, the expected percentage of workers with all low values equals the product of the percentages of jobs below the median for each characteristic: $(0.251) \times (0.190) \times (0.194) \times (0.185) = 0.0017$ (third column). The corresponding expected percent having all high values is, coincidentally, also 0.0017. The actual occurrence of both job types (LLLL and HHHH) is more than 30 times more likely than one would expect purely by chance. The actual occurrence of MMMM jobs is not as dramatic relative to the random case, but is still quite divergent – twice as likely. Moreover, jobs that are "almost all high" (index value of 11, which means three H and one M) or "almost all low" (index value of 5, which means three L and one M) occur three to four times as often as is expected by chance. Thus the patterns in the bottom panel of Table 3 provide strong evidence of coherence in job design at the individual job level.

It is worth asking whether the percentages of jobs falling into the high and low groups are what we would expect to see, given all that has been written about the trends toward modern job design. The fraction of all jobs that have an index value of either 11 ("almost all high") or 12 ("all high"), which we view as a reasonable proxy for modern jobs, is 14.5 percent. Similarly, the fraction of all jobs that have an index value of either 4 ("all low") or 5 ("almost all low"), which we view as a reasonable proxy for classical jobs, is 10.4 percent. Given that these are the first nationally representative data available with these types of job design measures, it is difficult to determine whether such a figure should be viewed as high, low, or "just right."

On one hand, 14.5 percent modern jobs suggests that the trend toward modern job design has not been very pervasive, though it is up to the reader to decide if almost one out of six jobs is a relatively large fraction, given that we have only cross-sectional data. On the other hand, the percentage of all jobs that are modern (combining index values 11 and 12) is proportionately almost one and a half times larger than the percentage of all jobs that are classical (combining index values 4 and 5). Viewed this way, it would appear that modern jobs are more pervasive than classical jobs, supporting the claim that there may have been a shift toward modern jobs in recent years.

Perhaps more interesting is the percentage of jobs with design attributes that cluster at the middle (index value of 8 and MMMM). At 25 percent, these account for one-quarter of all jobs, which is twice as prevalent as one would expect if job design attributes were chosen at random. While the literature and business press has focused predominantly on the two extremes – modern versus classical jobs – there is some evidence that firms face difficulties when attempting to implement modern job design. For example, teams are one example of modern job design that combines cross-functional responsibilities (multitasking), training (higher skills), and decentralized decision making (discretion, low supervision). The literature on teams is replete with evidence that they are difficult to set up, administer, and maintain (Mohrman, Cohen & Mohrman, 1995; Osterman, 2000; Gibson & Cohen, 2003). Thus organizations may be in a continual state of flux with respect to teams, sometimes expanding their use and sometimes contracting as they struggle to implement them effectively (Levenson, 2007).

If efforts at implementing teams and modern jobs often fall short of their intended goal, the end result could be a number of jobs that are more modern than classical, but "not quite modern enough" to fit the ideal as characterized by the "all high" jobs in Table 3. This is consistent with the evidence documented by Ichniowski and Shaw (1995) that firms tend to adopt clusters of HR practices that are consistent with modern job design, but that there are costs of adoption due to changing over from classical to modern job design. This leads new establishments to be more likely to adopt the most wide-reaching sets of HR practices and modern job design, while older establishments (that start off with more classical job designs) are more likely to adopt some, but not all, such modern job design practices. While we are unable to match our job design data to comparable measures of HR practices, the evidence in Table 3 of a disproportionately large number of "medium" (MMMM) jobs is consistent with a cost of adoption story.

The rest of the analysis in the chapter uses the classification of jobs into LLLL, MMMM, and HHHH categories defined in Table 3. As such, it is worth emphasizing what those classifications represent. Note that in each case the classification is *relative to the 3-digit occupation median*. Standard occupational classifications inherently represent job characteristic clustering: professional and technical occupations tend to be high on knowledge, discretion, and complexity, while manual labor jobs and administrative support occupations tend to be lower on knowledge, discretion, and complexity.

From a production standpoint, firms do not have a huge amount of latitude to substitute across broad occupation categories when designing jobs: lawyers and scientists typically cannot be substituted en masse for secretaries, laborers, and truck drivers without introducing massive distortions in the marginal cost of production (wage costs) and/or efficiency of production. The job design model focuses on the decisions firms make within occupation categories: the extent to which knowledge, discretion, and complexity vary *within* technical/professional jobs, or *within* manual labor jobs, or *within* administrative support jobs. The interesting question is what leads some scientists' jobs to have greater complexity, knowledge and/or discretion relative to other scientists' jobs; and the same thing for truck drivers relative to other truck drivers, secretaries relative to other secretaries, etc. Our analysis focuses on those job design decisions, not the decision of how many jobs of different occupational types the firm needs.

4.3. Effects of Establishment Characteristics on Job Characteristics

We have argued that no single job design strategy is optimal for all types of establishments, but that characteristics of the environment, such as product complexity, stability, and predictability will affect the choice of job design. We start by examining whether unionization, establishment size, and nonprofit status affect job design, modeling the probability that a job is "all modern" or "all classical" using logit regressions. Table 4 shows the results of this analysis.[10] The second and fourth columns include a full set of industry indicators.

Unionized jobs are much less likely to be "all classical" yet also less likely to be "all modern." The former is consistent with unions' traditional negative views of classical job design. The latter is consistent with the

Table 4. Determinants of Modern (HHHH) or Classical (LLLL) Job Design.

	Pr(LLLL)	Pr(LLLL)	Pr(HHHH)	Pr(HHHH)
Nonprofit	−0.1115	−0.2911**	−0.2193**	−0.2303**
Union	−0.8562*	−0.7078*	−0.1755*	−0.1801*
Employment/1,000	−0.0226*	0.0054	0.0820*	0.0387*
$(\text{Employment}/1{,}000)^2$	−0.0001**	−0.0001	−0.0011*	−0.0003*
Industry controls	No	Yes	No	Yes
Pseudo-R^2	0.0128	0.0679	0.0109	0.0817
N	42,750	41,586	42,750	41,870

Coefficients from logits. Sample = jobs in multi-establishment firms. Controls are included for percent of jobs in 14 job design clusters as described in Table 7a.
*p-value < 0.01.
**p-value < 0.05.

conventional wisdom that unions resist change, and to wider differences in compensation among nonmembers. Modern job design has potential benefits to employees in upgraded skills and potentially higher wages. But making that change can threaten the probability that existing union workers will keep their jobs, and might widen the dispersion in earnings among members. Nonprofits similarly reduce the probability that a job is either "all modern" or "all classical."

Larger establishments are more likely to choose modern job design and less likely to choose classic job design. This is consistent with the model, which argues that multitask output can exceed specialized output when coordination costs are large. In larger establishments there are often more hierarchical levels, making information transfer slower and more difficult, resulting in higher coordination costs. Finally, it is important to note that although these establishment characteristics alone do not explain a large fraction of the variance in the probability a job is modern or classical, the industry indicators add substantial explanatory power to the model. This suggests that other characteristics of the industry, such as product complexity and stability, do strongly affect an establishment's choice of job design.

One critique of our findings might be that they are driven not by inter-task learning, but instead by firms designing jobs to generate intrinsic motivation as in the social psychology literature. The fact that job design patterns vary systematically across different industries suggests that product or industry characteristics matter, which can be taken as evidence in favor of the inter-task learning explanation. However, we do not have sufficient data to rule out the possibility that the returns to generating intrinsic motivation through job design do not vary by industry. In a model such as Lindbeck and Snower's (2000), differences in worker preferences for modern jobs and ability to multitask are two of the factors that lead to observed differences in the adoption of modern job design. If the supply of workers to particular industries is determined in part by sorting on noneconomic preferences for working in those industries (e.g., an intrinsic preference for social work or education versus manual labor), and if workers' multitasking ability is related to those preferences, then firms in those different industries may face differential returns to using job design to tap into intrinsic motivation. Of course, it is most likely that both mechanisms play a role: there may be differential returns to generating intrinsic motivation at the same time that product/industry characteristics are an important determinant of the returns to adapting modern job design.

4.4. Technology and Job Design

While we do not have direct measures of industry characteristics such as product complexity and stability available in the NCS data, we were able to match the NCS job design characteristics at the industry level to measures of aggregate computer use and R&D spending to investigate the interaction of technology and job design.

Table 5 focuses on the relationship between job design choices (modern versus classical) and computer usage. The computer usage data comes from the September 2001 Internet and computer use supplement to the current population survey, and are matched at the 2-digit industry level using the CPS microdata. This enabled matching for 51 distinct industry groupings. Two sets of correlations with computer usage are presented: the percentage of jobs in an industry that are modern, and the percentage that are classical. In both cases the correlations using both percentages and ranks are presented at the bottom of the table. Computer usage and the percentage of jobs in the industry that are modern are fairly strongly correlated (0.50), indicating that computerization and the design of jobs to deal with complexity, interdependence, and autonomy are closely related, consistent with computers being a complement to skill, at least for some jobs. Computer usage is also positively correlated with the percentage of jobs in an industry that are classical (0.30), consistent with computers being used to increase monitoring, decrease autonomy, and lower the skill requirements for other jobs. These patterns are consistent with industries using computers to simultaneously upskill some jobs while downskilling other jobs (Goldin & Katz, 1998; Autor et al., 2002).

Table 6 shows the relationship between R&D spending and job design. The R&D data come from NSF, Division of Science Resources Statistics, Research and Development in Industry: 1999, NSF 02-312. R&D spending per capita was calculated using the aggregate employment for each industry from that same source. Accurate R&D numbers are not available at the same level of disaggregation as the computer usage data, hence, there are only 17 industries available for this analysis. Despite the small sample size, the correlation of per capita R&D spending with the percentage of jobs that are modern in an industry is very high (0.76) and is statistically significant. The correlation of per capita R&D spending with the percentage of jobs that are classical, in contrast, is both much smaller (0.20) and not statistically significant. Given the small sample size, it may be the case that a larger sample would produce different correlation patterns. Thus the results in Table 6 should be taken as preliminary evidence that R&D spending is

Table 5. Computer Usage and Industry Patterns of Job Design.

Industry	% Using Computers at Work	Rank	% Jobs Modern	Rank	% Jobs Classical	Rank
Brokers	0.912	1	0.120	1	0.056	33
Mfg. – Prof. Equipment	0.728	10	0.117	2	0.058	29
Mfg. – Chemicals	0.720	12	0.117	3	0.036	42
Service – Professional	0.837	6	0.115	4	0.096	4
Mfg. – Transport	0.509	28	0.112	5	0.037	41
Mfg. – Machine	0.584	21	0.096	6	0.050	37
Mfg. – Paper	0.492	30	0.087	7	0.031	46
Service – Legal	0.882	2	0.086	8	0.097	3
Mfg. – Stones	0.396	42	0.084	9	0.052	35
Mining	0.448	37	0.079	10	0.065	21
Insurance	0.867	3	0.077	11	0.064	23
Mfg. – Electric	0.621	19	0.073	12	0.078	13
W. Durables	0.641	17	0.072	13	0.085	8
Mfg. – Petroleum	0.844	5	0.067	14	0.094	6
Utility	0.608	20	0.066	15	0.034	45
Service – Nonprofessional	0.677	14	0.065	16	0.065	22
W. Nondurables	0.526	27	0.064	18	0.078	14
Public Administration	0.746	9	0.064	17	0.051	36
Mfg. – Printing	0.630	18	0.063	20	0.091	7
Real Estate	0.652	16	0.063	19	0.081	10
Service – Entertainment	0.472	33	0.062	21	0.048	38
Banking	0.853	4	0.060	22	0.075	15
Retail – Catalog	0.537	24	0.059	24	0.116	1
Mfg. – Rubber	0.477	32	0.059	25	0.063	25
Service – Social	0.446	38	0.059	26	0.062	26
Communications	0.812	7	0.059	23	0.060	27
Mfg. – Food	0.334	45	0.057	27	0.069	19
Mfg. – Metal	0.471	34	0.055	28	0.057	30
Transport	0.405	40	0.055	29	0.036	43
Service – Education	0.701	13	0.054	30	0.060	28
Mfg. – Toys, etc.	0.467	35	0.050	31	0.071	17
Service – Hotel	0.416	39	0.050	32	0.019	49
Retail – Gas	0.451	36	0.046	33	0.017	51
Mfg. – Lumber	0.298	48	0.041	34	0.057	31
Service – Hospital	0.722	11	0.037	35	0.036	44
Construction	0.256	50	0.035	37	0.072	16
Retail – Grocery	0.346	44	0.035	36	0.019	50
Service – Business	0.657	15	0.032	38	0.095	5
Retail – Vehicle	0.559	22	0.032	39	0.048	39
Service – Medical	0.549	23	0.032	40	0.04	40
Retail – Eating	0.240	51	0.029	41	0.027	48
Mfg. – Leather	0.531	26	0.028	42	0.067	20

Table 5. (*Continued*)

Industry	% Using Computers at Work	Rank	% Jobs Modern	Rank	% Jobs Classical	Rank
Mfg. – Apparel	0.282	49	0.027	44	0.064	24
Retail – Building	0.491	31	0.027	43	0.055	34
Retail – Other	0.493	29	0.026	46	0.109	2
Retail – Hobby	0.535	25	0.026	45	0.071	18
Mfg. – Textile	0.300	47	0.024	47	0.057	32
Service – Repair	0.378	43	0.023	48	0.079	11
Service – Personal	0.316	46	0.022	49	0.083	9
Retail – Apparel	0.403	41	0.014	50	0.029	47
Retail – Technology	0.752	8	0.006	51	0.079	12
Correlation between computer use and % jobs modern and classical:			0.50***	0.51***	0.30***	0.29***

highly complementary with modern job design, and much less complementary (if not unrelated) to classical job design. This is consistent with R&D spending being focused on innovations that increase product complexity and that require processes that are optimized when workers have greater autonomy and skills. Moreover, organizations that invest more in R&D tend to have greater opportunities for continuous improvement. Their industries are more likely to involve rapid technological change and unpredictability, so that ex ante optimization is less effective.

The combined results in Tables 5 and 6 provide good evidence that job design decisions are related to a firm's or industry's product characteristics and technology. There is one additional point about the patterns in Tables 5 and 6 that is worth noting. At first glance, the reader might find the prevalence of modern versus classical jobs in certain industries to be anomalous. For example, professional services has the highest rate of classical jobs in Table 6 and the fourth highest rate of classical jobs in Table 5. Professional services is commonly thought of as an industry in which discretion and customized work are widespread. Thus it might appear counterintuitive to find that this industry has a disproportionately large fraction of classical jobs. However, there are two reasons why this finding is not necessarily wrong and may in fact be reasonable.

First, note that no industry has more than about 10 percent purely classical jobs (all low, LLLL) in either table. Given the large number of tasks and jobs involved in any industry, even if the typical job in an industry might be modern, there is nothing preventing a minority of other jobs from

Table 6. R&D Spending and Industry Patterns of Job Design.

Industry	R&D ($Millions)	Domestic Employment (Thousands)	R&D per Thousand Employees	Rank	% Jobs Modern	Rank	% Jobs Classical	Rank
Mfg. – Chemicals	20,372	1,023	19.91	2	0.117	1	0.036	16
Service-Professional	23,640	761	31.06	1	0.115	2	0.096	1
Mfg. – Transport	34,059	2,159	15.78	4	0.112	3	0.037	14
Mfg.-Machine, Prof. Eq.	44,076	2,230	19.77	3	0.102	4	0.052	12
Durables, Nondurables	19,960	1,339	14.91	5	0.068	5	0.081	3
Mfg. – Petrol	615	116	5.30	9	0.067	6	0.094	2
Utility	142	410	0.35	17	0.066	7	0.033	17
Communications	15,421	1,665	9.26	8	0.059	8	0.060	8
Mfg. – Rubber	1,845	562	3.28	10	0.059	9	0.063	7
Mfg. – Food	1,159	1,043	1.11	13	0.057	10	0.069	6
Transport	466	756	0.62	16	0.055	11	0.037	15
Mfg. – Metal	2,174	1,120	1.94	12	0.055	12	0.057	11
Mfg. – Toys, etc.	4,226	351	12.04	7	0.050	13	0.071	5
Mfg. – Lumber	70	71	0.99	14	0.041	14	0.057	10
Construction	699	270	2.59	11	0.034	15	0.072	4
Svc. – Med., Hospital	660	51	12.94	6	0.034	16	0.039	13
Mfg.-Textile, Apparel, Leather	337	362	0.93	15	0.026	17	0.059	9
Correlation between per capita R&D spending and % jobs modern and classical:					0.76***		0.20	

being classical – particularly given the tendency of firms to segregate modern and classical jobs by establishment, as is shown in the next section below. An industry such as professional services that often produces highly customized products may be able to do so by employing one set of people who focus on the higher order knowledge work (and work in more modern jobs), while simultaneously employing a second set of people who focus solely on routine work (and work in more classical jobs). The former could include the client-facing work and most difficult problem-solving tasks that involve generating new knowledge and work routines for the clients, while the latter could include more routine tasks such as order processing, data entry, filing regulatory compliance forms, managing billing processes, etc.

Second, recall that we defined a job as high versus medium versus low on each job design dimension *relative to its occupational norm*. Thus an industry that typically employs college graduates in knowledge work jobs will only show up as having a large fraction of modern jobs if the amount of discretion, skills, etc. is high *relative to comparable jobs in other industries that also require college graduate-level skills to perform knowledge work*. Thus the patterns in Tables 5 and 6 are driven by relative differences in concentrations of modern versus classical jobs within, not between, occupations. A ranking of industries on the basis of job design characteristics that did not account for occupational norms would naturally give greater weight to industries employing larger number of more highly educated workers, who tend to have jobs with greater discretion in general. For our purposes, we find the rankings in Tables 5 and 6 to be more useful and informative.

4.5. Similarity of Job Designs within Firms and Establishments

We now analyze the prediction that job designs will tend to be similar within firms, and even more so within establishments. The relevant comparison for a job is not to all other jobs in the economy, but to other jobs in the same establishment or firm. We reestimate the logits of the previous section, including as regressors the percentages of other jobs in the establishment or firm that fall into each of the 81 unique combinations of the four job characteristics. For ease of interpretation, Table 7A reports the results when all jobs with common combinations are grouped together. For example, the "3L, 1M" group includes four subgroups: LLLM, LLML, LMLL, and MLLL.[11] We predict that the probability that any one job is "all modern" is positively related to how many other jobs in the establishment and/or the

Table 7A. Effect of Distribution of Other Jobs' Characteristics on Probability of Modern (HHHH) or Classical (LLLL) Job Design.

Skill Set	Pr(LLLL)		Pr(LLLL)		Pr(HHHH)		Pr(HHHH)	
	Establishment	Firm	Establishment	Firm	Establishment	Firm	Establishment	Firm
LLLL	**3.281***	**3.078***	**2.376***	**2.101***	**−0.547****	0.588	**−0.931***	0.191
3L, 1M	**1.262***	**1.045***	**1.199***	**0.848***	−0.395	−0.410	**−0.603****	**−0.615*****
2L, 2M	**1.176***	0.015	**1.158***	−0.120	**−0.572***	−0.408	**−0.585***	−0.417
1L, 3M	**0.520***	0.175	**0.539***	0.076	**−0.758***	**−0.800***	**−0.732***	**−0.670***
3L, 1H	2.104	5.729	1.477	3.907	−0.996	−2.412	−1.590	−4.747
2H, 1M, 1L	0.870	1.696	0.494	1.016	0.495	0.611	0.495	0.779
2H, 2L	−0.888	0.042	−4.151	−3.046	−11.67	7.032	−10.70	6.922
1L, 2M, 1H	−0.472	1.047	−0.390	1.038	0.073	−0.148	−0.243	−0.730
2L, 1M, 1H	−1.639	0.145	−1.289	0.430	−0.171	0.977	−1.252	−0.120
3H, 1L	0.426	−0.571	0.726	−0.115	−2.658	−2.720	−2.251	−1.369
1H, 3M	**−0.986***	−0.059	**−0.948***	0.234	**0.427***	−0.361	**0.431***	−0.109
2H, 2M	**−0.841***	−0.372	**−1.101***	**−0.948***	**1.019***	0.084	**0.887***	−0.202
3H, 1M	**−0.624****	0.495	**−0.946***	0.087	**1.354***	0.200	**1.275***	0.303
HHHH	**−0.816***	**0.970***	**−1.194***	0.338	**3.517***	**1.937***	**2.799***	**1.159***
Industry controls	No		Yes		No		Yes	
Pseudo R^2	0.0926		0.1143		0.1133		0.1297	
N	41,421		40,285		41,421		40,570	

Coefficients from logits. Controls included for nonprofit status, unionization, establishment size and its square. Sample = jobs in multi-establishment firms.
*p-value < 0.01.
**p-value < 0.05.
***p-value < 0.10.

firm are "all modern." For the firm variables, the percentages are calculated using jobs at other establishments in the same firm, excluding jobs at the same establishment. Thus firms with only one establishment are excluded from the analysis in Table 7A. The first set of columns predicts the probability of a classical (LLLL) job, both with and without 3-digit industry controls. The second set of columns predicts the probability of a modern (HHHH) job.

The results in Table 7A are consistent with the predictions. The probability of a classical job is correlated positively with the percentage of other jobs in the establishment that are classical (first row), and negatively with the percentage of other jobs in the establishment that are modern (last row). Similarly, the probability of a modern job is correlated positively with the percentage of other jobs in the establishment that are modern, and negatively with the percentage of other jobs in the establishment that are classical. There are similar positive, but smaller, correlations between Pr(LLLL) and many of the jobs that are "almost all" classical (3L1M) and "mostly classical" (2L2M; 1L3M). The opposite is true for Pr(HHHH) and jobs that are almost (3H1M) or mostly (2H2M; 1H3M) modern. Jobs that mix both high and low characteristics (3L1H; 2L2H; 1L2M1H; etc.) are much less likely to be positively correlated with either Pr(LLLL) or Pr(HHHH): none of those coefficients have p-values < 0.05. Thus, firms tend to choose pure job design approaches, opting for many jobs to be either high on all dimensions, or low on all dimensions.

To a lesser degree, firms make the same choice across establishments, as predicted. This provides evidence that respondent bias is not the explanation for correlations between job designs with those of other jobs in the establishment. Although we are concerned that a single human resource representative describing all sampled jobs in the establishment may scale up or down all responses, jobs across establishments within a single firm are described by separate individuals. If job design were not clustered within an establishment but merely appeared to be so due to respondent bias, we would not expect to find peer effects for other workers within the firm but outside the establishment – such effects confirms that respondent bias is not driving the results.[12] Patterns in job design within industries and occupations, described below, are further evidence that our findings are not driven by respondent bias.

Two additional patterns are worth noting in Table 7A. First, having many modern jobs in the same establishment reduces the probability that a job will be classical. At the same time, having a high percentage of modern jobs in the *other* establishments in the firm increases the probability that a job will be classical in the present establishment, too. This suggests that firms isolate similar jobs in the same establishment and also push job design toward the extremes, away from the middle. This pattern disappears when controlling for industry differences across establishments. Thus, such clusters of establishments are concentrated in some industries and not others, and this pattern likely is related to differences in product, technology and/or organizational change.[13]

Second, some within-establishment correlations get *stronger* when controlling for industry. Specifically when predicting Pr(LLLL), coefficients on the fraction of jobs that are HHHH and (3H1M) get more negative; and when predicting Pr(HHHH) coefficients on the fraction of jobs that are LLLL and (3L1M) get more negative. This means that the tendency for a firm to segregate modern and classical jobs across its establishments is consistent across industries, though more prevalent in some industries.

Table 7B presents the results from predicting Pr(MMMM), using the same set of regressors as Table 7A. As expected, the probability that a job will be MMMM is strongly correlated with the presence of similar "all medium" jobs in both the establishment and in the firm, with stronger within-establishment than within-firm correlations. Table 7B shows the same within-firm, across-establishment segregation of dissimilar jobs. In the case of "medium" jobs in Table 7B, the segregation occurs for jobs that are only slightly different. For example, the greater the fraction of (1H3M) jobs in the rest of the firm, the lower the probability of a MMMM job in the same establishment.

4.6. Within versus Outside 2-Digit Occupation Correlations

To this point, we have not distinguished between occupations except to control for nationwide differences in the median value for each leveling factor by occupation. An interesting question is the extent to which job design patterns within an establishment are driven by clustering of jobs in similar occupations, where occupations are defined by Census 2-digit classifications. We would expect some within-2-digit-occupation clustering, given task interdependencies and the consequent complementarity of such skills in production; for example, grouping modern chemical engineering with modern electrical engineering jobs. Less obvious is the prediction of between-2-digit-occupation clustering; for example, grouping modern engineering with modern administrative support jobs. It is reasonable to expect such clustering if the task interdependencies in production are

Table 7B. Effect of Distribution of Other Jobs' Characteristics on Probability of MMMM Job Design.

Skill Set	Pr(MMMM)		Pr(MMMM)	
	Establishment	Firm	Establishment	Firm
LLLL	0.059	**−0.453****	0.047	**−0.617***
3L, 1H	**−5.404***	−0.203	**−5.452***	0.250
2H, 1M, 1L	−0.386	−0.361	−0.522	−0.678
2H, 2L	−0.321	1.880	−0.396	1.099
3L, 1M	**0.338****	**−0.526***	0.280	**−0.654***
2L, 2M	**0.331***	**−0.541***	0.193	**−0.793***
1L, 3M	**0.422***	−0.188	**0.279****	**−0.490***
MMMM	**1.508***	**1.237***	**1.185***	**0.669***
1H, 3M	**0.465***	**−0.501***	**0.278****	**−0.959***
2H, 2M	**0.459***	**−0.467***	**0.454***	**−0.535***
3H, 1M	**0.427***	**−0.777***	**0.347***	**−1.046***
1L, 2M, 1H	−0.068	**−0.717****	−0.007	**−0.746****
2L, 1M, 1H	−0.850	−1.261	−0.872	−1.349
3H, 1L	0.283	1.307	−0.050	0.930
Industry Controls	No		Yes	
Pseudo R^2	.0406		.0459	
N	41,421		41,298	

Coefficients from logits. Controls included for nonprofit status, unionization, establishment size and its square. Sample = jobs in multi-establishment firms.
**p*-value < 0.01.
***p*-value < 0.05.

relatively "global" across the entire production process. For the most peripheral tasks, however, we would expect interdependencies to diminish to the point where there are fewer gains from clustering job design attributes; such tasks likely would include non-"core" processes such as janitorial work and food service. One characteristic of truly peripheral tasks is that they should be greater candidates for outsourcing (Abraham & Taylor, 1996).

Table 8 shows the proportion of jobs outside of one's own occupation that have the same job design (a) for the economy absent one's own firm, (b) for the firm absent one's own establishment, and (c) for the other jobs in the establishment. For the sample of single-establishment firms, only the first and third categories are relevant. The clustering of modern and classical jobs is greater at the establishment level than at the firm level and in the economy overall: both modern and classical jobs are approximately twice as

Table 8. Clustering of Job Design Outside Own 2-Digit Occupation.

Job	Proportion of jobs outside own occupation with same job design				
	Multi-Establishment Firms			Single-Establishment Firms	
	Like jobs in economy absent own firm	Like jobs in firm absent own establishment	Like jobs in establishment absent own firm	Like jobs in economy absent own firm	Like jobs in establishment absent own firm
LLLL	0.0525	0.0684	0.0949	0.0526	0.0967
MMMM	0.2482	0.2536	0.2513	0.2481	0.2460
HHHH	0.0618	0.1292	0.1604	0.0620	0.1132

likely to be observed within an establishment as in the economy at large. This confirms our findings in Tables 7A and 7B and suggests that occupational clustering intrinsic to the production process does not entirely drive the job design clustering results. For classical (LLLL) jobs, the establishment-level clustering is the same at single- versus multi-establishment firms. For modern (HHHH) jobs, the establishment-level clustering is much stronger in multi-establishment firms. Thus larger (multi-establishment) firms are much more likely to cluster dissimilar modern jobs together. The degree of clustering of all "medium" jobs, in contrast, is no greater within-firm or within-establishment than in the economy overall.

In Table 9, we perform a more rigorous test of the relative importance of within- and across-occupation clustering of job design, by reestimating the models in Table 7A, separating each within-establishment job design variable into two components: similarly designed jobs within the same occupation and similarly designed jobs in all other occupations. The results show there is both within- and across-2-digit-occupation clustering of job design types at the establishment level. For modern jobs, the coefficients on the percentage of other jobs in the establishment that are modern both within the same 2-digit occupation and in other 2-digit occupations are positive and significant at the $p<.01$ level (bottom row, fourth and fifth columns). The pattern is the same for classical jobs (top row, first two columns). Moreover, in both cases the within-2-digit-occupation correlation is stronger than the across-2-digit-occupation correlation, indicating that within-occupation clustering is more likely than across occupation clustering, as expected. More important is the fact that across-occupation clustering drives at least part of the results in Table 7A: firms tend to group together jobs that are all modern and all classical, even dissimilar jobs.

Table 9. Effect of Distribution of Other Jobs' Characteristics on Probability of Modern (HHHH) or Classical (LLLL) Job Design: Comparing Jobs Within and Outside Own 2-Digit Occupation.

Peers in Skill Set	Pr(LLLL)			Pr(HHHH)		
	Jobs in the establishment		Jobs in other establishments in firm	Jobs in the establishment		Jobs in other establishments in firm
	Within own 2-digit occupation	Outside own 2-digit occupation		Within own 2-digit occupation	Outside own 2-digit occupation	
LLLL	**1.8851**	**0.6491**	**2.1121**	**−0.724***	**−0.856***	0.263
3L, 1M	**0.5401**	**0.8971**	**0.9661**	**−1.375***	−0.352	−0.463
2L, 2M	**0.5051**	**0.7031**	−0.010	**−0.953***	**−0.364****	−0.193
1L, 3M	−0.207	**0.3875**	0.169	**−0.463***	**−0.683***	**−0.547****
3L, 1H	0.706	3.504	3.274	1.012	−0.771	−4.905
2H, 1M, 1L		0.514	1.326	−0.324	−0.363	1.062
2H, 2L	−1.004	−2.768	−3.699		−10.14	7.326
1L, 2M, 1H	0.078	0.065	1.297	**−0.944****	−0.235	−0.912
2L, 1M, 1H	−1.091	−1.427	0.855	−0.307	−1.088	0.333
3H, 1L	−2.098	1.199	−0.322	1.057	−2.071	−0.619
1H, 3M	**−0.935***	**−0.569***	0.278	−0.018	0.237	0.051
2H, 2M	**−0.560***	**−0.866***	**−0.955***	**0.4241**	**0.4831**	−0.110
3H, 1M	**−0.852***	**−0.735***	0.188	**0.2651**	**0.7301**	0.485
HHHH	**−0.7511**	**−0.9661**	0.379	**1.9481**	**0.8711**	**1.2571**
Industry controls		Yes			Yes	
R^2		0.13			0.15	
N		39,519			39,806	

Results from logits. Sample = jobs in multi-establishment firms.
*p-value<0.01.
**p-value<0.05.

To better understand these dynamics, Table 10 presents the analog of Table 8 for modern and classical jobs in multi-establishment firms for each of the 2-digit-occupation classifications. This enables an identification of which types of jobs drive the across-occupation clustering results in Table 9. For example, using the overall mean in the first row of column three as the comparison, the occupations for which modern jobs are more likely to be clustered with modern jobs in dissimilar occupations at the establishment

Table 10. Clustering of HHHH and LLLL Job Design Outside Own 2-Digit Occupation.

	Proportion of other jobs with same job characteristics mix					
	LLLL			HHHH		
	All jobs in economy, not in firm	All jobs in firm, not in establishment	All other jobs in establishment	All jobs in economy, not in firm	All jobs in firm, not in establishment	All other jobs in establishment
All workers	0.053	0.068	0.095	0.062	0.129	0.160
Public administration	0.054	0.047	0.283	0.062	0.081	0.105
Executives	0.052	0.053	0.085	0.058	0.132	0.173
Management related	0.051	0.069	0.096	0.062	0.209	0.258
Engineers	0.053	0.061	0.093	0.061	0.172	0.229
Math/computer science	0.053	0.062	0.104	0.062	0.363	0.408
Natural science	0.054	0.062	0.101	0.062	0.157	0.204
Health diagnostic	0.054	0.064	0.065	0.063	0.079	0.100
Health treatment	0.055	0.062	0.094	0.065	0.071	0.053
University professor	0.054	0.074	0.068	0.062	0.082	0.103
Teachers	0.054	0.036	0.181	0.065	0.033	0.118
Lawyer/judge	0.054	0.050	0.095	0.062	0.066	0.154
Other professional	0.053	0.084	0.101	0.063	0.124	0.182
Health technology	0.054	0.045	0.071	0.063	0.092	0.090
Engineering technology	0.054	0.041	0.082	0.063	0.189	0.241
Other technology	0.053	0.077	0.077	0.062	0.185	0.171
Sales manager				0.062	0.045	0.030
Finance/business ales	0.054	0.093	0.129	0.062	0.032	0.056
Service sales	0.054	0.023	0.013	0.062	0.346	0.347
Retail sales	0.056	0.135	0.167	0.065	0.082	0.117
Other sales	0.054	0.104	0.090	0.063	0.029	0.092
Admin. supervisor	0.055	0.004	0.000	0.063	0.138	0.171
Computer operator	0.054	0.058	0.063			
Secretary	0.055	0.156	0.197	0.062	0.101	0.152
Records	0.054	0.111	0.120	0.063	0.113	0.110
Mail distribution				0.063	0.024	0.086
Other admin.	0.050	0.074	0.099	0.064	0.135	0.168
Protective services	0.055	0.076	0.069	0.063	0.107	0.126
Food services	0.057	0.018	0.000	0.064	0.054	0.070
Health services	0.056	0.000	0.000	0.063	0.145	0.144
Building services	0.056	0.007	0.042	0.061	0.084	0.095
Personal services	0.055	0.026	0.025	0.061	0.082	0.059
Mechanic	0.054	0.059	0.076	0.065	0.191	0.167
Construction	0.054	0.034	0.023	0.064	0.120	0.197
Other precision	0.054	0.073	0.088	0.064	0.117	0.205
Machine operator	0.053	0.031	0.078	0.062	0.117	0.181
Assembler	0.055	0.047	0.116	0.062	0.091	0.127
Vehicle operator	0.054	0.116	0.053	0.063	0.135	0.115
Other transportation	0.054	0.047	0.169	0.063	0.083	0.182
Construction laborer				0.062	0.089	0.043
Handlers				0.061	0.069	0.075
Other laborer				0.062	0.077	0.142
Farm laborer	0.054	0.333	0.000	0.062	0.110	0.037
Forestry/fishing	0.054	0.625	0.000			

Sample = all jobs, by 2-digit occupation.

level include (a) management-related workers, (b) engineers, (c) mathematicians and computer scientists, (d) natural scientists, (e) engineering technologists, (f) service salespeople, (g) construction workers, (h) machine operators, and (i) other precision workers. In contrast, the occupations for which classical jobs are more likely to be clustered with classical jobs in dissimilar occupations include (a) public-administration workers, (b) mathematicians and computer scientists, (c) natural scientists, (d) teachers, (e) finance and business salespeople, (f) retail salespeople, (g) secretaries, (h) record keepers, and (i) assemblers.

Note that the similarities and differences in these two lists give an indication of the extent to which all modern and all classical job designs are used both within and across industries and establishments. Public administration and teaching jobs, for example, are concentrated in a narrow set of industries. Retail sales jobs are concentrated in certain types of establishments within multi-establishment firms. The tendency for classical jobs in these occupations to be concentrated with classical jobs in other dissimilar occupations helps explain the patterns in Table 7A when excluding and including controls for the type of industry. A similar argument can be made for the concentration of modern jobs for occupations such as engineers and construction workers.

In contrast, certain occupations are less likely to cluster with dissimilar occupations along both modern and classical lines, including health-related services, protective services, food services, building services, personnel services, and vehicle operators. Note that these resemble non-core activities that are likely to be found in a broad array of establishments (regardless of industry type), and thus are candidates for outsourcing (Abraham & Taylor, 1996).

5. DISCUSSION AND CONCLUSIONS

In this chapter, we presented a simple theory of job design that can be used to motivate observed trends and patterns in the empirical literature. The model is consistent with two broad approaches to job design. In the first approach, the firm uses ex ante optimization of methods. As a result, workers are given relatively narrow jobs to exploit gains from specialization and comparative advantage, and low discretion. However, ex ante optimization is not always feasible or profitable. When the firm faces greater complexity, unpredictability, or instability, it is less likely to effectively optimize production ex ante.

If so, then there is potential for the worker to learn on the job and engage in continuous improvement.

We argued that task interdependence is an important source of costs of both ex ante optimization and on-the-job learning. An alternative to ex ante optimization is continuous improvement, giving workers multitask jobs to take advantage of inter-task learning. Greater discretion complements this approach: it facilitates developing new ideas and implementing improvements. Thus, the theory is consistent with multitasking, interdependence, and discretion being positively correlated in the same job. Because the emphasis on ex ante optimization or continuous improvement depends on the firm's complexity, unpredictability, and stability, the firm's product, technology, and industry characteristics should be important factors influencing job design. Finally, there should be patterns of similar job design within firms, even more so within establishments, and also within industries.

These ideas are useful in linking the economic approach to the behavioral approach to job design, which emphasizes "intrinsic motivation" (Hackman & Lawler, 1971; Hackman & Oldham, 1976). The literature argues that multitasking and discretion may improve intrinsic motivation because the job is more intellectually challenging to the worker. Indeed, Adam Smith recognized that a cost to specialization is that workers may be bored and less motivated. The model can be interpreted as consistent with intrinsic motivation. If the marginal disutility of effort is lower when the worker performs both tasks, this yields an additional benefit to multitasking. Intrinsic motivation could be modeled by including the higher disutility of effort from specialization as one component of coordination costs of specialization compared to multitasking.

However, we purposely did not consider intrinsic motivation. Although we believe that many workers are intrinsically motivated by multitask jobs, the inter-task learning mechanism should hold regardless of any psychological effects, and is nicely complementary to the psychological explanation. The psychology story implies that multitask jobs will increase the extent to which workers are intellectually engaged in their work: thinking and curious about what they are doing. If so, this should only increase the degree of inter-task learning.

The role of skills is ambiguous in theory. Skills might reinforce the gains from specialization. However, to the extent that skills means problem-solving abilities, abstract-thinking skills, and other traits that improve the worker's learning, skills might instead reinforce continuous improvement. If so, then they would be positively associated with modern, not classical, job designs. Empirically, this is the case. This helps explain why returns to skills are associated with technological and organizational change – they put a premium on workers making continuous improvements in production methods.

We then analyzed data on job design attributes, using reasonable proxies for our concepts of multitasking, discretion, skills, and interdependence. The results are strongly consistent with our predictions. All of the job design attributes are strongly positively correlated. There is a tendency for firms to choose either a modern or classical job design approach, but not both (at the establishment level). This is consistent with our argument that job design approaches vary with the firm's product and market characteristics. At the firm level, in contrast, there is a tendency to push job design toward extremes, choosing modern job design in some establishments and classical job design in others. This is consistent with multi-establishment firms using establishments to isolate different types of jobs (and overall organizational design emphasis on centralized, ex ante versus decentralized, continuous optimization) from each other to capture the benefits of job design while minimizing the potential downsides from doing so. At the industry level, computer usage is related to both greater use of modern jobs and greater use of classical jobs. R&D spending, in contrast, is associated only with greater use of modern jobs. This provides further evidence that job design decisions depend on the firm's product and market characteristics.

We find strong evidence that firms choose coherent job design strategies, and that the same strategy is not optimal for all organizations. The current data provide some information on characteristics of the establishment's environment that may affect this choice: larger establishments are more likely to choose modern job design, while unionized and nonprofit organizations are less likely to choose either "all classic" or "all modern" job design. There are important differences across industries in the choice of job characteristics. In future work we hope to explore this area more thoroughly to determine whether technological considerations, market structure, competition, uncertainty, or product characteristics affect the design of jobs.

NOTES

1. Inter-task learning can also occur across workers through collaboration, but with coordination costs. A more complex model might consider whether a group can learn more or less effectively than an individual. The individual does not suffer from coordination costs of getting the team to function effectively. However, a well-functioning team might learn more effectively because of the value of different priors, points of view, etc.

2. Our goal here is not to model agency costs, so we assume the simplest form. One might extend the argument to predict that worker incentives will be complementary with discretion (Holmstrom & Milgrom, 1991, 1994; Ortega, 2004). Dessein and Santos (2006) consider this possibility, and show that increasing agency costs with greater discretion may make the relationship between multitasking and interdependence nonmonotonic. Our data do not contain sufficient information on compensation policies (see footnote 3 below) to test this, so we ignore that possibility.

3. This variable in the NCS indicates that only 3.2 percent of all jobs receive incentive pay, yet jobs that include incentive-based pay account for approximately 30 percent of all jobs in the economy (Lemieux, MacLeod, & Parent, 2007). Thus the NCS definition of incentive pay clearly is an extremely narrow measure that excludes many important sources of variable or incentive pay. For this reason we do not use the NCS incentive pay measure.

4. For a detailed description of the NCS, see Pierce (1999).

5. The remaining five are: personal contacts, purpose of contacts, physical demands, work environment, and supervisory duties. We do not use these because they are not clearly linked to the choice between centralized and decentralized job design.

6. An interesting way to think about these variables is that guidelines is a form of ex ante control, useful for foreseeable contingencies, while supervision received is a form of control used for more unpredictable or idiosyncratic events.

7. Our main results are essentially unchanged even without the inclusion of this variable in the analysis.

8. When controlling for industry-fixed effects, the point estimates in Table 2 versus Table A1 do not change much, though the explained variation increases and the increase in explanatory power for each of the models is significant with a p-value <0.00001. Thus industry differences account for part of the relationship between job design attributes; they just do not account for much of the positive correlations.

9. To simplify presentation, for the remainder of the paper we use guidelines as the sole proxy for discretion. Results are very similar for supervision received. We presented results for both proxies to this point simply to illustrate similarity in the findings.

10. The standard errors in Tables 4, 5A–B and 7 were adjusted to control for intra-group correlation due to observing multiple jobs in the same establishment.

11. For sake of comparison, Appendix Table A2 contains the results when all 81 unique categories are entered separately.

12. A different response bias, in which some occupations are rated systematically higher than others even if they should not be, is already controlled for by differencing observed values for each job design attribute from the three-digit occupation-specific mean.

13. Note that each establishment is assigned its own industry classification, which may differ from that of the parent firm's. This means that some of the establishment level (across industry) variation in the first set of columns represents within-firm variance (across establishments) within large integrated firms. Consequently, when the positive correlation between the fraction of modern jobs elsewhere in the firm and the probability of a job being classical becomes insignificant (when controlling for industry-fixed effects), this may partly be due to controlling for the within-firm variance in the large integrated firms.

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APPENDIX A

Table A1. Relationships between Pairs of Job Design Attributes Controlling for Industry or Occupation.

	Controlling for Industry				Controlling for Occupation			
	Guidelines	Supervision	Skills	Interdependence	Guidelines	Supervision	Skills	Interdependence
(a) Full sample								
Multitasking	4.403 (0.4904)	3.867 (0.5067)	1.780 (0.4473)	3.969 (0.4971)	2.488 (0.5514)	3.582 (0.5575)	2.715 (0.5358)	2.434 (0.4795)
Guidelines		3.929 (0.5094)	1.542 (0.4267)	3.731 (0.5403)		2.791 (0.5233)	2.184 (0.5357)	2.711 (0.4953)
Supervision			1.724 (0.4445)	3.504 (0.4842)			1.876 (0.5106)	3.208 (0.5424)
Skills				2.986 (0.3369)				1.919 (0.3418)
(b) Non-managers								
Multitasking	4.419 (0.4707)	3.870 (0.4878)	1.891 (0.4420)	3.854 (0.4732)	2.233 (0.4217)	2.647 (0.5331)	2.113 (0.5230)	3.283 (0.5254)
Guidelines		3.872 (0.4869)	1.676 (0.4344)	3.640 (0.5213)		2.847 (0.4965)	2.426 (0.5351)	3.430 (0.5524)
Supervision			1.807 (0.4381)	3.443 (0.4665)			2.549 (0.5061)	3.168 (0.5175)
Skills				3.072 (0.3402)				2.385 (0.5377)
(c) Managers only								
Multitasking	4.273 (0.4473)	4.021 (0.4583)	3.503 (0.4320)	3.595 (0.4906)	4.257 (0.4328)	3.885 (0.4330)	3.444 (0.4188)	2.675 (0.4001)
Guidelines		3.070 (0.3709)	2.200 (0.2998)	2.942 (0.4318)		4.541 (0.4590)	2.752 (0.3309)	3.994 (0.5352)
Supervision			2.883 (0.3843)	3.502 (0.4618)			2.797 (0.3640)	3.415 (0.4433)
Skills				2.903 (0.4182)				3.011 (0.3970)

Relationships between factors are coefficients from fixed-effect ordered logits; each cell represents a separate logit. Rows are dependent variables; columns are independent variables. Pseudo-R^2 are in parentheses. The 1990 US Census 3-digit industry and occupation codes were used to define the industry and occupation

Table A2. Effect of Distribution of Other Jobs' Characteristics on Probability of HHHH or LLLL Job Design.

	Pr(LLLL)		Pr(LLLL)		Pr(HHHH)		Pr(HHHH)	
Industry Controls	No		Yes		No		Yes	
% Other Jobs with	Establishment	Firm	Establishment	Firm	Establishment	Firm	Establishment	Firm
LLLL	**2.930***	**3.034***	**2.039***	**1.982***	**−0.7171***	0.3645	**−0.8802***	0.2058
MLLL	**1.074***	**1.625***	**0.9392***	**1.254***	**−0.7024****	**−1.345***	**−0.8194****	**−1.223****
LMLL	**1.844***	0.2090	**1.738***	−0.1919	−0.2427	−0.9928***	−0.4628	−1.153***
LLML	0.9338***	0.1835	**1.234***	0.5774	−1.234***	−0.1717	−0.9048	0.0405
LLLM	0.9570***	1.160	**1.169****	**2.239***	0.4330	0.6796	0.2028	0.6820
LLMM	**1.122***	0.3567	**1.133***	−0.0145	**−1.024***	**−1.003***	**−0.8834***	−0.7334***
LMLM	0.9415	1.622	0.7171	1.029	−1.824***	0.5012	**−2.455****	−0.1444
LMML	**2.303***	−1.604	**2.426***	−1.600	−1.629***	−0.2104	−1.948***	−1.410
MLLM	0.7638***	−0.6311	**0.8967****	−0.7383	−0.6879	0.4281	−0.4200	0.8707***
MLML	0.3937	0.9660	0.6890	1.262	**−1.576****	−1.614***	**−1.537****	−0.7724
MMLL	**1.591***	−0.1566	**1.351***	−0.2677	0.4982	0.1221	0.1671	−0.4334
LMMM	**0.7535***	**0.6972****	**0.7321****	0.4653	−0.3561	**−1.106***	−0.2394	−0.8151***
MLMM	**0.6803***	**−0.7866****	**0.6667***	**−0.7356****	**−0.9819***	**−1.174***	**−0.7175***	−0.5592***
MMLM	0.3717	0.7183	0.2871	0.2194	−0.3650	−0.8727	−0.4987	**−1.393****
MMML	0.0673	**1.344****	0.2761	0.6067	**−1.610***	0.4538	**−1.978***	0.6151
LLLH	4.776	−110.3	−0.9032	−150.8	1.185	2.907	1.769	0.1019
LLHL	3.561	6.108	2.391	1.221		−4.927		−46.84
LHLL	1.657	4.927	1.529	5.169	−0.8927	−0.6115	−1.127	−1.811
HLLL								
LLHH	−0.6134	6.032	−4.319	2.270	−7.676	7.197	−8.787	8.989
LHHL, HLLH, HLHL have no observations								
HHLL						−38.19		−51.80
LHHH	−0.3998	−17.99	−0.1042	−18.45	−5.380	−15.898	−5.326	−17.13
HLHH	2.028	1.647	2.523	2.622	0.1989	−1.965	2.308	2.711

Table A2. (*Continued*)

	Pr(LLLL)		Pr(LLLL)		Pr(HHHH)		Pr(HHHH)	
Industry Controls	No		Yes		No		Yes	
% Other Jobs with	Establishment	Firm	Establishment	Firm	Establishment	Firm	Establishment	Firm
HHLH	−1.508	11.60	−1.463	18.17***	−3.642	2.226	−5.912	0.3935
HHHL	0.6190	−5.713	−0.4054	−19.07	−0.3951	16.01		12.89
HMLL	7.553	−20.25	9.296	−13.67	−7.700	0.0131	−8.809	−0.7919
HLLM	−3.164		−9.150		1.100		2.320	
HLML		16.31		17.72	1.672	4.573	0.0613	1.326
LLMH	−1.218	1.124	−1.668	1.138	1.610	0.4258	−1.272	−2.921
LLHM	−2.698	−6.065	−2.379	−4.521	6.582*	5.145	5.594**	1.868
LMLH								
LMHL	−6.866	7.909	−8.165	3.076	−0.5411	−0.6187	−1.655	−1.677
LHLM	−1.098	−7.354	−1.007	−10.33	−5.564	−1.287	−8.235	−4.626
LHML	0.2737	−1.477	1.737	−0.4743	1.080	−2.689	0.2264	−4.215
MLLH						3.936		3.187
MLHL		−17.15		−7.612	−10.22	1.975	−11.02	4.926
MHLL	0.4121	−0.3604	0.3802	0.8369	−0.5419	2.338**	−1.262	1.602
LHMM	1.182	1.492	1.271	0.7813	1.262	0.1630	0.9830	−0.7765
LMHM	−0.0570	−1.117	0.3534	−1.771	3.639*	−0.6835	4.194*	−2.147
MLMH	−8.101**	4.030**	−8.666**	4.437**	−5.267***	−0.2540	−5.238***	0.8430
LMMH	−2.468	1.155	−2.037	2.536***	−0.2871	−4.371	−0.3278	−4.442
MLHM	−2.994	−1.163	−5.063**	−5.333	−0.6571	−2.246	−0.7093	−1.076
MMLH	−1.838	2.712***	−3.646	2.362	0.0641	−2.400	−1.248	−3.298
MMHL	−1.082	0.4636	−1.732	−0.9096	−0.2973	1.884	0.4413	2.465
MHLM	1.829	−0.6053	2.773***	0.7817	−0.4844	0.9438	−1.331	0.3649
MHML	0.5310	1.622	1.035	1.637	0.3212	0.8711	0.2347	0.7884
HMML	−1.089	−0.5937	−3.585	−0.2369	−3.512	1.572	−3.183	−0.0244
HLMM	−0.5964	−3.946	0.0959	−4.768	−1.776	−0.0359	−2.187	0.2914
HMLM	3.021	1.560	3.412	3.604	−25.77***	−0.7417	−25.69***	−3.794
MMMM = base case								
LHHM	3.748	8.707	2.430	2.675	−5.210	6.151	−5.910	−4.125
LHMH	7.090	−2.587	2.396	−11.98	−9.246	5.130	−7.530	11.95
LMHH	−2.878	2.628	−6.881	0.1668	−7.683	−7.829	−4.645	−4.754
MHLH		1.380		−2.372				
MLHH	2.908***	0.1066	2.473	−3.005	0.3599	0.9696	0.3063	0.3924
MHHL	−0.3631	−6.298	−1.121	−5.609	1.926	1.094	1.941	1.828
HLMH	0.5681	0.3618	1.290	1.502	0.7120	−4.041	1.926	0.6389
HLHM	−6.722	2.506	−5.985	−0.5327	3.174	0.1946	2.531	1.259
HMLH								
HMHL	−2.667	3.272***	−1.967	5.469**	1.292	1.999	1.058	1.548
HHLM	3.278	3.184	3.177	1.191	−1.645	7.408	−1.038	6.143
HHML	10.06***	−8.923	6.349	−11.11	8.463	−66.81	6.946	−61.94
HMMM	−0.1239	0.4239	−0.4195	−0.0931	0.9412*	−0.0846	0.7902*	−0.2015
MHMM	−0.9904*	0.4371	−0.7566***	0.9236***	0.2081	.2558	−0.0889	−0.2044
MMHM	−3.332*	−0.6602	−3.068*	−0.1621	0.5723	−1.473*	0.9796*	−0.8266
MMMH	−0.2135	−0.8186**	−0.7285***	0.3747	−0.2489	−0.2248	0.0724	
HHMM	−0.5866	0.3929	−0.8696***	−0.7068	1.394*	1.044**	1.220*	0.3106
HMMH	−1.334	−0.0209	−1.449	0.2831	0.2818	0.2708	0.0974	0.0132
HMHM	−0.1646	0.2349	−1.068	−0.2462	1.596*	−1.080	1.211*	−1.862**
MHMH	−2.012***	−2.688***	−1.823***	−3.515**	0.7688	0.7720	0.7921	0.5786
MHHM	−1.432**	−1.338***	−1.627**	−1.857**	−0.8736**	−1.313**	−0.4818	−0.3751
MMHH	−0.2920	−0.2982	−0.5473	−0.5960	1.743*	1.034*	1.537*	0.5108
MHHH	−0.9279**	−0.0668	−1.147**	0.1604	0.7060**	0.1495	0.7671*	0.6435
HMHH	−0.1202	1.402*	−0.8495	0.5875	2.171*	0.6445***	2.113*	0.5864
HHMH	−1.212**	−0.1656	−1.075***	−0.5682	−0.0479	0.6851***	−0.1722	0.5475
HHHM	−0.5029	−0.5579	−0.4967	−0.5042	1.640*	2.222*	2.082*	−0.6012
HHHH	−1.076*	0.7060**	−1.252*	0.3912	3.054*	1.640*	2.483*	1.101*
R^2	0.1029		0.1225		0.1270		0.1389	
N	41,164		40,028		41,323		40,472	

*p-value < 0.01.
**p-value < 0.05.
***p-value < 0.10

APPENDIX B. DISCUSSION OF MODEL

Proof that Multitasking is Preferred to Specialization for Some Range of k *and* s

From (1) and (3), multitasking is preferred to specialization if:

$$2\alpha^{\alpha}\left(\frac{s+k}{1+\alpha}\right)^{1+\alpha} > s^{1+\alpha} - C$$

For simplicity, assume that $C = 0$; if $C > 0$, multitasking is even more likely to be preferred. The condition above can then be rewritten as:

$$\left(\frac{s+k}{s}\right)^{1+\alpha} > \left(\frac{\alpha}{2}\right)\left(\frac{1+\alpha}{\alpha}\right)^{1+\alpha}$$

For fixed α and s, some k^* exists for which this expression holds for all $k > k^*$, since the left side is increasing in k (and similar logic would apply for any fixed $C > 0$). Setting both sides equal and solving yields:

$$k^* = s\left[\left(\frac{\alpha}{2}\right)^{1/1+\alpha}\left(\frac{1+\alpha}{\alpha}\right) - 1\right]$$

Proof of Equation (5)

$Q_{\text{multitask|centralization}} = \max_{\tau}[E(Q)]$ = expected output with τ chosen over the entire distribution of the unknown state of the world. $Q_{\text{multitask|discretion}} = \max_{\tau}[Q \mid \text{state of the world}]$. The τ chosen to maximize expected output can result in actual output no better than when the state of the world is known. Since this logic applies for any given state of the world, it also applies unconditional on the state of the world, as in Eq. (4). Finally, if there were agency costs associated with discretion, the worker would be given discretion only if the benefits outweighed those agency costs.