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Why are Jobs Designed the Way They Are?

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Working Paper No. 222

“Why are Jobs Designed The Way They Are?”

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of
the Economy and the State**

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WHY ARE JOBS DESIGNED THE WAY THEY ARE?*

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WHY ARE JOBS DESIGNED THE WAY THEY ARE?

Abstract

In this paper we study job design. Do organizations standardize how the job is done ex ante, or ask workers to determine the process as they go? We first model this decision and predict complementarity between these job attributes: multitasking, discretion, human capital, and interdependence of tasks. We argue that characteristics of the firm and industry (e.g., product, technology, or 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. Job designs also tend to follow similar patterns across jobs in the same firm, and especially in the same establishment. There is evidence that firms segregate different types of job designs across different establishments. Finally, we show that 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 1999; Autor, Levy & Murnane 2003; Zoghi & Pabilonia 2004).

In this paper we present an economic analysis of job design. First, we briefly present a simple model of learning that can provide for 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 from Lindbeck and Snower (2000): 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 human capital. The model predicts 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 job design are new to

both the economic and social psychology literatures on job design. The empirical literatures previously ignored such patterns because existing data were not drawn from representative national samples. Thus a contribution of the paper is the predictions at an economy-wide level.

The bulk of the paper analyzes a unique dataset that provides the first nationally representative view of the distribution of job design characteristics. The BLS National Compensation Survey measures job design attributes, including multitasking, discretion, human capital, 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 either 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, & Discretion

We now present a simple theory of job design based chiefly on Lindbeck & Snower (2000). See Holmstrom & Milgrom (1991, 1994), Gibbs & Levenson (2002) and Dessein & Santos (2005) for similar ideas. We augment the Lindbeck and Snower approach by considering employee discretion. Our first results are similar to the previous literature 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.

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 de-

ciding how workers should allocate their time between tasks, or giving them discretion to decide this 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. It is also designed explicitly to guide empirical work using the variables in our dataset. For these reasons, 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 across tasks. 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 the optimal scale of the firm, nor incentive problems.

Output depends on two tasks in a standard Cobb-Douglas production function $Q = X_1 \cdot X_2^\alpha$. Workers have 1 unit of time to allocate to tasks. Their marginal product of effort on a task is s . Thus, if two workers specialize in the different tasks, output is $Q = s^{1+\alpha}$. As in Becker & Murphy (1992), there is a constant coordination cost C if workers are specialized, but none if workers have multitask jobs. Thus,

$$(1) \quad Q_{\text{specialized}} = s^{1+\alpha} - C.$$

Now consider the opposite case, where workers spend some time on each task. The key idea in this paper is *intertask 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 each 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 a worker spends on task 1, with $1-\tau$ for task 2. To capture inter-task learning, 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 intertask learning. There are thus two competing effects on worker productivity. One is the standard gains from specialization s ; the other is the gains from intertask learning k . We do not assume that one effect is larger than the other. Output for a single worker i is:

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

τ is chosen to optimize Q_i :

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

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:

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

For example, if $k = 0$ and $\alpha = 1$, then $Q_{\text{multitask}} = \frac{1}{2}s^2$, and $Q_{\text{specialized}} = s^2 - C$, which is greater than $Q_{\text{multitask}}$ as long as C is not too large. In (2), for multitasking with $\tau \in (0, 1)$, α cannot be too different from 1 in either direction. Similarly, comparing (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. The elasticity of Q with respect to s in each case is:

$$E_{\text{multitask}} = (1 + \alpha) \left(\frac{s}{s + k} \right); \quad E_{\text{specialized}} = (1 + \alpha).$$

If $k > 0$ (the only reason for multitask jobs), output is more elastic with respect to s for specialized jobs. Even if multitask jobs are optimal for some range, as s gets very large specialization dominates.

a. Multitasking & Interdependence

An immediate result of (1) and (3) is that multitask jobs are more likely to be optimal, the more important is intertask learning:

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

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 intertask 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.

b. Multitasking & 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 to the two tasks 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. Suppose further that if workers perform both tasks, they observe the state of the world before choosing their allocation of time τ , 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 consider the second task. 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.

¹ Intertask 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 & Santos (2005) consider this possibility, and show that increasing agency costs with greater discretion may make the relationship between multitasking and interdependence non-monotonic. Our data do not contain information on compensation policies so we ignore that possibility.

$$(5) \quad E[Q_{\text{multitask} \mid \text{discretion}}] \geq E[Q_{\text{multitask} \mid \text{centralization}}].$$

[Proof: see Appendix B.] Moreover, discretion will tend to be more valuable in more uncertain production environments. From (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, putting together these ideas and the special case in (4) above, a reasonable empirical prediction is that discretion should be complementary with multitasking, especially in more uncertain environments.

Putting these two arguments together, the model predicts complementarity between multitasking, interdependence, and discretion. It similarly predicts complementarity between specialization, lack of interdependence, and centralization. This suggests two rough patterns of job design. The first corresponds to what we will call “Classical” job design: specialized jobs with little discretion. The second corresponds to what we will call “Modern” job design because it matches the apparent trend: “job enrichment” as described in the behavioral literature, using multi-tasking 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 type depends on the empirical importance of gains from specialization, compared to intertask learning. We expect to see “Classical” jobs more where interdependence is lower, and “Modern” jobs more where interdependence is higher.

c. The Role of Human Capital

Human capital plays a central role in labor economics research so it is of interest to consider its role in this context. There are two general off-setting effects. The first is that gains from specialization may be complementary to human capital. For example, specialization of job design may increase returns on investments in human capital 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 human capital may facilitate on-the-job learning. If more highly-skilled workers are better able to learn on the job, then human capital will be complementary to discretion. Returns to skills would be higher in more complex work environments, where the scope for intertask learning is higher. This effect is suggested by the literature on skill-biased technical change. Much of that literature (Autor, Katz & Krueger 1998; Goldin and Katz 1998; Autor, Levy & Murnane 2003) 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 intertask learning.

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

d. The Role of Product & 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. A greater expected return on this investment should induce more use of Classical job design. The expected return depends on the degree to which it uncovers methods close to the optimum, and the extent to which the effi-

ciency 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 (2000 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 that a product has been produced with few or no changes, the more is known about how to make it efficiently. The longer the firm expects to make the same product, 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. 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 human capital. 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 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, human capital, 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. This may help explain the often conflicting results found in studies of the effect of adoption and use of “high performance work systems” on productivity and profitability of organizations (Applebaum and Batt 1994; Cappelli and Neumark 2001; MacDuffie 1995; Ichniowski and Shaw 1995; Ichniowski, Shaw & Prennushi 1997). 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.

This logic might also help explain a recent trend toward “modern” jobs (Caroli & Van Reenen 2001). The last 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.

Such patterns should be stronger within establishments than within firms as a whole. At a naïve level, product attributes are likely to be more similar within than across establishments. Less naïvely, es-

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 relative preference for ex ante optimization or continuous improvement across industries. Therefore, industries should show some tendency toward greater use of Modern or Classical job design approaches. 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 U.S. The National Compensation Survey (NCS) is a restricted-use dataset collected by the Bureau of Labor Statistics. It covers the non-agricultural, non-federal sectors of the U.S. 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 data, and an indicator for use of incentive pay. 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 consis-

tently across occupations. These factors are based on the federal government's Factor Evaluation System, which is used to set federal pay scales.³ There are ten different leveling factors, or job design attributes, of which we use five in this paper: 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. 1-3 correspond roughly to blue collar levels of human capital. 4 is at the level of an apprenticeship. 5 is at the level of a college graduate, and so on. Thus, larger values imply greater Knowledge. This factor corresponds quite well to our **Human Capital** 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. 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 or not they are applicable, and how to adapt them. 4-5 indicate that few guidelines are available

³ For a detailed description of the NCS, see Pierce (1999).

or applicable to completing this job. Thus, we interpret both Supervision Received and Guidelines as indicators of our concept of **Discretion**.⁴

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 & Effect: Scope & 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 & 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**.⁵

⁴ An interesting way to think about Guidelines and Supervision Received 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.

⁵ Our main results are essentially unchanged even without the inclusion of this variable in the analysis.

4. Results

a. Bivariate Relationships between Job Characteristics

Table 1 shows the Spearman rank-order correlations between the five factors. The correlations are high, consistent with our prediction that there should be positive relationships between multitasking, discretion, and interdependence across jobs.

Table 2 replicates the bivariate relationships from Table 1 using ordered logit analysis, predicting Multitasking as a function of both measures of discretion (Guidelines and Supervision), Human Capital, and Interdependence; Guidelines as a function of Supervision, Human Capital, and Interdependence; Supervision as a function of Human Capital and Interdependence; and Human Capital as a function of Interdependence. Each cell in the table 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. Appendix Table A1 repeats the ordered logits adding first a set of indicators for the establishment's primary 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 Human Capital and Multitasking, Human Capital and Discretion, and Human Capital and Interdependence are also positive, but are not as strong. These suggest that, on balance, skills favor intertask 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 human capital.

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 Human Capital 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, Shaw & Prennushi 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).⁶ 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.

b. Multidimensional Relationships between Job Characteristics

The results in Tables 2 and A1 provide evidence that pairs of job design attributes – including Human Capital – 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.⁷ 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 three 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 nine 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

⁶ 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 < .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.

⁷ 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.

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 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: $(0.251) \cdot (0.190) \cdot (0.194) \cdot (0.185) = 0.0017$ (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 thirty 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.

c. 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 non-profit 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.⁸ The second and fourth columns include a full set of industry indicators.⁹

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 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 the specialized output can exceed the multitask 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 criticism of our findings might be that they are driven not by intertask learning, but instead by firms designing jobs to generate intrinsic motivation as in the social psychology literature. However, the fact that job design patterns vary systematically across different industries suggests that product or industry characteristics matter, which is strong evidence in favor of the intertask learning explanation. Of course, it is most likely that both mechanisms play a role.

⁸ The standard errors in Tables 4, 5.A, 5.B and 7 were adjusted to control for intragroup correlation due to observing multiple jobs in the same establishment.

⁹ Three-digit industries from the U.S. Census Bureau’s industry categorization.

d. 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 vs. 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 two digit industry level using the CPS micro data. 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; using percentages vs. ranks yields the same results. Computer usage and the percentage of jobs in the industry that are modern are fairly strongly correlated (.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 (.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, Levy & Murnane, 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 (.76) and is statistically significant. The correlation of per capita R&D spending with the per-

centage of jobs that are classical, in contrast is both much smaller (.20) and not statistically significant. Given the low degrees of freedom, it may be the case that a larger sample would produce a statistically significant correlation. However, it is doubtful the estimated correlation would change dramatically. Thus the results in Table 6 indicate the R&D spending is 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 which require processes that are optimized when workers have greater autonomy and human capital.

The combined results in Tables 5 and 6 provide good evidence that job design decisions are strongly related to a firm or industry's product characteristics and technology.

e. 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 re-estimate 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 7.A reports the results when all jobs with common combinations are grouped together. For example, the “3L, 1M” group includes four subgroups: LLLM, LLML, LMML and MLLL.¹⁰ 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 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 7.A. The first set of columns predict the probability of a classical (LLLL) job, both with and without 3 digit industry controls. The second set of columns predict the probability of a modern (HHHH) job.

¹⁰ For sake of comparison, Appendix Table A2 contains the results when all 81 unique categories are entered separately.

The results in Table 7.A 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 $\text{Pr}(\text{LLLL})$ and many of the jobs that are “almost all” classical (3L1M) and “mostly classical” (2L2M; 1L3M). The opposite is true for $\text{Pr}(\text{HHHH})$ 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 $\text{Pr}(\text{LLLL})$ or $\text{Pr}(\text{HHHH})$: 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.¹¹ 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 7.A. 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 es-

¹¹ 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 3 digit occupation-specific mean.

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.¹²

Second, some within-establishment correlations get *stronger* when controlling for industry. Specifically when predicting $\Pr(\text{LLLL})$, coefficients on the fraction of jobs that are HHHH and (3H1M) get more negative; and when predicting $\Pr(\text{HHHH})$ 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 7.B presents the results from predicting $\Pr(\text{MMMM})$, using the same set of regressors as Table 7.A. 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 7.B shows the same within-firm, across-establishment segregation of dissimilar jobs. In the case of “medium” jobs in Table 7.B, 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.

e. Within vs. 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

¹² Note that each establishment is assigned its own industry classification, which may differ from 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.

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 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 and 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 likely to be observed within an establishment than in the economy at large. This confirms our findings in Tables 7.A and 7.B 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 vs. 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 re-estimating the models in Table 7.A, 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 coeffi-

cients 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, first two columns). The pattern is the same for classical jobs (top row, fourth and fifth 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 7.A: firms tend to group together jobs that are all modern and all classical, even dissimilar jobs.

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 level include (a) management related, (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, (b) mathematicians and computer scientists, (c) natural scientists, (d) teachers, (e) finance and business sales, (f) retail sales, (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 7.A 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, 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 and Taylor, 1996).

5. Discussion and Conclusions

In this paper we presented a simple theory of job design that can explain observed trends and patterns in the empirical literature. The model generated 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 both costs of ex ante optimization, and of on-the-job learning. An alternative to ex ante optimization is continuous improvement, giving workers multitask jobs to take advantage of intertask learning. Greater discretion complements this approach: it facilitates developing new ideas and implementing improvements. Thus, the theory predicts that multitasking, interdependence, discretion, and human capital will be 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, this logic implies that 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). That 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 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 as increasing coordination costs C of specialization.

However, we purposely did not consider intrinsic motivation. Although we believe that many workers are intrinsically motivated by multitask jobs, the intertask 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 intertask learning.

The role of human capital is ambiguous in theory. It might reinforce the gains from specialization. However, to the extent that human capital means problem solving abilities, abstract thinking, and other traits that improve the worker's learning, it 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, human capital, 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* v. 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 non-profit 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.

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Table 1.
Correlations Between Job Design Attributes

		Discretion		Human Capital	Interdependence
		Guidelines	Supervision		
Multitasking		0.8475	0.8505	0.8341	0.8485
	Guidelines		0.8450	0.8234	0.8701
Discretion	Supervision Received			0.8274	0.8404
Human Capital					0.8176

Spearman 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		Human Capital	Interdependence
		Guidelines	Supervision		
a. Full Sample					
Multitasking		4.491 (.4759)	3.881 (.4848)	1.777 (.4218)	4.033 (.4776)
	Guidelines		3.395 (.4886)	1.470 (.3916)	3.756 (.5247)
Discretion				1.714 (.4308)	3.517 (.4702)
	Supervision				
Human Capital					2.952 (.3024)
b. Non-Managers Only					
Multitasking		4.541 (.4538)	3.907 (.4638)	1.894 (.4120)	3.949 (.4504)
	Guidelines		3.901 (.4613)	1.566 (.3887)	3.684 (.5004)
Discretion				1.806 (.4201)	3.473 (.4467)
	Supervision				
Human Capital					3.039 (.2957)
c. Managers Only					
Multitasking		4.290 (.4283)	3.901 (.4264)	3.455 (.4147)	4.182 (.4772)
	Guidelines		4.568 (.4534)	2.774 (.3255)	4.016 (.5321)
Discretion				2.793 (.3605)	3.439 (.4415)
	Supervision				
Human Capital					3.028 (.3903)

Relationships between factors are coefficients from ordered logits; each cell represents a separate logit. Rows are dependent variables; columns are independent variables. Pseudo-R²'s are in parentheses. Additional controls included in each regression: union status and nonprofit status.

Table 3.
Distribution of Leveling Factors

Distribution relative to median value in the economy			
	L (< median)	M (median)	H (> median)
Human Capital	.362	.199	.439
Guidelines	.333	.361	.306
Multitasking	.193	.351	.456
Interdependence	.309	.345	.346
Distribution relative to median value within 3 digit occupation			
	L (< median)	M (median)	H (> median)
Human Capital	.251	.540	.209
Guidelines	.190	.610	.200
Multitasking	.194	.603	.203
Interdependence	.185	.619	.196
Index (Σ MV) of Human Capital, Guidelines, Multitasking, & Interdependence (using distribution relative to median value within 3 digit occupation)			
Index relative to median	Fraction of all jobs (s.e.)	Pr(characteristics randomly assigned from empirical distribution)	Actual / predicted
4 (= LLLL)	0.0541 (0.0006)	.0017	31.6
5	0.0697 (0.0007)	.0202	3.4
6	0.1109 (0.0009)	.0957	1.2
7	0.1488 (0.0010)	.2320	.6
8 (= MMMM)	0.2502 (0.0012)	.1230	2.0
All other values of index = 8 except MMMM	0.0151 (0.0003)	.1856	.1
9	0.1268 (0.0009)	.2278	.6
10	0.0796 (0.0007)	.0929	.9
11	0.0823 (0.0007)	.0196	4.2
12 (= HHHH)	0.0626 (0.0007)	.0017	37.6

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

	Pr(LLLL)	Pr(LLLL)	Pr(HHHH)	Pr(HHHH)
Non-profit	-0.1115	-0.2911 ⁵	-0.2193 ⁵	-0.2303 ⁵
Union	-0.8562 ¹	-0.7078 ¹	-0.1755 ¹	-0.1801 ¹
Employment/1,000	-0.0226 ¹	0.0054	0.0820 ¹	0.0387 ¹
(Employment/1,000) ²	-0.0001 ⁵	-0.0001	-0.0011 ¹	-0.0003 ¹
Industry controls	No	Yes	No	Yes
Pseudo R ²	.0128	.0679	.0109	.0817
N	42,750	41,586	42,750	41,870

Coefficients from logits. Sample = jobs in multi-establishment firms. Controls are included for % of jobs in 14 job design clusters as described in Table 7a.

¹ = p-value < 0.01; ⁵ = p-value < 0.05; ¹⁰ = p-value < 0.10

Table 5.
Computer Usage and Industry Patterns of Job Design

Industry	% Using Computers at Work	Rank	% Jobs Modern	Rank	% Jobs Classical	Rank
Brokers	0.92	1	0.120	1	0.056	33
Professional equipment	0.73	10	0.117	2	0.058	29
Chemicals	0.72	12	0.117	3	0.036	42
Professional services	0.84	6	0.115	4	0.096	4
Transportation manufacturing	0.51	28	0.112	5	0.037	41
Machinery	0.58	21	0.096	6	0.050	37
Paper manufacturing	0.49	30	0.087	7	0.031	46
Legal services	0.88	2	0.086	8	0.097	3
Stone manufacturing	0.40	42	0.084	9	0.052	35
Mining	0.45	37	0.079	10	0.065	21
Insurance	0.87	3	0.077	11	0.064	23
Electrical manufacturing	0.62	19	0.073	12	0.078	13
Durable wholesale	0.64	17	0.072	13	0.085	8
Petroleum manufacturing	0.84	5	0.067	14	0.094	6
Utilities	0.61	20	0.066	15	0.034	45
Non-professional services	0.68	14	0.065	16	0.065	22
Nondurable wholesale	0.53	27	0.064	18	0.078	14
Public administration	0.75	9	0.064	17	0.051	36
Print manufacturing	0.63	18	0.063	20	0.091	7
Real estate	0.65	16	0.063	19	0.081	10
Entertainment services	0.47	33	0.062	21	0.048	38
Banking	0.85	4	0.060	22	0.075	15
Catalog retail	0.54	24	0.059	24	0.116	1
Rubber manufacturing	0.48	32	0.059	25	0.063	25
Social services	0.45	38	0.059	26	0.062	26
Communications	0.81	7	0.059	23	0.060	27
Food manufacturing	0.33	45	0.057	27	0.069	19
Metal manufacturing	0.47	34	0.055	28	0.057	30
Transportation	0.40	40	0.055	29	0.036	43
Education services	0.70	13	0.054	30	0.060	28
Miscellaneous manufacturing	0.47	35	0.050	31	0.071	17
Hotel services	0.42	39	0.050	32	0.019	49
Gas retail	0.45	36	0.046	33	0.017	51
Lumber manufacturing	0.30	48	0.041	34	0.057	31
Hospital services	0.72	11	0.037	35	0.036	44
Construction	0.26	50	0.035	37	0.072	16
Grocery retail	0.35	44	0.035	36	0.019	50
Business services	0.66	15	0.032	38	0.095	5
Vehicle retail	0.56	22	0.032	39	0.048	39
Medical services	0.55	23	0.032	40	0.040	40
Eating, drinking places	0.24	51	0.029	41	0.027	48
Leather manufacturing	0.53	26	0.028	42	0.067	20
Apparel manufacturing	0.28	49	0.027	44	0.064	24
Building retail	0.49	31	0.027	43	0.055	34
Other retail	0.49	29	0.026	46	0.109	2
Hobby retail	0.53	25	0.026	45	0.071	18
Textile manufacturing	0.30	47	0.024	47	0.057	32
Repair services	0.38	43	0.023	48	0.079	11
Personal services	0.32	46	0.022	49	0.083	9
Apparel retail	0.40	41	0.014	50	0.029	47
Technical retail	0.75	8	0.006	51	0.079	12
Correlation between computer use and:			0.50***	0.51***	0.30**	0.29**

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

Industry	R&D (\$ millions)	Domestic Employment (thousands)	R&D per 1,000 empl.	Rank	% Jobs Modern	Rank	% Jobs Classical	Rank
Chemical manufacturing	20372	1023	19.91	2	0.1168	1	0.036	16
Professional services	23640	761	31.06	1	0.1153	2	0.0957	1
Transportation mfg.	34059	2159	15.78	4	0.1121	3	0.0372	14
Machinery, prof. equip. mfg.	44076	2230	19.77	3	0.1023	4	0.0524	12
Wholesale	19960	1339	14.91	5	0.0682	5	0.0817	3
Petroleum manufacturing	615	116	5.30	9	0.0668	6	0.0944	2
Utilities	142	410	0.35	17	0.0659	7	0.0338	17
Communications	15421	1665	9.26	8	0.0589	8	0.0597	8
Rubber manufacturing	1845	562	3.28	10	0.0586	9	0.0626	7
Food manufacturing	1159	1043	1.11	13	0.0571	10	0.0687	6
Transportation	466	756	0.62	16	0.0554	11	0.0365	15
Metal manufacturing	2174	1120	1.94	12	0.0546	12	0.0569	11
Miscellaneous mfg.	4226	351	12.04	7	0.0502	13	0.0711	5
Lumber manufacturing	70	71	0.99	14	0.0413	14	0.0574	10
Construction	699	270	2.59	11	0.0345	15	0.0724	4
Medical, hospital services	660	51	12.94	6	0.0345	16	0.0385	13
Textile, apparel, leather mfg.	337	362	0.93	15	0.0255	17	0.0585	9
Correlation between per capita R&D spending and:					0.76***		0.20	

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

Industry controls	Pr(LLLL)		Pr(LLLL)		Pr(HHHH)		Pr(HHHH)	
	No		Yes		No		Yes	
	Estab.	Firm	Estab.	Firm	Estab.	Firm	Estab.	Firm
With skill set:								
LLLL	3.281¹	3.078¹	2.376¹	2.101¹	-0.547⁵	0.588	-0.931¹	0.191
3L, 1M	1.262¹	1.045¹	1.199¹	0.848¹	-0.395	-0.410	-0.603⁵	-0.615¹⁰
2L, 2M	1.176¹	0.015	1.158¹	-0.120	-0.572¹	-0.408	-0.585¹	-0.417
1L, 3M	0.520¹	0.175	0.539¹	0.076	-0.758¹	-0.800¹	-0.732¹	-0.670¹
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	-0.986¹	-0.059	-0.948¹	0.234	0.427¹	-0.361	0.431¹	-0.109
2H, 2M	-0.841¹	-0.372	-1.101¹	-0.948¹	1.019¹	0.084	0.887¹	-0.202
3H, 1M	-0.624⁵	0.495	-0.946¹	0.087	1.354¹	0.200	1.275¹	0.303
HHHH	-0.816¹	0.970¹	-1.194¹	0.338	3.517¹	1.937¹	2.799¹	1.159¹
Pseudo R ²	.0926		.1143		.1133		.1297	
N	41,421		40,285		41,421		40,570	

Coefficients from logits. Controls included for non-profit status, unionization, establishment size and its square. Sample = jobs in multi-establishment firms.

¹ = p-value < 0.01; ⁵ = p-value < 0.05; ¹⁰ = p-value < 0.10

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

Industry controls	Pr(MMMM)		Pr(MMMM)	
	No Estab.	Firm	Yes Estab.	Firm
With skill set:				
LLLL	0.059	-0.453⁵	0.047	-0.617¹
3L, 1H	-5.404¹	-0.203	-5.452¹	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	0.338⁵	-0.526¹	0.280	-0.654¹
2L, 2M	0.331¹	-0.541¹	0.193	-0.793¹
1L, 3M	0.422¹	-0.188	0.279⁵	-0.490¹
MMMM	1.508¹	1.237¹	1.185¹	0.669¹
1H, 3M	0.465¹	-0.501¹	0.278⁵	-0.959¹
2H, 2M	0.459¹	-0.467¹	0.454¹	-0.535¹
3H, 1M	0.427¹	-0.777¹	0.347¹	-1.046¹
1L, 2M, 1H	-0.068	-0.717⁵	-0.007	-0.746⁵
2L, 1M, 1H	-0.850	-1.261	-0.872	-1.349
3H, 1L	0.283	1.307	-0.050	0.930
Pseudo R ²	.0406		.0459	
N	41,421		41,298	

Coefficients from logits. Controls included for non-profit status, unionization, establishment size and its square. Sample = jobs in multi-establishment firms.

¹ = p-value < 0.01; ⁵ = p-value < 0.05; ¹⁰ = p-value < 0.10

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

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 estab.	Like jobs in establishment absent own	Like jobs in economy absent own firm	Like jobs in establishment absent own
Job is LLLL	.0525	.0684	.0949	.0526	.0967
Job is MMMM	.2482	.2536	.2513	.2481	.2460
Job is HHHH	.0618	.1292	.1604	.0620	.1132

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(HHHH)			Pr(LLLL)		
	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	-0.724¹	-0.856¹	0.263	1.885¹	0.649¹	2.112¹
3L, 1M	-1.375¹	-0.352	-0.463	0.540¹	0.897¹	0.966¹
2L, 2M	-0.953¹	-0.364⁵	-0.193	0.505¹	0.703¹	-0.010
1L, 3M	-0.463¹	-0.683¹	-0.547⁵	-0.207	0.387⁵	0.169
3L, 1H	1.012	-0.771	-4.905	0.706	3.504	3.274
2H, 1M, 1L	-0.324	-0.363	1.062		0.514	1.326
2H, 2L		-10.14	7.326	-1.004	-2.768	-3.699
1L, 2M, 1H	-0.944⁵	-0.235	-0.912	0.078	0.065	1.297
2L, 1M, 1H	-0.307	-1.088	0.333	-1.091	-1.427	0.855
3H, 1L	1.057	-2.071	-0.619	-2.098	1.199	-0.322
1H, 3M	-0.018	0.237	0.051	-0.935¹	-0.569¹	0.278
2H, 2M	0.424¹	0.483¹	-0.110	-0.560¹	-0.866¹	-0.955¹
3H, 1M	0.265¹	0.730¹	0.485	-0.852¹	-0.735¹	0.188
HHHH	1.948¹	0.871¹	1.257¹	-0.751¹	-0.966¹	0.379
Industry Included?		Yes			Yes	
R ²		.1532			.1295	
N		39,806			39,519	

Results from logits. Sample = jobs in multi-establishment firms.

¹ = p-value < 0.01; ⁵ = p-value < 0.05; ¹⁰ = p-value < 0.10

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

Proportion of other jobs with same job characteristics mix	All jobs in economy, not in firm	HHHH All jobs in firm, not in estab.	All other jobs in estab.	All jobs in economy, not in firm	LLLL All jobs in firm, not in estab.	All other jobs in estab.
All workers	.0618	.1292	.1604	.0525	.0684	.0949
Public Admin.	.0619	.0814	.1052	.0542	.0471	.2827
Executives	.0582	.1322	.1725	.0522	.0525	.0853
Mgmt-Related	.0622	.2091	.2578	.0511	.0685	.0957
Engineers	.0611	.1718	.2287	.0533	.0609	.0934
Math/CS	.0618	.3629	.4076	.0531	.0617	.1037
Natural Science	.0620	.1568	.2044	.0538	.0622	.1010
Health Diagnostic	.0627	.0789	.1000	.0540	.0643	.0645
Health Treatment	.0645	.0705	.0527	.0551	.0620	.0937
University Professor	.0615	.0815	.1025	.0540	.0742	.0676
Teachers	.0645	.0330	.1184	.0535	.0358	.1806
Lawyer/Judge	.0624	.0658	.1538	.0538	.0502	.0948
Other Professional	.0626	.1238	.1821	.0526	.0839	.1014
Health Technology	.0628	.0921	.0900	.0542	.0447	.0705
Engineering Tech.	.0629	.1888	.2411	.0538	.0411	.0819
Other Technology	.0622	.1847	.1712	.0534	.0770	.0768
Sales Manager	.0620	.0447	.0295			
Finance/Bus. Sales	.0619	.0323	.0560	.0544	.0928	.1286
Service Sales	.0617	.3464	.3471	.0535	.0230	.0133
Retail Sales	.0647	.0815	.1174	.0563	.1347	.1667
Other Sales	.0626	.0289	.0917	.0540	.1036	.0903
Admin. Supervisor	.0628	.1375	.1705	.0546	.0039	0
Computer Operator				.0541	.0583	.0632
Secretary	.0621	.1011	.1517	.0545	.1561	.1967
Records	.0630	.1128	.1102	.0542	.1111	.1198
Mail Distribution	.0625	.0243	.0863			
Other Admin.	.0640	.1354	.1675	.0497	.0742	.0986
Protective Services	.0625	.1066	.1255	.0546	.0763	.0688
Food Services	.0638	.0540	.0703	.0566	.0183	0
Health Services	.0632	.1454	.1444	.0556	0	0
Building Services	.0613	.0837	.0948	.0559	.0067	.0417
Personal Services	.0612	.0819	.0588	.0551	.0258	.025
Mechanic	.0648	.1907	.1667	.0535	.0586	.0759
Construction	.0636	.1199	.1972	.0541	.0340	.0226
Other Precision	.0638	.1166	.2046	.0535	.0731	.0879
Machine Operator	.0622	.1166	.1810	.0533	.0310	.0775
Assembler	.0615	.0913	.1267	.0546	.0471	.1162
Vehicle Operator	.0629	.1348	.1152	.0544	.1163	.0526
Other Transportation	.0629	.0825	.1821	.0543	.0472	.1688
Construction Laborer	.0623	.0890	.0434			
Handlers	.0613	.0689	.0746			
Other Laborer	.0622	.0768	.1424			
Farm Laborer	.0623	.1095	.0366	.0541	.3333	0
Forestry/Fishing				.0540	.625	0

Sample = all jobs, by 2-digit occupation.

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

	Controlling for Industry				Controlling for Occupation			
	Guidelines	Supervision	Human Capital	Interdependence	Guidelines	Supervision	Human Capital	Interdependence
a. Full Sample								
Multitasking	4.403 (0.4904)	3.867 (0.5067)	1.780 (0.4473)	3.969 (.4971)	2.488 (0.5514)	3.582 (0.5575)	2.715 (0.5358)	2.434 (.4795)
Guidelines		3.929 (0.5094)	1.542 (0.4267)	3.731 (.5403)		2.791 (0.5233)	2.184 (0.5357)	2.711 (.4953)
Supervision			1.724 (0.4445)	3.504 (.4842)			1.876 (0.5106)	3.208 (.5424)
Human Capital				2.986 (.3369)				1.919 (.3418)
b. Non-Managers								
Multitasking	4.419 (.4707)	3.870 (.4878)	1.891 (.4420)	3.854 (.4732)	2.233 (.4217)	2.647 (.5331)	2.113 (.5230)	3.283 (.5254)
Guidelines		3.872 (.4869)	1.676 (.4344)	3.640 (.5213)		2.847 (.4965)	2.426 (.5351)	3.430 (.5524)
Supervision			1.807 (.4381)	3.443 (.4665)			2.549 (.5061)	3.168 (.5175)
Human Capital				3.072 (.3402)				2.385 (.5377)
c. Managers Only								
Multitasking	4.273 (.4473)	4.021 (.4583)	3.503 (.4320)	3.595 (.4906)	4.257 (.4328)	3.885 (.4330)	3.444 (.4188)	2.675 (.4001)
Guidelines		3.070 (.3709)	2.200 (.2998)	2.942 (.4318)		4.541 (.4590)	2.752 (.3309)	3.994 (.5352)
Supervision			2.883 (.3843)	3.502 (.4618)			2.797 (.3640)	3.415 (.4433)
Human Capital				2.903 (.4182)				3.011 (.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-R²'s are in parentheses. The 1990 U.S. Census 3-digit industry and occupation codes were used to define the industry and occupation controls.

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

Industry controls % other jobs with:	Pr(LLLL)		Pr(LLLL)		Pr(HHHH)		Pr(HHHH)	
	No	Firm	Yes	Firm	No	Firm	Yes	Firm
LLLL	2.930¹	3.034¹	2.039¹	1.982¹	-0.7171¹	.3645	-0.8802¹	.2058
MLLL	1.074¹	1.625¹	.9392¹	1.254¹	-0.7024⁵	-1.345¹	-0.8194⁵	-1.223⁵
LMLL	1.844¹	.2090	1.738¹	-0.1919	-0.2427	-0.9928 ¹⁰	-0.4628	-1.153 ¹⁰
LLML	.9338 ¹⁰	.1835	1.234¹	.5774	-1.234 ¹⁰	-0.1717	-0.9048	.0405
LLLM	.9570 ¹⁰	1.160	1.169⁵	2.239¹	.4330	.6796	.2028	.6820
LLMM	1.122¹	.3567	1.133¹	-0.0145	-1.024¹	-1.003¹	-0.8834¹	-0.7334 ¹⁰
LMLM	.9415	1.622	.7171	1.029	-1.824 ¹⁰	.5012	-2.455⁵	-0.1444
LMML	2.303¹	-1.604	2.426¹	-1.600	-1.629 ¹⁰	-0.2104	-1.948 ¹⁰	-1.410
MLLM	.7638 ¹⁰	-0.6311	.8967⁵	-0.7383	-0.6879	.4281	-0.4200	.8707 ¹⁰
MLML	.3937	.9660	.6890	1.262	-1.576⁵	-1.614 ¹⁰	-1.537⁵	-0.7724
MMLL	1.591¹	-0.1566	1.351¹	-0.2677	.4982	.1221	.1671	-0.4334
LMMM	.7535¹	.6972⁵	.7321⁵	.4653	-0.3561	-1.106¹	-0.2394	-0.8151 ¹⁰
MLMM	.6803¹	-0.7866⁵	.6667¹	-0.7356⁵	-0.9819¹	-1.174¹	-0.7175¹	-0.5592 ¹⁰
MMLM	.3717	.7183	.2871	.2194	-0.3650	-0.8727	-0.4987	-1.393⁵
MMML	.0673	1.344⁵	.2761	.6067	-1.610¹	.4538	-1.978¹	.6151
LLLH	4.776	-110.3	-0.9032	-150.8	1.185	2.907	1.769	.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	.1989	-1.965	2.308	2.711
HHLH	-1.508	11.60	-1.463	18.17 ¹⁰	-3.642	2.226	-5.912	.3935
HHHL	.6190	-5.713	-0.4054	-19.07	-0.3951	16.01		12.89
HMLL	7.553	-20.25	9.296	-13.67	-7.700	.0131	-8.809	-0.7919
HLLM	-3.164		-9.150		1.100		2.320	
HLML		16.31		17.72	1.672	4.573	.0613	1.326
LLMH	-1.218	1.124	-1.668	1.138	1.610	.4258	-1.272	-2.921
LLHM	-2.698	-6.065	-2.379	-4.521	6.582¹	5.145	5.594⁵	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	.2737	-1.477	1.737	-0.4743	1.080	-2.689	.2264	-4.215
MLLH						3.936		3.187
MLHL		-17.15		-7.612	-10.22	1.975	-11.02	4.926
MHLL	.4121	-0.3604	.3802	.8369	-0.5419	2.338⁵	-1.262	1.602

(continued on next page)

LHMM	1.182	1.492	1.271	.7813	1.262	.1630	.9830	-0.7765
LMHM	-0.0570	-1.117	.3534	-1.771	3.639¹	-0.6835	4.194¹	-2.147
MLMH	-8.101⁵	4.030⁵	-8.666⁵	4.437⁵	-5.267 ¹⁰	-0.2540	-5.238 ¹⁰	.8430
LMMH	-2.468	1.155	-2.037	2.536 ¹⁰	-0.2871	-4.371	-0.3278	-4.442
MLHM	-2.994	-1.163	-5.063⁵	-5.333	-0.6571	-2.246	-0.7093	-1.076
MMLH	-1.838	2.712¹⁰	-3.646	2.362	.0641	-2.400	-1.248	-3.298
MMHL	-1.082	.4636	-1.732	-0.9096	-0.2973	1.884	.4413	2.465
MHLM	1.829	-0.6053	2.773 ¹⁰	.7817	-0.4844	.9438	-1.331	.3649
MHML	.5310	1.622	1.035	1.637	.3212	.8711	.2347	.7884
HMML	-1.089	-0.5937	-3.585	-0.2369	-3.512	1.572	-3.183	-0.0244
HLMM	-0.5964	-3.946	.0959	-4.768	-1.776	-0.0359	-2.187	.2914
HMLM	3.021	1.560	3.412	3.604	-25.77 ¹⁰	-0.7417	-25.69 ¹⁰	-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	.1668	-7.683	-7.829	-4.645	-4.754
MHLH		1.380		-2.372				
MLHH	2.908 ¹⁰	.1066	2.473	-3.005	.3599	.9696	.3063	.3924
MHHL	-0.3631	-6.298	-1.121	-5.609	1.926	1.094	1.941	1.828
HLMH	.5681	.3618	1.290	1.502	.7120	-4.041	1.926	.6389
HLHM	-6.722	2.506	-5.985	-0.5327	3.174	.1946	2.531	1.259
HMLH								
HMHL	-2.667	3.272 ¹⁰	-1.967	5.469⁵	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 ¹⁰	-8.923	6.349	-11.11	8.463	-66.81	6.946	-61.94
MMMM	-0.1239	.4239	-0.4195	-0.0931	.9412¹	-0.0846	.7902¹	-0.2015
MHMM	-0.9904¹	.4371	-0.7566 ¹⁰	.9236 ¹⁰	.2081	.2558	-0.0889	-0.2044
MMHM	-3.332¹	-0.6602	-3.068¹	-0.1621	.5723	-1.473¹	.9796¹	-0.8266
MMMH	-0.2135	-0.8186⁵	-0.7285 ¹⁰	.3747	-0.2489	-0.2248	.0724	
HHMM	-0.5866	.3929	-0.8696 ¹⁰	-0.7068	1.394¹	1.044⁵	1.220¹	.3106
HMMH	-1.334	-0.0209	-1.449	.2831	.2818	.2708	.0974	.0132
HMHM	-0.1646	.2349	-1.068	-0.2462	1.596¹	-1.080	1.211¹	-1.862⁵
MHMH	-2.012 ¹⁰	-2.688 ¹⁰	-1.823 ¹⁰	-3.515⁵	.7688	.7720	.7921	.5786
MHHM	-1.432⁵	-1.338 ¹⁰	-1.627⁵	-1.857⁵	-0.8736⁵	-1.313⁵	-0.4818	-0.3751
MMHH	-0.2920	-0.2982	-0.5473	-0.5960	1.743¹	1.034¹	1.537¹	.5108
MHHH	-0.9279⁵	-0.0668	-1.147⁵	.1604	.7060⁵	.1495	.7671¹	.6435
HMHH	-0.1202	1.402¹	-0.8495	.5875	2.171¹	.6445 ¹⁰	2.113¹	.5864
HHMH	-1.212⁵	-0.1656	-1.075 ¹⁰	-0.5682	-0.0479	.6851 ¹⁰	-0.1722	.5475
HHHM	-0.5029	-0.5579	-0.4967	-0.5042	1.640¹	2.222¹	2.082¹	-0.6012
HHHH	-1.076¹	.7060⁵	-1.252¹	.3912	3.054¹	1.640¹	2.483¹	1.101¹
R ²	.1029		.1225		.1270		.1389	
N	41,164		40,028		41,323		40,472	

¹ = p-value < 0.01; ⁵ = p-value < 0.05; ¹⁰ = p-value < 0.10

Appendix B.
Proof of Equation (5)

$Q_{\text{multitask} \mid \text{centralization}} = \max_{\tau}[E(Q)] = \text{expected output with } \tau \text{ chosen over the entire distribution of the unknown state of the world. } Q_{\text{multitask} \mid \text{discretion}} = \max_{\tau}[Q \mid \text{state of the world}]$. The τ chosen to maximize expected output can result in actual output no better than when the state of the world is known. If these benefits outweigh agency costs D , a multitask worker will be given discretion. Since this logic applies for any given state of the world, it also applies unconditional on the state of the world.