Performance, Career Dynamics, and Span of Control

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In this paper we focus on a classic idea concerning span of control, which is that a prime driver is the scale of operations effect. We extend the theory concerning the scale of operations effect by allowing firms' beliefs concerning a manager's ability to evolve over the manager's career. We empirically investigate the resulting testable predictions using a unique single-firm data set that contains detailed information concerning the reporting relationships at the firm. Our empirical analysis supports the notion that the scale of operations effect and learning are both important determinants of a firm's span of control.

I. Introduction

A key strategic decision for firms is how to efficiently allocate managerial talent within their organizations. Among the various policies firms use to administer their internal labor markets, an important feature is the span

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of control, or the number of subordinates a particular manager supervises. Span of control is an important decision because it defines how efficiently managers can supervise workers. It has strong implications for the quality of management and the internal economics of the firm. However, despite its importance, the determinants of span of control are not well understood. In this paper, we investigate both theoretically and empirically what drives managerial span of control, building on previous theoretical contributions studying firms' internal organization.

A standard building block for hierarchical models of the firm is the so-called scale of operations effect. As in studies by Lucas (1978), Rosen (1982), or Garicano (2000), a manager's ability has a larger effect on firm productivity the larger the number of workers that are below that manager in the firm's hierarchy.[1] Those models predict that higher ability or more productive managers should have larger spans of control. A subordinate's productivity is positively related to the ability of the manager because managers are able to leverage their ability over the workers they supervise. However, there are costs of a larger span of control; for example, assigning more workers to a manager limits the amount of attention she can devote to each worker. In deciding on a manager's span of control, a firm trades off the benefit of having this extra productivity apply to a larger number of workers with the cost associated with a larger span. This trade-off typically yields that higher-ability managers should have larger spans. Despite the fact that this argument appears in a number of classic papers, there has been almost no empirical investigation of the basic prediction. We close this gap by providing a direct empirical test of the scale of operations effect using detailed personnel records of a single large firm.

In the first part of the paper, we extend the theory by introducing labor market learning. Since the seminal contributions of Harris and Holmstrom (1982) and Holmstrom (1982), it is understood that firms' beliefs about worker ability levels are not fixed but rather evolve over time as performance is observed. This is important because span of control should be a function of beliefs concerning a manager's expected ability rather than the manager's actual ability. To investigate this idea theoretically, we incorporate the scale of operations effect into the internal labor market framework developed by Gibbons and Waldman (1999b, 2006) which has been

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[1] The argument first appeared in the paper by Mayer (1960).

successful in explaining various aspects of internal labor market operations. This framework is well suited for our purposes because it captures the basic idea of labor market learning in a job ladder–type model. In this framework, a worker in each period is characterized by a value for effective ability, where effective ability is a function of innate ability and human capital accumulation. Further, in our model, span of control depends on firms' beliefs concerning a manager's effective ability—what we refer to as expected effective ability—which evolves as workers age because of human capital accumulation and performance realizations.

Our theoretical investigation yields a number of results. We first show that the model is consistent with the basic scale of operations effect result that higher-ability managers have larger spans of control, where to be precise in our model this positive correlation is between a manager's expected effective ability and the manager's span of control. We then derive a number of results concerning span of control that are not found in previous theoretical analyses. For example, we find that, holding education fixed, a manager's span of control should be positively correlated with previous performance. The logic is that higher performance causes firms to positively update their beliefs concerning the manager's expected effective ability, so the positive correlation between expected effective ability and span of control translates into a positive correlation between prior performance and span of control. Similarly, holding performance fixed, a manager's span of control should be positively correlated with the manager's education. The logic here is similar. Because performance ratings are noisy measures of expected effective ability, higher education even controlling for performance ratings is positively correlated with expected effective ability. So the positive correlation between expected effective ability and span of control now translates into a positive correlation between the manager's education and span of control.

In the second part of the paper, we test these predictions using confidential performance and personnel data from a large European Union high-tech manufacturing firm that has production facilities in various counties around the world and whose products are sold globally. What distinguishes this data set from most other single-firm data sets used to study internal labor market operations (such as the one analyzed in Baker, Gibbs, and Holmstrom 1994a, 1994b) is that our data set includes information about the firm's chain of command. For every hierarchical layer, we know to which manager every individual worker reports. This gives us a very accurate picture of the firm's hierarchy and allows us to compute the span of control for each manager at various hierarchical layers. Because our data cover multiple years, our measure of the span of control also varies over time.

As discussed, our theoretical model predicts that span of control should be positively related to factors correlated with expected effective ability: performance ratings and education. We find evidence consistent with the prediction concerning performance ratings and mixed evidence concerning the education prediction. Our theoretical model also predicts positive correlations between current span of control and the current wage as well as between current span of control and the probability of subsequent promotion. Our empirical analysis finds clear support for the former prediction at managerial levels above the bottom one and some support for the latter prediction at managerial levels in the middle of the firm's job ladder.

We also conduct an additional test that we believe is a better test of the theory because it is less likely to be explained by alternative theories. If span of control is positively related to expected effective ability, as our theory predicts, then changes in span of control should be positively correlated with factors that are positively correlated with changes in expected effective ability. Specifically, performance ratings should be positively correlated with how a manager's span of control varies over time. Indeed, we find evidence that changes in span of control are positively correlated with performance ratings.

This paper is related to previous empirical work by Smeets and Warzynski (2008) that used personnel data from the same firm we study. Important differences include the fact that we incorporate performance data into the empirical analysis and also provide a formal theoretical model that we use to guide our empirical work. Our paper also contributes to the small but important empirical literature about hierarchical production.[2] While our paper relies on detailed personnel records directly provided by the firm, most of this literature employs survey or census data. Using a sample of Fortune 500 firms, Rajan and Wulf (2006) document an increased flattening of firms' organizational structures since the mid-1980s, resulting from the combination of an increase in the average span of control of managers and a decrease in the number of hierarchical layers. Garicano and Hubbard (2007, 2009) employ the 1992 US census of services to study hierarchical production in law firms and find, among other results, that span of control depends on the extent of the market and that strong local demand leads to increases in span of control. Caliendo, Monte, and Rossi-Hansberg (2015) use a large institutional data set of French manufacturing firms to investigate how firm growth affects reorganization. Their study documents the relationship between firm growth, changes in the number of hierarchical layers, wage, and employment changes.[3]

[2] Another related strand of the literature analyzes how information and communication technology and product market competition affect firm organization (for analyses related to information and communication technology, see Delmastro 2002; Bloom et al. 2014; for an analysis of product market competition, see Guadalupe and Wulf 2010). These issues are beyond the scope of our paper. For a more complete discussion, see Smeets (2017).

[3] A recent related theoretical paper is that of Ke, Li, and Powell (2018), which among other ideas considers how span of control may be distorted away from production efficiency because of its effect on promotion incentives.

A couple of other papers in this literature are closer to our paper in that they are related to the scale of operations effect. Fox (2009) uses a Swedish linked employer-employee data set and US data from the 1996 Survey of Income and Program Participation to show that the wage gap between large and small firms increases with job responsibility, which is consistent with predictions of hierarchical models characterized by the scale of operations effect. Finally, the closest paper to ours is the recent paper by Lazear, Shaw, and Stanton (2015), which focuses on the extent to which high-ability managers affect worker productivity. Although it is not their main focus, they do test for a scale of operations effect concerning span of control, but in their data set they find no evidence that higher-ability managers have larger spans of control.[4]

The paper also contributes to a set of papers that extend the internal labor market framework developed by Gibbons and Waldman (1999b, 2006) and investigate how well the extended models match empirical evidence. For example, Pastorino (2014) allows the speed of learning to vary across jobs and then structurally estimates the model using the data set of Baker, Gibbs, and Holmstrom (1994a, 1994b). She finds that allowing for a differential speed of learning is important for understanding the timing of promotions and wage increases. Lluis's (2005) earlier structural estimation exercise finds that the ability of young workers is important for workers moving up the job ladder. Gicheva (2013) adds the choice of hours worked and finds results that help us better understand the gender wage gap.

The outline for the paper is as follows. Section II presents and analyzes a theoretical model that combines the scale of operations effect with human capital acquisition and learning about worker ability as workers gain labor market experience. Section III describes the data and presents basic facts about the firm. Section IV focuses on tests of predictions of our theoretical model concerning span of control and discusses what we learn from our empirical findings. Section V provides concluding remarks.

II. Model and Theoretical Analysis

We first present and analyze a model with identical competitive firms described by a two-level job ladder and multiple divisions, where a division consists of a single manager at an upper level who supervises workers on a lower level. There are overlapping generations of workers, where workers are in the labor market for exactly two periods but enter the labor market with heterogeneous schooling levels. The model captures both the scale of operations effect (e.g., Lucas 1978; Rosen 1982) and symmetric learning about worker abilities (e.g., Harris and Holmstrom 1982; Holmstrom 1982;

[4] One possibility for why our empirical analysis supports the scale of operations effect and their analysis does not is that we employ the actual performance evaluations employed by the firm, while they construct performance data from data on worker productivity.

Gibbons and Waldman 1999b, 2006). We then discuss what happens when the analysis is extended to workers who are in the labor market for three periods, job ladders with a third job level, and a growing firm.

A. The Model

There is free entry into production, where firms are identical and the only input is labor. A worker's career lasts two periods, and labor supply in each period is fixed at one unit for each worker. A worker is referred to as young in the worker's first period in the labor market and old in the second. Worker i enters the labor market with schooling level s_i, where s_i can take on any integer value between 1 and S. We also assume that each cohort of workers has exactly z_s workers of schooling level s, where $z_s > 0$ for all s, $s = 1, \ldots, S$.

Let η_{it} denote worker i's effective ability in period t, where

$$\eta_{it} = \theta_i f(x_{it}). \tag{1}$$

In equation (1), θ_i is the worker's innate ability and x_{it} is the worker's labor market experience before period t; that is, $x_{it} = 0$ for young workers and $x_{it} = 1$ for old workers. Also, we assume that $f(1) > f(0) > 0$, which shows that workers acquire general human capital as they age. We assume that innate ability can be either high or low: $\theta_i \in \{\theta_L, \theta_H\}$. The ex ante probability that a worker with schooling level s has high innate ability equals $p(s)$, where $p(s) > p(s-1)$ for all s, $s = 2, \ldots, S$. That is, a higher schooling level translates into a higher probability that the worker has high innate ability. This can be the case either because innate ability and schooling are positively correlated (which could occur because of education signaling; e.g., Spence 1973) or because schooling enhances human capital. In the latter case, it might be more appropriate to refer to θ_i as worker i's starting ability rather than worker i's innate ability.

A firm consists of two job levels and m divisions, where in each division a single worker is assigned to job level 2 while the number of workers assigned to job level 1 in a division is a choice variable for the firm. Note that a richer and more realistic specification would make the number of divisions in each firm a choice variable but that enrichment would not change any of the testable predictions we derive in the next subsection. So for tractability reasons the number of divisions is exogenously determined.

If worker i is assigned to job 1 in period t, then the worker produces

$$y_{i1t} = (1 + v_{it})(\eta_{it} + \varepsilon_{it}), \tag{2}$$

where ε_{it} is a noise term drawn from a normal distribution with mean 0 and variance σ^2.[5] The term v_{it} equals v ($v > 0$) if the worker were employed at the

[5] Following various papers in the learning literature, we assume that the noise term is drawn from a normal distribution. But any log-concave distribution would produce similar results.

firm in the previous period and 0 otherwise (so all young workers assigned to job 1 in period t are characterized by $v_{it} = 0$). The term v_{it} thus shows that workers acquire firm-specific human capital as they gain experience at a firm and that this human capital increases productivity at job level 1.

It is assumed that firm-specific human capital is required to produce at the high-level job, so only an old worker with previous experience at the firm is ever assigned to job 2. The focus throughout is the behavior of a specific firm, call it firm k. If old worker i with previous experience at firm k is assigned to job 2 at division j in firm k in period t, then the worker produces

$$y_{i2jt} = g(n_{jt})(\eta_{it} + \varepsilon_{it}), \tag{3}$$

where n_{jt} is the number of level 1 workers employed in division j in firm k in period t. We assume that $g(0) = G$, $g' > 0$, and $g'' < 0$.[6] The assumption $g' > 0$ captures the scale of operations effect; formally, the partial derivative of y_{i2jt} with respect to η_{it} is increasing in n_{jt}.[7] We further assume that $G > (1 + v)c_2$, which ensures that each firm finds it profitable to assign its retained old workers with the highest expected effective abilities to the job 2 positions (for a related discussion, see Waldman 1984b).[8]

Consider a worker with schooling level s. At the beginning of the worker's career, all firms and the worker herself believe that the worker's innate ability equals θ_H with probability $p(s)$ and θ_L with probability $1 - p(s)$. Learning takes place at the end of the worker's first period in the labor market, when the realization of the worker's output for that period becomes common knowledge. The presence of the noise term in equation (2) means that learning at the end of this first period is incomplete; that is, there is updating after the worker's first period output is realized, but after this updating there is still uncertainty concerning the worker's true innate ability.

[6] Note that managerial output is a function of the number of workers supervised but not the ability levels of those workers. By allowing managerial output to be a function of worker ability levels, we could rationalize both higher-ability managers supervising high-ability workers and higher-ability managers supervising lower-ability workers. The former would arise if the extra managerial productivity due to higher worker ability was positively related to managerial ability, while the latter would arise if the extra managerial productivity due to higher worker ability was negatively related to managerial ability. The recent paper by Lazear, Shaw, and Stanton (2015) finds evidence of the former in the firm that they study.

[7] We also assume that the $g(.)$ function is such that in each period a firm hires at least m total young workers so that it is able to fully staff its managerial positions by promoting from within during the following period.

[8] Frequently, the scale of operations effect (as in the introduction) is described in terms of managerial ability positively affecting the outputs of workers below the manager in the hierarchy. Such a specification, however, would be analytically very challenging in our setting because when a worker's output is realized, there would be learning about both the worker's ability level and the ability level of the manager to whom the worker reports.

Workers and firms are assumed to be risk neutral and everyone faces a discount factor δ ($0 < \delta < 1$), while workers face no mobility costs and firms face no hiring or firing costs. To make the model consistent with standard wage determination at most firms, we assume spot market contracting. Also, we focus on wages paid in advance of production rather than piece rate contracts.

At the beginning of each period, all firms simultaneously offer each old worker a wage for that period, and the worker then chooses to work for the firm that offers the highest wage. Further, if multiple firms are tied for this highest wage, the worker chooses randomly among the firms unless one is the worker's employer from the previous period, in which case the worker remains with that firm. In choosing wages for old workers, firms maximize expected discounted profits. After this stage, firms hire young workers. Specifically, we assume that for each schooling group there is a single wage that equates supply and demand for workers with that schooling level; that is, we assume price taking behavior in the young worker labor market.

We also assume that in making hiring and assignment decisions in any period t, a firm ignores how its current period decisions may affect equilibrium wages in future periods. For example, by hiring an additional worker with a high schooling level this period, it is possible (because of the scale of operations effect) that the firm's expected demand for young workers in the following period goes up, and this increases the expected wages for young workers in the following period. We assume that firms ignore such effects in making hiring and assignment decisions. We do this both for tractability reasons and because we believe that in real-world labor markets these considerations have little effect. In particular, in large labor markets a single firm's decisions concerning hiring and assignment will likely have minor effects on subsequent market clearing wages, and so these effects are unlikely to affect hiring and assignment decisions in significant ways.[9]

Finally, by prior assumption we know that no old worker switches employers to work at job 2 in a new firm. We also assume that the magnitude of firm-specific human capital in the production function for job level 1, v, is sufficiently large that no old worker switches firms to work at job level 1 at a new firm and no old workers are unemployed. For related analyses that allow for turnover, see Ghosh (2004) and DeVaro and Morita (2012).[10]

[9] One can describe our approach as follows: in each period t, firms are perfectly competitive or price takers, where note that price taking is a standard assumption in many models of labor market equilibrium. As discussed by Mas-Colell (1980, 122), there is a "tendency of noncooperative behavior to approximate perfect competition" in large economies. We believe this is true in the model we analyze, but showing that formally is beyond the scope of the current paper.

[10] Because firms can vary in any period t in terms of the expected effective abilities of their managers, and because the scale of operations effect means that high-ability

Note that our specification includes a number of simplifying assumptions—such as firms have identical production functions and there is sufficient firm-specific human capital—so there is no turnover in equilibrium. We impose these assumptions both to make the model more easily tractable and to make the arguments more transparent.

B. Equilibrium and Testable Implications

Here we describe equilibrium behavior in this model and derive testable implications. In Section II.C we discuss extensions. Also, we focus on behavior in equilibria in which there is no entry or exit of firms after the first period.[11] Note that, consistent with the empirical analysis that follows, our focus is properties that wage and promotion practices must satisfy in equilibrium and how the choice of span of control varies across a firm's managers.

We start by describing the nature of equilibrium when $S = 1$; that is, workers do not vary in terms of schooling levels. This case is a bit simpler, and analyzing this case first helps build intuition. Consider firm k in period t. The firm starts the period with some number of old workers it employed in job 1 in period $t-1$ when the workers were young, where these workers vary in terms of their period $t-1$ outputs. Let η_{it}^{e} be the market's expectation of worker i's effective ability at the beginning of period t. Given that there is a single schooling level so all workers are ex ante identical, for every young worker i the firm employed in period $t-1$, we have $\eta_{it-1}{}^{e} = [p(1)\theta_{H} + (1-p(1))\theta_{L}]f(0)$. In turn, after observing period $t-1$ outputs, the market updates its beliefs on the basis of these outputs. Specifically, let θ_{it}^{e} denote the expected innate ability of old worker i in period t; that is, $\theta_{it}{}^{e} = \mathrm{E}(\theta_{it}|y_{i1t-1})$. Then the expected effective ability of old worker i in period t is given by $\eta_{it}{}^{e} = \theta_{it}{}^{e}f(1)$, where η_{it}^{e} is an increasing function of y_{i1t-1}. That is, because of Bayesian updating, the expectation concerning expected effective ability when a worker is old is positively related to the worker's output when the worker was young.

Now consider how the firm assigns these old workers to jobs in period t (remember we are focused on equilibria in which there is no turnover). Firm k has m divisions and a single job level 2 or managerial job in each division, and effective ability is more valuable in job level 2 than in job level 1. So the firm promotes the m old workers with the highest values for η_{it}^{e}; that is, the firm promotes the m old workers with the highest period $t-1$ outputs, and

managers should have larger spans of control, it is possible given little or no firm-specific human capital that an old worker moves from a firm with low-ability managers to a firm with high-ability managers. To make the logic of the analysis more transparent, we assume that v is sufficiently large that this does not occur in equilibrium.

[11] If firm-specific human capital is sufficiently high, there will never be an exit. Also, if the managerial job is sufficiently important in terms of a division's total production, then there will never be entry after the beginning of the game.

the remaining old workers are assigned to job level 1. In turn, taking the market clearing wage for young workers as given, the firm hires the number of young workers such that each division has the efficient number of level 1 workers.[12] The result is that, given the scale of operations effect captured by the $g(n)$ term in equation (3), the number of workers in a division is positively related to the division manager's expected effective ability.

Proposition 1 formalizes results from the above discussion. Note that all proofs are in the appendixes, available online.

PROPOSITION 1: Consider firm k and period t. If $S = 1$, then the following describe firm k's behavior in period t.

1. The firm promotes the m old workers it employed in the previous period who produced the highest outputs, while the other workers are assigned to job 1.
2. The wage increase from period $t-1$ to t for old workers at the firm is a strictly positive function of the period $t-1$ output.
3. Promoted workers receive larger pay increases from $t-1$ to t than the workers who were not promoted.
4. All young workers hired by the firm are assigned to job 1 and are paid the same wage.
5. Managerial span of control (weakly) increases with the manager's $t-1$ output.

We now consider how the nature of equilibrium changes when $S > 1$; that is, there are multiple education groups. Consider firm k in period t that starts the period with some number of workers it employed in job 1 in period $t-1$, where these workers vary in terms of their education levels and their period $t-1$ outputs.[13] Because the schooling level determines the ex ante probability a worker has high ability, for every young worker i with schooling level s_i the firm employed in period $t-1$, we now have $\eta_{it-1}{}^{e} = [p(s_i)\theta_H + (1-p(s_i))\theta_L]f(0)$. Further, we also again have that after observing period $t-1$ outputs, the market updates its beliefs concerning the workers' innate ability levels. So the expected innate ability of old worker i in period t

[12] In equilibrium, this market clearing wage is affected by the fact that hiring a young worker this period increases next period's profit, since the presence of firm-specific human capital means that old worker wages are below expected productivity. This is a standard result in models of this sort (such as found in Waldman 1984a).

[13] Although we do not show it formally, rather than a firm hiring a homogeneous group of young workers, in our model the typical case is that a firm hires a heterogeneous group of young workers. The reason is that the return to hiring a young worker with a high level of education falls with the number of other young workers employed who have high education levels.

is given by $\theta_{it}^{e} = \mathrm{E}(\theta_{it}|s_i, y_{i1t-1})$. In turn, the expected effective ability of old worker i in period t is still given by $\eta_{it}^{e} = \theta_{it}^{e}f(1)$. The difference is that now the expectation concerning expected effective ability when a worker is old increases with y_{i1t-1} (holding s_i) fixed and also increases with s_i (holding y_{i1t-1} fixed).

Now consider the firm's assignment decisions in period t. As in the single education group case, the firm promotes the m old workers with the highest values for expected effective ability to the level 2 or managerial jobs, and the remaining old workers are assigned to level 1 jobs. There is a difference, however, which is that this decision rule does not translate into promoting the m old workers who produced the highest outputs in period $t-1$. Because expected effective ability is a function of both the period $t-1$ output and the schooling level, there can be a pair of workers where only one of them is promoted and where the promoted worker had a lower $t-1$ output but a higher education level. Further, because of the scale of operations effect, a manager's span of control is again a positive function of the manager's expected effective ability. In this case, this means that span of control will be positively related to output in $t-1$ (holding the schooling level fixed) and will also be positively related to the schooling level (holding output in period $t-1$ fixed). Since span of control is a positive function of the manager's expected effective ability, there is also a positive correlation between span of control and managerial wages.

Proposition 2 formalizes results from the above discussion.

PROPOSITION 2: Consider firm k and period t. If $S > 1$, then the following describe firm k's behavior in period t.

1. The firm promotes the m old workers it employed in the previous period with the highest values for expected effective ability, while the other workers are assigned to job 1.
2. Within a schooling group, the old workers promoted are the ones who produced the highest outputs, but there can be pairs of old workers where only one is promoted, and this worker produced less in $t-1$ but has a higher education level.
3. The period t wage for old workers at the firm and the wage increase from $t-1$ to t for old workers at the firm both increase with the $t-1$ output (holding education fixed), while the wage for old workers increases with education (holding the $t-1$ output fixed).
4. Within a schooling group, promoted workers receive larger pay increases from $t-1$ to t than the workers who were not promoted.
5. All young workers hired by the firm are assigned to job 1, where the young worker wage increases with the worker's education level.
6. Managerial span of control (weakly) increases with the manager's $t-1$ output (holding education fixed) and also (weakly) increases

with the manager's education level (holding the $t-1$ output fixed).

7. Within a schooling group, managerial span of control is positively correlated with the managerial wage.

The above discussion and proposition 2 tell us that our model—characterized by the scale of operations effect and learning—yields a number of testable implications. Some of these concern wages, wage changes, and probability of promotion and can be found in studies by Gibbons and Waldman (1999b, 2006).[14] Thus, our focus is testable implications concerning span of control that are new. These are the following. First, a manager's span of control should be positively related to prior performance, holding the schooling level constant. Second, span of control should also be positively related to the schooling level, holding performance constant. Third, managerial span of control should be positively related to the wage paid.[15]

C. Extensions

In Section II.B, we formally analyzed a model with two job levels and workers whose labor market lives are two periods. Here we discuss three extensions. We begin with a discussion of what happens when workers are in the labor market for three periods. We then consider what happens when there are three job levels in addition to three periods. We end with a discussion of what happens when firm size changes over time.[16]

Everything is the same as in the model considered in Section II.B except that labor market careers last three periods rather than two and the equation for expected effective ability is changed to accommodate the longer labor market lives. Specifically, we now have the following. First, equation (1) still determines expected effective ability, where now we assume $f(2) > f(1) > f(0) > 0$. Second, worker i's output in job 1 in period t is still given by equation (2), and output in job 2 in period t for workers with at least one prior period of experience at the firm is still given by equation (3). In this extension, a worker in the first period in the labor market is referred to as young,

[14] The testable implications concerning wages, wage changes, and probability of promotion are as follows. First, wages for both young and old workers should be increasing functions of worker schooling levels. Second, within a schooling group, promoted workers should be those who performed better before promotion. Third, within a schooling group, performance should be positively related to subsequent wage increases, and there is a corresponding prediction that promoted workers receive larger wage increases than those who are not promoted.

[15] All of these implications would also hold in the absence of learning, that is, if each worker's innate ability was known with certainty when the worker entered the labor market. We come back to this issue in Sec. II.C, where we discuss extensions.

[16] Our discussion is based on formal analyses found in app. C.

a worker in the second period is referred to as old, and a worker in the third period is referred to as very old.

This model yields results similar to those found in Section II.B. For example, focusing on workers assigned to job 1 in period $t-1$ of a given schooling level, labor market experience, and performance history, the workers promoted to job 2 in period t will be those with higher period $t-1$ outputs.[17] One interesting aspect of this extension, however, is that it allows us to distinguish between our approach with symmetric learning and a model where firms have full information about each worker's effective ability. As mentioned in footnote 15, a model characterized by full information can capture most or all of the testable implications derived in Section II.B. The reason is that wages, probability of promotion, and span of control would depend on effective ability, and effective ability would be positively correlated with innate ability and schooling, thus yielding similar testable predictions.

But now consider our first extension with three periods rather than two. In this model, wage changes and changes in span of control will depend on performance in the previous period. In other words, wage changes and changes in span of control will be correlated with the most recent performance even after controlling for education, labor market experience, firm tenure, and the starting value for the variable, because the most recent performance is correlated with changes in expected effective ability even after controlling for all these factors. But in a world characterized by full information, this is not the case. Because firms know each worker's innate ability, wage changes and changes in span of control will be uncorrelated with the most recent performance after controlling for labor market experience, firm tenure, education, and the starting value for the variable.[18]

Now suppose that we extend this model further so that there is a third job level in each firm's hierarchy. Specifically, each firm continues to have m divisions with a single manager at the top of each division, but each division now has an endogenously determined number of subdivisions. Further, each subdivision is characterized by a single manager defined to be in the subdivision's single level 2 job and an endogenously determined number of workers reporting to the subdivision's manager. We assume that production

[17] One difference between this extension and model with two-period careers is that demotions are possible. However, if human capital accumulation is substantial, then demotions will be rare, which matches the empirical evidence. For a discussion, see Gibbons and Waldman (1999b).

[18] There is an alternative theoretical argument, however, that could explain a positive correlation between managerial performance and changes in span of control. Specifically, related to the analysis of Weiss (1984), who finds results similar to Harris and Holmstrom (1982) but without assuming any learning, this can arise if the speed of human capital accumulation is stochastic and high performance translates into faster human capital accumulation.

functions are such that the scale of operations effect applies both to a level 2 manager (in terms of the number of workers who report to that manager) and to a level 3 manager (in terms of the number of level 2 managers who report to this level 3 manager). To be precise, the productivity of level 2 manager i in period t with n level 1 workers reporting to this level 2 manager is given by $y_{i2t} = g_2(n)(\eta_{it} + \varepsilon_{it})$, where $g_2' > 0$ and $g_2'' < 0$, while the productivity of level 3 manager i in period t with n level 2 managers reporting to this level 3 manager is given by $y_{i3t} = g_3(n)(\eta_{it} + \varepsilon_{it})$, where $g_3' > 0$ and $g_3' < 0$. Also, we assume that $g_2(.)$ and $g_3(.)$ are such that it is efficient to staff the level 3 manager position with the highest expected effective ability old and very old worker and the level 2 positions with the next highest expected effective ability old and very old workers.

Analysis of this model yields results similar to those discussed above for firms with two job levels, except these results now apply to multiple levels of the hierarchy. For example, holding job level, schooling level, labor market experience, and previous performance fixed, it is the workers with high current performance who are promoted in the next period for workers in both job level 1 and job level 2.

Note that an alternative specification that would make similar predictions is that, instead of having the scale of operations effect apply to the level 3 manager in terms of the number of level 2 managers who report to this level 3 manager, the scale of operations effect applies in terms of the total number of workers below this level 3 manager in the firm's hierarchy. With this in mind, in the empirical analysis we conduct the span of control tests both in terms of the number of workers directly reporting to a manager and in terms of the total number of workers below the manager in the firm's job hierarchy.

In our final extension, we consider what happens if firm size changes over time. In the main model analyzed in Section II.B, all firms were similar in size, and that size did not change over time (at each date, every firm had two job levels and m divisions). We moved away from this only a little in the first two extensions; in particular, in the second extension the number of subdivisions reporting to a level 2 manager was assumed to be endogenous, but the number of job levels and the number of divisions was assumed to be fixed. In our empirical analysis, however, the firm we focus on is growing during the time period of our study.

But this is not an important concern. All the main predictions that we focus on generalize to the case of a growing firm. In particular, consider the main model analyzed in Section II.B with the single change that from $t - 1$ to t, one of the firms increases the number of divisions from m to $m + \Delta$, $\Delta > 0$. All of the main predictions continue to hold, even focusing on that firm during the period in which the growth occurred. That is, span of control rises with performance and education, while the predictions mentioned in footnote 14 concerning wages, wage changes, and probability of promotion also continue to hold.

III. Data

Here we describe our data and present some basic facts about the firm. In Section IV we provide tests of our model.

We received confidential performance data from one large European Union high-tech manufacturing firm that produces in various countries around the globe and sells its products in almost every country. The data cover the calendar years 2006–2011, where each year's data were collected in the spring of the following year. The firm employs a scale of 1–5 for its evaluation ratings, where 1 denotes the lowest performance and 5 the highest.[19] Performance evaluation is relatively recent in the company. While the firm initially focused its attention on the top managers of the firm, in later years the ratings were extended to include almost all of the firm's white-collar workers, with wider global coverage in later years (in particular, the United States, China, and Japan). Our focus will be on Danish workers since that is the location where the data are most complete and the distribution of performance ratings varied significantly across countries.[20]

Individuals are assessed by their direct supervisor. An assessment is made in December at the end of each year, which covers that year's performance. The assessment is entered into the human resources system and also communicated to the worker in a face-to-face interview with the supervisor. The supervisor and the worker also discuss an action plan for the following year, which includes various performance targets for the worker. At this firm, human resource managers spend significant time and effort ensuring that supervisors understand the importance of the evaluation process and provide fair ratings.

We combine the data on performance ratings with data from confidential monthly personnel records we received for all workers from January 2003 (January 1997 for Danish workers) to December 2011. In this way we create a panel data set for the years 2006–2011 that includes (for each observation) the worker's firm tenure, age, salary, bonus, cost center category, job level,

[19] To be precise, 1 means the worker does not meet expectations, 2 means the worker's performance approaches expectations and goals, 3 means performance meets expectations, 4 is for performance that exceeds expectations and goals, and 5 is for outstanding performance.

[20] For example, the percentage of workers who received a 4 or 5 was roughly twice as high in Denmark than in Japan, while this percentage for China and the United States is between the values for Denmark and Japan. There are various possible explanations for these differences, including differences in the quality of the firm's labor force across the countries, differences in organizational structures, and cultural differences that result in differences in how workers are evaluated across the countries.

nationality, gender, schooling level, a promotion indicator variable (1 if the worker was promoted that year and 0 if not), and performance evaluation.[21]

What is distinctive about this data set that sets it apart from other similar data sets based on firms' personnel records is that we were also provided information about the firm's chain of command. Before describing this part of the data set and how we used it, we need to describe the hierarchical structure of the firm. Until relatively recently, the firm was organized into five hierarchical layers. Workers at job level 0 are the nonmanagerial employees. Workers at job level 1 are lower management, and these workers are referred to as managers. Job level 2 refers to middle management, and these workers are referred to as vice presidents (VPs). Job level 3 refers to upper management, and workers at this level are referred to as senior vice presidents (SVPs). Workers at job level 4 are the top management, and these workers are referred to as executive vice presidents (EVPs). Also, to cope with significant growth during the past decade, the firm recently introduced two new levels. Team leaders or assistant managers are between the old job levels 0 and 1 (above nonmanagerial employees but below managers), while corporate vice presidents (CVPs) are between the old job levels 2 and 3 (above VPs but below SVPs).

As mentioned above, we were provided information about the firm's chain of command. That is, for each individual and each year, we were given the names of all the individuals directly above the worker in the firm's hierarchy. For example, in the latter part of the data set, for each worker at level 0 we know the names of the team leader, manager, VP, CVP, SVP, and EVP as well as the name of the department (defined as a cost center), the name of the subsidiary, and the geographic area where it operates. We use this information to construct span of control measures for workers above level 0 (for more detail, see Smeets and Warzynski 2008). In our empirical analysis of span of control, we focus on team leaders, managers, VPs, and CVPs.

We define span of control in two ways. An individual's direct span of control is the number of subordinates who report directly to the individual, while an individual's full span of control is the total number of subordinates underneath the individual in the firm's hierarchy. For example, consider a three-level job ladder with a single individual on level 3, two individuals on level 2 who report to the level 3 manager, and four individuals on level 1 (where two of these four report to one level 2 manager and the other two report to the other). For each manager on level 2, direct span of control and full span of control are the same and each equals 2. For the single level 3 manager, direct span of control equals 2 and full span of control equals 6.

[21] Cost center categories refer to the functional divisions of the firm. These are administration, administration in production, production, sales and marketing, and research and development.

Table 1 provides summary statistics by job level for our main variables of interest (including our two span of control measures) for each of the levels in our data set. We can see that firm tenure, experience, education, and performance increase with the job level, especially when we focus on the managerial levels. Workers tend to have relatively high firm tenure and experience because many of them are production workers with little probability of promotion. The promotion rate varies by job level and is particularly high for VPs. This is at least partly explained by the fact that the CVP layer was introduced during our period of analysis, and most CVPs were promoted from the VP level. Panel B in table 1 shows more detailed summary statistics concerning span of control for individuals with managerial responsibility. The direct span of control tends to decrease along the hierarchy, declining from around 25 subordinates at the manager level to fewer than two at the CVP level. On the other hand, the full span of control increases

Table 1
Summary Statistics by Rank

Variable	Worker	Team Leader	Manager	Vice President	Corporate Vice President
	A. Human Capital and Performance Variables				
Average firm tenure	9.56	9.35	10.67	13.15	15.03
Average experience	20.99	19.48	20.44	23.12	24.90
Performance	3.42	3.48	3.70	3.84	4.06
3 (%)	*56.59*	*50.32*	*37.12*	*27.57*	*20.05*
4 (%)	*34.85*	*40.58*	*51.42*	*56.46*	*52.81*
5 (%)	*5.20*	*5.75*	*10.02*	*14.64*	*26.65*
Promotion probability (%)	1.39	5.16	2.77	16.84	.98
Education					
Bachelor's (%)	18.08	22.95	21.58	16.43	12.86
Master's and above (%)	38.44	45.18	72.49	82.34	87.14
Worker-year data	18,817	1,703	2,365	526	409
	B. Span of Control 6 Months after Performance Evaluation				
Average direct span		17.50	25.84	2.84	1.69
25% percentile		*12*	*8*	*1*	*1*
Median		*16*	*14*	*2*	*1*
75% percentile		*21*	*30*	*4*	*2*
Average full span				41.41	136.63
25% percentile				*10*	*24.5*
Median				*22*	*60.5*
75% percentile				*52*	*177*
Worker-year data		1,350	1,953	375	356

NOTE.—Tenure is the number of years working for the firm. Experience is defined as age minus the number of years of education minus 6. Performance of year $t-1$ is assessed by the direct supervisor in December of year $t-1$. Promotion probability is the probability that the individual was promoted from December in year $t-1$ to December in year t. Bachelor's is a dummy equal to 1 if the individual has a bachelor's degree and 0 otherwise. Master's and above is a dummy equal to 1 if the individual has an MSc or PhD degree and 0 otherwise. The average span of control is the average number of individuals reporting (directly or indirectly) to their supervisor as observed in our data set. Values in italics show the distribution of performance and span of control variables.

along the hierarchy, as expected. We also see that variation in span of control within level increases at higher levels of the job ladder, which could be due to learning causing variation in perceived managerial ability to be larger at higher managerial levels.

IV. Results

We focus on testing predictions of the theory concerning span of control and changes in span of control.[22] We begin with tests concerning the determinants of span of control. The scale of operations effect—which is a driving force in our theoretical model—predicts that a manager's span of control should be positively related to the manager's ability level (expected ability level in the model). In turn, translating this into a testable prediction yields that an individual's span of control should be positively related to the manager's performance history and the manager's education level.

To investigate our predictions concerning the determinants of span of control, we conduct ordinary least squares regressions using a sample consisting of all observations of individuals who were team leaders, managers, VPs, and CVPs. The dependent variable in our regressions is the log of either the individual's direct span of control or full span of control, while independent variables include performance measures, indicator variables for the various job levels, education indicator variables, year indicator variables, and cost center indicator variables.

Results are reported in tables 2 and 3, where table 2 reports results for our direct span measure and table 3 for our full span measure. In column 1 of each table, we report results for ordinary least squares regressions where only the individual's most recent performance measure is included.[23] The coefficients on the job level indicator variables match how average span varies across levels, as found in table 1. In terms of the theoretical predictions, in each regression the coefficient on the performance variable is positive and statistically significant at the 1% level, while the coefficient on the bachelor's indicator variable is positive but not statistically significant. Additionally, in

[22] The model also makes predictions concerning wages, wage changes, and probability of promotion. These predictions are mostly consistent with various prior empirical studies of wage and promotion dynamics in internal labor markets (e.g., Lazear 1992; Baker, Gibbs, and Holmstrom 1994a, 1994b; Seltzer and Merrett 2000; Treble et al. 2001; Dohmen, Kriechel, and Pfann 2004; DeVaro and Waldman 2012). App. B reports empirical tests focused on wages, wage changes, and probability of promotion. In these tests, we do find large promotion wage increases even after controlling for performance, which suggests that either tournament (as in Lazear and Rosen 1981) or signaling (as in Waldman 1984a) may be important.

[23] In all of the tests we report that employ a performance measure, we use the raw performance score. We have also investigated alternative approaches, such as measuring performance as the difference between an individual's raw performance score and an average based on job level and period. In general, our results are robust to employing alternative performance measures.

Table 2
Direct Span of Control and Performance

Dependent Variable: log (direct span)	(1)	(2)	(3)
Performance in $t-1$	.077***	.063***	.058**
	(.022)	(.023)	(.023)
Performance in $t-2$	. . .	.045**	.041*
		(.022)	(.022)
Team leader	2.034***	2.055***	2.345***
	(.076)	(.080)	(.154)
Manager	2.350***	2.366***	2.361***
	(.069)	(.072)	(.072)
Vice president	.521***	.554***	.546***
	(.084)	(.088)	(.087)
Bachelor's	.058	.088	.405***
	(.067)	(.073)	(.144)
Master's and above	−.096	−.061	.154
	(.066)	(.073)	(.132)
Team leader × BA/BSc	. . .	. . .	−.556***
			(.157)
Team leader × master's and above	. . .	. . .	−.244*
			(.144)
Experience	.003	−.003	−.002
	(.012)	(.014)	(.014)
Experience^2/100	−.026	−.016	−.017
	(.026)	(.029)	(.028)
Tenure	.029***	.032***	.032***
	(.008)	(.009)	(.009)
Tenure^2/100	−.058**	−.062**	−.066**
	(.027)	(.031)	(.030)
Constant	.107	−.006	−.193
	(.201)	(.247)	(.266)
Year dummies	Yes	Yes	Yes
Cost center dummies	Yes	Yes	Yes
R^2	.61	.63	.63
N	3,776	2,929	2,929

NOTE.—Dependent variable is the log of the direct span of control as team leader, manager, vice president, or corporate vice president 6 months after the latest performance evaluation (i.e., in June of year t). Experience is defined as age minus the number of years of education minus 6. Tenure is the number of years working for the firm. Performance of year $t-1$ ($t-2$) is assessed by the direct supervisor in December of year $t-1$ ($t-2$). The other explanatory variables are job level dummies, education dummies for college education, cost center dummies, and year dummies. Standard errors are clustered by worker.
* $p < .1$
** $p < .05$.
*** $p < .01$.

column 1 of table 2, the coefficient on the advanced degree indicator variable is negative but not statistically significant, while in table 3 this coefficient is negative and statistically significant at the 5% level. We can translate the coefficient on the performance variable in column 1 of tables 2 and 3 into a prediction concerning how positive performance affects span of control. For example, the coefficient in the first column of table 2 (0.077) indicates that managers who are rated as exceeding rather than meeting expectations (a

Table 3
Full Span of Control and Performance

Dependent Variable: log (full span)	(1)	(2)	(3)
Performance in $t-1$	.094***	.086***	.081***
	(.027)	(.028)	(.028)
Performance in $t-2$	. . .	.054**	.050*
		(.027)	(.027)
Team leader	−1.831***	−1.834***	−1.538***
	(.154)	(.146)	(.195)
Manager	−1.430***	−1.467***	−1.473***
	(.144)	(.136)	(.137)
Vice president	−.973***	−.945***	−.954***
	(.170)	(.166)	(.166)
Bachelor's	.019	.054	.387***
	(.080)	(.078)	(.145)
Master's and above	−.172**	−.131*	.088
	(.078)	(.079)	(.129)
Team leader × BA/BSc	. . .	. . .	−.592***
			(.161)
Team leader × master's and above	. . .	. . .	−.241*
			(.143)
Experience	.002	−.001	−.001
	(.019)	(.017)	(.017)
Experience^2/100	−.046	−.036	−.037
	(.043)	(.038)	(.038)
Tenure	.042***	.046***	.047***
	(.010)	(.011)	(.011)
Tenure^2/100	−.078**	−.099***	−.103***
	(.034)	(.035)	(.036)
Constant	4.012***	3.800***	3.608***
	(.303)	(.323)	(.334)
Year dummies	Yes	Yes	Yes
Cost center dummies	Yes	Yes	Yes
R^2	.31	.32	.33
N	3,760	2,914	2,914

NOTE.—Dependent variable is the log of the full span of control as team leader, manager, vice president, or corporate vice president 6 months after the latest performance evaluation (i.e., in June of year t). Independent variables are as defined in table 2. Standard errors are clustered by worker.
* $p < .1$
** $p < .05$.
*** $p < .01$.

rating of 5 rather than 3) have on average 3.8 more workers reporting to them, which is approximately a 20% increase over the average.

In column 2 of each table, we add as an explanatory variable the lagged value for the individual's performance. In table 2, the main result is that the coefficient on each performance variable is positive, where the coefficient on the most recent performance variable is significant at the 1% level and the coefficient on the prior performance variable is significant at the 5% level. Also, the coefficient on the most recent performance variable is larger. In table 3, the pattern is similar. The coefficient on the most recent performance variable is positive and statistically significant at the 1% level, while the coefficient on the prior performance measure is positive but smaller than the coefficient on the most recent performance variable and is statistically significant at only the 10% level. One additional result worth pointing out is that in column 2 of table 3, the coefficient on the advanced degree indicator variable is negative (like in col. 1) but statistically significant only at the 10% level.

To further investigate why the education results in columns 1 and 2 of tables 2 and 3 do not support the theory, in column 3 of each table we add to the column 2 specification interactions of the team leader indicator variable with the two education variables. The results indicate that having a bachelor's degree increases span of control for individuals in managerial positions above the team leader level, but for the team leader level, having a bachelor's degree has a negative effect on span of control. For those with advanced degrees, we find no statistically significant effect on span of control for individuals in managerial positions above the team leader level or for those at the team leader level.[24] Overall, our tests concerning span of control support the predictions concerning performance, but the results concerning education are mixed.

We suspect that the education results are mixed because we are not fully controlling for differences across managerial jobs. Specifically, we suspect that some of the team leaders are managing blue-collar workers where span of control is larger and these team leaders have less education on average; this would explain the negative coefficient in column 3 of tables 2 and 3 for the variables that interact the team leader level indicator variable with the bachelor's and master's and above indicator variables.

The findings in tables 2 and 3 are generally consistent with the scale of operations effect being important at this firm. That is, the scale of operations effect predicts that span of control should be higher for higher-ability managers, so span of control being clearly positively correlated with performance and to some extent positively correlated with education is consistent with the scale of operations effect since performance and education should both be positively correlated with managerial ability. But these findings tell us nothing about whether learning is an important determinant of span of control at our firm. In other words, these findings can be explained by static analyses (such as in Lucas 1978 and Rosen 1982) and do not require the learning component of our theoretical approach.

In our next set of tests, we consider changes in span of control. To investigate changes in span of control, we begin with an ordinary least squares

[24] We have also looked at tests with interactions between indicator variables for other job levels and the education variables. These additional tests indicate no statistically significant differences concerning how education affects span of control across levels other than the results concerning the team leader level found in col. 3 of tables 2 and 3.

regression where changes in the logs of direct span of control and the full span of control are the dependent variables, while independent variables are the starting values for the logs of direct span of control and full span of control, indicator variables for job level, performance measures, year indicator variables, and cost center indicator variables. Results are reported in tables 4 and 5, where table 4 focuses on direct span of control and table 5 on full span of control.[25] In the first column in each table, we include only the most recent performance measure. One result in each regression is that the coefficient on the starting value for the log of the span of control measure is negative and statistically significant, which means that the percentage increase in the log of the span of control measure is on average smaller when the starting value for the measure is larger. The other main result is that the coefficient on the performance variable is positive and statistically significant in each regression, which is exactly what one would expect if changes in span of control are driven by changes in expected effective ability, as predicted by the theory.

In column 2 of tables 4 and 5, we add the lagged performance measure to the regression. The main result is that in each regression the coefficient on the most recent performance measure remains positive and statistically significant, while the coefficient on the lagged performance variable is statistically insignificant. This is consistent with span of control changing quickly in response to changes in expected effective ability.

In columns 3 and 4 of tables 4 and 5, we add the education indicator variables. In each regression, the coefficients on the education indicator variables are statistically insignificant, the size of the coefficients on the performance variables is basically unchanged, and the statistical significance of the coefficient on the most recent performance measure is also unchanged. Columns 3 and 4 in each table tell us that the positive correlation between change in the log of our span of control measure and the most recent performance measure is not driven by a positive correlation between performance and education. Note that one surprising result in table 5 is that there is evidence of a negative correlation between changes in span of control and experience, which is not predicted by the theory.[26]

Changes in span of control are positively correlated with the most recent performance measure, and this is the case even after controlling for education, consistent with learning being an important determinant of span of control. The logic is that if learning were unimportant, then perceptions about

[25] Because of outliers in this set of tests, the distribution is trimmed below the first percentile and above the ninety-ninth percentile.

[26] Another alternative explanation for our findings in cols. 1 and 2 of each table is that division-level profitability (controlling for true managerial performance) is positively correlated with the managerial performance rating and future division-level growth. Unfortunately, we are unable to test for this possibility because we do not have division-level profitability data.

Table 4
Change in Direct Span and Performance

Dependent Variable: Δlog (direct span)	(1)	(2)	(3)	(4)
log (direct span)	−.107***	−.105***	−.108***	−.105***
	(.009)	(.010)	(.009)	(.010)
Performance in $t-1$	.024**	.026**	.024***	.026**
	(.009)	(.011)	(.009)	(.011)
Performance in $t-2$	. . .	−.00002	. . .	.000
		(.010)		(.011)
Team leader	.246***	.234***	.237***	.227***
	(.031)	(.034)	(.032)	(.035)
Manager	.269***	.259***	.266***	.257***
	(.029)	(.034)	(.030)	(.034)
Vice president	.108***	.111***	.107***	.110***
	(.026)	(.027)	(.026)	(.027)
Bachelor's	. . .	. . .	−.007	−.009
			(.020)	(.021)
Master's and above	. . .	. . .	−.023	−.018
			(.021)	(.023)
Experience	−.002	−.003	−.003	−.004
	(.003)	(.004)	(.004)	(.004)
Experience^2	.002	.004	.003	.004
	(.008)	(.009)	(.008)	(.009)
Tenure	.003	.004	.002	.004
	(.003)	(.003)	(.003)	(.003)
Tenure^2	−.008	−.014	−.008	−.013
	(.010)	(.012)	(.010)	(.012)
Constant	.009	−.002	.043	.024
	(.060)	(.077)	(.069)	(.086)
Year dummies	Yes	Yes	Yes	Yes
Cost center dummies	Yes	Yes	Yes	Yes
R^2	.06	.06	.06	.06
N	3,612	2,805	3,612	2,805

NOTE.—Dependent variable is the difference between the log of the direct span of control 6 months after the latest performance evaluation (i.e., in June of year t), as in table 2, and the log of the direct span of control in December of year $t-1$. Explanatory variables are as defined in table 2. The distribution is trimmed below the first percentile and above the 99th percentile. Standard errors are clustered by worker.
** $p < .05$.
*** $p < .01$.

ability would not change with performance, so changes in span of control that should depend on changes in such perceptions would be uncorrelated with performance. That is, dynamic versions of Lucas (1978) or Rosen (1982) that do not incorporate learning would not be consistent with this finding. In the absence of learning, high performance in a period does not translate into changes in beliefs about the worker's ability. So there would be no prediction that high performance should be followed by a change in the span of control.

Overall we find results consistent with the scale of operations effect and span of control (as in Lucas 1978; Rosen 1982) and results that can be explained by incorporating a learning component, like we do in Section II's

Table 5
Change in Full Span and Performance

Dependent Variable: Δlog (full span)	(1)	(2)	(3)	(4)
log (full span)	−.085***	−.078***	−.085***	−.078***
	(.009)	(.011)	(.009)	(.011)
Performance in $t-1$	.022**	.028**	.022**	.028**
	(.009)	(.011)	(.009)	(.011)
Performance in $t-2$	. . .	−.002	. . .	−.002
		(.012)		(.012)
Team leader	−.140***	−.126***	−.149***	−.132***
	(.032)	(.036)	(.034)	(.037)
Manager	−.112***	−.098***	−.116***	−.100***
	(.029)	(.032)	(.030)	(.032)
Vice president	−.054*	−.039	−.056*	−.040
	(.030)	(.032)	(.030)	(.032)
Bachelor's	. . .	. . .	−.015	−.014
			(.020)	(.022)
Master's and above	. . .	. . .	−.021	−.014
			(.021)	(.023)
Experience	−.006*	−.009**	−.007*	−.009**
	(.004)	(.004)	(.004)	(.005)
Experience^2	.010	.015	.011	.015
	(.008)	(.010)	(.008)	(.010)
Tenure	.004	.0066*	.004	.0064*
	(.003)	(.0035)	(.003)	(.0035)
Tenure^2	−.013	−.019	−.012	−.019
	(.010)	(.012)	(.010)	(.012)
Constant	.374***	.321***	.407***	.343***
	(.075)	(.095)	(.083)	(.104)
Year dummies	Yes	Yes	Yes	Yes
Cost center dummies	Yes	Yes	Yes	Yes
R^2	.05	.05	.05	.05
N	3,578	2,774	3,578	2,774

NOTE.—Dependent variable is the difference between the log of the full span of control 6 months after the latest performance evaluation (i.e., in June of year t), as in table 3, and the log of the full span of control in December of year $t-1$. Explanatory variables are as defined in tables 2 and 3. The distribution is trimmed below the first percentile and above the 99th percentile. Standard errors are clustered by worker.
* $p < .1$
** $p < .05$.
*** $p < .01$.

model. Also, most alternative theoretical approaches are not consistent with our findings, although as we discuss in the conclusion, the pure symmetric learning assumption we employ in our theoretical model may not fully capture how learning works in our firm.

We now consider the relationship between wages and span of control. The theory predicts a positive relationship between the two because both are positively related to a worker's expected effective ability. In investigating this prediction, we employ an ordinary least squares regression where the dependent variable is the log of the individual's wage in period t. As control variables we include performance measures, indicator variables for the worker's education, experience and tenure variables, and year and cost center indicator variables. To test the prediction, we consider only individuals at the team leader level or higher and include variables that capture interactions between the log span measure and the various managerial levels (the team leader level is the omitted category). Columns 1 and 2 of table 6 use the log of the direct span of control, while columns 3 and 4 use the log of the full span of control instead. With both measures, we find clear support for the prediction at the manager, VP, and CVP levels in that for each of these levels the relevant coefficients are positive and statistically significant at the 1% level. But at the team leader level there is no support for the prediction since the coefficients are negative and statistically insignificant.[27]

The last set of tests we consider concerns the relationship between the current span of control of a worker who is currently in a managerial position and the probability the worker is subsequently promoted. Similar to the previous set of tests, the theory predicts that the two should be positively correlated because both are positively related to expected effective ability.

To investigate this prediction, we conduct probit tests where the dependent variable is an indicator variable that takes on a value of one if the worker was promoted that period and zero if not, and as in table 6, control variables include performance measures, indicators for the worker's education, experience and tenure variables, and year and cost center indicator variables. Our sample includes all observations of individuals who were workers, team leaders, managers, and VPs in the prior period, where we include indicator variables that capture whether the individual was a team leader, manager, or VP before the promotion decision (being a worker before the promotion decision is the omitted category). To test the prediction, we include the interaction variables employed in table 6, where columns 1 and 2 use the log of the direct span of control, while columns 3 and 4 use the log of the full span of control. Again, results are similar with both measures. The manager and VP levels both exhibit results consistent with the theoretical prediction. That is, in each set of tests there is evidence of a positive and statistically significant relationship for each of these managerial levels between current span of control and probability of subsequent promotion, where the correlation is stronger for the VP level than for the manager level. On the other hand, for the CVP level there seems to be no correlation, while at the team leader level there is evidence of a negative correlation.[28]

That there is no correlation for the CVP level (at least in col. 1 and 2 of table 7) is not surprising. As reported in table 1, the average direct span of control at the CVP level is only 1.69, so there may not be enough variability in the direct span of control at the CVP level to accurately identify

[27] For further discussion involving results in table 6, see app. B.
[28] For further discussion involving results in table 7, see app. B.

Table 6
Wages, Human Capital, and Performance

Dependent Variable: log (wage)	Controlling for Direct Span of Control (1)	Controlling for Direct Span of Control (2)	Controlling for Full Span of Control (3)	Controlling for Full Span of Control (4)
Experience	.004***	.003**	.004***	.003**
	(.001)	(.001)	(.001)	(.001)
Experience^2/100	−.008***	−.006**	−.008***	−.006**
	(.002)	(.003)	(.002)	(.003)
Tenure	.001	.001	.001	.0005
	(.001)	(.001)	(.001)	(.001)
Tenure^2/100	−.001	−.0003	−.0002	.0003
	(.002)	(.003)	(.002)	(.003)
Bachelor's	.061***	.064***	.061***	.064***
	(.008)	(.009)	(.008)	(.009)
Master's and above	.079***	.081***	.078***	.081***
	(.007)	(.008)	(.007)	(.008)
Manager	.196***	.198***	.195***	.196***
	(.018)	(.020)	(.018)	(.020)
Vice president	.461***	.454***	.418***	.429***
	(.018)	(.020)	(.022)	(.024)
Corporate vice president	.677***	.674***	.633***	.628***
	(.017)	(.019)	(.026)	(.027)
Performance in $t-1$	.021***	.018***	.021***	.018***
	(.002)	(.002)	(.002)	(.002)
Performance in $t-2$	. . .	.007***	. . .	.008***
		(.002)		(.002)
log (span)	−.008	−.007	−.007	−.007
	(.006)	(.006)	(.006)	(.006)
log (span) × manager	.023***	.023***	.023***	.023***
	(.006)	(.007)	(.006)	(.007)
log (span) × vice president	.043***	.032***	.030***	.021***
	(.010)	(.010)	(.007)	(.008)
log (span) × corporate vice president	.059***	.061***	.023***	.022***
	(.016)	(.015)	(.008)	(.008)
Constant	10.617***	10.605***	10.616***	10.601***
	(.023)	(.026)	(.023)	(.027)
Year dummies	Yes	Yes	Yes	Yes
Cost center dummies	Yes	Yes	Yes	Yes
R^2	.91	.92	.91	.92
N	4,084	3,128	4,084	3,128

NOTE.—Dependent variable is the log of the wage (not including bonuses) in June, 6 months after the latest performance evaluation. Other variables are as defined in table 2. In cols. 1 and 2, span refers to the direct span of control, while in cols. 3 and 4, span refers to the full span of control. Standard errors are clustered by worker.

* $p < .1$

** $p < .05$.

*** $p < .01$.

Table 7
Promotion and Performance, Probit Regression (Marginal Effects Reported)

	Controlling for Direct Span of Control		Controlling for Full Span of Control	
Dependent Variable: Promotion	(1)	(2)	(3)	(4)
Performance in $t-1$	.033***	.025***	.033***	.025***
	(.004)	(.004)	(.004)	(.004)
Performance in $t-2$	. . .	.016***	. . .	.015***
		(.004)		(.004)
log (span)	−.014*	−.007	−.009**	−.009**
	(.008)	(.008)	(.004)	(.004)
log (span) × manager	.018*	.015	.012**	.016***
	(.009)	(.009)	(.006)	(.006)
log (span) × vice president	.054***	.047***	.050***	.047***
	(.013)	(.014)	(.012)	(.013)
log (span) × corporate vice president	−.005	−.017	−.010	−.016
	(.015)	(.014)	(.013)	(.012)
Manager	−.109***	−.107***	−.089***	−.107***
	(.034)	(.039)	(.023)	(.028)
Vice president	−.047***	−.038***	−.040***	−.035***
	(.005)	(.005)	(.005)	(.005)
Corporate vice president	−.021	−.015	.025*	.015
	(.013)	(.014)	(.017)	(.015)
Experience	−.002	−.003	−.002	−.003
	(.002)	(.002)	(.002)	(.002)
Experience^2/100	.006	.006	.005	.005
	(.004)	(.004)	(.004)	(.004)
Tenure	−.001	.0002	−.001	.0004
	(.001)	(.001)	(.001)	(.0013)
Tenure^2/100	.002	−.0003	.002	−.001
	(.004)	(.004)	(.004)	(.004)
Bachelor's	.037**	.033***	.036**	.028*
	(.019)	(.010)	(.019)	(.020)
Master's and above	.033***	.030*	.032***	.030***
	(.010)	(.021)	(.010)	(.010)
Year dummies	Yes	Yes	Yes	Yes
Cost center dummies	Yes	Yes	Yes	Yes
Pseudo R^2	.14	.18	.14	.18
Log likelihood	−755.35	−539.92	−749.74	−534.15
N	4,100	3,137	4,098	3,135

NOTE.—Dependent variable is a dichotomic variable equal to 1 if the individual is promoted (1) from worker to team leader, (2) from worker to manager, (3) from team leader to manager, (4) from manager to vice president, and (5) from vice president to corporate vice president within a 12-month period following the performance evaluation (i.e., from January to December of year t). Independent variables are as described in table 2. In cols. 1 and 2, span refers to the direct span of control, while in cols. 3 and 4, span refers to the full span of control. Standard errors are clustered by worker.

* $p < .1$

** $p < .05$.

*** $p < .01$.

the relationship. The more surprising finding is the evidence for a negative relationship found at the team leader level between current span of control and the probability of subsequent promotion. But note that this result is in a sense consistent with results in column 3 of table 2 and results in table 6 in that it suggests that the theoretical predictions hold less well at the team leader level.

V. Conclusion

A standard idea in the theoretical literature concerning hierarchies is the scale of operations effect, that is, the idea that the return to managerial ability is higher the more resources the manager influences with his or her decisions. This theoretical idea leads to various testable implications, including the idea that higher-ability managers should have a larger span of control. Although the empirical literature on organizations finds evidence consistent with some predictions that follow from the scale of operations effect, predictions concerning span of control have received little attention.

In this paper, we first extended the theory by looking at the scale of operations effect in a model in which there is uncertainty concerning workers' abilities when they enter the labor market and firms learn about these abilities as careers progress. This model yields a number of testable predictions concerning span of control, including predictions that follow from combining the scale of operations effect with learning.

We then empirically investigated these predictions using a unique single-firm data set that contains detailed information concerning the reporting relationships at the firm. We find results consistent with both predictions that follow directly from the scale of operations effects and predictions that follow from combining the scale of operations effect with learning. Our conclusion, therefore, is that the scale of operations effect is an important factor in the operation of real-world hierarchies and, further, that the interaction of the scale of operations effect with learning—which has not previously been explored—is also an important factor.

An extension that we believe is promising is to introduce an element of asymmetric learning into the analysis. In this paper we have focused on symmetric learning, which means all firms are equally informed about each worker's ability at every point in time. An alternative approach first explored by Greenwald (1979, 1986) and Waldman (1984a) is that learning is asymmetric; that is, only a worker's current employer directly receives information about the worker's ability.[29] Numerous studies (e.g., Gibbons and Katz 1991; Schönberg 2007; Pinkston 2009; DeVaro and Waldman 2012; Kahn 2013)

[29] Friedrich (2016) is an interesting recent paper that employs this approach in a structural estimation exercise that shows how firm-specific training and internal promotion are used to both attract better workers and develop their talents. Also, see Gibbons and Waldman (1999a) for a discussion of the early part of this literature.

find evidence that supports a role for asymmetric learning. We thus believe that adding an element of asymmetric learning to our model could be interesting from both theoretical and empirical perspectives.

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