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Dieter Kuhn

The Author:

Dieter Kuhn, Assistant

Department of Human Resources and Organization (WWZ)

University of Basel

Peter Merian-Weg 6

CH - 4002 Basel

phone: +41(0)61 267 32 26

dieter.kuhn@unibas.ch

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Contact:

WWZ Forum | Peter Merian-Weg 6 | CH-4002 Basel | forum-wwz@unibas.ch | www.wwz.unibas.ch

Delaying and Firm Performance: Evidence from Swiss firm-level Data

Dieter Kuhn*

** University of Basel, Center of Business and Economics, Department for Human Resources and Organization, Peter Merian-Weg 6, CH-4002 Basel, Switzerland, Phone: +41-(0)61-267 32 26, E-Mail: dieter.kuhn@unibas.ch*

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Abstract

The past decades witnessed a broad trend towards flatter organizations with less hierarchical layers. A reduction of the number of management levels in a corporation can have both positive and negative effects on firm performance with the net effect being theoretically unclear ex ante. The present study uses a nationally representative data set of firms in Switzerland and empirically examines the direct performance effects of delayering. Applying ordinary least squares regressions and propensity score matching, this study finds that delayering significantly increases subsequent firm performance. It can be concluded that flatter hierarchical structures seem to enable firms to better realize their competitive advantage in today's fast moving and knowledge-intensive market environment.

Keywords: Delayering, management levels, hierarchical layers, hierarchy, firm performance, treatment effects, selection bias.

JEL classification: C21, J24, L22, L25, M51, M52.

1. Introduction

The most fundamental elements to describe the shape of an organization are its breadth and its depth (Colombo and Delmastro 2002, 2008; Rajan and Wulf 2006; Wang 2007). The depth of an organization is the number of hierarchical layers or management levels between the top management and operational employees.¹ The breadth can be measured by the span of control, i.e. the number of a supervisor's direct reports or subordinates. The span of control can be calculated at each hierarchical layer, but it can also be averaged across the levels of an organization.² Obviously, there exists an inverse relationship between depth and breadth, given organizational size (see Figure 1 in the appendix).³

Delaying means the reduction of the number of management levels in an organization, i.e. the flattening of an organization's hierarchy. However, it should not be confused with other related concepts of corporate restructuring, such as downsizing or decentralization (Littler, Wiesner and Dunford 2003; Rajan and Wulf 2006). Downsizing basically means workforce reduction. If certain management levels are targeted, this can lead to delaying.⁴ Accordingly, most delaying programs involve downsizing (Littler and Innes 2004; Littler, Wiesner and Dunford 2003). On the other hand, larger firms have even found to *increase* the number of hierarchical layers while downsizing (Wang 2007).⁵ Decentralization means the delegation of decision-making authority to lower management levels. If decision power of wiped-out managerial positions is relocated down the hierarchy, delaying would indeed imply more decentralization (Rajan and Wulf 2006). The

¹ It seems to be matter of convention whether one counts including or excluding top management or operational employees, or whether managers with center responsibility are considered instead of operational employees. For instance, considering (b) of Figure 1: Jost (2009) would label this as having a depth of one; Wang (2007) would attach two levels to that organization; the KOF questionnaires used in the present study exclude both the top and the bottom level so that, in this example, there would be a depth of zero; eventually, Rajan and Wulf (2006) count only the number of levels between the CEO and the divisional managers, excluding both.

² The average span of control s would then have to satisfy the following equation, where n is the number of employees and l is the number of hierarchical layers (Colombo and Delmastro 1999, 2008): $n = 1 + s + s^2 + \dots + s^{l-1}$

³ Accordingly, Rajan and Wulf (2006) report a significantly negative correlation between breadth and depth, based on a sample of 300 large US firms.

⁴ Consequently, Datta et al. (2010) consider delaying as one of various "phrases or euphemisms" for downsizing. Similarly, Littler et al. (1997) regard delaying, downsizing and other "restructuring concepts" as sharing the commonality of workforce reduction.

⁵ According to Wang (2007), this result could be explained by the greater need for solving control and coordination problems within larger firms.

same would hold true, if supervisors are confronted with more direct reports, i.e. a greater span of control. In this case, they would have to concentrate on key managerial tasks, such as communicating goals and managing exceptions, while employees' involvement in decision processes could be enhanced (Lazear and Gibbs 2009, BCG 2004, 2006a, b, Åhlström and Karlsson 2000). On the other hand, however, a CEO in a flatter hierarchy gets in touch with more unit heads and, thus, can influence more decisions. This perspective would suggest more centralization implied by delayering (Rajan and Wulf 2006).

The 1990s witnessed a broad trend towards flatter, i.e. less deep organizations. There is evidence from several developed countries based on large-scale data sets documenting this delayering trend (Table 1). The following factors are seen as causes for this delayering trend (Rajan and Wulf 2006; Sohr 2005; Littler, Wiesner and Dunford 2003): increased competition in product markets, the need of quickly taken and complex decisions, increased importance of human capital⁶, active institutional investors in the stock markets, and information technology that facilitates the coordination role of middle managers by reducing communication costs⁷. This view is in line with evidence from several large-scale quantitative studies (Colombo and Delmastro 2008; Acemoglu et al. 2007; Wang 2007; Rajan and Wulf 2006; Brews and Tucci 2004; Caroli and Van Reenen 2001; Whittington et al. 1999; Ruigrok et al. 1999; and Collins, Ryan and Matusik 1999).

[Insert Table 1 about here]

A reduction of the number of management levels in an organization can have both positive and negative effects on firm performance. Flatter organizations allow a better information flow and, thus, enable faster decisions (Colombo and Delmastro 2008, Carzo and Yanouzas 1969). Moreover, employees' intrinsic motivation is supposed to be higher in a flatter and, therefore, less bureaucratic working environment (Kettley 1995; see also Littler, Wiesner and Dunford 2003; McCann, Morris and Hassard 2008). Apart from that, monitoring employees in a flatter hierarchy can be easier (BCG 2004, 2006a, b). Competition for open positions may be tougher because of a larger number of employees at the same management level (Sohr 2005). Finally, total costs associated with management levels

⁶ Nikolowa (2010) presents a theoretical model that explains how firms react to a more abundant supply of skilled labor by lowering the number of hierarchical levels, i.e. by delayering.

⁷ However, to the extent to which information technology (IT) enhances the access to information, it is even possible that the introduction of IT *increases* the number of corporate layers (Rajan and Wulf 2006, Lazear and Gibbs 2009).

decrease with the number of hierarchical layers. Consequently, removing hierarchical layers could improve firm performance.

However, flatter organizations can also have adverse effects. If employees at certain levels have to leave the firm, valuable knowledge and human capital might get lost (Datta et al. 2010), while staying employees might suffer the so-called survivor syndrome (Datta et al. 2010; Cascio 1993; Littler, Wiesner and Dunford 2003; McCann, Morris and Hassard 2008). In general, employees' effort might decrease due to a small option value of any promotion in a flat hierarchy (Lazear and Rosen 1981; Littler, Wiesner and Dunford 2003; McCann, Morris and Hassard 2008). In flatter organizations, parts of resources are bound in an unproductive manner because more conflicts have to be resolved by colleagues without intermediation of a supervisor (Carzo and Yanouzas 1969). Finally, the introduction of reorganization measures could lead to influence activities; employees have to adjust to the new way of working; and investments in old production and/or communication processes become sunk costs (Colombo and Delmastro 2008). Consequently, removing hierarchical layers could deteriorate firm performance.

The aim of the present study is to empirically investigate the net effect of delayering programs on subsequent firm performance. Previous studies tackle this research question using experiments (Carzo and Yanouzas 1969), on a case study basis (Kettley 1995, $n = 8$), using small-scale data sets (Shaw and Schneier 1993, $n = 8$), on the basis of senior executives' subjective evaluation of middle managers' productivity (Littler, Wiesner and Dunford 2003), or within the framework of so-called high-performance work systems (Cristini et al. 2003). Against this background, the author of the present study is not aware of any large-scale quantitative-econometric study on the direct effect of delayering on firm performance.

For this purpose, the Innovation Survey 2005 is used, a nationally representative data set of 2'575 firms in Switzerland which was collected by the Swiss Economy Institute (KOF) at the Swiss Federal Institute of Technology Zurich (ETHZ). The empirical model is an augmented Cobb-Douglas production function. Productivity and profitability (efficiency) measures based on value added and wages are used as performance indicators. Controlling for a wide range of firm characteristics and market conditions, an ordinary least squares regression is applied. To control for a potential selectivity bias in evaluating the treatment effects of a delayering program, a propensity score matching procedure is additionally implemented.

The remainder of this paper is organized as follows. Section 2 theoretically discusses potential positive and negative performance effects of delayering. Section 3 presents related empirical literature. Section 4 contains the empirical investigation. At first, the data set and variables used are described. Next, the econometric modeling of various specifications is explained. Finally, the results obtained are presented. Section 5 concludes.

2. Theoretical Background

A reduction of management levels can have both positive and negative effects on firm performance. Both will be discussed in turn.

2.1 Positive effects on firm performance

Usually, flatter organizations are seen as allowing for a better information flow and thus faster decisions and execution of decisions (Colombo and Delmastro 2008, Carzo and Yanouzas 1969). Even if one abstracts from agency problems or conflicts of interest between organization members: in a steep hierarchy, a strategy approved by top management could differ from the measures taken by lower level managers to implement this strategy simply because of communication failures across layers. And even if the measures taken are the right ones to implement a given strategy, there may be a time delay between strategy approval and execution. So those measures could be obsolete at that point in time because critical conditions for the strategy decision might have changed in the mean time. That is why, in today's fast moving business environment, fast communication channels are a competitive advantage for firms.

In addition, the absolute number of decisions made can be increased by flattening a hierarchy in conjunction with decentralization (Lazear and Gibbs 2009, Colombo and Delmastro 2008). By delegating decision-making authority to lower levels, top management is less likely to exhibit information overload and, thus, to run the risk of being a bottle neck. Consequently, more – and more complex – decisions can be made by an organization as a whole.

Moreover, employees' attitudes, such as intrinsic motivation, satisfaction and commitment, are supposed to be higher in a flatter and, thus, less bureaucratic working environment because of more legitimacy, freedom to take decisions and

calculated risks as well as freedom to choose how to utilize available resources (Littler, Wiesner and Dunford 2003). Kettley (1995) relates this positive effect to “greater opportunities for ownership, involvement and responsibility”. It seems that in a flattened hierarchy, motivation stems not so much from promotion opportunities but rather from intrinsic – apart from financial – rewards concerning the job itself (McCann, Morris and Hassard 2008). In line with this reasoning, Dopson and Stewart (1994) find that most of the middle managers in their sample of 43 organizations in six Western-European countries have positive feelings about “the additional responsibility and variety of their work” related to flatter hierarchies.

In a flattened hierarchy, the number of employees at the same level increases. Thus, competition for open positions at higher levels may become tougher. If it is not undermined by sabotage activities, this strong competition could improve employees’ working effort, leading to higher labor productivity (Sohr 2005). A related point is that avoiding sideway career movements has already become an incentive for employees to show high effort level (McCann, Morris and Hassard 2008).

Apart from that, monitoring in a flatter hierarchy is easier, if tasks are allocated in a way such that employees specialize in either doing an operational job or supervising others. In that case, supervisors can focus on communicating goals and managing exceptions, i.e. situations in which those goals are not met (BCG 2004, 2006a, b).

Finally, total costs associated with layers (e.g., wages of managers at those layers, supervisory costs, etc.) decrease with the number of layers. So not only labor productivity but also labor efficiency (profitability) has the potential to increase.

The factors discussed in this section suggest that removing hierarchical layers could improve firm performance. However, delayering can also have adverse effects. Those are discussed in the next section.

2.2 Negative effects on firm performance

If employees at certain levels – most often: middle managers (Littler, Wiesner and Dunford 2003) – have to leave a firm, valuable knowledge and human capital might be lost and organizational relationship networks might be disrupted, diminishing the firm’s long-term competitive advantage (Datta et al. 2010). Staying

employees might suffer the so-called survivor syndrome, a set of attitudinal reactions that lead to lower levels of satisfaction, motivation and commitment and to higher levels of workload, stress, burnout, resistance, fluctuation and intention to leave (Datta et al. 2010; Cascio 1993; Littler, Wiesner and Dunford 2003; McCann, Morris and Hassard 2008; Armenakis and Beteian 1999). Those reactions could directly translate into lower labor productivity and employees' psychological contracts (Rousseau 1995) might suffer damage. For instance, employees could find it difficult to accept the above mentioned sideways career movements (McCann, Morris and Hassard 2008).

Furthermore, employees' reactions can depend on the reason for delayering (Sohr 2005). If adverse external demand developments threaten the firm as a whole, postponed promotions – an inevitable consequence of delayering – would be seen as more justified than if, e.g., top management decided to introduce new ICT complemented by fewer hierarchical levels. In this example, sluggish demand would be regarded as an exogenous factor, whereas investment decisions are endogenously made by managers. Indeed, recent research (Michel, Stegmaier and Sonntag 2010) shows that (perceived) procedural justice – i.e., giving employees the feeling that they are valuable members of the organization – directly affects employees' commitment to change. Moreover, the authors find that employees' change-supporting behavior can be improved by a positive organizational identification which, in turn, is positively influenced by (perceived) procedural justice.

According to tournament theory (Lazear and Rosen 1981), any promotion can be regarded as the winner prize in a competition among employees. The higher position is usually associated with a higher wage, but also with the perspective of another promotion to the next but one position. This is the option value of that promotion. Against this background, fewer management levels – due to delayering – imply that new entrants cannot be promoted as often as before. Thus, the option value of any promotion decreases. Consequently, employees' effort may decline because the winner prize has become lower (Littler, Wiesner and Dunford 2003; McCann, Morris and Hassard 2008; Sohr 2005). To uphold working effort, the wage level or wage dispersion could be increased

Since in flatter organizations – *ceteris paribus* – there are more people at the same hierarchical position, employees have to do several managerial tasks without the intervention of a supervisor (Carzo and Yanouzas 1969). They have to coordinate their actions with each other so as to prevent redundant work. Potentially, asymmetric information distribution would make it necessary to exchange infor-

mation. However, this could be hindered by conflicts of interests. Apart from that, conflicts unrelated to asymmetric information distribution also have to be solved directly by the opponents. This binds resources in an unproductive way.

Finally, Colombo and Delmastro (2008) pick up a dynamic perspective of organizational change. The authors develop a conceptual framework of factors affecting adjustment costs associated with organizational innovation. First, investments in physical capital or human resources usually are tied up with a specific production process. Changing this production process turns such investments into sunk costs.⁸ Second, organizational change requires that employees adapt to new processes and interaction modes. To the extent that old knowledge becomes redundant this adaption requires a learning curve, which could be negative before it turns positive. Thus, short-term productivity loss may be the price for (expected) long-term productivity gains. Third, any organizational change is associated with a redistribution of quasi-rents among organizational members. Thus, in order to protect the own (positive) rents or to increase (negative) rents, certain employees can have the incentives to engage in influence activities.

The factors discussed in this section suggest that removing hierarchical layers could deteriorate firm performance. Summing up the theoretical discussion, the net effect of the various positive and negative consequences of delayering programs is ex ante unclear. Therefore, the present study aims at investigating this issue applying econometric methods. But before turning to that, related empirical studies are discussed in the next section.

3. Related Literature

40 years ago, Carzo and Yanouzas (1969) conducted a laboratory experiment.⁹ Two organizations were simulated, a tall one and a flat one, but each with 15 members, one of which being the president. The tall organization had four hierarchical layers (including the highest and the lowest level) and a span of control of two at each level. The flat organization had two levels and a span of control of 14 (see Figure 1 in the appendix). Both organizations had to imitate the ordering of

⁸ Another, but connected argument is that any organizational change erases the option of adopting other innovations (path dependency). Therefore, firms might find it optimal to hold on to the old organizational structure for a longer time.

⁹ Although it was a refinement of prior experiments, this study was subject to methodological criticism (Hummon 1970, Carzo and Yanouzas 1970).

goods from suppliers, taking into account costs, inventory and expected revenues, given a probability distribution of demand. Clear procedures for communication and decision making were given. The experiment lasted for 60 rounds. Results indicate that the tall organization was significantly better in terms of profits and rate of return on sales. Given the rather stable task structure, this comes at no surprise. However, *no* statistically significant difference could be found in terms of decision time. The authors explain this result by a trade-off between information processing and coordination. Whereas information processing in the tall structure took longer, the flat structure needed more time to resolve conflicts and coordinate efforts. Both organizations exhibited a steady decrease in decision time, which is evidence for a learning curve effect.

Kettley's (1995) report contains eight case studies of organizations in the UK having reduced their number of management levels.¹⁰ In one case, a retailing firm realized faster decision-making processes in the field of temporary staffing through the relocation of the temporary staffing responsibility from the area management down to a network of local stores. Kettley's (1995) evidence seems to contrast with the experiment of Carzo and Yanouzas (1969) who found no difference in decision time between tall and flat organizations. However, the business environment has become more and more dynamic during the past decades (Snower 1999; Lindbeck and Snower 2000; Caroli, Greenan and Guellec 2001), so that flattened organizations today may be able to realize economies of speed, whereas in the 1960s, market conditions were rather stable.

Shaw and Schneier (1993) consider performance measures for eight corporations – among them are Hewlett-Packard, Intel, GE and PepsiCo – that have reduced management levels. The authors find that sales growth, profit growth and return on capital – each averaged over five years – are higher for these corporations than for their respective industry peers. This mean comparison provides some insight into positive quantitative performance effects of delayering.

Littler, Wiesner and Dunford (2003) use data on organizations with 50 or more employees in Australia, New Zealand and South Africa. The authors find that over half of 1'164 organizations report increased middle managers' productivity, as evaluated by senior executives. About a fourth of the organizations report no change, whereas a minority of them reports a decrease in productivity (remaining:

¹⁰ Unfortunately, there are no details on the case study organizations given in the report.

do not know). Additionally, the authors provide evidence of significant increase in workload within delayed organizations ($n = 2'757$). Finally, the extent to which middle managers of delayed organizations suffer from the so-called survivor syndrome is indicated. Important attitudinal variables such as morale, commitment, motivation and satisfaction mostly deteriorate in Australia and South Africa, but not in New Zealand, whereas there are lower perceived promotional opportunities and more concerns about job security in all three countries ($n = 1'164$).

Cristini et al. (2003) econometrically examine a data set of 100 Italian manufacturing firms. Being endowed with cross-sectional information on new work practices, but with longitudinal balance sheet data, the authors are able to apply a two-step procedure by Black and Lynch (2001) to control for unobserved time-invariant heterogeneity in estimating productivity effects of “new work practices”. In order to detect potential complementarities, interaction terms are tested. Strikingly, according to the authors, most of the pairwise interactions and *all* of the three-way interactions contain a flattened hierarchical structure as element of a so-called high-performance work system. This suggests that layering is an important condition for flexible workplace practices to have a positive performance effect.

Further insights into the shape of the performance effects of a flatter hierarchy can be gained by the study of Bauer and Bender (2001), who examine the effects of layering (and other “flexible work systems”) on wages and firms’ internal wage structure. Drawing on a nationally representative linked employer-employee panel data set for Germany and applying panel methods, the authors find that removing managerial levels increases subsequent mean wages and widens the wage distribution, especially at the upper parts. These results suggest that the effects of layering on productivity (e.g., value added per worker) could be larger than the effects on profitability (e.g., value added over total wages). The economic rationale for this expectation is that higher wages have to be paid in order to compensate employees for the smaller option value of any promotion in a flatter hierarchy to keep motivation and effort at a high level.

Given the literature presented in this section, the author of this study is not aware of any large-scale quantitative-econometric study on the direct effect of layering on firm performance. Therefore, based on a nationally representative data set of 2'575 firms in Switzerland, the present study aims at contributing to this field of research. An ordinary least squares regression is applied, which con-

trols for a wide range of firm characteristics and market conditions. A propensity score matching procedure is additionally implemented to control for a potential selectivity bias in evaluating the treatment effects of a delayering program. In this respect the present study should be able to add significantly to the existing literature.

4. Empirical Investigation

4.1 Data, Variables and Descriptive Statistics

This study uses the Innovation Survey 2005, a data set of firms in Switzerland, which was collected by the Swiss Economy Institute (KOF) at the Swiss Federal Institute of Technology Zurich (ETHZ). The data set is a (with respect to industry and firm size) stratified random sample of the Business Census, a total population survey of all establishments and firms of the Second and Third Sector in Switzerland, which was conducted by the Swiss Federal Statistical Office. Non-for-profit service industries were excluded by the KOF. For the Innovation Survey, the KOF sent out about 6'700 questionnaires, of which 2'575 were returned.

Dependent variables are log value added, $\ln VA$, (i.e., sales minus cost of materials and outside services) in CHF as a productivity measure and the log of value added over total wages, $\ln(VA/W)$, as a profitability (efficiency) measure. Both measures refer to 2004. It is important to also consider the latter performance indicator, since the discussion above suggested that, by delayering, firms decrease the option value of any promotion. To compensate for this potentially negative effect on working effort and to uphold incentives for employees, wages or wage dispersions within firms could have to increase if management levels are removed.

The key explanatory variable is a dummy variable indicating whether a firm has reduced the number of hierarchical layers since 2000 (*delayer*). Control variables are dummy variables indicating whether a firm has downsized by selling divisions or outsourcing functions since 2000 (*down*); whether decision power has been decentralized, i.e. the distribution of competencies at the workplace has shifted towards workers, since 2000 (*decentr*); whether a firm is mostly foreign-owned (*foreign*); whether the usage of information and communication technologies – the sum of computers, internet and intranet, each measured on a five-point Likert scale – is above the median (*ICT01*); whether the intensity of competition in the

main product market concerning both price and non-price criteria is above the median (*intens01*); and whether the number of competitors is above the median (*compet01*). Further controls are total investments in CHF as proxy for capital (*lnK*); the number of employees as proxy for labor (*lnL*); the number of management levels (*level*); the share of skilled workers (*skilled*); the percentage of staff having participated at training (*train*); the export share of sales (*export*); and controls for the seven Greater Regions in Switzerland and for seven sectors. Table A1 in the appendix provides descriptive statistics of the variables used.

Table 2 displays transition probabilities of 662 firms that had already been surveyed in 2000. The KOF Organization Survey 2000 is similar to the Innovation Survey concerning sampling methodology and sample size. The two surveys can be merged using a unique identifier. The rows in Table 2 represent the number of management levels in 2000, the columns those of 2005. As can be seen, over 60 % of firms with four hierarchical layers have undergone delayering during this period. For firms with more layers, this percentage is even higher. These numbers suggest that delayering still is a wide-spread phenomenon.

[Insert Table 2 about here]

4.2 Regression Analysis & Treatment Evaluation

4.2.1 Econometric Models

The baseline specification is a Cobb-Douglas production function, which is augmented by a dummy variable indicating whether a firm has removed management levels during the past five years (*delayer*). To eliminate other influences on firm performance, a wide range of firm characteristics and market conditions X_j is added to the estimation equation as well, which then becomes:

$$\ln VA_i = \beta_0 + \beta_1 \ln K_i + \beta_2 \ln L_i + \gamma \text{delayer}_i + \sum_{j=1}^n \delta_j X_{ij} + u_i, \quad (1)$$

where \ln is the natural logarithm operator, VA is value added, K represents the capital stock, L describes labor and u is an i.i.d. random variable (i is the firm index). As an alternative dependent variable, the log of value added over total wages, $\ln(VA/W)$, is also used throughout this study. Equation (1) is estimated by ordinary least squares (OLS). Standard errors are heteroscedasticity-robust according to White (1980).

OLS assumes that delayering is exogenous. However, a firm’s decision to remove management levels may well be endogenously determined. For instance, firms that are in the middle of a reorganization phase could be more likely to delayer in order to complement other measures like downsizing or decentralization. Other firms may be more prone to reorganizing measures in general. Not accounting for such a selectivity bias could lead to biased estimates of the performance effects of delayering.

Therefore, a propensity score matching (PSM) procedure (Heckman, Ichimura and Todd 1997) is additionally implemented to control for a potential selectivity bias in evaluating the treatment effects of a delayering program. The basic idea of matching in general is to compare the outcomes of two similar groups that differ only in one respect, namely whether they have delayered or not. The difference in mean outcomes between the two groups is the average treatment effect (ATE) (Cameron and Trivedi 2006, Caliendo and Kopeinig 2008):

$$\Delta_{ATE} = E(\ln VA^1 | d = 1) - E(\ln VA^0 | d = 0), \quad (2)$$

where d indicates whether or not a firm has delayered, i.e. whether it was “treated”. The ATE compares the actual outcomes of treated firms, $E(\ln VA^1 | d = 1)$, with that of non-treated, $E(\ln VA^0 | d = 0)$. However, to the extent to which those two groups differ with respect to other characteristics – i.e. in case of a selectivity bias – the ATE is not an adequate measure for the performance effect of delayering. Rather, the actual outcome of treated firms, $E(\ln VA^1 | d = 1)$, would have to be compared with the outcome that would have resulted, had these firms not been treated, $E(\ln VA^0 | d = 1)$. This is what the average treatment effect on the treated (ATT) does. The ATT is given by:

$$\Delta_{ATT} = E(\ln VA^1 - \ln VA^0 | d = 1). \quad (3)$$

The latter term, $E(\ln VA^0 | d = 1)$, denotes the so-called counter-factual outcome, i.e. the outcome of a treated firm, had it not been treated. Obviously, the counter-factual outcome cannot be observed. However, if an adequate control group can be generated on the basis of observable characteristics Z , the outcome of this control group can be used as a substitute for the counter-factual outcome. For this to be possible, three conditions have to hold (Caliendo and Kopeinig 2008; Pfeifer 2009; Bryson, Dorsett and Purdon 2002):

First, the conditional independence assumption (CIA) states that firm performance is independent of delayering, conditional on characteristics Z : $\ln VA^0, \ln VA^1 \perp d \mid Z$. This condition ensures that treatment is conditionally random and mitigates the selectivity bias. However, for the estimation of ATTs, a weak form of the CIA, the conditional mean independence assumption (CMIA), is sufficient. The CMIA states that the firm performance without delayering is – or would be – the same in both groups, i.e. in the treatment and the control group, given characteristics Z : $\ln VA^0 \perp d \mid Z$. The CMIA can be equivalently written as:

$$E(\ln VA^0 \mid d = 1, Z) = E(\ln VA^0 \mid d = 0, Z). \quad (4)$$

Second, the common support or overlap condition states that there must be a positive probability of having delayered and having not delayered, given Z : $0 < P(d = 1 \mid Z) < 1$. This condition ensures that there are treated and non-treated firms available for matching, given Z . This implies that Z does not allow the perfect prediction of the treatment status. For the estimation of ATTs, a weak form of the overlap condition is sufficient: $P(d = 1 \mid Z) < 1$.

Third, the stable unit treatment value assumption (SUTVA) states that the performance effects of a delayering program for a given firm are independent of the number of other firms that also undertake delayering. This condition rules out general equilibrium or spill-over effects.

Following Rosenbaum and Rubin (1983), firm characteristics Z are first combined to a one-dimensional propensity score $P[Z]$ applying a probit maximum likelihood estimation of delayering. Recognizing this and substituting equation (4) into (3) gives the ATT, which is then estimated by PSM (Caliendo and Kopeinig 2008, Pfeifer 2009):

$$\Delta_{ATT}^{PSM} = E_{P[Z] \mid d=1} \{E(\ln VA^1 \mid d = 1, P[Z]) - E(\ln VA^0 \mid d = 0, P[Z])\}. \quad (5)$$

To implement PSM, equation (5) can be rewritten (Muehler, Beckmann and Schauenberg 2007):

$$\Delta_{ATT}^{PSM} = \sum_{i \in T} \{\ln VA_i - \sum_{j \in C} \Lambda_{i,j} \ln VA_j\} \lambda_i, \quad (6)$$

where i and j are treated and non-treated firms, respectively; T and C indicate treatment and control group, respectively; $\Lambda_{i,j}$ is the weight placed on control

firm j when matched to treated firm i ¹¹; λ_i can be used to reweight the treated sample if $T > C$, which is not the case in this study.

Several PSM algorithms are available. They differ in how they trade off bias and efficiency of the estimator of the treatment effect (Caliendo and Kopeinig 2008). The most straightforward method is nearest-neighbor matching, which matches the performance of each treated firm with the non-treated that has the closest propensity score $P[Z]$. Replacement of the non-treated is allowed so as to reduce a potential bias through the avoidance of bad matches. To reduce the variance of the treatment estimator, more than one nearest-neighbor can be used. Specifically, $n = 4$ optimizes mean-squared error (Abadie and Imbens 2002, Abadie et al. 2004). However, some of the multiple nearest-neighbors could represent bad matches in terms of the propensity score and, thus, increase the estimation bias. Therefore, defining lower and upper limits of the distance between the propensity score of treatment and control observations (“caliper”) is an option. This could, on the other hand, exclude some of the controls and, thus, increase the estimation variance. Using all non-treated within this caliper could be a remedy and is called radius matching.

Since it is difficult to decide upon the adequate caliper ex ante, another method – kernel matching – uses (almost) all non-treated firms as matches for every treated firm. By assigning kernel weights to matched non-treated firms, this method takes the different distances between treated and controls into account. According to Smith and Todd (2005), kernel matching regresses the counter-factual outcome on a constant, weighted by kernel weights. The local linear regression (LLR) matching method, finally, adds the propensity score as a regressor to this estimation equation. Therefore, LLR outperforms kernel matching if control firms are distributed asymmetrically within the propensity score neighborhood of a treated firm. Kernel and LLR matching require setting the kernel function and the bandwidth parameter. Whereas the choice of the kernel function does not seem to be crucial (DiNardo and Tobias 2001), the bandwidth parameter imposes a trade-off (Caliendo and Kopeinig 2008). A high bandwidth aggregates much

¹¹ This weight differs between different PSM algorithms, such as one-to-one, nearest-neighbor ($NN > 1$), radius, Kernel or local linear regression matching. For every treated firm i , however, the weights of matched non-treated j should add up to one: $\sum_j \Lambda_{i,j} = 1$. On the contrary, at least when matching with replacement, $\sum_i \Lambda_{i,j}$ need not necessarily equal one, since, then, a non-treated firm can be matched more than once to (different) treated firms.

information. As a consequence, on the one hand the variance between the true and estimated density function decreases, but on the other the risk of a biased estimate also rises. As a compromise, this study applies the epanechnikov kernel function with a bandwidth of 0.06 for kernel matching and the tricube kernel function with a bandwidth of 0.8 for LLR matching. The empirical investigation in this study uses all of these matching algorithms to provide a sense of robustness of the results.

4.2.2 Empirical Results

Table 3 shows OLS estimates of the performance effects of delayering. The first three columns refer to estimations that use log value added as dependent variable; the last three columns refer to estimations that use the log of value added over total wages as dependent variable. Whereas the former is supposed to serve as a productivity measure, the latter should indicate profitability (efficiency) effects. As can be seen, firms having delayered in the past five years are about 20 % more productive than firms having not. This estimate is highly significant even after controlling for basic input factors (capital and labor), regions and sectors as well as for other corporate restructuring concepts (downsizing and decentralization) and other firm and market characteristics. As the number of control variables increases, the point estimate of the productivity effect of delayering slightly decreases from 21.6 % to 19.5 %. In addition, firms having delayered are over 10 % more profitable (efficient) than others. This estimate, too, stays significant and decreases only slightly from 13.4 % to 11.9 % as more and more control variables are added to the regression equation.

[Insert Table 3 about here]

To account for a potential selectivity bias in the evaluation of the treatment effects, a PSM procedure is implemented, which requires the estimation of the propensity score of delayering in a first step. This so-called participation model should include pre-treatment factors that simultaneously could influence a firm's delayering decision and firm performance (Caliendo and Kopeinig 2008; Bryson, Dorsett and Purdon 2002; Muehler, Beckmann and Schauenberg 2007). Since the key explanatory variable indicates whether a firm has removed management levels since 2000, the KOF Innovation Survey 2005 is merged with the KOF Organization Survey 2000, which is similar to the Innovation Survey in what relates to sampling methodology and sample size, using a unique identifier. To avoid over-

dentification of the participation model (Caliendo and Kopeinig 2008; Bryson, Dorsett and Purdon 2002; Augurzky and Schmidt 2001) and because underidentification should not lead to a large bias in this study, given the KOF data structure (Khandker, Koolwal and Samad 2010; Heckmann, Ichimura and Todd 1997, 1998), the participation model is defined in a way similar to that in Muehler, Beckmann and Schauenberg (2007). Each variable that potentially and simultaneously could influence a firm’s delaying decision and firm performance was added separately to a baseline specification, which consisted of regional and sector dummies (from the Organization Survey 2000) and a constant. The variables that were significant in the probit estimation were then entered simultaneously in the participation model. Those were *decentr* and *down* (from the Innovation Survey 2005), i.e. dummy variables indicating whether a firm had delegated decision-making authority to workers since 2000 and whether a firm had downsized by selling divisions or outsourcing functions since 2000, respectively.

The matching quality is assessed in Figure 2 and Tables A2 and A3 in the appendix. Table A2 displays the first-step probit estimations for the productivity and profitability sample, respectively. For both samples, goodness of fit of the regression as a whole is satisfactory. In particular, the two variables identified separately – i.e., decentralization and downsizing – are highly significant in predicting whether or not a firm has delayed. Table A3 lists standardized biases before and after matching as well as the percentage bias reduction for each variable in the participation model, which is a common procedure in the evaluation literature (Caliendo and Kopeinig 2008).¹² As can be seen, standardized biases after matching are below 5 % for most of the variables used; especially for *decentr* and *down* they are below 3 %. Moreover, huge reductions of over 80 % in the standardized biases are achieved through matching for most of the variables used; especially for *decentr* and *down* the reduction is over 90 %. Finally, Figure 2 graphs the distribution of the propensity scores for treated and controls. As can be seen, there is considerable overlap in the range of propensity scores for treated and control firms. In general, common support is implemented by dropping treated firms whose propensity score is higher than the maximum or less than the minimum propensity score of the controls. However, this has to be done extremely rarely in this study. To conclude, the matching quality seems to meet

¹² It refers to the nearest-neighbor matching ($n = 4$) variant with log value added as outcome considered. Standardized biases and percentage bias reduction in the cases of other matching algorithms and the alternative dependent variable are similar and can be obtained from the author upon request.

common quality standards. Thus, the data examined in this study seem to satisfy the identifying assumptions of the matching procedure discussed above.

Table 4 displays PSM estimates of the performance effects of delayering. Results are split between dependent variables (log value added vs. the log of value added over total wages) and, further, between ATEs and ATTs. For the purpose of robustness, several matching algorithms discussed further above are used and reported. As can be seen, there are significant and large ATEs on productivity ranging from 45.4 % to 78.5 %. However, controlling for selectivity by calculating the ATTs removes this positive productivity effect. As for profitability (efficiency), there are no significant ATEs. But by controlling for selectivity, highly significant ATTs in the range from 14.1 % to 18.8 % show up. This result is robust across almost all matching algorithms used; only one method fails to produce a significant estimate by only 1.2 percentage points.

[Insert Table 4 about here]

5. Conclusion

The aim of the present study was to empirically examine the performance effects of delayering. For this purpose, the KOF Innovation Survey 2005, a nationally representative data set of firms in Switzerland was used. Applying ordinary least squares (OLS) regressions and propensity score matching (PSM), this study provides first large-scale quantitative-econometric evidence on the direct net effects of delayering programs on firm performance. The findings show that delayering increases subsequent firm performance in terms of profitability (efficiency) by roughly 15 % accounting for selectivity based on observable factors. The estimated positive performance effects persist among different sets of control variables (in OLS) capturing firm characteristics and market conditions as well as among different matching algorithms (in PSM) such as nearest-neighbor, radius, kernel or local linear regression matching.

With respect to the theoretical discussion, it can be concluded that, on average, the positive performance effects of delayering – such as, e.g., a better information flow, faster and more complex decisions, as well as increased intrinsic motivation of employees – seem to outweigh the negative effects – such as, e.g., loss of knowledge and human capital, the occurrence of the survivor syndrome, dimin-

ished extrinsic motivation due to a smaller option value of any promotion, and more conflicts within the same management level.

The main contribution of the present study to the literature is in the field of organizational theory. The results obtained suggest that the broad delayering trend in the 1990s was not merely a pure managerial trend. Instead, flatter hierarchical structures indeed seem to enable firms to better realize their competitive advantage in today's fast moving and knowledge-intensive market environment. So, these results are in line with the economically oriented strategic management literature (Chandler 1962; Brickley, Smith and Zimmerman 2009) and the traditional industrial organization literature (Bresnahan 1989).

Apart from that, regarding the tournament theory (Lazear and Rosen 1981), the fact that the estimated productivity effects are larger than the estimated profitability (efficiency) effects suggests that firms removing hierarchical levels have to increase wages in order to uphold incentives for managers, given the decreased option value of any promotion in a flattened hierarchy. This result is in line with the findings of Bauer and Bender (2001), who found that delayering increases mean wages and the wage distributions within firms, especially at the top end.

In interpreting the results obtained in this study, admittedly, one has to bear in mind a potential limitation. Although considerable efforts have been made to eliminate biases arising from selection on observables, *unobserved* factors could still influence a firm's delayering decision and performance simultaneously. Time-invariant unobserved heterogeneity could be controlled for using a difference-in-differences or a combined matching difference-in-differences approach, which would require longitudinal data. However, the data base of this empirical investigation, namely the KOF Innovation Survey 2005 and the KOF Organization Survey 2000, is not supposed to represent a panel data set in a strict sense but is more appropriately seen as a set of repeated cross sections. Since the overlap of these surveys is about 40 %, a sample size that provides a sufficient number of degrees of freedom for the estimation may not be guaranteed. Additionally, another selection bias could emerge if firms participating in the Organization Survey differed from firms participating in the Innovation Survey with regard to observed or unobserved factors, e.g. interest in the emphasized content of the respective survey. To summarize, the potential gains of additional investigations have to be traded off against potential pitfalls.

References

- Abadie, A.; Drukker, D.; Leber Herr, J.; Imbens, G.W. (2004): Implementing matching estimators for average treatment effects in Stata. *Stata Journal* 1: 1–18.
- Abadie, A.; Imbens, G.W. (2002): Simple and bias-corrected matching estimators. NBER Technical Working Paper No. 0283, Cambridge, MA.
- Acemoglu, D.; Aghion, P.; Lelarge, C.; Reenen, J.; Zilibotti, F. (2007): Technology, Information, and the Decentralization of the Firm, in: *Quarterly Journal of Economics* 122(4): 1759-1799.
- Åhlström, P.; Karlsson, C. (2000): Sequences of manufacturing improvement initiatives: the case of delayering, in: *International Journal of Operations & Production Management* 20(11): 1259-1271.
- Armenakis, A.; Bedeian, A. (1999): Organizational Change: A Review of Theory and Research in the 1990s, in: *Journal of Management* 25(3): 293-315.
- Augurzky, B.; Schmidt, C. (2001): The propensity score: a means to an end. IZA Discussion Paper No. 271.
- BCG (2004): *Shaping Up: The Delayed Look*, BCG Perspectives, October 2004.
- BCG (2006a): *The Fallacy of the Player-Coach Model*, BCG Opportunities for Action, April 2006.
- BCG (2006b): *Global Delayering for Competitive Advantage*, BCG Opportunities for Action, October 2006.
- Bauer, T.K.; Bender, S. (2001): Flexible Work Systems and the Structure of Wages: Evidence from Matched Employer-Employee Data, IZA Discussion Paper No. 353.
- Bresnahan, T.F. (1989): Empirical Studies of Industries with Market Power, in: Schmalensee, R.; Willig, R.D. (Ed.): *Handbook of Industrial Organization* (Volume II), Elsevier Science Publishers B.V.
- Brews, P.; Tucci, C. (2004): Exploring the Structural Effects of Internetworking, in: *Strategic Management Journal* 25(5): 429-451.
- Brickley, J.A.; Smith, C.W.; Zimmerman, J.L. (2009): *Managerial Economics and Organizational Architecture*, 5th ed., Boston: McGraw-Hill Irwin.
- Bryson, A.; Dorsett, R.; Purdon, S. (2002): The use of Propensity Score Matching in the Evaluation of Active Labour Market Policies. Policy Studies Institute and National Centre for Social Research. Working Paper Number 4

- Caliendo, M.; Kopeinig, S. (2008): Some Practical Guidance for the Implementation of Propensity Score Matching, in: *Journal of Economic Surveys* 22(1): 31-72.
- Cameron, A.C.; Trivedi, P.K. (2006): *Microeconometrics – Methods and Applications*. Cambridge.
- Caroli, E.; Van Reenen, J. (2001): Skill-biased Organizational Change? Evidence from a Panel of British and French Establishments, in: *Quarterly Journal of Economics* 116(4): 1449-1492.
- Carzo Jr., R.; Yanouzas, J.N. (1969): Effects of Flat and Tall Organization Structure, in: *Administrative Science Quarterly* 14(2): 178-191.
- Carzo Jr., R.; Yanouzas, J.N. (1970): Justification for the Carzo-Yanouzas Experiment on Flat and Tall Structures. *Administrative Science Quarterly* 15(2): 235-241.
- Cascio, W.F. (1993): Downsizing: What Do We Know? What Have We Learned? In: *Academy of Management Executive* 7(1): 95-104.
- Chandler, A.D. (1962): *Strategy and Structure: Chapters in the History of the Industrial Enterprise*, Cambridge.
- Collins, P.; Ryan, L.; Matusik, S. (1999): Programmable Automation and the Locus of Decision-Making Power, in: *Journal of Management* 25(1): 29-53.
- Colombo, M.G.; Delmastro, M. (1999): Some stylized facts on organization and its evolution, in: *Journal of Economic Behavior & Organization* 40: 255-274.
- Colombo, M.G.; Delmastro, M. (2002): The Determinants of Organizational Change and Structural Inertia: Technological and Organizational Factors, in: *Journal of Economics & Management* 11(4): 595-635.
- Colombo, M.G.; Delmastro, M. (2008): *The Economics of Organizational Design: Theory and Empirical Insights*, Palgrave Macmillan.
- Cristini, A.; Gaj, A.; Labory, S.; Leoni, R. (2003): Flat Hierarchical Structure, Bundles of New Work Practices and Firm Performance, in: *Rivista Italiana degli Economisti* 8(2): 313-341.
- Datta, D.; Guthrie, J.; Basuil, D.; Pandey, A. (2010): Causes and Effects of Employee Downsizing: A Review and Synthesis, in: *Journal of Management* 36(1): 281-348.
- DiNardo, J.; Tobias, J. (2001): Nonparametric density and regression estimation, in: *Journal of Economic Perspectives* 15(4): 11–28.
- Dopson, S.; Stewart, R. (1994): What is Happening to Middle Managers in Europe? Problems and Promises Associated with Their Changing Roles and Responsibilities, in: *The International Executive* 36(1): 55-78.

- Heckman, J.J.; Ichimura, H.; Todd, P.E. (1997): Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme, in: *Review of Economic Studies* 64: 605-654.
- Heckman, J.J.; Ichimura, H.; Todd, P.E. (1998): Matching As An Econometric Evaluation Estimator, in: *Review of Economic Studies* 65(223): 261-294.
- Hummon, N. (1970): Criticism of "Effects of Flat and Tall Organization Structure", in: *Administrative Science Quarterly* 15(2): 230-234.
- Jost, P.-J. (2009): *Organisation und Koordination. Eine ökonomische Einführung.* 2nd ed., Gabler.
- Kettley, P. (1995): Is flatter better? Delaying the management hierarchy. The Institute for Employment Studies Report No. 290.
- Khandker, S.R.; Koolwal, G.B.; Samad, H.A. (2009): *Handbook on Impact Evaluation: Quantitative Methods and Practices.* Washington, D.C.: World Bank.
- Lazear, E.P.; Gibbs, M. (2009): *Personnel Economics in Practice*, 2nd ed., Hoboken, NJ: John Wiley & Sons.
- Lazear, E.; Rosen, S. (1981): Rank-Order Tournaments as Optimum Labor Contracts, in: *Journal of Political Economy* 89(5): 841-864.
- Littler, C.R.; Innes, P. (2004): The Paradox of Managerial Downsizing, in: *Organizational Studies* 25(7): 1159-1184.
- Littler, C.R.; Wiesner, R.; Dunford, R. (2003): The Dynamics of Delaying: Changing Management Structures in Three Countries, in: *Journal of Management Studies* 40(2): 225-256.
- McCann, L.; Morris, J.; Hassard, J. (2008): Normalized Intensity: The New Labour Process of Middle Management, in: *Journal of Management Studies* 45(2): 343-371.
- Michel, A.; Stegmaier, R.; Sonntag, K. (2010): I Scratch Your Back - You Scratch Mine. Do Procedural Justice and Organizational Identification Matter for Employees' Cooperation During Change? In: *Journal of Change Management* 10(1): 41-59.
- Muehler, G.; Beckmann, M.; Schauenberg, B. (2007): The returns to continuous training in Germany: new evidence from propensity score matching estimators, in: *Review of Managerial Science* 1(3): 209-235.
- Nikolowa, R. (2010): Supply of Skilled Labour and Organizational Change, in: *Labour Economics* 17: 514-522.
- Pfeifer, Ch. (2009): Homogene und heterogene Teilnahmeeffekte des Hamburger Kombilohnmodells: Ein Verfahrensvergleich von Propensity Score Match-

- ing und linearer Regression, in: *Wirtschafts- und Sozialstatistisches Archiv* 3(1): 41-65.
- Rajan, R.G.; Wulf, J. (2006): The Flattening Firm: Evidence from Panel Data on the Changing Nature of Corporate Hierarchies, in: *The Review of Economics and Statistics* 88(4): 759-773.
- Rosenbaum, P.; Rubin, D.; (1983): The central role of the propensity score in observational studies for causal effects, in: *Biometrika* 70: 41–50.
- Rousseau, D.M. (1989): Psychological and Implied Contracts in Organizations, in: *Employee Responsibilities and Rights Journal* 2(2): 121-139
- Ruigrok, W.; Pettigrew, A.; Peck, S.; Whittington, R. (1999): Corporate restructuring and new forms of organizing: Evidence from Europe, in: *Management International Review* 39(2): 41-64.
- Shaw, D.; Schneier, C. (1993): Making Organization Change Happen: The Keys to Successful Delaying, in: *Human Resource Planning* 16(1): 1-18.
- Smith, J.; Todd, P. (2005): Does matching overcome LaLonde's critique of non-experimental estimators? In: *Journal of Econometrics* 125(1–2): 305–353.
- Sohr, T. (2005): Wenn die Karriereleiter wegbricht: Fairness und der Abbau von Hierarchieebenen, in: *Zeitschrift für ArbeitsmarktForschung - Journal for Labour Market Research* 38(1): 68-86.
- Wang, L. (2007): Ownership Structure and Organizational Size Dynamics: Evidence on Business Firms, 1993-2003, Working Paper, San Francisco State University, College of Business.
- White, H. (1980): A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, in: *Econometrica* 48(4): 817-838.
- Whittington, R.; Pettigrew, A.; Peck, S.; Fenton, E.; Conyon, M. (1999): Change and Complementarities in the New Competitive Landscape: A European Panel Study, 1992-1996, in: *Organizational Science* 10(5): 583-600.

Tables

Table 1: Delaying Trend

Source	Data set	Period	Results
Colombo and Delmastro (1999, 2008)	438 Italian manufacturing plants with more than ten employees (stratified with respect to industry (within manufacturing), geographical area and size)	1989-1997	74% (65%, 36%) of plants with six (five, four) management levels have removed one or more level; span of control of large plants (> 500 employees) has increased from 8.74 to 12.51.
Whittington et al. (1999)	non-representative ¹³ survey of about 450 Western European large- and median-sized firm (i.e., with 500 or more employees)	1992-1996	30% of these firms delayed at least one level ¹⁴ ; average number of managerial levels between the CEO and the division heads – i.e., the lowest managers with profit center responsibility – decreased from 3.6 to 3.3.
Rajan and Wulf (2006)	300 large US firms (balanced sample: N = 51)	1986-1998	average number of positions between the CEO and the division heads – i.e., the lowest managers with profit center responsibility – has decreased by 25%; average (median) number of managers reporting directly to the CEO has gone up from 4.4 (4) to 8.2 (7).
Littler, Wiesner and Dunford (2003)	Great Britain, 150 employees	1987-1992	68% of these organizations had done delaying or another form of restructuring.
	---“--- 2'964 organizations with 50 or more employees in South Africa, Australia, and New Zealand	Late 1990s 1994-1996	34% of organizations had done delaying. 45.5% of organizations in South Africa had delayed, 44% in Australia, and 37.5% in New Zealand.
Littler and Innes (2004)	4'153 Australian firms ¹⁵	1990-1999	managerial span of control rose from 11.38 to 14.41.

Source: Own compilation.

¹³ According to the authors, questionnaires were sent out to the largest 1'500 UK firms and to 2'000 firms in other countries. No comprehensive list is provided but Germany, France, Spain, Italy, Netherlands and one or more Scandinavian countries seem to be covered. The non-UK sample was proportional to the GDP of the respective countries. The overall response rate was 13.1%.

¹⁴ Ruigrok et al. (1999) use the same data set and provide more detailed information. The extent of delaying varies among countries. For instance, in the UK, 28% of the firms have delayed, 32% in German-speaking countries, 29% in Southern Europe and 33% in Northern Europe.

¹⁵ The data used by Littler and Innes (2004) exclude the public sector, overrepresent the manufacturing industry, and do not cover small and medium-sized corporations. Despite this, the descriptive analysis of the authors provides valuable insights into the change of organizational structure on a large-scale basis for Australia.

Table 2: Transition Probability Matrix

number of levels in 2000	number of levels in 2005								Total
	0	1	2	3	4	5	6	7	
0	33.33	33.33	0.00	33.33	0.00	0.00	0.00	0.00	100.00
1	0.69	27.78	49.31	15.28	3.47	2.78	0.69	0.00	100.00
2	0.82	15.64	44.03	27.98	9.47	1.65	0.41	0.00	100.00
3	0.00	9.89	26.92	40.11	16.48	5.49	1.10	0.00	100.00
4	0.00	4.48	16.42	40.30	28.36	7.46	1.49	1.49	100.00
5	0.00	23.53	11.76	29.41	23.53	5.88	0.00	5.88	100.00
6	0.00	0.00	25.00	25.00	25.00	0.00	25.00	0.00	100.00
7	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	100.00
8	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	100.00
Total	0.60	15.71	36.40	29.91	12.39	3.78	0.91	0.30	100.00

Note: Calculation restricted to 662 firms covered in both surveys.

Source: Organization Survey 2000, Innovation Survey 2005, own calculations.

Table 3: OLS Estimates of Performance Effects of Delaying

Dependent variable	Log Value Added			Log (Value Added / Total Wages)		
<i>lnK</i>	0.140*** (0.000)	0.140*** (0.000)	0.143*** (0.000)	0.067*** (0.000)	0.065*** (0.000)	0.066*** (0.000)
<i>lnL</i>	0.866*** (0.000)	0.864*** (0.000)	0.837*** (0.000)	-0.058*** (0.002)	-0.059*** (0.002)	-0.069*** (0.000)
<i>delayer</i>	0.216*** (0.002)	0.206*** (0.003)	0.195*** (0.005)	0.134** (0.021)	0.114* (0.055)	0.119** (0.045)
<i>down</i>		0.040 (0.239)	0.012 (0.709)		0.038 (0.125)	0.036 (0.163)
<i>decentr</i>		0.004 (0.910)	-0.020 (0.533)		0.033 (0.227)	0.026 (0.333)
<i>level</i>			0.011 (0.503)			0.008 (0.433)
<i>foreign</i>			0.228** (0.002)			0.064* (0.067)
<i>skilled</i>			0.001 (0.436)			-0.002** (0.025)
<i>train</i>			0.001 (0.382)			0.000 (0.985)
<i>ICT01</i>			0.145*** (0.001)			0.073*** (0.010)
<i>export</i>			0.001 (0.108)			0.000 (0.634)
<i>compet01</i>			-0.072** (0.043)			-0.050* (0.052)
<i>intens01</i>			0.038 (0.218)			0.022 (0.373)
<i>founded</i>			0.001 (0.111)			0.000 (0.243)
<i>Regional dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Sector dummies</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	10.571*** (0.000)	10.569*** (0.000)	9.449*** (0.000)	-4.741*** (0.000)	-4.745*** (0.000)	-5.262*** (0.000)
N	1'066	1'066	1'066	1'025	1'025	1'025
R ²	0.8377	0.8379	0.8504	0.2115	0.2149	0.2330

Note: Numbers in parentheses are p-values. Standard errors are heteroscedasticity-robust according to White (1980). */**/** indicate significance on the 10/5/1% level.

Source: Innovation Survey 2005, own calculations.

Table 4: PSM Estimates of Performance Effects of Delaying

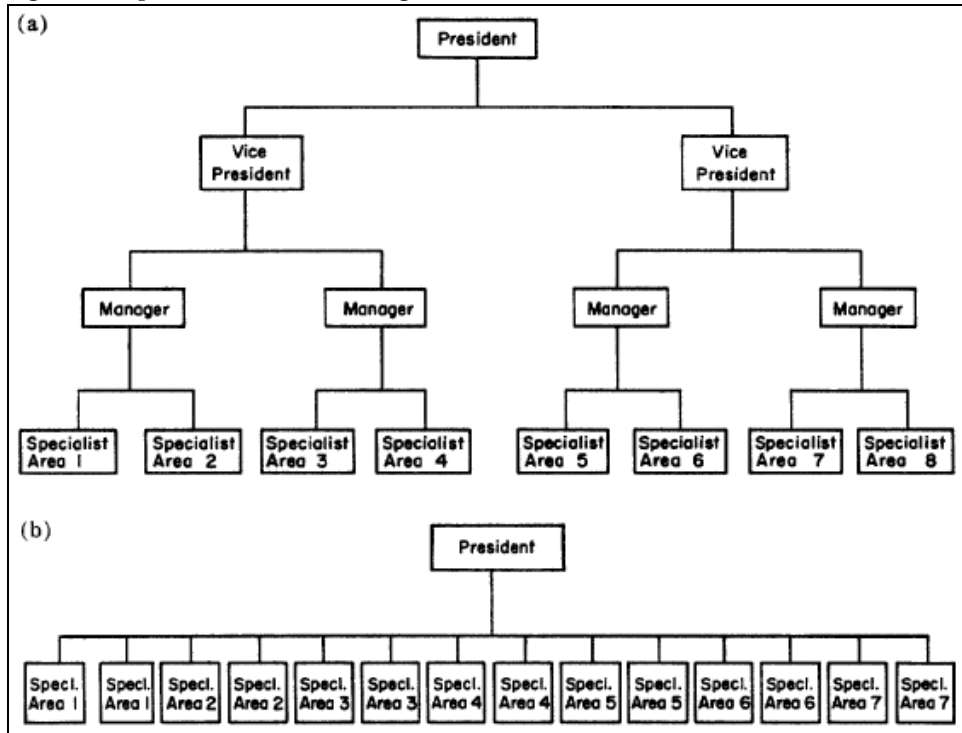
Dependent variable	Log Value Added		Log (Value Added / Total Wages)	
	ATE	ATT	ATE	ATT
Nearest-neighbor ($n = 4$)	0.520** (0.025)	0.195 (0.243)	0.031 (0.643)	0.096 (0.112)
Nearest-neighbor ($n = 1$)	0.785** (0.020)	0.341 (0.230)	0.014 (0.839)	0.188*** (0.003)
Radius (caliper = 0.01)	0.454** (0.042)	0.170 (0.267)	0.074 (0.181)	0.143** (0.011)
Radius (caliper = 0.005)	0.236 (0.321)	0.162 (0.313)	0.082 (0.239)	0.142** (0.016)
Kernel	0.290 (0.130)	0.225 (0.143)	0.083 (0.108)	0.141** (0.012)
LLR	0.462* (0.097)	0.190 (0.223)	0.062 (0.416)	0.153*** (0.009)
Treated	122		118	
N	1'242		1'191	

Note: Numbers in parentheses are p-values. */**/** indicate significance on the 10/5/1% level. LLR stands for local linear regression.

Source: Organization Survey 2000, Innovation Survey 2005, own calculations.

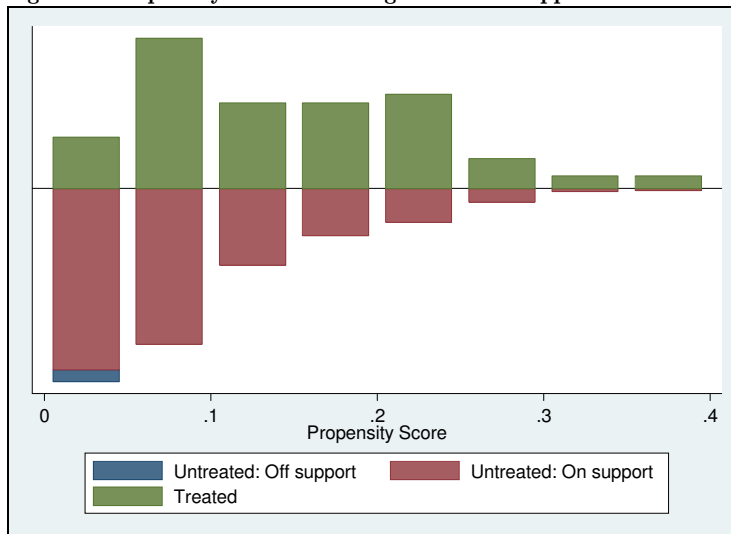
Appendix

Figure 1: Depth and Breadth of an Organization



Source: Carzo and Yanouzas (1969).

Figure 2: Propensity Score Matching: Common Support



Source: Organization Survey 2000, Innovation Survey 2005, own calculations.

Table A 1: Descriptive Statistics

Variable	Observations	Mean	Std.Dev.	Min	Max
$\ln(VA/W)$	1'025	-4.053	0.423	-4.605	-0.010
$\ln VA$	1'066	16.54	1.33	13.605	23.591
$\ln K$	1'066	13.46	1.89	2.303	24.750
$\ln L$	1'066	4.63	1.11	0	10.575
<i>delayer</i>	1'066	0.10	0.30	0	1
<i>down</i>	1'066	0.42	0.49	0	1
<i>decentr</i>	1'066	0.36	0.48	0	1
<i>level</i>	1'066	2.52	1.21	0	15
<i>foreign</i>	1'066	0.17	0.37	0	1
<i>skilled</i>	1'066	20.17	18.27	0	100
<i>train</i>	1'066	28.68	27.94	0	100
<i>ICT01</i>	1'066	0.48	0.50	0	1
<i>export</i>	1'066	25.97	35.29	0	100
<i>compet01</i>	1'066	0.39	0.49	0	1
<i>intens01</i>	1'066	0.43	0.49	0	1
<i>founded</i>	1'066	1942.29	46.34	1350	2005

Note: Calculation restricted to OLS regression sample (dependent variable: $\ln VA$). Regional and sector controls have been omitted due to space reasons.

Source: Innovation Survey 2005, own calculations.

Table A 2: Probit Estimates of Propensity Scores of Delaying

Dependent variable: Delaying (probit estimation)				
Outcome variable for PSM in 2 nd step:	Log Value Added		Log (Value Added / Total Wages)	
<i>decentr</i>	0.597***	(0.000)	0.599***	(0.000)
<i>down</i>	0.409***	(0.000)	0.441***	(0.000)
<i>reg002</i>	0.011	(0.954)	-0.014	(0.941)
<i>reg003</i>	0.010	(0.961)	-0.011	(0.955)
<i>reg004</i>	0.118	(0.523)	0.145	(0.436)
<i>reg005</i>	-0.135	(0.490)	-0.180	(0.366)
<i>reg006</i>	-0.040	(0.862)	-0.028	(0.901)
<i>reg007</i>	-0.184	(0.536)	-0.200	(0.504)
<i>sec002</i>	-0.150	(0.399)	-0.131	(0.467)
<i>sec003</i>	-0.139	(0.384)	-0.215	(0.201)
<i>sec004</i>	-0.480	(0.152)	-0.408	(0.235)
<i>sec005</i>	0.100	(0.660)	0.021	(0.930)
<i>sec006</i>	0.251	(0.156)	0.243	(0.175)
<i>sec007</i>	0.077	(0.774)	-0.085	(0.770)
<i>Constant</i>	-1.740***	(0.000)	-1.731***	(0.000)
N	1'242		1'191	
Pseudo R2	0.0843		0.0892	
chi2(14)	67.22		68.67	
Prob > chi2	0.000		0.000	
Log likelihood	-365.287		-350.417	

Note: Numbers in parentheses are p-values. */**/** indicate significance on the 10/5/1% level.

Source: Organization Survey 2000 (*reg002-reg007*, *sec002-sec007*), Innovation Survey 2005 (*delayer*, *decentr*, *down*), own calculations.

Table A 3: Standardized Bias

	Sample	Mean		%bias	%reduct bias
		Treated	Control		
<i>decentr</i>	Unmatched	0.615	0.316	62.6	
	Matched	0.615	0.607	1.7	97.3
<i>down</i>	Unmatched	0.631	0.404	46.7	
	Matched	0.631	0.643	-2.5	94.6
<i>reg002</i>	Unmatched	0.205	0.215	-2.5	
	Matched	0.205	0.162	10.5	-319.4
<i>reg003</i>	Unmatched	0.148	0.150	-0.7	
	Matched	0.148	0.205	-16.1	-2233.3
<i>reg004</i>	Unmatched	0.246	0.192	13.0	
	Matched	0.246	0.240	1.5	88.6
<i>reg005</i>	Unmatched	0.156	0.183	-7.3	
	Matched	0.156	0.164	-2.2	70.0
<i>reg006</i>	Unmatched	0.090	0.090	0.0	
	Matched	0.090	0.080	3.6	-69900.0
<i>reg007</i>	Unmatched	0.033	0.046	-7.0	
	Matched	0.033	0.035	-1.0	85.0
<i>sec002</i>	Unmatched	0.082	0.143	-19.3	
	Matched	0.082	0.080	0.7	96.6
<i>sec003</i>	Unmatched	0.131	0.153	-6.2	
	Matched	0.131	0.127	1.2	81.0
<i>sec004</i>	Unmatched	0.016	0.046	-17.3	
	Matched	0.016	0.020	-2.4	86.4
<i>sec005</i>	Unmatched	0.066	0.042	10.5	
	Matched	0.066	0.045	9.1	13.2
<i>sec006</i>	Unmatched	0.123	0.083	13.1	
	Matched	0.123	0.150	-8.8	33.3
<i>sec007</i>	Unmatched	0.041	0.039	0.9	
	Matched	0.041	0.025	8.3	-865.5

Note: This table refers to the propensity score estimation of delayering in which matching in the second step is performed applying nearest-neighbor matching ($n = 4$) and using log value added as outcome, i.e. to the middle column of Table A2.

Source: Organization Survey 2000 (*reg002-reg007*, *sec002-sec007*), Innovation Survey 2005 (*delayer*, *decentr*, *down*), own calculations.