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Testing the Role of Comparative Advantage and Learning in Wage and Promotion Dynamics*

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Abstract

Can job assignment based on comparative advantage and learning about workers' ability explain wage and promotion dynamics within firms? In order to answer this question the Gibbons and Waldman (1999b) model is estimated in a Generalized Method of Moments (GMM) framework using a unique data set on white collar workers in Norway for the years 1987-1997. The estimation is carried out on two different occupational groups: technical and administrative white collar workers. The selection of workers into a given position within a firm hierarchy is based on comparative advantage. Both measurable and unmeasurable skills are important. This holds in both occupations studied. When it comes to firms' learning about their workers the results are not so clear. But overall the results on learning seem to have stronger support than what previous studies have found. In general, there is more evidence for learning about administrative white collar workers than about technical white collar workers.

Key words: Internal labor markets, promotion, wages, comparative advantage, learning, linked employer–employee data.

JEL codes: M5

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1 Introduction

The literature on internal labor markets suggests that internal mobility of workers is important. The theory assumes that workers are hired at lower levels in the firm hierarchy (ports of entry) and promoted into higher positions. This internal mobility is an important part of a firm's personnel policy and serves two purposes. The first is to make an efficient assignment of workers to jobs. The second is to provide incentives. One way of creating incentives is to promote workers. Since internal mobility has consequences for both the individual worker and the firm, it is important to understand the underlying mechanisms. More specifically, the question asked in this paper is: Can job assignment based on workers' comparative advantage and firms learning about workers' ability explain wage and promotion dynamics within firms?

This paper contributes to a very small empirical literature on wage and promotion dynamics within firms using the Gibbons and Waldman (1999b) model (GW99) as a theoretical framework. Methodologically, I follow Lluis (2005), but extend on her paper along two dimensions. First, as pointed out by Osterman (1982), firms may consist of "several often quite different internal labor markets." Therefore I analyze two large and important occupational groups separately; technical white collar workers and administrative white collar workers. Second, Lluis (2005) has a relatively small survey from Germany, while I have a large administrative data set. My data cover a population of white collar workers within firms and changes in rank are reported by employers, not by the workers themselves. Also, the institutional setting in Norway is more suitable for studying learning than in Germany. Lluis speculates that her poor fit of the model with learning is due to the apprenticeship system affecting her data.

My results suggest the following: Selection of workers into a given position within a firm hierarchy is based on comparative advantage. Both measurable and unmeasurable skills are important. This holds in both occupations studied. When it comes to firms learning about their workers' abilities the results are not so clear. In general, there is more evidence for learning about administrative than for technical white collar workers. Overall, and in contrast to what Lluis finds in the German data, the results on learning seem to have support in the Norwegian data.

The paper unfolds as follows. Sections 2and 3 discuss relevant literature and present an overview of GW99. Sections 4 and 5 present the data and some descriptive analysis. Section 6 describes the empirical setup along with a discussion of several methodological challenges. Section 7 discuss the estimation results and Section 8 summarizes and concludes the paper.

2 Background

Empirical findings by Baker, Gibbs and Holmstrom (1994a) (BGH) have inspired much theoretical work including Gibbons and Waldman (1999b).[1] Gibbons and Waldman build an integrative model incorporating job assignment, on-the-job human-capital acquisition, and learning.[2] Comparative advantage implies that workers' skills are rewarded differently at different hierarchical levels and

[1]Gibbons and Waldman (1999a) present a survey of careers within organizations. See also Gibbons (1998, 1997) and Baker, Jensen, and Murphy (1988). See Lazear and Rosen (1981) for a specific theory of incentives and mobility; the tournament theory.

[2]In Gibbons and Waldman (2006) they enrich their 1999–model by including schooling and "task-specific" human capital. The latter extension produces cohort effects.

workers are sorted by their skills and abilities into a given position in the hierarchy.[3] Firms learn about the workers' innate abilities over time. In the Gibbons and Waldman model there is symmetric learning about workers' abilities, implying that any new information about the workers' abilities is publicly known to all firms. The GW99 model explains five important findings in BGH. (1) real-wage decreases are not rare, but demotions are. (2) Wage increases are serially correlated. (3) Promotions are associated with large wage increases. (4) Wage increases on promotion are small relative to the difference between average wages across levels of the job ladder. (5) Workers who receive large wage increases early in their stay at one level of the job ladder are promoted quickly to the next. Gibbons and Waldman derive their model both without and with learning. In general, the learning case gives better predictions. See Table 1.

Three previous papers use the GW99 model to study dynamics of wages and careers within firms. They all differ in terms of methodology applied. Lima and Pereira (2003) use Portuguese data for the years 1991–1995. The authors modify the GW99 model somewhat to fit it into a fixed effect panel data estimation framework. They assume full information about workers' innate abilities at all times and, as opposed to the comparative advantage hypothesis, that ability is rewarded the same at each hierarchical level. Given their simplifying assumptions they find "a stronger employer learning and/or human capital accumulation effect at the bottom of the hierarchy and a stronger job assignment effect at the top."

Dias da Silva and van der Klaauw (2006) also use Portuguese data. The years covered are 1991 to 2000. In contrast to the previous study they are more explicit in testing the predictions of the GW99 model within a dynamic panel setting.[4] Dias da Silva and van der Klaauw find significant positive serial correlation in wage increases and promotion rates, from which the authors conclude that employer learning about the worker's ability might be important. In their analysis they also conclude that the Portuguese labor market is not competitive. After discussing different definitions of promotion they "argue that employer–reported promotions relate to a large extent to wage increases rather than changes in job tasks and complexity."[5] [6]

The third paper, which stands out from the other two with respect to methodology, is Lluis (2005) using German survey data for the years 1985–1996. In contrast to the two papers discussed above, she looks for whether one can find evidence of comparative advantage and learning in her data, i.e. she investigates the underlying theoretical building blocks in the GW99 model. The estimation is performed within a Generalized Method of Moments (GMM) framework. She finds that both measured and unmeasured ability is important in the rank assignment, with unmeasured ability being most important at higher levels. However, it is hard to find evidence of learning in her data set. She attributes this to the German apprenticeship system where firms and workers have the opportunity to

[3]Formally, comparative advantage can be defined as follows (Sattinger, 1993). Define a_{ij} as the number of times that worker *i* can perform job *j*'s task per period. Worker 1 has a comparative advantage at job 1 and worker 2 has a comparative advantage at job 2 if $a_{11} / a_{21} > a_{12} / a_{22}$.

[4]See also Belzil and Bognanno (2005) for a similar (dynamic) approach but without the Gibbons-Waldman model as the theoretical framework.

[5]Matthews (1986) writes: "[Promotion] is so familiar that it is easy to overlook just how complicated it is. Typically is has all the following features. There is a system of ranks; responsibilities go with rank; so does pay and usually pension, so that rank maximisation becomes the proxy for income maximisation; promotion takes place only by one step at a time; there is property in rank, in the sense that demotion occurs seldom or never, poor performance being penalised instead by lack of future promotion or in extreme cases dismissal; there is retirement age, after which responsibilities fall at a stroke from a lifetime high to zero."

[6]Promotions can also be seen as pay for performance: "Promotions appear to be the most important form of pay for performance in most organizations, especially in hierarchical, white-collar firms" (Gibbs, 1996).

learn about the quality of the match before workers finish formal education and start the job search. One implication of this is reduced need for job mobility to learn about workers' abilities. This is supported by the low mobility figures she observes in the German data.

The findings in the BGH study, the empirical foundation for GW99, were based on evidence from one US firm only. However, labor market institutions differ between countries. This makes it interesting to estimate the model on data for different countries in order to facilitate comparative analysis, and assess whether the model is as general as intended. In particular it is interesting to see whether it is possible to find evidence of learning since Lluis did not find very compelling evidence for this.

I use data of white collar workers in Norway for the years 1987–1997. The data is collected by the main employers' organization in Norway, and as such it differs from the German data which is based on surveys among individuals. The data is collected for wage negotiation purposes and is of high quality. One of its unique features is that it contains information about the workers' ranks. Another important feature is that I have exact information on changes in the workers' positions due to detailed hierarchical codes recorded by the employers. In the German survey data the workers themselves report changes in their positions. Given the sample size, it is possible to estimate the model for two different occupations. The first is technical white collar workers, 202,142 observations. The second is administrative white collar workers, 227,077 observations. This makes it possible to compare two different occupational groups and see whether the parameters of the model differ between occupations. When estimating the GW99 model one needs a one period lag in the no-learning case and a two period lag in the learning case. Lluis in her paper maximizes the sample size depending on which version of the model she estimates. Given my large sample, I can afford to keep the same sample size in both the no-learning and learning case. In this way the results in the two model versions are not affected by changes in the sample.

3 Gibbons and Waldman (1999): An Integrative Model

There are two versions of the model, one with full information and one with symmetric learning.

Full information

In the model with full information, job assignment and human-capital acquisition drive the dynamics in the model.

The economy consists of identical firms. There is free entry into production, labor is the only input factor in production, and the firms and workers are risk-neutral and have a discount rate of zero. Worker *i*'s career lasts for *T* periods. Let θ_i denote *i*'s innate ability, and assume that θ_i is common knowledge at the beginning of the worker's career. $\theta_i \in \{\theta_H, \theta_L\}$ where *H* is high and *L* is low. Worker *i*'s effective ability at time *t* (*t*=1,…,*T*) is given by

$$\eta_{it} = \theta_i f(x_{it}) \qquad (f_x > 0 \quad \text{and} \quad f_{xx} \leq 0) \tag{1}$$

where $f(\cdot)$ is some function of *i*'s labor-market experience x_{it} prior to time *t*.

Firms have J hierarchical levels (jobs).[7] Worker i produces

$$y_{ijt} = d_j + c_j(\eta_{it} + \varepsilon_{ijt}) \tag{2}$$

if he is assigned to level j in period t. d_j and c_j are (technological) constants, with $0 < d_J < d_{J-1} < \ldots < d_1$ and $c_J > c_{J-1} > \ldots > c_1 > 0$, and ε_{ijt} is a noise term/productivity shock with characteristics $N(0, \sigma^2)$.

Define η^j as the solution to

$$d_j + c_j\eta^j = d_{j+1} + c_{j+1}\eta^j \tag{3}$$

that is, η^j is the level of effective ability that makes a worker equally productive at level j as at level j+1. The worker is assigned to job j if $\eta_{it} < \eta^j$. If $\eta_{it} = \eta^j$, then worker i is assigned to level j+1.

Since the production equation (3) is linear, the model is easy to depict graphically, see Figure 1 where J=3.

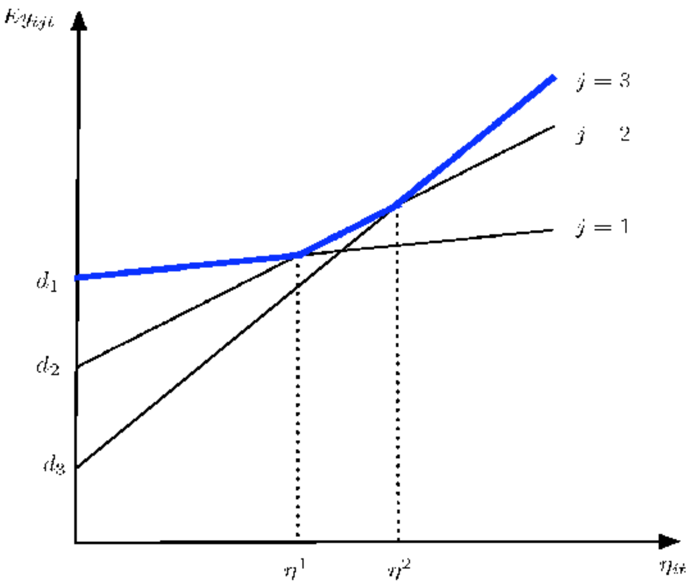

Figure 1: Worker assignment with J=3. Equilibrium job assignment is along the bold line.

[7] Gibbons and Waldman (1999b) use 3 hierarchical levels. Gibbons and Waldman (2006) use 2 since the model's main conclusion is not sensitive to the number of levels.

An effective job assignment is along the bold line. If $\eta_{ijt} < \eta^1$ a worker is assigned to level 1, if $\eta^1 < \eta_{ijt} < \eta^2$ he is assigned to level 2, and if $\eta_{ijt} > \eta^2$ he is assigned to level 3. We note that as we move up in the hierarchy the worker's output is more sensitive to effective ability. The c_j parameter is monotonically increasing with the levels.[8]

Because of competition among the firms wages *w* are equal to expected output

$$w_{ijt} = Ey_{ijt} = d_j + c_j\eta_i = d_j + c_j\theta_{it} f(x_{it}). \tag{4}$$

Note that since η_{it} increases monotonically with labor market experience demotions cannot occur.

<u>Symmetric learning</u>

In this version of the model, firms are uncertain about the worker's innate ability θ_i. Let p_0 be the firm's initial belief that a worker's innate ability is θ_H at the beginning of the worker's career and $(1 - p_0)$ that the worker's innate ability is θ_L. Learning occurs only gradually because of the stochastic element ε_{ijt} in the production function. A signal about worker's effective ability is given by

$$z_{it} = \frac{y_{ijt} - d_j}{c_j} = \eta_{it} + \varepsilon_{ijt}. \tag{5}$$

The expected innate ability of worker *i* in period *t* is denoted by η_{it}^e and is given by

$$\theta_{it}^e = E(\theta_i \mid z_{it-x}, \ldots, z_{it-1}) \tag{6}$$

and the effective ability is now

$$\eta_{it}^e = \theta_{it}^e f(x_{it}). \tag{7}$$

The worker's wage becomes

$$w_{ijt} = Ey_{ijt} = d_j + c_j\eta_{it}^e = d_j + c_j\theta_{it}^e f(x_{it}). \tag{8}$$

[8]This is in line with e.g. Leonard (1990) who writes: "Position in the corporate hierarchy is one of the strongest determinants of pay. In a number of economic models, this link is attributed to the greater sensitivity of corporate success to the acts of higher-level executives than to those of lower-level executives. Executives with a wider span of control are expected to have greater marginal revenue products."

As stated in the Introduction, the Gibbons and Waldman model sets out to explain five facts from the BGH study. Table 1 summarizes whether the two model versions are able to generate the predictions.

Table 1: Summing up the predictions of the GW99 model. FI = Full information. SL = symmetric learning

Prediction	FI	SL
1. Real wage decreases are not rare, but demotions are.	No	Yes
2. Wages are serially correlated.	Yes	Yes
3. Promotions are associated with large wage increases.	"weak form"	Yes
4. Wage increases on promotion are small relative to the difference between average wages across levels of the job ladder.	Yes	Yes
5. Workers who receive large wage increases early in their stay at one level of the job ladder are promoted quickly to the next.	Yes	Yes

4 Data description

I use data from the Confederation of Norwegian Enterprise (NHO). This is the main employers' organization in Norway. NHO has about 16,000 member companies. 73% of these companies have records for fewer than 20 person-years. The member companies employ about 450,000 workers, mainly in construction, services and manufacturing in Norway.[9] There is a bias towards manufacturing. Many of the member companies in NHO operate in export and import competing industries. The total labor force in Norway is about 2.3 million workers, of whom about half were employed in the public sector in the year 2000, hence the NHO cover roughly 40% of private sector employment. The members of NHO also produced about 40% of private sector GDP.

The data is based on establishment records for all white-collar workers employed by firms that are members of the NHO confederation. The data quality is high as the wage data were a major source of information for the collective wage bargaining process in Norway between the NHO and the unions. The data cover on average 97,000 white-collar workers per year in different industries (although biased towards manufacturing) during the years 1980-1997.[10] CEOs (and in large firms, vice CEO) are not included. The average number of plants is 5,000 and the average number of firms is 2,700 per year. To obtain more information we have merged the NHO with the main administrative matched employer-employee data base assembled by Statistics Norway. This database has a rich set of information on workers and plants for the period 1986-2002. One of the reasons for merging the NHO data set with the administrative register, besides obtaining more information, is that it is unclear whether the information reported in the NHO statistics pertains to plants, firms or a combination of the two. For more detailed information about the NHO data and the merging process, see Hunnes, Møen, and Salvanes (2007). Because of the merging with the administrative data set, I restrict the years used in this paper to 1987-1997.[11]

[9]NHO (2004)

[10]The year 1987 is missing. However, the data set for each year contains lagged values; hence, I was able to reconstruct 1987 by using lagged values in the 1988 file. This is of course not a perfect reconstruction, since I do not have information on workers who left the data set in 1987 and were not present in the 1988 file.

[11]For each observation I need two years of lagged values. This implies that I also use information from both the 1986 and 1985 files. See Section 6 for more information.

A great advantage of our data set is that it has information about occupations and hierarchical levels. Each worker is assigned an occupational group and a level *within* the occupational group. The groups are labeled A-F: Group A is technical white collar workers; Group B is foremen; Group C is administration; Group D is shops and Group E is storage. Group F is a miscellaneous group consisting of workers that do not fit in any of the other categories. Hierarchical level is given by a number where zero represents the top level. The number of levels varies by group and ranges from 1 (F) to 7 (A).[12] These codes are made by NHO for wage bargaining purposes, and as such, they are similar across plants and industries.

In this paper I restrict the sample to look at group A (technical white collar workers) and group C (administrative white collar workers) only. About 35% of the workers belong to group A and about 40% belong to group C. In the estimations I run separate regressions. This implies that I do not have to create a single hierarchy within the firm across different occupations. Such a harmonization is not straightforward.[13] Further, by analyzing the two occupations separately the estimation of the rank coefficients will not be influenced by workers who switch ranks because they switch occupation. Some workers switch occupations e.g. from technical jobs to administrative jobs.

The wage variable is monthly wage on September 1st including the value of fringe benefits and excluding overtime and bonuses. Indirect costs to the plant such as payroll tax, pensions etc are not included. I transform nominal wages to real wages using the Consumer Price Index with base year 1997.

In creating the sample I apply the following: (1) Monthly wage should be at least NOK 2,000 measured in 1980 kroner (to remove outliers) and I look at only full time workers (over the age of 16), i.e. numbers of hours worked per week should be at least 30. (2) Observations where one or several of the variables are missing are dropped from the sample. (3) Labor market experience is potential labor market experience. (4) Since the instruments matrices will be dominated by columns with zeros and ones, I restrict the moves up or down along the career path to 2 levels between each time period. In a small number of cases I do observe workers who move between one of the two lowest levels and the highest level. For group A, I have in addition aggregated the two highest levels into one and the two lowest levels into one.[14] [15]

5 Descriptive analysis

I start this section by presenting summary statistics by hierarchical level in Table 2.[16] As expected, average wage increases along the hierarchy with the wage at the top level being about twice the wage at the lowest level for technical workers. For administrative workers the ratio is about 2.8. At the three lowest levels the wages for technical workers are larger than for administrative workers, but on the two highest levels the average wages for administrative workers are larger than for technical workers. This is especially true for the highest level where administrative workers earn 17.5% more than technical workers. The same pattern holds more or less for wage increases as well. The ratio between top/bottom

[12]Note that not all firms will have workers on each of the seven levels.

[13]One problem lies in the fact that some levels overlap with respect to responsibility in the organization. For more on this, see Hunnes, Møen, and Salvanes (2007) using the data where a single hierarchy within the firm is created.

[14]By doing this, I reduce the instrument matrix Z from 49 possible instruments (i.e. interaction terms) to 25. I also drop columns in the instrument matrix which only contains zeros. See Section 6.

[15]Group C has by definition 5 hierarchical levels. To make the estimation results for the two occupational groups comparable I choose to keep all 5 ranks in the administrative group.

[16]In the descriptive analysis I treat all the firms as one big firm, i.e. I do not take into account firm heterogeneity.

in the two groups is now 2.6 and 3.6 implying that there is larger inequality in wage increases for administrative workers.

In general, the average age for administrative workers is a bit higher than for technical workers, except for the lowest level. And the age increases with the hierarchical levels. For both groups years of education increase with the rank. Overall, technical workers have one more year of schooling compared to administrative workers. Workers on the highest level have about a 4-5 year longer education than the workers at the lowest level.

Turning to experience, we see from the table that even if experience increases with rank, there is, on average, no large difference between top and bottom ranks for technical workers. For administrative workers, on the other hand, there is about 4 years difference in experience between top and bottom in the firm hierarchy. In general, administrative workers have more experience than technical workers. But this is not surprising since technical workers, in general, have more education.

On the two lowest levels, females are in the majority among administrative workers. But the female share decreases with rank, for both of the two groups. This is especially noticeable for administrative workers. Even if the female share is 88% at the lowest level it is only 3% at the top level. It is clear that very few women make it past middle management (level 3).

The skill index increases with the levels, and on average it is higher for administrative workers than for technical workers.[17]

[17]See Section 6.1 for a definition of the skill index.

Table 2: Summary statistics (means) by level. Standard deviation in parenthesis.

			Technical white collar workers (*N*=202,142)				
Level	Wage	Δ wage	Age	Education	Experience	Female	Skills
1	18,362	218	42.2	10.9	23.3	.23	-.27
	(2,463)	(889)	(11.2)	(1.9)	(12.1)	(.42)	(.24)
2	21,385	379	40.7	12.6	20.1	.12	-.13
	(3,069)	(1,098)	(10.7)	(2.3)	(11.9)	(.33)	(.25)
3	25,936	426	43.0	13.8	21.1	.07	.09
	(4,210)	(1,365)	(9.7)	(2.4)	(10.8)	(.25)	(.30)
4	31,181	480	45.4	14.5	22.9	.05	.25
	(4,415)	(1,655)	(9.1)	(2.5)	(10.1)	(.22)	(.33)
5	38,066	569	47.9	15.6	24.2	.03	.48
	(5,833)	(1,970)	(8.0)	(2.3)	(8.6)	(.16)	(.35)
			Administrative white collar workers (*N*=227,077)				
Level	Wage	Δ wage	Age	Education	Experience	Female	Skills
1	15,579	243	39.8	10.6	21.2	.88	-.19
	(2,066)	(852)	(11.8)	(1.5)	(12.6)	(.32)	(.22)
2	18,084	262	42.2	11.0	23.2	.68	-.07
	(2,476)	(919)	(10.7)	(1.7)	(11.4)	(.47)	(.23)
3	23,786	409	43.9	12.0	23.9	.30	.09
	(4,213)	(1,343)	(10.0)	(2.2)	(11.0)	(.46)	(.27)
4	31,867	543	46.1	13.3	24.8	.09	.32
	(6,159)	(1,805)	(8.7)	(2.43)	(9.6)	(.29)	(.35)
5	44,741	872	48.2	14.8	25.4	.03	.59
	(8,925)	(3,205)	(8.0)	(2.3)	(8.5)	(.16)	(.37)

Monthly real wage in 1997 kroner. Education in years of schooling. Experience is potential experience, that is, age minus years of schooling minus 7. Skills are given by the skill index, see Section 6.1.

Figure 2 shows that mean wage increases along the career path. For both groups the following is true: (1) There is large wage variation within a given level, and the standard deviation increases with the ranks. In other words, wage inequality within a given level increases along the career path. (2) There is considerable overlap between the wage intervals in the different hierarchical levels, which is in line with previous findings, see e.g. Baker, Gibbs and Holmstrom (1994a). The figure also reveals that the (level, wage)–curve is more convex for administrative than for technical workers. This implies that administrative workers are faced with more wage inequality between the ranks than technical workers. Also notice that both the average wage and its standard deviation are much larger for administrative workers at the two top levels.

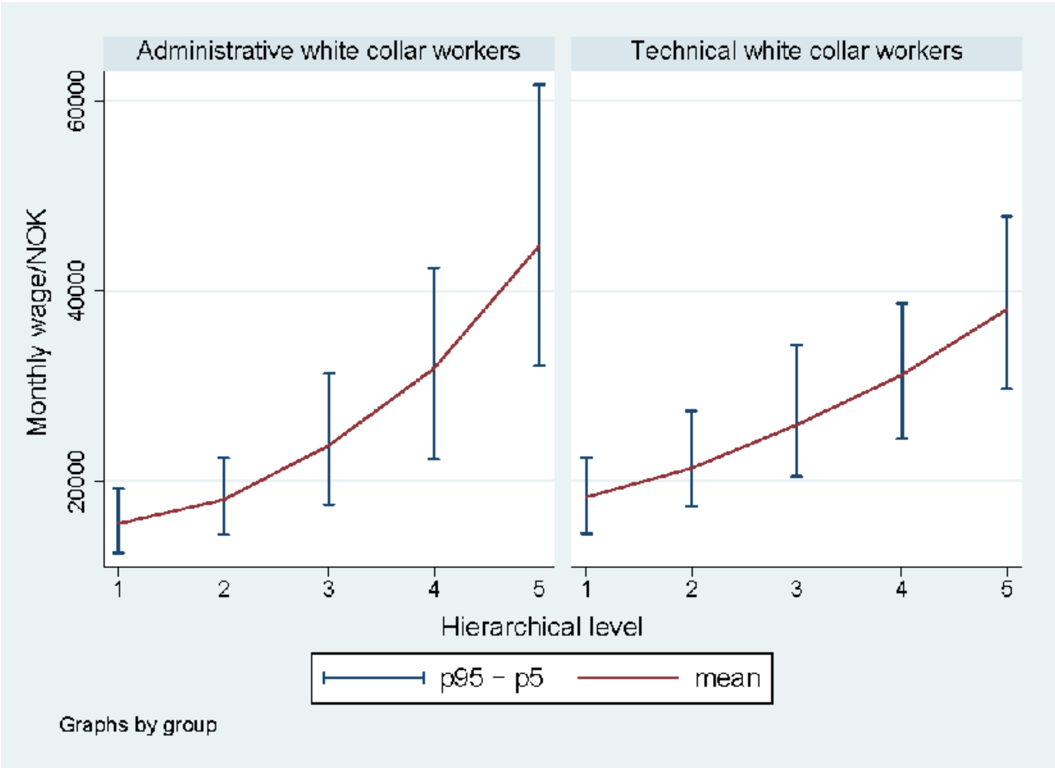

Figure 2: Average monthly real wage by hierarchical level.

The rest of the descriptive analysis is organized around the five predictions that the Gibbons and Waldman (1999b)–model generates. By looking for evidence of the predictions in the sample, one can get a sense of whether the data will support the GW99 model or not.

Are real wage decreases rare?

Real wage decreases are not rare as documented by Table 3. The fraction of workers who received a real wage decrease differed from as few as 6–9% in 1996 to as many as 76–80% in 1988, a recession year. One interesting observation is that during the late 80s the higher levels are more affected by real wage decreases than the lower levels. The fraction of workers who experienced a real wage decrease more or less increases with the hierarchy. This was a period with increasing unemployment and a downturn in the Norwegian economy. From 1991 and onwards it seems as if the top levels are those least affected by real wage decreases, at least for technical workers. Comparing the means for the two occupational groups, it seems as if there is a larger fraction of administrative workers experiencing real wage decreases. The bottom line is that real wage decreases are not rare.

Table 3: Fraction of workers who had a real wage decrease from *t*–1 to *t* by hierarchical level.

Year	Level 1	Level 2	Level 3	Level 4	Level 5	mean
Technical white collar workers (*N*=202,142)						
1987	.73	.69	.71	.77	.82	.75
1988	.80	.76	.79	.82	.82	.80
1989	.53	.62	.64	.70	.71	.64
1990	.20	.27	.27	.23	.23	.24
1991	.31	.29	.29	.29	.22	.28
1992	.42	.34	.35	.35	.30	.35
1993	.43	.35	.33	.35	.32	.36
1994	.16	.15	.17	.17	.17	.16
1995	.20	.22	.26	.22	.21	.22
1996	.07	.06	.06	.05	.04	.06
1997	.16	.14	.13	.12	.10	.13
Administrative white collar workers (*N*=227,077)						
Year	Level 1	Level 2	Level 3	Level 4	Level 5	mean
1987	.59	.69	.65	.65	.67	.65
1988	.73	.76	.79	.75	.76	.76
1989	.48	.58	.72	.77	.82	.67
1990	.19	.24	.29	.30	.33	.27
1991	.27	.28	.34	.31	.28	.30
1992	.40	.39	.41	.42	.43	.41
1993	.46	.39	.41	.42	.40	.42
1994	.18	.18	.18	.18	.17	.18
1995	.23	.26	.27	.24	.28	.26
1996	.09	.08	.09	.10	.09	.09
1997	.23	.25	.19	.16	.22	.21

Are demotions rare?

In Table 4 I show all the within firm mobility during the years studied.[18] The diagonal elements show the percentage of the workers who in a given level stay at that level. I define a promotion as a change from one level to a higher level.[19] The percentage promoted is given above the diagonal while the percentage of workers who got a demotion is given below the diagonal. Overall, I observe a mobility rate, i.e. change in ranks, of 9.21% (technical workers) and 8.83% (administrative workers). If we split these two numbers into demotion/promotion, we get 2.51/6.70% and 3.52/5.31%. In other words, there is a higher mobility rate for technical workers and they have a higher promotion and a lower demotion rate as compared to administrative workers. Looking at Table 4, we see that the demotion rate from a given level is about 2–4% for technical workers and about 3–8% for administrative workers. These numbers are not very different from those found in previous studies. Baker, Gibbs and Holmstrom (1994a) find that demotions and lateral transfers are rare. Seltzer and Merrett (2000) find that 6.96% of the transitions were promotions and 3.33% were demotions ("demotion was just an ordinary part of job rotation"). Dohmen, Kriechel, and Pfann (2004) find an annual promotion rate of 5.6% and demotion rate of 1.6%. Lazear (1999) find a great deal of downward mobility. McCue (1996) find that of the

[18]Note that the last row for each group gives the distribution of the workers on the different ranks.

[19]See Dias da Silva and van der Klaauw (2006) for a nice (but short) overview of different definitions of promotions that are being used in empirical literature.

20% who are mobile in her data, almost half move within the firm, and about half of these are considered promotions. In the study by Pergamit and Veum (1999), 24% of the workers reported a promotion at their firm the previous year, but many of the promotions did not involve any change in duties or position. Grund (2005) study a firm with plants in two different countries and finds a promotion rate of 1.2% in the German plant and 8.4% in the US plant. Belzil and Bognanno (2005) find that promotions are slightly more frequent than demotions making the authors conclude (p. 10) "It is evident [...] that, contrary to conventional wisdom, demotions are frequent enough to merit attention."

Table 4: Within firm mobility. The diagonal elements show the percentage of the workers who in a given level stay at that level. Promotions (demotions) are given above (below) the diagonal.

	Technical white collar workers (*N*=202,142)					
	Level					
Lag level	1	2	3	4	5	Total
1	91.49%	7.40	1.10	.00	.00	100.00
2	2.04	87.23	10.16	.57	.00	100.00
3	.15	2.30	91.66	5.50	.39	100.00
4	.00	.21	3.96	89.73	6.10	100.00
5	.00	.00	.50	3.61	95.89	100.00
Total	14.00	20.24	34.67	19.54	11.56	100.00
	Administrative white collar workers (*N*=227,077)					
	Level					
Lag level	1	2	3	4	5	Total
1	87.34%	11.97	.68	.00	.00	100.00
2	3.05	92.19	4.59	.17	.00	100.00
3	.13	4.62	90.67	4.53	.04	100.00
4	.00	.19	5.04	93.07	1.69	100.00
5	.00	.00	.18	7.60	92.22	100.00
Total	14.95	38.04	27.04	17.46	2.51	100.00

Are wage increases serially correlated?

One of the findings in Baker, Gibbs and Holmstrom (1994a,b) was positive serial correlation in wage increases even after controlling for observable characteristics. To study this question, I restrict my observations to a balanced panel over 11 years and follow 3,798 technical and 4,601 administrative workers over the years 1987–1997. The correlations in residual percentage real wage increase are given in Table 5. The controls in the OLS are education, gender, age, hierarchical level, sector and year dummies. For both occupations, there is, with three exceptions, statistical significant negative correlation between increase in year t and increase in year t–1. In many cases there is also statistical significant correlation beyond last year. If we look at technical workers and take 1996 as the "base year" we see that there are statistical significant correlations for all the years back to 1988 except for 1991. On the other hand, using 1991 as the "base year" there is no statistical significant correlation between the real wage increase residuals in 1990 and 1991, but positive correlation between 1991 and 1989. For both occupations, the overall pattern from Table 5 is a negative correlation between this years real wage increase residuals and last years residuals and in most cases, there are also statistical significant correlations further back in time. But with correlations between t and $t–i$ with $i > 1$ it is difficult to find any systematic pattern in the sign and statistical significance of the correlations.[20] One possible explanation for negative serial correlation may be institutional settings, in particular collective wage agreements. It is not uncommon that the agreements favor different groups of workers in different years. If one group of workers gets a large wage increase this year at the expense of other workers it is plausible that this group gets less next year. Negative correlation is also found in Gibbs and Hendricks (2004) for the wage system that roughly "covered white–collar professional or managerial jobs." But, as the authors argue "[negative serial correlation] is inconsistent with an interpretation based on differences in rates of human capital accumulation."[21] Using panel data techniques, Belzil and Bognanno (2005) find that "current compensation growth is [...] negatively correlated with past compensation growth." Dias da Silva and van der Klaauw (2006) and Dohmen (2004) find positive serial correlation in their studies, while Lluis (2005) find no evidence of serial correlation. In other words, the empirical evidence is mixed.

Table 5: Serial correlation in residual percentage real wage increases.

	Technical white collar workers (N = 3,798)								
	1997	1996	1995	1994	1993	1992	1991	1990	1989
1996	-.2089***								
1995	-.0221	-.0883***							
1994	-.0048	.0419***	-.0467***						
1993	-.0330**	.0330**	-.0369**	-.0252					
1992	.0411**	-.0371**	-.0079	-.0353**	-.1123***				
1991	.0027	.0232	-.0448***	-.0577***	.0547***	-.1377***			
1990	-.0194	.0320**	.0085	.0097	-.0225	.0679***	-.0210		
1989	.0628***	.0859***	.0412**	-.0027	-.0042	.0101	.0283*	.0580***	
1988	.0405**	-.0600***	-.0072	-.0265	.0271*	.0173	-.0107	-.0769***	-.0309*
	Administrative white collar workers (N = 4,601)								
	1997	1996	1995	1994	1993	1992	1991	1990	1989
1996	-.2179***								
1995	-.0145	-.1257***							
1994	-.0205	-.0108	-.0887***						
1993	.0179	-.0050	.0490***	-.1287**					
1992	.0297**	.0047	-.0241	.0128	-.1085***				
1991	.0240	.0274*	.0224	-.0257*	.0075	-.0516***			
1990	-.0239	.0115	.0075	.0348**	.0079	.0288*	-.0728***		
1989	-.0399***	.0465***	.0252*	.0338**	.0123	.0556***	.0361**	.0066	
1988	.0335**	.0408***	-.0572***	-.0209	-.0265*	-.0097	-.0134	-.1273***	-.0802***

***/**/* significant at 1, 5 and 10% significance level. Sample restricted to 3,798 technical and 4,601 administrative workers followed over 11 years (balanced panel). The controls in the OLS are education, gender, age, hierarchical level, sector and year dummies. Dependent variable is percentage real wage increase from $t - 1$ to t.

Are promotions associated with large wage increases?

Tables 6 and 7 show the wage level and wage change (respectively) and the levels with or without a move in the hierarchy. The tables show that workers who get promoted earn a higher wage and get a

[20] Regardless of statistical significance, about 50% of the correlations in the table are negative.

[21] See Gibbs and Hendricks (2004) for a detailed discussion of sources of serial correlations. One possible source of negative serial correlation is measurement error. They discuss this case and it is not a plausible explanation in my case either because of the way the data is collected, cfr. Section 4.

promotion premium (on average) compared to those who do not move.[22] Looking at Table 7 it is clear that a wage change associated with a promotion is significantly larger that a wage change for a worker who does not change position. This fact is in line with previous research. If a technical worker at level 4 stays in that level he gets a wage change of NOK 370 but if promoted the wage increase is NOK 1,400. The table also reveals that in most cases demotions are associated with a decrease in (real) wages.

Table 6: Monthly real wage by level in t–1 and level in t. Standard deviation in parenthesis.

	Technical white collar workers (N=202,142)					
	Level					
Lag level	1	2	3	4		Total
1	18,316	19,855	23,126	.	.	18,483
	(2,439)	(2,341)	(3,449)	.	.	(2,527)
2	19,432	21,415	23,613	28,121	.	21,636
	(2,623)	(3,045)	(3,280)	(4,268)	.	(3,194)
3	21,417	22,562	26,037	29,477	33,727	26,170
	(3,231)	(3,457)	(4,182)	(4,056)	(5,294)	(4,302)
4	.	26,057	28,463	31,346	34,966	31,442
	.	(4,611)	(4,608)	(4,389)	(4,383)	(4,530)
5	.	.	32,087	33,132	38,475	38,250
	.	.	(5,712)	(4,772)	(5,855)	(5,920)
Total	18,362	21,385	25,937	31,181	38,066	26,381
	(2,463)	(3,069)	(4,210)	(4,415)	(5,833)	(7,145)
	Administrative white collar workers (N=227,077)					
	Level					
Lag level	1	2	3	4	5	Total
1	15,543	16,730	18,716	.	.	15,707
	(2,042)	(2,170)	(3,015)	.	.	(2,116)
2	15,972	18,121	21,371	24,162	.	18,215
	(2,271)	(2,454)	(3,105)	(4,255)	.	(2,620)
3	16,685	19,017	23,920	29,134	35,330	23,924
	(2,581)	(2,696)	(4,190)	(4,819)	(8,530)	(4,450)
4	.	20,766	25,484	32,057	41,334	31,860
	.	(3,270)	(4,714)	(6,166)	(7,164)	(6,422)
5	.	.	25,472	36,248	45,233	44,514
	.	.	(5,169)	(6,492)	(9,015)	(9,193)
Total	15,579	18,084	23,786	31,867	44,741	22,327
	(2,066)	(2,476)	(4,213)	(6,159)	(8,925)	(7,689)

[22]In the sample there are 13,549 observations of promotions for technical workers and 12,062 for administrative workers. About 20% (2,627 and 2,690 workers) of these actually receive a real wage decrease upon promotion. An interesting question is of course why we observe this. One *possible* (although not verified) explanation could be a trade-off between status and wages. See e.g. Cardoso (2005) who find suggestive evidence of such a trade-off using Portuguese data for the years 1991–2000.

Table 7: Real wage change by level in t–1 and t. Standard deviation in parenthesis.

Technical white collar workers (N=202,142)						
	Level					
Lag level	1	2	3	4	5	Total
1	223	868	1,857	.	.	289
	(878)	(1,171)	(2,594)	.	.	(968)
2	92	364	1,179	2,702	.	455
	(1,029)	(1,070)	(1,575)	(3,231)	.	(1,193)
3	-70	103	380	1,514	2,768	445
	(1,861)	(1,285)	(1,306)	(2,127)	(3,855)	(1,416)
4	.	-632	-10	369	1,408	415
	.	(2,517)	(1,639)	(1,513)	(2,533)	(1,624)
5	.	.	-734	-337	445	411
	.	.	(3,127)	(1,895)	(1,814)	(1,833)
Total	218	379	426	480	569	414
	(889)	(1,098)	(1,365)	(1,655)	(1,970)	(1,412)
Administrative white collar workers (N=227,077)						
	Level					
Lag level	1	2	3	4	5	Total
1	248	753	1,666	.	.	318
	(827)	(1,205)	(2,255)	.	.	(919)
2	200	247	1,309	3,405	.	299
	(1,078)	(869)	(1,862)	(3,958)	.	(992)
3	-578	-9	357	1,821	6,796	408
	(1,527)	(1,137)	(1,244)	(2,514)	(5,274)	(1,371)
4	.	-1,655	-66	446	2,687	454
	.	(4,674)	(1,683)	(1,654)	(4,217)	(1,771)
5	.	.	-4,081	-469	607	516
	.	.	(6,430)	(2,925)	(2,924)	(2,953)
Total	243	262	409	543	872	363
	(852)	(919)	(1,343)	(1,805)	(3,205)	(1,328)

Are wage increases on promotion small relative to the difference between average wages across levels of the job ladder?

When looking at this prediction, I apply the methodology used in Gibbs and Hendricks (2004). Let us define an employee's location in the wage range within a given level in a given year (*location*) as the percentage distance from the lowest observed wage (*min*) to the highest observed wage (*max*) in that level. Formally,

$$location = 100\frac{wage - min}{max - min} \in [0,100]. \quad (9)$$

Table 8 shows the effect of a promotion on the location in the wage range.[23] The first thing to notice is that workers who are promoted come from all parts of the wage distribution. But most of them, roughly 60% and 54%, come from the lower part of the distribution (looking at the column marked *N*). The overall evidence from the table is clear: the workers are promoted into a lower location at their new level than the location they had at the previous level. Administrative workers with a location parameter below 40 the common pattern is to either stay in the same location range or get into a higher location range.

The last column of the table shows percentage wage increase upon promotion divided by the percentage difference in mean wage between the old and the new hierarchical level. Overall, this ratio is about .20. When a worker is promoted the wage increase associated with a promotion is about 20% of the difference in the mean wage between the two levels. This supports the evidence on the location mobility. The general pattern is that the ratio is decreasing with the increase in the location parameter prior to promotion. For the three highest location parameters the ratio is below .10.

Table 8: Wage range dynamics on promotion.

Technical white collar workers

Old location	New location											%raise / %Δ in mean wage
	<10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90<	*N*	
<10	81.3%	18.8	.0	.0	.0	.0	.0	.0	.0	.0	16	.24
10-20	17.8	28.9	7.2	34.9	10.0	1.0	.2	.0	.0	.0	499	.48
20-30	9.3	38.2	21.0	17.7	10.2	3.4	.1	.0	.0	.0	1,598	.32
30-40	2.8	24.9	32.2	27.1	11.9	1.0	.2	.0	.0	.0	2,498	.27
40-50	.3	10.0	27.9	31.7	26.9	2.9	.4	.0	.0	.0	3,649	.25
50-60	.2	5.3	18.4	36.0	31.4	8.3	.5	.0	.0	.0	2,996	.20
60-70	.1	5.5	10.9	21.5	38.6	20.7	2.7	.1	.0	.0	1,447	.15
70-80	.0	3.9	6.9	17.3	32.4	27.6	10.4	1.2	.3	.0	595	.06
80-90	.0	2.9	7.2	13.9	10.1	33.7	22.1	8.7	1.0	.5	208	.02
90<	.0	.0	2.3	2.3	11.6	23.3	18.6	30.2	9.3	2.3	43	.05
Total	2.5%	14.8	21.8	28.1	23.7	7.2	1.4	.3	.1	.0	13,549	.24

Administrative white collar workers

Old location	New location											%raise/ %Δ in mean wage
	<10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90<	*N*	
<10	16.7%	8.3	58.3	8.3	8.3	.0	.0	.0	.0	.0	12	.66
10-20	11.8	9.1	19.2	17.9	36.5	5.5	.0	.0	.0	.0	474	.38
20-30	6.5	29.0	32.4	25.0	4.0	3.0	.1	.0	.0	.0	907	.36
30-40	2.0	16.9	25.5	44.4	10.4	.5	.1	.1	.0	.0	2,205	.30
40-50	1.0	8.0	19.7	40.2	28.2	2.8	.1	.0	.0	.0	2,893	.24
50-60	.1	4.8	12.2	40.5	36.3	5.9	.2	.0	.0	.0	2,999	.17
60-70	.1	3.4	4.1	24.3	52.6	14.4	.9	.1	.0	.1	1,723	.12
70-80	.0	5.7	1.5	18.8	30.4	38.9	4.3	.5	.0	.0	655	.08
80-90	.0	2.8	1.4	4.2	21.7	39.2	27.3	3.5	.0	.0	143	.07
90<	.0	2.0	7.8	9.8	15.7	13.7	41.2	7.8	2.0	.0	51	-.00
Total	1.6%	9.6	16.4	35.0	28.9	7.4	1.0	.1	.0	.0	12,062	.22

The last column of the table shows percentage wage increase upon promotion divided by the percentage difference in mean wage between the old and the new hierarchical level.

[23] Since the location parameter can take on all values between 0 and 100, I have made 10 groups to make the table manageable.

Are wage increases a predictor for promotion?

To see whether or not a wage increase is a predictor for promotion I have run a probit model. The estimation results are reported in Table 9. For both occupations there is a positive relationship between percentage real wage change for both one and two lags back in time and the probability of getting a promotion. The effect for technical workers is larger than for administrative workers for the first lag, but when looking at the second lag it is the other way around. However, the marginal effects, computed at the mean, are very small for both occupations. The marginal effects more or less increase relative to where in the distribution I compute the marginals. An assumed real wage increase of 10% changes the marginal effects to .0021 (.00009 for the second lag) and .0001 (.0001) for the two occupations. In other words, even if the numbers increase they are of no practical significance. This implies that the wage increase is not a good predictor for promotion, at least when looking back one or two time periods.

Table 9: Results from a probit estimation. Dependent variable is promotion. Marginal effect (at mean) for % wage change in square brackets. Robust standard error in parenthesis.

	Technical white collar workers	*Administrative white collar workers*
1 lag %wage change	$.0065^{***}$ [.00019]	$.0059^{***}$ [.0001]
	(.0013)	(.0012)
2 lags %wage change	$.0029^{**}$ [.00008]	$.0045^{***}$ [.0001]
	(.0012)	(.0012)
female	$.1876^{***}$	$.4035^{***}$
	(.0249)	(.0162)
age	$-.0395^{***}$	$-.0272^{***}$
	(.0011)	(.0009)
edu	$-.0715^{***}$	$-.0665^{***}$
	(.0031)	(.0037)
level dummies	yes	yes
year dummies	yes	yes
sector dummies	yes	yes
N	104,035	119,706
Pesudo R^2	.1179	.1034

***/**/* significant at 1, 5 and 10% significance level.

Summing up

The descriptive analysis suggests that: (1) Real wage decreases are not rare. Demotions occur less often, but are not truly rare. (2) There is negative serial correlation in wages after controlling for observables between the wage increase in this period and the wage increase in the previous time period. (3) Promotions are associated with large wage increases. (4) Wage increases on promotion are small relative to the difference between average wages across levels of the job ladder. (5) There is a positive relationship between lagged wage increases and promotion. But the effect is of no practical significance.

The conclusion is that there is support in the data for most of the predictions in the model. Hence, the data set should be suitable for estimating the GW99 model.

6 Econometric setup

In explaining the econometric setup I draw heavily on Lluis (2005) and Gibbons, Katz, Lemieux, and Parent (2005).[24]

The wage equation in the model is given

$$w_{ijt} = d_j + c_j \theta_{it}^e f(x_{it}). \tag{10}$$

Let R_{ijt} be dummy variables indicating worker *i*'s rank *j* at time *t*. Let X_{it} be a vector with observable characteristics of the worker[25] and μ_{it} an error term. The equation I will estimate is

$$w_{ijt} = \sum_{j=1}^{J} R_{ijt} d_j + \sum_{j=1}^{J} R_{ijt} X_{it} b_j + \sum_{j=1}^{J} R_{ijt} c_j \theta_{it}^e f(x_{it}) + \mu_{it}. \tag{11}$$

As Lluis (2005) points out ordinary least squares (OLS) estimates will be inconsistent. The rank assignment is endogenous based on θ_{it}^e, making θ_{it}^e correlated with the rank dummies. Further, θ_{it}^e introduces another challenge by being interacted with the R_{ijt} terms and, thus, can not be eliminated by first differencing the wage equation. Note, however, that fixed-effect models can be applied if one assumes that (1) the unobserved heterogeneity term is not time varying, and (2) the heterogeneity is equally valued in the different ranks. This assumption is made throughout the study by Lima and Pereira (2003).

<u>Quasi-differencing the equation</u>

It is possible to eliminated θ_{it}^e from Equation (11) by using a quasi-differencing technique.[26] First solve Equation (11) with respect to θ_{it}^e

[24]Gibbons, Katz, Lemieux, and Parent (2005) write on page 684: "Although our empirical work explores two standard definitions of sectors (i.e., occupations and industries), other definitions are possible. For example, sectors could be jobs inside a firm [...], states or regions within a country [...], or entire countries [...]."

[25]Later in the paper I will summarize all the observable characteristics of the worker in a skill index in order to (significantly) reduce the number of parameters to be estimated (each observable characteristic is interacted with the hierarchical levels). See Section 6.1.

[26]This technique is first employed in Holtz-Eakin, Newey, and Rosen (1988) who look at models where the fixed effect is interacted with year dummies. Lemieux (1998) uses this technique when he estimates a model where the return to the fixed effect is different in the union and the non-union sectors. Gibbons, Katz, Lemieux, and Parent (2005) estimate models in which the fixed effect is differently valued in different sectors of the economy. Finally, Lluis (2005) employs the methodology when she estimates the Gibbons-Waldman model using German data.

$$\theta_{it}^{e} = \frac{w_{ijt} - \sum_{j=1}^{J} R_{ijt} d_j - \sum_{j=1}^{J} R_{ijt} X_{it} b_j - \mu_{it}}{\sum_{j=1}^{J} R_{ijt} c_j f(x_{it})}. \tag{12}$$

Then we use the property that the expected innate ability follows a martingale process.

$$\theta_{it}^{e} = \theta_{it-1}^{e} + u_{it}, \tag{13}$$

where u_{it} is assumed orthogonal to θ_{it-1}^{e} Substituting Equation (12) and its lagged version into Equation (13) we obtain

$$\begin{aligned} \frac{w_{ijt}}{\sum_{j=1}^{J} R_{ijt} c_j f(x_{it})} &= \frac{w_{ijt-1}}{\sum_{J=1}^{J} R_{ijt-1} c_j f(x_{it-1})} \\ &+ \frac{\sum_{J=1}^{J} R_{ijt} d_j + \sum_{J=1}^{J} R_{ijt} X_{it} b_j}{\sum_{J=1}^{J} R_{ijt} c_j f(x_{it})} \\ &- \frac{1}{\sum_{J=1}^{J} R_{ijt-1} c_j f(x_{it-1})} \left[\sum_{J=1}^{J} R_{ijt-1} d_j + \sum_{J=1}^{J} R_{ijt-1} X_{it-1} b_j \right] + \varepsilon_{it} \end{aligned} \tag{14}$$

where

$$\varepsilon_{it} = u_{it} + \frac{\mu_{it}}{\sum_{J=1}^{J} R_{ijt} c_j f(x_{it})} - \frac{\mu_{it-1}}{\sum_{J=1}^{J} R_{ijt-1} c_j f(x_{it-1})}. \tag{15}$$

Equation (14) is the one to be estimated.

In the model without learning it is possible to take the lagged version of Equation (12) and substitute into Equation (11) since $\theta_{it}^{e} = \theta_{it-1}^{e}$. This implies that u_{it} drops from Equation (15).

The quasi-differencing corrects the endogeneity in the assignment of workers to the ranks, but it is not possible to estimate Equation (14) using nonlinear least squares because of further endogeneity problems (Lluis, 2005). First, w_{ijt-1} is correlated with μ_{it-1}. Second, in the model with learning u_{it}, i.e. the new information in the learning process about innate ability at time *t*, is correlated with R_{ijt}, since beliefs about ability influence the current rank assignment. To get consistent estimates one must correct for these endogeneity problems by choosing valid instruments for w_{ijt-1} and R_{ijt}.

Full information

In the model with full information, the random shock u_{it} in the learning process drops from the martingale $\theta^e_{it} = \theta^e_{it-1} + u_{it}$, and hence, drops from Equation (15). The quasi-differencing method corrects for the endogeneity in the assignment of workers to job ranks. But since w_{ijt-1} is correlated with μ_{it-1} we must find a suitable instrument for w_{ijt-1}. The instrument must be (highly) correlated with the wage, but not correlated with the error term. In explaining the choice of instruments it is helpful to look at Figure 1. Assume two workers *A* and *B* with $\theta_A = H$ and $\theta_B = L$ $(H > L)$ and the same labor market experience. Their wages are different because $\theta_A \neq \theta_B$ More specifically $w_{At} > w_{Bt}$ since $\theta_A > \theta_B$. Information on contemporaneous rank assignment is not enough to identify wage differences. But worker *A*'s effective ability $\eta_{At} = \theta_A f(x_{At})$ may be at the level of effective ability to get promoted next period. In other words, having information on the worker's contemporaneous rank and his rank in the next period gives information about the ability level and, hence, on his wage. In the model with full information it is possible to use the interaction terms between R_{ijt-1} and R_{ijt} as instruments.

Symmetric learning

The mobility in the model is driven by the learning process, hence R_{ijt} is correlated with the new information u_{it}. Recall that $\theta^e_{it} = \theta^e_{it-1} + u_{it}$ This implies that R_{ijt} must be instrumented in addition to w_{ijt-1} Because of the martingale process, R_{ijt-1} and R_{ijt-2} is not correlated with u_{it} since current rank is only affected by u_{it}. The instrument we are looking for should therefore help identify differences in ability from one period to the next. As argued in Lluis (2005), the interaction between R_{ijt-1} and R_{ijt-2} "constitutes a good predictor of current rank affiliation because it helps identify differences in expected ability in period *t*–1 (using the same argument as in the perfect information case) as well as in period *t*."

Looking at Equation 14, we see that there are interaction terms between the rank indicator and the skill index and between the rank indicator and the labor market experience. But since R_{ijt} is endogenous in the learning case, I instrument this variable with R_{ijt-2}. In other words, I include the interaction between the skill index and the levels and the experience and the levels in the instrument matrix *Z*.[27] Table 10 sums up the discussion of the instruments.

[27]Note that Lluis (2005) also includes these instruments when estimating the model without learning only using R_{ijt} instead of R_{ijt-2}. This is not necessary since R_{ijt} is not endogenous in that case. To be more precise, the quasi-differencing takes care of the endogeneity problem with the rank assignment in the model without learning, as explained above.

Table 10: Variables in the instrument matrix *Z*. *SI* is the skill index and *E* is experience.

	Full information	Symmetric learning
Endogenous variables	w_{ijt-1}	w_{ijt-1}
		R_{ijt}
		$S \times R_{ijt}$
		$E \times R_{ijt}$
Instrument matrix *Z*	$R_{ijt} \times R_{ijt-1}$	$R_{ijt-1} \times R_{ijt-2}$
		$S \times R_{ijt-2}$
		$E \times R_{ijt-2}$

To estimate Equation (14) I apply a GMM estimator in which the set of instruments Z_i must satisfy the usual orthogonality condition

$$E[\varepsilon_i Z_i] = 0. \tag{16}$$

The objective function in the minimization problem is given by

$$\min_{\gamma} \quad \varepsilon(\gamma)' Z (Z' \Omega Z)^{-1} Z' \varepsilon(\gamma) \tag{17}$$

where γ is the parameter vector.[28]

Lluis (2005) applying the same estimation procedure, imposes the following normalization on the minimization problem

(18)

where *N* is the number of individuals, *T* is the number of time periods (number of observations) for each individual, and

$$\theta_{it}^{e} = \frac{w_{ijt} - \sum_{j=1}^{J} R_{ijt} d_j - \sum_{j=1}^{J} R_{ijt} X_{it} b_j}{\sum_{j=1}^{J} R_{ijt} c_j f(x_{it})}. \tag{19}$$

[28]The estimation is carried out in SAS v. 9.1. using the `proc model` procedure in the SAS/ETS package.

According to Lluis (2005) this normalization to zero is necessary for the parameters to be identified.[29]

6.1 From econometric setup to practical implementation

Equation (14), is complex and it is necessary to make several simplifying assumptions to estimate the model.

Skill index

X_{it} is a vector with observable characteristics of the worker that is interacted with the hierarchical levels. To restrict the number of parameters to be estimated, I summarize these observable characteristics by a skill index. A similar approach is taken in Lluis (2005) and Gibbons, Katz, Lemieux, and Parent (2005). The skill index is constructed as follows: Log monthly wage is regressed on years of education, experience and squared experience, marriage, and dummies for year (12), gender and industries (7). The skill index is then defined as predicted wage in levels based solely on the coefficients of education and experience.[30] Finally, the skill index is normalized with a mean of zero.

Functional form for $f(x_{it})$

Lluis (2005) argues that a natural choice for the accumulated labor market function $f(x_{it})$ is

$$f(x_{it}) = exp(\alpha_0 + \alpha_1 x_{it} + \alpha_2 x_{it}^2). \tag{20}$$

In the estimation, however, she ends up replacing this expression with $f(x_{it}) = 1$. "For any other functional forms where *f* varies with experience, the parameters of the *f* function could not be estimated" (p. 753). I experience the same problem, and follow Lluis' solution. Restricting $f(x_{it})$ to one implies that we take away the dynamics in the model in the no-learning case. The wage equation changes from $w_{ijt} = d_j + c_j \theta_i f(x_{it})$ to $w_{ijt} = d_j + c_j \theta_i$ and effective ability changes from $\eta_{it} = \theta_i f(x_{it})$ to $\eta_{it} = \theta_i = \eta_i$. In other words, we assume that the assignment of workers to jobs is based on the workers innate ability only. Unless the thresholds for a promotion (η^j) changes, the worker is not assigned to a new position.

The simplification above has implications for the instrumental matrix. With $f(x_{it}) = 1$ it is not necessary to instrument the interaction between $f(x_{it})$ and current rank.

7 Results

7.1 Ranks, measured skills and unobserved ability

I start the analysis by presenting some simple regressions. In column 1 of Table 11 I have estimated monthly wage in NOK 10,000 on the hierarchical levels (no other controls included). The first thing to notice is that the rank variables explain about 70% of the variation in monthly wage implying that the rank variable is important in explaining a worker's wage. This supports the claim that in internal labor markets wages are strongly attached to the hierarchical levels. All the coefficients are statistically

[29]She refers the reader to Lemieux (1993, 1998). This normalization is not explicitly discussed in Gibbons, Katz, Lemieux, and Parent (2005).

[30]I use wage in levels to get consistency with the GW99 model specification.

significant at the 1% level. In column 2 I have added the skill variable (see Section 6.1 for the definition) as a control. Controlling for the workers' measured skills reduces the impact of the ranks somewhat, but still the rank dummies are statistically significant and increase with the hierarchical levels. The size of the skill parameter is about the same as the dummy for the middle rank. In the last column of the table I have used the fixed effects estimator. This implies that, contrary to the theoretical model of Gibbons and Waldman (1999b), I assume that the unobserved ability is constant over time and is rewarded the same in each hierarchical level. The results show that unobserved ability is important. The size of the rank dummies, however, is significantly smaller than when applying OLS. Hence, it is important to control for unobserved ability. Also note that when controlling for unobserved ability, the importance of the observed part of the skills more than doubles.

Table 11: Rank wage differentials.

Specification no.	(1)	(2)	(3)
	Technical white collar workers (N=202,142)		
Level 2	.302***	.218***	.066***
	(.002)	(.002)	(.003)
Level 3	.757***	.543***	.166***
	(.002)	(.002)	(.004)
Level 4	1.282***	.970***	.332***
	(.003)	(.003)	(.005)
Level 5	1.969***	1.521***	.563***
	(.004)	(.005)	(.008)
skills		.602***	1.437***
		(.003)	(.011)
N	202142	202142	202142
R^2	.674	.736	.485
	Administrative white collar workers (N=227,077)		
Level 2	.250***	.185***	.044***
	(.001)	(.001)	(.002)
Level 3	.821***	.663***	.166***
	(.002)	(.002)	(.003)
Level 4	1.629***	1.341***	.370***
	(.003)	(.003)	(.005)
Level 5	2.916***	2.477***	.762***
	(.012)	(.012)	(.015)
skills		.566***	1.342***
		(.004)	(.010)
N	227077	227077	227077
R^2	.723	.761	.343

Dependent variable: monthly wage in NOK 10,000. Robust standard errors in parentheses. Base group: level 1. Note that the within R^2 is reported for the fixed effects model, specification (3). ***/**/* significant at 1, 5 and 10% significance level.

7.2 Comparative advantage based on measurable skills only

Comparative advantage implies that skills are rewarded differently along the firm's job ladder and that workers are sorted by their skills and ability into a given position in the firm hierarchy. Empirically I can test this by first estimating the Gibbons-Waldman model as outlined in Section 6 and then use a Wald test statistic to test whether the slopes in the model (i.e. the b_j 's and c_j 's coefficients) are different from one another.

I start by presenting evidence on comparative advantage based on measurable skills (the b_j 's) only. I do this by estimating a simple OLS model where I have interacted the skill index with the hierarchical levels. Instead of a Wald test it is now possible to use the standard *F* test.

Technical white collar workers

Table 12 shows that all the coefficients are statistically significant. The size of the b_j coefficients increase up to level three and then decrease (inverse *U*-shape). This means that measured skills, i.e. education and experience, are most important in level three. But even if the importance of measured skills are less in the two top levels compared to level three, their estimated coefficients are still larger than in the two lowest levels. The comparative advantage hypothesis has support since the joint test of equalities in the slopes and all the pair-wise tests reject the null hypothesis.[31]

Administrative white collar workers

The results for administrative workers follows the same pattern as for technical workers with the exception that measured skills increase up to level four and then decline. Further, the size of the coefficients for the b_j 's are smaller for administrative workers than for technical workers for the three lowest levels. This means that the return to the skill index is higher for technical than for administrative workers at the lower ranks, but lower at the top level.

[31]The H_0 for the joint test is that all of the pair-wise slopes are equal.

Table 12: Comparative advantage based on measurable skills only.

Level	1	2	3	4	5
	Technical white collar workers (*N*=202,142)				
Level dummies	d_1	d_2	d_3	d_4	d_5
	.	.26***	.59***	1.03***	1.62***
	.	(.003)	(.003)	(.003)	(.007)
Skill measured	b_1	b_2	b_3	b_4	b_5
	.37***	.48***	.74***	.63***	.52***
	(.006)	(.007)	(.005)	(.006)	(.011)
Tests for equality:					
b_j's	joint	b_2=b_1	b_3=b_2	b_4=b_3	b_5=b_4
F-statistic	611.45	140.82	978.04	179.47	75.55
p-value	.0000	.0000	.0000	.0000	.0000
	Administrative white collar workers (*N*=227,077)				
Level dummies	d_1	d_2	d_3	d_4	d_5
	.	.23***	.72***	1.32***	2.53***
	.	(.002)	(.002)	(.004)	(.021)
Skill measured	b_1	b_2	b_3	b_4	b_5
	.25***	.35***	.61***	.82***	.58***
	(.005)	(.004)	(.006)	(.008)	(.032)
Tests for equality:					
b_j's	joint	b_2=b_1	b_3=b_2	b_4=b_3	b_5=b_4
F-statistic	1,200.81	261.32	1,263.41	399.46	53.10
p-value	.0000	.0000	.0000	.0000	.0000

***/**/* significant at 1, 5 and 10% significance level. Dependent variable is monthly real wage in 1,000. Robust standard errors in parentheses.

7.3 Comparative advantage based on both measured and unmeasured skills

In addition to measurable skills we now enrich the estimation by also controlling for unmeasured skills, but no learning (i.e. the full information case in GW99).

<u>Technical white collar workers</u>

The first panel in Table 13 shows the estimation results of the model with comparative advantage using both measurable (the b_j's) and unmeasurable skills (the c_j's), but without learning. First we notice how well the parameter estimates of the c_j's fit the theoretical parameter bounds. From Section 3 we remember that $c_J > c_{J-1} > \ldots > c_1 > 0$ with $J = 5$ in our case. All the parameter estimates are statistically significant with *p*-values below .0001 except for the parameter d_5 which is not significant (*p*-value of .446). Along the career path we see that the unmeasured skills (the c_j's) increases, suggesting, as suspected, that the worker's unmeasured skills become more important as the worker climbs the hierarchy. One more unit of unmeasured skill at the top level is valued almost four times as much as at the lowest hierarchical level.

As already noted in the beginning of this section, the comparative advantage hypothesis suggests different rewards for skills at different hierarchical levels. The table also shows that all the formal statistical tests for equality reject the null hypothesis of equality in the slope coefficients. In other words, we have support for the comparative advantage hypothesis when looking at unmeasured skills. The same story can be told about measured skills (the b_j 's). Measured skills also become more important as the worker climbs the job ladder. Compared to the OLS case (Table 12) the size of the estimated measured skills coefficients is larger and they increase in a monotonic way with the hierarchical levels.

The largest change in the parameter values for measured skills is from level 4 to level 5. For unmeasured skills the largest change is between level 3 and 4. These two "kinks" for measurable skills and unmeasurable skills can be interpreted (in the language of BGH) as critical choke points in the career path. If a worker wants to climb the corporate ladder he or she must face a higher demand for both measurable and unmeasurable skills. In other words, the competition for higher jobs increase along the career path, and the best workers are selected into the highest ranks. Also note that the pure rank effects (the d_j 's) are all statistically significant and larger than zero. This means that there is some other mechanism going on in addition to measurable and unmeasurable skills in explaining wage increases and mobility.

<u>Administrative white collar workers</u>

The estimation results for the no learning case is reported in Table 13. All the estimated coefficients are statistical significant at the 1%-level except for the parameter d_5 which is significant at the 5%-level. The coefficients for both measurable and unmeasurable skills increase along the career path. This means that these skills are becoming more important for the workers' output as they climb the career ladder. Compared to the technical white collar worker sample, the size of these coefficients are larger meaning that the return to both measurable (the b_j 's) and unmeasured (the c_j 's) skills are higher for administrative workers than for technical workers. All the equality tests reject the null hypothesis and, hence, stress the importance of comparative advantage in the allocation of workers to the jobs.

Table 13: Results comparative advantage.

Level	1	2	3	4	5
	Technical white collar workers (*N*=202,142)				
Level dummies	d_1	d_2	d_3	d_4	d_5
	.	$.116^{***}$	$.197^{***}$	$.203^{***}$	.028
	.	(.011)	(.011)	(.012)	(.037)
Skill unmeasured	c_1	c_2	c_3	c_4	c_5
	1	1.374^{***}	1.779^{***}	2.977^{***}	3.732^{***}
	.	(.064)	(.093)	(.223)	(.344)
Skill measured	b_1	b_2	b_3	b_4	b_5
	1.201^{***}	1.347^{***}	1.437^{***}	1.581^{***}	2.109^{***}
	(.026)	(.020)	(.019)	(.036)	(.066)
Tests for equality:					
c_j's	joint	c_2=c_1	c_3=c_2	c_4=c_3	c_5=c_4
χ^2 statistic	97.71	34.53	55.64	45.14	12.36
p-value	.0001	.0001	.0001	.0001	.0004
b_j's	joint	b_2=b_1	b_3=b_2	b_4=b_3	b_5=b_4
χ^2 statistic	202.18	22.62	10.85	13.10	49.00
p-value	.0001	.0001	.0010	.0003	.0001
	Administrative white collar workers (*N*=227,077)				
Level dummies	d_1	d_2	d_3	d_4	d_5
	.	$.122^{***}$	$.222^{***}$	$.122^{***}$	$-.347^{**}$
	.	(.008)	(.009)	(.016)	(.141)
Skill unmeasured	c_1	c_2	c_3	c_4	c_5
	1	1.632^{***}	2.405^{***}	3.492^{***}	4.685^{***}
	.	(.072)	(.121)	(.234)	(.412)
Skill measured	b_1	b_2	b_3	b_4	b_5
	1.278^{***}	1.470^{***}	2.062^{***}	2.728^{***}	3.737^{***}
	(.025)	(.020)	(.033)	(.056)	(.283)
Tests for equality:					
c_j's	joint	c_2=c_1	c_3=c_2	c_4=c_3	c_5=c_4
χ^2 statistic	154.50	76.25	128.46	43.67	18.60
p-value	.0001	.0001	.0001	.0001	.0001
b_j's	joint	b_2=b_1	b_3=b_2	b_4=b_3	b_5=b_4
χ^2 statistic	824.42	37.83	237.31	106.63	12.35
p-value	.0001	.0001	.0001	.0001	.0004

***/**/* significant at 1, 5 and 10% significance level. Dependent variable is monthly real wage in 1,000. Standard errors in parentheses.

7.4 Comparative advantage and learning

Now we deviate from the full information case in GW99 and allow firms to learn about their workers' ability.

Technical white collar workers

Table 14 shows the estimation results. Even if most of the estimated coefficients are statistically significant they are much less systematic than in the case with comparative advantage only. The parameters d_2, d_5, c_2 and b_2 are not statistically significant. The other parameters are significant at the 1% significance level. Ignoring c_2 and b_2, which are not statistically significant, we again see that the parameters for both measurable and unmeasurable skills increase with the levels. Both the joint tests for equality in the slopes reject the null hypothesis about equality and, hence, give support to the comparative advantage and learning case. However, all the individual tests for equality fail to reject the null when looking at the measurable part of the skills. In other words, there is no support for the comparative advantage based on measurable skills. For the unmeasurable part of skill, it seems that the comparative advantage and learning hypothesis get support at the top levels of the hierarchy. This implies that learning about workers' unmeasurable skills is important at the top levels, but not at lower levels.

Administrative white collar workers

The lower part of Table 14 shows the estimates for the model with learning for administrative white collar workers. All the parameters are statistically significant at the 1%-level which was not the case for the sample consisting of technical workers. The parameters for measurable and unmeasurable skills do not increase in the same monotonic way as in the model without learning. Statistically speaking, both versions of the model fit the administrative worker sample very well. However, the model with learning does not fit the structure of the model (increasing b_j's and c_j's along the hierarchy) as well as the model without learning.

The joint equality test for both measurable and unmeasurable skills gives support for firms learning about the workers. The individual tests for measurable skills all reject the null hypothesis giving support to selection based on comparative advantage and learning. Recall that none of the individual tests for equality hold for the b_j's in the technical white collar sample. Two of the four individual tests for unmeasurable skills reject the null hypothesis about equality in the slope parameters. This means that we have partial support for the learning model, at least between rank 1 and 2 and between rank 3 and 4.

Table 14: Results comparative advantage and learning.

Level	1	2	3	4	5
	Technical white collar workers (*N*=202,142)				
Level dummies	d_1	d_2	d_3	d_4	d_5
	.	1.132	.505***	.520***	-.073
	.	(1.294)	(.064)	(.146)	.505
Skill unmeasured	c_1	c_2	c_3	c_4	c_5
	1	16.203	5.135***	9.445***	28.102***
	.	(28.005)	(.997)	(2.319)	(8.784)
Skill measured	b_1	b_2	b_3	b_4	b_5
	.679***	3.507	1.435***	1.513***	1.641***
	(.046)	(4.530)	(.047)	(.069)	(.141)
Tests for equality:					
c_j's	joint	c_2=c_1	c_3=c_2	c_4=c_3	c_5=c_4
χ^2 statistic	18.85	.29	.16	7.05	6.53
p-value	.0008	.5872	.6891	.0079	.0106
b_j's	joint	b_2=b_1	b_3=b_2	b_4=b_3	b_5=b_4
χ^2 statistic	311.09	.38	.21	.75	.73
p-value	.0001	.5357	.6497	.3862	.3941
	Administrative white collar workers (*N*=227,077)				
Level dummies	d_1	d_2	d_3	d_4	d_5
	.	.734***	.579***	.288***	.500***
	.	(.086)	(.018)	(.061)	(.156)
Skill unmeasured	c_1	c_2	c_3	c_4	c_5
	1	14.946***	10.106***	24.885***	24.133***
	.	(4.028)	(1.591)	(5.777)	(6.070)
Skill measured	b_1	b_2	b_3	b_4	b_5
	.548***	3.658***	2.070***	2.749***	1.571***
	(.021)	(.665)	(.081)	(.158)	(.366)
Tests for equality:					
c_j's	joint	c_2=c_1	c_3=c_2	c_4=c_3	c_5=c_4
χ^2 statistic	33.42	11.99	2.28	9.84	.04
p-value	.0001	.0005	.1313	.0017	.8391
b_j's	joint	b_2=b_1	b_3=b_2	b_4=b_3	b_5=b_4
χ^2 statistic	639.25	20.99	5.61	12.13	8.71
p-value	.0001	.0001	.0178	.0005	.0032

***/**/* significant at 1, 5 and 10% significance level. Dependent variable is monthly real wage in 1,000. Standard errors in parentheses.

<u>Robustness</u>

To check for robustness in the technical white collar sample I have used two different subsamples. The first included, in addition to stayers, workers who moved between firms. Overall the previous results hold. The second sample was restricted to workers under the age of 35. This restriction is based on the hypothesis that firms learn most about workers early in their careers. In the model without learning, there were two more parameters not statistically significant compared to the main sample. But overall this subsample did not produce any new insight. It was not possible to get convergence in the model with learning.

I did the same robustness checks for the administrative white collar worker sample with similar results. In the sample including movers between firms the individual test for $c_2 = c_3$ (p-value =.0936) in the learning case also rejected the H_0. This was not the case when looking at only internal mobility. In other words, there is even more support for learning when including movers between firms. For young workers (age not greater than 35) the test $c_4 = c_5$ (p-value = .1438) no longer rejected the H_0 in the full information case. As in the case of young technical workers, it was not possible to get convergence in the model with learning.

8 Summary and conclusion

In this paper I have used a large data set of white collar workers in Norway during the years 1987–1997 to study wage and promotion dynamics within firms.

Through a comprehensive descriptive analysis I have shown that (1) Real wage decreases are not rare. Demotions occur less often, but are not truly rare. (2) There is negative serial correlation in wages after controlling for observables between the wage increase in this period and the wage increase in the previous time period. Even if there is statistically significant correlation further back in time, it is hard to find any systematic pattern. (3) Promotions are associated with large wage increases. (4) Wage increases on promotion are small relative to the difference between average wages across levels of the job ladder. (5) Wage increases predict promotion. But the effect is of no practical significance. There is support in the data for most of the predictions in the GW99 model.

The estimation of the GW99 model showed that selection of workers into a given position within a firm hierarchy is based on comparative advantage. Both measurable and unmeasurable skills are important. This holds for both occupations studied. When it comes to firms learning about their workers, the results are not so clear, although the joint test for equality holds for both occupations. That is, the comparative advantage hypothesis has support in both occupations when taking learning into account. For technical white collar workers there seems to be some support for learning about innate ability explaining mobility at higher ranks. For administrative white collar workers the comparative advantage hypothesis has full support when looking at measurable skills and partly support when looking at unmeasurable skills. Compared to Lluis' work on Germany, it seems that the learning aspect of the GW99 model has more support in the Norwegian data. This fits Lluis' argument about apprenticeships in Germany reducing the importance of learning and the fact that such an apprenticeship system is not present in my sample.

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