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# TWO-SIDED LEARNING, LABOR TURNOVER AND WORKER DISPLACEMENT

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**ABSTRACT**

We construct a general dynamic structural model of two-sided learning between a firm and its workers. We estimate an empirical version of the model using personnel data from Fokker Aircraft that cover the path of layoffs and quits through its bankruptcy. We find that the firm learns about its workers' loyalty (demonstrating the role of information in repeated cooperative principal-agent relationships). There is no evidence that workers learn (consistent with earlier empirical results on American workers). The type of data that we use also generates information on the value of learning and on whether and how the characteristics of workers who remain until the firm's death differ from those of all affected workers. It thus allows us to measure the increases in the firm's value from learning about its workers' behavior and to infer the extent of biases in estimated losses from displacement from samples restricted to displaced workers.

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## I. Introduction

We propose the simple idea that the parties to an employment relationship may learn about each other's intentions about ending the relationship by forming expectations based on the other party's prior behavior that ended similar relationships. Workers may observe how the employer's firing has varied with differences in voluntary mobility and may adjust their own mobility accordingly. Employers may observe which workers have quit in the past and adjust their firing behavior to reflect their altered expectations about individual workers' future mobility.

In addition to this general issue the notions that we examine are relevant to understanding the nature of worker displacement.[1] A plant shutdown is not an experiment whose impact we can infer by comparing displaced workers to other workers. As in many other examples where selection on one or both sides of the market comes into play (Heckman et al, 1998), we need information on workers' mobility over the firm's pre-shutdown history to evaluate whether the losses estimated for workers who are actually displaced provide an unbiased estimate of the losses of all workers affected by the eventual closing.

The process of worker-firm interactions that lead up to a plant closing is missed by a literature that concentrates on comparisons of displaced workers' pre- and post-displacement earnings. If the agents are rational, that process must involve attempts by both sides to gather information about each other's expectations and intentions, information that is partly revealed by the firm's recent turnover history.[2] Moreover, the typical firm is not accustomed to decline and needs information to design an optimal policy to adjust downwards. This

[1]See Fallick (1996) for a survey of the literature, which except for Jacobson et al (1993) is based on household data.

[2]Hamermesh (1987) used household data on the time path of wage-tenure relationships to infer learning on the workers' side of this information exchange. While useful, such data cannot provide a picture of the extent and types of labor turnover generated as a firm heads toward oblivion.

information may be collected optimally during a sequence of downsizing operations.[3] Interestingly, the focus on displacement in the 1950s and early 1960s was as much on the process of displacement as on workers' post-displacement adjustment. Those studies (e.g., Shultz and Weber, 1966) had the data required to analyze information exchanges along the path to displacement, but the necessary theoretical and econometric tools were lacking.

In this study we address what we believe are lacunae in recent research on mobility while updating/modernizing the early displacement literature. We have data describing workers at each episode along the road to the eventual demise of a large Dutch corporation. These data allow us to examine the various modes of turnover before the firm's death and to use them to infer how workers and the firm learn about the firm's prospects and the workers' intentions. They also enable us to study whether and how the characteristics of workers who remain until the firm's death differ from those of all of its affected workers and thus to infer the extent of biases in measuring the losses arising from displacement when the sample is restricted to workers who are actually displaced. The richness of the data set and the questions it allows us to examine more than offset any potential biases that might result if the firm is unrepresentative of large firms that disappear.

In the next section we present a stylized theoretical model of learning by workers and firms that stresses the exchange of information between the two parties. In Section III we describe our data and provide summary statistics charting the firm's demise, while in Section IV we estimate an empirical version of the model presented in Section II. Section V uses data on the entire pre-displacement history of the firm in order to infer the selectivity-adjusted losses generated by worker displacement, while Section VI illustrates the monetary gains a firm would make if it accounted for learning in structuring its layoff policies.

[3]The annual labor cost attributable to workers involved in plant closings is large. Assume, following Farber's (1997, Table A-6) calculations, that the fraction 0.015 of manufacturing employees lost their jobs in 1999 due to plant closings. Average annual earnings in manufacturing are \$13.91*41.7*52, and there are 18.432 million manufacturing employees. Assume also that non-wage costs are 20 percent of wages. Then the annual labor cost attributable to workers involved in plant closings in manufacturing is \$10.01 billion. Since Farber includes only workers with at least three years of tenure with the firm, his numbers, and thus our estimates, are probably lower bounds.

## II. Learning, Mobility, and Firm Death

Downsizing not only dislocates workers. It also changes the prospects of the workers who remain with the firm. A firm hit by a sequence of negative shocks that result in workforce adjustments can learn about how the quit behavior of its workers is affected by the adjustments and can update its firing policy accordingly. Workers who remain also have the opportunity to learn about the firm's preferences and can likewise update the information that enters their decision about quitting. We develop a two-sided learning model of the firm that accounts for these changes during downsizing episodes. While learning about workers' abilities in the context of analyzing wage dynamics has been studied before (Farber and Gibbons, 1996; Felli and Harris, 1996, Altonji and Pierret, 2001), the more general issue of two-sided learning in the context of employment decisions has not heretofore been analyzed.

We assume that the firm faces fixed costs of firing. When shocks arrive the firm must decide whether to downsize or not, and if it downsizes it does so by lumpy adjustments (Hamermesh, 1989; Pfann and Verspagen, 1989). Under a fixed-cost regime there is an option value for the firm of waiting to adjust, and during that period some workers decide to leave. Announcements of corporate restructuring change the values of contracts between the workers and the firm, and wage adjustments may be needed to continue some of the relationships, or unintended separations may follow (see also McLaughlin, 1991; Pfann, 2001).

### A. The Initial Episode of Decline

If the firm is hit by an unexpected shock in product demand that makes a downward adjustment of its workforce imperative, neither it nor its workers knows about the outcomes of each other's strategic choices in response to that shock. We assume that workers act first and that the firm waits to adjust until after it has observed its workers' responses. Waiting and collecting this extra information is an optimal strategy for a firm that faces irreversible adjustment costs.

*Worker-initiated separations during the initial episode*

The firm employs $N_1$ tenured workers. First we consider optimization by worker $i$, $i=1,..,N_1$. She makes a decision whether or not to stay in the firm and continue making firm-specific investments based on a comparison of the expected streams of future earnings inside and outside the firm. Her decision under uncertainty is written as

$$Q_{i1}^{*} = Q^{*}(X_{i1}; e_{i1}), \qquad i=1,..,N_1 \tag{1}$$

where $Q_{i1}{}^{*}$ is the unobserved quit propensity of worker $i$ during Episode 1, $X_{i1}$ is a vector of individual characteristics explaining $Q_{i1}{}^{*}$, and $e_{i1}$ is a worker-specific normally distributed error with zero mean and variance $(s_1{}^{Q})^2$. Although $Q_{i1}{}^{*}$ is unobserved, other workers' behavior reveals to the firm which workers are likely to quit. Denote $Q_{i1} = 1$ if $Q_{i1}^{*} > 0$ for the $N_1{}^{Q}$ worker-initiated separations, and $Q_{i1} = 0$ if $Q_{i1}^{*} \leq 0$ for the $N_1{}^{S} = N_1 - N_1{}^{Q}$ workers who stay until the end of the first episode. The probability of observing that worker $i$ quits is

$$\Pr\{Q_{i1} = 1\} = \Phi[(b_1 / s_1^{Q}) X_{i1}], \tag{2}$$

where $ß_1$ is a vector of unknown parameters.

*Employer-initiated separations at the end of the initial episode*

The optimizing firm decides whom to layoff by comparing the expected stream of a worker's future wages to his future productivity. The unobserved propensity to fire worker $i$ in Episode 1, $F_{i1}{}^{*}$, is written under uncertainty as

$$F_{i1}^{*} = F^{*}(Z_{i1}; n_{i1}), \qquad i=1,..,N_1{}^{S}, \tag{3}$$

where $Z_{i1}$ is a vector of the individual worker's characteristics explaining $F_{i1}{}^{*}$, and $?_{i1}$ is a worker-specific normally distributed productivity shock with zero mean and variance $(s_1{}^{F})^2$.

Firing decisions are related to the worker's age. In general, after an initial period of increase, a worker's productivity declines with age. To avoid shirking the firm will fire the most experienced workers with the lowest output (Stiglitz and Weiss, 1983). Firing can also be explained by the firm's (asymmetric) information about the worker's performance. Annual evaluation scores, which may be included in $Z$, measure relative performance, and low-scoring workers have a higher chance of being fired. In its layoff decision at the end of the initial episode the firm incorporates the quit behavior of the workers that it observed during the episode. Firing decisions also depend on statutory replacement costs that vary among workers. Given a worker's productivity, this variation is in large part due to differences in tenure at the time of firing.

An announcement of workforce reorganization changes the contingent contract between the worker and the firm. This may discourage some workers, who interpret the announcement as a departure from the informal agreement with the employer. The firm sees workers stay who are observationally identical to those who quit and realizes that these workers have, *ceteris paribus*, a high reservation wage $w_i^r$, or a low $e_{i1}$.

The firm can either react non-cooperatively or cooperatively. On the one hand, it can interpret a worker's low $e_{i1}$ as too high a reservation wage. In that case, the non-cooperative firm will match it with a high $n_{i1}$, so that $corr(n_{i1}, e_{i1}) = r_1^F < 0$. On the other hand, the cooperative firm can observe $e_{i1}$ to learn about a worker's loyalty to the firm when things turn bad. A high reservation wage—a low $e_{i1}$ –signals loyalty to the firm. Especially in times of economic distress, disloyal workers can be extremely harmful to the firm. In a model of monitoring cooperative agreements in a repeated principal agent relationship, Radner (1981) showed that the principal (the firm) observes the agent's (the worker's) disloyalty by means of a "statistical method of detecting 'cheating' by the agent rapidly enough to deter him from doing so" (1981, p.1128). Radner does not say what that method is. We propose a method for detecting idiosyncratic disloyalty based on each worker's observed reservation wage. If the firm's objective is to identify and retain the most loyal workers, it will couple a low $e_{i1}$ with a low $n_{i1}$, so that $r_1^F > 0$. In accordance with Radner's results, disloyalty is especially harmful to a firm that faces a high bankruptcy risk. Even though one might rationalize either sign for this correlation, a positive correlation should become more likely as the firm's chance of demise increases.

$F_{i1}^*$ is revealed in part to worker *i* when she sees other workers being fired. $F_{i1} = 1$ if $F_{i1}^* > 0$, for $N_1^F$ workers. Others are allowed to stay with the firm until the beginning of Episode 2, so that $F_{i1} = 0$ if $F_{i1}^* \leq 0$ for $N_2 = N_1^S - N_1^F$ workers. The probability individual *i* is fired at the end of Episode 1 conditional on not having quit during Episode 1 is

$$\Pr\{F_{i1} = 1 \mid Q_{i1} = 0\} = \Phi[(g_1 / s_1^F) Z_{i1} + (r_1^F / s_1^F) l_{i1}^Q], \tag{4}$$

where $g_1$ is a vector of unknown parameters, and $l_{i1}^{Q} = f[(b_1 / s_1^{Q}) X_{i1}]/(1-\Phi[(b_1 / s_1^{Q}) X_{i1}])$.

B. Subsequent Episodes of Downsizing

Initially the firm may have considered the negative shock to product demand to be a temporary blip. When new information becomes available with no sign of recovery, or additional negative shocks jeopardize the value of the firm, more downward adjustments may be necessary. The difference now is that the workers as well as the firm can optimally use the experience of the previous episode to recalculate the net present value of the match and act accordingly. If downsizing continues, two-sided learning should incorporate the information gathered about each other's expectations and intentions revealed during the previous episode.

*Worker-initiated separations during subsequent downsizing episodes*

The essential point, and the novelty of our analysis of turnover, is that the employer's behavior and prior patterns of mobility by the worker's fellow employees reveal information to her about her future earnings inside the firm. We assume that her wage inside the firm will be higher if her firm-specific skills are relatively scarce, since the employer will wish to induce her to remain in the firm in order to retain her services. A high rate of quits by workers similar to her during the previous episode *t-1*, $\hat{Q}_{it-1}$, signals this scarcity to her.

Obversely, she infers that her inside wage will be lower if the employer's demand for her skills has declined. A decline is signaled to her by the employer's recent layoff behavior, in particular by layoffs of workers like her at the end of Episode *t-1*, $\hat{F}_{it-1}$. We can thus write the worker's propensity to quit as

$$Q_{it}^{*} = Q^{*}(X_{it}; \hat{Q}_{it-1}; \hat{F}_{it-1}; e_{it}), \qquad i=1,..,N_t;\ \ t=2,..,T, \tag{5}$$

where $e_{it}$ is a worker-specific normally distributed residual with mean zero and variance $(s_t^{Q})^2$, and T marks the firm's final reorganization episode before its bankruptcy. In the absence of new shocks the effects of a worker's altered marginal productivity due to previous quits and layoffs imply that $v_{Qt}^{Q} \equiv \partial Q^{*} / \partial \hat{Q} < 0$ and $v_{Ft}^{Q} \equiv \partial Q^{*} / \partial \hat{F} > 0$. The signs of these partial derivates might be changed over subsequent episodes by the arrival of new information. For example, we might observe $v_{Qt}^{Q} > 0$, suggesting that workers' quit behavior in response to this information is similar to that of their predecessors. We might observe $v^{Q}_{Ft} < 0$, suggesting that workers who were likely to be fired before are not quitting. This behavior could suggest—and hence identifies—a change in beliefs about the permanence of the decline in product demand.

The expectations that workers form about the likelihood of being fired at the end of this episode are based on a rational decision process that uses what occurred at the end of Episode *t-1*. The information used by the employer at the end of the current episode *t* that renders $u_{it}$ different from $u_{it-1}$ is unknown to the worker at the time of the quit decision during Episode t and is thus uncorrelated with $Q^{*}_{it}$. There are two ways the worker can interpret the observed $u_{it-1}$ and act on that interpretation. On the one hand, low $u_{it-1}$ signals that, compared to observationally equivalent colleagues, she was unlikely to be fired during the last episode. As a consequence workers like her have become scarce to the firm. This would raise her reservation wage, $w_t^r$, and lower $e_{it}$, so that $corr(n_{t-1}, e_{it}) = r^{Q}_{t} > 0$. On the other hand, she might also think, "I escaped unexpectedly last time, but I did not quit, so I may be on the chopping block this time." This could lead her to reduce her reservation wage and raise $e_{it}$, so that $r^{Q}_{t} < 0$. Here too one might rationalize either sign for the correlation. Unlike the declining firm's decision-making process, for workers we cannot predict its direction and how it may evolve as the firm approaches its demise. Given (5) the conditional probability that worker i quits during episode *t* is:

$$\Pr\{Q_{it} = 1 \mid F_{it-1} = 0\} = \Phi[\Lambda^{Q}_{it}], \qquad i=1,..,N_t;\ \ t=2,..,T, \tag{6}$$

where $\Lambda^{Q}_{it} = (b_t / s^{Q}_{t}) X_{it} + (v^{Q}_{Qt} / s^{Q}_{t}) \hat{Q}_{it-1} - (v^{Q}_{Ft} / s^{Q}_{t}) \hat{F}_{it-1} + (r^{Q}_{t} / s^{Q}_{t}) l^{F}_{it-1}$.

*<u>Employer-initiated separations at the ends of subsequent downsizing episodes</u>*

Deriving the firm's firing policy proceeds essentially identically to the derivation of the workers' quit decisions in Episodes 2 to T. At the end of Episode t a worker's productivity is raised if recent quits and layoffs of similar workers have made his skills relatively scarce. A high rate of quits by similar workers during Episode *t*,

$\hat{Q}_{it}$, and a high rate of comparable layoffs at the end of the previous episode, $\hat{F}_{it-1}$, signal this scarcity to the manager. The firm's firing decision then becomes

$$F_{it}^{*} = F^{*}(Z_{it}; \hat{Q}_{it}; \hat{F}_{it-1}; n_{it}), \qquad i=1,..,N_t^F; \quad t=2,..,T, \tag{7}$$

where $u_{it}$ is a worker-specific normally distributed error with mean zero and variance $(s_t^F)^2$. When no new shocks arrive, the effects of the altered value of available skills due to previous separations imply that $v_{Qt}^F \equiv \partial F^* / \partial \hat{Q} < 0$ and $v_{Ft}^F \equiv \partial F^* / \partial \hat{F} < 0$. The arrival of new unexpected information about the firm's product demand can reverse the sign of either derivative. Similar to the first episode, the firm observes the workers' quit behavior during the period, so that $corr(e_{it}, n_{it}) = r_t^F$. The probability that worker *i* is fired is

$$\Pr\{F_{it} = 1 \mid Q_{it} = 0\} = \Phi[\Lambda_{it}^F], \qquad i=1,..,N_t, \; t=2,..,T, \tag{8}$$

with $\Lambda_{it}^F = (g_t / s_t^F) Z_{it} + (v_{Qt}^F / s_t^F) \hat{Q}_{it} + (v_{Ft}^F / s_t^F) \hat{F}_{it-1} + (r_t^F / s_t^F)\, l_{it}^Q$.

## III. The Demise of Fokker Aircraft

We investigate the empirical content of this model using personnel data from Fokker, the world's oldest aircraft manufacturing company, which was founded in 1919 and based in the Netherlands. Between 1984 and 1996 the company developed and produced three types of aircraft. Figure 1 shows that the global market for these airplanes grew steadily until 1990, after which it plummeted for five years. In the beginning the firm attempted to overcome the negative demand shock by lengthening its production process; but when demand remained low it ran out of resources and went bankrupt. After 1995 global demand recovered (see Figure 1), but this recovery came too late for Fokker. It was officially declared bankrupt on March 15th, 1996.

Figure 2 shows that from 1987 until 1991 the firm's total workforce grew steadily from 10,000 to over 12,500 permanent workers, while average hourly earnings were stable at approximately 25 guilders (US$14.3) in constant 1995 terms. The sharp global decline in demand for aircraft forced the company to reorganize and reduce its workforce. The reorganization started off with a new early retirement scheme for workers aged 55 years and older that became effective on March 1, 1991. During the period of decline employment fell from 12,500 to 0 after the bankruptcy, while real hourly wages increased from 25 guilders to 28.8 guilders (US$16.5).

Table 1a, taken from the report of the bankruptcy trustees, gives an overview of the employment reductions and dismissals that were announced between 1991 and 1996. Five episodes can be distinguished, each marked by advance notification of workforce reductions. In the descriptive and econometric analyses here we consider only tenured workers ages 17 to 54 years for whom positive payroll amounts appear in the corporate records. Table 1b shows the status of these workers distinguished by whether they quit, were laid off or remained with the firm. When the firm died at the end of Episode 5, approximately half of the remaining workforce was permanently displaced, while the other half was offered a one-year contract in a newly created, leaner, but eventually unsuccessful firm that the bankruptcy trustees launched.

The variables that we use in our analysis are ones commonly used in studies of worker turnover (e.g., Blau and Kahn, 1981; Topel and Ward, 1992), such as age, tenure, gender, educational level, educational type (general vs. vocational/technical), hours worked, and marital status. We also include information on the number of internal training courses provided by the firm to the worker, the number of external courses provided by other training agencies but commissioned by the firm, the outcomes of annual performance evaluations, and workers' commuting distances.

To elucidate the process of worker turnover during the firm's final years we distinguish six different employee groups. Groups 1 to 4 consist of those workers who left the firm – quits and layoffs – during the Episodes 1 to 4 respectively. The fifth group comprises workers who stayed until the firm's death and who on the Monday after the bankruptcy received an envelope with only the official dismissal notification. The sixth group consists of those workers who received two letters that day, one the dismissal letter from the bankrupt firm, and the other a one-year contract with the newly created company.

One way to look at the turnover process in this dying firm is presented in Tables 2. Table 2a shows the means of selected variables at Episode 1 for all groups. Tables 2b-2e present the means of selected variables at Episodes 2 to 5 for all groups remaining in the firm. We summarize only the variables that differ or change across episodes or groups. Tables 2 provide an initial view of the potential biases to losses from displacement that arise from considering only those workers employed in the firm at its closure (Groups 5 and 6, in the left-most two columns). These workers are disproportionately male, married, technically educated, and have longer tenure, better job evaluations, more internal (intramural) training courses and fewer external (extramural) training courses. Very clearly, basing inferences about losses to displacement on those workers who leave when a plant closes leads to overestimates – if one bases one's inferences on the wage-tenure profile. Clearly too, the workers who stay until the end seem to be of more value to the firm than to other firms.

## IV. Estimating the Learning Model of Turnover

The novelty of our model is the introduction of past patterns of mobility, both worker- and employer-induced separations, into the worker's choice of when to leave and the employer's choice of whom to layoff. The central economic question in this study is whether learning occurs—whether workers and their employer make their decisions about turnover based not only on the workers' objective characteristics, but also on inferences about the impact of recent patterns of mobility on future wages and (unobservable) productivity. In this Section we specify the formulation of measures of $\hat{F}_i$ and $\hat{Q}_i$, estimate the model's parameters, and examine their significance and how they change as the firm's demise approaches.

The covariates in the quit equations ($X_{it}$) and the layoff equations ($Z_{it}$) have both common and specific components. The common components include indicators for seven age groups, for females, for three levels of educational attainment (with basic education as the reference group), for technical/vocational education, part-time work, and marital status, and continuous measures of years of firm tenure, number of internal training courses and number of external training courses. The specific component—the exclusion restriction—in the quit equation is a variable that measures commuting distance (in kilometers). It is hard to argue for inclusion of this variable in the layoff equation, but barring complete foresight by workers one would expect that distance to work would affect the quit decision. The specific component in the layoff equation is the measure of job performance. The informational content of this variable is clearly asymmetric, so that its value lies in the firm's comparisons across workers. That information is available to the employer but not to the employee, so that it cannot affect quit decisions. Expanding beyond the formal model, in the empirical application we allow workers' educational attainment to affect their perceptions of the impact of past patterns of mobility on their prospects in the firm. By doing so we allow for the possibility that the assessments take place at different rates or for reasons that are not observed by the econometrician but that are correlated with educational attainment.

For each Episode $t$ the parameters are only identifiable relative to the standard errors $s_t^Q$ and $s_t^F$ in the probits. One way to treat this identification problem is by setting all the standard errors equal to 1. In our application, however, it is very likely that the errors are different for quits and layoffs and that the associated variances change over time. Assuming constancy of these variances would also severely restrict the estimates of the two-sided learning model in Section II. Hence we do not impose these identifying restrictions, but instead present the unrestricted parameter estimates for all episodes. The results are given in Tables 3a and 3b.

## A. Quit equations

The demographic differences in propensities to quit generally accord with what has been demonstrated in the prior literature. Workers with lower quit propensities are between 35 and 50 years old, have longer tenure, and (surprisingly) are less well educated (except in Episode 2). That they have also taken more internal courses is consistent with the observation that these courses may represent shared firm-specific investments that inhibit workers from leaving the firm. That they are workers who live closer to their jobs is consistent with the expectation that propinquity to the workplace can offset other incentives to quit when the firm's prospects worsen.

The coefficients of $\hat{Q}_{it-1}, \hat{F}_{it-1}$ and $\hat{l}_{it-1}^{F}$ are generally insignificant, except for Episode 3, when the estimated $v_{F3}^{Q}$ is negative for all levels of education and significantly negative for two. That $v_{F3}^{Q} < 0$ indicates that workers with low expected conditional firing probabilities in the second episode were more likely to quit in the third episode. This estimate suggests a change in their beliefs about the character of the decrease in product demand and the firm's future prospects as of the third episode. Also, in Episode 3 the estimated correlation coefficient $r_t^Q$ is significantly negative, suggesting that workers believed that the firm would continue a layoff policy similar to that of the previous period. Implicitly, a low idiosyncratic firing probability in the second layoff round reduced workers' reservation wages during the third episode.

B. Layoff equations

The results in Table 3b show that workers with lower firing probabilities have longer job tenure, are males (in Episodes 2, 3, 4 and 5), have higher educational attainment, have technical/vocational schooling (Episodes 1, 2, 3 and 5), have taken more internal and external training courses (Episodes 1, 3 and 5), are married (Episodes 1, 2, 3 and 5), and have a higher job evaluation during all episodes.[4] The firm chooses to retain workers with whom it shares more firm-specific capital, whose demographic characteristics pay off in the labor market, and who have the best relative annual job evaluation scores, all else equal.

In the layoff equations most of the coefficients of $\hat{Q}_{it}, \hat{F}_{it-1}$ and $\hat{l}_{it}^{Q}$ are significant in Episodes 2, 3 and 4. At the early stages of the reorganization, in Episodes 2 and 3, $v_{Qt}^{F}$ is positive and significant. Due to its prolonged economic distress the firm increased its propensity to layoff workers whose observably similar counterparts quit during the previous episode. We estimate $v_{Qt}^{F} < 0$ for all educational levels at the final reorganization before bankruptcy (at the end of Episode 4). These estimates show that the workers who had quit were the ones that the firm most wished to retain. The estimated $v_{Ft}^{F} > 0$ for all educational levels indicate that the firm maintained its layoff policy between Episodes 3 and 4.

C. Learning over time

One way to draw inferences from Table 3 about the parties' learning processes through time is by examining how the coefficients change. The interpretation of these comparisons is difficult, however, because of the identification problem that results from the nonconstancy of the variances over time. One simple solution is to compute tests of the hypotheses that the correlation coefficients, weighted by the variances, are zero or constant over time for the respective quit and layoff equations.

[4]We also experimented with including the annual job performance evaluation score as a covariate in the quit probits. It had no explanatory power. This confirms the validity of our exclusion restriction and that the asymmetric information argument of the principal-agent theory holds for this firm.

Let $\bar{r}^F$ and $\bar{r}^Q$ be the averages over time of $r_t^F$ and $r_t^Q$ respectively. The first set of tests yields the hypotheses that $\bar{r}^F = 0$ and $\bar{r}^Q = 0$.[5] The estimated correlation coefficients and the accompanying test statistics for employer learning in the layoff equations are:

Employer learning: $\bar{r}^F = .918$ ; $c^2(5) = 54.2$, p<.001 ;

Time constancy: $c^2(5) = 62.0$, p<.001 .

The test statistics for workers' learning in the quit equations are:

Employee learning: $\bar{r}^Q = -.028$ ; $c^2(4) = 6.4$, p=.169

Time constancy: $c^2(4) = 5.8$, p=.218 .

Our estimates thus imply that $\bar{r}^F > 0$ and $\bar{r}^Q = 0$. The employer clearly learns, but that learning is not constant through time (either because of hysteresis in the learning process or because $s_t^F$ varies through time as a result of temporal variation in the arrival rate of shocks to product demand). That $\bar{r}^F > 0$ implies that in a repeated cooperative game between a firm and its workers the employer learns about workers' loyalty.

Workers exhibit no evidence of learning. This result might indicate that some workers form rational expectations one way ( $r_t^Q < 0$ ) and some the other way ( $r_t^Q > 0$ ), and that their numbers are roughly equal. Alternatively, it might show that the workers simply fail to form expectations in any systematic way. We also find no evidence of changes through time in the workers' inability to learn. This result is consistent with the finding that there was no change in patterns of investment in firm-specific human capital among a random sample of American workers as displacement approached (Hamermesh, 1987).

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[5]The test statistics describing the hypotheses on F and Q are: $c^2(df^j) = (r_t^j - \bar{r}^j)'(\hat{\Omega}^j)^{-1}(r_t^j - \bar{r}^j)$, with $j=F,Q$, and $df^F=5$, $df^Q=4$. The $\hat{\Omega}^j$ are the variance-covariance matrices of the respective vectors of estimated correlation coefficients. A consistent but inefficient estimator for $\hat{\Omega}^j$ is the diagonal matrix of the correlation coefficients' estimated variances. The second set of tests is of the hypotheses that $r^F$ and $r^Q$ are constant over time. The corresponding test statistics are $c^2(df^j) = (r_t^j)'(\hat{\Omega}^j)^{-1}(r_t^j)$, with $j=F, Q$.

If learning about loyalty in a cooperative game of downsizing between the firm and its workers is important, and learning is not constant through time, following Radner (1982) we expect that the learning will converge faster to an optimal rate as the date of demise approaches. If the employer's learning develops through time, a crucial question then is in what direction, if any, it develops. Do the coefficients that describe its layoff policy indicate that the firm is steadily learning more about employees' loyalty (learning as a stationary autoregressive process), learning less (learning as a non-stationary or trending process), or merely that learning varies randomly across periods (learning as an i.i.d. process)?

To investigate this question we look at possible time-dependence in the process that generates the parameters of the layoff equations describing the firm's turnover policy as a function of each worker's observable characteristics $Z_{it}$ . The existence of a temporal pattern in $\tilde{g}_t$ can be interpreted as evidence that the firm incorporates what it has learned about its workers' loyalty through time. (The coefficients $\tilde{g}_t \equiv g_t / s_t^F$ belong to the variables $Z_{it}$ in equations (3) and (7).) During each episode of downsizing the employer constructs layoff decisions under uncertainty, basing its turnover policy on $Z_{it}$. To test for an underlying dynamic mechanism that affects the entire set of relevant parameters $\tilde{g}_t$ similarly, we investigate if the firm's layoff policy reveals a "parameter-generating process" that can be described by the dynamic fixed-effect model

$$\tilde{g}_{jt} = d_0 + d_1 t + \tilde{g}_i + f_1 \tilde{g}_{jt-1} + m_{jt} \qquad , \ m_{jt} \sim NID(0, s_m^2), \tag{9}$$

t=1,.., 5 (the number of episodes), and j=1,..,19 (the length of the parameter vector $Z_{it}$). The stationarity condition for this model is $|f_1|<1$, with $d_1=0$ indicating the absence of a trend affecting the process exogenously.

We consider four possible descriptions of the dynamics of the firm's incorporating learning into its turnover policy:

| | | |
|---|---|---|
| *i:* | $f_1=0$ | i.i.d. learning; |
| *ii:* | $0<f_1<1$ | stationary smooth learning; |
| *iii:* | $-1<f_1<0$ | stationary alternate learning; |
| *iv:* | $\lvert f_1\rvert {}^{3} 1$ | nonstationary learning. |

The parameter estimates (based on first-differences from fixed-effects estimates) are $\hat{f}_1$ =0.67 (s.e.=0.03), and $\hat{d}_1$ = 0.07 (s.e.=0.11). The time-trend term is small and statistically insignificantly different from zero. The estimate $\hat{f}_1$ suggests a stationary smooth learning process: The magnitude of the autocorrelation of the process dies out essentially exponentially. In other words, the firm learns increasingly more about its workers' behavior through time, but the accretion of knowledge decreases exponentially, with a smaller $f_1$ indicating a more rapid decay. Stated differently, the more downsizing episodes the firm goes through, the closer its turnover decisions approach the optimal layoff policy under uncertainty that incorporates what it has learned over time about individual workers' loyalty.

Our results imply that, in the presence of fixed adjustment costs, it is optimal for the firm to spread the downsizing process across a number of consecutive episodes. This allows it to analyze its workers' quit behavior and learn about the remaining workers' loyalty to the firm. While lumpy mass layoffs occur frequently, our results indicate that a once-and-for-all reorganization early in the process of corporate demise is sub-optimal for the downsizing firm, for that prevents it from designing a firing policy that takes advantage of learning about its employees' attachment.

## V. Measuring the Losses to Displacement Accounting for Prior Two-Sided Selection

A major focus of the literature on labor-market displacement has been on the losses that workers incur when the firm downsizes or closes. The goal of much of this literature has been to infer the magnitudes of these losses in order to structure policies to compensate displaced workers (e.g., Kiefer and Neumann, 1979; Hamermesh, 1987). Much of this research has assumed that the losses can be measured by the firm-specific human capital embodied in the displaced workers and destroyed when they are laid off (and even more clearly so if the plant closes). These losses have been proxied by the value, in terms of higher wages, generated by the workers' tenure with the employer at the time when displacement occurs.

The difficulty with this common approach should be apparent from the analysis thus far. The workers who remain to be displaced are not a random sample of those who were employed when the prospect of displacement first arose. One of the variables strongly affecting selection into quitting and layoff before the plant closed was the worker's tenure with the firm. Thus workers remaining until the plant's demise will have different (presumably greater) tenure when the firm's difficulties began than the average worker present then. Moreover, wage-tenure profiles calculated based on those more senior workers who remain until the plant's demise are also unlikely to characterize wage determination among all the workers who were in the plant *ab initio*. Losses of firm-specific human capital cannot be indexed based on the non-randomly selected workers who remain with the firm throughout its decline.

To examine this issue we estimate standard log-earnings equations at two points in time: 1) Episode 1, the first time that information became publicly available that Fokker was having severe difficulties; and 2) Episode 5, i.e., including only those workers who were present when bankruptcy was declared. Various characteristics observed at Episode 1 of all workers included in the first group, of those in the first group who were eventually fired before bankruptcy, and of workers in the second group, are presented in the first three columns of Table 4. The workers who remained until bankruptcy were more senior than their fellow workers at Episode 1, had received higher job evaluations, and were more likely to be married and male and to have had a technical/vocational education.

The standard measure of the annual wage loss of the average worker displaced when a plant closes (in our case, at bankruptcy) calculates

$$L^* = \int_0^4 f^*(T)W^*(T)dT \ , \tag{10}$$

where T indexes firm tenure, $f^*(\cdot)$ is the density function describing the tenure of workers who are displaced at bankruptcy, and $W^*(\cdot)$ are wages at the time of bankruptcy as a function of tenure, conditional on other wage determinants. Recognizing that the structure of wages changes during the firm's decline, we can correct the errors in (10) by calculating an average loss based on the wage structure before it became contaminated by the non-random departure of workers and by the firm's adjustments to its wage policies. We substitute $W^0(T)$, the wage structure at Episode 1, for $W^*(T)$ in (10) to compute $L^0$. Even this measure fails to account for non-randomness in the distribution $f^*(T)$, however. The best measure of the loss to all employees affected by the firm's decline substitutes into (10) both $W^0(T)$ and $f^0(T)$, the distribution of firm tenure at their departure of workers who were present when the decline began.

The upper panel of Table 5 shows the coefficients of the quadratic in tenure from log-earnings equations calculated at Episode 1, and from the same regressions estimated at Episode 5 for those workers who remained until bankruptcy and who are thus the only workers who would be included in a conventional study of plant closings. Clearly, the apparent returns to tenure diminished as the firm approached its end, no doubt because the non-random selection of workers out of the firm during this time resulted in a more homogeneous, and substantially more senior workforce at the time of its demise. (The coefficient of variation of tenure was 0.95 at Episode 1, but only 0.55 at Episode 5.) This apparent decline in the returns to firm tenure means that previous estimates of lost firm-specific human capital understate the losses because they understate the returns to tenure in a healthy firm. The calculations of $L^*$ and $L^0$ shown in the bottom panel of Table 5 confirm this observation. In this sample the average annual earnings lost by those workers who remain until the end are somewhat (3.6 percentage points) higher when we base the measure on the structure of wages before it was influenced by the non-random departure of other workers during the firm's decline.

While $L^0$ accounts for the change in the structure of wages, it is still based on the distribution of tenure of only those workers who chose and whom the firm chose to remain until the end. To calculate the average loss to all workers affected by the firm's decline and eventual demise, the next calculation in Table 5 bases $L^*$ on what the tenure of the average worker who left the firm (voluntarily or involuntarily) would have gained him or her under the wage structure prevailing when the decline began. This measure of the annual earnings loss of workers whose employment relation was severed is remarkably close to the conventional measure. The flattening earnings-tenure profile as the firm nears its demise almost exactly offsets the impact of increasing average tenure among the remaining workers.

Finally, we showed in the previous section that voluntary quitting appears in this sample not to have reflected workers' learning (not to have been informed by the firm's declining prospects). That being the case, one might argue that there are no extraordinary losses to workers who quit, so that including them in the calculation of average tenure is mistaken. In Table 5 we thus present an alternative calculation of $L^*$ based on the tenure when they were fired of all those employees who were present at Episode 1 and who did not subsequently quit. The results suggest that this measure exceeds the conventional one, but the differences are slight.

The appropriate measure for evaluating the loss faced by displaced workers must be uncontaminated by the effects of non-random selection on inferences about the average loss per worker. That being so, the best estimate of the wage that workers leaving Fokker would have received elsewhere is 19.9 percent (1 - exp(-.222)) below what they received at Fokker. This wage loss engendered by displacement is quite similar to the wage loss that we would infer was experienced by those workers who were directly affected at Fokker's eventual bankruptcy. Basing compensation only on the experiences of those workers present when Fokker gives the correct per-worker calculation in this case only because the wage-tenure profile changed so as to offset the rising tenure in the firm.

The specific example in this calculation is not important. The issue is the more general one that conventional calculations of the losses to displaced workers are incorrect for two reasons: 1) The wage structure used to infer losses is estimated incorrectly because the workers included in the estimation are selected non-randomly; and 2) Non-random selection means that the characteristics of the group directly affected by a plant closing are not necessarily those of all workers who are affected by the entire process of a firm's death. Both kinds of selectivity need to be accounted for when constructing policies to compensate displaced workers.

## VI. Measuring Employers' Gains from Learning

Estimates like those in Section IV can also be used to infer how much a firm gains by learning about the productivity and market opportunities of its workers as it approaches shutdown. Viewed differently, we can use the estimates to calculate the gains from considering this additional set of determinants of firms' layoff behavior. In our specific example the interesting question is how much the company gained at Episode 5 from the learning that we inferred it did over the entire period. We are thus asking what the value of that learning was to the company, but only at the point of the bankruptcy. The gains are presumably in the increased value of the firm attributable to the firm-specific human capital that would otherwise have been lost had the firm not learned about its workers' productivity and opportunities.

To calculate the gains to learning that are realized when the firm reorganizes at bankruptcy we compare the layoff probits that include learning (those presented in Table 3b) to a counterfactual layoff probit. The restricted estimating equation excludes the measures of altered productivity (the interactions of the education indicators with lagged fires and quits) and the correlations between the unexplained idiosyncratic quit and firing propensities.

To calculate the gains to learning we ask how many workers are correctly predicted not to be fired in the enhanced probit in the final column of Table 3b compared to the number correctly predicted in a simple counterfactual probit that excludes the possibility of learning. We then value this difference by valuing the firm's share of firm-specific human capital. We use the estimate in Table 5 of the lost earnings of those fired at Episode 5 (all those who would usually be counted as displaced in a plant closing) and assume that this is the value of returns to the retained workers' firm-specific human capital. On a per-worker retained basis the calculation is

$$\text{Gain}=W\cdot\exp[-.242]*\{s/(1-s)\}\{[f_{LEARN}-f_{NoLEARN}]/\Pr(\text{NotFired}\}, \tag{11}$$

where W is the average wage of workers at this point, s is the firm's share of the specific human capital in which it and its workers have invested, $f_{LEARN}$ and $f_{NoLEARN}$ are the fractions of workers retained after Episode 5 predicted correctly in the expanded and simple probits respectively.

Of the workers remaining just before Episode 5, 48.8 percent were retained. 25.8 percent of all workers were correctly predicted as being retained in the expanded probits that included learning. Only 23.7 percent of all workers were correctly predicted as retained in the probits that did not account for learning. Taking mean annual earnings per worker as 52,080 guilders, the calculation in (11) yields 1082 guilders per worker retained under the assumption that s=0.5. The firm retained 2619 workers (Table 1b), which sums to an estimated value of learning of $1.6 million in 1996. Stated differently, the gain per retained worker is about 2.1 percent of the average worker's annual earnings. If the firm's share of the returns to firm-specific training exceeds 0.5, its monetary gains from learning about workers' behavior are still greater.

The result here is for Fokker alone; and it would be interesting to expand it to an entire economy. Based on the figure of $10.01 billion in labor costs among displaced manufacturing workers in the United States that we noted in Section I, our estimates here suggest that employers' learning might lead to an annual savings of $210 million on these workers (.021 x $10 billion). The cohort of firms that close each year reaps this gain, however, over the entire length of the process leading up to closing. In our example this process took six years, but we have no idea whether that is typical. Assuming it is, however, then for U.S. manufacturing the annual gain arising from employers' learning rises to $1.26 billion. Since this calculation is for manufacturing alone, and since plant closings are more common among smaller firms, it is likely that the total annual value to employers of this type of learning as their businesses decline is still greater.

## VII. Conclusions

In this study we have examined possibilities of workers' and employers' learning using a unique data set describing the history of mobility in a large Dutch firm during its final six years of existence. The evidence suggests that workers' quitting is unaffected by expectations about the employer's layoff policies. The firm learns which employees are likely to quit, however, and alters its layoff policies accordingly. That learning, moreover, is quite rapid early in the process of the firm's decline but decelerates as more information is accreted. Learning about its workers' loyalty enhances the value of the firm, as it is able to optimize its layoff policy to retain a greater proportion of its prior investment in its workers' firm-specific human capital.

That learning occurs adds another reason why the workers who remain until a plant closes are selected non-randomly from the group of workers who were present when the firm's initial negative demand shocks arrived. This non-randomness means that any attempt to measure workers' losses from a plant closing will be biased, as it is based on a selected sample of workers. To evaluate the extent of this bias we adjust usual measures of losses resulting from displacement to account for this two-sided selection. While both of these adjustments are important, in our particular example they are roughly offsetting.

We have presented a theory of learning and an econometric case history to illustrate it. The basic idea can be expanded upon in a variety of ways. First, within the context of our model the behavior of other declining firms could be studied—nothing guarantees that workers in all such firms fail to learn, nor that all employers learn in the way that the employer that we studied did. A second, more important avenue would note that a more general model could also encompass the learning process in growing firms by accounting for the role of employers' learning about quits in determining the pattern of hiring and firing. (A very specific, mundane example might be the behavior of university economics departments in hiring/tenure decisions about junior faculty in the face of a changing entry-level job market for economists.) Similarly in such a model, one might envision workers' learning about their future prospects by observing their employers' past hiring and firing decisions. One might even expand such a model further to include how two-sided learning is modified by promotion decisions and productivity changes resulting from internal mobility. The general point we have made—that studying prior interactions between learning by firms and workers is useful in analyzing mobility patterns—seems applicable to understanding the dynamics of all types of mobility.

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**Figure 1:**

**World Aircraft Market, Orders and Deliveries**

**40-70-125 Seaters**

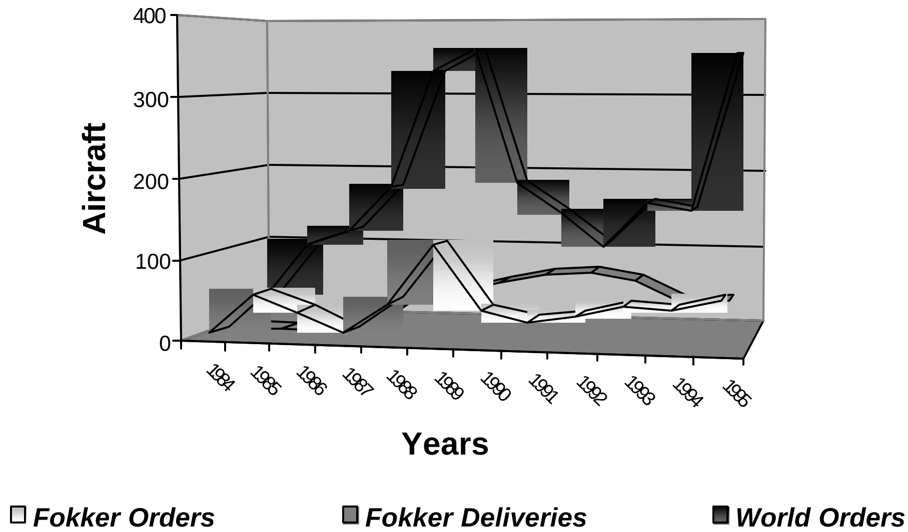
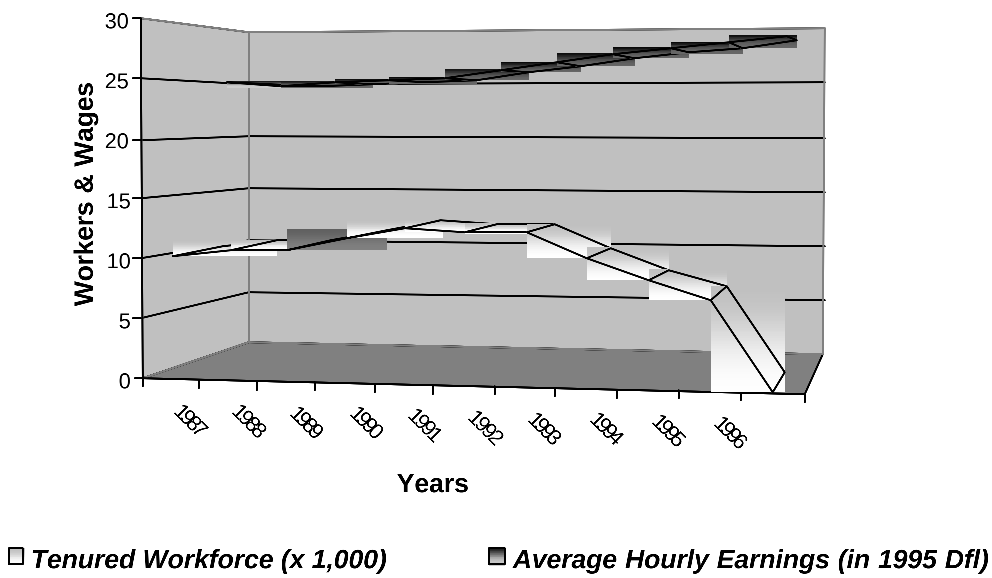



**Figure 2:**

**Workforce & Hourly Earnings**

**Fokker Aircraft b.v.**



**<u>Table 1a.</u>**

**Reorganizations and Officially Announced Staff Reductions**

| Release of Announcement | Episode 1: March 1, 1991 | Episode 2: October 1, 1992 | Episode 3: April 23, 1993 | Episode 4: April 13, 1994 | Episode 5 June 19, 1995 |
|---|---|---|---|---|---|
| Workforce Reductions (in FTEs) | 1,000 | 950 | 2,118 | 1,900 | 1,760 |
| Compulsory Dismissals | 0 | 220 | 1,350 | 1,100 | 450 |

<u>Source</u>: A.A.M. Deterink, B.F.M. Knüppe, A. L. Leuftink, R.J. Schimmelpenninck, *Bankruptcy Trustees' Investigation of the Causes of the Bankruptcy of N.V. Koninklijke Nederlandse Vliegtuigfabriek Fokker*, *Fokker Aircraft B.V.* , *and FokkerAdministration B.V.*, 1997, p. 117.

**Table 1b.**

**Stylized Sequence of Layoff and Quit Events at Fokker**

**(All workers between 17 and 54 years old with positive payroll amounts)**

| | **Episode 1:** | **Episode 2:** | **Episode 3:** | **Episode 4:** | **Episode 5:** |
|---|---|---|---|---|---|
| **Period between Announcements** | **March 1, 1991 Sept. 30, 1992** | **Oct. 1, 1992 April 22, 1993** | **April 23, 1993 April 12, 1994** | **April 13, 1994 June 18, 1995** | **June 19, 1995 March 15, 1996** |
| Quits | 363 | 306 | 491 | 505 | 243 |
| Lay-offs | 66 | 885 | 676 | 285 | 2578 |
| Remaining workforce | 9606 | 8396 | 7099 | 5990 | 2619 |

Source: Fokker Administration B.V. Personnel Files.

## Table 2a.

**Means of Selected Variables at Firing Episode 1, by Date of Departure from Fokker[a]**

| | | | **Group** | | | | |
|---|---|---|---|---|---|---|---|
| | **6** | | **5** | **4** | **3** | **2** | **1** |
| | **Remained** | | | | **Left at:** | | |
| **Variable** | | | **t=5** | **4£t<5** | **3£t<4** | **2£t<3** | **1£t<2** |
| Male | .871 | | .913 | .900 | .890 | .848 | .798 |
| Married | .688 | | .613 | .582 | .488 | .446 | .467 |
| Education: | | | | | | | |
| Basic | .589 | | .534 | .294 | .546 | .590 | .593 |
| Low | .264 | | .251 | .280 | .268 | .253 | .219 |
| Medium | .109 | | .146 | .191 | .111 | .090 | .097 |
| High | .037 | | .070 | .236 | .076 | .068 | .090 |
| Education: | | | | | | | |
| Technical | .723 | | .746 | .678 | .704 | .628 | .604 |
| Years of tenure | 10.63 | | 10.10 | 8.65 | 5.99 | 4.99 | 7.12 |
| | (.15) | | (.15) | (.23) | (.18) | (.19) | (.31) |
| Job evaluation | 3.57 | | 3.49 | 3.27 | 3.34 | 3.26 | 3.27 |
| | (.01) | | (.01) | (.02) | (.02) | (.01) | (.02) |
| Number of internal | 4.00 | | 3.54 | 2.46 | 4.15 | 3.92 | 3.01 |
| training courses (.10) | | (.09) | (.12) | (.13) | (.13) | (.14) | |
| Number of external | .50 | | .51 | .68 | .60 | .59 | .38 |
| training courses | (.02) | | (.02) | (.04) | (.03) | (.03) | (.03) |
| Real salary | 47.06 | | 49.22 | 56.86 | 43.10 | 40.98 | 43.30 |
| (1,000 guilders) | (.33) | | (.38) | (.68) | (.48) | (.46) | (.69) |

Standard errors of means in parentheses here and in Tables 2b-2e.

[a]Here and in Tables 3 and 4 Basic educational level means secondary schooling only; Low means lower-level vocational training (lbo) or lower-level general schooling (mavo); Middle is middle-level vocational training (mbo) or middle-level general schooling (havo/vwo); High refers to higher-level vocational training (hbo) or a university degree.

**Table 2b.**

**Means of Selected Variables at Firing Episode 2, by Date of Departure from Fokker**

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | **Group** | | | |
| | **6** | | **5** | **4** | **3** | **2** |
| | **Remained** | | | **Left at:** | | |
| **Variable** | | | **t=5** | **4£t<5** | **3£t<4** | **2£t<3** |
| Job evaluation | 3.63 | | 3.51 | 3.30 | 3.45 | 3.31 |
| | (.01) | | (.01) | (.02) | (.02) | (.01) |
| Number of internal | 6.12 | | 5.19 | 3.78 | 5.76 | 5.04 |
| training courses (.12) | | (.11) | (.15) | (.15) | (.14) | |
| Number of external | .79 | | .84 | .99 | .93 | .72 |
| training courses (.03) | | (.02) | (.05) | (.04) | (.03) | |
| Real salary | 49.19 | | 51.52 | 59.60 | 45.94 | 42.72 |
| (1,000 guilders) | (.34) | | (.38) | (.68) | (.47) | (.44) |

## Table 2c.

**Means of Selected Variables at Firing Episode 3, by Date of Departure from Fokker**

| | Group | | | |
|---|---|---|---|---|
| | **6** | **5** | **4** | **3** |
| | **Remained** | | **Left at:** | |
| **Variable** | | **t=5** | **4£t<5** | **3£t<4** |
| Job evaluation | 3.61 | 3.51 | 3.29 | 3.40 |
| | (.01) | (.01) | (.02) | (.02) |
| Number of internal | 6.84 | 5.71 | 4.06 | 6.09 |
| training courses (.13) | (.12) | (.16) | (.16) | |
| Number of external | .88 | .93 | 1.05 | .99 |
| training courses | (.03) | (.03) | (.05) | (.04) |
| Real salary | 49.17 | 51.58 | 59.89 | 46.05 |
| (1,000 guilders) | (.35) | (.38) | (.67) | (.47) |

**Table 2d.**

**Means of Selected Variables at Firing Episode 4, by Date of Departure from Fokker**

| | Group | | |
|---|---|---|---|
| | 6 Remained | 5 Left at: | 4 |
| **Variable** | | **t=5** | **4£t<5** |
| Job evaluation | 3.63<br>(.01) | 3.49<br>(.01) | 3.26<br>(.02) |
| Number of internal training courses | 7.62<br>(.14) | 6.30<br>(.13) | 4.30<br>(.16) |
| Number of external training courses | .99<br>(.03) | 1.01<br>(.03) | 1.10<br>(.05) |
| Real salary (1,000 guilders) | 51.48<br>(.36) | 53.66<br>(.39) | 61.02<br>(.67) |

**Table 2e.**

**Means of Selected Variables at Firing Episode 5, by Date of Departure from Fokker**

| | Group | |
|---|---|---|
| | **6** | **5** |
| **Variable** | **Remained** | **Left at t=5** |
| Job evaluation | 3.62<br>(.01) | 3.49<br>(.01) |
| Number of internal training courses | 7.80<br>(.14) | 6.31<br>(.13) |
| Number of external training courses | 1 03<br>(.03) | 1.01<br>(.03) |
| Real salary (1,000 guilders) | 52.08<br>(.36) | 53.88<br>(.41) |

**<u>Table 3a.</u>**

**Determinants of Turnover Probabilities:  Worker Initiated Separations**

| *Variables* | *Episode 1* | *Episode 2* | *Episode 3* | *Episode 4* | *Episode 5* |
|---|---|---|---|---|---|
| Constant | -.842 (.556) | .742 (.829) | .115 (1.03) | -.1.13 (1.27) | -.891 (1.34) |
| Age: | | | | | |
| [17 ; 25) | .044 (.021)* | -.042 (.026) | -.022 (.026) | -.034 (.027) | -.057 (.038) |
| [25 ; 30) | .029 (.017) | -.042 (.022) | -.017 (.023) | -.019 (.022) | -.023 (.030) |
| [30 ; 35) | .020 (.015) | -.037 (.018)* | -.018 (.021) | -.022 (.020) | -.027 (.026) |
| [35 ; 40) | .020 (.013) | -.037 (.016)* | -.017 (.019) | -.026 (.017) | -.030 (.024) |
| [40 ; 45) | .009 (.011) | -.029 (.014)* | -.015 (.016) | -.026 (.015) | -.032 (.021) |
| [45 ; 50) | .004 (.011) | -.029 (.013)* | -.014 (.015) | -.029 (.014)* | -.032 (.019) |
| [50 ; 54] | .005 (.011) | -.035 (.013)* | -.018 (.014) | --- | -.017 (.018) |
| Tenure | -.042 (.007)* | -.072 (.012)* | -.023 (.009)* | -.038 (.023) | -.030 (.013)* |
| Female | -.045 (.081) | .058 (.096) | .072 (.086) | .090 (.096) | .176 (.129) |
| Education: (reference is 1: Basic Level) | | | | | |
| 2: Low | .049 (.064) | -.220 (.115)* | .097 (.100) | .234 (.125) | .480 (.187)* |
| 3: Medium | .121 (.086) | -.237 (.200)* | .301 (.124) | .091 (.388) | .800 (.213)* |
| 4: High | .021 (.102) | -.291 (.197) | .423 (.147) | .003 (.392) | .448 (.253)* |
| Techn.Educ. | -.181 (.064)* | -.216 (.083)* | -.141 (.075) | -.109 (.115) | -.252 (.092)* |
| Full-time | -1.37 (.331)* | -.761 (.557) | -.124 (.370) | .309 (.477) | .318 (.511) |
| Int. Courses | -.009 (.006) | -.008 (.016) | -.024 (.005)* | -.007 (.010) | -.006 (.006) |
| Ext. Courses | -.027 (.026) | -.036 (.052) | .086 (.017)* | .077 (.046) | .069 (.033) |
| Married | -.191 (.056)* | -.048 (.093) | .031 (.064) | .118 (.104) | .132 (.088) |
| Distance | .005 (.001)* | -.000 (.002) | .003 (.001)* | .001 (.002) | .000 (.002) |

**<u>Table 3a, *continued*</u>**

| | ***Episode 1*** | ***Episode 2*** | ***Episode 3*** | ***Episode 4*** | ***Episode 5*** |
|---|---|---|---|---|---|
| ***Variables*** | | | | | |
| Educ1* $\hat{Q}_{it-1}$ | --- | -1.53 (2.96) | .728 (3.51) | -1.31 (3.28) | -4.61 (2.90) |
| Educ2* $\hat{Q}_{it-1}$ | --- | -.535 (2.75) | 5.89 (4.25) | -.997 (1.83) | -3.16 (2.10) |
| Educ3* $\hat{Q}_{it-1}$ | --- | -5.73 (3.88) | -2.42 (5.09) | -.769 (3.30) | -4.14 (1.92) |
| Educ4* $\hat{Q}_{it-1}$ | --- | 3.77 (3.64) | 2.32 (3.11) | .327 (2.54) | -2.25 (1.74) |
| Educ1* $\hat{F}_{it-1}$ | --- | -6.49 (4.39) | -.741 (.556) | .569 (.739) | .858 (2.98) |
| Educ2* $\hat{F}_{it-1}$ | --- | -9.35 (7.42) | -3.63 (1.02) $^{*}$ | .371 (1.20) | -.894 (3.16) |
| Educ3* $\hat{F}_{it-1}$ | --- | 66.4 (38.0) | -2.01 (1.78) | 3.96 (3.37) | -.616 (5.41) |
| Educ4* $\hat{F}_{it-1}$ | --- | -41.9 (36.3) | -9.05 (3.59) $^{*}$ | 6.27 (4.45) | 7.25 (4.24) |
| $l^{F}_{it-1}$ | --- | .049 (.175) | -.387 (.166) $^{*}$ | .194 (.428) | .072 (.407) |
| <u>Diagnostic statistics</u> | | | | | |
| Pseudo $\overline{R}^2$ | .099 | .108 | .078 | .091 | .079 |
| Log *L* | -1388.4 | -1196.8 | -1687.0 | -1558.3 | -885.5 |
| Observed $\overline{Q}^{*}_{it}$ | .036 | .032 | .061 | .083 | .045 |
| Predicted $\overline{Q}^{*}_{it}$ | .021 | .016 | .046 | .063 | .033 |
| N = | 9935 | 9485 | 7992 | 6014 | 5221 |

Standard errors in parentheses.

$^{*}$ = $p<.05$ here and in Table 3b.

**<u>Table 3b.</u>**

**Determinants of Turnover Probabilities: Firm Initiated Seperations**

| *Variables* | *Episode 1* | *Episode 2* | *Episode 3* | *Episode 4* | *Episode 5* |
|---|---|---|---|---|---|
| Constant | -2.57 (1.57) | -5.07 (.741)* | -.394 (.937) | -4.34 (1.71)* | 1.44 (.937) |
| Age: | | | | | |
| [17 ; 25) | .042 (.049) | -.016 (.026) | -.011 (.023) | -.014 (.041) | .044 (.025) |
| [25 ; 30) | .022 (.037) | .002 (.023) | -.000 (.019) | .009 (.030) | .042 (.018)* |
| [30 ; 35) | .012 (.031) | .010 (.020) | -.004 (.017) | .001 (.027) | .041 (.016)* |
| [35 ; 40) | .023 (.028) | .006 (.019) | .008 (.015) | -.020 (.027) | .040 (.014)* |
| [40 ; 45) | .010 (.021) | .010 (.016) | .004 (.013) | -.016 (.025) | .038 (.013)* |
| [45 ; 50) | .001 (.019) | .004 (.015) | .007 (.012) | -.031 (.027)* | .036 (.012)* |
| [50 ; 54] | .004 (.019) | -.004 (.016) | .023 (.011)* | .037 (.014)* | .041 (.012)* |
| Tenure | -.094 (.033)* | -.179 (.025)* | -.030 (.012)* | -.057 (.023)* | -.017 (.005)* |
| Female | -.167 (.152) | .079 (.080) | .026 (.091) | .207 (.132)* | .353 (.082)* |
| Education: | | | | | |
| 2: Low | -.004 (.130) | -.514 (.122)* | -.185 (.105) | .476 (.262) | -.190 (.161) |
| 3: Medium | -.570 (.340) | -.889 (.198)* | -1.09 (.233)* | .151 (.283) | -.467 (.269) |
| 4: High | -.515 (.268)* | -.862 (.193)* | -1.10 (.342)* | -.021 (.305) | .306 (.293) |
| Techn.Educ. | -.387 (.183)* | .007 (.088) | .309 (.070)* | -.429 (.125)* | .171 (.071)* |
| Full-time | -1.41 (1.16) | -.528 (.375) | .890 (.379)* | -.341 (.425) | -1.07 (.306)* |
| Int.Courses | -.104 (.024)* | .002 (.004) | .038 (.006)* | -.018 (.008)* | -.013 (.003)* |
| Ext.Courses | -.322 (.118)* | -.114 (.023)* | -.143 (.027)* | .221 (.068)* | -.015 (.014) |
| Married | -.635 (.183)* | -.346 (.050)* | -.211 (.053)* | .294 (.141)* | -.292 (.048)* |
| Job Evaluation | -.308 (.112)* | -.213 (.040)* | -.012 (.040) | -.082 (.046) | -.143 (.030)* |

**Table 3b, *continued***

| | *Episode 1* | *Episode 2* | *Episode 3* | *Episode 4* | *Episode 5* |
|---|---|---|---|---|---|
| ***Variables*** | | | | | |
| Educ1* $\hat{Q}_{it}$ | --- | 24.1 (1.67)$^*$ | 3.85 (1.98)$^*$ | -5.16 (1.86)$^*$ | -2.41 (5.97) |
| Educ2* $\hat{Q}_{it}$ | --- | 26.8 (2.42)$^*$ | .013 (1.99) | -5.19 (1.47)$^*$ | -2.31 (2.99) |
| Educ3* $\hat{Q}_{it}$ | --- | 12.1 (5.74)$^*$ | 4.93 (2.44)$^*$ | -4.54 (1.63)$^*$ | 1.53 (2.62) |
| Educ4* $\hat{Q}_{it}$ | --- | 17.6 (2.50)$^*$ | 2.89 (2.63) | -4.93 (1.93)$^*$ | -3.83 (2.69) |
| Educ1* $\hat{F}_{it-1}$ | --- | -4.66 (3.70) | .614 (.341) | 2.60 (.650)$^*$ | -1.58 (1.18) |
| Educ2* $\hat{F}_{it-1}$ | --- | -1.49 (4.93) | 2.45 (.763)$^*$ | 5.57 (1.18)$^*$ | -.137 (1.16) |
| Educ3* $\hat{F}_{it-1}$ | --- | 76.8 (63.8) | -.617 (2.32) | 19.0 (4.53)$^*$ | -2.62 (2.36) |
| Educ4* $\hat{F}_{it-1}$ | --- | -66.9 (30.9)$^*$ | 2.60 (4.15) | 32.5 (9.33)$^*$ | -10.1 (5.32) |
| $l_{it}^{Q}$ | 1.51 (.819) | 2.45 (.398)$^*$ | -.954 (.390)$^*$ | 2.03 (.960)$^*$ | -.451 (.290) |
| <u>Diagnostic statistics</u> | | | | | |
| Pseudo $\overline{R}^2$ | .173 | .240 | .181 | .064 | .032 |
| Log L | -309.6 | -2186.7 | -1853.2 | -1043.3 | -3342.7 |
| Observed $\overline{F}_{it}^*$ | .006 | .095 | .089 | .046 | .512 |
| Predicted $\overline{F}_{it}^*$ | .001 | .050 | .053 | .037 | .513 |
| N= | 9575 | 9182 | 7507 | 6020 | 4985 |

**Table 4.**

**Statistics Describing Workers at Episode 1 and After Episode 5**

| | At Episode 1 | | | At Episode 5 |
|---|---|---|---|---|
| | All Workers | Workers Laid Off Episodes 1-4 | Workers Remaining Through Episode 5 | Workers Remaining Through Episode 5 |
| Male | .872 | .865 | .892 | .892 |
| Married | .565 | .397 | .651 | .629 |
| Education: | | | | |
| Basic | .537 | .684 | .562 | .519 |
| Low | .258 | .247 | .258 | .273 |
| Medium | .123 | .041 | .127 | .141 |
| High | .082 | .028 | .053 | .067 |
| Education: | | | | |
| Technical | .691 | .680 | .735 | .731 |
| Years of tenure | 8.30 | 5.00 | 10.37 | 14.06 |
| | (.08) | (.16) | (.11) | (.10) |
| Job evaluation | 3.40 | 3.28 | 3.53 | 3.55 |
| | (.01) | (.01) | (.01) | (.01) |
| Number of internal training courses | 3.62 | 4.51 | 3.78 | 7.02 |
| | (.05) | (.12) | (.07) | (.09) |
| Number of external training courses | 0.53 | 0.38 | 0.50 | 1.03 |
| | (.01) | (.02) | (.01) | (.02) |
| N | 10027 | 1912 | 5435 | 5435 |

Standard errors of means in parentheses.

**Table 5.**

**Coefficients Describing Firm Tenure in Log-Earnings Equations, and Estimates of Losses Due to Displacement**

**Tenure Coeffients**

| Variable[a] | At Episode 1 | At Episode 5 |
|---|---|---|
| Years of tenure | .024 | .020 |
| | (.001) | (.001) |
| (Years of tenure)$^2$/100 | -.049 | -.036 |
| | (.002) | (.004) |
| Adjusted $R^2$ | .811 | .744 |
| N | 10027 | 5435 |

**Estimated Average Losses (log-points of annual earnings)**

| | |
|---|---|
| Loss based on Firm Closing $L^*$ | .213 |
| Loss based on workers Remaining at Episode 5 Facing Wage Structure $L^0$ | .242 |
| Loss based on all workers Facing Wage Structure $L^0$ | .208 |
| Loss based on non-quitters Facing Wage Structure $L^0$ | .222 |

[a]The equations also contain indicators of age, educational attainment, part-time status, marital status and sex, and continuous measures of job evaluation and the numbers of internal and external training courses pursued.