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Abstract

We study the determinants of plant closures in Swedish manufacturing using linked employer-employee data. From our theoretical framework we derive and empirically test hypothesis regarding the linkages between the probability of plant failure and: 1) industry-specific characteristics of production and product demand; 2) local labor market conditions; and 3) plant-specific sources of heterogeneity, including the importance of insider mechanisms in wage determination, plant specific human capital, selection mechanisms and technology vintage effects. Our results suggest that all these factors matter in ways that by and large conform to the *a priori* hypotheses.

Keywords: Plant closures, job reallocation, insider wage determination, selection mechanisms, capital vintage effects, linked employer-employee data

JEL-Code: J21, J23

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1 Introduction

This study sheds some new light on possible sources of producer heterogeneity, within and across industries, by studying the determinants of plant failure in Swedish manufacturing during the 1990-96 period using longitudinal linked employee-employer data.

The creation and destruction of production units play an integral part in the growth process and have important implications for the individuals in the work force. For instance: In Swedish manufacturing at least some 10 percent of the growth in productivity over the 1989-1996 period can be directly attributed to the fact that entering plants had higher than average productivity and that exiting plants had lower than average productivity. Measured in terms of annual job reallocation, plant turnover constitutes some 15-30 percent of all jobs reallocated in Swedish manufacturing and becomes increasingly important in the longer run (Andersson, 1999). In spite of their important consequences, the existing knowledge about the driving forces of plant closures is quite scarce.[1]

We derive hypotheses about the determinants of plant exit from a model of imperfect competition in which plants are exposed to stochastic productivity shocks that are realized after wages have been determined in plant-level negotiations. This way there are direct links between the likelihood of plant failure and industry-specific characteristics of production and product demand, on the one hand, and between the likelihood of plant failure and the local labor market conditions, on the other hand. If it further is assumed that only 'insiders' (workers with some seniority) are party of the negotiations (Lindbeck and Snower, 1989), insider mechanisms are introduced as a possible explanation for within-industry differences in the failure probability across plants. In particular, we expect higher wage pressure and higher risks of plant closures in plants with relatively few insiders, since the *ex ante* risk of dismissal for an insider is lower as compared to the risk of dismissal for an insider in a plant with many insiders. Access to longitudinal linked employer-employee data enables us to separate insiders from outsiders in terms of their plant-level seniority.

[1] The special issue of *International Journal of Industrial Organization* (Vol. 13, No. 4, 1995) is dedicated to plant turnover and growth pattern of firms and plants. Also in the job flow literature, many contributions to our understanding of the post-entry behavior of plants can be found (e.g. Davis, Haltiwanger, and Schuh, 1996).

Another virtue of using linked employer-employee data is that we are able to analyze possible effects of the plant's human capital structure on the exit probability. Investments in plant-specific human capital through training or learning-by-doing would generally increase the rents to be shared between the worker and the firm. Given that the extra rents generated are not fully captured by the workers, this would provide a rationale for why plants with workers having a high degree of plant-specific human capital exhibit a higher reluctancy to shut down operations. Another reason why the human capital structure of a plant could make a difference for the shut-down decision is if there are non-uniform costs associated with the dismissal of workers.

Another possible source of heterogeneity that we consider are plant-specific age effects. Models that emphasize selection mechanism (e.g. Jovanovic, 1982; Pakes and Ericson, 1992) predict that younger establishments are more likely to exit than older ones are because of greater uncertainty surrounding their true efficiency level. The empirical support is strong for high exit rates among young plants (Audretsch and Mahmood, 1994; Audretsch and Mahmood, 1995; Persson, 1999; Sanghamitra and Krishna, 1997; Boeri and Bellman, 1995; Mata and Portugal, 1994).

A partly competing hypothesis could be derived from the capital vintage literature (e.g. Solow, 1956). Interpreted at the micro level, this literature suggests that establishments using technologies of older vintages are more likely to exit, as they utilize less efficient technologies. Technology vintage effects have received little empirical attention and, if at all discussed, been rejected as important based on the finding that the hazard of plant failure is decreasing in plant age. This conclusion might be premature, since plant and technology age do not need to coincide, as is the case in some more recent capital vintage models that stress the possibility of updating to newer technology without shutting down the establishment. If this is the case a negative duration dependence with respect to plant age cannot be interpreted in terms of the importance of selection mechanisms, since the omission of technology age as an explanatory variable could generate the negative duration dependence *per se*.[2] To our knowledge, the

[2] See Kiefer (1988); Lancaster (1990). The intuition behind this result is simple: Since plants with favorable technology on average will live longer, the mixture distribution will change over time so that the fraction of plants with favorable technology will increase as time goes by. Thus, the longer spells are overrepresented by plants with the low failure probability.

only previous empirical study of plant failure that disentangle different age effects is the study of Salvanes and Tveterås (1998), in which plant age is separated from capital age. It finds distinct and different effects from capital and plant age. It is not obvious to us, however, that the vintage of capital is a good proxy for the vintage of technology, as the introduction of new technology not necessarily can be captured by a single-dimensioned index like a capital vintage index. Our measure of technology age is based on the view that new technology can be introduced and implemented in a myriad of ways, which result in changes in the productivity level. Empirically we capture this by analyzing the plants' 'Solow-residual'.

Our empirical findings suggest that, besides industry-specific and regional labor market effects, insider mechanisms, the structure of human capital, as well as the different age effects are important determinants of plant failure. By and large the results conform to our *a priori* hypotheses.

The remainder of this paper is organized in the following way. It starts out with a general motivation for our research topic by presenting some evidence on the importance of plant turnover in Swedish manufacturing in terms of its links to productivity growth (section 2). Section 3 puts our empirical analysis into the context of a theoretical model of plant failure that we develop. Section 4 describes the empirical counterparts of the variables in the theoretical model. Data and the statistical model are presented in section 5. The results from the empirical analysis is presented in section 6, before finally concluding in section 7.

2 Plant turnover and productivity growth

In this section we motivate our research topic by presenting some basic facts on how plant turnover and its components relate to productivity growth. (The implications on individuals, in terms of changes in income, employment status, etc., because of the reshuffling of jobs induced by plant turnover could have served as another motivation.) The close relationship between plant turnover and productivity growth is hardly a new idea, but has been around at least since the days of Schumpeter. For instance, the notion of creative destruction expresses the necessity to replace old technologies in order to adopt new ones, which often is assumed to be accommodated by plant turnover.

To get a feeling of how important this process might be, Table 1 presents the current average labor productivity[3] of plants that have entered within the $t-n$ period and of plants that will exit within the $t+n$ period, relative to the productivity of continuing plants, P_{en}/P_c and P_{ex}/P_c. The figures are annual averages and refers to the stock of manufacturing plants in the 1985-96 period.

Table 1: Relative Productitivity of entering and exiting plants[1]

	Entering Plants			Exiting Plants		
Time span	$\mathbf{P_{en}/P_c}$	$\mathbf{N_{en}/N}$	**Effect**[2]	$\mathbf{P_{ex}/P_c}$	$\mathbf{N_{ex}/N}$	**Effect**[3]
$t \pm 1$	0.97	0.03	-0.1	0.75	0.04	1.0
$t \pm 3$	1.03	0.06	0.2	0.76	0.12	2.9
$t \pm 5$	1.04	0.08	0.3	0.77	0.19	4.4

[1] The table reports the productivity in period t of plants that have entered (will exit) within the $t-n$ $(t+n)$ period relative to the productivity of continuing plants in period t.
[2] Refers to the effect on the manufacturing productivity in t (in percentage points) because entering plants differ in productivity from continuing plants in period t.
[3] Refers to the effect on the manufacturing productivity in $t+n$ (in percentage points) because exiting plants differ in productivity from continuing plants in period t.

From the first row of entries, we learn that plants that have entered during the course of a year on average contribute negatively to the growth in manufacturing productivity, as their productivity is somewhat lower relative to the productivity of continuing plants. Plants that will exit within the next year on average contribute positively to the growth in manufacturing productivity, as their productivity is substantially lower as compared to the productivity in continuing plants.

In the second and third row of entries, the time horizon is increased, so that an entering (exiting) plant is defined as a plant that has entered (will exit) within the $t-3$ $(t+3)$ and $t-5$ $(t+5)$ period, respectively. In the longer run, exiting as well as entering plants contribute positively to manufacturing productivity growth. The productivity of plants that have entered within the last 3 and 5 years is actually higher relative to the productivity of continuing plants. The different results for the entering plants in the long and short run suggest that the returns to entry do not come immediately and/or that the less efficient entrants are sorted out in

[3]Measured as the value-added per worker deflated by a three-digit level producer price index.

the longer run.

The effect on manufacturing productivity growth is quite large in the longer run ($t \pm 5$), partly because the employment shares, N_{en}/N and N_{ex}/N, get large as the time horizon is increased. The average labor productivity in Swedish manufacturing would on average had been 0.4 percentage points lower if the entering plants had not entered and 4.4 percent lower if the exiting plants had not exited.

We end this section by concluding that the entry and, in particular, the exit of plants are important phenomena in the process of growth. Furthermore, the close relationship between the plant turnover and productivity growth indicates that the productivity of the plant is likely to be a good predictor of plant exit. However, based on these "raw" facts we are not able to discriminate between the various possible underlying forces of plant exit mentioned in the introduction, since most of them, in one way or another, are related to plant-level productivity.

3 A model of plant failure

In order to fix ideas and to provide guidance for what variables to include in the empirical analysis, it is useful to consider a simple theoretical framework.[4]

We assume an economy in which plants produce slightly differentiated products that are sold in monopolistic competition.[5] In the short run labor is the only variable factor of production. Production and the inverse demand function for a plant are assumed to be

$$Y = \varepsilon A L^{\alpha} = \varepsilon q \tag{1}$$

and

$$P = D q^{-1/\eta} \tag{2}$$

[4]See Hamermesh (1993) for an alternative model of plant failure. Also see Antelius and Lundberg (2000) for a study of the determinants of job reallocation across industries.

[5]By focusing on plants we assume that the important economic decisions are made at the plant-level, rather than at the firm-level. The empirical analysis is also conducted at the plant-level. However, we also analyze single-unit plants (i.e. plants in which firm- and plant-level decision making coincide) separately.

where $\varepsilon > 0$ is a stochastic productivity parameter with unit mean[6], $\alpha < 1$, D is demand index and $\eta > 1$. Apart from the stochastic productivity parameter, the parameters of production and demand are assumed to be the same for all plants within an industry.

In each period the plant is, with probability λ, exposed to an idiosyncratic productivity shock drawn from the distribution $f(\varepsilon)$. Conditional on the stochastic productivity component the plant will decide whether to continue operations and, if so, employment, output and prices.

According to equation (1) and (2) profit is given by

$$\pi = \varepsilon D q^{\kappa}(L) - wL \tag{3}$$

where $\kappa = 1 - 1/\eta$. Labor is assumed to be determined optimally at all times by the first order condition, such that the marginal revenue product equals the bargained wage rate or

$$L = (w/\alpha\varepsilon\kappa D A^{\kappa})^{-1/(1-\alpha\kappa)} \tag{4}$$

It is assumed that a plant exits the market if maximized current profits fall below a certain target profit value, π^*, or

$$\pi\left(L(\varepsilon)\right) \leq \pi^* \tag{5}$$

where $\pi\left(L(\varepsilon)\right)$ is obtained by inserting equation (4) in equation (3). For now on π^* is assumed to be exogenous, but possible determinants of the target profit value will be discussed later on.

According to the previous, the reservation productivity, ε^*, which solves $\pi(\varepsilon^*) = \pi^*$, expressed in logarithms, is

$$\ln\varepsilon^* = (1-\alpha\kappa)[\ln\pi^* - \ln(1-\alpha\kappa)] + \alpha\kappa[\ln w - \ln(\alpha\kappa)] - \ln D - \kappa\ln A \tag{6}$$

and the implied probability that a plant will close, θ, is then

$$\theta = \lambda\int_0^{\varepsilon^*} f(\varepsilon)d\varepsilon = \lambda F(\varepsilon^*) \tag{7}$$

[6]This shock can equally well be thought of as a demand shock or a combination of both without changing anything in the analysis.

Equation (7) implicitly defines a relationship between θ and the arguments of π and π^*.

The engine of plant closures in this theoretical framework is unfavorable productivity (or demand) shocks, but how responsive a plant is to a shock depends to a large extent on industry-specific factors such as the parameters of production and product demand. Note that, so far, this model has no predictive power of which plants within a certain industry and region that are most likely to shut down. From comparative statics on equation (6) and (7) we learn that the probability of plant failure is higher the higher is the shock intensity, λ, the lower is the labor productivity, A, the lower is the product demand, D, the lower is the labor intensity, α, and the higher is the product market competitiveness, $\eta(\kappa)$. Also exogenous increases in wages, w, and in the target profit value, π^*, would increase the failure probability. However, we extend the model to allow for the possibility that these latter variables are determined endogenously and, thus, plant-specific explanations for within-industry differences in the failure probabilities across plants are introduced.

3.1 Wage determination

Although the wage setting in the Nordic countries is often thought to be highly centralized, the wage setting process actually takes place at two levels, at the industry level (centralized) and in local negotiations (wage drift). Thus, industry- as well as plant-specific effects may both play important parts in wage determination. Another institutional feature that may be of importance is the strict employment protection legislation in Sweden, which, for instance, determines the order by which employees should be dismissed.

Based on these facts, we think it is appropriate to explicitly take into account that wages are determined locally in negotiations between the workers and the employers in our model. Also, we should consider the fact that not all workers face the same risk of being dismissed, because of the employment protection rules.

Wages are assumed to be determined in plant-level negotiations and the timing of the model is such that wages are set before the idiosyncratic shock is realized. Extending slightly to the model presented in Layard, Nickell, and Jackman (1991), we assume that the bargain over wages at the plant level is the one which maximizes

$$\chi = [(w - O)S]^{\beta}[\pi^e - \pi^*] \tag{8}$$

where w is the real wage, O is the worker's expected income if no agreement is reached and e denotes expectations. The owner of the plant is assumed to receive π^* in case of no agreement.[7] S is the probability of remaining in the same plant the next period given the outcome of the bargain. Only workers who remain in the plant from the previous period, L^I, are assumed to take part of the wage bargain and they only care about their own utility. More formally, if we define δ as the fraction of employees with no seniority (newly hired since the last period), then at any given point of time the number of insiders is given by $L^I = (1 - \delta)L$. These assumptions then imply that the probability of remaining in the plant for an 'insider' is higher if the number of insiders is relatively small as compared to expected employment, (i.e. $S'(L^I/L^e(w)) < 0$).

Utilizing the envelope theorem, the bargained wage that satisfies equation (8) is

$$\frac{w - O}{w} = \frac{1}{-\frac{w}{s}\frac{\partial S}{\partial w} + \frac{wL^e}{\beta(\pi^e - \pi^*)}} \tag{9}$$

and with the previous assumptions about production and product demand, utilizing that $\eta_{Sw} = \frac{\delta S}{\delta w}\frac{w}{S} = \frac{\delta S}{\delta L}\frac{L}{S} * \frac{\delta L}{\delta w}\frac{w}{L} = \eta_{SL} * \eta_{Lw} = \eta_{SL} * (1 - \alpha\kappa)^{-1}$ we arrive at the following expression for the wage mark-up over the outside option

$$\frac{w - O}{w} = \frac{1 - \alpha\kappa}{\eta_{SL}(L^I/L^e(w)) + \left[\frac{\beta}{\alpha\kappa}\left(1 - \frac{\pi^*}{\pi^e}\right)\right]^{-1}} \tag{10}$$

where η_{SL} is the individual employee's elasticity of remaining in the same plant with respect to expected employment and with $\eta'_{SL} > 0$.[8]

We assume that the option value of the worker is given by $O = p(u)\overline{w} + (1 - p(\ u))b$. $p(u)$ is the probability of remaining unemployed in the case

[7] An alternative threat point of the owner, which simplifies matters but may be less realistic in the face of the previous discussion concerning the target profit, would be to assume that the owners receive nothing in case of no agreement.

[8] In the case where the plant owner's threat point is zero equation (10) reduces to the wage equation in partial equilibrium in Layard, Nickell, and Jackman (1991). This extension does not change any comparative statics.

of dismissal, being a function of the unemployment rate with $p' < 0$; $\overline{w}$ is the outside wage level and b the benefit level in case of unemployment.

Thus, with wage bargaining at the plant level, local labor market conditions, in terms of outside incomes and the probability to obtain a new job in case of unemployment, will also make a difference on the shut-down probability, since these factors affect the wage pressure. Furthermore, with the assumption made that only insiders take part of the wage negotiation, the share of insiders at the plant level will also affect the survival capacity of the plant, because the dismissal probability for an insider is affected by the composition of outsiders and insiders at the plant.

Working through the comparative statics of (6), (7) and (10) enables us to summarize the implications of the model by that the probability of plant failure is higher:

- the higher is the shock intensity in the industry, λ
- the greater is the union power, β
- the lower is the unemployment rate, u
- the higher is the relevant outside wage, $\overline{w}$
- the higher is the unemployment benefit level, b
- the smaller is the share of insiders in the plant as compared to current employment, L^I/L
- the higher is the target level of profits at the plant, π^*.

Furthermore, the probability of plant failure is indeterminate with respect to,

- the product market competitiveness, κ
- the labor intensity, α
- the product demand, D
- the common productivity level, A.

The latter effects are indeterminate to the extent that the direct effect on the reservation productivity is counteracted by an indirect effect working through wages. Consider for instance an increase in product demand: as a direct effect this will increase the likelihood to survive because of larger revenues, but this effect is counteracted, at least in the longer run, by the indirect effect working through higher wage pressure.

3.2 Endogenous target profit

It may very well be the case that the target value of profits, π^*, should not be regarded as exogenous either. Factors that may influence π^* could be more closely examined if the model would be formulated as a dynamic optimization problem. One such possible formulation of the target profit could be derived from a search model framework, in which potential entrepreneurs each period make an innovation corresponding to a specific value in the distribution of idiosyncratic shocks and then choose between becoming an operational entrepreneur or remain idle. Without providing any further details of the derivation (available upon request), one possible formulation of the target profit is

$$\pi^* = z - K - \frac{\lambda}{r+\lambda}\int_{\varepsilon^*}[1-F(x)]\pi'(x)dx \tag{11}$$

where z is the alternative income of the owner of the plant; K sunk costs associated with plant entry and plant exit; and r is the discount rate. Then the target profit would be increasing in alternative incomes of the owner, decreasing in sunk costs associated with entry and decreasing in the option value of continuing production. The option value of continuing production, in turn, is higher the higher is the expected value of a shock, the less likely it is to be exposed to a shock and the lower the discount rate is.[9]

We consider a number of theoretical mechanisms, namely plant-specific human capital, selection mechanisms, and technology vintage effects, that could be thought of as affecting the shutdown condition through the determinants of the target profit level. We in the proceeding only discuss

[9] One should note that if the target profit is endogenously determined, then it is no longer possible to determine the sign of the effect of an increased shock intensity, λ, on the exit probability. As far as we can tell, this is not the case for any other variables in the model.

how these considerations may affect the shutdown condition through the determinants of the target profit (equation (11)).

3.2.1 Plant-specific human capital

The acquisition of plant-specific human capital through training or learning-by-doing would generally increase the rents to be shared between the worker and the owners of the plant. Given that the extra rents generated are not fully captured by the workers (i.e. $\beta \neq 1$), this would provide a rationale for why plants intense in specific human capital exhibit a higher reluctancy to shut down operations (Oi, 1962; Becker, 1964).

In terms of equation (11) investments in specific human capital could be thought of as increases in $\pi'(x)$. Thus, the option value of continuing operations increases and the target profit value, π^*, decreases, which in turn would decrease the reservation productivity, ε^*, and the failure probability, θ.

Another reason why the human capital structure of a plant may make a difference for the shut-down decision is if there are non-uniform (sunk) costs associated with the dismissal of workers. Higher dismissal costs decreases π^* (through higher K) and lowers the failure probability.

3.2.2 Selection mechanisms

In Jovanovic's (1982) selection model, growth and survival of firms is the result of heterogeneity in the efficiency level across producers. Generally, the individual producer does not know the true cost relative to other competitors in the industry at the time of entry. (All producers have the same initial belief about the true $\pi'(x)$) In the selection process, the true efficiency relative to others is gradually unveiled via the outcome of production (which implies heterogeneity in π^* with respect to the relative efficiency level of the plant). This is a model of passive learning, in the sense that producers cannot influence its true efficiency level, but costliness upgrade its belief about their true level of efficiency in the production process.[10]

[10] See Pakes and Ericson (1992) for an alternative model in which the assumption of passive learning is relaxed. Unlike the passive learning model, the producer can improve its position in the distribution of efficiency levels across plants through investments in research and development. Both these models predict that younger plants are more likely to exit than older plants.

3.2.3 Technology vintage effects

A partly competing hypothesis is derived from capital vintage models (e.g. Solow, 1956). The main point in capital vintage models is that capital of later vintages is more efficient than capital of older vintages. Technologies of various vintages will coexist because of sunk costs associated with the installation of new capital. The strength of vintage effect in an industry is dependent on the level of sunk costs and the degree of substitutability between factors of production. Industries with high sunk costs and low elasticity of substitution should be characterized by strong vintage effects and low turnover rates, while industries with low sunk costs and unstable relative input and output prices show high exit rates (Lambson, 1991).

Interpreted at the producer level we would expect higher exit rates among plants utilizing older technologies inferior to newer more efficient technologies. In terms of the determinants of the target profit level in equation (11), using technologies that become inferior relative to newer ones will reduce $\pi'(x)$ and the option value of continuing production (because wages are expected to increase through the workers' outside option value) and increase the alternative income of the owner, z (i.e., investing in a new plant becomes a more attractive alternative). Thus, the target profit level increases and the failure probability is expected to increase with the age of technology.

4 The empirical counterparts

The quest is to find the empirical counterparts to the variables motivated by theory in the preceding section. Here we briefly describe the variables included and put forward our hypothesis. Summary statistics, spell characteristics and exact definitions of the variables are found in Appendix A.1.

As a measure of the shock intensity, λ, we include the job reallocation rate at the industry level. There are possibly two counteracting effects of an increased shock intensity. The direct effect is that the probability of exit increases, because the employers are more likely to be exposed to a bad outcome. The indirect effect, if target profits are assumed to be endogenous, is that the employers option value of continuing operation decreases, which lowers the exit probability.[11]

[11] It should be noted that job reallocation is likely to be dependent on not only the

With respect to the parameters of the production function, we include the share of wage costs in the industry as a measure of α and as a measure of A we use the average labor productivity deflated by a producer-price index at the three-digit level.

With respect to the parameters of the product demand function: We include the 'Herfindahl index' as a measure of κ. With $\kappa \rightarrow \infty$ (perfect competition) the 'Herfindahl' index, which has been calculated as the squared sum of the plant's share of sales in the industry, is expected to approach zero and with $\kappa \rightarrow 0$ (monopoly) it would approach unity.[12] We construct industry-specific indexes of demand as a proxy for D, based on the development of average working hours per employee in the industries.

These considerations more or less cover the implications from the basic theoretical framework with exogenous wage and target profit determination, apart from some variables, such as unemployment benefits and union power, for which we either cannot obtain any good measures or do not have any variation to explore.

4.1 Measuring wage determinants

As a measure of the share of insiders in the plant $((L^I/L) = 1 - \delta)$, we include the share of employees who remained in the plant at least since the previous year. For instance, assume that employment in period $t - 1$ is 15 and 10 in period t. If this employment change has been the resulting sum of 10 quits and/or layoffs and 5 hirings, then the share of insiders in period t would be 0.5 according to our definition. The outside options for a worker, O, is captured by including the average wage and the unemployment rate in the region. We expect the exit probability to increase as the share of insiders decreases and as the outside option for the worker increases, because of the effects on the wage pressure.

shock intensity in the industry *per se*, but also on the other parameters of production, demand and the wage bargain. Also the rate of job reallocation may approximate other factors, like the product life cycle and the pace of technological progress in the industry. Thus, this variable may serve as proxy for several factors and should be treated with some caution when interpreted.

[12] Ideally we would like to obtain measures also on the competion from abroad, which we do not have in our data.

4.2 Measuring determinants of the target profit

We include average plant size in the industry to approximate sunk costs and minimum efficient scale, having the hypothesis that the exit probability decrease with plant size. It should be noted that if sunk costs mainly are associated with capital in general our measure of the wage cost share may pick up the effects of sunk costs.

Theoretically we also argued that the plant-specific human capital, selection mechanisms and technology vintage effects affect the target profit value and, thereby, the failure probability.

4.2.1 Measuring human capital

We control for the human capital structure of the plant by including the average age in the workforce, the share of males, the share of Swedish citizens, the fraction of workers with university education and the fraction of workers with educations oriented towards technical subjects. Which types of labor that are intense in plant-specific human capital and/or are associated with high firing costs is pretty much an empirical question. Though, through longer experience, we expect that the degree of plant specificity in the human capital to be higher among older workers than younger. If highly educated workers and workers with educations oriented towards technical educations are more involved in the development of plant specific technologies, we may expect that there are larger quasi rents to be shared, and presumably lower probabilities of plant exit, in plants with workers with these characteristics.

4.2.2 Measuring age effects

In order to test the importance of selection mechanisms, i.e. that newly created plants face a higher risk of plant failure, we include plant age, which is simply measured as the number of years since plant entry. If selection mechanisms are important we would expect the exit probability to decrease with plant age.

Measuring the age of technology is clearly a more problematic task and deserves to be put in some focus. Capital vintage models differ with respect to how technology advances are implemented at the micro level. In some models (e.g. Caballero and Hammour, 1995), new technology is embodied in the plant and, thus, productivity advances is implemented through the entry and exit of plants. This type of capital vintage models has motivated the use of plant age as a proxy for the vintage of technology in empirical studies (Davis and Haltiwanger, 1990; Caballero and Hammour, 1996). This presumption probably has poor empirical support (Dunne, 1994). In other models technology advances takes place through investments in physical capital (Solow, 1956; Cooper, Haltiwanger, and Power, 1995; Greenwood and Jovanovic, 1998; Mortensen and Pissarides, 1998). This type of models have in turn motivated the use of capital vintage indexes as a proxy for technology age (Salvanes and Tveterås, 1998). However, the empirical support for this presumption is questionable as well.

Our view is that technology advances is implemented in a myriad of ways, for instance by changes in the human capital and in organization. This view is consistent with the view in Harberger (1998), where it is argued that aggregate productivity growth stems "from 1001 different sources". Therefore, we do not believe that the vintage of technology - which really is the concern of capital vintage models - can be captured along a single dimensioned measure like the vintage of physical capital, which furthermore is probably hard to measure with any greater accuracy. That is, new technologies may as well consist of new ways to organize production and not only of investments in new machines, which has been the traditional view. No matter what the underlying sources of technological change are, it is likely that they involve some degree of sunk costs and, thus, give rise to vintage effects if the input is subject to technology advances. Given that no set of measures probably ever can cover all the dimensions of new technology, it seems reasonable to base the measure of technology on its consequences rather than on its exact sources.

We conjecture that the introduction of new technology at the plant level is associated with changes in the plant-level productivity. However, not all changes in productivity is associated with technology vintage effects. In particular, new technology that is not associated with any sunk costs should not give rise to vintage effects. Since such technologies can be easily adopted by all plants without changing the relative productivity distribution across plants, we instead associate the introduction of new technology with changes in the plant-specific productivity level. That is, we decompose the state of technology, A_{et}, of a plant into the three components

$$A_{et} = A_t + A_{st} + \widetilde{A}_{et} \tag{12}$$

where A_t is the productivity component common to all plants at period t, A_{st} is the component common to all plants in the same industry and, finally, $\widetilde{A}_{et}$ is the plant-specific component of productivity.

Empirically we use the plant's average producer-price deflated labor productivity as a measure of A_{et}, from which we determine $\widetilde{A}_{et}$ by subtracting the corresponding aggregate measures.

There are at least four worries associated with such a approach. The idiosyncratic productivity component, besides technology, could also reflect: 1) the scale of operations, unless technology is characterized by constant return to scale; 2) the degree of capacity utilization; 3) the mix of inputs used in production; and 4) measurement errors, for instance unobservable inputs. To account for the degree of capacity utilization and scale effects, we require that the change exceed a certain threshold value in order to be associated with the introduction of new technology. Empirically the threshold value is chosen such that it represents a certain percentile in the distribution of idiosyncratic labor productivity changes. Our measure of technology age is defined as the number of years since the change in productivity exceeded a certain threshold value. To overcome the issue of changes in the mix of inputs an alternative approach could be to estimate the "Solow residual" of the plant, instead of using the "raw" idiosyncratic labor productivity component. The reason why this is not undertaken is that we deliberately want to keep our notion of technology broad, in the sense that changes in the scale of operations and mix of inputs by producers within the same industry facing similar conditions could very well be thought of as representing changes in technology. (Another important reason is that we lack data on important inputs other than labor, e.g. managerial skills and plant-level capital measures.) As a sensitivity analysis (reported in appendix) we experiment with different threshold values and with other identifying assumptions about when new technology is introduced. In particular we test the hypothesis that the results are caused by measurement errors and other temporary movements in productivity, by requiring long-lasting effects.

We expect the probability of plant failure to be decreasing in plant age and increasing in our measure of technology age.[13]

[13]Becuase the complementarity between technologies of different vintages is likely to be decreasing in the age distance, this argument is true even for given profit levels and given sunk costs.

5 Data and statistical model

5.1 Data

This section describes data. More details on data and on how the analytical data set was created can be found in Appendix A.1.

Our data set consists of information from three different data sources, namely *Manufacturing Statistics* ("Industristatistiken" or IS), the *Central Firm and Establishment Registry* ("Centrala Företags- och Arbetsställeregistret" or CFAR) and the *Regional Employment Statistics* ("Årlig regional sysselsättningsstatistik" or Årsys). IS contains plant-level information about almost the universe of plants in mining and manufacturing (major division 2-3) over the 1970-96 period. (There are some restrictions with respect to the very smallest of plants.) IS has been merged with CFAR, which contains explicit information about the date of entry and the possible date of exit of all plants in the population, and with Årsys, which contains human capital information about the individuals in the plants from 1985-96. The linkage to CFAR has enhanced the quality of data, in the sense that we are able to discriminate between plants missing in data from true plant exits.

Our analysis is limited to the stock of plants in the 1991 and the inflow of plants in our observation period 1991-96, the period in which we have full information about the variables of interest.[14] This period covers a rather extreme recession as well as a peak. As compared to the period 1970-90, employment has never declined so fast as it did in the 1991-93 period and it has never increased by as much as it did in the 1994-96 period.

From the stock of plants in the 1991 we sample those plants that entered after 1972, which is the earliest year of entry that we can identify in CFAR. This implies that we observe spells as long as 24 years.[15] Of all different plants in our sample, 23 percent entered during our observation period. In total the analytical data set covers 22 998 observations on 7 228 different plants.

To fully understand the concept of plant failure, we stress that mergers, acquisitions, changes in ownership and so on will generally not result in

[14]Another reason why we limit the analysis to this period is changes in the population in IS in 1990 that are hard to handle longitudinally.

[15]Because very few spells with a plant age of more than 20 years are observed, we treat those as having a plant age of exactly 20 years in the empirical analysis.

plant failures in our data, unless the plant is actually physically shut down.[16]

5.2 Statistical model and maximum likelihood estimation

Data is such that we only observe whether a plant continues its operation or is shut down, but, of course, not the actual risk of plant failure. This is normally analyzed in limited dependent variable models, such as the logit or the probit model. We instead analyze data in terms of a discrete hazard model, since duration dependence is of interest in some of our specifications. However, in the case when time is of no interest the model generalizes to the limited dependent variable model known as the *Weibull probability model.*

The data in our analysis is interval censored, such that we only observe time to lie between a pair of consecutive follow-ups.[17] Time is divided into k intervals $[0,1),[1,2),\dots,[q,\infty)$ where $q=k-1$. In our analysis k is 24 years, which corresponds to the maximum number of years of a completed spell. The discrete hazard function is given by

$$\lambda\left(t|\mathbf{x}(t)\right)=\Pr(T=t|T\geq t,\mathbf{x}(t)),\quad t=1,...,q \tag{13}$$

where $T=t$ denotes failure in the $[t-1,t)$ interval and $\lambda\left(t|\mathbf{x}(t)\right)$ is the conditional probability of failure in that interval, given the interval is reached and given a vector of (possibly time-varying) covariates, $\mathbf{x}(t)$.[18] Correspondingly, the discrete survival function of the probability of *reaching* the $[t-1,t)$ interval is

$$\Pr(T\geq t|\mathbf{x}(t))=S(t|\mathbf{x}(t))=\prod_{i=1}^{t-1}(1-\lambda(i|\mathbf{x}(i)). \tag{14}$$

To account for left-censored cases with known entry times, which is a feature of data, we need to modify (14) slightly. The conditional probability of reaching the $[t-1,t)$ interval for a left-truncated case must be

[16]The concept of a plant is defined only in terms of geographical location and production. (See SCB, Various years)

[17]Overviews of the econometric analysis using duration data can be found in Fahrmeir and Tutz (1994), Lancaster (1990), and Kiefer (1988)

[18]In fact, by failure in t we mean that the plant is not in existence at any time during $t+1$. This way we reduce possible problems with endogeneity and are able to measure the covariates with higher accuracy.

conditional of having reached the censoring point. Thus,

$$\Pr(T \geq t|\mathbf{x}(t), T \geq s) = S(t|\mathbf{x}(t))/S(s|\mathbf{x}(s))$$
$$= \prod_{i=1}^{t-1}(1-\lambda(i|\mathbf{x}(i))/\prod_{i=1}^{s}(1-\lambda(i|\mathbf{x}(i)) = \prod_{i=s}^{t-1}(1-\lambda(i|\mathbf{x}(i)) \qquad (15)$$

where s indicates the truncation point.[19] (For all non-left censored cases in the proceeding s equals zero).

Consider first the likelihood contribution of plant-failure in the $[t-1, t)$ interval. The unconditional probability of failure in the $[t-1, t)$ interval is given by the product of (13) and (15)

$$\Pr(T = t|\mathbf{x}(t)) = \lambda(t|\mathbf{x}(t))S(t|\mathbf{x}(t))/S(s|\mathbf{x}(s))$$
$$= \lambda(t|\mathbf{x}(t))\prod_{i=s}^{t-1}(1-\lambda(i|\mathbf{x}(i)) = \prod_{i=s}^{t}\lambda(i|\mathbf{x}(i))^{y_i}\prod_{i=s}^{t}\left[1-\lambda(i|\mathbf{x}(i))\right]^{1-y_i} \qquad (16)$$

where $y_i = (y_{is}, ..., y_{it}) = (0, ..., 0, 1)$ for a non-censored case and where $y_{it} = 1$ indicates failure in the $[t-1, t)$ interval. Similarly the contribution of the right-censored observation is given by (15), which can be written as (16), but where $y_i = (y_{is}, ..., y_{it}) = (0, ..., 0)$. Summing over all n plants, the total log likelihood, assuming independence between individuals, is given by

$$l = \sum_{j=1}^{n}\sum_{i=s}^{t_j}\left[y_{ij}\log\lambda(i|x_{ij}) + (1-y_{ij})\log(1-\lambda(i|x_{ij})\right]. \qquad (17)$$

Once a parametric model of the hazard function is chosen, it is straight forward to estimate (17) by maximum likelihood. We consider the proportional hazard model, which in continuous time is given by

$$\lambda_c(t|\mathbf{x}(t)) = \lambda_0(t)\exp(\mathbf{x}(t)'\gamma) \qquad (18)$$

where λ_c denotes the continuous hazard function and where $\lambda_0(t)$ is the baseline hazard at time t and where γ is a vector of unknown parameters. The proportional hazard specification assumes that all covariates, including technology age, only have proportional effects on the baseline hazard,

[19] How to handle left-truncated cases with known dates of entry is analyzed in Guo (1993)

λ_0. The discrete counterpart of (18) is given by

$$\lambda(t|\mathbf{x}(t)) = 1 - \exp[-\int_t^{t+1} \lambda_0(u) \exp\{\mathbf{x}(u)'\gamma\} du = 1 - \exp(-\exp(\eta(t) + \mathbf{x}(t)'\gamma)) \tag{19}$$

where the second equality follows assuming constant hazard and covariates in each time interval and where $\eta(t) = \ln \int_t^{t+1} \lambda_0(u)du$. Inserting (19) into (17) gives us the following expression for the log likelihood to be estimated

$$l = \sum_{j=1}^{n} \sum_{i=s}^{t_j} \left[y_{ij}(1 - \exp(-\exp(\eta_t + \mathbf{x}'_{ij}\gamma))) - (1 - y_{ij}) \exp(\eta_t + \mathbf{x}'_{ij}\gamma) \right] \tag{20}$$

If $\eta_t = \eta$, i.e. there is no duration dependence the expression is reduced to the likelihood function of the Weibull probability model (Greene, 1993).[20]

6 Results

Our empirical strategy is to estimate versions of the empirical equivalent to equation (7), which defines a relationship between the probability of plant failure and the arguments of profit and target profit. We first estimate our basic model of plant failure assuming that wages are exogenous. After having rejected the hypothesis that wages are exogenous, we then successively add to our analysis the effects of endogenous wage and target profit determination.

The results (not reported) from the model in which plant-level wages are assumed to be exogenous are implausible, in the sense that higher wages are associated with lower failure probabilities. A likely interpretation of this result is that higher plant-level wages reflect larger rents to be shared between the workers and the owners of the plant. Higher wages could of course also reflect differences in the human capital structure of

[20]Apart from the less familiar Weibull probability model, we have estimated our specifications as logit models, but since the results do not differ substantially we do not comment on those.

the plant that may have an influence on the failure probability and which we do not control for.

To control for differences in the human capital structure across plants and to test for the assumed exogeneity of wages, we first estimated a simple plant level wage equation by ordinary least squares and then inserted the plant level wage measure together with the predicted residual from the first stage wage equation in the exit equation (specification (i) of Table 2).[21] Variables denoted by s are specific to the 18 industries in our data, those denoted by r are specific to the 24 regions used and those denoted by e are specific to the plant. Under the hypothesis that wages are exogenously determined, the effect of the residual is expected to be zero. However, this model suggests that wages are not exogenously determined, since the effect of the predicted residual is negative and highly significant, i.e. higher unexplained wages are associated with a lower failure probability. Thus, we reject the hypothesis of exogenously determined wages.[22]

6.1 Industry effects and endogenous wage determination

In specification (ii) in Table 2 we report the results from a model in which wages are assumed to be endogenously determined and, thus, the plant-level wage measure is replaced by a measure for the outside wage, as defined previously. Furthermore, it is assumed that the unions are egalitarian (i.e. unions that care equally for insiders and outsiders) and thus we do not include the insider share variable.

All estimates are statistically significant and conform to our *a priori* hypotheses. The probability of plant failure is higher for plants in industries characterized by high job reallocation rates, which is our proxy for the shock intensity in the industry.[23] With respect to the parameters of

[21]The dependent variable in the wage regression is the logarithm of the deflated average wage cost in the plant and the included human capital variables are: average age and age squared of the workers, fraction of males, fraction of workers with Swedish citizenships, fraction of workers with university education and fraction of workers with educations oriented towards technical subjects.

[22]One could of course argue that unobserved differences in the human capital structure that are correlated with the failure probability is the main cause for the results, rather than endogenous wages. However, if we to the first stage equation add fixed plant effects, the sign and significance of the residual in the exit equation are virtually unchanged.

[23]There might be endogeneity problems associated with this variable, but at least it does not make any difference whether plant reallocation induced by plant turnover is excluded from our job reallocation measure or not.

the production function, our estimates suggest that failure risk is higher, the lower is the wage cost share and the lower is the average labor productivity. Correspondingly, for the parameters of demand function, the risk is higher, the more competitive the industry is and the lower the product demand is, as measured by the Herfindahl index and working hours, respectively. The risk of plant closure increases with the local wage level and decreases with the local unemployment rate. We like to interpret this as that when the option value of the workers increases this results in higher wage pressure which reduces the survival capacity of the plant.

In specification (iii) we test the hypothesis that insider wage determination is of importance by including the measure of the share of insiders in the plant. The parameter estimate of the share of insiders suggests that there are also important elements of insider mechanisms in wage bargaining. The magnitude is such that a 10 percentage point increase in the share of insiders in the plant reduces the failure probability by some 5 percent. We like to interpret this as that when the share of insiders in a plant is low, then the *ex ante* risk of loosing the job is lower for an insider and the insiders therefore exert higher wage pressure.

However, we are at risk of underestimating the importance of insider mechanisms if plant exit is a long-lasting process in which employment is gradually decreased until exit, which then endogenously would create a large fraction of insiders in plants about to exit the market. To, at least partly, test the importance of this we replace our insider-share measure by the average share of insiders in the plant (excluding the possible year of exit). Now, the parameter estimate of the insider share changes quite a deal. The implied magnitude is such that a 10 percentage point increase in the share of insiders in the plant reduces the failure probability by some 8 percent. In the proceeding we use the plant average insider share as the insider share measure.

Common for the previous specifications is an underlying assumption that all differences between industries and regions are captured by the included variables. In column (v) we check the robustness of the previous results when we in addition control for fixed regional and industrial effects. This reduces the significance of many of the industry variables, although the effects of the local labor market conditions and the share of insiders at the plant level remain intact. It should be noted, though, that this specification probably is over-parameterized, since there is little variation in data across industries and regions to explore in order to identify the

Table 2: Determinants of plant exit with insider wage determination

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Variable			**Parameter estimates**			
Job reallocation$_s$ (λ)	**5.294**	**2.631**	**2.612**	**2.399**	-0.406	-0.844
	(0.564)	(0.618)	(0.619)	(0.623)	(0.788)	(0.918)
Wage cost share$_s$ (α)	-0.096	**-0.855**	**-0.926**	**-0.992**	-0.491	-0.321
	(0.344)	(0.361)	(0.361)	(0.362)	(1.550)	(1.591)
ln(Labor prod.$_s$) (A)	**-0.216**	**-0.684**	**-0.746**	**-0.793**	*-0.619*	0.015
	(0.085)	(0.133)	(0.133)	(0.133)	(0.455)	(0.497)
Herfindahl index$_s$ (κ)	**-5.313**	**-2.468**	**-2.303**	*-1.880*	-2.317	-4.185
	(1.291)	(1.312)	(1.311)	(1.319)	(6.511)	(6.809)
ln(Working hours$_s$) (D)	0.018	**-0.391**	**-0.432**	**-0.447**	**-3.511**	**-3.293**
	(0.175)	(0.183)	(0.183)	(0.184)	(0.589)	(0.625)
ln(Avg. plant size$_s$) (π^*)	**0.117**	**-0.144**	**-0.144**	**-0.119**	**-1.451**	**-0.890**
	(0.051)	(0.057)	(0.057)	(0.057)	(0.414)	(0.453)
ln(wage$_{e/r}$) (w)	*0.332*	**0.649**	**0.741**	**0.823**	**2.132**	*0.911*
	(0.206)	(0.131)	(0.131)	(0.132)	(0.506)	(0.579)
Wage residual	**-0.274**					
	(0.043)					
Unemployment$_r$ (u)		**-4.397**	**-3.698**	**-3.785**	**-7.485**	*-8.326*
		(0.565)	(0.564)	(0.564)	(1.407)	(5.413)
Sh. of insiders$_e$ (L^I/L)			**-0.613**	**-1.588**	**-1.578**	**-1.576**
			(0.046)	(0.047)	(0.048)	(0.048)
Industrial dummies	no	no	no	no	yes	yes
Regional dummies	no	no	no	no	yes	yes
Time dummies	no	no	no	no	no	yes
Log likelihood	-8403	-8366	-8287	-7945	-7853	-7843

Standard errors are reported within the parentheses. Parameter estimates in **bold** (*italics*) indicate significance on the 5- (10-) percent level.
All specifications also include a constant.
In specification (i) the (time-varying) wage measure is specific to the plant and in specifications (ii)-(vi) it is specific to the region. See text for details.

effects of the aggregated variables.

In column (vi), as compared to (v), we add a full set of time dummies. As expected this has an impact on the significance of some of the presumably trended variables, such as unemployment, productivity and wages.[24]

In short: Our results suggest that endogenous wage determination are of importance in explaining plant failure, in the sense that the effects of the worker's outside option and the effect of the insider share at the plant are robust throughout the various specifications. The results on the industry variables also support our *a priori* hypotheses, but they are not robust against the inclusion of a full set of industry dummies.

Additional sensitivity analyses have been performed by the inclusion of controls for various initial conditions, such as the plant's size at the time of entry[25] and whether the plant was created as a part of an already existing firm or not, but these extensions do not change results in any substantial ways and, thus, they are not reported. Also, in the analysis we have excluded the mining industry and multi-plants (i.e. plants in which firm- and plant-level decision making do not coincide) , but we find no major changes in results.

6.2 Human capital effects

We have argued that differences in the human capital structure could be one potential source of heterogeneity across plants. Either because these differences also reflect differences in the degree of plant-specific human capital or because they reflect differences in firing costs. Another motivation why we should control for the human capital at the plant level is that our previous results regarding the effects of the insider share could be spurious, in the sense that the variable could approximate plant specific human capital.

In column (i) of Table 3 we add plant-level human capital measures to specification (v) of Table 2. The estimates of the aggregated variables are not shown in the table, since they remain by and large unchanged as compared to column (v) in the previous table.

[24]Instead of time dummies we have tried capturing the effects of the business cycle by including the net employment change at the industry level. However, no major differences were found as compared to using time dummies.

[25]This variable could be motivated to include as a proxy for plant-level capital, for

Table 3: Determinants of plant exit including human capital and age effects

	(i)	(ii)	(iii)	(iv)	(v)
Variable			**Parameter estimates**		
Sh. of insiders$_e$ (L^I/L)	**-1.582**	**-1.555**	**-1.529**	**-1.551**	**-1.267**
	(0.048)	(0.051)	(0.052)	(0.053)	(0.053)
Age$_e$	0.001	0.001	0.001	0.004	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Man$_e$	-0.098	-0.101	-0.087	-0.079	*-0.205*
	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Swedish$_e$	**-0.474**	**-0.475**	**-0.459**	**-0.418**	**-0.711**
	(0.146)	(0.146)	(0.146)	(0.145)	(0.144)
University$_e$	-0.123	-0.126	-0.116	-0.138	*0.164*
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
Technical$_e$	*0.185*	*0.184*	*0.175*	*0.156*	**0.385**
	(0.115)	(0.115)	(0.115)	(0.115)	(0.115)
Plant Age$_e$		-0.004	**-0.011**	**0.033**	*-0.023*
		(0.003)	(0.004)	(0.014)	(0.018)
(Plant Age)^2_e				**-0.002**	0.001
				(0.001)	(0.001)
Tech Age$_e$			**0.017**	**0.055**	**0.105**
			(0.005)	(0.015)	(0.020)
(Tech Age)^2_e				**0.004**	**0.005**
				(0.002)	(0.002)
(Plant Age*Tech Age)$_e$				**-0.007**	**-0.009**
				(0.002)	(0.002)
Log likelihood	-7838	-7836	-7830	-7806	-7920

Standard errors are reported within parentheses. Parameter estimates in **bold** (*italics*) indicate significance on the 5- (10-) percent level.
In addition all specifications include controls for the same aggregate variables as in specification (v) of Table 2.

The inclusion of human capital variables do not change the estimated effect of the insider share. Somewhat surprisingly, although the *a priori* expectations regarding these variables are not all that clear, we do not find any strong effects of the human capital structure of the plant, except for the fraction of workers with Swedish citizenship. One could perhaps

which we do not have any measurs on.

argue that the latter variable correlates positively with experience in the Swedish labor market, but it is open question what the exact mechanisms generating the results are. The estimates may reflect the fact that when a plant is about to shut down, the employer ranks among the employees when firing, such that the most "valuable" workers are fired last. The employer protection legislation in Sweden may contribute to this, especially with respect to the estimate of the mean age of the worker. To partly, but not fully, overcome this potential problem the human capital measures are averaged over the plant's life time (excluding the possible year of failure), as was done with the insider share variable.

6.3 Plant and technology age effects

Implicitly, so far, it has been assumed that the risk of plant failure exhibits no duration dependence. However, as was argued previously there are good reasons to believe that various age effects are important sources of plant heterogeneity. Furthermore, the previous estimates of the insider share are at risk of being biased because young plants by construction have a large fraction of "outsiders".

For illustrative purposes we have estimated the effects of plant and technology age semi-parametrically, by allowing for piece-wise constant effects, without any other covariates than industrial and regional dummies. The result is illustrated in Figure 1 where the hazard rate with respect to plant age is evaluated at different "technology ages". The result with respect to the age of the establishment conforms to what has been found in previous studies, namely that the risk of plant failure is decreasing in the age of the plant. This could be interpreted in terms of the importance of selection mechanism, but an alternative hypothesis is that omitted variables (other than technology age, industrial and regional effects) generate the negative duration dependence. Also, there seems to be important effects of the technology age, such that the likelihood of plant closure is higher the older technology being used.

In column (ii) of Table 3 we add a linear effect of plant age to the previous specification. Although negative, the linear effect of plant age on the failure probability is not statistically significant. It should be noted that the inclusion of plant age does not affect the point estimate of the share of insiders.

When we in column (iii) add our measure of technology age the effect

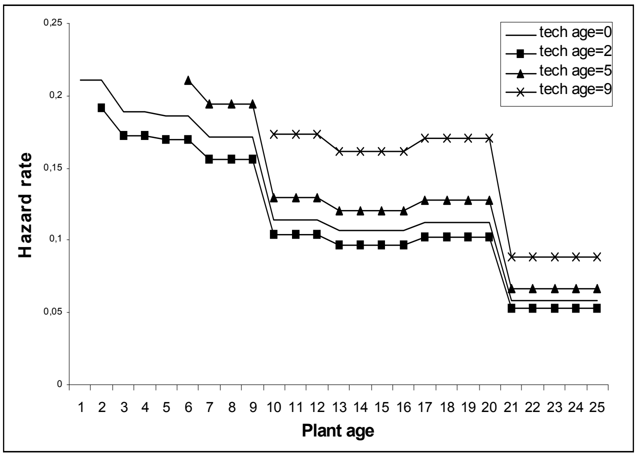

Figure 1: Baseline hazard functions evalutated at different technology ages

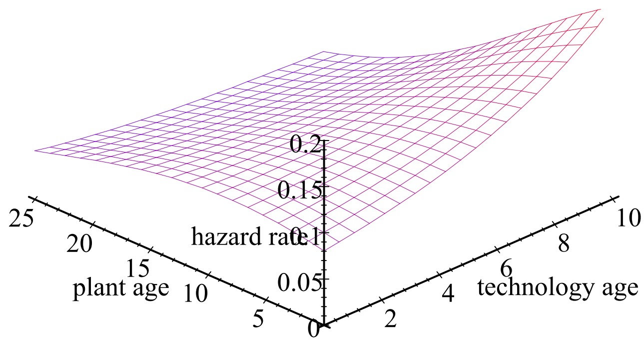

Figure 2: The hazard function with respect to plant and technology age according to specification (iv) in Table 3 where the rest of the covariates are set at their mean value.

of plant age is significantly negative. The estimate of plant age suggests that a newly created plant faces an 11 percent higher risk of plant failure as compared to a plant that has been in existence for 10 years. The hazard is increasing in our measure of technology age, which then lends some support to technology vintage models. For instance, the results imply that utilizing technology with an estimated age of 10 years relative to new technology increases the probability of plant failure by 19 percent.[26]

The result in column (iv), in which we add an interaction term between plant and technology age and second degree polynomials of plant and technology age, indicates that the effects of plant and technology age are not independent from each other. The estimates of the effect of plant age suggest that the risk of plant failure increases until approximately the eighth year of the plant's life time and thereafter the risk decreases. This pattern is not contradicted by the prediction from the theory of selection (Jovanovic, 1982). The hazard rate with respect to plant age is also more decreasing the older technology used. The hazard rate with respect to technology age, on the other hand, is increasing at an increasing rate. The relationship between the hazard rate, plant age and technology age from column (v) of Table 3 is perhaps best illustrated in a three dimensional plan (Figure 2).

As our theoretical model is specified, the employment and the exit decisions are simultaneously undertaken and what we estimate is a reduced form of plant failure in which employment has been replaced by its determinants. However, it can be argued that some of the variables used in the estimation are partly determined by current employment. If this would be the case, our estimates are at risk of being contaminated by endogeneity bias. For instance, it has been argued that smaller plants utilize temporary employment to a larger extent than larger plants do. If this is correct, the effect of the share of insiders at the plant partly captures the effect of the endogenously determined current plant size. Also, the definition of our technology age measure involves the volatility in plant-level productivity, which is likely to be decreasing in plant size. Thus, there might be a spurious positive correlation between technology age and plant size.

To overcome possible bias resulting from this, we in specification (vi) replace the plant-level measures by their size-orthogonal equivalents (except for plant age, which is a truly exogenous variable). That is, we

[26]The qualitative results are about the same if we instead model the age effects semiparemetrically, by allowing for piece-wise constant effects.

instead use the residuals from an ordinary least squares regression of the plant-level variables on current employment. Indeed, the results change somewhat. The effect of the insider share is reduced, but it is still highly economically and statistically significant; the effect of technology age is reinforced by the "size correction", as expected; the hazard is still decreasing in plant age, but the shape is somewhat different from the previous specification; the effects from the plant-level human capital structure tell us, in addition to what was previously found, that the failure probability is higher the lower the fraction of men in the work force is and the more educated the work force is.

In short: Our results indicate weak and mixed effects of the plant-level human capital structure on the failure probability. We find support for selection mechanisms in the sense that older plants have lower failure probabilities, *ceteris paribus.* We also find strong support for technology vintage effects. In Appendix A.1 we show that our main conclusion regarding technology age is not very sensitive with respect to various assumptional changes about how technology age is measured. Still, admittedly there are remaining uncertainties surrounding what our technology age measure exactly reflects and, therefore, we stress that this effect should be interpreted with some caution.[27]

7 Conclusions

Despite a growing literature on producer heterogeneity, its exact sources are not very well explored. In the face of this, the main contribution of this paper is that we address the empirical importance of a number of potential such plant-specific sources by studying the determinants of plant failure on a sample of establishments in the Swedish mining and manufacturing industries over the 1991-96 period.

From our theoretical framework we test hypotheses regarding the link-

[27] Because of the uncertainties surrounding the technology age measure, we do not pursue the analysis further. Still it could be interesting information that in a previous version of this study, we extended the analysis to allow for heterogenous technology vintage effects by including interactions between our technology age measure and the human capital structure of the plant. One interesting result that came out was that labor intense plants with older workers experienced the strongest vintage effects. This could perhaps be interpreted in terms of the importance of technologial advances in the human capital during the 1990s.

ages between the probability of plant closure and industry specific characteristics of production and product demand. The results do at least not contradict what we can expect from our theoretical framework. Nevertheless, a model including only variables reflecting characteristics of the industry and the region is of limited interest, since it has no predictive power of why certain plants within a specific industry and region face higher risks of failure than others and, thus, do not add very much to our understanding of the sources of producer heterogeneity at the micro level.

However, we argued theoretically that insider mechanisms in wage determination may be one potentially important source of heterogeneity in the risk of plant failure across plants. If only insiders take part in the plant-level wage negotiation, then a low fraction of insiders relative to expected employment in the plant implies an increased wage pressure, since the risk for an insider of being laid off is relatively low. This in turn would increase the risk of plant failure. Our empirical analysis indeed suggests that this is the case and that the result seems to be quite robust to alternative hypothesis. The order of magnitude is such that if the share of insiders in the plant increases by ten percentage points, then the probability of plant closure decreases by approximately eight percent.

Another potential source of producer heterogeneity that we have addressed is differences in the structure of human capital across plants. However, we find weak effects from the variables reflecting the human capital structure of the plant. On the other hand, it is neither clear cut what we should expect *a priori* from these variables.

Previous studies have also looked upon the importance of selection mechanisms by studying the hazard rate with respect to plant age. We address this source of heterogeneity as well, but unlike most previous studies we also make an attempt to disentangle and empirically test the importance of plant and technology age. (The access to spells that are much longer than most previous studies makes the analysis of the latter effect meaningful). In accordance to what has been previously found, our results suggest that selection mechanisms are of importance, in the sense that older plants have lower failure probabilities.

There is also evidence that the hazard of plant failure is increasing in our technology age measure, thus, lending some support to the hypothesis stemming from the capital vintage literature that plants utilizing old technologies are more likely to shut down.

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A Appendix

This appendix serves two purposes: A.1 describes how the analytical data set was constructed along with definitions and summary statistics of the most important variables used in the empirical analysis. One crucial assumption in our analysis is how technology age is measured. Therefore we in A.2 conduct some sensitivity analysis in order to give some indications on how robust our previous conclusions are.

A.1 The analytical data set and variables

Our analysis is limited to the stock of existing plants and the inflow of entrants in mining and manufacturing industries during the 1991-96 period. From this sample in *Manufacturing Statistics* (IS) we have made a number of restrictions that deserve to be put in focus. First of all we have excluded all plants in existence prior to 1972, which is the earliest year of entry that we can identify in the *Central Firm and Establishment Registry* (CFAR). Human capital information has been appended to the analytical data set through a linkage between IS and the *Regional Employment Statistics* (Årsys). A number of observations had to be excluded from the analytical data set because the match quality was not satisfying, evaluated by comparing the employment and changes in employment according to the two data sets. Because of missing information on human capital variables we have imputed (through extrapolation) values in some cases, where it has been regarded as possible, while deleted observations in other cases, in which the basis for imputation was not satisfying (i.e. when we would have had to impute more than 3 consecutive values). All in all, we had to exclude some 5 percent of the plants from the original sample because of poor match quality or because of missing information, and we had to impute human capital information values in some 7 percent of the remaining cases.

- Job reallocation (λ) in the industry in period t is calculated as the sum of the number of jobs created and destroyed across plants between $t-1$ and t divided by the average number of jobs in the industry.
- The wage cost share (α) is measured as wage costs over total input costs in the industry.

- Productivity (A) is measured as the average labor productivity in the industry deflated by a producer price index at the three-digit level. This variable is transformed into logarithms.

- The Herfindahl index (κ) is measured as the sum of the squared shares of plant sales in the industry.

- Working hours (D) is measure as average working hours (in 1000) per workers and year. This variable is transformed into logarithms

- Average plant size (π^*) is measured as the average number of employees in the plants in an industry.

- Wage (w) is measured as the average, producer-price deflated, wage-costs in the region (corresponding to "län"). This variable is transformed into logarithms.

- The unemployment rate (u) is measured as the total (openly unemployed and in labor market programs) unemployment divided by the labor force in the region.

- The share of insiders ($(L^I/L) = 1 - \delta$) in the plant is measured as the fraction of employees in period t that were also employed by the same plant the previous year.

- The age of the employees in each plant (Age) is expressed as an average over the number of employees and over the plant's existence, excluding the possible year of failure. This variable is divided by 100.

- The number of men (Man); individuals with Swedish citizenship ($Swedish$); individuals with more education than high school (*University*); and individuals with an education within the engineering programs, either in high school or in the university, ($Technical$), are expressed as fractions.

- Plant age ($Plant\ Age$) is defined as the number of years since plant entry.

- Our preferred measure of technology age ($Tech.\ Age$) is defined as the number of years, since the last time the change in the idiosyncratic labor productivity exceeded a threshold value. In our preferred specification we compare the productivity in t with that in

$t-1$ and use the 90:th percentile in the distribution of idiosyncratic labor productivity changes as our threshold value.

A.2 Sensitivity analysis with respect to how technology age is measured

Our measure of technology age is based on the idea that the introduction of new technology can be determined by analyzing the "Solow residual". However, how large the change in the Solow residual must be in order to represent the introduction of new technology is arbitrarily chosen. Therefore, it is of interest to find out whether our results are robust against choosing different threshold values.

Our preferred measure of technology age was constructed such that new technology was identified when the annual change in the idiosyncratic productivity exceeded the 90:th percentile in the distribution of annual changes in plant-level productivity (see the first column of Table 6). The second column shows how the age parameters change when a much lower percentile value (the 25:th) is chosen. The remaining covariates throughout Table 6 coincide with specification (v) in Table 3. In the third and fourth column we have used the absolute change in the idiosyncratic productivity with different threshold values. This is done in order to capture the idea that also negative changes could reflect the introduction of new technology, because of a possibly long lasting retooling process. Finally, in the fifth and sixth column, we test the hypothesis that the results are caused by temporary movements (or possible measurement errors) in the idiosyncratic productivity. That is, contrary to previous specifications, we require the shifts in the productivity to have permanent effects, in the sense that we compare average lag and lead productivity for each year of the plants' life-time and if the difference exceeds the threshold value in the distribution of changes then we identify the introduction of new technology. Needless to say this procedure may introduce new problems, since our measure now is conditional on future events.

The results in Table 6 show that the estimated effects are somewhat sensitive with respect to how technology age is measured, in the sense that the effects of plant age and that the exact functional form of the relationship between the age effects and the hazard vary between the specifications. However, the main conclusion - that the hazard is increasing in technology age - seems to be robust against these different measures considered.[28]

Table 4: Summary statistics of variables

Variable	Mean	Std. dev.	Min	Max
Job reallocation$_s$	0.163	0.037	0.066	0.312
Wage cost share$_s$	0.369	0.097	0.166	0.526
ln (productivity)$_s$	4.458	0.349	3.876	5.444
Herfindahl index$_s$	0.017	0.019	0.004	0.139
ln (working hours)$_s$	1.009	0.194	0.571	1.327
ln (average plant size)$_s$	3.450	0.605	2.026	4.994
ln (wage)$_r$	3.777	0.287	3.773	4.487
Unemployment$_r$	0.102	0.038	0.025	0.183
Share of insiders$_e$	0.669	0.364	0	1
Age$_e$	38.627	5.275	20.333	66
Male$_e$	0.750	0.212	0	1
Swedish$_e$	0.907	0.122	0	1
University$_e$	0.132	0.154	0	1
Technical$_e$	0.395	0.218	0	1
Plant age$_e$	9.257	6.735	0	24
Tech. age$_e$	4.038	5.146	0	24
# of obs.	22998			

The table shows the summary statistics of the transformed variables, as used in the empirical analysis. Foot index s denotes variables that are specific to the industries, r variables specific to the regions and e variables specific to the plants.

[28] The rest of the parameters (see Table 3, column (v)) remain about unchanged.

Table 5: Spell characteristics of plant age

Plant age	Censoring	Failures
0	150	196
1	210	279
2	210	266
3	224	194
4	310	222
5	429	182
6	201	135
7	168	145
8	202	142
9	166	105
10	172	101
11	185	97
12	187	82
13	146	83
14	139	54
15	156	56
16	118	93
17	79	81
18	116	82
19	116	81
20	244	53
21	116	35
22	207	16
23	91	3
24	101	2
Sum	4443	2785

The table shows the distribution of plantfailure and censoring by plant age.

Table 6: The impact of different measures of technology age

	Temporary				Permanent	
Threshold (percentile)	90:th	25:th	abs(90:th)	abs(25:th)	90:th	25:th
Variable	Parameter estimates					
Plant age	*-0.022*	**-0.024**	0.003	0.001	**-0.204**	0.009
	(0.014)	(0.012)	(0.014)	(0.012)	(0.026)	(0.012)
$(\text{Plant age})^2$	0.000	-0.001	-0.001	**-0.002**	**0.006**	**-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Tech. age	**0.070**	**0.101**	**0.032**	**0.054**	**0.244**	**0.041**
	(0.015)	(0.016)	(0.014)	(0.019)	(0.025)	(0.017)
$(\text{Tech. age})^2$	**0.007**	-0.002	**0.019**	**0.023**	**-0.008**	**-0.011**
	(0.015)	(0.003)	(0.003)	(0.008)	(0.003)	(0.002)
Plant age*Tech. age	**-0.011**	-0.001	**-0.021**	**-0.024**	0.000	**0.010**
	(0.002)	(0.003)	(0.003)	(0.008)	(0.003)	(0.002)
Log likelihood	-8095	-8076	-8090	-8104	-7957	-8088

Standard errors within parentheses.Parameter estimates in **bold** (*italics*) indicate significance on the 5- (10-) percent level.

In addition all specifications include controls for the same variables as in specification (v) of Table 3.

"Temporary" refers to the analysis of the annual change in the idiosyncratic productivity and "Permanent" refers to the difference between the lag and lead mean productivity throughout the plant's life-time for each year.