Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

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2005-23

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April 26, 2005

Abstract

It is well known that turnover rates fall with employee tenure and employer size. We document a new empirical fact about turnover: Among surviving employers, separation rates are positively related to industry-level exit rates, even after controlling for tenure and size. Specifically, in a dataset with over 13 million matched employee-employer observations for France, we find that, all else equal, a 1 percentage point increase in exit rates raises separation rates by 1/2 percentage point on average. Among current-year hires, the average effect is twice as large. This relationship between exit rates and separation rates is robust to a host of data and statistical considerations. We review several standard models of worker turnover and argue that a model with firm-specific human capital accumulation most easily accounts for this new empirical fact.

Keywords: Firm survival; Employee turnover; Human capital.

JEL classification: J24; J31; J63.

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1 Introduction

The economies of industrialized nations are characterized by a tremendous amount of churning. Establishments die, workers quit or lose their jobs, industries contract, and occupations decline in importance. This churning has important implications for workers' decisions about human capital accumulation, job search, and the nature of employment contracts workers write with their employers. Of course, the reverse is also true: workers' decisions have important implications for turnover and establishment survival. Regardless of the direction of causality, credible models of turnover need to be consistent with a set of well-established empirical facts: "(1) long-term employment relationships are common, (2) most new jobs end early, and (3) the probability of a job ending declines with tenure" (Farber, 1999, page 2441) and (4) turnover rates tend to decrease with employer size (see, for example, Anderson and Meyer, 1994). In this paper, we argue that theoretical models of turnover should be consistent with an additional fact: Among surviving establishments, turnover is positively related to industry-level exit rates even after controlling for differences in the distribution of employee tenure and establishment size.

Figure 1 illustrates the positive relationship between turnover and exit rates at the industry level. This relationship reflects, among other things, the fact that industries with lower exit rates tend to have larger firms and workers with more tenure. We find, however, that exit rates and turnover rates remain strongly correlated even after controlling for differences in employer size and employee tenure. Using a dataset of over 13 million matched employee-employer observations for France, we estimate that, all else equal, a 1 percentage point increase in exit rates implies a 1/2 percentage point increase in the likelihood of the worker separating from his employer. Among current-year hires, a 1 percentage point increase in exit rates is associated with a 1 percentage point increase in the likelihood of a separation.

This new empirical finding raises the bar for theoretical models of turnover. We review several standard approaches to modeling worker turnover and discuss the assumptions each theory needs in order to be consistent with the fact that workers are more likely to separate when establishment exit rates are higher. The approaches we consider are a model with firm-specific human capital (as in Oi, 1962, Becker, 1962, or Jovanovic, 1979b), a model with learning-by-doing (as in Jovanovic and Nyarko, 1995), and a model with job matching (as in Jovanovic, 1979a, or Mortensen and Pissarides, 1994). Models with firm-specific human capital immediately predict the desired correlation. Learning-by-doing and matching models require stronger assumptions. In the learning-by-doing case for instance, the exogenous pace of learning needs to differ across employers with different propensities to exit. Naturally, the pace of learning does in fact vary across industries.[1] The point of these theoretical exercises is not to suggest that matching models and models in which learning is exogenous are flawed or inconsistent with the evidence on turnover. Rather, we want to illustrate how the empirical regularity we document should help us build better models of turnover by stressing the importance of certain assumptions.

2 Data and institutional background

Our principal source of data is the Déclaration Annuelle des Données Sociales (DADS) database, which is distributed by France's national statistical institute, Institut National de la Statistique et des Etudes Economiques (INSEE). These data include detailed information on workers and their employers. French law requires all employers to provide information on all employment spells during the year by January 31 of the following year. For each employment spell, employers provide a beginning and an end date, the total number of hours worked, the employee's age, gender, whether the employee works on a full-time basis,[2] and some occupation information (in 34 categories). The employer information includes the establishment's industry (in 36 categories), geographical location, employment size on December 31, and gross payroll. The 2002 "Postes Exhaustif" version of the database we used excludes all payroll and earnings information.[3]

The DADS data are more comprehensive than other sources of data on French employees.

[1] Whether or not learning varies systematically with exit rates is an empirical question that is beyond the scope of this paper.

[2] The survey classifies employees in four categories: full-time, part-time, "intermittents," and home-based. Intermittent workers are employees with a long-term contract who do not work year-round.

[3] These data are a cross-sectional version of the panel data used by Abowd et al (1999). The panel version of these data is no longer available from INSEE.

In particular, France's Déclaration Mensuelle de Main-d'Oeuvre (DMMO), which Abowd et al (1996) and Nagypál (2002) have used for other purposes, only covers establishments with at least 50 employees.[4] Furthermore, to obtain a matched employee-employer data set, the DMMO must be linked with sources of information on employers, for instance France's Enquête sur l'Emploi. Many observations are lost in the matching process, and the resulting data set emphasizes employment relationships less prone to separations, which is a problematic bias given our purposes (see Nagypál, 2002).

But unlike DMMO, the DADS data we use do not contain any information on what causes employment spells to end. Possible causes include 1) transfers within the firm, 2) military service, retirement, sickness, leave, or death, 3) end of apprenticeship or internship, 4) end of a short-term contract (Contrat à Durée Déterminée, or CDD), 5) end of trial hire, 6) dismissal, or 7) quit. Standard models of turnover do not make any prediction for the first three types of separations. The first two account for less than 10 percent of all separations, and the bulk of these separations reflect retirements (Abowd et al, 1996, table 4). In order to minimize the number of retirement episodes in our sample, we drop all employees 55 years of age or older. We also exclude apprentices and interns from the analysis.

More generally, we want to concentrate our attention on potentially durable employment relationships. To that end, we only include full-time employees in our analysis. We also exclude temporary workers by dropping all observations from the "Operational Services" category in France's NES36 classification.[5] We exclude most summer jobs by dropping employees under 26 years of age[6] and the declarations filled by not-for-profit associations and employers in the recreative activity industry. The details of our sampling decisions are provided in appendix B.1. The resulting sample contains 13,068,665 observations and is referred to in the following sections as the "all-employees sample."

[4]In 2000, over 90 percent of French firms outside of the Agriculture and Finance sectors counted fewer than 50 employees. In the industrial sector (mining and manufacturing), *firms* with fewer than 50 employees represented one-third of all employment. See INSEE, 2000/2001, p137. In our sample, *establishments* with fewer than 50 employees represent approximately 45 percent of all employment.

[5]That industry includes all temporary work agencies but also includes establishments that rent vehicles, machinery, equipment and appliances to businesses and individuals, establishments that provide investigation, security and cleaning services, and establishments involved in research and development activities.

[6]The age restriction also reduces the likelihood of a separation due to military service. In any event, separations due to military service in the 2002 DADS are likely very few. Since 1997, males born after 1978 are exempt from the conscription.

The empirical question we ask is whether employment spells with similar observable employer-employee characteristics are more likely to end in industries with high exit rates than in industries with low exit rates, even at similar tenure levels and comparable employer sizes. We calculated two proxies for industry-level exit rates from two distinct data sources. Our 2002 DADS dataset reports employer size as of December 31, 2002. Establishments with positive employment at some point during 2002 but no employment on December 31 are assigned size zero. Our first proxy for exit rates is the fraction of employees in each industry whose employer reported size zero in the 2002 DADS. Note that by construction this proxy for exit rates is employment weighted. Our second proxy for exit rates comes from the OECD firm-level data project (see Bartelsman, et al., 2003, for a detailed description of the project). The French section of the OECD firm-level database reports for each year between 1991 and 1996 the number of continuing firms in 61 industries (constructed from two-digit ISIC categories) at the beginning of the year, the number of entering firms during the year, the number of firms that exited the industry by the end of the year, and the number of employees in each of these categories of firms. In particular, it is possible to calculate the fraction of employees in exiting firms in each industry. To make this measure compatible with our DADS database, it is necessary to map the ISIC-based categories used by the OECD into France's NES36 classification. The details of this concordance are in appendix B.3. The resulting proxy for exit rates differs from the DADS-based proxy for two main reasons: it is firm based rather than establishment based, and it is based on data for the 1991-96 time period rather than for 2002.

Table 1 shows the sample means of the variables we use in our analysis. In particular, note that like in the U.S. (e.g., Anderson and Meyer, 1995, table 2), separation rates and establishment exit rates are higher in the trade sector (wholesale trade, retail trade and transportation) than in the service sector, higher in the service sector than in the manufacturing sector, and lowest in the public sector. Exit and separation rates also fall with the establishment's employment size. Table 2 reports means for those workers hired after January 1; we refer to this sample in subsequent sections as the sample of "current-year hires." As in the U.S., separation rates in France are uniformally and markedly higher in the first year of employment than in subsequent years.

When comparing these statistics to their U.S. counterparts however, it is important to bear in mind key distinguishing features of French labor markets. Legal restrictions on hiring and firing are more stringent in France than in the U.S., and, not surprisingly, hiring and firing rates are lower in France than in the U.S. In fact, the *annual* separation rates shown in table 1 are of the same order of magnitude as the *quarterly* separation rates reported by Anderson and Meyer (1995, table 2). Another key feature of French labor markets is the importance of short-term contracts (CDDs). Abowd et al. (1996) calculate that roughly one-half of all terminations are ends of short-term contracts, and that roughly 70 percent of new employees are hired under CDDs. Under French law, employers may use CDDs for youth employment programs, completing temporary tasks, and testing new hires. These contracts can be renewed once for a total length of up to 18 months. Employers use CDDs for the majority of hirings, because CDDs carry fewer mandated costs (e.g., severance payments) than contracts of indefinite length (CDIs). Upon expiration, one-third of CDDs become long-term contracts, while the remainder are either renewed or terminated. Our data do not permit us to examine whether our main result—that separations are more frequent in industries with high exit rates—holds for both types of contracts.

3 Empirical Results

At the industry level, a higher rate of establishment exits is positively related to the rate of worker separations (figure 1). This relationship suggests that workers in industries with high exit rates are more weakly attached to their employers than employees in industries where establishments are more likely to survive. However, this conclusion does not control for systematic differences in the industry-level characteristics of employees and employers. For example, older workers are known to have lower rates of separation, therefore, a high-survival industry will exhibit lower separation rates if it tends to employ older workers. This section investigates whether the positive correlation between exit rates and separation rates persists after controlling for the employer-employee characteristics we observe in the data described in the previous section.

We begin by modeling the worker's separation outcome using a probit model that controls for the worker and establishment characteristics available to us, as well as the estimated industry-level exit rates. As shown in the all-employees columns of table 3, coefficients have the expected signs.[7] Older workers are less likely to separate, and the marginal decrement to the probability of separation declines with age. Generally, employees whose occupation ranks higher in the French occupational classification system (see appendix B.2) are less likely to separate. For instance, employees in occupational category 1 are less likely to separate than those in occupational category 4; however, occupational category 2, which includes top-level managers and other high-level professionals, appears to be an exception. The likelihood of a separation also declines monotonically with the employment size of the establishment. Workers in establishments with 100 to 199 employees are considerably less likely to separate than employees in establishments with 1 to 19 employees (the excluded category). Employees in the Paris agglomeration are more likely to separate. Separations are more likely in the services sector than in the manufacturing sector and more likely in the private sector than in the public sector. Most significantly for our purpose, exit rates continue to exhibit a strong positive correlation with the likelihood of a separation even after controlling for the employee and employer characteristics just described. Finally, a dummy variable that equals one if the employee is not a current-year hire indicates that workers with more tenure are, unsurprisingly, much less likely to separate from their employer.

In order to better control for the effects of tenure on the likelihood of a separation, for the remainder of this study we restrict our attention to current-year hires. All employees in this sample have a year of tenure or less. Within that sample, it is in fact possible to control for tenure more finely as we know the exact date of hire; in the next section we make use of this information to better control for seasonal employment. This tenure category is also of particular importance for understanding the determinants of turnover as, in France like in the U.S., separations are much more likely to occur within the first year of employment than at higher tenure.[8]

The results for this sample of current-year hires, shown in table 3, are qualitatively similar to the results for the all-employees sample. Among the differences, separation rates

[7] Statistical significance is not an issue given the size of our sample.

[8] Separation rates exceed 40 percent among current-year hires, compared to about 11 percent among returning employees. Half of all separation episodes in our sample occur among current-year hires.

now decline monotonically across all of the occupation codes (employment category 2 is no longer an exception). Also, the sign of the coefficient of the geographical location dummies changes, and suggests that among current-year hires, separation rates are lower in urban areas, particularly outside of Paris. Importantly, the coefficient on exit rates is larger in the sample of current-year hires than it was for the all-employees sample. Workers hired during the current calendar year are more sensitive to the industry-level exit rates. A possible explanation for this finding is that tenure dilutes the effect of exit rates, as workers have time to learn about any idiosyncratic differences between the establishment's likelihood of exit and the overall likelihood suggested by the industry exit rates. Table 4 translates the coefficients on the exit rate into marginal effects.[9] For example, a 1 percentage point increase in the industry exit rate (from the mean) raises predicted separation rates by 1.115 percentage points (from the mean) in the sample of current-year hires, as compared to 0.447 percentage point in the all-employees sample. This difference is not terribly surprising given the much smaller rate of worker separations in the all-employees sample. The two rightmost columns of table 4 present some relative effects. A 1 standard deviation increase in the exit rate (which varies between the two samples) is associated with a 0.14 standard deviation increase in predicted separation rates in the all-employees sample and a much larger 0.34 standard deviation increase in predicted separation rates for the sample of current-year hires. Similarly, a 1 standard deviation increase in exit rates is associated with an 8.5 percent increase in predicted separation rates in the all-employees sample and a 9.8 percent increase in predicted separation rates for the current-year hires. Thus, the relationship in figure 1 appears robust to controlling for the characteristics of employees and employers.

A shortcoming of the probit model, however, is that it is a model of worker separations conditional on the establishment having survived. In general, whether a termination occurs is the result of two binary outcomes in each period: whether or not the establishment survived, and whether or not the employment relationship was terminated for reasons other than establishment failure. We are primarily interested in this latter outcome, but it is only partially observable. Specifically, we only observe the separation decision if the establishment does not exit the industry. Our data do not permit us to identify whether a separation would

[9] We computed the marginal effect for each observation. The effects shown in table 4 are sample averages.

have occured had the establishment survived.

The probit model sidesteps the partial observability problem by discarding, in the case of the sample of current-year hires, the roughly 7-1/2 percent of observations in which the establishment exits. Intuitively, we would expect separation rates to be higher in establishments that are more prone to exit, therefore, discarding these observations should downwardly bias the coefficient on exit rates. One way to control for this potential bias is to use a bivariate probit model (see Poirier, 1980; Meng and Schmidt, 1985; Greene, 1998). The bivariate probit is the discrete-choice analog to the standard sample selection correction frequently used in regression-based models.

Index workers by i and let $S_i \in \{0,1\}$ be an indicator variable for whether or not worker i separates from their employer; likewise, let $A_i \in \{0,1\}$ be an indicator variable for whether or not the worker's establishment survives the year. The function of interest is $\Pr(S_i = 1|A_i = 1)$, that is, the probability that the worker separates conditional on the establishment surviving the year. The basic idea is that there are characteristics of employers seen by workers but unobserved by the econometrician. For example, the worker may know that the establishment is exiting and quit prior to its actual demise. However, if both events occur within the same year, our data do not reveal the fact that the worker quit. Formally, the model consists of a worker separation equation, an establishment survival equation, and a selectivity relationship that links the erros in the other two equations. The separation equation is

$$S_i^* = \beta' x_i + \epsilon_i$$
$$S_i = 1 \text{ if and only if } S_i^* > 0 \text{ and } 0 \text{ otherwise,}$$

where x_i includes the industry exit rate and controls for worker and establishment characteristics. These controls include worker age, gender, occupational and broad industry dummies, establishment size dummies, dummies for location in Paris or other urban areas, and a dummy variable for being in the private sector. The establishment survival equation is

$$A_i^* = \alpha' z_i + u_i$$
$$A_i = 1 \text{ if and only if } A_i^* > 0 \text{ and } 0 \text{ otherwise.}$$

Note that S_i is observed only if $A_i = 1$ whereas A_i, x_i, and most elements of z_i are observed for all workers. In our benchmark model, z_i contains the same covariates as x_i except that the establishment size dummies are excluded because we do not observe the size of establishments that exit. Other exclusion restrictions are introduced and motivated in the next section. The selectivity relationship is governed by the correlation $\rho_{\epsilon u}$ between the errors in the worker and establishment equations, where:

$$\begin{pmatrix} \epsilon_i \\ u_i \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{\epsilon u} \\ \rho_{\epsilon u} & 1 \end{bmatrix} \right)$$

If $\rho_{\epsilon u} = 0$, there is no selection effect: the firm's exit outcome and the worker's propensity to separate are independent given observable employer and worker characteristics.

Column 1 in table 5 displays the results of the bivariate probit estimation. As shown in the last row, $\rho_{\epsilon u} < 0$, which implies that establishments more likely to fail because of characteristics not spanned by our control variables (unobserved characteristics) also tend to have lower separation rates, when they survive. This should bias downward the coefficient on exit rates in the probit model. Indeed, establishments more likely to fail for unobserved reasons are less likely to survive in high failure rate industries. All else equal then, in industries with high failure rates, our data will emphasize employers more likely to survive for unobserved reasons. Not surprisingly then, the estimated coefficient on exit rates in the separation equation of the bivariate model is larger than in the probit model. The coefficients on establishment size are smaller in the bivariate probit model. This likely reflects the fact that exit rates are negatively related to establishment size, so that explicitly modeling exit partially mitigates the role of establishment size. The signs and magnitudes of other variables are otherwise little changed. The results for the establishment survival equation may be of independent interest. Naturally, those working in industries with high exit rates are more likely to see their establishment exit. Older workers, women, and workers in urban areas are also more likely to see their establishment exit.

There are many marginal effects one can compute in a bivariate probit model such as ours, but the one most directly comparable to the single equation case is the sample average of the partial derivative of $\Pr(S_i = 1|A_i = 1)$ with respect to exit rates.[10] The third row of table 4 shows that this marginal effect is a bit larger in the bivariate probit case than in the single equation case, both in absolute and in relative terms.

4 Robustness

In this section we explore the sensitivity of our findings to features of French labor markets and various statistical considerations. The last four columns of table 5 include results from several of these robustness checks, and table 4 has the corresponding marginal effects for exit rates.

Exclusion restrictions. Our bivariate model is formally identified. However, Keane (1992) points out (in a different context, that of multinomial probit models) that identification can be tenuous even in formally identified models.[11] For that reason, it is now common practice to use exclusion restrictions to aid with identification in multi-equation models. Given the data available to us, we chose to include statistics from the empirical distribution of surviving establishments in the employer's industry in the survival equation.[12] Specifically, we included for each industry the fraction of surviving establishments in the four following categories: 0 to 49 employees, 50 to 99 employees, 100 to 199 employees, and 200 employees

[10]Formally, let β_x and α_x be the coefficients of the exit rate variable in the separation and the survival equations, respectively. Then the marginal effect for worker i is

$$\frac{1}{\Phi(\alpha' z_i)}\left[\beta_x \phi(\beta' x_i)\Phi(\frac{\alpha' z_i - \rho_{\epsilon u}\beta' x_i}{\sqrt{1-\rho_{\epsilon u}^2}}) + \alpha_x \phi(\alpha' z_i)\Phi(\frac{\beta' x_i - \rho_{\epsilon u}\alpha' z_i}{\sqrt{1-\rho_{\epsilon u}^2}}) - \alpha_x \Phi_2(\alpha' z_i, \beta' x_i, \rho_{\epsilon u})\frac{\phi(\alpha' z_i)}{\Phi(\alpha' z_i)}\right]$$

where ϕ, Φ denote the density function and the cumulative distribution of the standard normal distribution, respectively, while , Φ_2 is the cumulative distribution of the bivariate normal distribution with unit standard deviations. See Greene (1997, p.910).

[11]We did not experience any of the classic symptoms of fragile identification with any of our specifications: in all cases, our maximum likelihood algorithm converges to the same solution from any set of initial conditions, and estimated standard errors are very small for all coefficients.

[12]Recall that due to data limitations, we cannot include individual establishment size information in the survival equation. Establishments that do not survive all report size 0 in the survey.

or more. Given that we know the actual size of the worker's establishment, these statistics should contain little new information about the worker's separation decision. But, from an establishment survival perspective, the size distribution of surviving establishments is likely correlated with the industry's overall size distribution. Therefore, it should provide some information on the survival prospects of individual establishments. We do find that these new variables significantly affect survival outcomes. But as shown in table 5, these exclusion restrictions have almost no effect on the coefficients of the separation equation. Obviously, the marginal effects change little as well.

Alternative exit rates. We repeated our analysis using the firm-level exit rates we obtained from the OECD. The rates we used previously were effectively employee-weighted establishment-level exit rates, therefore we chose to weight the OECD firm-level rates by employment to make them more comparable.[13] Although the correlation between the two sets of exit rates is only 9 percent, some of the industries that deviate from the regression line between the rates are fairly small industries that have little effect on the aggregate. For example, removing just the realty industry boosts this correlation to 26 percent. Realty is dominated by large, multi-establishment companies; at the corporate-level survival rates are high, despite considerable churning at the establishment level. The bivariate probit results we obtain with these alternative exit rates are qualitatively unchanged, as can be seen in column 3 of table 5.[14] The fourth row of table 4 shows that although the absolute marginal effect is nearly 3 times larger in this case, the relative marginal effects are qualitatively similar and only a bit larger quantitatively than what we obtain with the sample of current-year hires using DADS-based establishment exit rates. The large marginal effect has a considerably smaller impact on the relative effects because the firm-level exit rates we calculated with OECD data are less volatile than the DADS-based rates.

Another virtue of using OECD exit rates is that they alleviate the concern that cyclical factors could drive our results. A negative industry-specific demand shock might result in

[13]The results we obtain using the unweighted firm-level rates (not shown), are qualitatively similar.

[14]Estimating $\rho_{\epsilon u}$ precisely proved difficult in this case. This likely owes to the fact that we now have fewer industries (21 vs. 34), which raises the collinearity between exit rates and our set of broad industry dummies. In fact, dropping any of the 3 industry dummies from the survival equation solves the convergence problems we experienced with our initial specification. The results we show in column 3 of table 5 are for the case where the trade dummy is excluded from the survival equation. Coefficients change little when another industry dummy is excluded.

the exit of some establishments and layoffs at the remaining establishments, which would give rise to a positive relationship between exit rates and separation rates. The OECD exit rates we use are 6-year averages, which mitigates the possible effect of cyclical shocks. In addition, demand shocks that occured in the first half of the 1990's are less likely to affect separation rates in 2002.

Non-seasonal workers. Despite our sampling restrictions, our data may still contain some seasonal workers. To test whether our results are sensitive to seasonal employment, we further restrict our data by removing all workers with less than 6 months of tenure. More precisely, the sample of non-seasonal workers only includes workers hired during the first 3 months of the year whose employment spell lasts at least 6 months. We then consider a separation to have occurred if the spell ends between month 6 and month 9 of employment.[15] This procedure removes all workers hired for short-lived tasks and reduces the number of observations among current year hires by about 85 percent. Nonetheless, the qualitative relationships we found in the base case are largely unchanged (column 4). The marginal effect of exit rates is smaller than in the base case, but that is because separations occur at a lower rate in this sample as they can only occur in a three-month window. In fact, the relative effects are of a magnitude similar to what we found with the sample of current-year hires.

Industry restrictions. Substantial government involvement in some industries (both directly and via preferential treatment) likely affects the relationship between establishment exit and worker separation. Therefore, we repeated our analysis excluding the roughly 331,000 establishment found in industries where government involvement is often significant; these industries include agriculture, postal services and telecommunications, education, social work, public administration, and associations. The bulk—about 80 percent—of the excluded establishments were attributable to the exclusion of social work and public administration. The bivariate probit results with these industry restriction (column 5) are qualitatively little changed from the base model and the marginal effects (table 4) are quantitatively quite similar to the model with the alternative exit rates.

Looking within size classes and broad industry categories. The size class and broad in-

[15] This definition gives all workers in the sample the same window for a separation to occur.

dustry dummies we include as controls in our model specifications are correlated with exit rates. For instance, small establishments are more likely to fail than large establishments, and exit rates are higher in the trade sector than in the manufacturing sector. In principle, the statistical significance of exit rates could reflect the fact that size classes and broad industry categories are associated with separation rates in complex, nonlinear ways that dummy variables cannot capture. To assuage this concern, we re-estimated our models separately for each size class and broad industry category. In all cases, the coefficients and marginal effects of exit rates remain positive, large, and significant. These results are available upon request.

Occupation-specific differences. Occupational differences may matter in ways not captured by our five broad occupational controls. In order to assess this possibility we ran separate probits for 26 occupational categories (the number of categories with which our sampling restrictions leave us). In 23 cases, the coefficient on exit rates was positive and statistically significant; in the remaining three cases—public service executives, intermediate public service executives, and farm hands—the coefficient on exit rates was insignificantly different from zero.[16] The occupational probits also help to minimize concerns that our results reflect a correlation between occupations and particular worker unobservables. For example, some occupations tend to be characterized by workers that have a greater degree of "footlooseness," such as truck drivers or farm hands. Footloose workers may care less about the risk of establishment failures as they anticipate separating from their employer anyway. Therefore the data might show a positive correlation between establishment exit rates and worker separation rates due to this particular unobservable characteristic of workers. The occupational probits suggest that our results are either robust to this concern, or that these worker unobservables have little correlation with occupations.

5 Three models of turnover

This section discusses the consistency of standard models of employee turnover with the empirical regularity we document in this paper. We first argue that models of turnover

[16] These results are included in a separate appendix available from the authors.

founded on specific human capital predict that separation rates should be higher in firms (or establishments) more likely to exit, even at equal levels of employee tenure. Exogenous learning-by-doing models, on the other hand, only predict a positive correlation between exit rates and separation rates at equal tenure provided the rate of learning differs across employers with different likelihoods of survival. For matching models to predict the desired correlation, the process that governs the evolution of worker productivity must differ across employers, or search must be endogenous. We emphasize once again that our objective when comparing simple models of turnover is not to suggest that matching models or exogenous learning models are flawed, but rather to stress the importance of certain features of these models.

We make these points in the context of a stylized general equilibrium environment in which time is discrete and infinite. Each period, constant measures of firms and workers are born. Firms belong either to industry H or to industry L.[17] The fraction of firms born in each industry does not vary over time, and firms remain in the industry to which they are born until they die. In industry H, firms survive from one period to the next with likelihood p_H while in industry L they survive with likelihood $p_L < p_H$.[18] Industries are otherwise identical. In each period, firms in both industries can transform labor $n \geq 0$ into quantity $f(n)$ of the consumption good, where f is strictly concave, strictly increasing, and $\lim_{n \mapsto 0} f'(n) = +\infty$.

Workers are risk neutral and endowed with the same ownership share of all firms. They die with likelihood $1 - \beta \in (0, 1)$ at the end of each period. In each period, workers are employed by exactly one employer. The maximum quantity x of labor a worker can deliver to their employer is drawn from X, a finite set. We refer to $x \in X$ as a worker's *productivity*. The three models we study differ only in terms in the stochastic process that governs the evolution of each worker's productivity.

[17]While we refer to these two sets of firms as industries throughout this section, our arguments apply immediately when comparing employers whose perceived likelihood of survival differs for any reason, including size or geographical location.

[18]Dunne et al. (1988) show that exit rates differ markedly across industries in the U.S. and that those differences tend to persist over time. Our assumption that exit rates are exogenously fixed is strong, but it can be relaxed without altering our results.

5.1 Firm-specific human capital

Our first model is a two-industry version of Jovanovic's (1979a) firm-specific human capital model.[19] Let $X = \{0, 1, 2\}$. In the first period of employment with a given firm, $x = 1$ with probability 1. The evolution of a worker's productivity in subsequent periods depends on the time s she devotes to training. With probability $h(s)$, x moves up to 2, and with probability $\delta(s)$, x falls to 0, where δ is decreasing in s while h is increasing and strictly concave in s with $h(0) > 0$ and $h'(1) = 0$. For simplicity, we assume that $x = 0$ and $x = 2$ are absorbing states. At the beginning of any period, workers can choose to separate from their current employer and begin providing labor to a new employer.

The process governing the evolution of x may be correlated across workers in a given subset of firms, but we assume no aggregate uncertainty. Specifically, in each industry, a fraction $h(s)$ of the workers of productivity $x = 1$ who devote time s to training see their productivity rise, while a fraction $\delta(s)$ of these workers see their productivity fall. Productivity is firm specific in this model since workers of productivity $x = 2$ whose employer dies revert to $x = 1$ when they find a new employer. In practice, much of human capital is general in nature, or occupation specific (e.g., Kambourov and Manovskii, 2002) rather than firm specific. We make the assumption that all human capital is firm specific for convenience. The result we establish below only requires that human capital be firm specific in part, or, in a model where all human capital is occupation specific, that workers whose employer die run the risk of not finding employment in the same occupation.

We assume that firms behave competitively and pay workers the value of their marginal product in each period.[20] We consider steady state equilibria, i.e. equilibria in which the price w_i of labor (the wage rate per efficiency unit of labor) in industry $i \in \{H, L\}$ is constant. A steady state equilibrium is a pair of wage rates such that labor markets clear in both industries in all periods. Quintin and Stevens (2003) show that a unique steady state equilibrium exists in this environment provided that $\beta h(1) < \delta(1)$. Under this assumption, all firms must hire new workers in every period in steady state. Therefore, wages adjust so

[19] A more general version of this model is analyzed in detail in Quintin and Stevens (2003).

[20] Different bargaining power assumptions would lead to different equilibria, but would not change our basic result: all else equal, workers in firms more likely to survive devote more time to human capital accumulation.

that new workers are indifferent between the two industries. This also implies that incumbent workers at productivity level $x = 1$ are indifferent between quitting or staying with their firm.[21] We assume, for concreteness, that they stay. With this convention, workers quit if, and only if, their productivity level falls to $x = 0$. Denote by s^i be the fraction of time workers with $x = 1$ devote to training in industry $i \in \{H, L\}$.[22] Let $S^i(t)$ denote the fraction of workers of tenure t who separate from their employer in industry i in any given period. By tenure we mean the number of periods a worker has worked for their current employer at the beginning of a given period. In particular, all workers have tenure 0 in their first period of employment, and workers of tenure 0 do not separate from their employer by construction. We can now state:

Proposition 1. *A unique steady state equilibrium exists. Furthermore, in steady state,*

1. $w_H < w_L$,
2. $s^L \leq s^H$ *with a strict inequality if and only if* $s^H > 0$,
3. $S^i(t) < S^i(t+1)$ *for all* $t \geq 0$ *and* $i \in \{H, L\}$,
4. $S^H(t) \leq S^L(t)$ *for all* $t > 0$, *with a strict inequality if and only if* $s^H > 0$.

The third item of the proposition says that this model, like all reasonable models of turnover, predicts a negative correlation between tenure and separation rates. This is because workers with more tenure tend to have more firm-specific human capital. But the model also predicts that when $s^H > 0$, which occurs for instance when $\lim_{s \mapsto 0} h'(s) = +\infty$, workers in the high-survival industry should accumulate more firm-specific capital than workers in low-survival industries. That is because workers employed in firms more likely to survive are more likely to reap the benefits from their investment in firm-specific human capital. However, formalizing this simple intuition is complicated by general equilibrium considerations: the wage rate is higher in firms less likely to survive (a compensating differential) which makes the opportunity cost of human capital investment higher in those firms. The proof we provide

[21] In this model, as in Jovanovic's (1979a) model, all separations are initiated by the worker. Different rent-sharing arrangements would lead to different outcomes (see Jovanovic, 1979a for a discussion.)

[22] Workers with $x = 2$ devote no time to training because, by assumption, that state is absorbing.

in appendix A consists of arguing that this general equilibrium effect is dominated by the direct impact of survival rates on returns to human capital investments.

Importantly, the fact that the wage rate (the price of effective labor) is higher does not imply that earnings are higher in firms more likely to fail. Earnings per period depend on workers' productivity and the time they spend in training. Because they devote more time to human capital accumulation, workers in firms more likely to survive are more productive. When workers do not discount future consumption flows, it is in fact easy to argue that average earnings must be the same in the two industries. With discounting, average earnings comparisons depend on parameter selections.[23] Note also that the compensating differential stems solely from general equilibrium considerations. Whether human capital is specific or not is irrelevant for this feature: the three models we consider all predict it.

If we strictly interpret s as time devoted to training, then we can, in principle, test the endogenous view of firm-specific capital by comparing training intensity across industries. However, in our view, the state of existing evidence on training, particularly informal training, does not allow for a convincing test along those lines (see Barron, 1997). But the last item of proposition 1 can be tested, as we have shown in this paper. Models where firm-specific capital is in part endogenous correctly predict that turnover rates should be higher in high survival industries, even at equal employee tenure.

5.2 Learning-by-doing

In the second model (as in the learning-by doing model of Jovanovic and Njarko, 1995) the accumulation of firm-specific capital is exogenous. It differs from the firm-specific human capital model in one respect only: function h satisfies $h(s) = h(0) > 0$ for all $s \in [0, 1]$. As a result of this assumption, workers always choose $s^H = s^L = 0$, and the average rate of growth of productivity with tenure is exogenous, and the same in the two industries. Proposition 1 continues to hold, except that separation rates are now the same at each tenure level in the two industries.

Remark 1. *If $h(s) = h(0)\ \forall s \geq 0$, then, in steady state, $S^H(t) = S^L(t)\ \forall t > 0$.*

[23] See Quintin and Stevens (2003) for more details.

Although separation rates are the same across industries at each tenure level, *average* separation rates are higher in the low-survival industry than in the high-survival industry even if $s^H = s^L = 0$. That's because workers have more tenure on average in industries with high survival rates, and are therefore more productive on average as $h(0) > 0$. Unlike in the firm-specific capital model, the correlation between exit and separation rates disappears in this model after controlling for tenure.

Remark 1 implies that making the learning-by-doing model consistent with the correlation between separation and exit rates at equal tenure requires introducing employer heterogeneity beyond differing survival probabilities. It suffices, for instance, to assume that the learning function (h) is steeper in the high-survival industry.

5.3 Matching

In matching models (e.g. Jovanovic, 1979b), a worker's productivity depends on how well she is matched with her employer. She learns about her match quality over time, and a separation occurs when expected match quality falls below a certain threshold. Our goal in this section is to highlight the features matching models need in order to imply that separation rates should be higher in low-survival industries among observably similar workers.

Assume that $X = \{x_1, x_2\}$ with $x_1 < x_2$ and that a worker-employer match is either good, or bad. In any given period, well-matched employees draw productivity $x = x_2$ with probability p_G, while poorly matched employees draw $x = x_2$ with probability $p_B < p_G$. Match quality is unknown to both the employer and the employee, but they know that in the first period of employment, half the matches are good while the other matches are bad. Productivity draws are independent across periods, and workers update their prior probability of being in a good match according to Bayes' rule as they observe more draws. The optimal separation rule in this environment is simple: a worker separates from their employer at the beginning of period t given her productivity history if the corresponding prior probability that she is in a good match falls below 1/2. Indeed, in that event, their expected future income falls below what they would expect if they started a new job. Since the separation rule is the same across industries, the distribution of beliefs is also the same in the two industries *at each tenure level*. It now follows that:

Remark 2. *In steady state, $S^H(t) = S^L(t)$ for all $t > 0$.*

As in the learning-by-doing model, separation rates are the same in the two industries at each tenure level. This is because in this most simple of matching models all workers have the same outside option, namely separate from their current employer and start a new job where the likelihood of a good match is 1/2. One way to make separation thresholds differ across industries is to introduce unemployment risk. Intuitively, this could make the opportunity cost of separating from one's employer lower in low-survival industries as jobs are more likely to end for exogenous reasons in those industries. On the other hand, workers in low-survival industries would forgo more current-period income by separating as they have higher wage rates. In an appendix available upon request we show that at least for certain parameter values, matching models with unemployment predict that separation rates should be *higher* in high-survival industries.

This suggests that for matching models to predict a positive correlation between separation rates and firm death rates, features such as on-the-job search or heterogenous matching processes across employer are necessary. As in the firm-specific human capital model, and for similar reasons, returns to on-the-job search are related to firm survival. Intuitively, time devoted to on-the-job search is more likely to pay off in establishments less likely to survive. On the other hand, as in the firm-specific human capital model, general equilibrium considerations imply that the wage rate is higher in establishments less likely to survive, which makes the opportunity cost of time devoted to on-the-job search higher. Establishing that the direct effect of exit rates on on-the-job search dominates may be difficult. But the discussion above shows that without such a feature, matching models make ambiguous predictions, at best, for turnover rates across industries.

6 Conclusion

Using a French data set with matched employer-employee data, this paper provides new evidence that employee turnover is higher in industries where firms or establishments are more likely to exit. We find that tenure alone cannot explain the higher separation rates in low-survival industries. Models of turnover founded on firm-specific human capital models are strongly consistent with this empirical regularity. Other standard models of turnover require additional assumptions. Our empirical result also has implications for the literature on industry rents. Specifically, it suggests that industry rents could reflect differences in job security across industries. Workers may accumulate less human capital in low survival industries, than their counterparts in industries where jobs are more secure.

A Proof of Proposition 1

Existence and uniqueness can be established with standard arguments (see Quintin and Stevens, 2003). In order to prove the other items of the proposition, we will first describe the problem solved by workers in equilibrium. Let $V_i(x)$ denote the expected income of a worker of productivity level x in industry $i \in \{H, L\}$. In steady state, new workers are indifferent between working in the two industries, so we must have $V_H(1) = V_L(1)$. Therefore, the expected income of a worker of productivity x in industry $i \in \{H, L\}$ can be written as

$$V_i(x) = \max_{s \in [0,1]} (1-s)xw_i + \beta \{V_i(1) + p_i[(1-h(s))V_i(x) + h(s)V_i(2)]\} \tag{A.1}$$

where $(1-s)xw_i$ is current period earnings if a fraction s of time is devoted to training. Because the worker can change employers if necessary, her productivity is at least 1 in the next period. If her employer survives, which occurs with likelihood p_i, and if her training efforts pays off, which occurs with likelihood $h(s)$, she moves up to productivity $x = 2$.

Now assume by way of contradiction that $w_H > w_L$ in steady state. Then, since the expected income associated with any training policy is strictly higher in industry H, we have $V_H(1) > V_L(1)$. In that case, no worker would take a job in industry L which can't be in steady state since labor demand is positive at all wages in both industries.

Consider now the second item in the proposition. Given (A.1), workers in industry $i \in \{1, 2\}$ choose a level s^i of training such that

$$w_i \leq h'(s^i)\beta p_i[V_i(2) - V_i(1)]$$

with a strict equality if and only if $s^i > 0$. (Recall that $h'(1) = 0$.) We only need to argue that $p_H[V_H(2) - V_H(1)] > p_L[V_L(2) - V_L(1)]$. Assume that this inequality does not hold. Then, because $w_L > w_H$, inspection of (A.1) shows that $V_L(1) > V_H(1)$, an inequality which cannot hold in equilibrium as no worker would join firms of industry H. This result yields the second item of the proposition.

Consider finally the last two items of the proposition. In industry $i \in \{1, 2\}$, the evolution of a worker's productivity with tenure follows a Markov chain with states $\{1, 2\}$ and transition $P^i(x = 2|x = 1) = h(s^i)$. Because $h(0) > 0$ the chain's expected value rises strictly with tenure in both industries, which is item 3 of the proposition. In addition, $s^H \geq s^L$ implies that the Markov process governing a worker's productivity in industry H first order stochastically dominates the process governing the evolution of a worker's productivity in industry L. This yields the last item of the proposition, and completes the proof.

B Description of the data

B.1 Sample restrictions

Our main source of data is the “Postes Exhaustif” version of the 2002 France’s Déclaration Annuelle des Données Sociales. The database contains 32,951,110 observations. Below is a list of our sampling restrictions, with the size of the sample shown in parenthesis after each step:

Drop observation if employee’s age is 55 years of more	(30,933,580)
Drop observation if employee’s age is 25 years or less	(22,599,270)
Drop observation if job status is not full-time	(15,404,185)
Drop observation if employer is in “Operational Services” industry	(14,384,621)
Drop observation if employer is an association	(13,469,154)
Drop observation if occupation is intern or apprentice	(13,344,781)
Drop observation if occupation is clergy	(13,344,371)
Drop observation if industry is recreative activities, or missing	(13,068,663)

These restrictions produce the “all-employees sample” which we use to estimate the first probit specification of table 3. In the other probit specification, as well as the baseline bivariate probit specification, we further restrict the sample to employees hired during the current calendar year. This sample of “current-year hires” has 2,970,323 observations.

B.2 Definition of variables

The following table defines the variables we use in our analysis. When appropriate, we express in parenthesis each variable's defining criteria in terms of the variable names used by INSEE. Occupation category 5 and the smallest size category (1-19 employees) were the excluded dummy variables.

Age	Employee age in years;
Male	Employee gender (1 if male, 0 if female);
Occupation 1	1 if occupation is CS=1 (e.g., heads of firms, store-owners and artisans), 0 otherwise;
Occupation 2	1 if occupation is CS=2 (e.g., top-level managers and high-level professionals), 0 otherwise;
Occupation 3	1 if occupation is CS=3 (e.g., intermediate-level managers, technicians and foremen), 0 otherwise;
Occupation 4	1 if occupation is CS=4 (e.g., other employees, with the exception of factory and farm workers), 0 otherwise;
Occupation 5	1 if occupation is CS=5 (e.g., factory and farm workers), 0 otherwise;
Size, 1-19	1 if establishment size has 1 to 19 employees (TREFF=2), 0 otherwise;
Size, 20-49	1 if establishment size has 20 to 49 employees (TREFF=3), 0 otherwise;
Size, 50-99	1 if establishment size has 50 to 99 employees (TREFF=4), 0 otherwise;
Size, 100-199	1 if establishment size has 100 to 199 employees (TREFF=5), 0 otherwise;
Size, 200+	1 if establishment size is 200 employees or more (TREFF=6), 0 otherwise;
Private	1 if employer is in private sector (DOMEMPL=1 or 9), 0 otherwise;
Paris agglomeration	1 if region of employment is Paris and its area (REG=01), 0 otherwise;
Other urban	1 if department of employment had more than 1 million inhabitants in 2002 (DEP $\in \{06, 13, 31, 33, 38, 44, 57, 59, 68, 76\}$), 0 otherwise;
Manufacturing	1 if industry is manufacturing and mining (NES5=ET), 0 otherwise;
Services	1 if industry is services (NES5=EX), 0 otherwise;
Trade	1 if industry is distribution (NES5=EW), 0 otherwise;
Exit rate	Fraction of employees in each industry (NES36) whose employer reports size 0 (TREFF=00) on December 31, 2002;
Alive	1 if employer reports positive size on December 31 (TREFF>00), 0 otherwise;
Tenure	1 if employee is a returning employee (DEBREMU=1), 0 otherwise;
Separation	1 if job terminated before 12/31/02 (FINREMU<360) and if Alive=1, 0 if job did not terminate before 12/31/02 (FINREMU=360) and Alive=1, missing if Alive=0;

B.3 Construction of industry exit rates with OECD data

Our second proxy for exit rates by industry in France comes from the OECD's "Firm-level study."[24] The French section of the data is constructed using the Fiscal database ('BRN' file) and the Enterprise survey ('EAE' file). The unit of reference is the firm. For years 1990-96, the database covers all sectors and all firms whose sales exceed FF3.8mn in manufacturing and FF1.1mn in the service sector. Firms are generally classified by 2-digit ISIC category, although some categories are merged. Our DADS database classifies establishments using France's NES36 categories. To make the two classifications compatible, some NES36 categories must be merged. We then use the following mapping:

NES36 categories	2-digit ISIC categories
A0	01, 02, 03 , 04, 05
B0	15 ,16
C1, F2	17, 18 , 19
C2, F3	20, 22
C3, F4	24, 25
C4, E2, E3, F5, F6	28, 29, 33
D0	34
E1	35
F1, G1	10, 11, 12, 13, 14, 23, 26
G2	40, 41
H0	45
H1, J1, J2, J3	50, 51, 52
J0, K0	65, 67
L0	65, 66, 67
M0	70
N1	64
N4	73
P1	55
Q1	80
Q2	85
R1	75

In each industry, firms present at the beginning of a given year are split in two categories: continuing firms (firms also present in the register the following year) and exiting firms (other firms). Firms that enter the industry in a given year are classified as one-year firms (firms that exit the industry before the end of the year) or entrants. For $t \in \{1990, \dots 1996\}$, we define $empstock_t$ as the number of employees in continuing firms, exit firms and one year firms in year t, and $empexit_t$ as the number of employees in one-year firms and exiting firms. For each of the 21 categories shown in the table above, we calculate the average fraction of employees in exiting firms in year as :

$$\text{OECD exit rate} = \frac{1}{7} \sum_{t=1990}^{1996} \frac{empexit_t}{empstock_t}.$$

[24] A detailed description of the study is available on the OECD website at http://www.oecd.org/dataoecd/22/7/2767629.htm.

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Table 1: Sample Means for All Employees

	Obs.	Age	Tenure	Male	Occupation Category 1	2	3	4	Exit rate	Separation rate
All-employees sample	13,068,663	39.034	0.773	0.637	0.017	0.134	0.249	0.265	0.051	0.178
By industry										
Manufacturing	3,585,564	39.658	0.815	0.732	0.011	0.121	0.218	0.087	0.041	0.152
Services	6,197,297	39.161	0.778	0.533	0.012	0.169	0.284	0.378	0.045	0.175
Trade	2,239,950	37.699	0.714	0.631	0.035	0.100	0.261	0.338	0.084	0.218
Other	1,045,854	38.997	0.718	0.940	0.028	0.043	0.125	0.048	0.057	0.207
By geographical location										
Paris agglomeration	3,394,233	38.560	0.731	0.600	0.017	0.247	0.286	0.264	0.053	0.213
Other urban	2,953,830	39.150	0.780	0.664	0.016	0.113	0.254	0.264	0.051	0.168
Non-urban	6,720,600	39.22	0.790	0.644	0.017	0.086	0.229	0.266	0.051	0.165
By establishment size										
1-19 employees	4,297,673	38.137	0.677	0.666	0.043	0.089	0.215	0.277	0.069	0.281
20-49 employees	1,811,327	38.399	0.744	0.684	0.012	0.110	0.231	0.228	0.057	0.205
50-99 employees	1,204,828	38.745	0.773	0.657	0.005	0.133	0.240	0.225	0.053	0.174
100-199 employees	1,253,367	38.979	0.794	0.630	0.003	0.147	0.246	0.223	0.050	0.153
200+ employees	4,501,470	40.238	0.869	0.587	0.001	0.183	0.292	0.291	0.032	0.092
By sector										
Public	2,480,995	40.891	0.910	0.489	0.000	0.118	0.308	0.472	0.020	0.073
Private	10,587,668	38.598	0.740	0.672	0.021	0.138	0.235	0.217	0.059	0.204

Note. Tenure, male, and occupation categories are dummy variables.

Table 2: Sample Means for Current-Year Hires

	Obs.	Age	Male	Occupation Category 1	2	3	4	Exit rate	Separation rate
Current-year hires	2,970,323	36.220	0.639	0.011	0.137	0.215	0.278	0.062	0.404
By industry									
Manufacturing	661,566	36.910	0.681	0.006	0.135	0.183	0.097	0.043	0.379
Services	1,373,109	35.809	0.571	0.010	0.183	0.242	0.366	0.060	0.422
Trade	640,448	35.880	0.601	0.020	0.088	0.244	0.386	0.087	0.398
Other	295,202	37.326	0.947	0.012	0.031	0.097	0.042	0.057	0.393
By geographical location									
Paris agglomeration	910,769	36.079	0.622	0.011	0.248	0.256	0.275	0.062	0.379
Other urban	648,655	36.292	0.665	0.011	0.106	0.218	0.273	0.061	0.396
Non-urban	1,410,889	36.279	0.640	0.012	0.079	0.186	0.283	0.062	0.425
By establishment size									
1-19 employees	1,386,096	36.580	0.658	0.022	0.082	0.193	0.313	0.073	0.491
20-49 employees	463,936	36.124	0.671	0.005	0.111	0.217	0.247	0.061	0.407
50-99 employees	273,549	35.972	0.642	0.003	0.143	0.226	0.238	0.057	0.368
100-199 employees	258,209	35.848	0.618	0.002	0.166	0.228	0.234	0.055	0.350
200+ employees	588,535	35.728	0.580	0.001	0.269	0.252	0.257	0.042	0.271
By sector									
Public	222,120	35.839	0.458	0.000	0.206	0.275	0.457	0.022	0.318
Private	2,748,203	36.251	0.654	0.012	0.131	0.210	0.264	0.065	0.412

Note. Male and occupation categories are dummy variables.

Table 3: Estimated Coefficients in Probit Models of Worker Separations

	All employees	Current-year hires
Intercept	1.147	0.279
Age/100	-6.781	-2.112
$(\text{Age}/100)^2$	6.215	2.508
Male	0.004	-0.073
Occupation 1	-0.573	-0.834
Occupation 2	0.075	-0.376
Occupation 3	-0.053	-0.325
Occupation 4	-0.007	-0.016
Size, 20-49	-0.207	-0.192
Size, 50-99	-0.298	-0.286
Size, 100-199	-0.371	-0.330
Size, 200+	-0.546	-0.521
Private	0.184	-0.076
Paris agglomeration	0.156	-0.013
Other urban	0.015	-0.041
Manufacturing	0.093	0.211
Service	0.131	0.255
Trade	-0.007	0.026
Exit rate	2.005	3.022
Tenure dummy	-0.789	n.a.
No. observations	12,446,132	2,744,502

Notes. See the data appendix for a discussion of these variables. All coefficients are statistically significant at conventional levels as a result of the large sample size.

Table 4: The Effect of Exit Rates on Separation Rates

		Mean & standard deviation		Relative effects	
Model	Marginal effect	Predicted Separation rate	Exit rate	Number of std. dev.'s	%-change from mean
Probit					
1. All employees	0.447	0.184 (0.110)	0.051 (0.035)	0.14	8.5
2. Current-year hires	1.115	0.411 (0.119)	0.062 (0.036)	0.34	9.8
Bivariate probit					
3. All current-year hires	1.153	0.411 (0.119)	0.062 (0.036)	0.35	10.1
4. Exclusion restrictions	1.126	0.411 (0.119)	0.062 (0.036)	0.34	9.9
5. Alternative exit rates	3.354	0.458 (0.123)	0.054 (0.016)	0.43	11.7
6. Worker restrictions	0.520	0.159 (0.059)	0.058 (0.033)	0.29	10.8
7. Industry restrictions	1.575	0.454 (0.131)	0.067 (0.034)	0.41	11.8

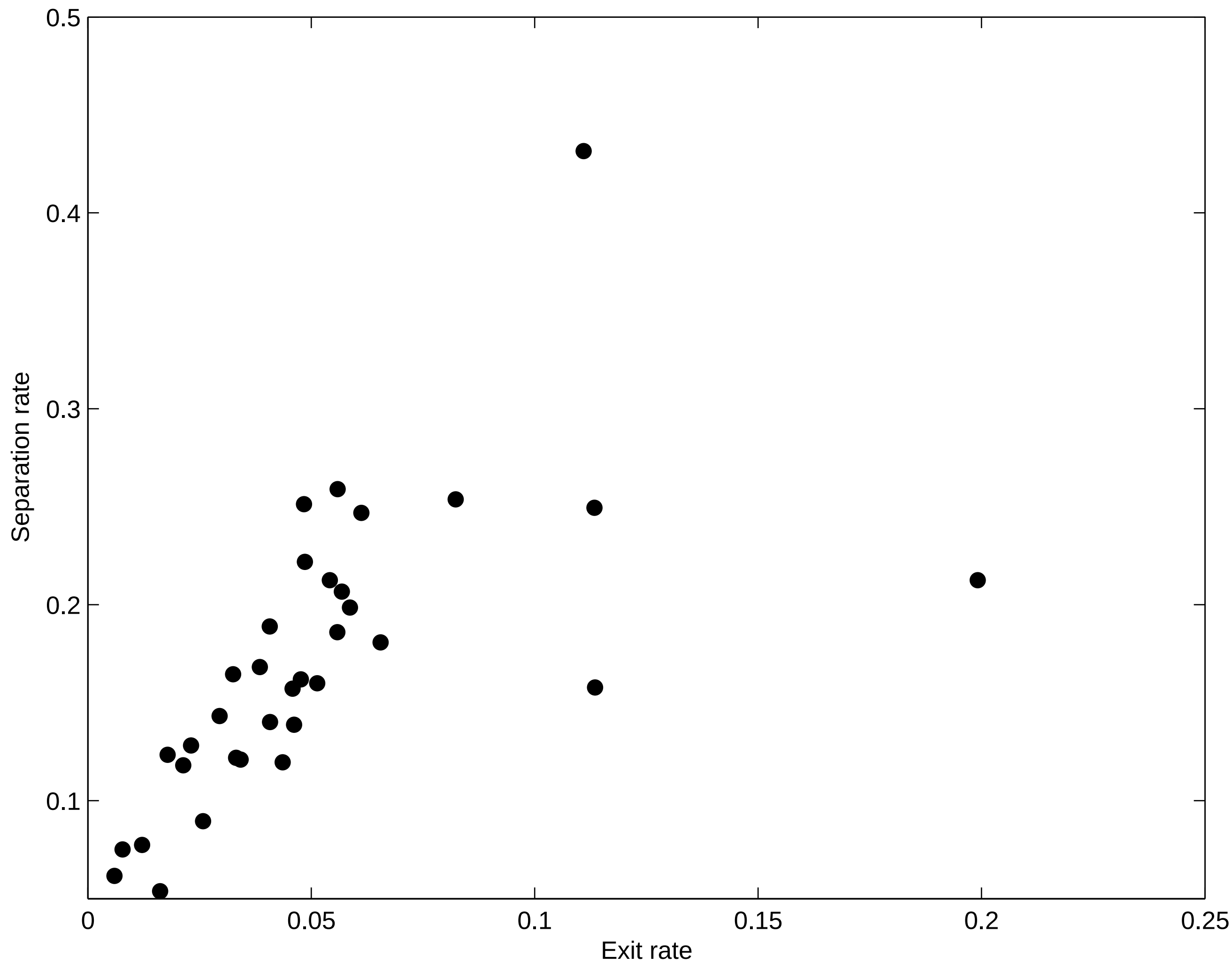
Notes. The marginal-effect column shows the marginal effect of exit rates on predicted separation rates. For the bivariate-probit models, this column shows the marginal effect of exit rates on predicted separation rates *conditional* on the establishment surviving. The first of the two relative-effects columns shows the number of standard deviations by which predicted separation rates increase for a 1 standard deviation increase in exit rates, and the second shows the percent change in predicted separation rates due to a 1 standard deviation increase in exit rates.

Table 5: Estimated Coefficients in Bivariate Probit Models of Worker Separations

	(1) Baseline Model	(2) Exclusion Restrictions	(3) Alternative Exit Rates	(4) Non-seasonal Workers	(5) Industry Restrictions
Separation equation					
Intercept	0.159	0.159	-0.337	-0.692	-0.492
Age/100	-1.642	-1.641	-2.181	-2.066	-1.246
$(\text{Age}/100)^2$	2.110	2.108	2.659	1.922	1.507
Male	-0.072	-0.072	-0.090	-0.074	-0.057
Occupation 1	-0.511	-0.511	-0.414	-0.336	-0.544
Occupation 2	-0.353	-0.353	-0.235	-0.232	-0.412
Occupation 3	-0.304	-0.304	-0.252	-0.179	-0.328
Occupation 4	-0.005	-0.005	0.059	-0.005	-0.024
Size, 20-49	-0.177	-0.177	-0.198	-0.152	-0.179
Size, 50-99	-0.264	-0.263	-0.282	-0.234	-0.271
Size, 100-199	-0.305	-0.304	-0.320	-0.222	-0.313
Size, 200+	-0.477	-0.477	-0.499	-0.319	-0.482
Private	-0.022	-0.022	-0.068	0.166	0.482
Paris agglomeration	-0.059	-0.059	-0.047	-0.040	-0.011
Other urban	-0.057	-0.057	0.189	-0.076	-0.051
Manufacturing	0.178	0.178	0.238	0.106	0.221
Service	0.241	0.241	0.464	0.246	0.196
Trade	0.039	0.039	0.315	0.017	0.020
Exit rate	4.010	4.014	9.038	2.669	5.134
Establishment survival equation					
Intercept	2.630	2.728	2.726	2.910	2.713
Age/100	-1.839	-1.827	-2.206	-2.549	-2.033
$(\text{Age}/100)^2$	1.343	1.333	1.764	2.444	1.770
Male	0.030	0.029	0.050	0.054	0.022
Occupation 1	-0.612	-0.617	-0.840	-0.380	-0.629
Occupation 2	0.016	0.014	0.006	0.148	0.020
Occupation 3	0.027	0.025	-0.065	0.071	0.014
Occupation 4	-0.043	-0.051	-0.222	-0.032	-0.056
Private	-0.410	-0.398	-0.727	-0.631	-0.462
Paris agglomeration	0.255	0.255	0.305	0.103	0.242
Other urban	0.097	0.098	0.116	0.091	0.091
Manufacturing	0.119	0.151	0.339	0.182	0.113
Service	-0.029	-0.017	0.064	-0.022	-0.015
Trade	-0.046	-0.029	n.a.	0.189	-0.037
Exit rate	-6.001	-6.388	-3.220	-4.311	-6.128
Correlation between errors					
$\rho_{\epsilon u}$	-0.805	-0.805	-0.725	-0.363	-0.763
No. observations	2,970,323	2,970,323	2,590,387	488,874	2,639,413

Notes. See the data appendix for a discussion of these variables. All coefficients are statistically significant at conventional levels as a result of the large sample size. The model in column 2 also included the share of surviving establishments in the four size categories 20-49, 50-99, 100-199, 200+; the coefficients were -0.300, 0.025, -0.559, and -0.037 respectively.

Figure 1: Industry exit rates and separation rates



Source: Déclaration Annuelle des Données Sociales, "Postes Exhaustif" version, and authors' calculations. Industries are defined using France's NES36 classification. Separation and exit rates are defined in appendix B.1. Importantly, separation rates exclude terminations due to establishments exiting the industry.