Working Paper No. 72

When a Door Closes, a Window Opens? Long-term Labor Market Effects of Involuntary Separations

Simone Balestra and Uschi Backes-Gellner

Universität Zürich
IBW – Institut für Betriebswirtschaftslehre

b
UNIVERSITÄT
BERN

Leading House Working Paper No. 72

When a Door Closes, a Window Opens? Long-term Labor Market Effects of Involuntary Separations

Simone Balestra and Uschi Backes-Gellner

November 2015 (first version: 2012)

A previous version of this Working Paper No. 72 was first published in 2012 under the title "When a Door Closes, a Window Opens? Investigating the Effects and Determinants of Involuntary Separations".

Published as: "When a Door Closes, a Window Opens? Long-Term Labor Market Effects of Involuntary Separations." German Economic Review, 18(2016)1: 1-21. By Uschi Backes-Gellner and Simone Balestra.
DOI: https://doi.org/10.1111/geer.12086

The Swiss Leading House on Economics of Education, Firm Behavior and Training Policies is a Research Programme of the Swiss Federal Office for Professional Education and Technology (OPET).

www.economics-of-education.ch

When a Door Closes, a Window Opens? Long-term Labor Market Effects of Involuntary Separations*

Simone Balestra[†] and Uschi Backes-Gellner[‡]

November 2015

Abstract

This study estimates the earning losses of workers experiencing an involuntary job separation. We employ, for the first time in the earning losses literature, a Poisson pseudo-maximum-likelihood estimator with fixed effects that has several advantages with respect to conventional fixed effects models. The Poisson estimator allows considering the full set of involuntary separations, including those with zero labor market earnings because of unemployment. By including individuals with zero earnings and by using our new method, the loss in the year of separation becomes larger than in previous studies. The loss starts with roughly 30 percent and, although it quickly shrinks, it remains at around 15 percent in the following years. In addition, we find that compared to other reasons for separation, the earning loss pattern is unique for involuntary separations, because no other type of separation implies such permanent scarring. This latter finding makes us confident that the self-reported involuntariness of a separation is a reliable source of information.

Keywords: wage trajectories, job loss, earning loss, PPML.

JEL Classification: C33, J31, J63.

* We thank the Swiss Federal Statistical Office for data provision and John Addison, Isabel Baumann, Eric Bettinger, Simon Janssen, Edward Lazear, and the participants at the 15$^{\text{th}}$ colloquium on personnel economics in Paderborn for helpful comments. This study is partly funded by the Swiss Federal Office for Professional Education and Technology through its Leading House on the Economics of Education, Firm Behavior and Training Policies. We are grateful to the Editor and two anonymous referees for their time and effort invested in this paper.

† Research associate at the Graduate School of Business at the University of Zurich, Switzerland. Corresponding author: simone.balestra@uzh.ch

‡ Full professor at the Faculty of Economics, Business Administration and Information Technology at the University of Zurich, Switzerland.

1 Introduction

In the last two decades, concerns about the plight of job loss have been a relevant issue for both researchers and policymakers (Couch and Placzek, 2010; Eriksson, 2006; Hijzen et al., 2010). Previous studies analyzing job losses, or "involuntary separations" as we call them, have shown that this type of job loss implies monetary costs in terms of immediate wage reductions (Curti, 1998; Monks and Pizer, 1998) and non-monetary costs in terms of re-employment conditions (Farber, 2010; Polsky, 1999). It remains unclear, however, whether and to what extent these wage reductions are lasting.

To fill this gap, the purpose of this paper is to shed light on the effects of involuntary separations on wages in the long term. To do this, we first estimate the earnings losses of those who find re-employment over several years after an involuntary job loss. Second, we are not only interested in measuring earnings losses of those that are re-employed, but we are also interested in the total foregone earnings or the total productivity loss of those that experience unemployment spells. Therefore, in a second step we also include unemployed workers with zero earnings in our analysis. To do so, we have to use a new empirical approach: a Poisson pseudo-maximum-likelihood estimator similar to the one applied to gravity models (Lameli et al., 2014). Including these "zeros" is important for at least two reasons. First, by considering the zeros, we are no longer only measuring firm-specific loss of human capital (Addison and Portugal, 1989; Carrington, 1993; Neal, 1995) but instead estimating the total foregone productivity caused by an involuntary separation.[1] The unanswered question here is whether these productivity losses are also long-lasting or whether they affect only the year of separation. Second, from the methodological side, it reduces the selection bias due to the exclusion of one portion of the population, as underlined by von Wachter et al. (2008).

In a third step we also investigate the determinants of an involuntary separation, asking whether quantity and type of education can act as a protection against job loss. Previous literature (Kettunen, 1997; Mincer, 1991) suggests that unemployment incidences are lower among highly educated workers. For example, Polsky (1999) shows that college education is negatively correlated with job separation. In this paper, we consider for the first time both educational level (i.e., years of schooling) and type of education (i.e., academic or vocational).

Our data source is the Swiss Labor Force Survey from 1996 to 2009, a rotating panel representative of the adult population permanently living in Switzerland. It is produced annually by the Swiss Federal Statistical Office, and the main advantage of this data source is that we can fully observe the reason of each job separation. Therefore, we can distinguish between workers who separated involuntarily from those who separated voluntarily or left for other reasons (e.g., injury, working conditions, or personal issues) and obtain valid estimates of the wage trajectories following an individual before, during, and after an involuntary job loss. Furthermore, we can compare the earnings patterns for different types of separation to test whether the consequences of self-reported reasons for separation are in line with

[1] For example, if we did not include these zeros, we would analyze the wage losses of those workers who directly find a job after separation, excluding all individuals experiencing an unemployment spell.

our theoretical expectations.

Our results show that wage losses following an involuntary separation are significant and long-lasting. We find that separated workers without unemployment spells suffer an immediate wage reduction of about 7 percent, which remains statistically significant for at least four years after separation. This is in line with results of previous studies. However, if we include unemployed individuals, i.e. with zero earnings to get an estimate for total productivity loss, we find losses of 30 percent in the year of separation and a long-term loss of about 15 percent four years after separation. These losses are much larger and can be seen as an indicator of the total productivity loss caused by an involuntary separation, as they comprise both zero labor market productivity during unemployment and the loss of firm-specific human capital that is reflected by the lower wages after re-employment (Addison and Portugal, 1989).

Compared to other reasons for separation, this earnings loss pattern is unique for involuntary separations, because no other type of separation is followed by such permanent scarring. Regarding the role of education, we find that tertiary education—in the form of academic or vocational tertiary education alike—plays a major role in reducing the risk of job loss.

2 Theory and Empirical Background

Economic theory suggests that worker mobility has important repercussions on wage trajectories (Topel, 1991). In general, the impact of labor mobility on wage trajectories can be either positive (wage gain) or negative (wage loss), depending on the individual human capital endowment (Fallick, 1996), the individual characteristics (Ruggles and Ruggles, 1977), and the type of separation (Lazear, 2009).

From a human capital perspective (Becker, 1962), wage losses occur if separated workers have not only general human capital but also firm-specific human capital. If an individual with a large portion of specific human capital loses the job, the consequences of the separation will be more severe than for an individual who has more general human capital. Because firm-specific skills do not increase the workers' productivity outside a particular firm, workers with a large stock of firm-specific human capital cannot transfer to a firm in which productivity—and thus wages—will be as high. If we take this theoretical argument literally, we should always expect a loss associated with a separation, independent of the type of separation. However, such is not always the case, as many job changes—especially voluntary ones—result in wage gains (Altonji and Williams, 1992; Antel, 1991).

Somewhat different patterns can be expected when referring to Lazear's skill-weights approach (Lazear, 2009) to explain differences in earnings losses across different types of separations. In Lazear's model, all skills are general but firms use them in different combinations with different weights attached to them. The advantage of his view of human capital is that it provides a more differentiated explanation of wage changes following a separation. According to Lazear's model, the expected wage change is likely to be negative whenever turnover is involuntary, because if workers choose not to move they have difficulties in finding a firm with exactly the same skill-weights profile on the external labor market. This implies a negative wage change in terms of expected wages (keeping market thickness constant). Conversely, we should expect a positive wage change for voluntary leavers (quitters), because the quitters would be those who only go if they find an outside offer with a favorable skill-weights profile.

A similar conclusion arises from mobility and search models, which predict different long-term wage trajectories for movers and for stayers. Mobility models also distinguish between voluntary and involuntary mobility, suggesting that layoffs are usually associated with earnings losses, whereas quits are associated with wage gains (Bingley and Westergaard-Nielsen, 2006). The explanation for these patterns is due to the presence of unemployment spells and worker human capital endowments (Mincer and Jovanovic, 1981). Taken together, these theoretical arguments suggest that we should indeed observe wage changes after a separation. However, in which direction such wage changes go—either positive or negative—depends on the type of separation. We should expect persistent earnings losses whenever the firm initiates the separation (layoffs), whereas we should expect a wage gain whenever the worker initiates the separation (quits).

From the empirical perspective, Monks and Pizer (1998) present early evidence on involuntary separations. They use data from the U.S. National Longitudinal Survey to estimate the increase in the probability of changing jobs from 1971 to 1990, and identify how much of this change was voluntary. Overall, they find a positive trend in the probability of job turnover of about 13 percent, mostly consisting of an increase in the probability of involuntary separation. Confirming Monks and Pizer's results, Polsky (1999) examines the consequences of job loss between 1976-81 and 1986-91. In general, he finds stability in the incidence of job separation but a significant increase in the incidence of involuntary job loss relative to voluntarily quitting. Polsky also shows that the consequences of involuntary separation worsen over time: The re-employment rate of workers who experienced involuntary job loss drops from 67 percent to 62 percent in 15 years. Moreover, among those who found new jobs, the odds of receiving a considerable wage cut rose from 9 percent to 17 percent during the same period. When these earnings losses start and whether they are long lasting remains unclear at this point.

Regarding the persistence of earnings losses after separation, Ruhm (1991) introduces the concept of long-lasting scars following job displacements. Using household data from the Michigan Panel Study of Income Dynamics, he shows that four years after displacement, displaced workers continue to earn 10-13 percent less than their non-displaced counterparts. The methodological standard for the earnings losses literature is Jacobson et al. (1993), who use administrative data[2] combining workers' earnings histories with information about their firms to estimate the magnitude and temporal pattern of displaced workers' earnings losses. They find that high-tenure workers separating from distressed

[2]Administrative records of the State of Pennsylvania, 1974-1986.

firms suffer an immediate loss of more than 40 percent and a long-term loss of about 25 percent per year.

Couch and Placzek (2010) argue that past estimates and the size of those reductions vary strongly with the type of data used and the state of the business cycle, demonstrating that under ordinary economic conditions, earnings losses are smaller than the estimations of Jacobson et al. White (2010) obtains similar results, finding the typical displaced worker realizing total long-term losses of USD 34,065, equivalent to an 11-percent loss compared to the earnings of similar non-displaced workers. However, the literature on earnings losses focuses primarily on displaced workers, who are high-tenured individuals who have been involuntarily separated due to plant closings or mass layoff.[3] This focus on displacements is meant to avoid selection problems: Displacements are considered exogenous and usually affect the entire workforce to the same extent. However, the selection problem then remains at the firm level, because establishments that have to close are likely to be in the low-performing tail of the distribution of plants and most likely also workers (Cornelissen and Hübler, 2011; Hijzen et al., 2010).

In contrast to the U.S. evidence, most European studies find displacement losses rather small and not always long-lasting (Couch, 2001; Eliason and Storrie, 2006; Hijzen et al., 2010). As European countries usually have stronger labor market regulations in which wages are bargained between employers and unions for each industrial sector, earnings losses studies for European workers generally find small losses, often significant only in the short term. Given these differences between regulated and non-regulated labor markets, it is particularly interesting to study the effects in Switzerland. This is because Swiss labor market regulations are more like in the U.S. than in many European countries, but many other economic conditions are very close to the European model (e.g., the educational system). This unique feature of Switzerland makes it interesting to study the determinants of involuntary separations, as we do in a second step during our empirical analysis. Given the literature and the Swiss institutional setting, we thus expect to find earnings losses following a separation. In terms of magnitude, Swiss estimates probably range between U.S. and European estimates, because, in spite of the Swiss low-regulated market, Switzerland also has low unemployment rates and an important social security system.

3 Data and Descriptive Statistics

We base the analysis on data from the Swiss Labor Force Survey (SLFS) between 1996 and 2009.[4] The Swiss Federal Statistical Office produces the SLFS annually and it is representative for the adult population permanently living in Switzerland. This includes Swiss citizens whose main residence is

[3]The U.S. Bureau of Labor Statistics definition of a displaced worker is [s]omeone at least 20 years old, with at least three years of tenure on a job, who lost that job due to slack work, abolition of a position or shift, or plant closing or relocation.

[4]For detailed information, methodological procedures, and data availability please visit: www.slfs.bfs.admin.ch.

Switzerland and foreigners who stay for at least 12 months in Switzerland, aged 15 and over. The main purpose of the SLFS is to provide information on the structure of the labor force and employment behavior patterns. It is strictly adherent to international definitions (e.g., of the International Labor Organization), particularly concerning the definition of employment, unemployment and the different working time concepts. This allows Swiss data to be compared with OECD, European, and U.S. data.

The SLFS is a rotating panel based on a sample of some 30,000 interviews per year in the considered period, in which four-fifths of the households from the previous year's survey are re-interviewed. This enables accurate monitoring of labor market trends and insightful analysis of individual employment histories over several years. Moreover, sampling errors in the measurement of changes can be minimized and the sample remains representative of the population living in Switzerland. The surveys take place annually in the second quarter and are carried out using Computer Aided Telephone Interviews (CATI). Although the SLFS has low attrition rates,[5] some individuals are lost as a result of change of residence, emigration, death, or refusal to further participate until the final survey. A logit model calculates the probability of such a failure due to the characteristics of the individuals (age, gender, previous investments, etc.). This model is then used to weight the data and to prevent nonrandom attrition.

With this data set we are able to distinguish the involuntary separations from all other types of separations, in addition to the classical demographic, educational, and occupational characteristics. From a question asking the reason for the last job loss, we can isolate those who separated involuntarily from those who separated for other reasons, such as quit, retirement, injury, working conditions, limited contract, or personal issues. Thus, we are able to achieve valid estimates of the earnings pattern by observing a worker before, during, and after an involuntary separation. Since one might be concerned that asking people about the reasons for their separation might not reveal the true reasons but rather socially desirable answers, we address the problem by analyzing earnings losses for each other type of separation (e.g., quit) to see whether the respective results are consistent with what one would expect from theory if the answers were correct. For example, we should observe that (on average) voluntary separations go together with wage gains and not wage losses.

To avoid special circumstances, such as those that might arise from retirement, our sample takes into account only individuals aged 18-65. We also restrict the sample to individuals who are either employed or unemployed, so as to avoid misspecification due to people who are in school, retired, or not active in the labor force. The earnings variables come from the Swiss Survey on Income and Living Conditions, a very precise data source for income resulting from labor activity. Thus, for those who are unemployed at the time of the interview, we have zero earnings in the data.

After creating the panel and removing missing values, we are left with a sample of 67,590 observations, divided among 13,518 individuals. Table 1 provides descriptive statistics. Over the period 1996-2009, the incidence of a job loss due to involuntary separation is 7.07 percent. Over the same

[5]The response rate is 65-72 percent for the initial interview and 83-89 percent for the following.

Table 1: Descriptive Statistics

	Mean (1)	Std. Dev. (2)	Min (3)	Max (4)
Involuntary separation	0.07	0.26	0.00	1.00
Annual income	66,478	39,326	0.00	571,654
Hourly wage	34.73	16.83	0.00	173.41
Weekly working hours	35.96	12.51	0.00	97.00
Male	0.56	0.50	0.00	1.00
Age	42.22	9.84	18.00	65.00
Full-time worker	0.68	0.47	0.00	1.00
Swiss	0.75	0.44	0.00	1.00
Tenure (in years)	9.86	8.88	0.00	48.41
Firm size ≥ 50	0.47	0.50	0.00	1.00
Years of schooling	13.39	2.44	9.00	18.00
Primary education	0.09	0.28	0.00	1.00
Secondary education	0.58	0.49	0.00	1.00
Tertiary education	0.33	0.47	0.00	1.00
Mandatory education	0.08	0.27	0.00	1.00
Vocational education	0.72	0.45	0.00	1.00
Academic education	0.20	0.40	0.00	1.00
Observations	67,590			

Notes: Swiss Labor Force Survey, Authors' calculations.

period, the average worker works 36 hours per week, earns 34.73 Swiss Francs[6] (CHF) per hour, and has a net annual income of CHF 66,478. Almost 70 percent of the sample has a full-time employment for the entire period of observation.

4 Methods

4.1 The Wage Equation

To quantify the earnings losses and their temporal pattern, we employ an approach similar to Jacobson et al. (1993) by defining a worker's earnings loss as the difference between his or her observed and expected earnings had the events that led to the job loss not occurred. Letting y_{it} denote the earnings[7] of worker i in period t and letting $S_{i,s} = 1$ if worker i experienced an involuntary separation at time s (and $S_{i,s} = 0$ otherwise[8]), the definition of the loss is hereafter illustrated:[9]

$$\mathrm{E}(y_{it} \mid S_{i,s} = 1, I_{i,s-v}) - \mathrm{E}(y_{it} \mid S_{i,s} = 0 \;\forall\; s, I_{i,s-v}) \tag{1}$$

[6] Wages are inflated to the year 2010. In 2010, 1 CHF = 1 USD. In Switzerland, inflation is very low and stable over time.

[7] We use the net annual income and the hourly wage as earning measures.

[8] "Otherwise" denotes individuals who did not experience an involuntary separation, but it does not necessarily exclude the possibility that they separated for other reasons. We also performed our investigation by comparing those who involuntarily separated with those who did not separate at all, with results similar to those we present in section 5. We stay with our approach because it better represents the typical working life of an employee.

[9] The index t refers to continuous time, whereas the index s refers to the time relative to the separation.

where $I_{i,s-v}$ is an information set at time $(s-v)$ containing individual-specific earnings determinants (either observable or unobservable), regardless of whether the individual experienced an involuntary separation. We also assume v to be sufficiently large that the events that led to separation have not yet begun. We focus on the first reported separation only, because any subsequent separation is likely to be endogenous (Stevens, 1997).

The earnings in a given period are assumed to depend on the event of an involuntary separation and on some controls for fixed- and time-varying characteristics. Thus we can rewrite the earnings equation as follows:[10]

$$\ln(y_{it}) = \alpha_i + \gamma_t + X'_{it}\beta + \sum_{k=-4}^{4} \delta_k \cdot S^k_{it} + \varepsilon_{it} \tag{2}$$

Note that equation (2) is not defined for observations with zero earnings. To overcome this issue, we take the exponential on both sides of equation (2) and obtain our model of interest:

$$y_{it} = \exp[\alpha_i + \gamma_t + X'_{it}\beta + \sum_{k=-4}^{4} \delta_k \cdot S^k_{it} + \varepsilon_{it}] \tag{3}$$

which can be defined for any zero or positive y_{it}. In equation (3), the individual fixed effect α_i captures the impact of time-invariant differences among individuals in observed and unobserved characteristics, and γ_t is a set of dummy variables for each year in the sample that gauges the general time pattern of earnings. The vector X_{it} consists of the observed, time-varying characteristics of the individual. As most available variables—such tenure or occupation—might be endogenous to the involuntary job loss and thus constitute a form of separation costs themselves, we restrict our controls to age (as proxy for labor market experience), age squared, and interactions among these controls and gender. We nevertheless provide regressions with additional controls (tenure, tenure squared, firms size, and occupation dummies), which are presented and discussed in section 5.

The set of dummy variables S^k_{it} represents the event of involuntary separation and δ_k measures the effect of such job loss in the years before, during, and after separation. Specifically, $S^k_{it} = 1$ if worker i experienced an involuntary separation k years prior to (k is then negative), during (k equals zero), or since (k is positive) year t; and $S^k_{it} = 0$ if individual i experienced no involuntary job loss during period t. Therefore, decomposing the sum $\sum \delta_k \cdot S^k_{it}$ yields a measure of the earnings loss during each year k.

4.2 Estimation Strategy

In the earning losses literature, the conventional empirical approach would be log-linearize equation (3) and estimate it by fixed-effects (Couch, 2001; Jacobson et al., 1993; Kletzer and Fairlie, 2003; Stevens, 1997; White, 2010; Zwick, 2012). OLS estimates with no individual fixed effects are probably

[10] Consistent with the literature, we assume that the conditional expectation function of the dependent variable is described by a constant-elasticity model of the form $y_i = \exp(x_i\beta)$ (Heckman and Polachek, 1974).

biased because of the endogeneity of different types of job losses and because of the unobservable worker characteristics that may cause them. Researchers' inability to distinguish between workers with high or low productivity, leads to a sample of involuntary separations that might not properly represent the overall working population. We use the panel structure of our data to mitigate this selection bias by filtering out the time-constant heterogeneity at the individual level with the within transformation.

Two general problems, still not properly covered in the existing literature, remain. The first problem concerns the practice of interpreting the parameters of log-linear models estimated by least squares as semi-elasticity. This practice can be misleading, especially in the presence of heteroskedasticity and measurement error. With heteroskedastic errors, the log-linear model does not consistently estimate the semi-elasticities.[11] Because of this issue, Santos Silva and Tenreyro (2006) argue that constant elasticity models should preferably not be linearized but rather estimated by Poisson pseudo maximum likelihood (PPML). Furthermore, due to Jensen's inequality, in log-linear models we cannot predict levels, because the expected value of the logarithm of a random variable is different from the logarithm of its expected value.

The second problem is related to the specification of the dependent variable, the natural logarithm of earnings. If an individual is unemployed at the time of the interview, his or her earnings resulting from labor market activity are zero. The logarithm of zero is undefined, and we are left with an unbalanced panel. Including the zeros has at least three advantages. First, it allows us to fully exploit the sample of individuals who experienced an involuntary separation. Second, it mitigates the selection problem because job separation affects the probability of working (von Wachter et al., 2008). Third, it introduces a new measure of losses, because we otherwise exclude all spells with zero earnings. If we include the zeros, we are not only measuring the earning loss after re-employment due to a loss of specific human capital but rather the total loss resulting from an involuntary separation. We call this new measure "productivity loss," because it reflects the value of the forgone productivity while the worker is not active in the labor market. The unanswered question is whether the productivity loss is also long-lasting or whether it affects only the year of separation.

To simultaneously overcome both these problems, we use a PPML estimator similar to the one introduced by Santos Silva and Tenreyro (2006) and further discussed in Santos Silva and Tenreyro (2011). The PPML estimator identifies the coefficients using the same first-order conditions that are used by the maximum-likelihood estimator derived from the Poisson distribution. However, the PPML estimator does not require the dependent variable to be Poisson distributed (Gourieroux et al., 1984). Following Cameron and Trivedi (2013), we can estimate the parameters of interest by solving the

[11] With heteroskedastic ε, $\mathrm{E}(\varepsilon|x) = f(x)$ and $\mathrm{E}(y|x) = \exp(x'\beta)f(x)$. In this case, $\partial \mathrm{E}(y|x)/\partial x \neq \beta$.

following set of first-order conditions:

$$\sum_{i=1}^{n}[y_i - \exp(x_i\beta)] \cdot x_i = 0 \tag{4}$$

The PPML approach can be seen as a nonlinear-least-square specification of an equation with uniform weights given to observations.[12] Without further information—or assumptions—on the pattern of heteroskedasticity, giving the same weight to all observations is the more natural way of proceeding.[13] In terms of estimated parameters, PPML has two main differences with respect to OLS. First, as already underlined, the coefficients of PPML do not suffer from bias that arises from estimating semi-elasticities with a log-linear model. Second, PPML allows for predictions of wage levels and not only in terms of log-wages as in the case of OLS.

Another important feature of the PPML estimator is that it does not require the dependent variable to be an integer, and it is also consistent in the presence of over-dispersion (Fally, 2015).[14] Santos Silva and Tenreyro (2006) and Santos Silva and Tenreyro (2011) provide additional evidence on the good performance of PPML by presenting a simulation study using different heteroskedasticity patterns, and showing that the PPML estimator is the least biased of various OLS functional forms, non-linear least squares, Tobit models, gamma pseudo-maximum-likelihood methods, and in the presence of a large fraction of zeros in the dependent variable.

Finally, the PPML approach can be applied to panel data, with the use of PPML with fixed effects (Fally, 2015; Wooldridge, 1999). This PPML panel estimator is consistent to serial correlation but requires the appropriate robust standard errors suggested by Wooldridge (1999) for valid inference.[15] Considering all these advantages, we decided to use the PPML approach, which has never been applied to research on separations and earning losses.

5 Empirical Findings

5.1 Effect of Involuntary Separation on Annual Income and Hourly Wage

Table 2 provides estimates of equation (3) using fixed-effects PPML (columns 1 and 2) and conventional fixed-effects methods (columns 3 and 4). The number of observations in Table 2 is lower than the one reported in the descriptive statistics because we exclude—for now—observations with zero earnings. We do so because we want to compare the marginal effects obtained with PPML to those obtained using conventional fixed-effects. In Table 2 we restrict our controls to age, age squared, and interactions

[12] A necessary condition for the PPML estimator to be consistent is that the conditional mean is correctly specified. We can test this assumption with a RESET test. The result of such test performed on our sample has a p-value of 0.869, which means that we cannot reject the null hypothesis that the functional form of the conditional expectation function is correctly specified.

[13] We reject the null hypothesis of the Breusch-Pagan test at all conventional levels of significance (p-value < 0.000).

[14] Over-dispersion means that the variance exceeds the mean, a common data property in applied research (Cameron and Trivedi, 2013).

[15] To do so, we use the Stata command `xtpqml`, publicly available at http://people.bu.edu/tsimcoe/data.html.

Table 2: Earning Effects of Involuntary Separations, ppml and fe models

Variables	PPML with fixed effects Annual income dY/dX (1)	PPML with fixed effects Hourly wage dY/dX (2)	Fixed effects estimation ln(annual income) dY/dX (3)	Fixed effects estimation ln(hourly wage) dY/dX (4)
3 years before separation	0.005	-0.017	-0.011	-0.019
	(0.013)	(0.034)	(0.028)	(0.024)
2 years before separation	-0.012	-0.024	-0.027	-0.023
	(0.012)	(0.033)	(0.026)	(0.022)
1 year before separation	-0.024*	-0.037	-0.052*	-0.035*
	(0.013)	(0.032)	(0.027)	(0.021)
Year of separation	-0.066***	-0.068*	-0.104***	-0.071***
	(0.017)	(0.035)	(0.032)	(0.024)
1 year after separation	-0.076***	-0.073**	-0.120***	-0.084***
	(0.018)	(0.037)	(0.033)	(0.026)
2 years after separation	-0.080***	-0.101***	-0.132***	-0.098***
	(0.018)	(0.039)	(0.034)	(0.026)
3 years after separation	-0.062***	-0.095**	-0.114***	-0.101***
	(0.020)	(0.041)	(0.036)	(0.029)
4 years after separation	-0.074***	-0.091**	-0.113***	-0.093***
	(0.021)	(0.043)	(0.039)	(0.030)
Individual fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
(Pseudo) R^2	0.218	0.059	0.227	0.064
N	66,255	66,255	66,255	66,255

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered at the individual level are in parenthesis. All models include a constant and the following controls: age, age squared, and interactions between gender and age variables. The pseudo R^2 is computed as the square of the correlation between the dependent variable and its fitted values.
Swiss Labor Force Survey, Authors' calculations.

among these controls and gender. Although we recognize that tenure and occupation are important earnings determinants, we also recognize that those variables are likely to be endogenous, thus biasing the estimated effects. Therefore, we base our main analysis on regressions including a simple set of predetermined controls, and provide separately in appendix Table A.1 results with additional controls (tenure, tenure squared, firm size, and occupation dummies).[16]

In terms of annual income (table 2, column 1), the marginal effects of the post-separation dummies are negative and significant at the 1 percent level, from the year of involuntary job loss up to four years thereafter. Individuals who experience an involuntary separation have—on average—an immediate loss in annual income of 6.6 percent and a long-term loss of 6.2 percent three years after separation and 7.4 percent four years after separation. Conventional fixed-effects estimation provides larger marginal effects, ranging from an immediate 10-percent loss to a long-term loss of 11 percent. However, these latter estimates are biased due to Jensen's inequality and the presence of heteroskedasticity. The difference in effect size between PPML and conventional fixed effects is rather large, casting some doubts on the effects documented by the literature so far.

As we already discussed, one of the advantages of using PPML is that we can provide predictions

[16] Adding additional controls produces results similar to the ones presented in the main analysis.

in earning levels instead of log-earnings, which are difficult to interpret and rather uninformative. Furthermore, we are not only interested in the statistical significance of our results but also—as suggested by Krämer (2012)—care about their importance in the labor market context we analyze. To give economic significance to our results, we estimate the total losses in actual earnings and compare it to the average annual earnings. In terms of Swiss Francs, the typical involuntarily separated worker loses on average about CHF 4,400 in the year of separation and roughly CHF 5,000 four years after separation, compared with their expected income had the separation never happened. Altogether, the average post-separation loss within the first four years amounts to CHF 23,790, which represents 36 percent of a year's wage (on average).

Columns 2 and 4 of Table 2 present estimates with hourly wage and the log of hourly wage as the dependent variable. We do this additional analysis for two reasons: First, the hourly wage takes into account the potential reduction in working hours in the new job; and, second, the hourly wage filters out company bonuses and other potential biases not related to productivity. The post-separation marginal effects are all negative and significant, with an immediate wage loss of 6.8 percent and a wage loss of 9.1 percent four years later. Hourly wage losses are slightly larger than annual income losses, suggesting that re-employed workers suffer from not only a wage cut but also a reduction in working hours. In terms of Swiss Francs, the typical involuntarily separated worker loses on average CHF 3 per hour worked in the years following a separation, compared with their expected income had the separation never happened. Altogether, the average post-separation loss within the first four years amounts to CHF 15 per hour worked, which corresponds to 43 percent of the mean hourly wage. Looking at the marginal effects estimated by fixed effects reveals that, once again, conventional fixed effects overestimate the real effect of a separation.

These first estimates constitute an important result, because they give clear evidence of the consequences of an involuntary separation, an event that jeopardizes an individual's earnings not only at the moment of separation but also in the long run. This supports the theoretical argument that involuntary separations involve a permanent loss of parts of human capital. Looking at the time pattern of earning losses, we note that there is no sign of a complete recovery in the first four years after an involuntary separation. This is somewhat different from what the literature usually finds (Couch and Placzek, 2010), but we consider a time interval that might be too short to observe a wage recovery;[17] studies with similar time intervals also estimate no post-separation recovery (Kletzer and Fairlie, 2003; Ruhm, 1991).

Table 3 reports regression outputs if we include individuals with zero earnings from labor market activities. As we discussed previously, the PPML approach allows us to include such individuals in the analysis, and thus estimate the total productivity loss caused by an involuntary separation. As for Table 2, the first two columns of Table 3 present results with the annual income as dependent variable,

[17] In the displacement literature, this time interval ranges between two years after separation (Couch and Placzek, 2010) and twenty years after separation (von Wachter et al., 2008).

Table 3: Earning Effects of Involuntary Separations, including zeros

	PPML with Fixed Effects			
Variables	Annual income	Annual income	Hourly wage	Hourly wage
	dY/dX	dY/dX	dY/dX	dY/dX
	(1)	(2)	(3)	(4)
3 years before separation	0.003	0.005	-0.015	-0.013
	(0.016)	(0.017)	(0.031)	(0.027)
2 years before separation	-0.011	-0.009	-0.022	-0.020
	(0.015)	(0.015)	(0.030)	(0.027)
1 year before separation	-0.044**	-0.041**	-0.060*	-0.054*
	(0.018)	(0.018)	(0.032)	(0.028)
Year of separation	-0.338***	-0.355***	-0.418***	-0.393***
	(0.044)	(0.051)	(0.076)	(0.069)
1 year after separation	-0.149***	-0.164***	-0.165***	-0.169***
	(0.027)	(0.030)	(0.043)	(0.041)
2 years after separation	-0.130***	-0.143***	-0.161***	-0.163***
	(0.026)	(0.029)	(0.043)	(0.040)
3 years after separation	-0.116***	-0.128***	-0.158***	-0.159***
	(0.028)	(0.030)	(0.045)	(0.042)
4 years after separation	-0.134***	-0.144***	-0.163***	-0.161***
	(0.031)	(0.034)	(0.049)	(0.045)
Individual fixed effects	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
Further controls	NO	YES	NO	YES
R^2	0.220	0.229	0.082	0.080
N	67,590	67,590	67,590	67,590

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered at the individual level are in parenthesis. All models include a constant and the following controls: age, age squared, and interactions between gender and age variables. The pseudo R^2 is computed as the square of the correlation between the dependent variable and its fitted values. The full set of controls also entails tenure, tenure squared, an indicator whether the firm has more than 50 employees, and occupation dummies.
Swiss Labor Force Survey, Authors' calculations.

whereas columns 3 and 4 present results with the hourly wage as dependent variable. In columns 2 and 4 we additionally control for tenure, occupation, and firm size. However, adding further controls does not change the estimated marginal effects dramatically.

A look at the set of dummies representing the post-separation loss reveals that the coefficients are all negative and significant at the one percent level. In terms of annual income, involuntarily separated workers suffer from an immediate loss of 33.8 percent in the year of separation and a long-term loss of 11.6 percent and 13.4 percent in the third and fourth year after separation, respectively. As before, in terms of hourly wage the estimated losses are slightly larger. We find an immediate loss of 41.8 percent (per hour) and a long-term loss around 16 percent (per hour) for the third and fourth year after separation.

Including the zeros in the analysis has a large impact on the immediate loss. This large immediate loss shrinks quickly and stabilizes in the years following a separation. However, the estimated effects including the zeros never converge to the effects obtained without the zeros, suggesting that both the earning loss and the foregone productivity persist in the long run.

As commonly found in the earning losses literature, involuntarily separated workers already experience a small earning loss one year before separation. According to our estimates, this loss is on the order of 3-5 percent in we exclude the zeros (table 2) and 4-6 percent if we include the zeros (table 3). The presence of a pre-separation loss is usually attributed to wage renegotiation aimed at avoiding separation or to negative time-varying unobservables for those who lose their jobs later (Zwick, 2012). This latter case is a potential threat to internal validity, because it would suggest that involuntary job losses are not conditionally exogenous. However, because the pre-separation loss is small and similar throughout all regressions, it indicates either that the impact of negative time-varying unobservables is negligible or that these negative time-varying unobservables affect all separated individuals to the same extent (which is rather unlikely). We further discuss this issue in the concluding section.

5.2 Robustness Checks

To check the robustness of our estimates and test the sensitivity of our results, we perform two analyses. First, we repeat the regressions of section 5.1 for sub-samples of the data, to verify that the estimated effects are not arising from specific groups of the population. Given that the results of this first robustness check are very similar to the ones presented in the main analysis, they are available in the web appendix. Second, we implement the same econometric specifications to other reasons for separation, to verify the plausibility of the self-reported separation measure.

We might be concerned that elements like type of employment (full-time or part-time), age, or gender drive the effects we estimate in the main analysis. Therefore, to test the sensitivity of our results, Table A.2 in the web appendix presents sub-sample analyses according to type of employment, age intervals, and gender. In columns 1 and 2, we study the earning losses of workers that lose a full-time job and are re-employed in another full-time job. We do so because this type of workers are likely to be high productive, and if our identification strategy based upon fixed-effects is invalid, we should observe different results for the sub-sample of full-time workers.[18] The regression outputs in columns 1 and 2 show earning losses (either including zeros or not) that are in line with the main analysis, indicating that our fixed-effects are controlling effectively for time-constant individual heterogeneity.

The next robustness check pertains the potential impact of early retirement and education on re-employment probability. We thus exclude individuals that are younger than 30 years and older than 55, to make sure that the sample is not influenced by individuals in education or retiring earlier. Columns 3 and 4 of Table A.2 present regression outputs for the age-restricted sample, showing marginal effects that are in line with the ones depicted in Table 3. This suggests that neither early retirement nor education are driving the results.

Finally, as common in the literature, we run a separate regression for men to make sure that gender is not determining the significance and magnitude of the earning losses. Columns 5 and 6 of Table A.2 in the web appendix present the results and show the same loss pattern and significance as in the main analysis. In terms of magnitude, however, it appears that men suffer from slightly smaller

[18] Böheim and Weber (2010) use a similar strategy to identify the signaling effect of marginal employment in Germany.

Table 4: Wage Effects for Different Types of Job Loss, ppml estimation

	Working conditions		Personal/family reasons		Voluntary separation	
	Excluding zeros	Including zeros	Excluding zeros	Including zeros	Excluding zeros	Including zeros
	dY/dX	dY/dX	dY/dX	dY/dX	dY/dX	dY/dX
	(1)	(2)	(3)	(4)	(5)	(6)
3 years before separation	-0.008	-0.004	-0.007	-0.005	0.016	0.012
	(0.013)	(0.014)	(0.015)	(0.017)	(0.013)	(0.012)
2 years before separation	-0.011	-0.007	-0.021	-0.021	-0.007	-0.016
	(0.013)	(0.014)	(0.016)	(0.018)	(0.013)	(0.013)
1 year before separation	-0.029**	-0.034**	-0.022	-0.029	0.007	-0.003
	(0.014)	(0.014)	(0.015)	(0.018)	(0.014)	(0.014)
Year of separation	-0.017	-0.037**	-0.035**	-0.094***	0.033**	0.019
	(0.014)	(0.015)	(0.016)	(0.022)	(0.015)	(0.014)
1 year after separation	-0.018	-0.009	-0.028*	-0.038**	0.045***	0.033**
	(0.014)	(0.015)	(0.016)	(0.019)	(0.016)	(0.015)
2 years after separation	-0.017	-0.016	-0.003	-0.008	0.047***	0.036**
	(0.015)	(0.016)	(0.017)	(0.020)	(0.017)	(0.016)
3 years after separation	-0.018	-0.016	-0.018	-0.018	0.058***	0.042**
	(0.016)	(0.017)	(0.019)	(0.021)	(0.018)	(0.017)
4 years after separation	-0.009	-0.013	-0.019	-0.015	0.061***	0.036*
	(0.018)	(0.019)	(0.019)	(0.022)	(0.020)	(0.019)
Individual fixed effects	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
(Pseudo) R^2	0.216	0.209	0.216	0.210	0.218	0.210
N	66,255	67,590	66,255	67,590	66,255	67,590

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Robust standard errors clustered at the individual level are in parenthesis. The dependent variable is the annual income. All models include a constant and the following controls: age, age squared, and interactions between gender and age variables. The pseudo R^2 is computed as the square of the correlation between the dependent variable and its fitted values.
Swiss Labor Force Survey, Authors' calculations.

losses compared to the full sample, especially when we include the zeros in the analysis (column 6). This indicates that there are less zeros among men, which might suggest that men tend to stay out of the labor market for a shorter time than women. This is in line with previous research on the topic on gender differences in employment (Maxwell and D'Amico, 1986; White, 2010).

To find out whether involuntary job losses are the only type of separation that implies a significant loss, we implement the same econometric specifications to other reasons for separation. Doing so constitutes an important falsification test for the reliability of our method of identifying an involuntary separation, because we expect distinct differences in earning losses between involuntary separations and other reasons. The rationale is that involuntary job losses should be the only reason for a persistent earning loss because the other separation motives do not imply a depreciation of human capital, as suggested by Lazear (2009). To verify this hypothesis, we consider three additional motivations: separation due to (bad) working conditions, separation due to personal or family reasons, and voluntary leave.

Table 4 presents regression results of equation (3) divided by reason for separation, estimated by fixed-effects PPML with and without the zeros. For the ease of comparison, we present results only for annual income losses, but appendix Table A.3 depicts the results for hourly wage and shows similar patterns. The first important result throughout Table 4 is that no separation reason other than involuntary job loss implies a permanent wage loss. In detail, we find that separations due to (bad) working conditions and personal reasons imply small losses (if any), all concentrated around the year of separation. In terms of magnitude, the marginal effects range between 2 and 4 percent and there is almost no difference whether we either exclude or include the zeros (except for the effect in the year of separation due to personal reasons).

For workers who voluntarily quit their jobs we observe a statistically significant increase in wage in the years following the separation (columns 5 and 6 of table 4). This post-separation increase is permanent and ranging between 3 to 6 percent depending on the year and whether we include the zeros in the analysis. This is as expected by Lazear's skill-weights approach. According to Lazear, while the expected wage loss is necessarily positive if turnover is involuntary, we should expect a wage gain for voluntary leavers, because the quitters would be those who find an outside offer from a firm with a better skill-weight profile. Therefore, we are confident that our way of identifying the type of separation produces valid results, because it is in line with theory and because results are not sensitive to alternative specifications.

5.3 The Determinants of Involuntary Separations

In the presence of such relevant losses following an involuntary separation, one corollary question arises: What determines an involuntary separation? Specifically, we want to investigate whether education level and education type are associated with a lower probability of involuntary separation. On the relation between education and involuntary separation, it has been previously shown that education has labor market returns such as reduced unemployment risk (Mincer, 1991), shorter unemployment spells (Kettunen, 1997), and smaller earning losses following a displacement (Eliason and Storrie, 2006; White, 2010). More generally, Farber (2010) finds that while the job loss rate of more educated workers increased during the period 1984–2002, less educated ones continue to have the highest rates of job loss overall. We complement these results by analyzing whether this is also valid for involuntary separations and whether the relation holds for all educational types.

To fill this gap we estimate a Probit model in which the dependent variable equals one if an individual suffered from involuntary separation during the period 1996–2009 and zero otherwise.[19] According to the official definitions of the Swiss State Secretariat for Education and Research, we code education in three ways according to the highest degree obtained: years of schooling, education level (primary, secondary, and tertiary), and type of education[20] (compulsory, vocational, and academic). Beyond the educational variables, we include demographic characteristics, region fixed effects, time fixed effects, and industry fixed effects according to the General Classification of Economic Activities (NOGA).

Table 5 presents the results. Focusing on the explanatory variables related to education, we estimate an average marginal effect of –0.4 percentage points for a one-unit increase in years of schooling (column 1). In terms of predicted probabilities, the overall likelihood of experiencing an involuntary separation is 7.07 percent. An individual with 9 years of schooling (only compulsory education) has a predicted probability of experiencing an involuntary job loss of 11.0 percent, which is significantly higher than the sample average. An individual with 13 years of schooling (high school degree or vocational maturity) has a 6.2-percent predicted probability of being dismissed, which is below the sample average and almost half the probability of those holding only a compulsory education as their highest degree. For individuals who completed a university degree or a higher vocational degree (18 years of schooling), the predicted probability of experiencing an involuntary job loss is only 5.9 percent. Thus, the more years of education, the better a worker is protected against involuntary job losses. However, whether it is academic or vocational does not make a difference.

We obtain similar results and predicted probabilities in column 2, where we split education into primary (base category), secondary, and tertiary levels. According to our estimates, having a tertiary degree—be it an academic or a vocational tertiary degree—is the best protection against involuntary job loss, reducing the overall probability of separation by one third. Column 3 focuses on the type of education, and shows that the worst off are those individuals with only a compulsory education degree.

[19] Here we do not claim the estimated effects to be causal, because we suspect the education variables to be endogenous in the job loss equation. We mitigate this problem by including as many control variables as possible.

[20] Due to data limitations, we have to ignore individuals with mixed educational paths, i.e., individuals with both academic and vocational degrees. According to Tuor and Backes-Gellner (2010), the proportion of individuals with a mixed path in Switzerland are roughly 10 percent of the working population.

Table 5: DETERMINANTS OF INVOLUNTARY SEPARATION, PROBIT MODELS

Variables	Involuntary separation dY/dX (1)	Involuntary separation dY/dX (2)	Involuntary separation dY/dX (3)
Age	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
Age squared/100	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)
Tenure (in years)	-0.018***	-0.018***	-0.018***
	(0.001)	(0.001)	(0.001)
Tenure squared/100	0.036***	0.036***	0.036**
	(0.002)	(0.002)	(0.002)
Firm size $\geq$ 50	-0.007**	-0.007**	-0.007**
	(0.003)	(0.003)	(0.003)
Swiss	-0.022***	-0.022***	-0.024***
	(0.005)	(0.005)	(0.005)
Male	0.007	0.005	0.003
	(0.005)	(0.005)	(0.004)
Years of schooling	-0.004***		
	(0.001)		
Level of education			
Secondary education		-0.008	
		(0.007)	
Tertiary education		-0.025***	
		(0.008)	
Type of education			
Vocational education			-0.007
			(0.008)
Academic education			-0.026***
			(0.009)
Industry fixed effects	YES	YES	YES
Time fixed effects	YES	YES	YES
Region fixed effects	YES	YES	YES
(Pseudo) R^2	0.170	0.170	0.170
N	67,590	67,590	67,590

Notes: ** $p < 0.01$, * $p < 0.05$, *$p < 0.10$. Robust standard errors clustered at the individual level are in parentheses. All models include a constant.
Swiss Labor Force Survey, Authors' calculations.

6 Conclusions

Using Swiss Labor Force Survey data from 1996 to 2009, we estimate the earning and productivity losses of workers experiencing an involuntary job loss. We introduce a new estimation strategy, the fixed-effects PPML estimator, which has several advantages compared to conventional fixed-effects models. Using PPML and including individuals with zero earnings, we find losses of around 30 percent in the year of separation, which then quickly shrink but still remains at roughly 15 percent in the following years. Our estimates are larger than previous estimates because we are able to include individuals with zero earnings, thus taking into consideration that their labor productivity is fully lost during that time.

We also find that while involuntary separations cause permanent scars, the other types of separation, as expected, cause either light blemishes or even wage gains, as in the case of voluntary separations. In a second step, we analyzed whether education level or type is related with a lower probability of involuntary separation. We complement the existing literature and find that tertiary education—in the form of academic or vocational tertiary education alike—plays a major role in reducing the risk of job loss.

We are the first study to use fixed-effects PPML to estimate the earning losses after a job separation, and we contribute to the methodological literature by adding a new (and better) approach to analyze separation-related losses. The fixed-effects PPML has at least three advantages: First of all, by using the PPML approach we can identify the total productivity loss following an involuntary separation, and not only the post-separation earning loss of workers after they found a new job. This means that we are also able to account for the time to find a new job and the earnings that are forgone during that period, with relatively soft assumptions and without manipulating the dependent variable. Second, the PPML is more appropriate when the conditional expectation function is described by a constant-elasticity model, and it performs very well when the dependent variable is non-negative. Third, the PPML estimator is consistent to arbitrary heteroskedasticity patterns, allowing the researcher to obtain an unbiased estimate of the effect of interest.

Our study could be extended in a number of ways. For example, the event of an involuntary job loss might not be completely (conditionally) exogenous, which could bias our estimated effects. One would be particularly worried about time-varying unobservable characteristics that affect a worker's performance and thus impact the likelihood of getting dismissed. Unfortunately, it is difficult to find appropriate exclusion restrictions in the job loss literature, and unless relying on strong assumptions and using the matrix of (internal) instruments suggested by Hausman and Taylor (1981), we cannot apply instrumental variable approaches to estimate causal effects. Using matching estimators is also not very helpful in our case, because we would match individuals according to observable characteristics, while our true interest would be in individuals' unobserved traits or at least valid proxies for such traits. We thus prefer to mitigate the potential endogeneity by filtering out the time-invariant heterogeneity among individuals and assuming the impact of bad time-varying unobservables to be negligible. To further strengthen this claim, we could allow for arbitrary heterogeneity between separated and non-separated workers in both levels and trends of their unobserved characteristics by adding a set of worker-specific time trends to our main equations. This technique, already suggested by Jacobson et al. (1993), does not change the results and our current model fits the data much better.[21]

To conclude, in this paper we were interested in the window of risks and opportunities that individuals face after an involuntary separation. Our estimates suggest that a window of opportunity does indeed open following a job separation, because most of the individuals find a job after a separation. However, it is not another door that opens but rather a small window, because after the door closes individuals are faced with earning losses that last at least for another four years. This result highlights the importance of reducing the likelihood of an involuntary job loss before it happens, given the near impossibility of avoiding persistent losses once the involuntary separation occurs. A better education, be it in the form of academic or vocational alike, helps to prevent such involuntary job losses.

[21] Regression output available upon request.

References

Addison, J. T. and Portugal, P. (1989). Job displacement, relative wage changes, and duration of unemployment. *Journal of Labor Economics*, 7(3):281–302.

Altonji, J. G. and Williams, N. (1992). The effects of labor market experience, job seniority, and job mobility on wage growth. NBER Working Papers 4133, National Bureau of Economic Research, Inc.

Antel, J. J. (1991). The wage effects of voluntary labor mobility with and without intervening unemployment. *Industrial and Labor Relations Review*, 44(2):299–306.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy*, 70(1):9–49.

Bingley, P. and Westergaard-Nielsen, N. (2006). Job changes and wage growth over the careers of private sector workers in denmark. *Contributions to Economic Analysis*, 275:309–329.

Böheim, R. and Weber, A. (2010). The effects of marginal employment on subsequent labour market outcomes. *German Economic Review*, 12(2):165–181.

Cameron, A. C. and Trivedi, P. K. (2013). *Regression Analysis of Count Data*. Cambridge University Press.

Carrington, W. J. (1993). Wage losses for displaced workers: Is it really the firm that matters? *Journal of Human Resources*, 28(3):435–462.

Cornelissen, T. and Hübler, O. (2011). Unobserved individual and firm heterogeneity in wage and job-duration functions: Evidence from German linked employer-employee data. *German Economic Review*, 12(4):469–489.

Couch, K. A. (2001). Earnings losses and unemployment of displaced workers in Germany. *Industrial and Labor Relations Review*, 54(3):559–572.

Couch, K. A. and Placzek, D. W. (2010). Earnings losses of displaced workers revisited. *American Economic Review*, 100(1):572–89.

Curti, M. (1998). Does economic stagnation affect unemployed workers, even when re-employed? *International Journal of Manpower*, 19(6):410–423.

Eliason, M. and Storrie, D. (2006). Lasting or latent scars? swedish evidence on the long-term effects of job displacement. *Journal of Labor Economics*, 24(4):831–856.

Eriksson, S. (2006). Skill loss, ranking of job applicants and the dynamics of unemployment. *German Economic Review*, 7(3):265–296.

Fallick, B. C. (1996). A review of the recent empirical literature on displaced workers. *Industrial and Labor Relations Review*, 50(1):5–16.

Fally, T. (2015). Structural gravity and fixed effects. *Journal of International Economics*, forthcoming.

Farber, H. S. (2010). Job loss and the decline in job security in the United States. In *Labor in the New Economy*, NBER Chapters, pages 223–262. National Bureau of Economic Research.

Gourieroux, C., Monfort, A., and Trognon, A. (1984). Pseudo maximum likelihood methods: Applications to Poisson models. *Econometrica*, 52(3):701–20.

Hausman, J. A. and Taylor, W. E. (1981). Panel data and unobservable individual effects. *Journal of Econometrics*, 16(1):155–155.

Heckman, J. and Polachek, S. (1974). Empirical evidence on the functional form of the earnings-schooling relationship. *Journal of the American Statistical Association*, 69(346):350–354.

Hijzen, A., Upward, R., and Wright, P. W. (2010). The income losses of displaced workers. *Journal of Human Resources*, 45(1):243–269.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, 83(4):685–709.

Kettunen, J. (1997). Education and unemployment duration. *Economics of Education Review*, 16(2):163–170.

Kletzer, L. G. and Fairlie, R. W. (2003). The long-term costs of job displacement for young adult workers. *Industrial and Labor Relations Review*, 56(4):682–698.

Krämer, W. (2012). Das Signifikanztest-Ritual und andere Sackgassen des Fortschritts in der Statistik. *AStA Wirtschafts- und Sozialstatistisches Archiv*, 5(4):299–308.

Lameli, A., Nitsch, V., Südekum, J., and Wolf, N. (2014). Same same but different: dialects and trade. *German Economic Review*, 16(3):290–306.

Lazear, E. P. (2009). Firm-specific human capital: A skill-weights approach. *Journal of Political Economy*, 117(5):914–940.

Maxwell, N. L. and D'Amico, R. J. (1986). Employment and wage effects of involuntary job separation: Male-female differences. *American Economic Review*, 76(2):373–377.

Mincer, J. (1991). Education and unemployment. NBER Working Paper 3838, National Bureau of Economic Research.

Mincer, J. and Jovanovic, B. (1981). Labor mobility and wages. In *Studies in Labor Markets*, NBER Chapters, pages 21–64. National Bureau of Economic Research, Inc.

Monks, J. and Pizer, S. D. (1998). Trends in voluntary and involuntary job turnover. *Industrial Relations*, 37(4):440–459.

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics*, 13(4):653–77.

Polsky, D. (1999). Changing consequences of job separation in the united states. *Industrial and Labor Relations Review*, 52(4):565–580.

Ruggles, N. D. and Ruggles, R. (1977). The anatomy of earnings behavior. In *The Distribution of Economic Well-Being*, NBER Chapters, pages 115–162. National Bureau of Economic Research, Inc.

Ruhm, C. J. (1991). Are workers permanently scarred by job displacements? *American Economic Review*, 81(1):319–324.

Santos Silva, J. M. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658.

Santos Silva, J. M. and Tenreyro, S. (2011). Further simulation evidence on the performance of the poisson pseudo-maximum likelihood estimator. *Economics Letters*, 112(2):220–222.

Stevens, A. H. (1997). Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics*, 15(1):165–88.

Topel, R. H. (1991). Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy*, 99(1):145–76.

Tuor, S. N. and Backes-Gellner, U. (2010). Risk-return trade-offs to different educational paths: vocational, academic and mixed. *International Journal of Manpower*, 31(5):495–519.

von Wachter, T., Song, J., and Manchester, J. (2008). Long-term earnings losses due to job separation during the 1982 recession: An analysis using longitudinal administrative data from 1974 to 2004. Discussion Paper 0708-16, Columbia University, Department of Economics.

White, R. (2010). Long-run wage and earnings losses of displaced workers. *Applied Economics*, 42(14):1845–1856.

Wooldridge, J. M. (1999). Distribution-free estimation of some nonlinear panel data models. *Journal of Econometrics*, 90(1):77–97.

Zwick, T. (2012). Earnings losses after non-employment increase with age. *Schmalenbach Business Review*, 64(1):2–19.