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The Impact of Displacement on the Earnings of Workers in Ireland

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Abstract: In this paper we estimate the earnings losses of displaced workers. We use a novel matched worker-firm dataset to estimate earnings losses associated with mass-layoff and closure events in Ireland. Using propensity score matching and difference-in-differences estimators, we find that in the year following displacement, workers who experience a mass-layoff incur losses of 77 per cent compared to losses of 46 per cent for those displaced following a closure, relative to earnings five periods prior to displacement. However, those who are re-employed immediately after displacement suffer much smaller losses of 36 per cent and 19 per cent in the mass-layoff and closure groups respectively. Those displaced in the 2008-2010 group suffer greater earnings losses than those displaced between 2005 and 2007.

I INTRODUCTION

With the slowdown in economic growth and the onset of the financial crisis in 2008, the business environment in which employers and employees operated changed dramatically in Ireland. The years of high economic growth at the latter stages of the 'Celtic Tiger' were followed by a significant decrease in Gross Domestic Product (GDP). The contraction in GDP in 2008-2009 was unprecedented (Voitchovsky *et al*., 2013). The unemployment rate increased from approximately 4 per cent in 2005 to around 14 per cent in 2011 (The World Bank, 2018). In Ireland, the effects of the recession were compounded by the collapse in the construction sector (Holton and O' Neill, 2017). Many of these unemployed individuals are likely to have involuntarily separated from their employers during this time. In this

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context, workers who are displaced from their jobs may face significant adjustment costs. These include the prospect of long spells of unemployment and for those who find a new job, they may experience a decrease in earnings relative to earnings in their previous job. This paper sheds light on the experience of displaced workers over the years 2005-2011, thus spanning an initial period of sustained growth followed by the sharp downturn in 2008.

The impact of job displacement, either through a mass-layoff or closure event, on the subsequent earnings of workers has been studied in many countries, particularly in the United States but also across European and OECD countries. Many studies have found large losses which are slow to recover over time. In this paper, we specifically focus on Ireland and it is the first study of its kind to be conducted on displaced Irish workers. We provide estimates of the employment earnings losses associated with displacement from both firm closure and mass-layoff events using a unique linked employer-employee (P35) dataset for the period 2005-2011. We do so implementing propensity score matching and difference-in-differences estimators to ensure that valid counterfactuals are provided. The dataset, based on information collected by the Revenue Commissioners and available through the Central Statistics Office (CSO) Ireland, contains around two million employee observations in each file annually.[1]

This paper makes the following contributions. Firstly, we provide the first estimates of earnings losses resulting from displacement for Irish workers using a novel dataset consisting of virtually all paid employees in Ireland.[2] The country-wide data used in this study set it apart from previous studies in the area which use either survey data or a sample of administrative data. This dataset spans a unique period of dramatic shifts in the Irish economy and labour market. Its size allows for detailed examination of displacement through the implementation of matching techniques. Secondly, we examine the impact of the length of an unemployment spell on subsequent earnings losses in an Irish context. Thirdly, we focus on the role of demographic characteristics (gender and age) in explaining earnings losses of workers in Ireland. Finally, we split our period of analysis in two and examine the displacement experience of those displaced between 2005 and 2007 compared to those displaced between 2008 and 2010.

We find evidence of large earnings losses for displaced workers in Ireland, particularly for those displaced as a result of a mass-layoff. The mass-layoff and closure groups experience losses of 77 per cent and 46 per cent respectively immediately following displacement, relative to their earnings before displacement. While we do observe a recovery in earnings during the period studied, they do not return to their pre-displacement level for either the closure or mass-layoff groups.

[1] Following the lead author's successful application and subsequent appointment as Officer of Statistics under the terms of the Statistics Act (1993), this microdata source was available from the Central Statistics Office and accessed on-site. Strict protocols and principles were adhered to.

[2] The top 0.1 per cent of earners are removed by the CSO for confidentiality reasons.

However, those who find re-employment immediately after displacement experience smaller losses in both the closure and mass-layoff samples. Those who experience a non-employment spell, and so have zero employment earnings, experience greater losses for longer. Estimates from both samples suggest those who switch employment to another industry experience greater losses relative to displaced workers who secure re-employment in the same industry they have been displaced from. When analysing earnings losses associated with displacement before and after 2008, we find that those displaced after 2008 experience greater losses, particularly in the mass-layoff group.

This paper proceeds as follows. Section II briefly reviews the literature and empirical results in relation to displacement and associated earnings losses in various countries. Section III describes the data and the methodology used in this study, while Section IV describes the results and Section V concludes the paper.

II LITERATURE REVIEW

Many of the earlier studies exploring the impact of displacement on earnings originated in the United States. Initial studies by Podgursky and Swaim (1987), Addison and Portugal (1989), Gibbons and Katz (1991), Carrington (1993), Kletzer (1996) and Farber et al. (1993) all used the Displaced Workers Supplement (DWS) survey data and compared work income before and after displacement for the group of displaced workers.

Research in the field has evolved in the methodological approach taken, given the availability of administrative data sources. The seminal paper in the area by Jacobson *et al*. (1993) exploited administrative data and moved away from the before-and-after approach of previous studies by employing a difference-in-differences methodology using a fixed effect estimator. This necessitates the identification of a control group of non-displaced workers in an effort to more accurately capture how earnings of the displaced would have changed if they had not been displaced. Jacobson *et al*. (1993) report large losses, finding that workers displaced due to mass-layoff experience on average a 25 per cent reduction in income compared to the non-displaced workers in the control group, even six years after the separation event. They note that this is more likely to be attributed to a reduction in wages rather than spells of unemployment. The large losses reported by Jacobson *et al*. (1993) are consistent with earlier work in the US by Ruhm (1991) who also reports that displaced workers experience a considerable and long lasting impact on their wages using Panel Study of Income Dynamics (PSID) survey data. Hijzen et al. (2010) note some of the features of the sample used by Jacobson et al. (1993) may have impacted the magnitude of their findings. For example, their sample consists of high tenure workers and so it may be reasonable to expect that such workers would experience greater losses following displacement relative to a random sample of workers.

The development of large administrative datasets has facilitated the use of other econometric techniques in estimating the impact of displacement on earnings. Couch and Placzek (2010) set out to measure the earnings losses of displaced workers in Connecticut over the 12-year period from 1993 to 2004, and initially employ the methods used by Jacobson *et al*. (1993) which involve using a fixed effects and time trend estimator. Couch and Placzek (2010) extend their work to use matching estimators whereby they match a displaced worker with a person in the non-displaced group with a similar likelihood of being displaced. Couch and Placzek (2010) report similar findings for their fixed effects estimator and matching estimators – those displaced following a mass-layoff event saw a 12 per cent reduction in their earnings after six years.

The role of individual characteristics in explaining displacement losses is also explored in the literature and results vary across studies. For example, while Hijzen *et al*. (2010) report greater earnings losses for displaced men relative to displaced women, Couch and Placzek (2010) find that men and women experience similar losses five years after displacement. The age of the displaced worker may also play a role. As noted by Eliason and Storrie (2006), a number of reasons may explain why the earnings of older workers could be more negatively impacted post-displacement relative to those of younger workers. For example, older workers may have accumulated long tenure within a firm and have a high level of firm-specific capital. If this person is displaced, such skills may not be of value to a new employer. This is also noted by Couch *et al*. (2009) who point to the work of Becker (1962) and the finding that firm-specific skills of workers can be an important factor in explaining wages of individuals. Chan and Stevens (1999) find that half of workers who are aged 50 and over and displaced, experience a wage loss of 19 per cent relative to their pre-displacement earnings. Couch (1998) finds a large effect for displaced workers aged between 51-60 years who experienced a decrease in earnings of between 30 per cent and 39 per cent in the year following their displacement. Later work by Couch *et al*. (2009) on displaced workers aged 40 and over find that earnings losses increase as age increases. They also find that earnings recover faster for younger workers.

While individual characteristics may play a role in explaining earnings losses, the role of industry of employment may also be important. Specifically, the magnitude of earnings losses of the displaced may be affected by the industry or sector in which they find re-employment. For example in the US, Carrington (1993) has shown that the losses for those who switch industry or occupation are persistent. These findings are supported by the later work of Stevens (1997) who reports that workers who are displaced from their industry appear to suffer long-term reductions in their earnings. For those displaced but who do not switch industry, earnings recover quickly. These findings for the US are also supported by the later work of

Couch and Placzek (2010) and Couch *et al*. (2009). In Europe, Burda and Mertens (2001) and Carnerio and Portugal (2006) find similar results in Germany with regards to the negative impact of switching industries and wage growth.

III DATA AND METHODOLOGY

To measure the impact of displacement, we require details of an individual's employment over time. The P35 dataset, spanning the years 2005-2011, is formed by merging three data sources. These are the P35L data from Revenue Commissioners, the Client Record System (CRS) from the Department of Social Protection and the Central Business Register (CBR) in the CSO. The P35L data file is the primary source of data which contains information on each registered employment in Ireland for the years 2005 to 2011 and links employee and employer details. It consists of over two million employee observations in each file annually and the dataset contains the total taxable earnings (gross earnings less employee contributions to health insurance, superannuation, union subscriptions and the travel pass scheme)[3] received from each employer. The file also contains a person identifier and an enterprise identifier which facilitates its merger with the CRS to assign person-based attributes which are age, gender and nationality. The availability of an enterprise identifier means the file can be merged with the CBR to assign the enterprise-based attributes of the NACE Rev.2 sector it belongs to as well as its legal form.

Employment is computed for each enterprise in each year, based on the number of individually assigned employment records attached to the enterprise. An individual is judged to be employed by an enterprise if they work for that establishment for more than 30 weeks of the year.[4] In the case where a worker has multiple employment records in a given year, the individual is assigned to the enterprise for which they worked the greatest number of weeks.

As is the case with many administrative datasets, such as the New Earnings Survey (NES) in the UK, the P35 data do not directly record the reason for an individual separating from their employer. As a consequence, we use the P35 data to define the displacement events. An enterprise is identified as having closed if its final year in the data is at time t. An employee is classified as being displaced due to a closure event if they were employed by an enterprise at time t that no longer exists at $t+1$. An individual is classified as having experienced a mass-layoff event if they have left the enterprise in which they were employed at time t, and that enterprise decreased in employment by 30 per cent or more between t and $t+1$.

[3] It is deflated using the Consumer Price Index [Base year = 2011].

[4] This may include full-time and part-time workers, who are not separately distinguished. According to the Central Statistics Office (2015) the number in part-time employment as a percentage of those in employment increased from 17 per cent in Quarter 1, 2005 to 25 per cent in Quarter 1 of 2011.

The mass-layoff and closure samples are mutually exclusive. While we retain all enterprises in the closure sample, enterprises with less than 50 employees are excluded from the mass-layoff sample.[5,6] This is consistent with previous studies such as Jacobson *et al*. (1993) and Couch and Placzek (2010). The restriction is imposed due to the potential volatility of employment in small firms (Couch and Placzek, 2010) where their inclusion would mean that small absolute changes in employment, such as a reduction from five to two employees, would be identified as a mass-layoff.

Following this process we define cohorts for each time period. The 2007 displaced (treated) cohort comprises those having a single job and employed in the same firm for more than 30 weeks in 2007 who then experience a displacement before they are next observed in 2008. The non-displaced (control) are those employed in the same firm for more than 30 weeks in 2007 who are not displaced before 2008.

To facilitate our estimation procedure, a relative time variable is constructed. This variable is a measure of time relative to the displacement event, t. For all those displaced, the displacement event is deemed to have occurred at $t = 0$. Thus within each cohort, there are seven relative time observations. For example, if a person was displaced in 2007 ($t = 0$), their employment records are available for $t = -2$, or 2005 and $t = -1$, 2006. We also have an observation for this person at $t = +1$ (2008), $t = +2$ (2009), $t = +3$, (2010) and $t = +4$ (2011). Table 1 shows the relative time variables associated with the six available cohorts. As the table shows, the maximum number of relative time observations for an employee is six, given that the data span six years from 2005-2011.[7]

Each of the cohorts was then "stacked" to produce an unbalanced panel with time dimension t from -5 to +6. Note than no one employee spans all relative time periods from $t = -5$ to $t = +6$. A separate unbalanced panel was created for the closure group and mass-layoff groups respectively.

Note that if an individual is not in employment in a given year, then the row contains only the individual's identification number, age, gender and nationality. In each year, a dummy variable is constructed to identify if the person is in the treatment (displaced due to either closure or mass-layoff) or control (non-displaced) group. For an individual not in employment, earnings are recorded as zero.

A limitation of the dataset is that it does not contain any human capital or productivity measures. This is unfortunate as such variables may be expected to

[5] As a robustness check, we also conducted analysis on the mass-layoff sample without imposing this restriction. Estimated earnings losses are less than those of the restricted sample. We believe that this provides evidence to support the use of the restricted sample as the unrestricted sample may include far more voluntary separations - possibly to higher paying jobs, which may reduce the magnitude of earnings losses.
[6] This enterprise size restriction results in the removal of 43 per cent of observations from the sample.
[7] While we use data for 2011, it is not possible to define displacement events in this year, given that 2011 is the final year of available data in this paper.

Table 1: Cohorts and Relative Time Variables

	Cohort					
Year	*2005*	*2006*	*2007*	*2008*	*2009*	*2010*
2005	***t* = 0**	*t* = –1	*t* = –2	*t* = –3	*t* = –4	*t* = –5
2006	*t* = 1	***t* = 0**	*t* = –1	*t* = –2	*t* = –3	*t* = –4
2007	*t* = 2	*t* = 1	***t* = 0**	*t* = –1	*t* = –2	*t* = –3
2008	*t* = 3	*t* = 2	*t* = 1	***t* = 0**	*t* = –1	*t* = –2
2009	*t* = 4	*t* = 3	*t* = 2	*t* = 1	***t* = 0**	*t* = –1
2010	*t* = 5	*t* = 4	*t* = 3	*t* = 2	*t* = 1	***t* = 0**
2011	*t* = 6	*t* = 5	*t* = 4	*t* = 3	*t* = 2	*t* = 1

Source: Authors' analysis.

contribute to explaining the earnings losses of employees. For example, in the case of a mass-layoff, it may be reasonable to suggest that lower productivity workers would be the first to be selected and this may bias our reported earnings losses.

There is also no direct measure of tenure available. We do not therefore attempt to impose restrictions on the sample based on tenure, which contrasts with typical practice. However, it is in line with the work of Podgursky (1992) who does not exclude displaced workers on the basis of tenure from their sample, which has the benefits of not eroding the sample size and allowing for a greater level of disaggregation when analysing the data.

3.1 Matching Procedure

Matching methods have been used in several studies to estimate treatment effects, in which displacement is the treatment event (e.g. Couch and Placzek, 2010, for the US; Hijzen *et al*., 2010, for the UK). The matching process involves pairing those in the treatment group with those in the control group who have similar likelihoods of treatment based on their observable characteristics (Dehejia and Wahba, 2002). Rosenbaum and Rubin (1983) and Austin (2009) argue that propensity score matching can eliminate a greater amount of bias in estimating treatment effects, relative to other methods.

We match displaced individuals with non-displaced individuals who have a similar propensity to be displaced.[8] The individual-level variables used in the matching process in this paper are a person's age, age squared, gender and nationality. We also have information on enterprise characteristics which are used in the matching procedure. These include firm size and the NACE Rev.2 sector an enterprise belongs to. As noted by Hijzen *et al*. (2010), such pre-displacement firm characteristics could prove to "be important if selection is non-random with respect to firm types" (p.253).

[8] See Appendix A for further details on variables used in the matching procedure.

We use single nearest-neighbour propensity score matching within each cohort, based on the set of pre-displacement characteristics outlined above. To ensure the closeness of the propensity score match, a caliper was used. In this paper, a caliper of 0.001 and 0.002[9] was used in the closure and mass-layoff samples respectively, thus giving confidence in the quality of matches achieved.[10] Because of the size of the control group, the matching procedure resulted in all displaced workers being matched successfully with a non-displaced worker in each cohort.[11] The number of displaced workers ranges from around 10,000 in 2005 in the closure sample to over 45,000 in 2008. In the mass-layoff sample, the numbers displaced range from just under 2,000 displaced workers in 2005 to over 8,000 in 2008.

As noted earlier, one limitation of the dataset used is the relative lack of individual-level variables on which to match, including those related to the human capital of the employee for example. While we acknowledge the somewhat limited set of characteristics used may potentially bias our estimates, they are similar to the variables available to other studies based on administrative date, such as Hijzen *et al*. (2010) in their UK study.[12] In mitigation, the size of the dataset helps to ensure close matches between displaced and non-displaced workers.

3.2 Estimation Methodology

As outlined above, matched cohorts are stacked resulting in an unbalanced panel from $t = -5$ to $t = +6$, or 12 time periods. We now turn to the estimation of the effect of displacement for the closure and mass-layoff samples respectively. Ultimately as noted by Hijzen *et al*. (2010), this enables the estimation of the pooled effect of the displacement event at each relative time period t.

We proceed by estimating the following equation:

$$y_{it} = \alpha D_i + \sum_{k=-5}^{6} \gamma^k T_{it}^k + \sum_{k=-4}^{6} \delta^k D_i * T_{it}^k + \varepsilon_{it} \tag{1}$$

Here y_{it} is the earnings of worker i at time t. D_i is a displacement dummy which is equal to one if the person is displaced and zero otherwise.[13] α therefore captures the mean difference between the treated and untreated in the control period. Each T_{it}^k is a dummy variable which is equal to one if $t = k$ and zero otherwise, capturing time relative to the displacement event.

[9] A slightly higher caliper was used in the mass-layoff sample as the lower caliper of 0.001 results in an inability to find matches in a number of cases.

[10] Appendix A reports the results of balancing tests in more detail. It shows that differences in the treatment and control groups have been removed after matching. No issues were identified in relation to common support.

[11] See Table A3 for further details.

[12] Hijzen *et al*. (2010) also have details on occupation and union coverage.

[13] As it is possible for individuals to be in more than one cohort, the standard errors for all regressions are clustered using the individual identifier number.

We create an interaction term between the displacement dummy D_i and our relative time variable within each cohort. The coefficient on this variable δ^k is our difference-in-differences estimate of the earnings losses of the treatment group. This regression equation is estimated separately for the closure and mass-layoff samples.

In estimating counterfactual income, the choice of the pre-displacement control period is important. Hijzen *et al*. (2010) choose the average differences in income of the treatment and control group between periods $t = -4$ and $t = -8$. They argue that selecting a time period closer to the displacement event risks not picking up genuine pre-displacement falls in earnings. Due to the relative shortness of our sample period, we take as our control period $t = -5$.[14]

IV RESULTS

Table 2 reports the difference-in-differences estimates of displacement on earnings, for each relative time period, for both the closure and mass-layoff samples respectively. We follow the approach of Couch and Placzek (2009) in reporting both monetary and percentage losses. We can see the large costs associated with displacement and its immediate aftermath. The mass-layoff sample does appear to experience greater earnings losses relative to the closure sample. While displaced workers in the closure sample experience losses of around €13,500 at $t = 1$, those in the mass-layoff sample experience earnings losses of just over €27,000 at $t = 1$. This represents losses of 46 per cent and 77 per cent for the closure and mass-layoff samples respectively, relative to their earnings in our base period of $t = -5$. Although earnings do recover for both samples, they do not reach their pre-displacement level in the time period considered.

The difference-in-differences estimates and associated confidence intervals as presented in Table 2 are graphed in Figure 1 and Figure 2.[15]

This evidence of smaller losses for the closure group is consistent with the theory and evidence provided by Gibbons and Katz (1991). They suggest that if firms have discretion over who is selected for layoff, as they would in a mass-layoff event as opposed to a closure event, the market will assume that those who are subject to layoff are of lower ability. Because of this, those displaced through mass-layoff may receive a lower post-displacement wage, relative to the closure group. On the other hand, those affected by a closure are different because all employees are let go and thus a negative signal is not sent to the market, as is the case with the mass-layoff event. Evidence from the Irish labour market presented here would seem to support this theory.

[14] It should be noted that only the 2010 cohort has observations that extend back to $t = -5$ and it is the mean difference between the treated and control for this cohort which is used to estimate α.

[15] The earnings losses of displaced workers were also estimated with the inclusion of cohort dummies and their inclusion had very little impact on estimated earnings losses.

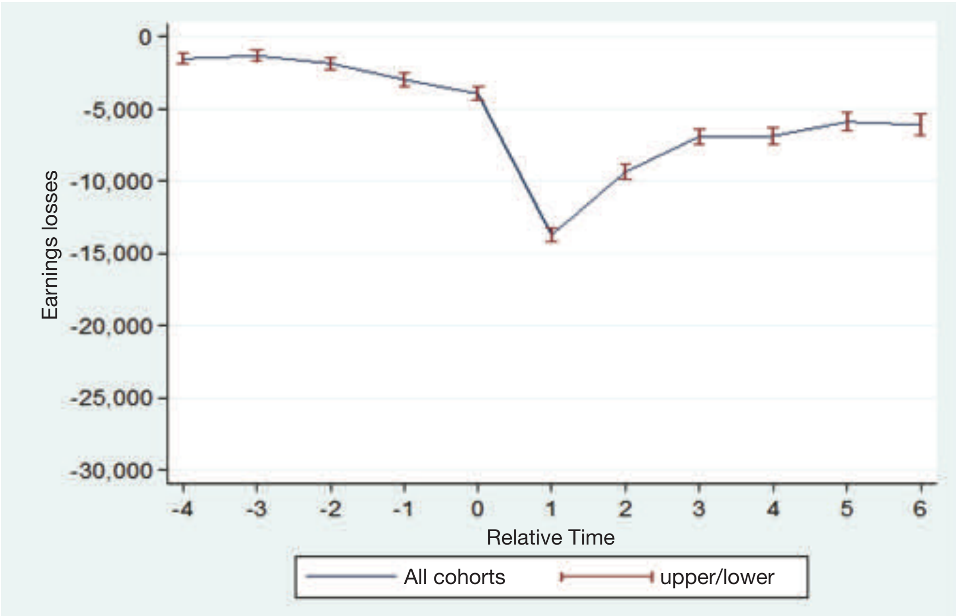
Table 2: Results for Closure and Mass-layoff samples

RELATIVE TIME	*Closure Sample Earnings*	*RELATIVE TIME*	*Mass-layoff Sample Earnings*
$t^* = -4$	–1,487***	$t^* = -4$	–2,215***
	(180.5)		(809.1)
$t^* = -3$	–1,228***	$t^* = -3$	–3,150***
	(206.9)		(900.1)
$t^* = -2$	1,816***	$t^* = -2$	–3,720***
	(216.8)		(928.9)
$t^* = -1$	–2,939***	$t^* = -1$	–4,734***
	(224.4)		(948.4)
$t^* = 0$	–3,914***	$t^* = 0$	–6,123***
	(227.2)		(961.1)
$t^* = 1$	–13,689***	$t^* = 1$	–27,124***
	(234.1)		(971.4)
$t^* = 2$	–9,339***	$t^* = 2$	–22,964***
	(251.0)		(1,002)
$t^* = 3$	–6,894***	$t^* = 3$	–18,375***
	(258.9)		(1,014)
$t^* = 4$	–6,828***	$t^* = 4$	–15,544***
	(283.3)		(1,050)
$t^* = 5$	–5,873***	$t^* = 5$	–14,221***
	(322.3)		(1,096)
$t^* = 6$	–6,084***	$t^* = 6$	–10,382***
	(394.1)		(1,203)
Observations	2,001,473	*Observations*	284,346
Fstat	4,039.67	*Fstat*	1,147.37
Prob > F	0.000	*Prob > F*	0.000
R-squared	0.0562	*R-squared*	0.165

Source: Authors' analysis.
Notes: (a) Table reports estimates of δ^k from Equation 1. These figures are in real Euros (Base period = 2011).
(b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

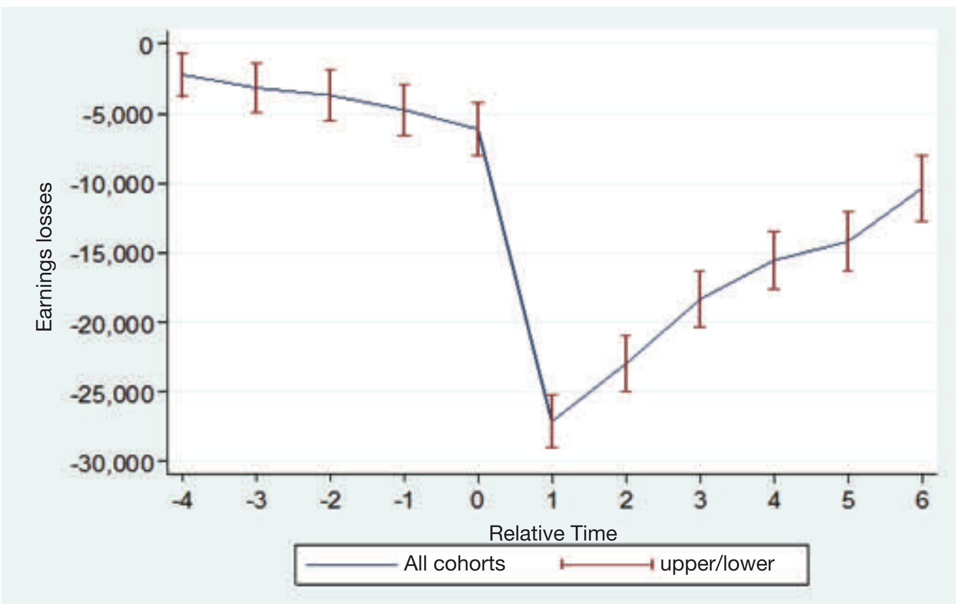
In both samples, we see some evidence of an "Ashenfelter" dip in the pre-displacement earnings (Ashenfelter, 1978). This is particularly true in the mass-layoff sample. In the context of this study, such a dip could be the result of a decrease in the pre-displacement earnings of the displaced group, due perhaps to enterprises implementing a shorter working week or cutting back on overtime in an effort to cut costs. As such, earnings losses start accruing before $t = 0$, and difference-in-differences estimates may understate the impact of displacement on

Figure 1: The Earnings Losses of Displaced Workers – Closure



Source: Authors' analysis.

Figure 2: The Earnings Losses of Displaced Workers – Mass-layoff



Source: Authors' analysis.

the earnings losses of displaced workers if the pre-displacement effect is not included in the loss. We have mitigated this by choosing a base period which is well in advance of the displacement event, and prior to a dip occurring.

4.1 Earnings Losses and Unemployment

In our results, reported earnings losses are a combination of lower wages in the new job and zero earnings during non-employment. To examine this further, we split the samples based on their post-displacement employment status. Specifically displaced workers are grouped into seven categories. These are those re-employed in the year after displacement, and six further groups representing those unemployed by between one and six periods after displacement. The control group consists of workers who are not displaced and have no employment gap.[16]

We see in Figure 3 and Figure 4 that, in both samples, those who are re-employed immediately in the period after displacement suffer the smallest earnings losses. The closure sample experiences a fall of just over €5,000 representing a decrease of 19 per cent relative to earnings immediately before displacement. The mass-layoff group experience greater losses of around €12,500 or a 36 per cent drop in earnings. This result supports the findings of Hijzen *et al*. (2010) who suggest that income losses are largely driven by spells of non-employment. However, we do see evidence here of declining losses for this group as time progresses. Our results here generally point to a recovery in earnings for those who are displaced, but particularly in the mass-layoff sample we note the widening confidence intervals as time progresses.[17]

It is possible that the relatively healthy position of those who are re-employed at $t + 1$ is driven by the fact that some of these individuals are voluntary leavers going for better jobs. However the P35 data do not allow us to distinguish between quits and layoffs. However, as explained earlier, we do attempt to identify and capture involuntary separations by only including enterprises with 50 or more employees that experience a 30 per cent reduction or more in employment.

4.2 Displacement and Earnings Losses – Individual Characteristics

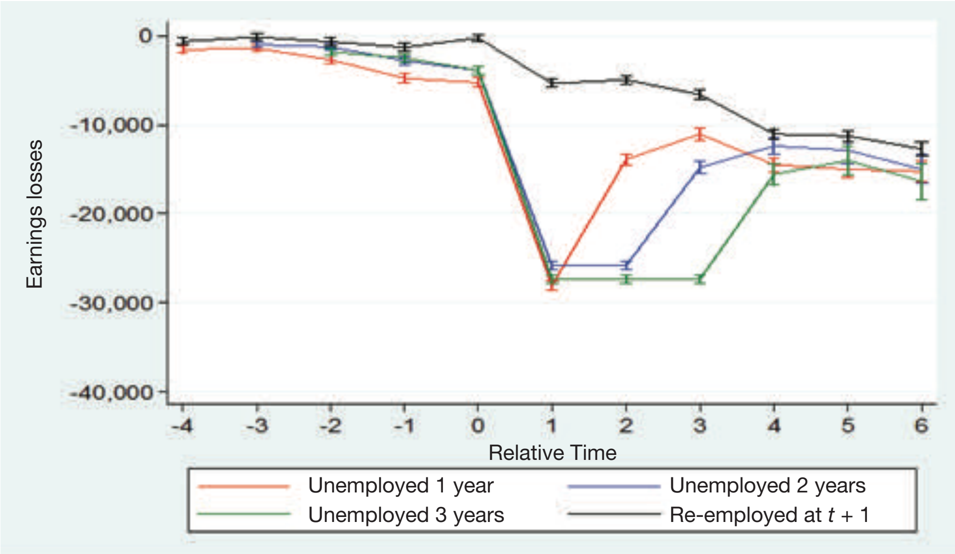
We further explore the earnings losses by looking at differences associated with gender and age by splitting the closure and mass-layoff samples by gender and age respectively. We proceed with a graphical presentation of results with detailed tables of results in Appendix B.

Beginning with gender, males appear to experience a greater earnings loss compared to females in both samples in Figure 5 and Figure 6. In the closure sample, males experience a loss of just over €16,200 (46 per cent) with females

[16] For clarity only four groups are included in Figures 3 and 4.

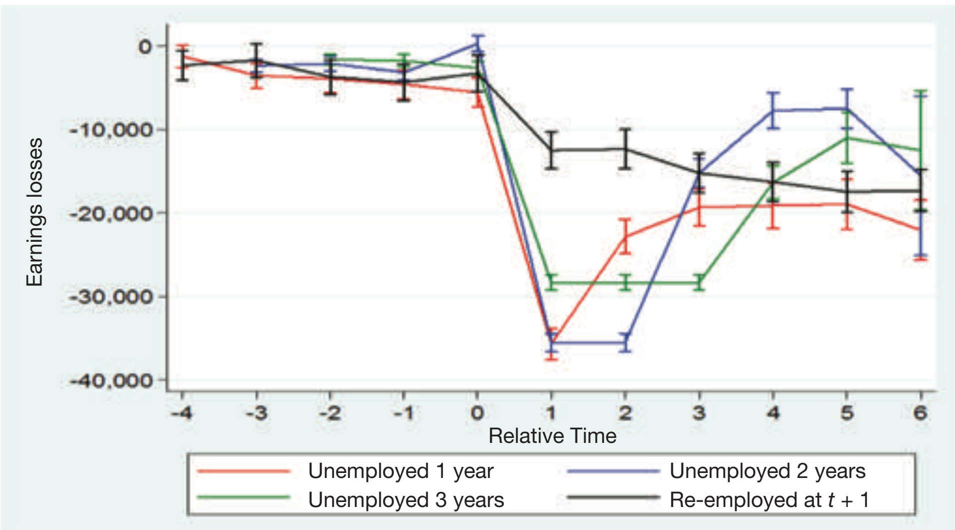
[17] It is interesting to note that even those that find re-employment experience declining earnings post-displacement relative to those who are not displaced. Such a scenario may be attributable to the turbulence in the domestic economy during the later years of the sample.

Figure 3: Earnings Losses and Unemployment Spell – Closure



Source: Authors' analysis.

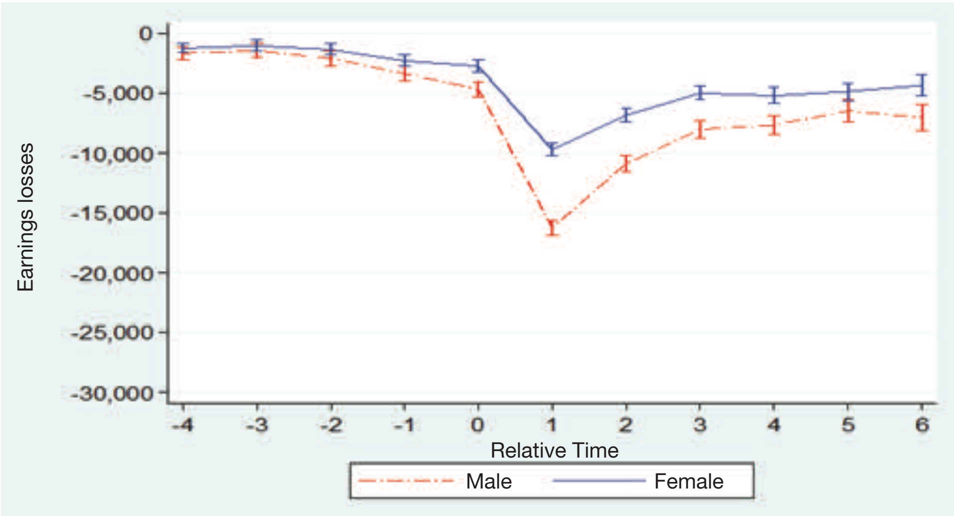
Figure 4: Earnings Losses and Unemployment Spell – Mass-layoff



Source: Authors' analysis.

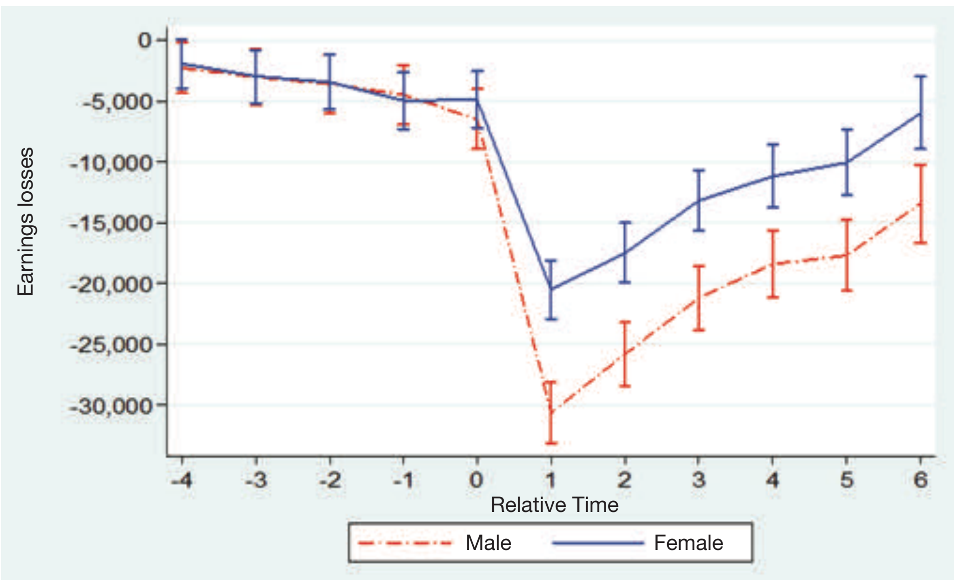
experiencing a loss of just under €10,000 (45 per cent), relative to $t = -5$. However in the mass-layoff sample, displaced males experience a loss of over €30,000 (75 per cent) at $t = 1$ with the corresponding figure for females standing at just over €20,000 (84 per cent).

Figure 5: Earnings Losses of Displaced Workers and Gender – Closure



Source: Authors' analysis.

Figure 6: Earnings Losses of Displaced Workers and Gender – Mass-layoff



Source: Authors' analysis.

This is consistent with evidence from Hijzen *et al*. (2010) for the UK who report that displaced men experience greater earnings losses when compared to displaced women.[18] It is possible in the Irish case that the observed losses represent a greater loss of specific human capital for male workers. The existence of such firm or sector specific human capital may mean that workers found it difficult to secure re-employment in a similar role or may have had to accept employment in roles where their firm-specific skills were not required or valued. Consistent with earlier observations, both males and females in the mass-layoff group experience greater earnings losses than those in the closure sample.

Turning to age, empirical work in both the US and Europe does suggest that older workers experience a greater earnings loss in comparison to younger workers. It is possible for example, that older workers have been working with one employer for a long period of time and acquired significant firm-specific capital which may be of little value to a potential new employer after displacement. In the US, Couch (1998) finds that older workers aged 51-60 years experience a loss of 30-39 per cent in the year after displacement. In the UK, Hijzen *et al*. (2010) report that, examining a five-year post-displacement period, displaced workers experience a loss of 40 per cent relative to what they were earning the year before the displacement event.

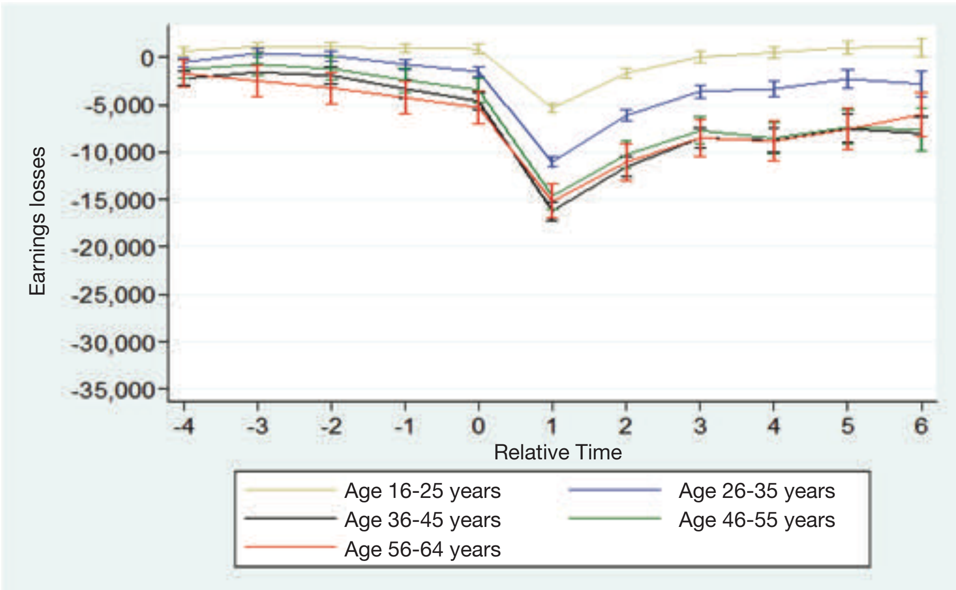
Figure 7 and Figure 8 show the earnings losses associated with each age category. We generally observe that the younger categories experience smaller earnings losses when compared to older age categories. As previously, the mass-layoff group display greater losses immediately after displacement. For example, while 56-64-year-olds in the closure sample experience a loss of around €15,000 (46 per cent), those in the mass-layoff group experience a loss of almost €29,000 (69 per cent) at $t = 1$. The losses for the closure sample are very similar to those of Couch (1998), while again we see that the mass-layoff sample is more adversely impacted. We do observe wider confidence intervals in the mass-layoff sample, attributable to the smaller sample size.

4.3 Displacement and Industry Switching

Next we explore the losses of displaced workers who find re-employment in the same sector they were displaced from and those who were displaced and move to a new sector of employment, relative to those who are not displaced. We do this for both the closure and mass-layoff samples. As noted earlier, evidence from Couch *et al*. (2009) and Couch and Placzek (2010), as well as Burda and Mertens (2001) in Europe, suggests that finding re-employment in a different sector after displacement can have a negative impact on subsequent earnings relative to those who stay within the same sector to secure re-employment. Displaced workers are identified as being either (i) industry switchers, (ii) industry stayers or (iii) continuously unemployed. A worker is deemed to be an industry switcher if the industrial classification of the enterprise they secure re-employment in after

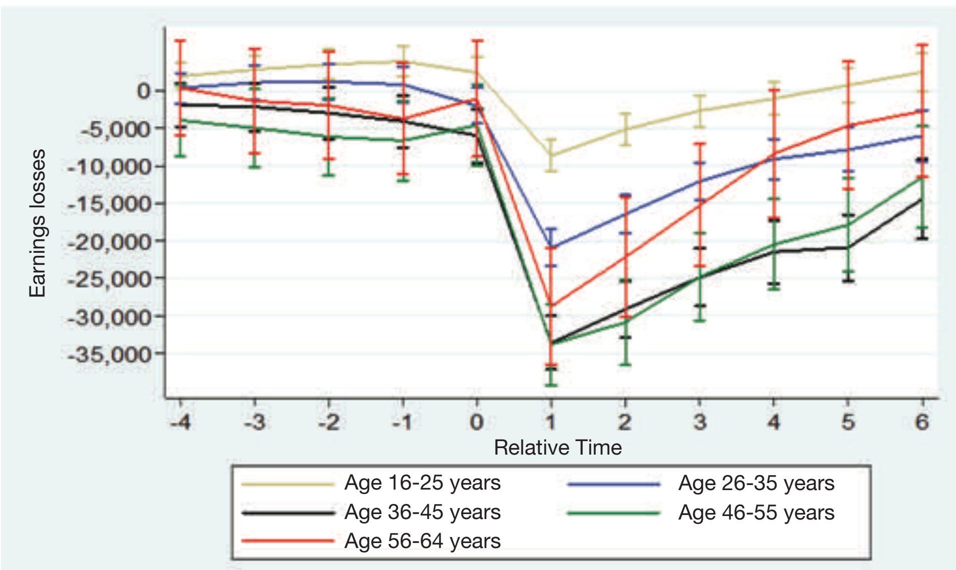
[18] As mentioned earlier, this finding is different to some of the results presented for the US. Couch and Placzek (2010) suggest that five years after displacement, men and women experience similar losses.

Figure 7: Earnings Losses of Displaced Workers and Age Category (Closure)



Source: Authors' analysis.

Figure 8: Earnings Losses of Displaced Workers and Age Category (Mass-Layoff)



Source: Authors' analysis.

displacement is different to the industrial classification of the enterprise they were displaced from.[19]

To identify the earnings losses of displaced industry switchers and stayers, earnings y_{it} is regressed on a series of interaction terms as per the Equation 2.

$$y_{it} = \alpha_1\, Dswitch_i + \alpha_2 Dstay_i + \alpha_3 NoDswitch_i + \alpha_4 Unemp_i + \sum_{k=-5}^{6} \gamma^k\, T_{it}^k$$
$$+ \sum_{k=-4}^{6} \delta^k\, Dswitch_{it} * T_{it}^k + \sum_{k=-4}^{6} \alpha^k\, Dstay_{it} * T_{it}^k + \sum_{k=-4}^{6} \beta^k\, NoDswitch_{it} * T_{it}^k \qquad (2)$$
$$+ \sum_{k=-4}^{6} \sigma^k\, Unemp_{it} * T_{it}^k + \varepsilon_{it}$$

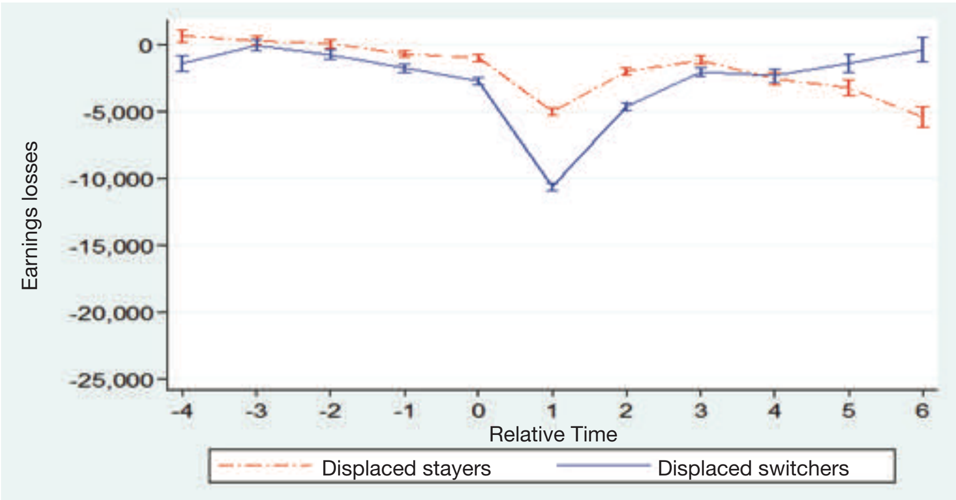
Specifically, *Dswitch* is a dummy variable equal to one if an individual is displaced and finds employment in another sector, and zero otherwise. The next variable of *Dstay* is a dummy variable equal to one if an individual is displaced and stays in the same sector after displacement, and zero otherwise. The variable *NoDswitch* is a dummy variable and equal to one if an individual is not displaced and switches sectors and zero otherwise. Finally, *Unemp* is another dummy variable equal to one if a person is unemployed in all periods following displacement, and zero otherwise.

The γ^k coefficient represents the earnings of non-displaced workers who stay employed in the same industry. Therefore, all earnings losses (or increases) described are relative to this group of workers.

We observe in Figure 9 and Figure 10 firstly that all displaced workers suffer large losses but the losses are greater for those who switch industry. Secondly as noted previously, it appears that the mass-layoff group suffer a greater penalty, with losses of over €23,000 (68 per cent) at $t = 1$ for those who switch to another industry. This is in comparison to losses of around €10,000 (36 per cent) at $t = 1$ for the group of workers from the closure sample who switch to another industry. Displaced workers who stay in the same industry after displacement experience losses of 17 per cent and 39 per cent respectively in the closure and mass-layoff samples.

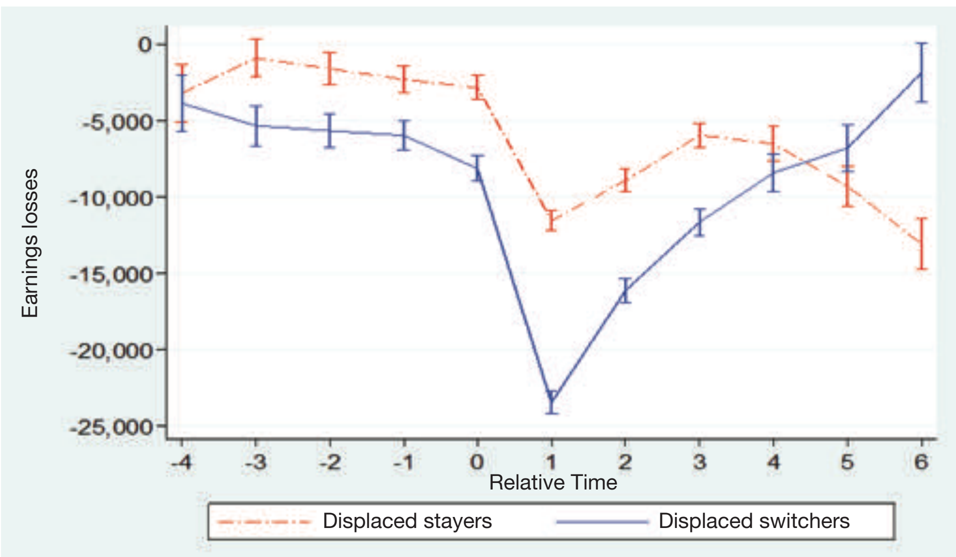
[19] The first employment record following displacement is identified, which allows for the possibility that an individual may have an intervening unemployment spell. A worker is classified as unemployed if there is no employment record in any period following displacement. We acknowledge that this worker may alternatively be deceased or have emigrated but it is not possible to distinguish such outcomes in the dataset. Emigration increasing from 46,000 in 2007 to over 80,000 in 2011 while net migration over the period fell from almost +105,000 in 2007 to -27,400 in 2011 (CSO, 2018a).

Figure 9: The Earnings Changes of Displaced Workers who Switch or Stay in the Same Sector Following Displacement – Closure



Source: Authors' analysis.

Figure 10: The Earnings Changes of Displaced Workers who Switch or Stay in the Same Sector Following Displacement – Mass-layoff



Source: Authors' analysis.

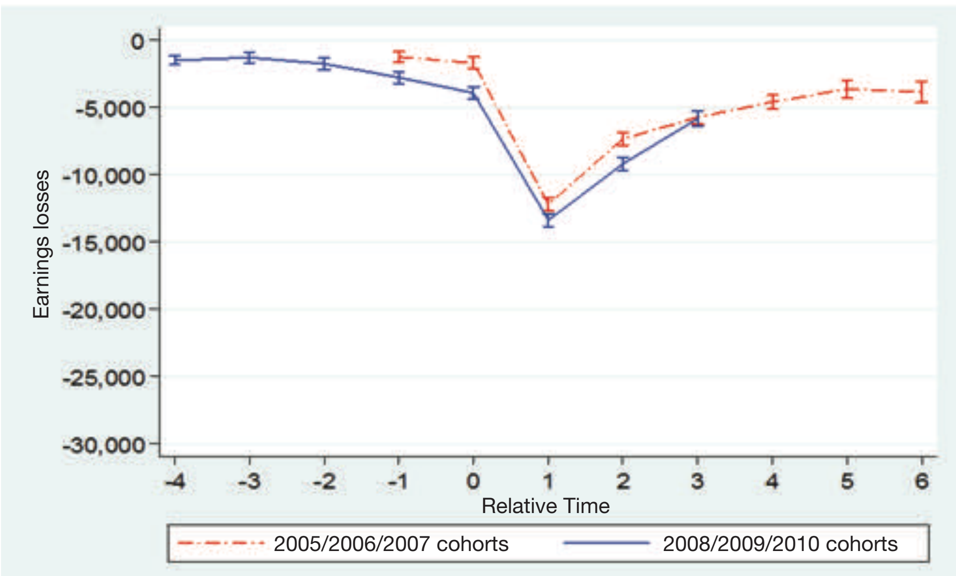
Interestingly, we observe that the earnings losses of the displaced switchers do recover quickly and at $t = 5$ they actually appear to have smaller losses than the displaced stayers, although we do note the widening confidence intervals for both sets of workers in both samples.

4.4 Earnings Losses and Displacement Pre- and Post-2008

Before the onset of the Great Recession, workers who lost their jobs had more opportunities to find re-employment. Therefore, we now explore the impact of displacement on the earnings of workers before and after 2008. The pre-2008 group consists of cohorts 2005-2007, while the post-2008 group consists of cohorts from 2008-2010.

In estimating earnings losses,[20] we find the same qualitative result – the mass-layoff sample experience greater losses than those in the closure sample. Examining earnings losses of those displaced pre-2008 and post-2008 in both samples in Figures 11 and 12, we observe little difference in earnings losses at $t = 1$ for the closure sample. Earnings losses pre-2008 are around €12,000 (41 per cent) compared to roughly €13,000 (42 per cent) for the post-2008 group. So it appears that those who experience displacement due to closure post-2008 have only slightly greater percentage losses relative to the base period of $t = –5$.

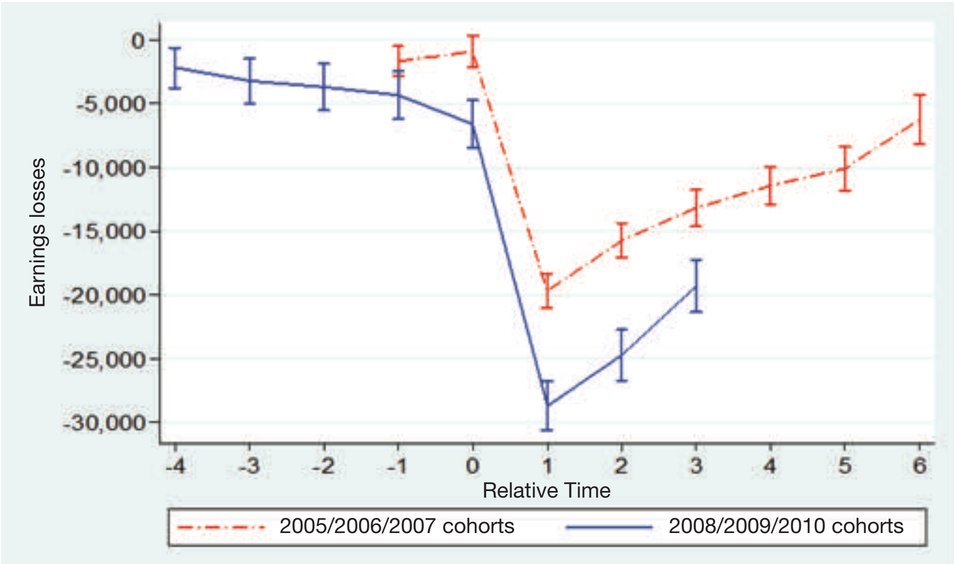
Figure 11: Earnings Losses of Displaced Workers Pre- and Post-2008 – Closure



Source: Authors' analysis.

[20] Equation 1 is used and the sample is split into two periods.

Figure 12: Earnings Losses of Displaced Workers Pre- and Post-2008 – Mass-layoff



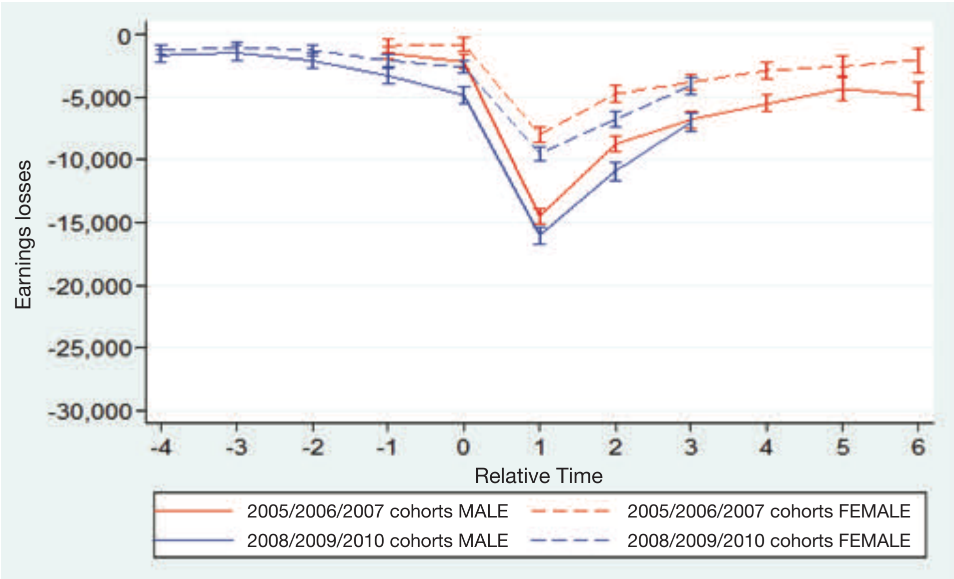
Source: Authors' analysis.

However, we see that workers displaced due to mass-layoff pre-2008 experience loss of around €20,000 (61 per cent) compared to almost €29,000 (91 per cent) for those displaced after 2008. Those displaced as a result of a mass-layoff post-2008 appear to suffer the largest earnings losses.

To examine gender differences in earnings losses pre- and post-2008, the sample is split by gender as well as time. As we see in Figures 13 and 14, those displaced following a mass-layoff suffer the greatest earnings losses compared to those in the closure sample. Also, we observe that male workers appear to be adversely affected and suffer a large fall in earnings. In the post-2008 period, males in the mass-layoff sample experience losses of around €32,000 (89 per cent), while males in the closure sample have estimated losses of €16,000 (44 per cent).

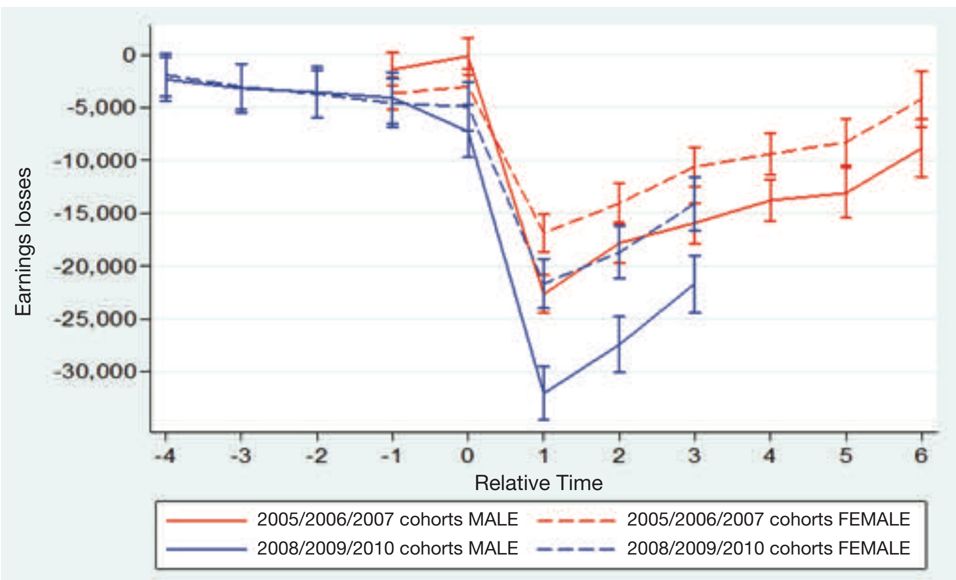
While unemployment increased significantly in Ireland over the period of investigation, the incidence of unemployment was not spread evenly across all sectors. The construction sector (F) was particularly adversely impacted with the numbers in employment falling from approximately 240,000 in Quarter 1 of 2007 to just over 157,000 in Quarter 1 of 2009. Employment continued to decline and in Quarter 1 of 2013 the numbers employed in the sector were just over 80,000 (CSO, 2018b). Here we explore the earnings losses associated with displacement from this sector in Figure 15 and Figure 16 pre- and post-2008.

Figure 13: Earnings Losses of Displaced Workers and Gender; Pre- and Post-2008 – Closure



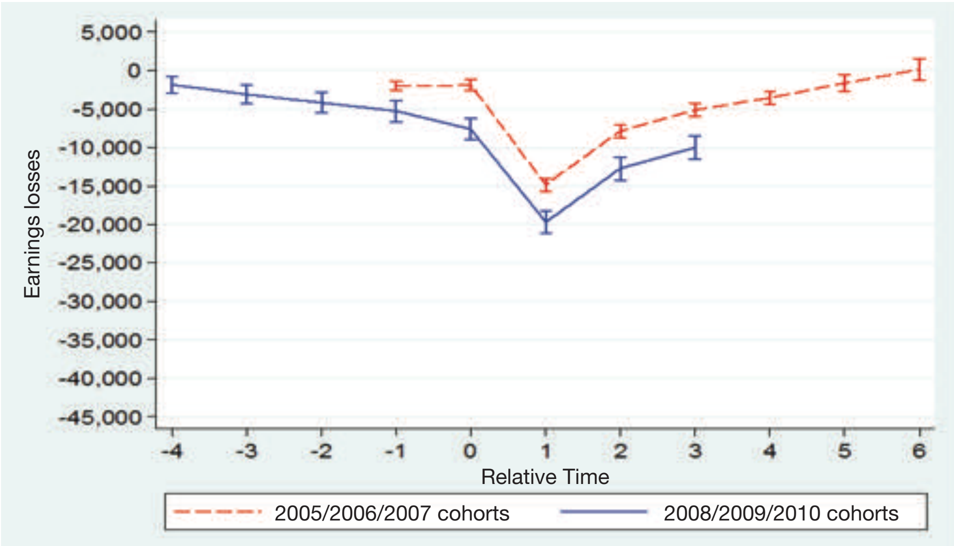
Source: Authors' analysis.

Figure 14: Earnings Losses of Displaced Workers and Gender; Pre- and Post-2008 – Mass-layoff



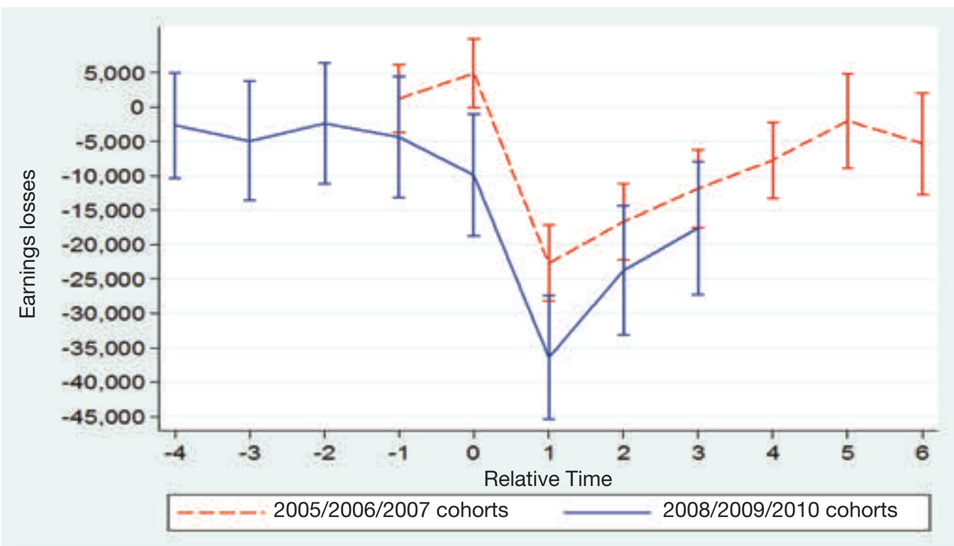
Source: Authors' analysis.

Figure 15: Earnings Losses of Displaced Workers and the Construction Sector; Pre- and Post-2008 - Closure



Source: Authors' analysis.

Figure 16: Earnings Losses of Displaced Workers and the Construction Sector; Pre- and Post-2008 – Mass-layoff



Source: Authors' analysis.

In the case of both the closure and mass-layoff samples, we see that those displaced in the post-2008 group suffer greater losses relative to those displaced in the pre-2008 group. We again see the mass-layoff group experiencing greater earnings losses relative to those in the closure sample. The mass-layoff group post-2008 experiences losses of almost €24,000 (79 per cent) while those displaced due to firm closure in the same time period suffer losses of almost €20,000 (58 per cent). We do observe wider confidence intervals in the mass-layoff sample relative to the closure sample, attributable to the smaller sample size caused by looking at one sector.

V CONCLUSIONS

We have examined the impact of displacement on the subsequent earnings of workers in Ireland for those who experience a mass-layoff or a closure event during the period 2005-2011 using the P35 linked employer-employee dataset. This time period saw dramatic changes in the Irish economy and labour market. Displaced workers are likely to have found it increasingly difficult to secure re-employment following the economic downturn in 2008. Those who did find re-employment may have had lower post-displacement earnings.

We find that those who are displaced following a mass-layoff are more adversely impacted in terms of their earnings losses relative to those displaced following an enterprise closure. Consistent with Gibbons and Katz (1991), our results suggest that an unfavourable information signal may be sent to the market regarding workers displaced through a mass-layoff event. At the same time, this was a period of severe economic turbulence which made securing re-employment in a comparable paying job more challenging for all displaced workers, but particularly it seems for the mass-layoff group. Also for the displaced, securing re-employment quickly is important. Our findings are consistent with Hijzen *et al.* (2010), who note that displacement costs for workers are greatly driven by periods of non-employment. This helps contextualise our findings regarding the large losses experienced by both the closure and mass-layoff groups immediately after displacement. The larger post-displacement losses reported here relative to previous European and US studies could be indicative of the time period studied in this paper and reflect the challenging labour market faced by displaced workers in securing employment.

It appears that earnings losses vary depending on whether an individual secures employment in the same sector that they have been displaced from, with those switching to a new sector experiencing a larger earnings penalty. While suffering greater losses than those who stayed within the same sector, it is interesting to note that after $t = 5$, the earnings losses of switchers are actually less than those who were displaced and secured re-employment in the same sector.

We find evidence that older workers also experience greater losses when compared to younger workers. Such findings are consistent with those of Couch *et al*. (2009) who report that earnings losses increase as age increases. We also see that earnings recover faster for younger workers, particularly for those in the closure sample. If losses for older workers are related to lack of skills or training, there is a role for government in the provision of appropriate training options and re-skilling opportunities.

Displaced male workers are more likely to experience greater earnings losses compared to female workers. This may be due to a greater loss of specific human capital for male workers over the period of this study. From a policy perspective, ensuring adequate skills provision for such workers would seem to be vital, given that we might expect that more of these workers would be required to switch to another sector to secure re-employment. Direct financial support for displaced workers, while relevant, needs to be provided in conjunction with appropriate activation policies.

Finally, given the dramatic shift in the economic environment in the time period under investigation, we also explore the losses of those displaced before and after the year 2008. Those displaced in the 2008-2010 group suffer greater earnings losses than those displaced between 2005 and 2007. This reflects the difficult labour market conditions that displaced workers experienced as the economy entered the deep recession in 2008. As well as difficulty securing re-employment, those who did so may have had to accept lower wages after the displacement event.

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APPENDIX A: MATCHING PROCEDURE – KEY VARIABLES AND RESULTS

Here we provide details on the variables used in the matching procedure.

Table A1: Overview of Nationality, NACE Rev.2 Sector and Firm Size Categories Used in Matching

(A) Nationality groups	
Nationality Group	*Countries*
Group 1	Ireland
Group 2	UK, Northern Ireland, Isle of Man
Group 3	Western Europe
Group 4	Eastern Europe
Group 5	Asia
(B) Age categories	
Age Category	*Years*
Group 1	16-25 years
Group 2	26-35 years
Group 3	36-45 years
Group 4	46-55 years
Group 5	56-64 years
Group 6	65+ years
(C) NACE sector groups	
NACE Group	*NACE Rev.2 Sectors*
Group 1	Agriculture (A), Mining and Quarrying (B), Manufacturing (C), Electricity, Gas, Steam and Air Conditioning Supply (D), Water Supply; Sewerage, Waste Management and Remediation Activities (E), Construction (F)
Group 2	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles (G), Transport and Storage (H), Accommodation and Food Service Activities (I), Information and Communication (J), Real Estate Activities (L), Arts, Entertainment and Recreation (R), Other Service Activities (S), Activities of Households as Employers (T), Activities of Extra Territorial Organisations and Bodies (U)
Group 3	Financial and Insurance Activities (K), Professional, Scientific and Technical Activities (M), Administrative and Support Service Activities (N)
Group 4	Public Administration and Defence; Compulsory Social Security (O), Education (P), Human Health and Social Work Activities (Q)

Table A1: Overview of Nationality, NACE Rev.2 Sector and Firm Size Categories Used in Matching (Contd.)

(D) Firm size groups	
Firm Size Group	*Firm size (No. of employment records)*
Group 1	0-9
Group 2	10-19
Group 3	20-49
Group 4	50-249

Source: Authors' analysis.

Our results in Table A2 suggest that matching on the observable characteristics has been successful. The results of the *t-tests* for the closure and mass-layoff samples are presented. We can see that in the unmatched data, the treatment group and the control group are different in terms of their observable characteristics as denoted by the significant t-test results for variables. However, it is clear that after matching, all of these differences have been removed in each cohort.

Table A2: Results of Balancing Tests

Cohort	*Closure sample*		*Mass-layoff sample*	
	Unmatched	*Matched*	*Unmatched*	*Matched*
2005	15/15	0/15	10/12	0/12
2006	15/15	0/15	10/12	0/12
2007	14/15	0/15	11/12	0/12
2008	12/15	0/15	11/12	0/12
2009	12/15	0/15	11/12	0/12
2010	14/15	0/15	11/12	0/12

Source: Authors' analysis.
Note: Each cell of the table denotes the fraction of t-tests that are significant (at the 5 per cent) level in the mean between the displaced and non-displaced groups.

Table A3 displays the number of displaced workers before and after the implementation of the propensity score matching. As can be seen, the matching procedure resulted in all of displaced workers being matched successfully with a non-displaced worker in each cohort.

Table A3: The Number of Displaced Workers in the Before and After Matching

	Number of displaced workers			
Year	*Closure Sample*		*Mass-Layoff Sample*	
	Before Matching	*After Matching*	*Before Matching*	*After Matching*
2005	10,221	10,221	1,979	1,979
2006	14,120	14,120	2,270	2,270
2007	20,516	20,516	3,005	3,005
2008	45,258	45,258	8,079	8,079
2009	32,452	32,452	4,656	4,656
2010	29,963	29,963	2,232	2,232

Source: Authors' analysis.

APPENDIX B: RESULTS OF DIFFERENCE-IN-DIFFERENCES ESTIMATES ON MATCHED SAMPLES

Table B1: Regression Output for Figure 3 and Figure 4

Relative Time	*Closure Earnings*	*Mass-layoff Earnings*
Unemployed 1 year		
$t^* = -4$	–1,603***	–1,233*
	(197.7)	(673.6)
$t^* = -3$	–1,408***	–3,535***
	(233.5)	(775.2)
$t^* = -2$	–2,718***	–3,893***
	(247.9)	(842.3)
$t^* = -1$	–4,826***	–4,590***
	(264.4)	(874.6)
$t^* = 0$	–5,258***	–5,555***
	(266.3)	(904.3)
$t^* = 1$	–28,038***	–35,685***
	(279.7)	(946.9)
$t^* = 2$	–13,926***	–22,826***
	(318.6)	(1,053)
$t^* = 3$	–11,054***	–19,338***
	(347.8)	(1,135)
$t^* = 4$	–14,489***	–19,120***
	(392.8)	(1,420)
$t^* = 5$	–14,994***	–18,969***
	(486.9)	(1,533)
$t^* = 6$	–15,292***	–22,044***
	(592.5)	(1,834)
Unemployed 2 years		
$t^* = -3$	–1,033***	–2,336***
	(174.7)	(379.9)
$t^* = -2$	–1,250***	–2,076***
	(203.7)	(447.0)
$t^* = -1$	–2,848***	–3,151***
	(210.2)	(489.0)
$t^* = 0$	–3,951***	293.3
	(224.9)	(502.0)
$t^* = 1$	–25,849***	–35,517***
	(236.3)	(562.3)
$t^* = 2$	–25,849***	–35,517***
	(236.3)	(562.3)

Table B1: Regression Output for Figure 3 and Figure 4 (Contd.)

Relative Time	*Closure Earnings*	*Mass-layoff Earnings*
t = 3*	–14,810***	–15,212***
	(352.2)	(883.2)
t = 4*	–12,399***	–7,748***
	(457.5)	(1,093)
t = 5*	–12,865***	–7,460***
	(784.1)	(1,208)
t = 6*	–14,986***	–15,520***
	(800.1)	(4,881)
Unemployed 3 years		
t = –2*	–1,822***	–1,591***
	(200.8)	(313.6)
t = –1*	–2,512***	–1,732***
	(212.9)	(377.1)
t = 0*	–3,945***	–2,583***
	(222.8)	(406.6)
t = 1*	–27,333***	–28,338***
	(257.0)	(482.4)
t = 2*	–27,333***	–28,338***
	(257.0)	(482.4)
t = 3*	–27,333***	–28,338***
	(257.0)	(482.4)
t = 4*	–15,587***	–16,321***
	(621.4)	(1,012)
t = 5*	–14,012***	–10,979***
	(797.2)	(1,535)
t = 6*	–16,380***	–12,491***
	(1,044)	(3,657)
Re-employed at *t*+1		
t = –4*	–665.5***	–2,301***
	(188.1)	(883.8)
t = –3*	–194.0	–1,716*
	(211.2)	(1,029)
t = –2*	–698.2***	–3,674***
	(217.7)	(1,076)
t = –1*	–1,303***	–4,333***
	(219.7)	(1,096)
t = 0*	–277.5	–3,245***
	(222.6)	(1,108)

Table B1: Regression Output for Figure 3 and Figure 4 (Contd.)

Relative Time	*Closure Earnings*	*Mass-layoff Earnings*
t = 1*	–5,368***	–12,505***
	(226.8)	(1,116)
t = 2*	–4,977***	–12,342***
	(251.4)	(1,195)
t = 3*	–6,632***	–15,199***
	(258.5)	(1,201)
t = 4*	–11,032***	–16,286***
	(281.5)	(1,232)
t = 5*	–11,280***	–17,445***
	(314.9)	(1,256)
t = 6*	–12,705***	–17,311***
	(393.8)	(1,298)
Observations	2,001,473	284,346
Fstat	–	–
Prob > F	–	–
R-squared	0.150	0.264

Source: Authors' analysis.
Notes: (a) Table reports estimated earnings losses for those displaced and unemployed for 1, 2 and 3 years as well as losses for those re-employed immediately after displacement at $t + 1$
(b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Regression output for Figure 5

Relative Time	*Closure Male Earnings*	*Closure Female Earnings*
$t^* = -4$	–1,665***	–1,235***
	(259.9)	(201.1)
$t^* = -3$	–1,451***	–1,041***
	(296.0)	(233.2)
$t^* = -2$	–2,082***	–1,357***
	(310.6)	(242.6)
$t^* = -1$	–3,363***	–2,284***
	(321.8)	(248.2)
$t^* = 0$	–4,669***	–2,733***
	(325.7)	(250.5)
$t^* = 1$	–16,230***	–9,723***
	(336.2)	(257.1)
$t^* = 2$	–10,896***	–6,857***
	(358.9)	(282.5)
$t^* = 3$	–8,015***	–5,019***
	(369.3)	(296.1)
$t^* = 4$	–7,670***	–5,205***
	(399.4)	(336.4)
$t^* = 5$	–6,489***	–4,874***
	(460.4)	(378.4)
$t^* = 6$	–7,044***	–4,349***
	(554.6)	(472.9)
Observations	1,222,873	778,600
Fstat	2,965.24	1,338.23
Prob > F	0.000	0.000
R-squared	0.073	0.037

Source: Authors' analysis.
Notes: (a) Table reports estimates of δ^k from Equation 1. These figures are in real Euros (Base period = 2011).
(b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table B3: Regression output for Figure 6

Relative Time	*Mass-Layoff Male Earnings*	*Mass-layoff Female Earnings*
$t^* = -4$	–2,303**	–1,952*
	(1,062)	(1,019)
$t^* = -3$	–3,032**	–2,976***
	(1,185)	(1,110)
$t^* = -2$	–3,595***	–3,434***
	(1,222)	(1,152)
$t^* = -1$	–4,492***	–4,988***
	(1,244)	(1,183)
$t^* = 0$	–6,499***	–4,870***
	(1,263)	(1,188)
$t^* = 1$	–30,620***	–20,508***
	(1,275)	(1,210)
$t^* = 2$	–25,796***	–17,480***
	(1,317)	(1,249)
$t^* = 3$	–21,191***	–13,180***
	(1,333)	(1,265)
$t^* = 4$	–18,401***	–11,177***
	(1,391)	(1,322)
$t^* = 5$	–17,691***	–10,076***
	(1,483)	(1,375)
$t^* = 6$	–13,438***	–5,993***
	(1,635)	(1,524)
Observations	180,164	104,182
Fstat	1,007.86	535.20
Prob > F	0.000	0.000
R-squared	0.182	0.148

Source: Authors' analysis.
Notes: (a) Table reports estimates of δ^k from Equation 1. These figures are in real Euros (Base period = 2011).
(b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table B4: Regression output for Figure 7

	Closure Sample by Age				
Relative Time	*16-25 Years Earnings*	*26-35 Years Earnings*	*36-45 Years Earnings*	*46-55 Years Earnings*	*56-64 Years Earnings*
$t^* = -4$	652.9***	–536.6**	–2,243***	–1,268**	–1,739**
	(209.9)	(218.8)	(381.7)	(519.8)	(708.3)
$t^* = -3$	1,092***	446.5*	–1,607***	–775.3	–2,509***
	(234.4)	(248.5)	(438.1)	(593.0)	(818.9)
$t^* = -2$	1,039***	105.5	–1,938***	–1,211*	–3,265***
	(245.4)	(264.2)	(459.6)	(623.0)	(838.3)
$t^* = -1$	921.8***	–772.2***	–3,365***	–2,434***	–4,278***
	(252.1)	(273.0)	(475.3)	(649.0)	(870.2)
$t^* = 0$	859.4***	–1,563***	–4,649***	–3,472***	–5,311***
	(252.6)	(276.2)	(481.4)	(653.3)	(892.5)
$t^* = 1$	–5,386***	–11,050***	–16,194***	–14,648***	–15,201***
	(261.3)	(288.6)	(496.1)	(677.1)	(910.8)
$t^* = 2$	–1,696***	–6,151***	–11,581***	–10,303***	–11,077***
	(271.8)	(317.7)	(540.8)	(727.8)	(970.8)
$t^* = 3$	10.54	–3,617***	–8,541***	–7,761***	–8,560***
	(282.6)	(336.0)	(563.6)	(751.3)	(985.6)
$t^* = 4$	481.0	–3,375***	–8,779***	–8,555***	–8,861***
	(308.5)	(397.5)	(636.4)	(832.1)	(1,060)
$t^* = 5$	995.1***	–2,319***	–7,530***	–7,390***	–7,617***
	(367.1)	(490.5)	(748.0)	(935.9)	(1,110)
$t^* = 6$	1,048**	–2,862***	–8,085***	–7,681***	–6,041***
	(492.7)	(661.9)	(933.0)	(1,138)	(1,178)
Observations	350,481	644,697	484,019	319,733	162,270
Fstat	1,200.58	1,583.18	941.13	605.08	435.01
Prob > F	0.000	0.000	0.000	0.000	0.000
R-squared	0.072	0.060	0.057	0.064	0.098

Source: Authors' analysis.
Notes: (a) Table reports estimates of δ^k from Equation 1. These figures are in real Euros (Base period = 2011).
(b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table B5 Regression output for Figure 8

	Mass-layoff Sample by Age				
Relative Time	*16-25 Years Earnings*	*26-35 Years Earnings*	*36-45 Years Earnings*	*46-55 Years Earnings*	*56-64 Years Earnings*
$t^* = -4$	1,926**	349.3	–1,907	–3,946	389.3
	(894.6)	(1,041)	(1,469)	(2,429)	(3,215)
$t^* = -3$	2,817***	1,077	–2,140	–4,968*	–1,358
	(981.6)	(1,171)	(1,658)	(2,612)	(3,544)
$t^* = -2$	3,533***	1,215	–3,000*	–6,148**	–1,971
	(1,017)	(1,198)	(1,749)	(2,648)	(3,642)
$t^* = -1$	3,943***	833.5	–4,046**	–6,660**	–3,772
	(1,032)	(1,212)	(1,776)	(2,705)	(3,777)
$t^* = 0$	2,424**	–2,003	–6,010***	–4,555	–1,015
	(1,033)	(1,220)	(1,788)	(2,777)	(3,946)
$t^* = 1$	–8,619***	–20,895***	–33,564***	–33,818***	–28,692***
	(1,044)	(1,241)	(1,820)	(2,770)	(3,979)
$t^* = 2$	–5,179***	–16,436***	–29,121***	–30,819***	–22,137***
	(1,062)	(1,275)	(1,912)	(2,918)	(4,088)
$t^* = 3$	–2,660**	–12,040***	–24,832***	–24,760***	–15,253***
	(1,068)	(1,294)	(1,955)	(2,980)	(4,150)
$t^* = 4$	–1,025	–9,116***	–21,449***	–20,482***	–8,388*
	(1,120)	(1,353)	(2,122)	(3,082)	(4,325)
$t^* = 5$	752.3	–7,833***	–20,867***	–17,829***	–4,631
	(1,201)	(1,495)	(2,248)	(3,157)	(4,328)
$t^* = 6$	2,518*	–5,980***	–14,386***	–11,477***	–2,706
	(1,316)	(1,744)	(2,703)	(3,446)	(4,491)
Observations	61,659	102,807	57,919	38,364	20,325
Fstat	494.74	730.28	305.45	192.96	163.64
Prob > F	0.000	0.000	0.000	0.000	0.000
R-squared	0.172	0.201	0.188	0.187	0.252

Source: Authors' analysis.
Notes: (a) Table reports estimates of δ^k from Equation 1. These figures are in real Euros (Base period = 2011).
(b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table B6: Regression Output for Figure 9

Industry Switchers and Stayers: Closure sample	
Relative Time	*Earnings*
DSwitch	
$t^* = -4$	–1,372***
	(295.1)
$t^* = -3$	–27.53
	(211.2)
$t^* = -2$	–712.5***
	(185.7)
$t^* = -1$	–1,712***
	(165.9)
$t^* = 0$	–2,691***
	(153.3)
$t^* = 1$	–10,590***
	(153.4)
$t^* = 2$	–4,591***
	(164.7)
$t^* = 3$	–2,016***
	(183.0)
$t^* = 4$	–2,256***
	(241.9)
$t^* = 5$	–1,373***
	(324.7)
$t^* = 6$	–339.6
	(465.5)
DStay	
$t^* = -4$	701.5***
	(228.0)
$t^* = -3$	322.4*
	(169.5)
$t^* = -2$	101.0
	(153.1)
$t^* = -1$	–655.3***
	(139.1)
$t^* = 0$	–933.2***
	(130.9)
$t^* = 1$	–4,960***
	(126.4)
$t^* = 2$	–1,955***
	(136.9)
$t^* = 3$	–1,131***
	(154.7)

Table B6: Regression Output for Figure 9 (Contd.)

Industry Switchers and Stayers: Closure sample	
Relative Time	*Earnings*
DStay (contd.)	
$t^* = 4$	–2,498***
	(222.0)
$t^* = 5$	–3,209***
	(296.2)
$t^* = 6$	–5,366***
	(398.8)
Observations	2,001,473
Fstat	5,793.06
Prob > F	0.000
R-squared	0.541

Source: Authors' analysis.
Notes: (a) Table reports estimated losses for displaced industry switchers and non-switchers. (b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table B7: Regression output for Figure 10

Industry Switchers and Stayers: Closure sample	
Relative Time	*Earnings*
DSwitch	
$t^* = -4$	–3,844***
	(919.1)
$t^* = -3$	–5,310***
	(664.6)
$t^* = -2$	–5,658***
	(571.7)
$t^* = -1$	–5,965***
	(488.1)
$t^* = 0$	–8,115***
	(425.6)
$t^* = 1$	–23,446***
	(373.3)
$t^* = 2$	–16,110***
	(399.5)
$t^* = 3$	–11,616***
	(444.9)
$t^* = 4$	–8,395***
	(626.4)
$t^* = 5$	–6,779***
	(772.4)
$t^* = 6$	–1,847*
	(967.2)
DStay	
$t^* = -4$	–3,196***
	(964.4)
$t^* = -3$	–893.8
	(633.1)
$t^* = -2$	–1,580***
	(529.6)
$t^* = -1$	–2,291***
	(448.9)
$t^* = 0$	–2,821***
	(407.4)
$t^* = 1$	–11,524***
	(357.0)
$t^* = 2$	–8,920***
	(376.5)
$t^* = 3$	–5,942***
	(394.3)

Table B7: Regression output for Figure 10 (Contd.)

Industry Switchers and Stayers: Closure sample	
Relative Time	*Earnings*
DStay (Contd.)	
$t^* = 4$	–6,494***
	(563.5)
$t^* = 5$	–9,278***
	(667.8)
$t^* = 6$	–13,055***
	(831.0)
Observations	284,346
Fstat	1,013.17
Prob > F	0.000
R-squared	0.582

Source: Authors' analysis.
Notes: (a) Table reports estimated losses for displaced industry switchers and non-switchers. (b) Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table B8: Regression output for Figure 11

	Closure Sample Pre- and Post-Crash	
	Pre-2008	*Post-2008*
Relative Time	*Earnings*	*Earnings*
$t^* = -4$	–	–1,488***
	–	(180.5)
$t^* = -3$	–	–1,283***
	–	(206.9)
$t^* = -2$	–	–1,763***
	–	(217.5)
$t^* = -1$	–1,259***	–2,780***
	(201.8)	(224.3)
$t^* = 0$	–1,679***	–3,909***
	(220.5)	(226.8)
$t^* = 1$	–12,210***	–13,370***
	(246.1)	(236.0)
$t^* = 2$	–7,329***	–9,202***
	(254.4)	(260.5)
$t^* = 3$	–5,729***	–5,821***
	(260.2)	(279.0)
$t^* = 4$	–4,581***	–
	(266.9)	–
$t^* = 5$	–3,625***	–
	(329.3)	–
$t^* = 6$	–3,837***	–
	(399.6)	–
Observations	610,105	1,391,368
Fstat	1,598.07	3,778.34
Prob > F	0.000	0.000
R-squared	0.064	0.045

Source: Authors’ analysis.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B9: Regression output for Figure 12

	Mass-layoff Sample Pre- and Post-Crash	
Relative Time	*Pre-2008 Earnings*	*Post-2008 Earnings*
*t** = –4		–2,196***
		(809.6)
*t** = –3		–3,238***
		(900.1)
*t** = –2		–3,708***
		(931.8)
*t** = –1	–1,682***	–4,336***
	(590.0)	(948.1)
*t** = 0	–935.1	–6,640***
	(646.8)	(957.9)
*t** = 1	–19,700***	–28,725***
	(684.8)	(972.3)
*t** = 2	–15,733***	–24,736***
	(702.7)	(1,018)
*t** = 3	–13,188***	–19,333***
	(730.9)	(1,041)
*t** = 4	–11,425***	
	(743.5)	
*t** = 5	–10,101***	
	(859.0)	
*t** = 6	–6,262***	
	(1,072)	
Observations	97,916	186,430
Fstat	500.82	1,446.25
Prob > F	0.000	0.000
R-squared	0.152	0.171

Source: Authors' analysis.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B10: Regression output for Figure 13

	Closure Sample Pre- and Post-Crash By Sex			
	Male	*Female*	*Male*	*Female*
	2005-2007	*2005-2007*	*2008-2010*	*2008-2010*
Relative Time	*Earnings*	*Earnings*	*Earnings*	*Earnings*
$t^* = -4$	–	–	–1,665***	–1,235***
	–	–	(259.9)	(201.1)
$t^* = -3$	–	–	–1,447***	–1,040***
	–	–	(296.1)	(232.7)
$t^* = -2$	–	–	–2,099***	–1,262***
	–	–	(311.8)	(243.8)
$t^* = -1$	–1,506***	–916.3***	–3,277***	–2,059***
	(263.0)	(268.7)	(321.9)	(249.5)
$t^* = 0$	–2,177***	–784.2***	–4,826***	–2,594***
	(286.3)	(293.4)	(325.7)	(250.7)
$t^* = 1$	–14,499***	–7,973***	–16,037***	–9,513***
	(321.8)	(319.9)	(339.4)	(260.3)
$t^* = 2$	–8,742***	–4,730***	–10,899***	–6,752***
	(332.8)	(330.8)	(373.0)	(295.7)
$t^* = 3$	–6,791***	–3,789***	–7,013***	–4,071***
	(339.7)	(341.1)	(397.4)	(327.5)
$t^* = 4$	–5,520***	–2,870***	–	–
	(348.6)	(350.2)	–	–
$t^* = 5$	–4,337***	–2,539***	–	–
	(444.5)	(423.6)	–	–
$t^* = 6$	–4,892***	–2,016***	–	–
	(542.3)	(509.5)	–	–
Observations	396,957	213,148	825,916	565,452
Fstat	1,290.36	432.65	2,711.70	1,326.44
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.079	0.046	0.060	0.035

Source: Authors' analysis.
Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B11: Regression output for Figure 14

	Mass-layoff Sample Pre- and Post-Crash By Sex			
	Male	*Female*	*Male*	*Female*
	2005-2007	*2005-2007*	*2008-2010*	*2008-2010*
Relative Time	*Pay2*	*Pay2*	*Pay2*	*Pay2*
*t** = –4	–	–	–2,302**	–1,901*
	–	–	(1,062)	(1,019)
*t** = –3	–	–	–3,149***	–3,014***
	–	–	(1,185)	(1,111)
*t** = –2	–	–	–3,548***	–3,678***
	–	–	(1,226)	(1,151)
*t** = –1	–1,365*	–3,644***	–4,046***	–4,566***
	(795.7)	(783.7)	(1,246)	(1,173)
*t** = 0	–135.8	–3,007***	–7,215***	–4,898***
	(878.5)	(845.8)	(1,262)	(1,172)
*t** = 1	–22,635***	–16,839***	–32,010***	–21,654***
	(922.1)	(910.3)	(1,279)	(1,202)
*t** = 2	–17,793***	–14,027***	–27,425***	–18,691***
	(948.2)	(935.5)	(1,339)	(1,264)
*t** = 3	–15,921***	–10,593***	–21,671***	–14,068***
	(989.5)	(963.7)	(1,370)	(1,294)
*t** = 4	–13,757***	–9,358***	–	–
	(1,005)	(986.2)	–	–
*t** = 5	–13,049***	–8,257***	–	–
	(1,203)	(1,127)	–	–
*t** = 6	–8,796***	–4,174***	–	–
	(1,393)	(1,338)	–	–
Observations	55,539	42,377	124,625	61,805
Fstat	318.83	247.89	1,067.50	490.94
Prob > F	0.000	0.000	0.000	0.000
R-squared	0.177	0.133	0.185	0.176

Source: Authors' analysis.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table B12: Regression output for Figure 15

	Closure sample, Construction sector	
	2005-2007	*2008-2010*
Relative Time	*Earnings*	*Earnings*
$t^* = -4$		–1,852***
		(534.8)
$t^* = -3$		–3,102***
		(620.9)
$t^* = -2$		–4,155***
		(666.2)
$t^* = -1$	–1,988***	–5,281***
	(333.9)	(690.5)
$t^* = 0$	–1,914***	–7,607***
	(370.8)	(705.5)
$t^* = 1$	–14,833***	–19,715***
	(423.4)	(726.8)
$t^* = 2$	–7,885***	–12,747***
	(439.5)	(755.8)
$t^* = 3$	–5,129***	–10,003***
	(449.4)	(768.8)
$t^* = 4$	–3,552***	
	(456.4)	
$t^* = 5$	–1,630***	
	(556.7)	
$t^* = 6$	150.2	
	(709.5)	
Observations	155,091	217,246
Fstat	1,158.21	1,982.38
Prob > F	0.000	0.000
R-squared	0.180	0.180

Source: Authors' analysis.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B13: Regression output for Figure 16

	Mass-layoff Sample, Construction sector	
	2005-2007	2008-3010
Relative Time	*Earnings*	*Earnings*
$t^* = -4$		–2,663
		(3,921)
$t^* = -3$		–4,935
		(4,416)
$t^* = -2$		–2,345
		(4,492)
$t^* = -1$	1,227	–4,376
	(2,524)	(4,513)
$t^* = 0$	4,903*	–9,886**
	(2,552)	(4,560)
$t^* = 1$	–22,728***	–36,405***
	(2,804)	(4,573)
$t^* = 2$	–16,678***	–23,778***
	(2,859)	(4,804)
$t^* = 3$	–11,861***	–17,578***
	(2,904)	(4,925)
$t^* = 4$	–7,712***	
	(2,840)	
$t^* = 5$	–1,996	
	(3,517)	
$t^* = 6$	–5,324	
	(3,793)	
Observations	6,196	19,199
Fstat	123.11	414.43
Prob > F	0.000	0.000
R-squared	0.350	0.349

Source: Authors' analysis.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.