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ABSTRACT

This study explores the impacts of occupational injuries on workers up to five years after the incident. The authors implement propensity score techniques and make use of longitudinal administrative data that merge social security information with workers' compensation records. Results show that Italian blue-collar workers with severe temporary disabilities suffer larger long-term earnings losses than permanently but mildly partially disabled workers. This is not because of lower post injury wages, but because of losses in terms of future employability. Results are more pronounced in the case of women. They also suffer a long-term decline in quality of life as measured by a relative increase in the use of sick leave. These workers are not entitled to any compensation after returning to work, differently from those facing mild permanent partial disabilities. Hence, the workers' compensation system "fails" these temporary disabled workers, even in a generous system that guarantees return to work.

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KEY WORDS: Injury, workers' compensation, employment, sick leave, gender, propensity score matching.

JEL codes: I18, J28

1. Introduction

Adults who suffer health shocks suffer economic consequences such as a decline in employment and income (Prinz et al., 2018). The different institutions and social insurance programs that characterize each country heavily affect the magnitude of these effects. Differences in terms of generosity of benefits, incentives to provide accommodations, connections between health care, disability, and unemployment systems interact so that consequences of health shocks are more severe in countries where individuals face more difficulties in reentering the labor market after the event (García-Gómez 2011; Prinz et al. 2018).

One type of health events that has received relatively little attention in the economic literature is occupational injuries. This is surprising given that occupational incidents can lead to even larger negative economic outcomes compared to more general health shocks. Work injuries in fact can lead not only to reduction in total earning and employment, but to a long lasting reduction in wages because they can result in permanent disabilities, or because of the litigious climate they can generate, and the “stigma” that marks injured workers. Furthermore, on-the-job injuries are responsible for substantial costs carried not only by workers, but also by their families, employers, government agencies, and taxpayers (European Agency for Safety and Health at Work, 2014). Recent estimates presented by the EU-OSHA and by the ILO have set the value of worldwide losses caused by work related injuries and illnesses at approximately 3.9% of GDP (European Agency for Safety and Health at Work, 2017).

However, stakeholders of workers’ compensation systems are aware that such figure may underestimate the real burden that work related incidents put on workers. On one site, there is growing awareness that statistics regarding on the job injuries dramatically undercount such incidents because of systematic underreporting (Concha Barrientos et al. 2005; Boden and Ozonoff, 2008; Tucker at al. 2014). In addition, in several countries the income replacement provided by workers' compensation benefits is far below 100% so that injured workers and their households suffer large income losses. Injuries resulting in permanent partial or total disabilities (PPD or PTD) are likely to produce negative consequences also in terms of both physical and mental wellbeing.

This paper wants to explore a specific problem that has not received enough attention both in terms of economic analysis and policy discussion. We want to focus on a specific group of injured workers that seem to be severely shortchanged by the workers' compensation system. They are employees who suffer temporary total disabilities (TTD), but injuries that are severe enough to require long recovering time. Given the temporary nature of such disabilities, workers' compensation systems do not compensate such workers after they have officially "healed". However, the very few studies that have discussed separately this group using US data (Biddle, 1998, Boden and Galizzi 1999; Seabury et al. 2014) have highlighted that this category of workers suffer losses equal or even larger than the ones carried by permanently disabled workers who instead can usually count on continuous compensation. Different mechanisms could cause this result. On one side, when the job is not guaranteed after an injury, workers may feel pressure to return to work before they have fully recovered. This could have negative consequences on their future health and, therefore, future productivity. Also, if workers' compensation benefits do not fully compensate lost income during the time off work, workers may face a liquidity constraint and lower their reservation wage or career expectations when they return to work after the injury, especially if they need start with a new employer. A third hypothesis is that occupational injuries "scar" a workers' employment history and affects them negatively over time despite their recovery. To cast light on this set of potential explanations we study an institutional setting that is characterized by a higher degree of employment protection compared to the US labor market that has been studied most often before. The Italian workers' compensation system is more "generous" than the ones analyzed in previous studies. Prior research has focused mainly on countries with wage loss systems where most workers are only partially compensated for their injury related earning losses. In the Italian labor market injured workers are guaranteed a return to work with their preinjury employers. Also, temporary disabilities are compensated through a de facto 100% wage replacement rate. Under this scenario, if workers with severe but only temporary disabilities suffer large income losses over time, we can conclude that the scarring effect of injuries is indeed present across all labor markets, regardless the level of employment protection. These workers are “failed” by the system. Our research examines outcomes across all types of workers’ compensation disability cases, but it is the first to study this group of workers with long lasting TTD as the specific “treatment” group.

In addition, we conduct a separate analysis by gender. It is striking that despite the continuous increase in women labor force participation across all countries, almost no analysis has focused specifically on the income losses experienced by injured women. It is true that women experience fewer job related injuries than men do. For example, in 2017 only 34.7% and 38.7% of all occupational injuries occurred to women in Italy (INAIL 2018) and in the U.S. (BLS, 2020). However, Italian women have also experienced a slower decline in the number of occupational incidents: a decline of 5.8% vs. a decline of 8.8% for men between 2013 and 2107 (INAIL, 2019). We need a much better understanding of the costs carried by this increasing segment of the workforce (Cruz et al. 2016).

Finally, as in previous studies we look at the effect of injuries on employment and wages. However, we introduce a new distinction in terms of worked days and paid sick days to also explore another outcome that has been almost completely ignored by the literature: additional health related absences suffered by workers after their return to work. These absences suggest additional costs in terms of diminished quality of life. Such costs no longer fall under the workers’ compensation system. Instead, individuals, households and the public health insurance absorb them. Therefore, this potential outcome adds another ignored dimension of the cost of occupational injuries for both workers and taxpayers.

For our analysis, we access an unusually rich dataset that merges workers' compensation data with employer–employees administrative data covering both careers of workers over a 20-year time span, and detailed information on work incident, disability and length of the healing period.

2. Previous Literature

The effects of occupational injuries are similar to the ones experienced by displaced workers. In both cases, benefits could induce moral hazard behavior or liquidity effects (Boden and Galizzi, 2017). Both the experiences of unemployment and of injuries may "scar" workers' reputation and jeopardize their future employability (Strunin and Boden, 2000; Arulampalam, 2001). Time off work can lead to an obsolescence of skills that will result in decreased productivity and earning potentials. Therefore, the study of the long-term economic effect of occupational injuries has mirrored the analysis of the experience of displaced workers (Jacobson et al. 1993).

There are some differences, however. An injury implies productivity, adjustment, and insurance costs for the firm, injuries. Workers' compensation cases are often handled in more adversarial and litigious climate between employers and employees. Conflicts arise also potentially with coworkers who have to absorb extra duties and tasks while the injured worker is off work (Galizzi et al. 2010). Injuries may result in residual or permanent disabilities that last after the day of return to work and/or the day of maximum recovery. Finally, third parties, the medical examiners, affect the decisions about time off work.

Over the last twenty-five years, the availability of large administrative and employer-employees data sets have facilitated the development of longitudinal studies that have explored the effect of injuries on workers' earnings over time. As in the case of displaced workers, or of adult individuals suffering because of more general health shocks (Prinz et al. 2018), the approach usually consists in making use of difference in differences methods (Jacobsen et al. 1993; Charles 2003), or matching methods (Hyslop and Townsend 2018; García-Gómez 2013) to compare post-injury earnings of the affected workers against the ones of a comparison group that did not experience the same event (Prinz et al. 2018).

Most of the evidence on injured workers' earnings losses comes from studies that have focused on the U.S. and Canada. A first set of analyses exploited large administrative workers' compensation data to compare the experience between workers with long lasting temporary or permanent injuries, and workers who filed for short-duration claims (Boden and Galizzi, 1999 and 2003), or medical-only claims (Biddle, 1998). Other studies merged workers' compensation data with unemployment insurance records to match the experience of workers' compensation claimants against the ones of uninjured workers employed at the same pre-injury firm (Berkowitz and Burton, 1987; Reville, 1999; Biddle et al. 2001; Boden et al., 2005; Dworsky et al. 2016). While this second set of studies improved on the first ones by comparing earnings histories *within* the same firms, they sacrificed other dimensions important for comparisons. In fact, U.S. unemployment insurance records do not contain information about gender, age, occupation and job tenure. They are also state specific and do not permit to capture the compensation or future earning experiences of workers who are employed or move out of state. All these studies also focused *only* on workers who experienced permanent disabilities. Finally, a recent set of studies has made use of survey data from national samples of workers (Woock 2009; Dong et al. 2016, Mazzolini 2020). This last approach has the great advantage of accounting also for the experience of workers who were injured, but did not report the injuries, or did not file for workers' compensation. Survey data also permit to control for several additional demographic and firm information. The drawback is that the experiences of earning losses, job separations, and unemployment are self-reported and, therefore, subject to recall bias.

Despite the different data sources and methodologies, a relatively clear picture emerges. Workers who suffer lost-time injuries experience lasting earnings losses that continue for several years, far beyond the time off work. This is particular true for workers who suffer permanent disabilities. They may end up losing up to 40% of their income compared to their uninjured counterparts (Reville, 1999; Seabury et al. 2014). Particularly challenging are the findings that earnings losses are also experienced by workers who only suffered temporary disabilities, but temporary disabilities that were severe enough, however, to require a long spell of recovery time (Biddle, 1998, Boden and Galizzi 1999; Seabury et al. 2014). We will focus on this last group.

Our study improves on previous analyses in several ways. As mentioned above, most studies that have made use of workers' compensation and unemployment insurance data have focused on assessing losses for only the most expensive cases, i.e. permanently disabled cases (McLaren and Baldwin, 2017). Instead, our research studies economic outcomes across both temporary and permanent disabilities. At the same time, with merged social security data we can still compare the experience of injured workers with the ones of workers who were not injured after accounting for a rich set of preinjury characters. Only very few studies have made use of social security data to study work injuries outcomes but, differently from us, have not done it for a whole country (Seabury et al. 2014), or specifically for occupational injuries (Crichton et al. 2011).

Furthermore, we conduct our analysis separately by gender. In a 2003 paper, Boden and Galizzi examined this topic for the first time. More than three years after the injury, they found larger earnings losses for women (9.2%) than for men (6.5%). This difference could not be all explained by changes in employment. Since then, only a handful of studies have looked at work injuries and economic outcomes by gender (Crichton et al. 2011; Seabury et al. 2014). They have also found larger proportional losses for women, especially in cases where injuries resulted in more severe/longer TD and PPD cases.

Finally, no economic study has looked at sickness absences as an additional post return to work outcome. We know that earnings over time are affected by potential new spells off work after a first return to work (Butler et al. 2006). We know that a large percentage of injured workers experience new injuries and file new workers' compensation claims (Campolieti, 2001; Galizzi 2013), are likely to become beneficiaries of the disability insurance system (O'Leary et al., 2012), or report poor health years after the injury (Dong et al., 2015). However, we know very little in terms of injured workers' increased use of sickness absences. In Larsson and Björnstig (1995) 23% of injured workers reported persistent medical problems five years after their injury. Molinero-Ruiz et al. (2015) found that around 3% of injured workers had a sickness absence within six months after their return to work. Regardless of whether such sick leaves are, or are not, directly caused by the work injury, these results suggest that injured workers carry a cost that is not acknowledged and compensated by workers' compensation systems. Our data permits us to observe sickness absences and we study them.

Our study builds on this body of largely Northern American evidence. We aim to provide an additional international perspective on wider and new impacts of workplace injuries, leveraging on a deeply different institutional setting.

3. Institutional setting

In Italy, a public insurance system provides medical and disability benefits to all injured employees. The system is managed by the National Workers' Compensation Agency (INAIL) and is financed by firms through premiums. Workers who are injured are entitled to a recovery period, the length of which is established by a doctor specialized in occupational medicine and who is certified to work for INAIL (Galizzi et al. 2016). According to Italian law, injured workers' jobs are preserved until the employees return to work, i.e., all injured workers return to their previous firm, if they were originally hired with a permanent contract. Temporary contract workers, however, have to leave the firm if the contract expires before the end of the healing period. Recent evidence suggests that injured workers found more easily jobs with new employers after 2001, but fewer jobs with permanent contracts (Galizzi et al., 2019). In this study, we account for such differences in workers' contractual status.

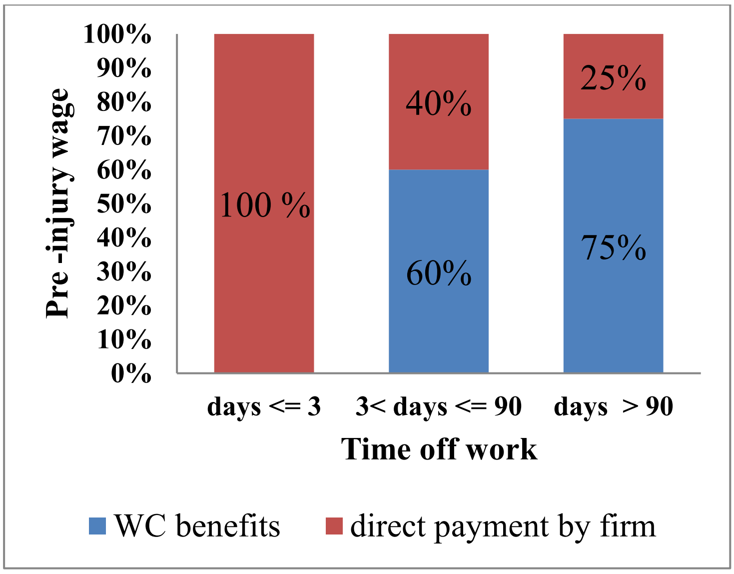
Employers have to carry the adjustment costs that they incur when injured workers return to work. They have to offer accommodations for long-lasting temporary or permanent work disabilities. If there are no viable tasks, workers can be dismissed following a judicial sentence.

Employees receive free medical care and rehabilitation services. If their spell off work lasts more than 3 days, they receive workers' compensation benefits from INAIL ranging from 60% to 75% of their pre-injury earnings subject to a maximum and a minimum (Eurogip, 2005). However, a top-up granted by employers according to collective agreements[1] allows injured employees to earn a de-facto full wage replacement during their absence from work. This means that, in practice, Italian injured workers are guaranteed benefits corresponding to a 100% wage replacement rate (i.e., benefits cover the full labor cost, including taxes and social security contributions like the normal salaries) (Figure 1). The time off work may still lead to

[1] All collective agreements on job contracts entail a top up of INAIL's disability benefit to 100% of the wage, with just a few exceptions that are not relevant to our study (Leombruni and Costamagna, 2013).

the loss of overtime payments.

Figure 1: ***TTD payments***



Workers suffering injuries resulting in temporary total disabilities (TTD) receive benefits only during time of recovery. When the injury results in a permanent partial disability (PPD), workers are entitled to further compensation that is a function of the degree of disability and of their demographic characteristics and wages, as summarized in Table 1. Annuities and lump sums workers' compensation benefits are updated over time according to the official inflation rate and are not taxed.

Table 1: **INAIL provisions after a work injury**

Replacement rate (TTD and PPD)	
Length of absence from work < 4 days	no involvement of INAIL. Responsibility of the firm, according to collective contract agreements
>= 4 days	full wage replacement (INAIL + employer)
Additional Compensation for PPD	
Degree of permanent disability	
0% - 5%	no further compensation, but totally free health care
6% - 15%	lump sum according to age, gender and permanent disability rating

16% - 100%	annuities paid according to the permanent disability rating and the wage earned before the injury

4. The Whip-Salute dataset

The data used in this study is extracted from the Work and Health Histories Italian Panel (Whip-Salute). This is a database of individual work histories (Whip) developed from the merge of the administrative archives of several public administrations holding data on employment (among which INPS, the National Institute for Social Security) with data on occupational injuries from INAIL. It represents a unique source of information for the analysis of occupational injuries for a 7% random sample of Italian workers over the period 1994-2012 (see Bena *et al.,* 2012, for details)[2].

The WHIP database consists of the employment records of dependent workers, self-employed workers, and subcontracted employees; some professional categories, such as architects and lawyers, are not included. It covers all private production sectors in manufacturing, construction and services, as well as temporary contract workers in the public sector, but excludes most permanent workers in the public and in the agricultural sectors.

[2] The linkage between the two was implemented through an encrypted unique identifier based on the individual's tax code; it was carried out independently by the two organizations. All activities, regardless of their complexity or depth, were conducted in accordance with Italian regulations on privacy and with the approval of the national institutes involved. In 2013, the WHIP-Salute database has been included in the National Statistics Program under the responsibility of the Ministry of Health. According to the Italian regulation on privacy, the institute releases microdata files for research purposes, upon request based on a research protocol.

This employer-employee database comprises a great variety of demographic and employment information: start and end dates of each employment spell, worker's characteristics (age, sex, place of birth), job's characteristics (temporary vs. permanent contract, full-time vs. part- time, occupation, location), labor market outcomes (the number of days and weeks worked in a year and annual earnings), and firm characteristics (size, opening and eventual closing date, sector, location, monthly new hires, and separations).

Both earnings and weeks are recorded annually as total yearly gross wages and total number of worked weeks. We do not have records for worked hours but we know workers' part-time or full-time status and therefore the number of full-time equivalent (FTE) worked weeks. With this set of variables, we compute average FTE weekly earnings.

The data on occupational injuries originate from the archives of INAIL, that records all injury events resulting in time off longer than three days. The data records a description of the injury event itself (type of injury, nature of accident and body part) and its consequences (length of temporary disability payment, degree of permanent disability – if any). It is important to note that in the Italian institutional setting and data the measure of spells off work is a function of date of injury and of the actual date when the workers return to actual employment, which coincides with the time when benefits end.

4.1 Our sample

For this work, from the WHIP-Salute database we select a subset of workers (Table 2). First, among individuals suffering a work incident, we single out only workers experiencing their first work injury in year *t*, where *t* refers to any year in the period 2001-2007. To be more specific, we impose that no work incident occurs in the previous 7 years, a moving period of equal length for everybody. This way we observe a pre injury time spell that is same in length across all workers (the INAIL data start in 1994). We also separate events by long enough time so that a work injury after 7 years can be considered as unrelated to any potential previous injury event.[3]

We then select blue-collar workers, who face work related risks that are quite different with respect to those faced by white-collar workers or managers. The much smaller number of total work injuries experienced by non-blue-collar workers prove this (Table 2).

We finally exclude non-native workers, a more vulnerable segment of the working population that faces more difficulties after a work injury (Galizzi et al., 2019).

Pooling all years (2001-2007), we end up analyzing about 70 thousand injured workers (Table 2). The number of injured women is much lower than that of men, as they represent about 20% of the whole sample. This is the consequence of the selection of blue-collar workers only, where they are under-represented (in the whole nationally representative WHIP sample, women were about 38.3% of total workers in 2004; among Italian blue collars they were 27.7%).

Table 2: sample selection (number and percentage by gender)

Steps in sample construction	**Men**	**Women**	**Total**	**% of Total**	**% of previous row**
Individuals working at least one day in years 2001-2007	4,939,561 (62%)	3,091,203 (38%)	8,030,764	100%	-
Restrict to Individuals experiencing one work injury	175,118 (83%)	35,445 (17%)	210,563	2.6%	2.6%
Restrict to individuals for whom	99,203 (79%)	26,183 (21%)	125,386	1.6%	59%

[3] Table 2: sample selection shows that repeated incidents are quite a common feature in Italy, as half of men and one fourth of women do experience such repeated events. These percentages are consistent with what was found in previous studies for other countries (Galizzi, 2013).

this was first injury in 7 years					
Restrict to blue collar workers	81,754 (83%)	16,688 (17%)	98,442	1.2%	79%
Restrict to native workers	**57,437** (80%)	**13,947** (20%)	**71,384**	**1%**	**72%**

In terms of injury characteristics, Table 3 shows that about 88% of all injured workers in the 2001-2007 period experiences temporary disability (TTD) consequences[4]. We define "severe" TTD workers those returning to work after more than 60 days since the work incident (about 5% of all TTD workers), while "mild" TTD workers are those returning earlier and represent 82% of our total sample. The choice of the 60 days threshold is informed by findings of previous studies (Biddle, 1998; Boden and Galizzi, 1999 and 2003; Crichton et al. 2011; Seabury et al. 2014). As expected, Table 3 shows also that the number of PPD workers decreases sharply as the permanent partial disability ratings increase. In the following section, we describe further characteristics of the sample.

[4] For comparison it is important to stress that in the US PPD cases "have varied between 27-41 percent of cases involving cash benefits in the years 1993-2013" (NASI, 2020). The difference from the Italian records is possibly explained by different filing criteria. For example in Italy back injuries fall under the "illness" and not under the "injury" category as in the US..

Table 3: Number of injured workers by compensation group and gender, all years pooled (2001-2007)

group	Women	Men	Total
TTD	12,639	49,595	62,234
Mild	12,014	47,390	59,404
Severe	625	2,205	2,830
PPD	1,308	7,842	9,150
1%-5%	930	5,144	6,074
6%-15%	350	2,314	2,664
16% +	28	384	412
Total	13,947	57,437	71,384

5. Empirical Strategy

5.1 Hypotheses to be tested

Our goal is to assess the economic outcomes of work injuries in an institutional setting that should guarantee income and employment protection to injured workers. We also want to explore whether such protection is guaranteed across all types of injured workers. To be more precise the hypotheses we test are:

H1: *Whether our group of interest (severe TTD injuries) suffers a penalty in terms of employability, labor earnings, and future health that bears long lasting consequences with respect to milder TTD's long term outcomes;*

H2: *Whether their long-term penalty is comparable to that suffered by PPD workers, who instead – because of the permanent characteristic of their injury - are entitled to an additional compensation.*

To do so we implement an empirical strategy where different workers are matched so that we can compare the experience of our treatment group (severe TTD cases, as above defined) with the one of different control groups. Table 4 summarizes the models we estimate.

Table 4: **Estimated models**

Model	Treated (T)	Controls (C)
1.	Temporary disability and RTW **after 60**+ days	**No** work injury
2.	same	Temporary disability and RTW **before 60 days**
3.	same	**1%-5%** permanent disability
4.	same	**6%-15%** permanent disability
5.	same	**16% +** permanent disability

Model 1 compares severe TTD workers to those not experiencing a work incident. It will be presented for completeness, but as we discuss below, it is debatable whether the observable variables we use for matching and discuss in section V are enough to reach unconfoundedness (Rubin, 1990).

Model 2 compares our group of interest (severe TTD) to milder TTD; both groups are not entitled to any compensation after returning to work. Model 3 compares them to mild PPD, who are not entitled to any compensation after returning to work as well, despite the permanent nature of their impairment, as they are not supposed to bear lasting economic consequences (see section III). Model 4 compares severe TTD and medium PPD workers, who receive lump sum compensation. If their long run economic performance was similar, then we should question the fairness of the compensation system. It would be even more so in model 5, where we compare them to severe PPD workers who are entitled to an annuity payment.

We follow the career of all groups of injured workers during the five years preceding the year of the work incident to match treated and controls in that year. Then we follow them in the subsequent five years to measure the outcomes.

We define three main outcomes of interest and we compute them as yearly averages over the period *t+1* to *t+5*, where *t* is the year in which the injury occurs. First, we focus on wages, measured as average real FTE weekly wages earned by the worker in the year. The yearly earning information included in our administrative data represents all what is paid to the workers by the employer, i.e. their gross wage[5]; hence, we calculate weekly wages by dividing total yearly wages by total weeks in paid employment, expressed in full time equivalent terms. Second, we focus on "actual" employment, i.e. on the number of FTE weeks worked in the year, excluding weeks on paid sick leave. Third, we examine the number of FTE weeks on paid sick leave during the year. Average yearly earning losses can then be calculated as weekly wage multiplied by weeks in employment (either at work or on paid sick leave) (presented in Table 7).

We examine two periods: short run, i.e. the average outcomes in years *t+1* to *t+3*; and long run, i.e. the average outcomes in years *t+4* to *t+5.* Our main interest is in the long run consequences, i.e. outcomes 4 - 5 years after the injury. In our sample, the mean length of time off work due to the injury was 32 days and its 90th and 99th percentile was 69 and 251 days respectively. Therefore, we can safely assume that all the observations recorded after *t+2* correspond to a time after the injured worker's return to work. We present our results also by plotting treated and controls average outcomes by *t*, to display their yearly dynamics.

[5] Real wages are measured in 2012 Euro and during the off-work healing period they include the reduced wage and employers' top up. They do not include the INAIL compensation or any other transfer such as unemployment benefits that the worker could have received while non-working in t+1 to t+5.

5.2 Econometric methods

We use matching estimators based on the propensity score, a method originally proposed in Rosenbaum and Rubin (1983) which is widely used to estimate causal effects in observational studies (Abadie and Imbens, 2016). The methods relies on the a key assumption about the selection on observables: if selection into treatment depends only on observable characteristics, then, when they are balanced, any difference in outcomes between treated and controls can be interpreted as the effect of only the treatment (Conditional Independence Assumption, CIA, or unconfoudedness). The key result of Rosenbaum and Rubin (1983) is that adjusting for the propensity score – defined as the conditional probability of treatment given a vector of covariates – is also sufficient to eliminate confounding.

We base our assumption of unconfoundedness on three grounds. Indeed, there may be unobservable factors leading to a selection into injuries that are important also for the outcomes we are considering. As an example, risk aversion is plausibly correlated both with the probability of being injured and with salaries. However, due to the longitudinal nature of our sample, we can observe the rich set of individual characteristics and outcomes we are measuring for several years before the injury. In general, conditioning on the past outcome variables already controls for the part of the unobservables that manifested themselves in the lagged outcome variables themselves (Lechner, 2015). Secondly, although personality traits and attitudes play a significant role for labor market outcomes, there is evidence that for the most part they do not make a significant difference in the estimation of treatment effects when detailed labor market histories are included in the specification (Caliendo, Mahlstedt and Mitnik, 2017). Finally, we build most of our comparison groups considering only individuals who were injured. We deem realistic that most unobserved heterogeneity may determine whether an individual get injured or not, while the consequences in terms of recovery time and/or the precise degree of disability are driven by more idiosyncratic factors. The fact that we achieve a lower balancing when comparing injured and not-injured individuals (Model 1) is supportive to this point (see results below).

The results by Rosenbaum and Rubin have been applied in the literature using different algorithms to perform the matching, with different bearings in terms of bias-reduction and variance of the estimates (Caliendo and Kopeinig, 2008). The choice driving the bias-variance tradeoff is between a more inexact matching – i.e., build a matched sample with some level of unbalance – and a more incomplete matching – i.e., drop more units from the sample in order to maximize bias-reduction and limit model dependence (Parsons, 2001; Iacus, King and Porro, 2011).

In a recent paper, King and Nielsen (2019) pointed out that in pursuing bias-reduction some matching algorithms may accomplish the opposite of their intended goal: inefficiency, model dependence and even bias. It is particularly so in the case of the matching algorithm most used in the literature, the Nearest propensity score neighbour within caliper (NNPS). The authors pointed out a "Propensity Score Matching paradox", where maximizing the similarity in terms of propensity scores between pairs of treated and control units eventually leads to higher imbalance in the characteristic of the individuals and hence in higher bias. To overcome this potential issue King and Nielsen (2019) recommended as alternatives other matching estimators, such as Mahalanobis Distance Matching (MDM) or Coarsened Exact Matching (CEM).

The point has been further discussed by Guo, Fraser and Chen (2020), who stressed that the criticism does not automatic apply to all matching methods, since it is due to the particular way propensity scores interact with matching in the classical NNPS model. In addition to MDM and CEM, already suggested by King and Nielsen (2019), they discuss other methods such as optimal matching and PSM with nonparametric regression that are not prone to the critique.

They present also a Monte Carlo study comparing several estimators in different contexts, concluding that there is not a single model that works well across all scenarios: considering both bias reduction criteria and the external validity of results, NNPS is not always inferior to other models such as MDM.

In our analyses, we use both the widely adopted NNPS and two alternative estimators that are not prone to the "PS Paradox": Mahalanobis distance matching within calipers defined by the propensity score (Rosenbaum and Rubin, 1985), and PSM with nonparametric regression, or Kernel matching, as originally proposed by Heckman, Ichimura and Todd (1997).

We use each of these three methods to compute point estimates, confidence intervals and balancing statistics on the individual characteristics, before and after the matching, over all the 60 combination of comparison groups, outcomes and gender described in the above sections (5 models, 2 genders, 2 periods, 3 outcomes). We estimate confidence intervals by bootstrap in the case of Kernel matching. We use one of the formulas proposed in Abadie and Imbens (2008) in the case of Nearest Mahalanobis neighbor and Nearest propensity score neighbor, a methodology originally presented in Leombruni and Mosca (2019). We conduct our estimates using the SAS System version 9.4, and the macro %PSMatching.

In the following sections, we will present our choice of balancing variables and our preferred estimates, i.e. the results for the Kernel estimator that was most effective in achieving a good balance in the comparison groups. We will also discuss the quality of matches obtained with the different estimators. In **Online Appendix A**, we report all our results and diagnostics.

5.3 Specification of the propensity score

We match treated and controls separately by gender over a wide set of balancing variables, i.e., variables we use both in the estimation of the propensity score and in the computation of the

Mahalanobis distance. They refer to workers and their jobs' characteristics. More specifically, they describe:

- workers' demographics at *t*, year of the injury (age and area of birth);
- preinjury job's characteristics at *t*, i.e. related to the job where the incident occurred (geographical location – province -, industry, firm size, temporary or permanent contract, tenure, total worked weeks);
- pre injury employment experience between *t-1* and *t-5*, i.e. related to any job held in that period (yearly earnings, weekly FTE wages, yearly worked weeks, yearly weeks on sick leave, number of jobs held, average size of firms for which the person worked, number of years the person worked, work experience, and modal occupation - blue, white collar, apprentice, manager)

Table 5 lists the average values of all these variables across the treated and different control groups before the match.

Table 5: average values of the variables for the matching procedure, before the match

Panel A: blue-collar women

	control 1	control 2	treated	control 3	control 4	control 5
	Non-injured	Mild TTD	Severe TTD	Mild PPD	Medium PPD	Severe PPD
at t (year of injury):						
age at t	38.0	38.1	40.6	41.2	44.9	43.6
weeks worked in t	38.3	43.9	41.8	42.5	41.1	41.4
log of firm size	3.7	4.9	4.8	4.3	3.9	4.0
share temporay contracts	21%	18%	16%	19%	20%	21%
lagged:						
log months of tenure at Dec.t-1	2.6	2.7	2.8	2.9	2.9	3.4
total wages earned in *t-1*	11,072	12,935	12,773	13,021	12,628	14,089
no. weeks worked in *t-1*	36.6	40.2	39.9	41.0	40.6	44.3
no. weeks on sick leave in t-3	0.6	1.0	1.5	1.0	0.9	0.2
no. weeks on sick leave in t-4	0.6	0.9	1.0	0.9	0.9	0.4
no. weeks on sick leave in t-5	0.5	0.8	0.9	0.8	0.8	0.6
Over previous 5 years:						
Average real FTE weekly wage	299.8	313.7	315.8	308.4	304.6	302.9
total number of FTE weeks worked	149.9	151.4	152.8	155.9	154.4	147.4

total number of weeks on sick leave	3.5	5.6	7.7	5.4	5.6	3.9
number of different jobs held	1.9	2.1	2.0	1.9	1.9	1.6
number of years in which the person worked	4.0	4.0	4.0	4.1	4.1	4.0
average size of the firms (5 categories)	2.5	3.1	3.1	2.8	2.7	2.7
area of birth:						
Northwest	23.8	24.2	22.6	20.4	22.3	17.9
Northeast	21.5	23.4	21.1	18.8	18.0	21.4
Center	18.6	17.1	16.2	21.2	20.6	10.7
South	25.5	24.6	26.1	28.3	26.9	46.4
Islands	10.6	10.7	14.1	11.3	12.3	3.6
no. Obs	100,047	12,014	625	930	350	28

Panel B: blue-collar men

	control 1	control 2	treated	control 3	control 4	control 5
	Non-injured	Mild TTD	Severe TTD	Mild PPD	Medium PPD	Severe PPD
at t (year of injury):						
age at t	39.0	37.3	40.2	40.1	42.2	43.2
weeks worked in t	41.3	45.2	42.5	44.7	42.6	39.6
log of firm size	3.6	4.1	3.9	3.7	3.4	2.9
share temporay contracts	14%	12%	10%	10%	9%	9%
lagged:						
log months of tenure at Dec. t-1	2.9	2.9	2.8	3.0	2.8	2.7
total wages earned in t-1	17,605	19,019	18,220	19,122	18,247	16,976
no. weeks worked in *t-1*	40.0	42.6	41.0	42.8	41.7	39.4
no. weeks on sick leave in t-3	0.5	0.8	0.9	0.8	0.8	0.8
no. weeks on sick leave in t-4	0.5	0.7	0.8	0.7	0.7	0.7
no. weeks on sick leave in t-5	0.4	0.6	0.8	0.7	0.7	0.7
Over previous 5 years:						
Average real FTE weekly wage	412.8	419.0	416.6	423.5	415.2	414.7
total number of FTE weeks worked	186.6	186.2	180.9	191.0	188.2	182.8
total number of weeks on sick leave	2.9	4.0	5.0	4.1	4.1	4.6
number of different jobs held	1.9	2.1	2.1	2.0	2.1	2.0
number of years in which the person worked	4.2	4.2	4.1	4.2	4.2	4.1
average size of the firms (5 categories)	2.5	2.7	2.6	2.5	2.3	2.1
area of birth:						
NW	20.3	21.9	19.0	18.0	15.3	14.1
NE	14.9	19.4	13.8	15.2	15.2	13.5
CE	15.7	15.4	13.8	17.2	16.2	11.5
SO	34.2	30.0	32.9	34.6	36.3	45.1
IS	14.9	13.3	20.5	15.1	17.1	15.9
no. Obs	99,503	47,390	2,205	5,144	2,314	384

NOTE: additional variables included province (105 provinces, considering also the distance between them, i.e. if two provinces are closed, the score is higher; 1-digit industry code and 2-digit industry code considering the "distance" between two sectors (i.e. if two sectors are similar the score is higher); modal occupation (blue, white collar, apprentice, manager). The average size of the firms in which the person worked was grouped in five categories (<10, 10-19, 20-199, 200-999, 1000+ employees). These statistics are available under request.

A few differences emerge across both males and females. Injury severity increases with age and workers with severe TTD are closer in age to workers with PPD claims. All TTD workers are employed in larger firms with respect to the PPD ones, a result that could suggest a problem of underreporting of less severe injuries in smaller firms. Underreporting of TTD case could also explain the much larger concentration of PPD claims (more difficult to "hide") among workers born and presumably residing in the south, although differences in cultural norms about the use of welfare programs could of also explain this difference. The severity of TTD cases seems also to increase with the time spent on sick leave during the preinjury years. Finally, across all groups women are much more likely to be employed with a temporary contract. Our matching procedure accounts for all these differences. Post-match averages and balancing statistics are reported in Online Appendix A.

6. Results

6.1 Average Treatment Effect of the Treated Estimates

Table 6 summarizes our main results. We study our three outcomes – weekly wages, worked weeks and sick leave weeks – both over the short (t+1 to t+3) and long (t+4 and t+5) run. We compare our treated groups (severe TTD cases) with different control groups as we described before in table 4. We conduct our analysis by gender. For each outcome, we report the Average Treatment effect on the Treated (ATT) and the number of matched treated individuals (i.e. those for which all the balancing variables were not missing and that were on the common support). For each model, we present results from the Kernel estimator, the one that was most effective in achieving balancing between our treatment and the chosen comparison group. We further discuss this choice below and Online Appendix A reports the standard errors and the full results and diagnostics on the quality of the match for all estimators, comparing their performance. For completeness, we report also Model 1 but, as we expected for reasons discussed before, balancing was not very satisfactory, and we do not further discuss it. Again, we refer to “severe TTD” for cases that resulted in time off work longer than 60 days.

Table 6: **ATT estimates - Kernel**

Panel A :
unit real weekly wages

model	**short run (t+1 - t+3)** Men		Women		**long run (t+4 - t+5)** Men		Women	
1: Severe TTD vs. No injury	-6.6		4.0		4.3		9.3	
2: Severe TTD vs. Mild TTD	-10.9	**	-6.6		1.5		0.7	
3: Severe TTD vs. 1-5% PPD	-8.3	**	-2.4		-2.6		0.9	
4: Severe TTD vs. 6-15% PPD	0.6		9.2		5.9		6.7	
5: Severe TTD vs. 16+% PPD	30.1	**	16.4		17.8		79.0	
no. Treated	1560		415		1424		363	

Panel B :
FTE worked weeks per year not on sick leave

model	**short run (t+1 - t+3)** **Men**		**Women**		**long run (t+4 - t+5)** **Men**		**Women**	
1: Severe TTD vs. No injury	-2.8	**	-1.4	**	-2.1	**	-2.2	**
2: Severe TTD vs. Mild TTD	-2.7	**	-2.0	**	-1.8	**	-2.4	**
3: Severe TTD vs. 1-5% PPD	-2.5	**	-3.0	**	-2.3	**	-3.0	**
4: Severe TTD vs. 6-15% PPD	-1.8	**	0.5		-2.0	**	0.9	
5: Severe TTD vs. 16+% PPD	5.6	**	5.5		3.6	**	1.9	
no. Treated	2060		517		2060		517	

Panel C :
FTE sick leave weeks per year

model	**short run (t+1 - t+3)** **Men**		**Women**		**long run (t+4 - t+5)** **Men**		**Women**	
1: Severe TTD vs. No injury	1.7	**	2.3	**	0.6	**	0.9	**
2: Severe TTD vs. Mild TTD	1.1	**	1.4	**	0.2	**	0.1	
3: Severe TTD vs. 1-5% PPD	0.9	**	0.5		0.2	**	0.1	
4: Severe TTD vs. 6-15% PPD	-0.3	**	-0.6		0.0		-0.2	
5: Severe TTD vs. 16+% PPD	-3.4	**	-4.6	**	0.0		-1.2	
no. Treated	2060		517		2060		517	

NOTE: Models 1-5: kernel. Estimates with ** are significantly different from 0 at 95% confidence level; bootstrapped confidence intervals. No other confidence intervals were bootstrapped, not to increase the computational burden.

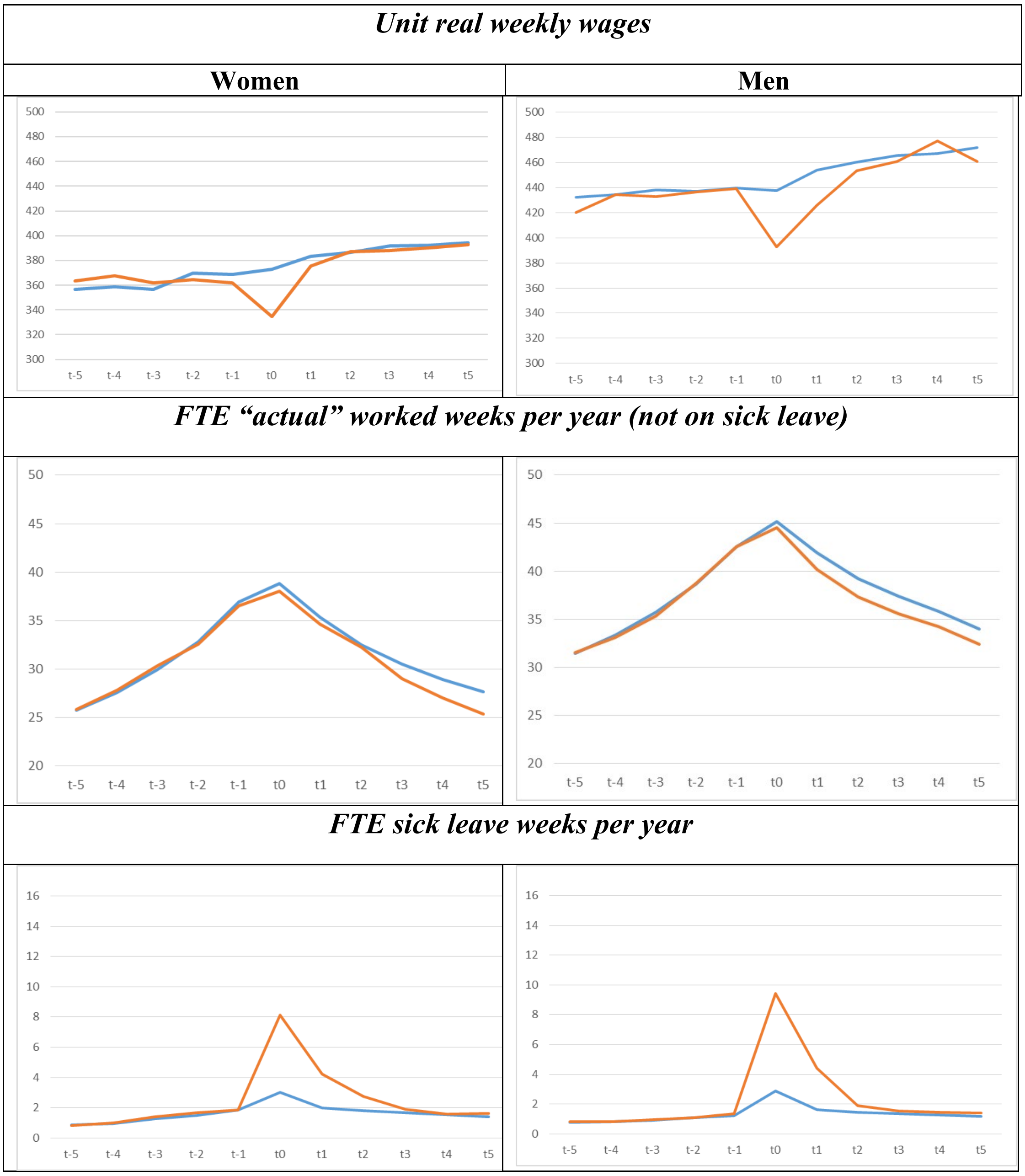
Our first set of estimates indicates no *wage penalty* for severe TTD workers with respect to all control groups. Only a few values are statistically different from each other. The only exception is in the short run when "treated" men lose more in wages than other men with less severe TTD or very low PPD ratings. The loss is quite negligible, however (11 and 8 euro respectively -table 6- out of an average weekly wage of 417 euro over the previous 5 years). We do not observe any differences among women' groups. These first results suggest that, conditional on working, wages were protected after the injury.

Vice versa, across both men and women we find a clear effect in terms of lost *"actual" employment*, i.e. weeks on payroll and actually worked, not on sick leave. As expected, workers with severe TTD cases fare better in terms of worked weeks than workers who suffer serious permanent disabling injuries (PPD rating larger than 16%). However, compared to all other groups of injured workers, our treated group experiences a significant decline in the number of their worked weeks both in the short and long run. The decline is larger for women, and we recall that the small sample size for women in model 5 leads to low statistical power. In addition, while men seem to recover some of their worked weeks over time, for women the lost worked time seems to be constant or increases over time. The decrease is also economically relevant, as in *t-5* to *t-1* (the pre-injury period), worked weeks averaged a total of 36 for men and 30 for women (Table 5). Hence, the loss in "actual" worked weeks we estimate and show in Table 6 amounts to 10%. This suggests that our treated group faces long run worse working opportunities with respect to both mild TTD workers and mild PPD workers (all categories of disabilities that are not entitled to additional workers' compensation after RTW). However, men seem to fare worse also than medium PPD workers (with 6-15% disability rating) who are instead entitled to a lump sum in addition to the full coverage all injured workers receive during their recovery period. The result highlights permanent consequences of the severe temporary injury that are not fully acknowledged and compensated by the workers' compensation insurance system.

Our third set of results refers to our last outcome of interest: weeks during which the worker is on payroll and receives the full wage, but is actually absent because on *sick leave*. This is to explore potential additional health costs experienced by the workers, as well a potential transfer of the injury financial costs to other social insurance programs such as the social security system. We estimate that the number of weeks on sick leave is much larger for severe TTD workers with respect to mild TTD (about 1 week for men and even more for women in the short run). In the long run, the effect almost disappears; we detect only a very small increase, for men. This suggests the presence of lasting consequences of severe TTD in terms of decline in health, at least over the first three years after the injury. The result highlights a potential gap in the compensation system.

To visualize our findings Figure 2 describes the different results for Model 2 (Severe TTD vs. Mild TTD). It plots the different average outcomes for matched treated and controls in each model. It shows the common trend achievement before t0 and the different values afterward. See online **Online Appendix B** for plots for each model in Table 6.

Figure 2: Model 2- Severe TTD vs. Mild TTD



NOTE: Orange: treated; Blue: controls

Finally, we use the results from Table 6 and use information about weekly wages, worked weeks and weeks on sick leave (that are paid at the current wage) to compute yearly earning losses (that we set equal to zero when our estimated ATT is not significant). Table 5 showed that over the five preinjury years (period *t-5* to *t-1)* average weekly wage for the treated group was 417 euro for men and 316 euro for women. Average FTE worked weeks were 36 for men and 30 for women. Therefore, the average yearly income was about 15,000 euro for men and 9,500 for women. Table 6 showed estimated decreases in employment (worked weeks plus sick leave) and some decline in wages in the short run. Based on these figures, our estimates lead to the following percentages of yearly earning losses for each model, gender and period (table 7).

Table 7: yearly earnings losses

model	short run		long run	
	M	W	M	W
1	3.1%	-3.0%	4.2%	4.3%
2	6.7%	2.1%	4.6%	8.0%
3	6.2%	9.9%	5.8%	10.0%
4	5.6%	0.0%	5.6%	0.0%
5	-13.6%	15.4%	-9.9%	0.0%

These results show sizable annual earning losses over the years following the injury. Our treated injured men lose about 6% of their labor earnings in the short run, and only slightly less in the longer run. For women losses are in general much larger (up to 10%) and their increase over time is even more dramatic. Again, severe TTD men face larger losses also with respect to medium-severity PPD workers (about 6% both in the short and in the long run) who do receive lump-sum compensation upon returning to work. Such compensation is not included in our calculation but, as an example, can amount to 15,000 euro for a man who is in his 30s and faces a 10% PPD degree, i.e. about one year of pre-injury income. Severe TTD cases fare worse in terms of earning losses even before such additional compensation is accounted for. Notice that, as expected, severe TTD workers fare better than severe PPD workers (model 5, negative loss, i.e. a gain), but this is true only if they are men.

6. 2 Match quality

Although the results we presented in table 6 refer to our "best performing" estimators, overall, the results we obtained with the different estimators (propensity score or Mahlanobis or Kernel) where highly consistent with each other. Out of the sixty models we analyzed, in 26 cases all three estimators produced statistically significant results consistent in sign, while in 23 models all three estimators produced a null-result. In these latter not statistically significant cases, however, the point estimates were also coherent in sign in half of the cases. In the remaining 11 models, we obtained a mix of significant and not-significant results[6].

As expected and discussed above, the balancing of observable characteristics was difficult in model 1 despite the fact that we match on a large set of finely defined controls. This reinforces the hypothesis that several unobservable or difficult to measure individual and job characteristics make injured and not injured workers intrinsically different. Balancing was also more difficult when the sample size was smaller. Overall, kernel estimator was the most effective in achieving a good balancing in all comparison groups, but in model 1. In the case of male workers, the maximum standardized difference in the characteristics of treated and controls was about 3-4% in models 2 to 4 and it reached 6% in the case of one outcome in model 5. These percentages should be compared with a value of 10% commonly considered as a threshold and corresponding to a correlation coefficient of 0.05 (indicating negligible correlation) between the treatment variable and the covariates (Austin, 2009). In models 2 to 4, average standardized differences where below 1% for all outcomes. In model 5, they hovered between 1-2%. In the case of model 1, kernel matching was less able to well balance the characteristics and the nearest propensity score was somewhat at its threshold limit (maximum standardized differences between 12-14% and about 10% respectively).

In case of women, sample size issues allowed us to reach a good balancing only in

[6] In these 11 models the point estimates where always consistent in sign, but in a single case (model 3, males, weeks spent in sick leave in the medium run) where the Nearest propensity score neighbor estimate was slightly negative and non-significant (-0,014, 95% C.I. [-0.473, 0.445]), while kernel and Mahalanobis estimators pointed to a positive effect (0.380 and 0.505 respectively).

models 2 to 4, being again the kernel algorithm the most effective. For model 1 and 5, the best estimators in term of balancing effectiveness were the kernel and Mahalanobis, but the results we are presenting for these two models require caution in their interpretation. In fact, both the average and maximum standardized differences were well above the 10% threshold for most outcomes.

7. Discussion and Conclusions

Our study explores the economic outcomes of occupational injuries in an institutional setting that differs from the ones analyzed in most previous studies. Italian workers enjoy a formal higher level of employment protection compared to the North American workers who were often studied before. Our results present a picture that is consistent with previous findings about the long term negative effects of occupational injuries on earnings. Our findings highlight additional unaccounted or uncompensated consequences.

Most existing studies on the topic have focused only on the most "expensive" cases, i.e. workers who end up suffering permanent disabilities. We build on limited but important evidence (Biddle 1998; Boden and Galizzi, 1999; Seabury et al. 2014) to highlight another category of employees who suffer larger losses over time, but who are not fully compensated for those. These are the workers with severe temporary total disabilities (TTD). We focus on blue-collar workers hired with a regular permanent or temporary contract. We discuss and explore different matching estimators and exploit a large number of demographic, job, and preinjury employment characteristics. We compare the severe TTD workers (our treatment group, with injuries requiring more than 2 months of healing time) with different control groups made of other injured workers who suffered either milder TTD or PPD of different degrees. We present results from the Kernel estimator.

We find that in Italy our "treated' workers did not experience a substantial wage penalty over the two or five years following their injury. This suggests that regulation and norms indeed act to protect injured workers against potential retaliation resulting in demotion. This wage protection may be particularly strong because the Italian labor markets and workers' remunerations are largely covered by collective agreements. At the same time, we find that our treated workers suffer in the short and long run in terms of declined employment and, therefore, declined total earnings. They fare even worse than workers with mild PPD cases (6-15% disability rating). This confirms the existence of a group of injured workers (with very long/severe TTD) whose careers is severely affected over time, but whom both private and public workers' compensation systems fail to fully compensate. Even in a more protected labor market, a work injury resulting in a temporary total disability (TTD) but also a long time off work may attach a stigma that affect workers' long-term employability (Kirsh et al. 2012; Francis et al. 2014).

Our study is one of the very first ones to highlight an additional cost suffered by injured workers. We show that our treated workers suffer more sickness absences after their RTW and over time. This confirms what was found in a medical study by Larsson and Björnstig (1995): that several injured workers keep reporting persistent medical problems over time. In our case, this is true also for the ones who had been diagnosed only with a temporary disability. Surprisingly, there is very limited additional research on this topic to date. Our findings suggest additional costs carried by injured workers in terms of diminished productivity and quality of life, but also an injury cost that is transferred from the workers' compensation to other social insurance programs such as the social security system in Italy.

Given the increasing weight of women's labor force participation in most labor markets, it is important to conduct also our analysis by gender. Our sample is made of blue-collar workers, and we have relatively fewer observations for female than for male workers leading to a loss of statistical significance in some of our comparisons. Still, our analysis pictures a labor market where injured women with severe TTD have overall similar experiences to the ones of men in terms of limited wage losses. Nevertheless, losses in terms of worked weeks and total labor earnings are larger, both over the short and long run. This result is consistent with what previously found by the few studies that have conducted a similar analysis by gender (Boden and Galizzi 2003; Crichton et al. 2011; Seabury et al. 2014; Dong et al., 2016). We know that women are generally a more vulnerable segment of the labor market. This result suggests that an occupational injury may further weaken their employment status, labor force participation, or further trigger employers' gender discrimination. The identification of a causal mechanism goes beyond the scope of this study but it is clearly a very important area of future research. We also find that women suffer more in terms of future sick leaves but only in the first three years after the injury and only with respect to mild TTD and PPD cases. This result is still consistent with what we know: that women suffer of different injures compared to men. Their incidents are more frequently associated with falls or assaults on the job, and they more often result in musculoskeletal injuries and mental problems, conditions that can be quite debilitating over time (Hoskins, 2005; Berecki-Gisolf et al., 2015; Cruz Rios et al. 2016; INAIL, 2019).

Our research faces some limitations. Some arise from the characteristics of our data. The administrative records we are using report yearly labor earnings making challenging to assess the full injury impact. Although we know the day of the injury and the day of return to work, we cannot capture with precision the wage that was paid to workers before and after those times. We can only calculate the full time equivalent weekly wage that was paid to workers across the years we are studying. Also, as in previous studies using workers' compensation data, we are not able to assess the impact of injuries for workers who only receive medical care, or for workers who are not covered by the national workers' compensation agency (Italian employees with a TTD lasting less than 4 days). Furthermore, we cannot capture the long-term employment outcomes of workers who are injured, but decide not to report the incident. This is a plausible scenario in a country where workers have access to a national health care system, and are entitled to several paid vacation days (a statutory minimum of 4 weeks in Italy vs. 2 weeks in Canada and 0 days in the U.S. (Ray et al. 2013). Indeed, previous research has shown that injury underreporting may be a significant problem especially among injured Italians employed in small firms (Galizzi et al. 2016). Our comparison between injured and not injured workers is also problematic. We present it, but do not discuss it in detail because our balancing statistics in the case of such comparison are poor. This suggests that there are systematic differences between workers who are exposed to occupational injuries and workers who are not.

Further research is needed to assess to which extent our results are driven by workers' decisions to leave permanently the labor force or by their difficulty to maintain an employment contract with their preinjury employer. Studies have highlighted the important role played by a change in employer in injury income losses over time (Campolieti and Krashinsky, 2006; Baldwin et al. 2009). In addition, the discussion of this study focuses on the experience of workers with severe TTD cases, but highlights the worst outcomes experienced by the ones with severe PPD cases. Our findings suggest much larger losses (in terms of both future employment and future health) among those PPD workers who are compensated with annuities compared to the ones who receive lump sum payments. Future research should assess to which extent such findings are driven by differences in the compensation mechanism vs. differences in severity of the permanent disability. When data about annuities and lump sum will be available, research should also assess the income replacement offered by the Italian workers' compensation system to PPD workers.

In terms of gender differences, we find almost no disparities in terms of wage losses. Probably this is also the result of an institutional setting where EPL was high, and coverage of national collective contracts was large. However, after the 2008 recession both these features of the Italian labor market were reduced after the 2008 recession (Ardito et al, 2019). When data will be available, future research should reassess this comparison for the more recent years and examine the reasons behind the larger employment losses that we estimated for women.

To conclude, we study a setting where the labor market has been characterized by strong EPL, and where injured workers are fully protected by wage losses during the time off work and are guaranteed reemployment after the injury. Even under these favorable circumstances, the workers' compensation system "fails" those workers who suffer severe but only temporary injuries. Italian injured workers are protected in terms of future wages, but not in terms of future "actual" employment, future labor earnings, and future health. Possibly this reflects the smaller variation in remunerations that characterizes a labor market with national collective bargaining agreement. Here losses may be more associated with the productivity losses or "stigma" caused by the injury so that severely injured workers face difficulties in maintaining their employment status over time. This is even truer for women for whom the injury becomes one more obstacle to continuous employment even after a return to work. Severe incidents have detrimental consequences on individuals' long-term well-being regardless of the different degrees of generosity of workers' compensation policies and rules, although the magnitude of the effects is clearly driven by institutional differences (about generosity, mode of payment of disability benefits, termination, and the scope of collective bargaining agreement).

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Online Appendix A – full results and diagnostics

Here we present all results and diagnostics. The table makes use of the following acronyms:

FTE: fulltime equivalent

Method: kernel = Kernel matching; nnmd = nearest Mahalanobis neighbour distance; nnps = nearest propensity score neighbour

Reversed: in the computations the treated group is always the smallest one, hence when "reversed" = 1, treated and controls are swapped, i.e. what we see here as the treated group is actually the control group as presented in the tables in text.

ATT: Average Treatment Effect of the Treated

LB and UB: 5% and 95% lower (LB) and upper bounds (UB) of the ATT estimates

ATT_std: the estimated standard error, according to the method chosen as discussed in section V.

Avg_ and max_std_diff: Average and maximum values of the standardized differences across all characteristics.

In the short run models, weeks are to be divided by 3 to calculate the annual value reported in the text; in the long run models, they are to be divided by 2.

model	outcome	period	gender	method	reversed	No.treated	No.controls	ATT	LB_CI95	UB_CI95	ATT_std	avg_std_diff	max_std_diff
1	FTE sick leave weeks	short run	F	kernel	0	571	88731	6.900	5.697	8.328	0.724	12.418	34.112
1	FTE sick leave weeks	short run	F	nnmd	0	571	88730	5.651	4.286	7.017	0.697	6.305	17.381
1	FTE sick leave weeks	short run	F	nnps	0	571	88731	6.609	5.246	7.973	0.696	9.871	21.135
2	FTE sick leave weeks	short run	F	kernel	0	571	11129	4.087	2.732	5.505	0.692	1.088	5.582
2	FTE sick leave weeks	short run	F	nnmd	0	571	11129	3.704	2.336	5.072	0.698	6.631	18.978

2	FTE sick leave weeks	short run	F	nnps	0	571	11129	4.291	2.829	5.752	0.746	4.650	14.145
3	FTE sick leave weeks	short run	F	kernel	0	571	872	1.532	-0.196	3.298	0.884	1.664	4.108
3	FTE sick leave weeks	short run	F	nnmd	0	571	872	2.837	0.998	4.675	0.938	10.001	34.058
3	FTE sick leave weeks	short run	F	nnps	0	571	872	1.803	-0.097	3.702	0.969	3.752	10.702
4	FTE sick leave weeks	short run	F	kernel	1	326	571	1.728	-0.193	3.827	1.092	2.749	7.663
4	FTE sick leave weeks	short run	F	nnmd	1	326	571	-1.034	-4.137	2.069	1.583	12.388	32.614
4	FTE sick leave weeks	short run	F	nnps	1	326	571	1.537	-1.359	4.433	1.478	5.521	14.655
5	FTE sick leave weeks	short run	F	kernel	1	26	571	13.900	1.814	28.150	6.711	6.788	14.150
5	FTE sick leave weeks	short run	F	nnmd	1	26	571	17.115	6.381	27.850	5.477	14.742	39.589
5	FTE sick leave weeks	short run	F	nnps	1	26	571	14.240	0.897	27.583	6.808	29.294	199.129
1	FTE sick leave weeks	short run	M	kernel	0	2060	90852	5.025	4.382	5.638	0.301	3.106	11.262
1	FTE sick leave weeks	short run	M	nnmd	0	2060	90852	4.822	4.208	5.436	0.313	4.832	12.740
1	FTE sick leave weeks	short run	M	nnps	0	2060	90852	4.986	4.355	5.617	0.322	3.998	10.536
2	FTE sick leave weeks	short run	M	kernel	0	2060	44650	3.434	2.883	4.003	0.287	0.856	2.880
2	FTE sick leave weeks	short run	M	nnmd	0	2060	44650	3.758	3.106	4.409	0.332	5.700	17.552
2	FTE sick leave weeks	short run	M	nnmd	0	2060	44650	3.758	3.106	4.409	0.332	5.700	17.552
2	FTE sick leave weeks	short run	M	nnps	0	2060	44650	3.271	2.584	3.957	0.350	4.032	12.234
2	FTE sick leave weeks	short run	M	nnps	0	2060	44650	3.271	2.584	3.957	0.350	4.032	12.234
3	FTE sick leave weeks	short run	M	kernel	0	2060	4826	2.790	2.200	3.406	0.326	0.746	1.447
3	FTE sick leave weeks	short run	M	nnmd	0	2060	4826	3.093	2.366	3.821	0.371	6.549	20.363
3	FTE sick leave weeks	short run	M	nnps	0	2060	4826	2.220	1.436	3.004	0.400	2.232	4.870
4	FTE sick leave weeks	short run	M	kernel	0	2060	2164	-0.820	-1.733	0.136	0.474	0.667	1.853
4	FTE sick leave weeks	short run	M	nnmd	0	2060	2164	0.259	-0.729	1.246	0.504	8.196	23.037
4	FTE sick leave weeks	short run	M	nnps	0	2060	2164	-0.284	-1.391	0.823	0.565	1.455	5.250
5	FTE sick leave weeks	short run	M	kernel	1	344	2060	10.289	8.001	13.167	1.335	1.116	4.532
5	FTE sick leave weeks	short run	M	nnmd	1	344	2060	10.913	7.815	14.010	1.580	8.999	27.256
5	FTE sick leave weeks	short run	M	nnps	1	344	2060	10.239	7.081	13.397	1.611	6.478	17.293
1	FTE sick leave weeks	long run	F	kernel	0	571	88731	1.735	1.012	2.477	0.345	12.418	34.112
1	FTE sick leave weeks	long run	F	nnmd	0	571	88730	1.289	0.461	2.117	0.422	6.305	17.381
1	FTE sick leave weeks	long run	F	nnps	0	571	88731	1.324	0.581	2.067	0.379	9.871	21.135
2	FTE sick leave weeks	long run	F	kernel	0	571	11129	0.246	-0.428	0.950	0.362	1.088	5.582

2	FTE sick leave weeks	long run	F	nnmd	0	571	11129	0.068	-0.775	0.912	0.431	6.631	18.978
2	FTE sick leave weeks	long run	F	nnps	0	571	11129	-0.114	-1.011	0.783	0.458	4.650	14.145
3	FTE sick leave weeks	long run	F	kernel	0	571	872	0.105	-0.815	1.036	0.474	1.664	4.108
3	FTE sick leave weeks	long run	F	nnmd	0	571	872	0.472	-0.479	1.422	0.485	10.001	34.058
3	FTE sick leave weeks	long run	F	nnps	0	571	872	-0.217	-1.255	0.822	0.530	3.752	10.702
4	FTE sick leave weeks	long run	F	kernel	1	326	571	0.304	-0.777	1.620	0.592	2.749	7.663
4	FTE sick leave weeks	long run	F	nnmd	1	326	571	0.708	-0.569	1.984	0.651	12.388	32.614
4	FTE sick leave weeks	long run	F	nnps	1	326	571	0.772	-0.674	2.217	0.738	5.521	14.655
5	FTE sick leave weeks	long run	F	kernel	1	26	571	2.496	-1.694	8.491	2.595	6.788	14.150
5	FTE sick leave weeks	long run	F	nnmd	1	26	571	0.615	-4.355	5.586	2.536	14.742	39.589
5	FTE sick leave weeks	long run	F	nnps	1	26	571	0.280	-5.759	6.319	3.081	29.294	199.129
1	FTE sick leave weeks	long run	M	kernel	0	2060	90852	1.208	0.946	1.492	0.131	3.106	11.262
1	FTE sick leave weeks	long run	M	nnmd	0	2060	90852	1.179	0.839	1.519	0.173	4.832	12.740
1	FTE sick leave weeks	long run	M	nnps	0	2060	90852	1.211	0.860	1.562	0.179	3.998	10.536
2	FTE sick leave weeks	long run	M	kernel	0	2060	44650	0.366	0.084	0.730	0.154	0.856	2.880
2	FTE sick leave weeks	long run	M	nnmd	0	2060	44650	0.413	0.040	0.786	0.190	5.700	17.552
2	FTE sick leave weeks	long run	M	nnps	0	2060	44650	0.439	0.054	0.823	0.196	4.032	12.234
3	FTE sick leave weeks	long run	M	kernel	0	2060	4826	0.380	0.046	0.775	0.188	0.746	1.447
3	FTE sick leave weeks	long run	M	nnmd	0	2060	4826	0.505	0.096	0.915	0.209	6.549	20.363
3	FTE sick leave weeks	long run	M	nnps	0	2060	4826	-0.014	-0.473	0.445	0.234	2.232	4.870
4	FTE sick leave weeks	long run	M	kernel	0	2060	2164	0.085	-0.394	0.594	0.237	0.667	1.853
4	FTE sick leave weeks	long run	M	nnmd	0	2060	2164	0.616	0.119	1.112	0.253	8.196	23.037
4	FTE sick leave weeks	long run	M	nnps	0	2060	2164	0.214	-0.296	0.725	0.260	1.455	5.250
5	FTE sick leave weeks	long run	M	kernel	1	344	2060	0.056	-0.811	1.051	0.503	1.116	4.532
5	FTE sick leave weeks	long run	M	nnmd	1	344	2060	0.190	-0.994	1.373	0.604	8.999	27.256
5	FTE sick leave weeks	long run	M	nnps	1	344	2060	0.219	-0.942	1.379	0.592	6.478	17.293
1	FTE worked weeks per year not on sick leave	short run	F	kernel	0	571	88731	-4.235	-8.012	-0.171	2.102	12.418	34.112
1	FTE worked weeks per year not on sick leave	short run	F	nnmd	0	571	88730	-9.235	-13.714	-4.756	2.285	6.305	17.381
1	FTE worked weeks per year not on sick leave	short run	F	nnps	0	571	88731	-3.387	-9.155	2.381	2.943	9.871	21.135
2	FTE worked weeks per year not on sick leave	short run	F	kernel	0	571	11129	-6.002	-10.327	-2.196	1.946	1.088	5.582

2	FTE worked weeks per year not on sick leave	short run	F	nnmd	0	571	11129	-9.351	-14.211	-4.490	2.480	6.631	18.978
2	FTE worked weeks per year not on sick leave	short run	F	nnps	0	571	11129	-6.670	-12.230	-1.111	2.836	4.650	14.145
3	FTE worked weeks per year not on sick leave	short run	F	kernel	0	571	872	-8.943	-15.036	-3.929	3.053	1.664	4.108
3	FTE worked weeks per year not on sick leave	short run	F	nnmd	0	571	872	-13.968	-19.712	-8.223	2.931	10.001	34.058
3	FTE worked weeks per year not on sick leave	short run	F	nnps	0	571	872	-11.281	-18.015	-4.547	3.436	3.752	10.702
4	FTE worked weeks per year not on sick leave	short run	F	kernel	1	326	571	-1.638	-13.572	8.624	5.452	2.749	7.663
4	FTE worked weeks per year not on sick leave	short run	F	nnmd	1	326	571	-3.682	-11.718	4.354	4.100	12.388	32.614
4	FTE worked weeks per year not on sick leave	short run	F	nnps	1	326	571	-1.163	-11.328	9.002	5.186	5.521	14.655
5	FTE worked weeks per year not on sick leave	short run	F	kernel	1	26	571	-16.542	-44.359	12.387	14.018	6.788	14.150
5	FTE worked weeks per year not on sick leave	short run	F	nnmd	1	26	571	-33.672	-54.992	-12.352	10.877	14.742	39.589
5	FTE worked weeks per year not on sick leave	short run	F	nnps	1	26	571	-23.687	-51.620	4.247	14.252	29.294	199.129
1	FTE worked weeks per year not on sick leave	short run	M	kernel	0	2060	90852	-8.388	-10.569	-5.394	1.299	3.106	11.262
1	FTE worked weeks per year not on sick leave	short run	M	nnmd	0	2060	90852	-13.204	-15.725	-10.683	1.286	4.832	12.740
1	FTE worked weeks per year not on sick leave	short run	M	nnps	0	2060	90852	-6.295	-9.508	-3.082	1.639	3.998	10.536
2	FTE worked weeks per year not on sick leave	short run	M	kernel	0	2060	44650	-8.013	-10.118	-5.345	1.160	0.856	2.880
2	FTE worked weeks per year not on sick leave	short run	M	nnmd	0	2060	44650	-14.306	-16.833	-11.779	1.289	5.700	17.552
2	FTE worked weeks per year not on sick leave	short run	M	nnmd	0	2060	44650	-14.306	-16.833	-11.779	1.289	5.700	17.552
2	FTE worked weeks per year not on sick leave	short run	M	nnps	0	2060	44650	-5.429	-8.386	-2.472	1.509	4.032	12.234
2	FTE worked weeks per year not on sick leave	short run	M	nnps	0	2060	44650	-5.429	-8.386	-2.472	1.509	4.032	12.234
3	FTE worked weeks per year not on sick leave	short run	M	kernel	0	2060	4826	-7.438	-10.513	-4.427	1.425	0.746	1.447
3	FTE worked weeks per year not on sick leave	short run	M	nnmd	0	2060	4826	-11.583	-14.493	-8.673	1.485	6.549	20.363
3	FTE worked weeks per year not on sick leave	short run	M	nnps	0	2060	4826	-10.080	-13.406	-6.755	1.697	2.232	4.870
4	FTE worked weeks per year not on sick leave	short run	M	kernel	0	2060	2164	-5.264	-8.221	-1.373	1.667	0.667	1.853
4	FTE worked weeks per year not on sick leave	short run	M	nnmd	0	2060	2164	-9.489	-12.942	-6.037	1.761	8.196	23.037

4	FTE worked weeks per year not on sick leave	short run	M	nnps	0	2060	2164	-4.546	-8.752	-0.340	2.146	1.455	5.250
5	FTE worked weeks per year not on sick leave	short run	M	kernel	1	344	2060	-16.739	-23.661	-10.437	3.520	1.116	4.532
5	FTE worked weeks per year not on sick leave	short run	M	nnmd	1	344	2060	-19.765	-27.516	-12.014	3.954	8.999	27.256
5	FTE worked weeks per year not on sick leave	short run	M	nnps	1	344	2060	-17.175	-25.667	-8.682	4.333	6.478	17.293
1	FTE worked weeks per year not on sick leave	long run	F	kernel	0	571	88731	-4.498	-8.020	-1.081	1.692	12.418	34.112
1	FTE worked weeks per year not on sick leave	long run	F	nnmd	0	571	88730	-8.358	-12.093	-4.623	1.906	6.305	17.381
1	FTE worked weeks per year not on sick leave	long run	F	nnps	0	571	88731	-4.366	-8.752	0.020	2.238	9.871	21.135
2	FTE worked weeks per year not on sick leave	long run	F	kernel	0	571	11129	-4.810	-8.015	-1.821	1.527	1.088	5.582
2	FTE worked weeks per year not on sick leave	long run	F	nnmd	0	571	11129	-7.944	-12.023	-3.864	2.081	6.631	18.978
2	FTE worked weeks per year not on sick leave	long run	F	nnps	0	571	11129	-6.070	-10.491	-1.650	2.255	4.650	14.145
3	FTE worked weeks per year not on sick leave	long run	F	kernel	0	571	872	-5.976	-10.808	-0.937	2.460	1.664	4.108
3	FTE worked weeks per year not on sick leave	long run	F	nnmd	0	571	872	-10.749	-15.643	-5.855	2.497	10.001	34.058
3	FTE worked weeks per year not on sick leave	long run	F	nnps	0	571	872	-8.002	-13.188	-2.816	2.646	3.752	10.702
4	FTE worked weeks per year not on sick leave	long run	F	kernel	1	326	571	-1.887	-10.468	6.658	4.258	2.749	7.663
4	FTE worked weeks per year not on sick leave	long run	F	nnmd	1	326	571	-0.444	-6.866	5.979	3.277	12.388	32.614
4	FTE worked weeks per year not on sick leave	long run	F	nnps	1	326	571	-1.441	-9.639	6.757	4.182	5.521	14.655
5	FTE worked weeks per year not on sick leave	long run	F	kernel	1	26	571	-3.818	-25.630	16.145	10.194	6.788	14.150
5	FTE worked weeks per year not on sick leave	long run	F	nnmd	1	26	571	-11.418	-29.840	7.003	9.399	14.742	39.589
5	FTE worked weeks per year not on sick leave	long run	F	nnps	1	26	571	-5.915	-26.715	14.885	10.612	29.294	199.129
1	FTE worked weeks per year not on sick leave	long run	M	kernel	0	2060	90852	-4.281	-6.149	-2.044	1.023	3.106	11.262
1	FTE worked weeks per year not on sick leave	long run	M	nnmd	0	2060	90852	-7.198	-9.243	-5.152	1.044	4.832	12.740
1	FTE worked weeks per year not on sick leave	long run	M	nnps	0	2060	90852	-3.234	-5.747	-0.721	1.282	3.998	10.536
2	FTE worked weeks per year not on sick leave	long run	M	kernel	0	2060	44650	-3.667	-5.534	-1.871	0.965	0.856	2.880
2	FTE worked weeks per year not on sick leave	long run	M	nnmd	0	2060	44650	-7.927	-10.071	-5.783	1.094	5.700	17.552

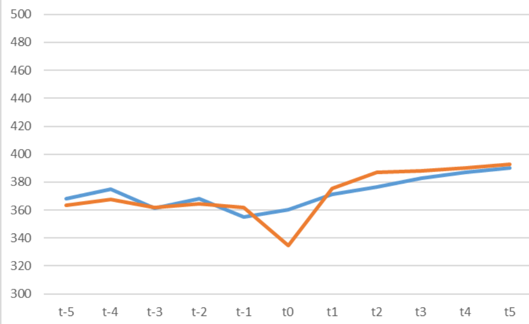
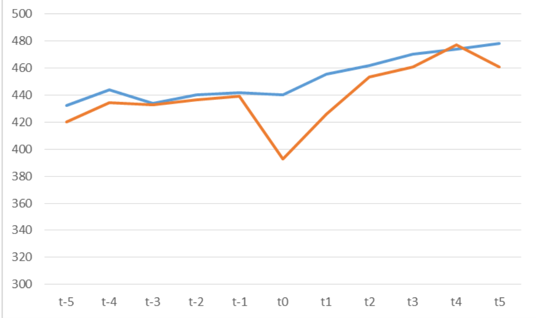
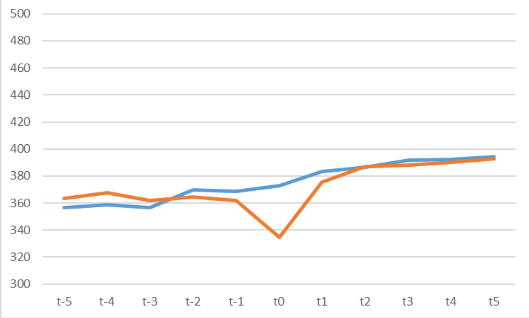
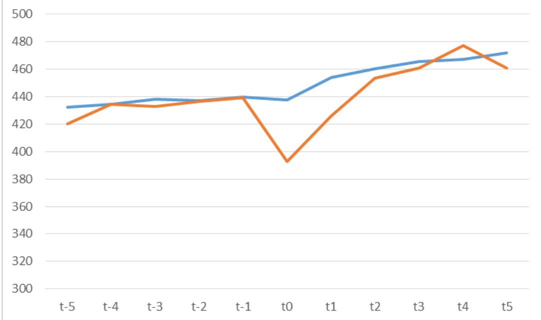
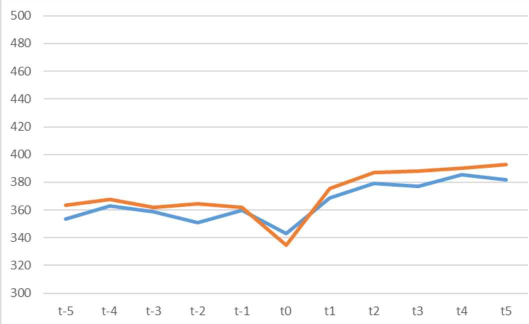
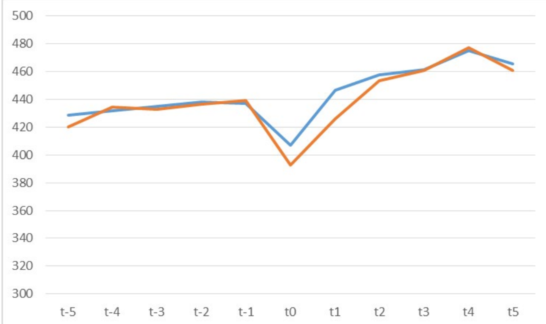
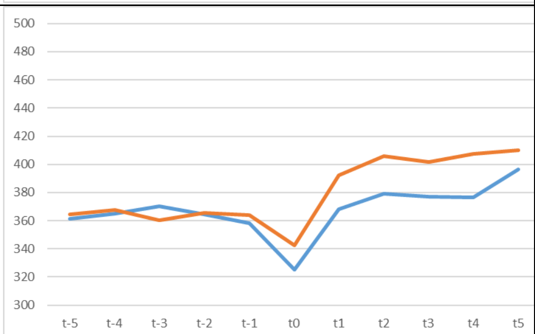
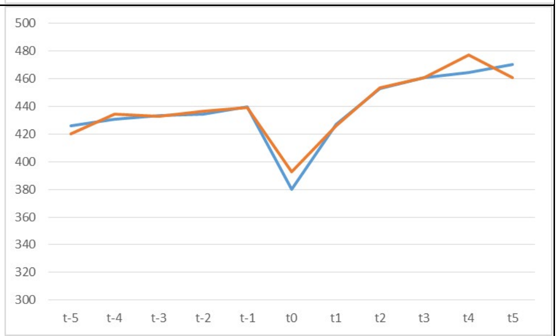
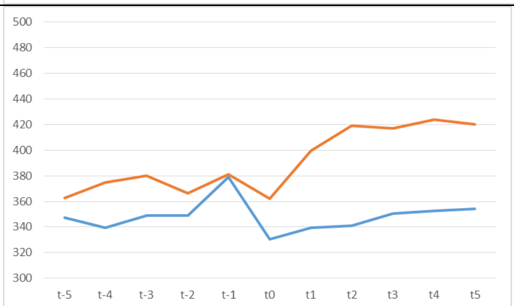
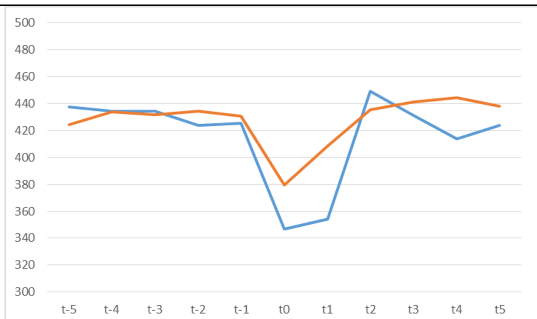
2	FTE worked weeks per year not on sick leave	long run	M	nnps	0	2060	44650	-3.275	-5.607	-0.943	1.190	4.032	12.234
3	FTE worked weeks per year not on sick leave	long run	M	kernel	0	2060	4826	-4.524	-6.432	-1.966	1.147	0.746	1.447
3	FTE worked weeks per year not on sick leave	long run	M	nnmd	0	2060	4826	-6.528	-9.015	-4.041	1.269	6.549	20.363
3	FTE worked weeks per year not on sick leave	long run	M	nnps	0	2060	4826	-5.604	-8.349	-2.859	1.400	2.232	4.870
4	FTE worked weeks per year not on sick leave	long run	M	kernel	0	2060	2164	-4.027	-6.801	-1.106	1.385	0.667	1.853
4	FTE worked weeks per year not on sick leave	long run	M	nnmd	0	2060	2164	-7.225	-10.058	-4.392	1.445	8.196	23.037
4	FTE worked weeks per year not on sick leave	long run	M	nnps	0	2060	2164	-3.449	-6.768	-0.130	1.693	1.455	5.250
5	FTE worked weeks per year not on sick leave	long run	M	kernel	1	344	2060	-7.117	-12.791	-2.154	2.738	1.116	4.532
5	FTE worked weeks per year not on sick leave	long run	M	nnmd	1	344	2060	-8.718	-14.423	-3.013	2.911	8.999	27.256
5	FTE worked weeks per year not on sick leave	long run	M	nnps	1	344	2060	-8.622	-14.845	-2.399	3.175	6.478	17.293
1	unit real weekly wages	short run	F	kernel	0	415	91794	4.019	-10.834	17.018	7.164	15.434	44.984
1	unit real weekly wages	short run	F	nnmd	0	415	91794	-7.120	-16.446	2.207	4.758	6.273	17.528
1	unit real weekly wages	short run	F	nnps	0	415	91794	9.210	-6.095	24.515	7.809	6.965	15.301
2	unit real weekly wages	short run	F	kernel	0	415	8885	-6.571	-19.618	6.244	6.346	1.533	4.942
2	unit real weekly wages	short run	F	nnmd	0	415	8885	-7.128	-16.575	2.319	4.820	6.344	18.182
2	unit real weekly wages	short run	F	nnps	0	415	8885	-4.634	-19.820	10.553	7.748	6.057	13.505
3	unit real weekly wages	short run	F	kernel	0	415	690	-2.420	-16.374	13.761	8.161	2.147	4.754
3	unit real weekly wages	short run	F	nnmd	0	415	690	-1.136	-13.232	10.960	6.172	11.503	30.161
3	unit real weekly wages	short run	F	nnps	0	415	690	8.788	-10.383	27.960	9.782	4.115	11.960
4	unit real weekly wages	short run	F	kernel	1	239	415	-9.231	-32.867	19.509	12.803	3.243	7.057
4	unit real weekly wages	short run	F	nnmd	1	239	415	-13.378	-32.080	5.325	9.542	13.001	29.040
4	unit real weekly wages	short run	F	nnps	1	239	415	-17.345	-43.169	8.478	13.175	6.145	19.592
5	unit real weekly wages	short run	F	kernel	1	16	415	-16.407	-84.276	70.637	40.557	13.980	37.988
5	unit real weekly wages	short run	F	nnmd	1	16	415	-63.123	-118.944	-7.303	28.480	24.514	58.238
5	unit real weekly wages	short run	F	nnps	1	16	415	-5.147	-108.315	98.020	52.637	41.652	291.416
1	unit real weekly wages	short run	M	kernel	0	1506	93828	-6.612	-13.093	2.021	3.726	5.180	13.712
1	unit real weekly wages	short run	M	nnmd	0	1506	93828	-10.688	-16.261	-5.115	2.843	5.388	17.857
1	unit real weekly wages	short run	M	nnps	0	1506	93828	-2.517	-12.434	7.399	5.059	4.698	10.346

2	unit real weekly wages	short run	M	kernel	0	1506	37012	-10.918	-17.510	-4.489	3.273	0.776	3.056
2	unit real weekly wages	short run	M	nnmd	0	1506	37012	-11.329	-16.714	-5.943	2.748	5.645	17.514
2	unit real weekly wages	short run	M	nnps	0	1506	37012	-11.918	-21.399	-2.437	4.837	2.848	7.178
3	unit real weekly wages	short run	M	kernel	0	1506	3913	-8.268	-17.384	-1.085	4.219	0.907	2.830
3	unit real weekly wages	short run	M	nnmd	0	1506	3913	-19.631	-26.231	-13.032	3.367	7.636	21.878
3	unit real weekly wages	short run	M	nnps	0	1506	3913	-2.345	-13.254	8.564	5.566	5.081	12.746
4	unit real weekly wages	short run	M	kernel	0	1506	1676	0.590	-10.087	11.644	5.214	0.706	1.749
4	unit real weekly wages	short run	M	nnmd	0	1506	1676	-3.260	-11.110	4.589	4.005	9.011	25.217
4	unit real weekly wages	short run	M	nnps	0	1506	1676	0.793	-11.939	13.526	6.496	2.393	5.820
5	unit real weekly wages	short run	M	kernel	1	215	1506	-30.060	-48.129	-11.561	9.206	1.476	4.459
5	unit real weekly wages	short run	M	nnmd	1	215	1506	-33.969	-49.725	-18.212	8.039	11.204	34.093
5	unit real weekly wages	short run	M	nnps	1	215	1506	-43.238	-67.430	-19.047	12.343	6.462	21.894
1	unit real weekly wages	long run	F	kernel	0	363	91273	9.312	-3.900	22.645	6.588	16.443	47.537
1	unit real weekly wages	long run	F	nnmd	0	363	91273	10.076	-2.430	22.582	6.381	7.084	21.204
1	unit real weekly wages	long run	F	nnps	0	363	91273	8.249	-8.411	24.909	8.500	9.487	23.210
2	unit real weekly wages	long run	F	kernel	0	363	8174	0.671	-11.083	14.604	6.398	1.072	4.435
2	unit real weekly wages	long run	F	nnmd	0	363	8174	2.331	-9.379	14.040	5.974	8.243	18.472
2	unit real weekly wages	long run	F	nnps	0	363	8174	-6.850	-24.843	11.143	9.180	5.596	14.884
3	unit real weekly wages	long run	F	kernel	0	363	613	0.943	-17.193	17.826	8.403	2.105	7.936
3	unit real weekly wages	long run	F	nnmd	0	363	613	-6.271	-21.783	9.241	7.914	13.613	31.597
3	unit real weekly wages	long run	F	nnps	0	363	613	1.325	-19.042	21.691	10.391	4.896	10.874
4	unit real weekly wages	long run	F	kernel	1	201	363	-6.688	-29.202	17.993	12.609	3.245	9.624
4	unit real weekly wages	long run	F	nnmd	1	201	363	8.813	-15.634	33.261	12.473	14.560	36.120
4	unit real weekly wages	long run	F	nnps	1	201	363	-7.062	-36.073	21.949	14.801	6.472	17.746
5	unit real weekly wages	long run	F	kernel	1	15	363	-78.981	-165.477	3.677	44.809	13.343	38.853
5	unit real weekly wages	long run	F	nnmd	1	15	363	-66.099	-129.697	-2.501	32.448	20.711	73.352
5	unit real weekly wages	long run	F	nnps	1	15	363	-131.095	-202.276	-59.914	36.317	39.625	90.521
1	unit real weekly wages	long run	M	kernel	0	1424	93590	4.312	-11.446	33.914	11.285	5.580	14.968
1	unit real weekly wages	long run	M	nnmd	0	1424	93590	3.803	-16.257	23.863	10.235	5.741	14.978
1	unit real weekly wages	long run	M	nnps	0	1424	93590	11.680	-11.122	34.482	11.633	3.773	13.542
2	unit real weekly wages	long run	M	kernel	0	1424	34667	1.503	-13.875	26.375	11.194	1.189	3.577

2	unit real weekly wages	long run	M	nnmd	0	1424	34667	3.247	-17.683	24.176	10.678	5.755	17.951
2	unit real weekly wages	long run	M	nnps	0	1424	34667	11.034	-11.560	33.629	11.528	4.169	9.899
3	unit real weekly wages	long run	M	kernel	0	1424	3622	-2.640	-25.965	25.148	13.350	0.412	1.208
3	unit real weekly wages	long run	M	nnmd	0	1424	3622	-3.130	-27.173	20.912	12.267	7.323	18.795
3	unit real weekly wages	long run	M	nnps	0	1424	3622	-11.569	-51.060	27.922	20.149	2.810	8.618
4	unit real weekly wages	long run	M	kernel	0	1424	1535	5.911	-11.574	30.039	11.412	0.759	2.142
4	unit real weekly wages	long run	M	nnmd	0	1424	1535	2.490	-24.855	29.835	13.951	8.847	24.120
4	unit real weekly wages	long run	M	nnps	0	1424	1535	12.248	-17.457	41.952	15.155	2.591	6.155
5	unit real weekly wages	long run	M	kernel	1	195	1424	-17.823	-37.336	3.477	10.498	1.979	6.054
5	unit real weekly wages	long run	M	nnmd	1	195	1424	-19.999	-39.334	-0.663	9.865	10.821	30.774
5	unit real weekly wages	long run	M	nnps	1	195	1424	-6.918	-30.505	16.669	12.034	9.961	30.322

Appendix B – plots from Table 6

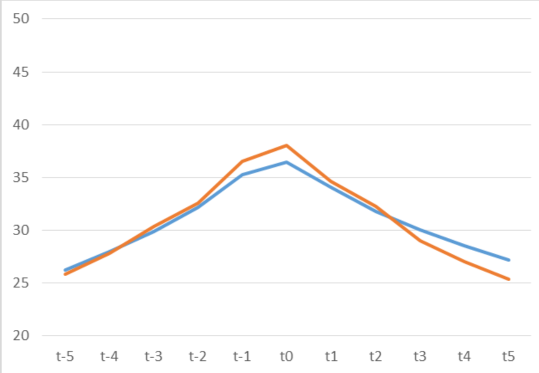
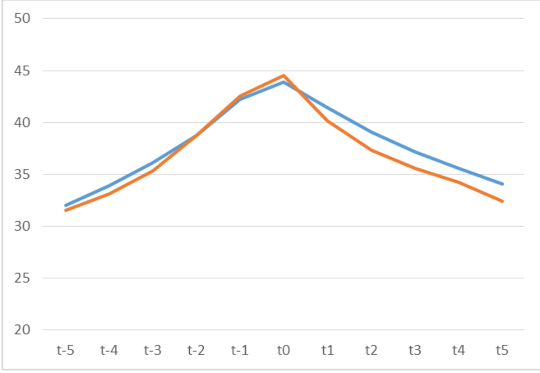
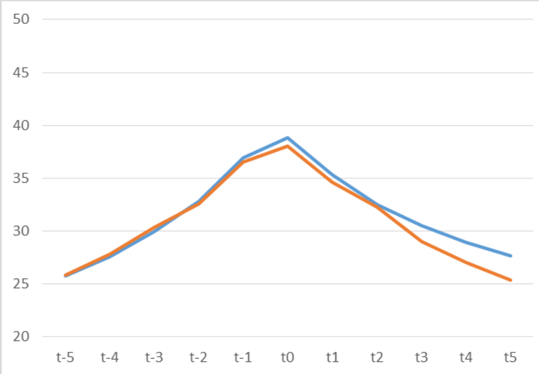
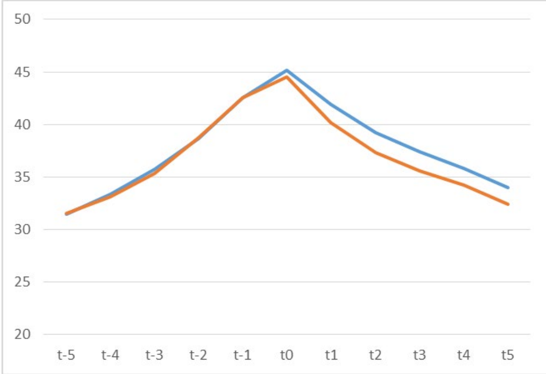
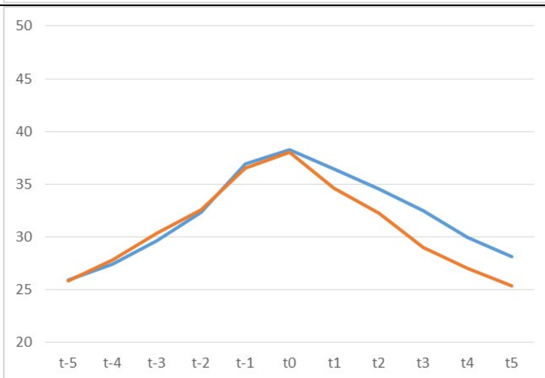
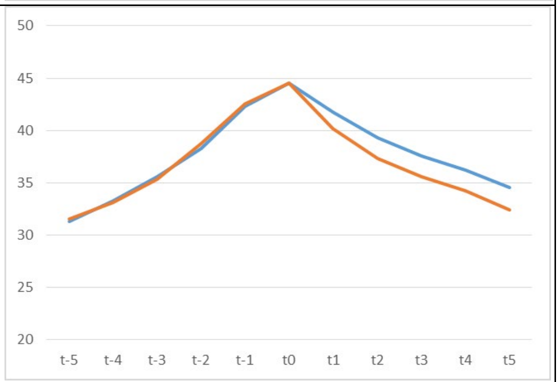
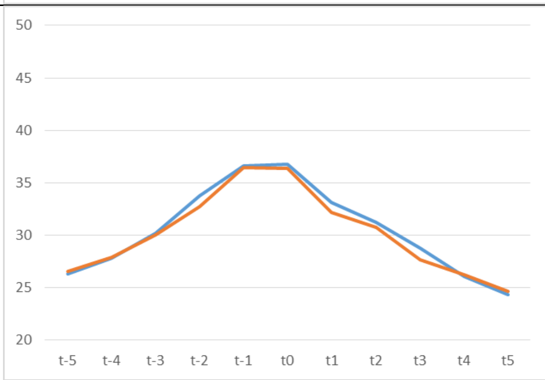
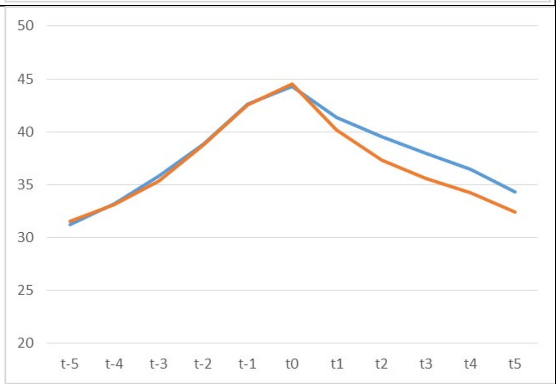
Figure B1: ***Unit real weekly wages***

Model	Women	Men
1		
2		
3		
4		
5		

Orange: treated; Blue: controls

NOTE: treated profile is not always identical across models, because the common support changes in each model. As shown in table 6, the only significant ATT differences on average over period t+1-to t+3 are estimated in models 2, 3, 5 for men.

Figure B2: ***FTE "actual" worked weeks per year (not on sick leave)***

model	Women	Men
1		
2		
3		
4		

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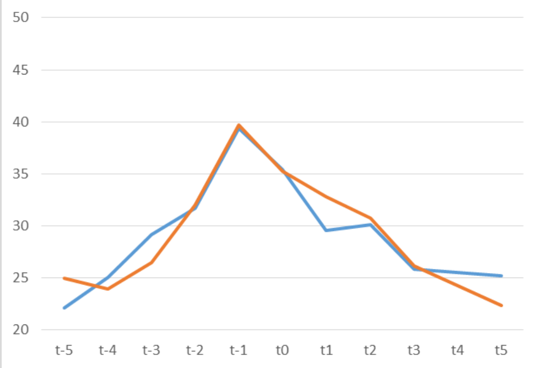
<td>
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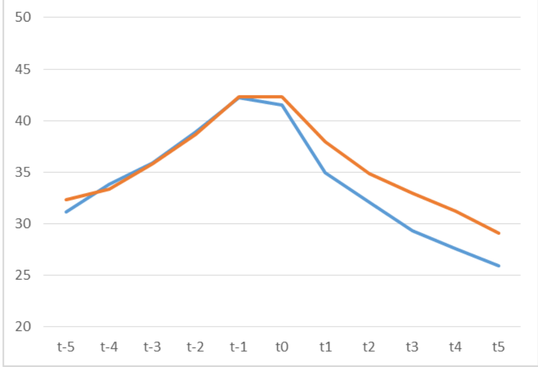
<td>
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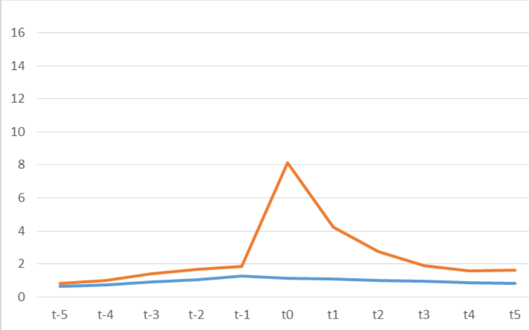
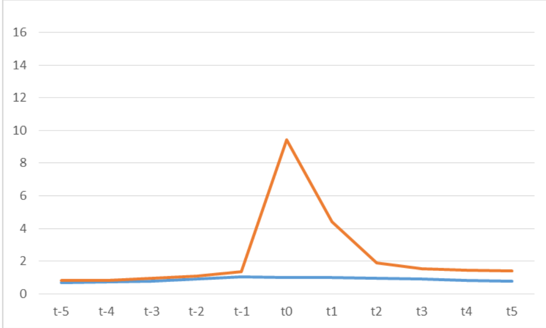
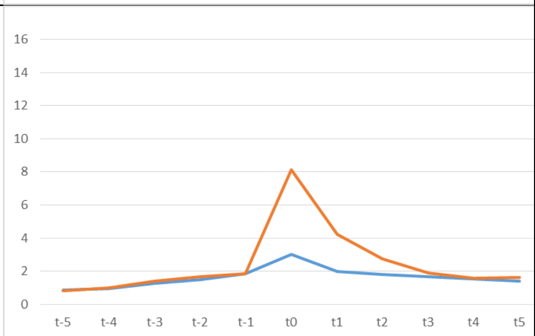
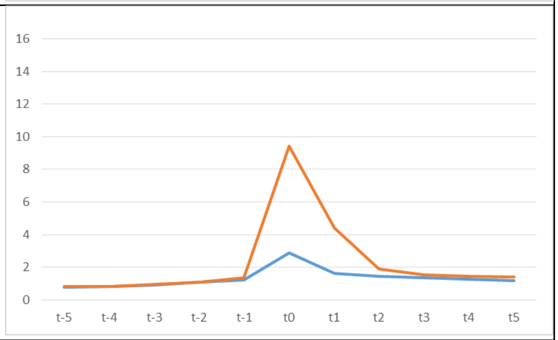
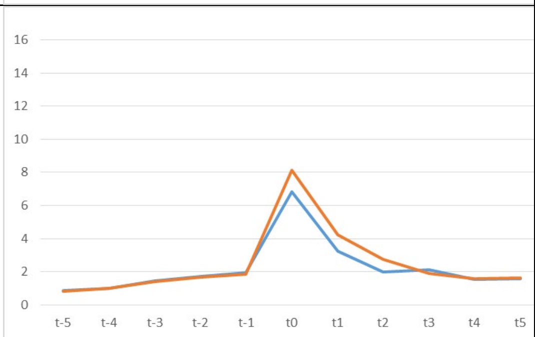
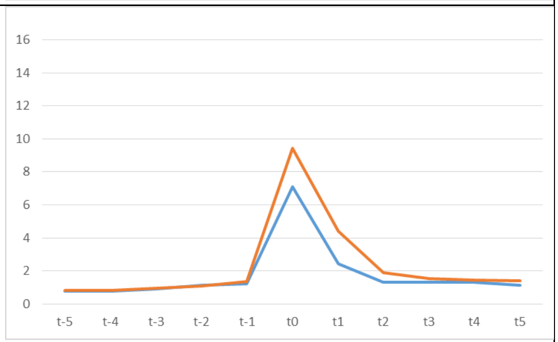
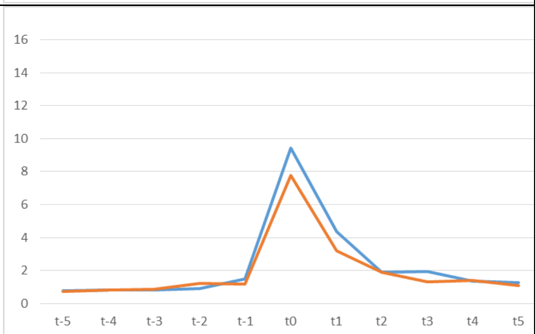
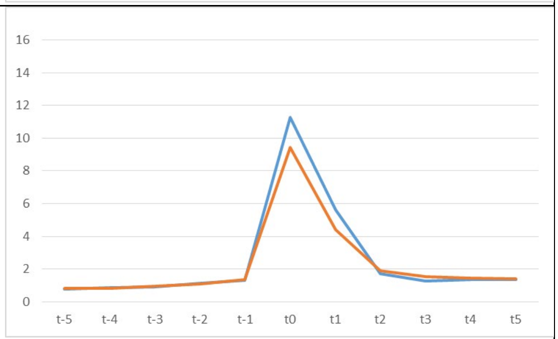
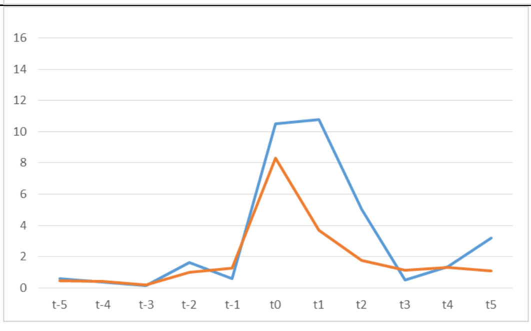
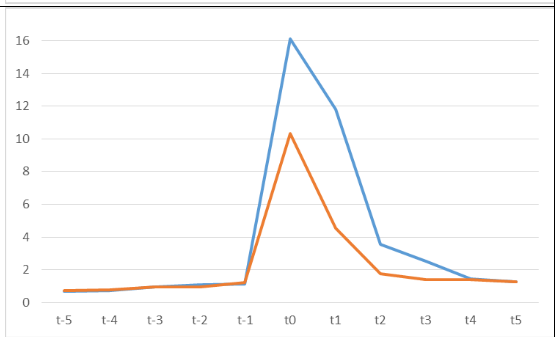
Orange: treated; Blue: controls
NOTE: treated profile is not always identical across models, because the common support changes in each model. As shown in table 6, the significant ATT differences on average over both period t+1-to t+3 and period t+4 to t+5 are estimated in all models for men and in models 1,2,3 for women.

Figure B3: ***FTE sick leave weeks per year***

Model	Women	Men
1		
2		
3		
4		
5		

Orange: treated; Blue controls

NOTE: treated profile is not always identical across models, because the common support changes in each model. As shown in table 6, the significant ATT differences on average over period t+1-to t+3 are estimated in all models for men, and in models 1,2,5 for women; over period t+4 to t+5 in models 1,2,3 for men, and in model 1 for women.