Supplement to

What Happens When Compensation for Whiplash Claims Is Made More Generous?

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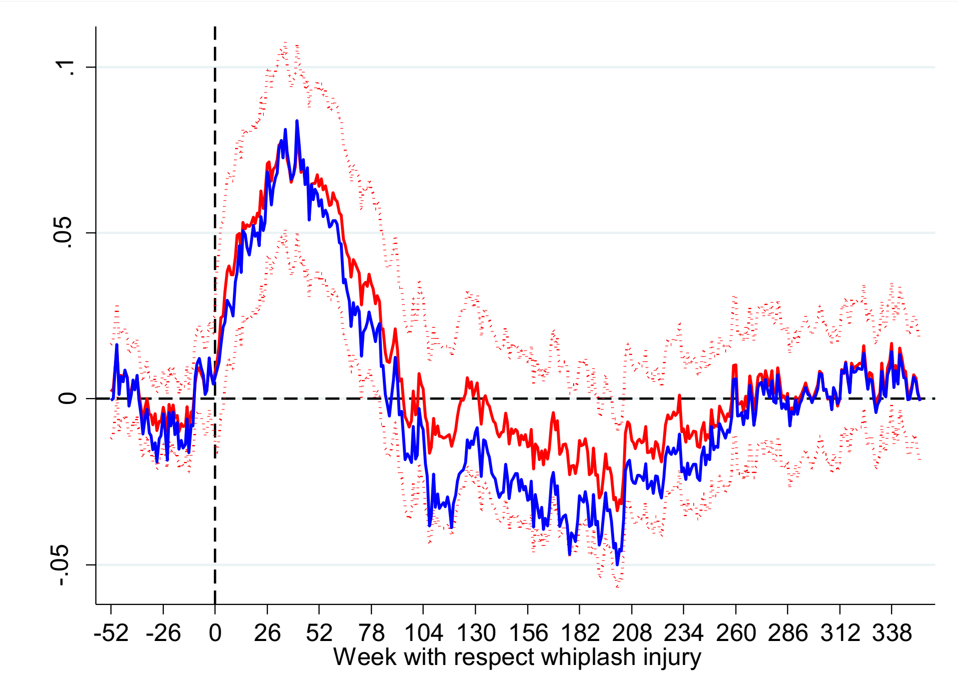
This supplement presents robustness analyses complementing the analyses in the paper.

S.1. Logit Model

Figure 3 in the paper presents the main result of the paper. It shows that the reform lead to an increase in temporary disability. Figure 3 is constructed from estimates of β_{3t} obtained by running OLS regressions. Because the outcome is binary, this model is a linear probability model, and the linear probability model has a well-known disadvantage in that does not confine predicted probabilities to be within the [0;1] interval. To make sure that this assumption does not lead to biased estimates we have also estimated the effect of the reform using a logit estimator. Specifically, we estimate the differences-in-differences (DiD) estimator using Puhani's (2012) method and assuming a logistic model for the potential outcomes. The result is presented in Figure S.1. The logit DiD estimates are calculated as $\hat{\beta}_{3t} = logit^{-1}(\hat{\beta}_{1t} + \hat{\beta}_{2t} + \hat{\gamma}_t + \hat{\beta}_{4t}\bar{X}_i^{Pre}) - logit^{-1}(\hat{\beta}_{1t} + \hat{\beta}_{2t} + \hat{\beta}_{4t}\bar{X}_i^{Pre})$, where $\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\gamma}_t, \hat{\beta}_{4t}$ are the estimated coefficients of a logistic regression of temporary disability indicator on D_i^{Post}, W_i , $D_i^{Post} \times W_i$, and X_i^{Pre}, and $\bar{X}_i^{Pre}$ is the mean of the covariate set $\bar{X}_i^{Pre}$.

This specification matches equation (1) in the paper. The full line presents estimates of $\hat{\beta}_{3t}$ based on OLS, i.e, the same estimates as in figure 3 in the paper. The dashed line presents estimates of $\hat{\beta}_{3t}$ from the logit specification and the dotted lines denote the DID estimated 95% confidence interval. The figure shows that the logit is never significantly different from the OLS estimates.

Figure S.1. Comparing logit and OLS estimators



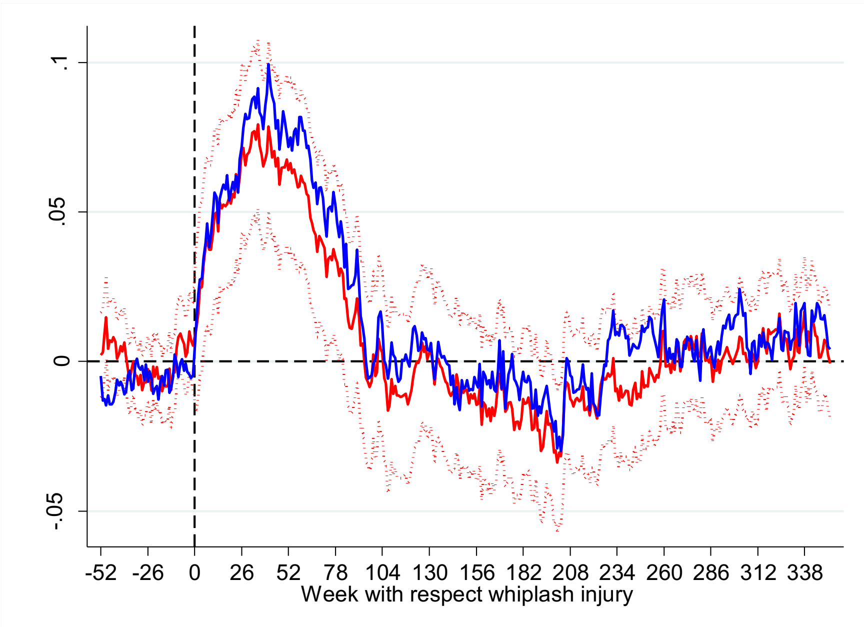
Note: The solid red line denotes the OLS estimates (same as figure 3) with the associated 95% confidence interval (red dotted lines). The blue line is a nonlinear Difference-in-Differences estimator obtained with Puhani (2012) method assuming a logistic model for the potential outcomes, and the dotted lines denote the DID estimated 95% confidence interval. The logit DID estimates are given by $\hat{\beta}_{3t} = logit^{-1}\left(\hat{\beta}_{1t} + \hat{\beta}_{2t} + \hat{\gamma}_t + \hat{\beta}_{4t}\bar{X}_i^{Pre}\right) - logit^{-1}\left(\hat{\beta}_{1t} + \hat{\beta}_{2t} + \hat{\beta}_{4}\bar{X}_i^{Pre}\right)$, where $\hat{\beta}_{1t}, \hat{\beta}_{2t}, \hat{\gamma}_t$, $\hat{\beta}_{4t}$ are the estimated coefficients of a logistic regression of temporary disability indicator on D_i^{Post}, W_i , $D_i^{Post} \times W_i$, and X_i^{Pre}, and $\bar{X}_i^{Pre}$ is the mean of the covariate set $\bar{X}_i^{Pre}$ among those treated individuals $D_i^{Post} \times W_i = 1$.

S.2. Matching

Equation (1) corrects for differences between whiplash claimants and control units by controlling parametrically for differences in observed pre-whiplash characteristics. To check that our results are not driven by these functional form assumptions or imbalances between the claimant and the control groups, we estimated the effect of the reform by applying a nearest neighbor propensity score-matching estimator that balances the covariates of the whiplash claimants with that of the 2 percent random sample.

Specifically, we use propensity score matching on the covariate set entering the regressions underlying Figure 3 and a measure of temporary disability in weeks -52 to -1. The matching method will assist in controlling differences in the propensity to stay out of work that are unrelated to the whiplash as long as the whiplash is not incurred deliberately. After matching whiplash claimants with individuals from the random population sample, we obtain the effect of the reform in a second step by regressing the estimated individual effects on a dummy indicating whether the individual had a whiplash after the reform.[1] Figure S.2 shows that the estimates reported in Figure 3 and the matching estimate coincide very closely.

Figure S.2. Results using matching estimator



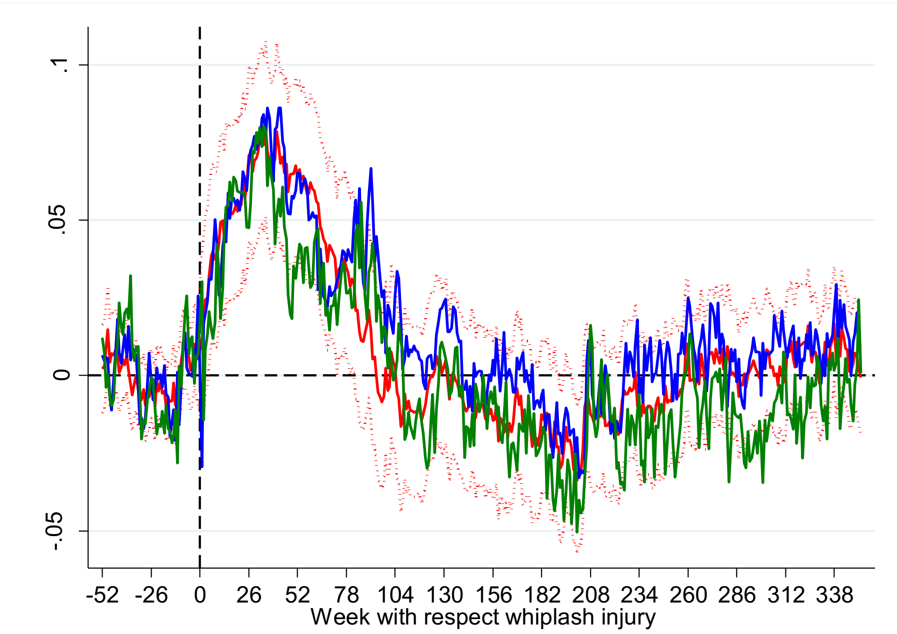
Note: The solid red line denotes the OLS estimates (same as figure 3 in the paper) with the associated 95% confidence interval (dotted lines). The blue line is a matching estimator, and the dotted lines denote the DID estimated 95% confidence interval. The matching estimates are obtained in two steps. Step 1: Individual effects are estimated with propensity score 1-"nearest neighbor" matching without replacement on the entire sample of whiplash claimants and 2% control population. The propensity score is estimated using the covariate set including the covariates included in the estimation reported in Figure 3 and lagged outcomes spanning 1-52 weeks before the week of the whiplash injury. Step 2: We obtain the effect of higher compensation by regressing the estimated individual effects on a dummy indicating wether the individual was exposed to reform.

[1] This procedure does not correct for potential differences in the composition of covariates between claimants before and after the reform. We have also tried to match pre- and post-reform claimants in the second step, but that did not change the results, and we do not report this set of estimates.

S.3. Testing for underlying trends by narrowing the window of analysis.

Our estimation approach relies on common trends between the pre- and post-reform groups (after comparing them with the random sample). While the reform did not discretely change the selection around the time of the reform, we estimate the change in outcomes using a five-year period. The estimated increase could potentially have been generated by a slowly moving upward trend across this period and thus be unrelated to but coincident with the reform. However, given that the change in incentives was strong, we expected that the change in behavior would occur immediately after the onset of the reform. Therefore, we re-estimated equation (1) and Figure 3, using a narrower window around the reform. Specifically, we have selected two narrower windows spanning six and nine months before and after July 1, 2002. Figure S.3 shows the results. The estimated effect is almost identical for all window sizes, confirming that the compensation reform impacted the propensity for immediately going on temporary disability.

Figure S.3. Sensitivity of estimated effect of reform to smaller sample time spans



Note: The solid red line denotes the OLS estimates (same as figure 3 in the paper) with the associated 95% confidence interval (dotted lines). The blue line shows OLS estimates with a sample restricted to whiplash injuries within 9 months before and after July 1, 2002. The green line shows OLS estimates with a sample restricted to whiplash injuries within 6 months before and after July 1, 2002.

Reference

Puhani, P.A. 2012. “The treatment effect, the cross difference, and the interaction term in nonlinear “difference-in-differences” models.” Economics Letters 115. Pp. 85-87.