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Innovation, Profits, Wages and Spillovers

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Abstract

Innovations are the engine of economic growth. Moreover, innovations also affect profits and wages, which, in turn, affect the distribution of income. The main aim of this paper is to understand the effects of innovations on profits, wages and labor turnover. We first analyze if profits and wages increase in innovative firms (more than others), and if high wage workers benefit more than low wage workers. We also look at the effects of innovations on gender wage differentials. Finally, we analyze if the rate of labor turnover changes after innovations. We use the data on the population of Turkish manufacturing companies in the 2005-2020 period, and our findings indicate that after innovations, as proxied by patent applications and R&D activities, wages and profits increase. However, the effect of innovations on wages is not homogenous: high wage earners (and men) benefit more than low wage earners (and women) from innovation, i.e., intra-firm wage differentials increase after innovation. The effect on labor turnover is weak and ambiguous.

Keywords: innovation, wage, profit, spillover, wage differentials, income distribution

1. Introduction

Innovations are the main determinant of long run economic growth. By increasing productivity or by creating new markets, innovations generate substantial benefits for the society, and may lead to an increase in profits. However, the innovator shares a part of the benefits with workers and other firms. Workers may share a part of the increase in value added through higher wages, whereas other firms may benefit from the innovation through labor turnover, i.e., human capital accumulated by the innovator firm can spillover to other firms through the transfer of workers. Wage and spillover effects will determine how the benefits of innovation is shared by the society, and, therefore, could have important implications for inclusive growth. Moreover, these effects feed back to the processes of innovation and diffusion by changing incentive structures.

This paper analyzes the relationship between innovations, wages, and labor turnover. The main aim is to understand the impact of innovations on manufacturing wages and labor turnover. We first analyze if wages increase in innovative firms (more than others) and if high-wage workers benefit more than low-wage workers. We also look at the effects of innovations on gender wage differentials. Finally, we analyze if the rate of labor turnover changes after innovations.

We use the data on the balance sheets, income statements and patent applications of all Turkish manufacturing companies for the 2006-2020 period. The firm level data is matched with the employee level data for the 2006-2020 period so that we can calculate firm-level labor turnover rates, and average wages of leaving and incoming employees. In order to eliminate the effects of firm entry and exit, a balanced panel data is used, i.e., we excluded firms that enter or exit within the period. The data on patent applications and R&D activities are used as a proxy for innovations. Since the aim is to estimate the effect of "innovations", we further restricted the sample to those firms that apply for patents or start to conduct R&D after 2009. Two control groups were selected, one for patent applicants, and the other one for R&D performers, by using the coarsened exact matching (CEM) method (for the method, see Iacus, King & Porro, 2021). Finally, the effects of innovation on a number of outcome variables are estimated by difference-in-difference (DiD) methodology[1] as suggested by Wooldridre (2021).

The paper is organized as follows: After this introduction, we provide a summary of a number of papers on the relationship between innovation, wages and labor turnover. The methodology and data sources are explained in sections 3 and 4, respectively. Section 5 presents estimation results. Main findings are summarized in Section 6.

1 According to Callaway & Sant'Anna (2020), the difference-in-differences (DiD) study design has become one of the most common ways to assess the causal effects of the policy changes. In the standard setup of the DiD, there are two time periods and two groups: no one is treated in the first period, and some units are treated (the treated group) while others are not treated in the second period (the comparison group). One of the main assumptions of the DiD is the parallel trends assumption i.e., the average outcomes for treated and comparison groups would have followed parallel paths over time. If this assumption holds, the average treatment effect for the treated subpopulation can be estimated by comparing the average change in outcomes experienced by the treated group to the average change in outcomes experienced by the comparison group. Since our data includes firms innovating in multiple time periods, we use the staggered DiD design.

2. Innovations, profits and wages

Innovations generate benefits for the society by reducing production costs (process innovations) or by generating new or better products (product innovations). These benefits are usually shared between innovators, employees, other firms, and the society at large. How the benefits of innovation are shared have significant implications for incentives for innovation, income distribution, and inclusive growth.

Although there is a substantial literature on the productivity effects of innovation, research on wage and labor turnover effects are scarce. There are some studies that suggest that supporting innovation can provide room for expansion of wages (Pianta & Tancioni, 2008), and it also increases the labor turnover (Eriksson, 2013), which allows employees to work in industries that suit their skills and enables earning gains (Akgunduz, 2019). Labor turnover is one of the primary mechanisms for knowledge spillover (Lenger, 2006).

A positive relationship between wages and innovation has been found because it is expected to increase the income of innovative firms through increased productivity or new/improved products. The dynamics of wages and profits are, at the same time, a major determinant and a consequence of innovation (Pianta & Tancioni, 2008). Innovations bring extra profit to the firms, and this profit is shared between employers and employees. While the increase in skilled labor wage is high, unskilled labor wage does not change, or the change is lower. Van Reenen (1996) found that innovations positively impact in the case of British firms. The estimation result shows that the average wage in innovative firms is higher than in non-innovative firms, and rival innovation negatively affects wages. Using firm-level data of Chile, Crillo (2014) points out that innovations positively affect average wages compared to non-innovating firms. She argues that product innovations positively impact wages for all professional groups such as managers, clerks, and skilled workers except unskilled manual workers. Martinez Ros (2001) analyzed Spanish manufacturing firm data to determine how the real wage paid by firms changes when they engage in innovation activity. He found that wages increase with innovations and that increase is correlated with workers' bargaining power (see also Ballot, Fakhfakh and Taymaz, 2006). Incumbent workers have the highest wage increase. Using the community innovation surveys (CIS), Pianta and Tancioni (2008) found that wage increases with innovations, and also, when innovation expenditure is higher, wages grow faster. This wage growth mainly comes from salaries for high-skilled researchers and technicians. According to Castillo et al. (2013), the Argentinean Support Program caused an increase in innovations in small and medium-sized enterprises, leading to a rise in wage and employment. Kline et al. (2019) identify how patent-induced shocks to labor productivity affect worker compensation and utilize U.S. patent applications. The result shows that the earning effect of patent allowances is heavily concentrated among employees in the top half of the earnings distribution. Patent allowances worsen the gender earnings gap. Male workers' earnings grow strongly in response to a patent allowance, whereas female workers' earnings are less responsive to the patent decisions.

Labor turnover is a major source of knowledge spillovers. The literature has focused on how labor turnover affects innovation, and the effect of innovation on labor turnover has not been examined much. In previous studies, it was concluded that labor turnover has positive effects on innovation, but some article states the opposite. Kiaser et al. (2011) utilized the data on R&D active Danish firms with matched registered employer and employee data between 1999 and 2004. The estimation results show a positive link between labor turnover and innovation. If workers come from innovative firms, the link is stronger. The total effect of hiring and firing the workers is associated with a rise in total innovation of the old and new businesses. Braunerhjelm et al. (2015) argue that innovativeness is affected positively and significantly by labor mobility. They used the matched employer-employee dataset with patent applications of the firms in Sweden. Labor mobility has a positive impact on firms' output, but it is more effective if labor comes from innovative firms. Also, the firm benefits from the lost employee because of the diaspora effect. Smaller firms gain less than larger firms from labor mobility. Eriksson et al. (2014) point out the relationship between labor turnover, HRM practices, and innovation using the survey data containing the five high technology sectors in Chinese firms. The study shows that the technical labor turnover is higher in innovative firms compared to non-innovative firms. It means labor turnover has a positive impact on the innovativeness of the firms. They state that the result of the study supported the theoretical reasons, which is new workers bring new ideas to the firm. In contrast, some research suggests that higher labor turnover affects innovation significantly and negatively (Pieroni & Pompei, 2007; Abbasi & Hollman, 2000).

In this study, we will analyze the effects of innovation on labor turnover to understand if labor moves from innovative firms to others so that a part of the knowledge generated in the innovative firms spillovers within the economy.

3. Methodology

In order to estimate the effects of patents and R&D activities, we use the DiD estimator by estimating a two-way fixed effects (TWFE) model as proposed by Wooldridge (2021). Assume that a firm is observed for a time period, 1 to T, and applies for a patent (or starts conducting R&D) at time r ($1 < r < T$)[2]. We assume that the effect of the patent/R&D will continue at $t > r$, i.e., we assume staggered entry for technological (patent and R&D) activities.

Following the literature on the treatment effect, we will call this firm “treated” at time r, and the cohort of firms treated at r is defined by the cohort dummy d_r ($d_r = 1$ for firms treated first at time r). The outcome variable, y, is observed in all years. Some firms are never treated, and the potential outcome variable at time t for never treated firms is denoted by $y_t(\infty)$.

The effect of treatment (patent application or R&D activities) at time t ($t \geq q$) is the difference between the outcome under treatment and no treatment cases:

[1] $$te_t(r) = y_t(r) - y_t(\infty), r = q, \dots, T$$

In this equation, q is the first treatment year (there is no firm in the sample that is treated before q). $y(1)$ refers to the treatment case which is observed, and $y(0)$ the no-treatment case, which is not observed. Since the no-treatment case is not observed, we can estimate only the average treatment effect on the treated (ATT) for different cohorts of treated firms as follows:

[2] $$\tau_{rt} = E[te_r(r) | d_r = 1], r = q, \dots, T; t = r, \dots, T$$

2 In our context, “innovation” (“treatment”) means “patent application” or “conducting R&D”.

For example, $r = 3$ denotes the set of firms treated at time 3. We select the sample of firms for the analysis such that all treated firms are observed for least two untreated period ($q = 3$, $r \geq 3$).

There are two assumptions made to estimate the ATT (Equation 2):

A1. No-anticipation assumption: For treatment cohorts, $r = q, \ldots, T$

[3a] $E[y_t(r) - y_t(\infty) | \boldsymbol{d}] = 0, t < r$

The no-anticipation assumption states that there is no difference between the potential outcomes of treated and untreated cases before the treatment period. Note that if there is an anticipation effect, for example, for one year, it can easily be controlled for by setting the treatment time one year ahead.

A2. Common trend assumption: Given the treatment cohort dummies $d_q, \ldots, d_T$,

[4a] $E[y_t(\infty) - y_1(\infty) | d_q, \ldots, d_T] = E[y_t(\infty) - y_1(\infty)], t = 2, \ldots, T$

The common trend assumption states that the expected *changes* in the outcome variables for treated and untreated firms would be the same had the treated firms not been treated.

If the trend in the outcome variable depends on some covariates, these two assumptions can be written conditional on these variables (the $\boldsymbol{x}$ vector) as follows:

[3b] $E[y_t(r) - y_t(\infty) | d_r = 1, \boldsymbol{x}] = 0, t < r$

[4b] $E[y_t(\infty) - y_1(\infty) | \boldsymbol{d}, \boldsymbol{x}] = E[y_t(\infty) - y_1(\infty) | \boldsymbol{x}], t = 2, \ldots, T$

Then, the expected outcome conditional on $\boldsymbol{d}$ and $\boldsymbol{x}$ can be written as:

[5] $E(y_t | \boldsymbol{d}, \boldsymbol{x}) = E[y_t(\infty) | \boldsymbol{d}, \boldsymbol{x}] + d_q \tau_{qt}(\boldsymbol{x}) + \ldots + d_T \tau_{Tt}(\boldsymbol{x})$

By definition, the cohort dummies, $d_q, \ldots, d_T$, are mutually exclusive, and the sum of those dummies will be equal to one for treated firms, and 0 for never treated firms. Thus $E[y_t(\infty)]$ is the expected value of the outcome variable for untreated firms at time t, and τ_{rt}*'s* are cohort-time specific ATTs.

As shown in Wooldridge (2021), assuming a linear expectations function, the ATTs can be consistently and efficiently estimated by fixed effects estimator of the following equation:

[6] $y_{it} = \eta_i + \sum_{s=2}^{T} \theta_s fs_t + \sum_{s=2}^{T} (fs_t \boldsymbol{x_i}) \pi_s + \sum_{r=q}^{T} \sum_{s=r}^{T} \tau_{rs} (w_{it} d_{ir} fs_t) + \sum_{r=1}^{T} \sum_{s=r}^{T} (w_{it} d_{ir} fs_t \dot{\boldsymbol{x}}_{\boldsymbol{ir}}) \rho_{rs}$

where y_{it} is the value of the outcome variable for firm i at time t, w a time-varying treatment dummy, d cohort dummies (d_{ir}= 1 if firm i belongs to cohort r), fs time dummies, $\boldsymbol{x}$ the vector of covariates, and $\dot{\boldsymbol{x}}$ the vector of covariates centered around the within-cohort mean.

In Equation 6, the estimated value of τ_{rs} is equal to the average treatment effect for the cohort *r* at time *t* where $r = q, \ldots, T$ and $s = r, \ldots, T$, i.e., there are $(T - q + 1)(T - q + 2)/2$ number of treatment effect coefficients to be estimated. Since we are interested in the treatment effects over time, we impose the following restrictions:

[7] $\tau_{rt} = \tau_{t-r}, r = q, \ldots, T; t = r, \ldots, T$

Equation 7 implies that the treatment effect depends on the time after treatment. For example, when $t = r$, τ_0 shows the average treatment effect in the year the firm applied for a patent (or conducted R&D).

In order to estimate the treatment (innovation) effects (τ_{rt}'s), we first retrieve the data on all firms that operate throughout the period under investigation (2006-2020). Then, we select never treated firms and those firms treated in or after 2009, and form two control groups, one for patent applicants, and the other one for R&D performers by using the 2008 data by the coarsened exact matching method. Finally, the treatment effects are estimated by Equation 6 under restrictions imposed by Equation 7 by a fixed effects estimator as suggested by Wooldridge (2021).

4. Data

We use the Entrepreneur Information System (EIS) dataset, compiled by the Ministry of Industry and Technology in Turkey. The EIS dataset matches the data from various administrative sources including bilateral trade relations (the Ministry of Trade), balance sheets and income statements (the Revenue Administration), employees and wage payments (the Social Security Institution), R&D support recipients (the Scientific and Technological Research Council of Turkey), patent, trademark, utility model applications (the Turkish Patent and Trademark Agency), and SME support recipients (the Small and Medium Enterprises Development and Support Administration). The dataset includes all non-financial and private firms operating and registered in Turkey, and all employees working in these firms. By matching the employee data with the firm level data, it is possible to calculate labor entry and exit rates.

The firm level data are available at the annual frequency from 2006 to 2020. It covers information on the firm's sector code, geographical location, balance sheet, income statement, foreign and domestic trade, number of employees, wage bill, patents, R&D expenditures, sector code (4-digit, NACE Rev 2), province, and year of establishment. The employee level data are available at the quarterly frequency from 2006 to 2020, and includes variables on employees' age, gender, the number of days worked, and wages. After 2012, it also includes the registration number of workers, which allows us to follow workers over time. Therefore, the analysis on labor entry and exit is conducted for the 2013-2020 period. We use only the manufacturing firms' data because they account for the highest share of patent applications.

Table 1. Number of firms, firm size and wages

	Number of firms			Relative firm size		Relative wage rate	
	All firms	Patent applicant	R&D performer	Patent applicant	R&D performer	Patent applicant	R&D performer
2006	106347	16	2167	15.9	10.4	1.9	1.7
2007	122936	70	2402	41.3	11.0	1.8	1.7
2008	129037	26	2497	26.2	11.0	1.5	1.6
2009	131741	278	2481	24.5	11.7	1.8	1.6
2010	133487	406	2439	21.0	12.1	1.8	1.6
2011	137557	462	2527	20.5	11.9	1.7	1.6
2012	141423	549	2601	18.9	11.6	1.7	1.6
2013	148055	581	2704	18.8	11.9	1.7	1.5
2014	154699	614	2803	21.2	11.7	1.7	1.5
2015	161540	625	2866	23.9	12.4	1.6	1.5
2016	167977	668	2911	24.4	13.3	1.5	1.5
2017	170159	707	2926	25.0	14.1	1.6	1.5
2018	185468	855	3140	24.9	14.7	1.6	1.4
2019	192279	913	3256	24.7	15.3	1.5	1.4
2020	180494	888	3132	28.0	15.4	1.5	1.4

Source: Authors' calculations based on EIS dataset

The number of firms, relative firm size and relative wages are shown in Table 1. There were about 106 thousands firms in the dataset, and it increased to 180 thousands in 2020. There were only a few firms that applied for a patent in 2006. After a jump in 2009, the number of patent applicants increased continuously, but remained less than 0.5% of all firms throughout the period. There were about 2200 firms that conducted R&D in 2006, and that number also increased continuously until 2020 (3132).

There seems to be substantial size (number of employees per firm) and wage differences between innovative firms and others. An average patent applicant employs about 20 times more people than an average firm in manufacturing whereas the size difference between R&D performers and others is about 10 times.

As may be expected, patent applicants and R&D performers pay higher wages than the average of manufacturing. The wage difference was close to 2 in 2006, and it declined gradually over the period. In 2020, patent applicants and R&D performers paid 40-50 % higher wages than the average of all firms.

Within-firm wage differentials reveal some significant differences between innovative and other firms. Among all manufacturing firms, the ratio between the 90th percentile wage to 10th percentile wage is around 1.9-2.0 (see Table 2). For example, if there are 100 employees in a firm, the employee with the highest 10th wage earns almost two times more the wage of the lowest 10th wage earner. Wage differentials are substantially higher among patent applicants (around 3). Since almost all firms employ some workers earning the minimum wage, the within-firm wage differential may arise due to higher average wages. However, the within-firm wage differential is lower in R&D performers (almost around the average of all firms). Since R&D performers pay about 40 % higher than the average, low level of within-firm wage differential among R&D performers could be due to homogenous labor quality.

Table 2. Wage differentials, 2006-2020

	Within-firm wage differentials*		
	All firms	Patent applicant	R&D performer
2006	1.84	3.57	1.71
2007	1.85	3.42	1.73
2008	1.91	3.12	1.76
2009	1.89	3.10	1.78
2010	1.88	2.95	1.77
2011	1.90	2.86	1.79
2012	1.91	2.78	1.82
2013	1.97	2.88	1.87
2014	2.01	2.74	1.94
2015	2.08	2.73	1.99
2016	1.91	2.83	1.83
2017	1.96	2.77	1.88
2018	1.95	2.82	1.88
2019	1.85	2.72	1.79
2020	1.93	2.97	1.87

Source: Authors' calculations based on EIS dataset
* q9/q1 ratio

Table 3. Labor entry and exit rates, 2012-2020

	Labor exit rates			Labor entry rates		
	All firms	Patent applicant	R&D performer	All firms	Patent applicant	R&D performer
2012	0.302	0.169	0.198			
2013	0.307	0.173	0.208	0.362	0.220	0.257
2014	0.309	0.175	0.199	0.347	0.237	0.253
2015	0.304	0.172	0.201	0.340	0.234	0.257
2016	0.278	0.153	0.185	0.296	0.190	0.208
2017	0.299	0.172	0.198	0.304	0.191	0.215
2018	0.311	0.184	0.211	0.287	0.173	0.197
2019	0.251	0.118	0.158	0.289	0.158	0.181
2020				0.296	0.186	0.209

Source: Authors' calculations based on EIS dataset

Labor entry and exit rates are shown in Table 3. Entry and exit rates are calculated from December to December. If an employee employed in December 2012 is not employed in December 2013 in the same firm, it is regarded as an exit, and an employee in December 2013 is an instance of entry if she was not employed in the same firm in December 2012. There are some employees who change their jobs too frequently. If an employee changes her job more than 2 times per year on average, that employee is not taken into account in entry and exit rates, because, most probably, that person is employed on a temporary basis, or is employed through a temporary employment agency.

Labor exit and entry rates are quite high among Turkish manufacturing firms. About 30 % of employees leave their firms in a year, and the entry is about the same. The difference in entry and exit rates is equal to employment growth rate in the firm, which is positive in all years except 2018.

Labor entry and exit rates are much lower for patent applicants and R&D performers (about 15-20%). This could be either because of their size (innovative firms are larger than others), or because of long-term attachment between employees and the firm. Low entry and exit rates due to long-term attachment could facilitate the accumulation of firm specific knowledge and technologies.

A simple comparison between innovative firms and others reveal that there are substantial differences in terms of the variables of interest. However, these differences do not necessarily imply any causation. In order to test if innovation leads to changes in these variables, we will use DiD estimator.

As mentioned in the Methodology section, the DiD analysis requires observations before and after treatment for the treated unit in order to take the difference ("slope") between after and before treatment values. Since we need at least two years of observations before treatment and there is a jump in patenting in 2009, we select firms that apply for a patent or start conduction R&D in or after 2009. The firms that apply for a patent (or conduct R&D) form a cohort. The number of firms in 2009-2020 cohorts are shown in Table 4. There are about 100 firms in patent and 200 firms in each innovation cohort.

Table 4. Number of firms in innovation cohorts

Cohort	Patent applicant	R&D performer
2009	75	224
2010	107	201
2011	113	196
2012	90	200
2013	91	163
2014	88	177
2015	87	162
2016	88	157
2017	82	149
2018	102	154
2019	77	135
2020	95	92
Total	1095	2010

Source: Authors' calculations based on EIS dataset

For each firm in innovation cohorts, we select a firm from the never treated group (those firms that never apply for a patent and never conduct R&D) by applying the coarsened exact matching (CEM). The CEM is "is a nonparametric method of controlling for the confounding influence of pretreatment control variables in observational data." (Iacus et al., 2011). Blackwell et al.(2009) state that the CEM algorithm better estimates causal effects by reducing imbalance in covariates between treated and control groups so that the empirical distributions of the covariates would be similar between the treatment and control groups. We use 2008 firm size (in log), firm age (in log), export dummy and sector codes (NACE Rev. 2, 2-digit level) for matching. After balancing the data, 2190 observations were left to observe the impact of patent applications for the treatment and control group, and 4022 observations for R&D activities.

Dependent variables we use in the DiD model are as follows; log of wages at the 10th, 50th, and 90th percentiles, log of value-added per employee (labor productivity), and log of wages for male and female employees. In addition, we use labor exit and entry rates, and logs of entrants', and leavers' wages. Covariates in the DiD model are log of firm size, log of firm age, and the export dummy.

5. Estimation results

For the DiD model, we use the data for the 2007-2020 period (the 2006 data are used to calculate value added). There is no patent applicant and R&D performer in 2007 and 2008 in the selected sample, and the firms start treatment in 2009. The DiD model estimates change in dependent variables for treated and untreated firms at time t (t = 2009, …, 2020) and 2007-2008, then takes the difference between treated and untreated firms, conditional on covariates. Since we imposed restrictions as in Equation 7, 12 treatment effects are estimated. The common trend assumptions were not rejected by hypothesis tests (for common trend assumption test, see Wooldrige, 2021: 57-60).

Estimation results are presented in figures 1-5. In all figures, a circle on the estimated value indicates that it is statistically significant at the 5% level.

Wage effects for patent applicants show that there is no change in wages of low wage earners (10th percentile, q1), possibly because all low wage earners earn the minimum wage (see Figure 1a). However, the median wage (q5) in patent applicants increases continuously after patent application, and reaches its maximum 8 years after innovation. The increase in the wage rate (compared to the case of no innovation) is 4%. The wage rates of high wage earners increase more rapidly and reache higher levels (about 7% in year 8). These results indicate that within-firm wage differentials increase after innovation.

Wage effects for R&D performers is somewhat similar (Figure 1b). High wage earners benefit more from R&D activities, but low wage earners also benefit from innovation in R&D conducting firms. It seems that employees at the 10th percentile of the wage distribution earn more than the minimum wage in R&D conducting firms.

The increase in wages after innovation can be explained by Nash wage bargaining models. These models suggest that the wage rate is a weighted average of the reservation wage (the outside wage) and labor productivity where the weights are the bargaining powers of workers and the firm (Ballot, Fakhfakh and Taymaz, 2006). The wage rate after innovation can increase due to an increase in the reservation wage (because of an increase in human capital), an increase in the workers' bargaining power, or, if the workers had any bargaining power, an increase in labor productivity. Note that because of all these effects, high wage earners (more skilled employees) are likely to increase their wages more than low wage earners. It seems that low wage earners in patent applicants do not have any bargaining power so that they earn their reservation wage (the minimum wage).

Wage differentials between men and women are also likely to increase after innovation (Figures 2a and 2b). It seems that the increase in wages is slightly higher for men than for women, i.e., innovation wides gender wage differentials.

As mentioned above, wages may increase after innovation if it causes an increase in labor productivity (value added per employee). Figure 3 presents the estimated treatment effects on labor productivity. Although there are significant fluctuations over time, labor productivity increases are about 5-10 % after innovation. These results show that, in spite of wage increases after innovation, gross operating surplus of firms increases even more after innovation. In other words, innovative firms share the benefits of innovation with their employees, but they retain a bigger share, and become more profitable after innovation.

Labor turnover is an important channel to transfer knowledge between firms. The estimation results indicate that labor entry and exit rates increase considerably after innovation in the case of patent applications (Figure 4a). Entry and exit rates increase more than 4 percentage points in the year of patent application, and stay around 2-3 percentage points in later years. The entry and exit rates increase only slightly among R&D performers (about 1-2 percentage points), but increases in entry and exit rates are not statistically significant in most of the years (Figure 4b). This is yet another difference between patent applicants and R&D performers.

In order to understand the qualifications of entrants and leavers, we can look at their average wages. Figure 5a shows changes in average wages of those employees who leave (exit) and join (entry) the innovative firm after innovation. Although the estimated effects are not statistically significant at the 5% level, entrants' wages decline more (2-3%) after innovation. In other words, it seems that patent applicants hire employees at a lower wage after innovation. For R&D performers, there is an increase in entrants and leavers wages after R&D (Figure 5b), and the effect on entrants wage is higher and stronger (statistically significant in two years). It is likely that R&D performers, when they start conducting R&D, tend to higher more qualified employees.

6. Conclusions

In this paper, we analyzed the effects of innovation on profits, wages, and labor turnover. By using the population of Turkish manufacturing firms active in the 2004-2020 period, and by utilizing the DiD setup, we showed that, after innovation labor productvity and profits increase considerably. There is a positive effect on median wages as well, but the effect on higher wages is stronger than the effect on lower wages so that within-firm wage differentials increase after innovation. Similarly, gender wage differentials also increase to some extent because the increase in men's wages is higher than the increase in women's wages.

The effect of innovation on labor turnover is weak and ambiguous. There is a significant increase in labor entry and exit rates after innovation in the case of patent applicants, whereas labour turnover does not change much in the case of R&D performers. Regarding wages of leavers and entrants, the findings are the opposite: no significant effect in patent applicants whereas entrants and leavers wages increase slightly in R&D performers.

Our estimation results show that there could be important differences between R&D performers and patent applicants, at least in Turkish manufacturing. Although R&D and patents are used as a proxy for "innovation" in empirical studies, the differences between patent applicants and R&D performers need to be examined in detail.

Our findings indicate that innovation provides substantial benefits to the society, but these benefits are not shared equally. Income distribution is likely to increase after innovation, at least in the short- and medium-term.

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Figure 1a. Treatment effects on wages, patent applicants

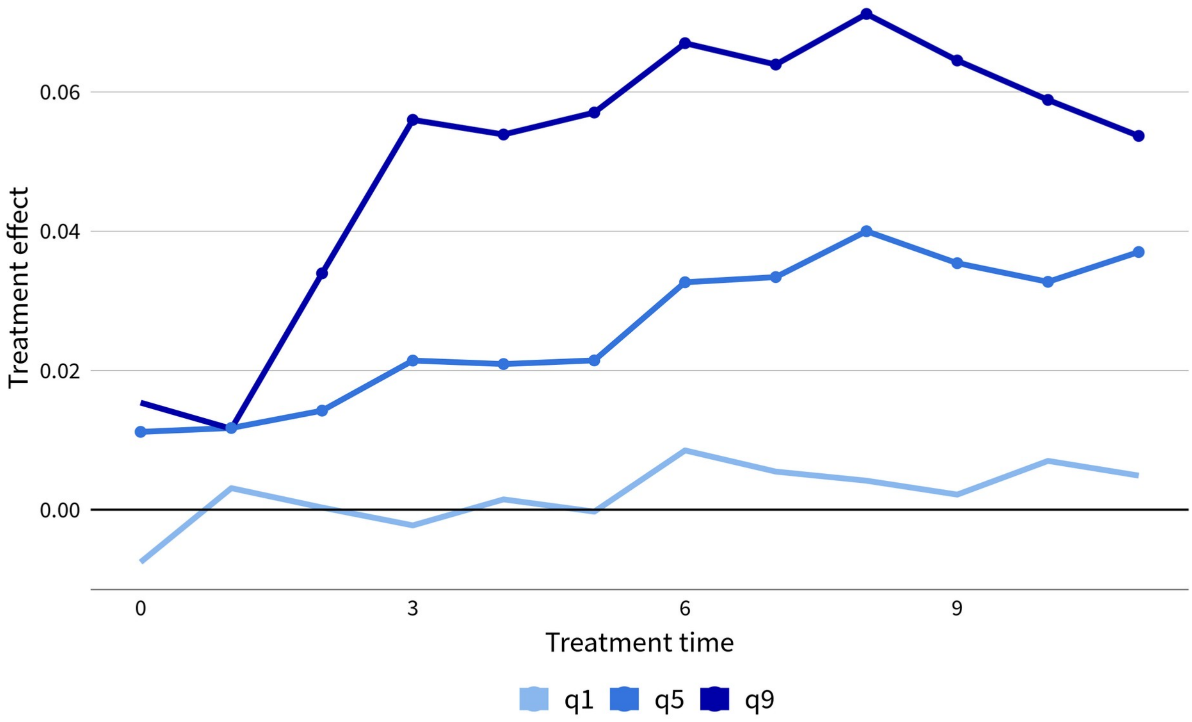

Figure 1b. Treatment effects on wages, R&D performers

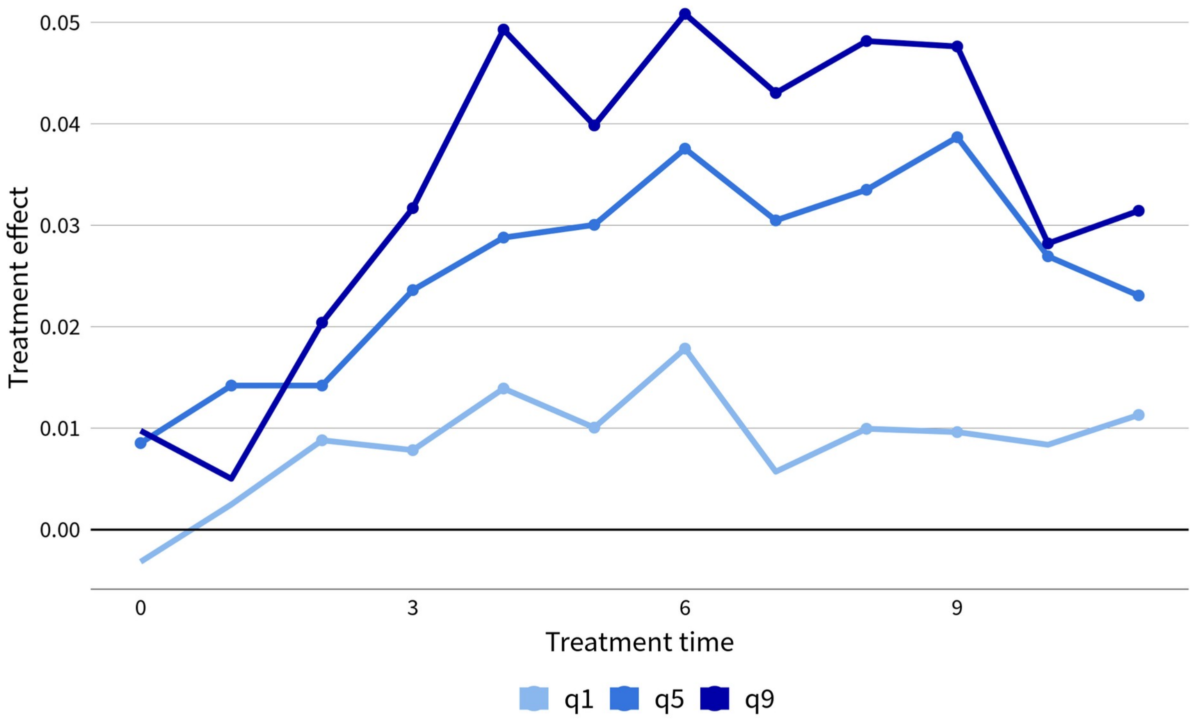

Figure 2a. Treatment effects on men's and women's wages, patent applicants

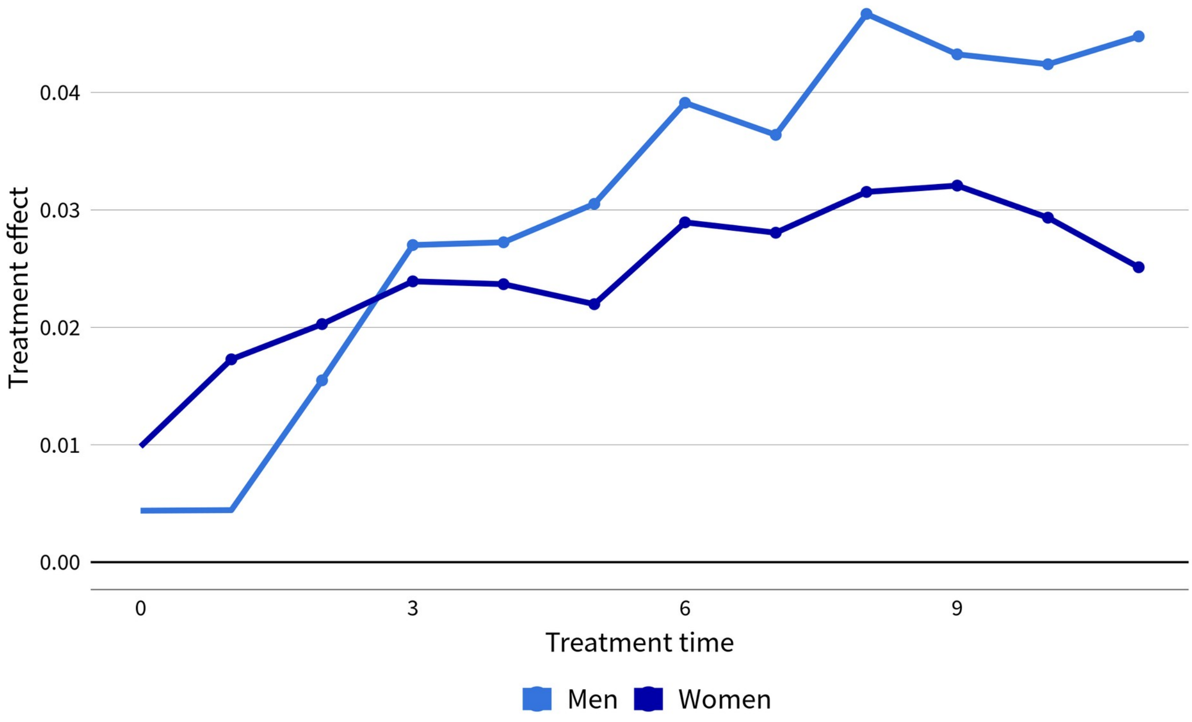

Figure 2b. Treatment effects on men's and women's wages, R&D performers

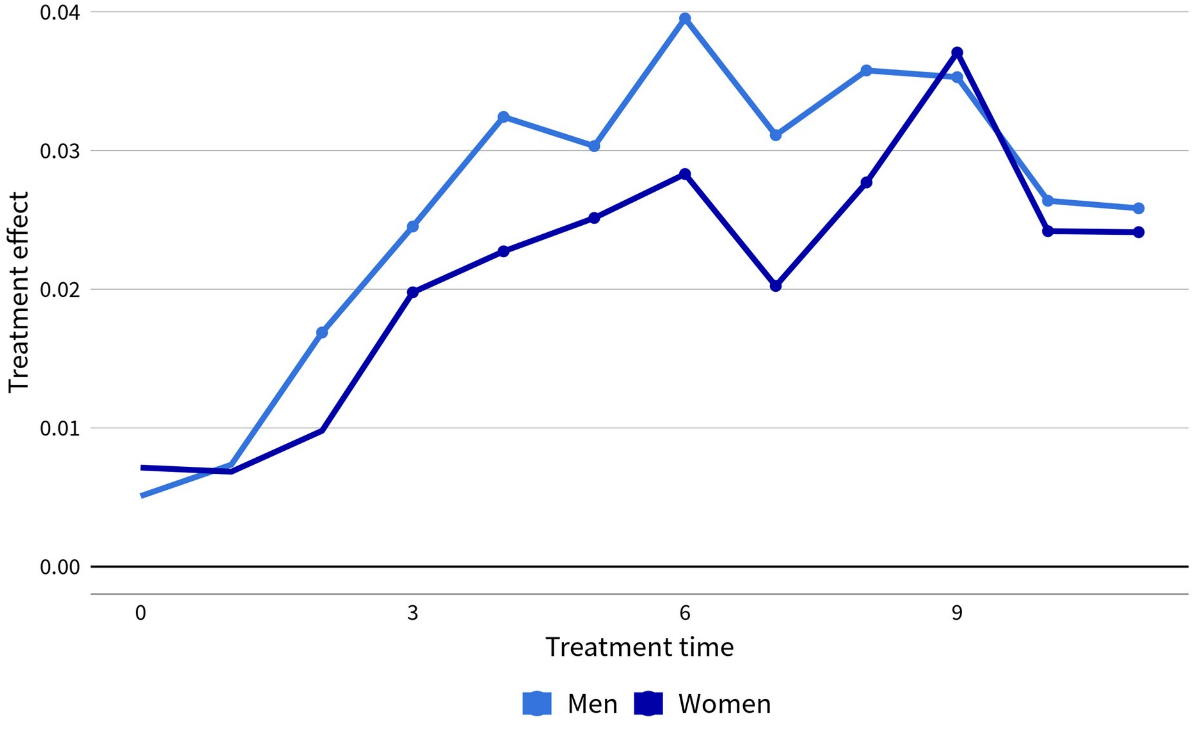

Figure 3. Treatment effects on labor productivity

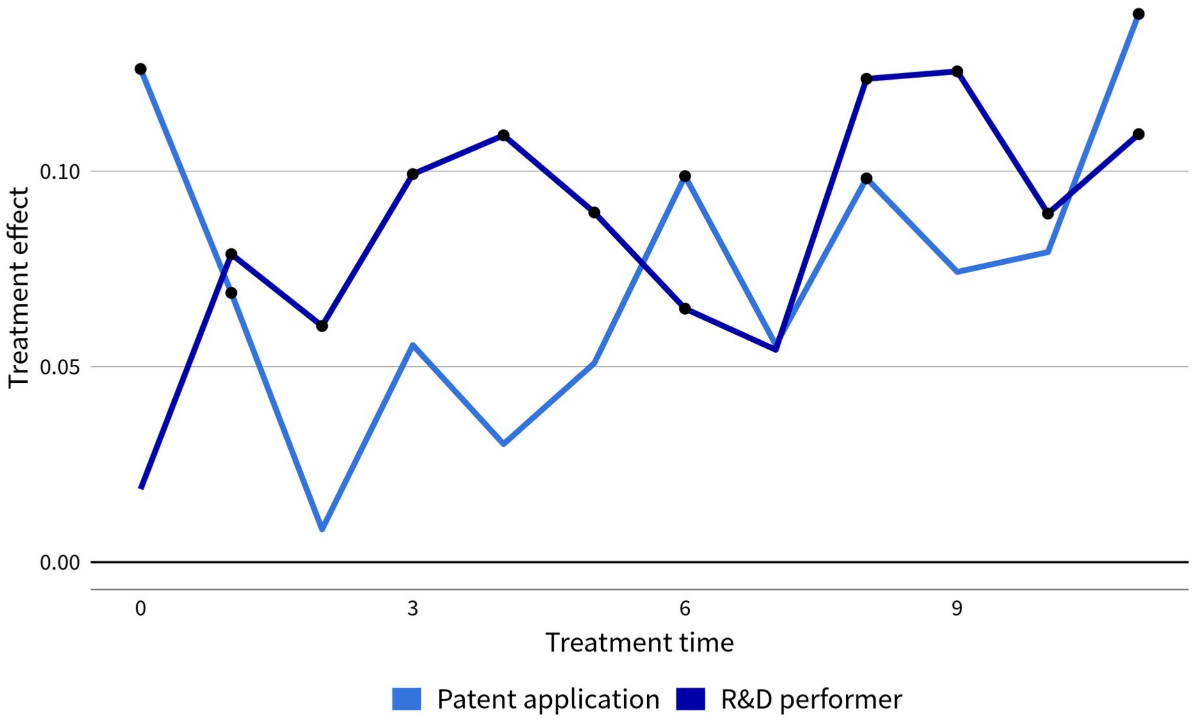

Figure 4a. Treatment effects on labor entry and exit rates, patent applicants

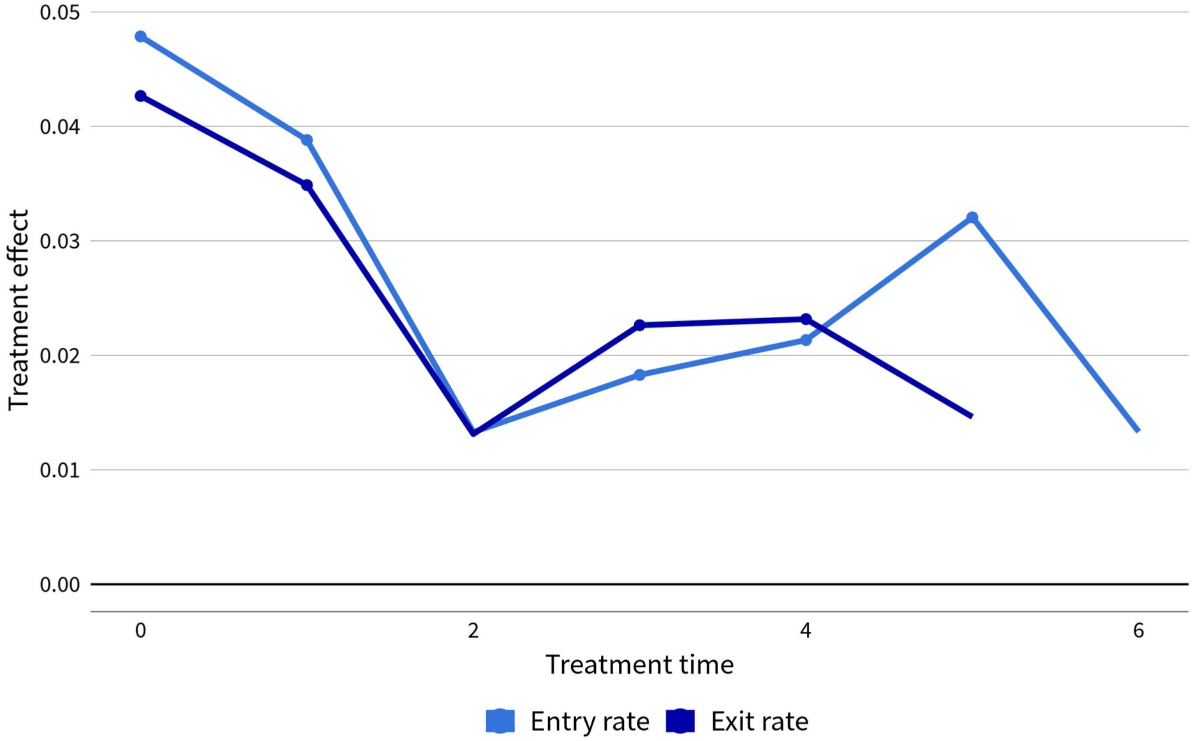

Figure 4b. Treatment effects on labor entry and exit rates, R&D performers

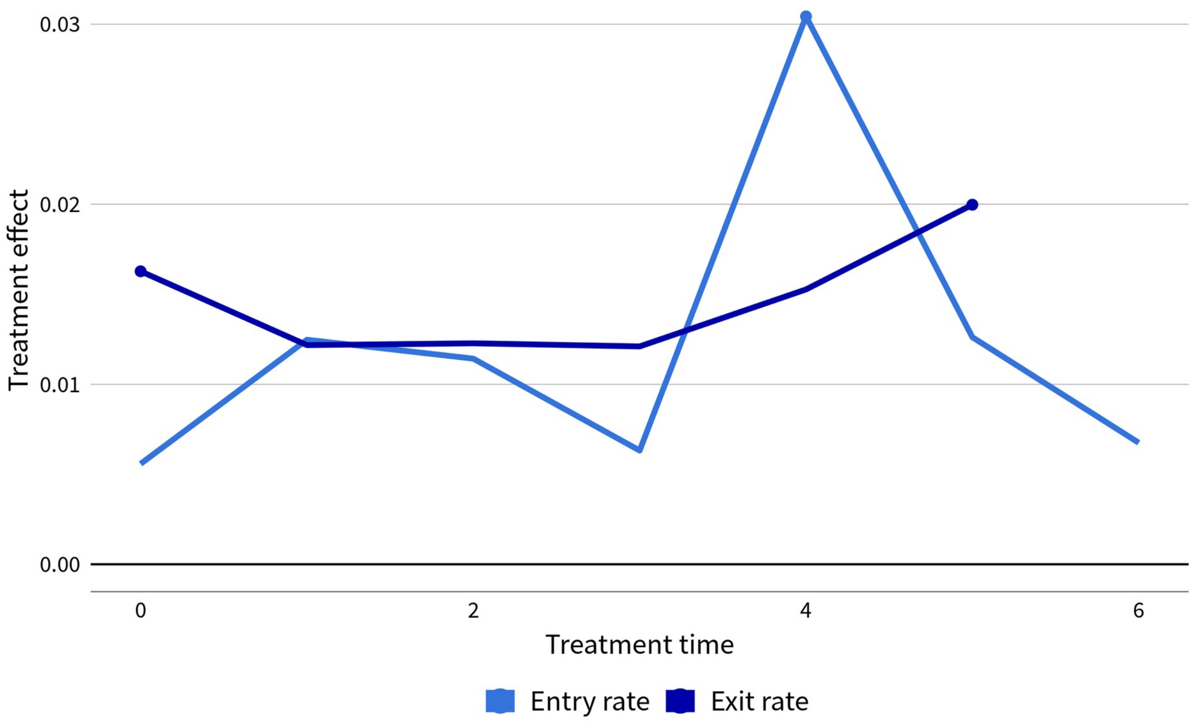

Figure 5a. Treatment effects on labor entry and exit wage rates, patent applicants

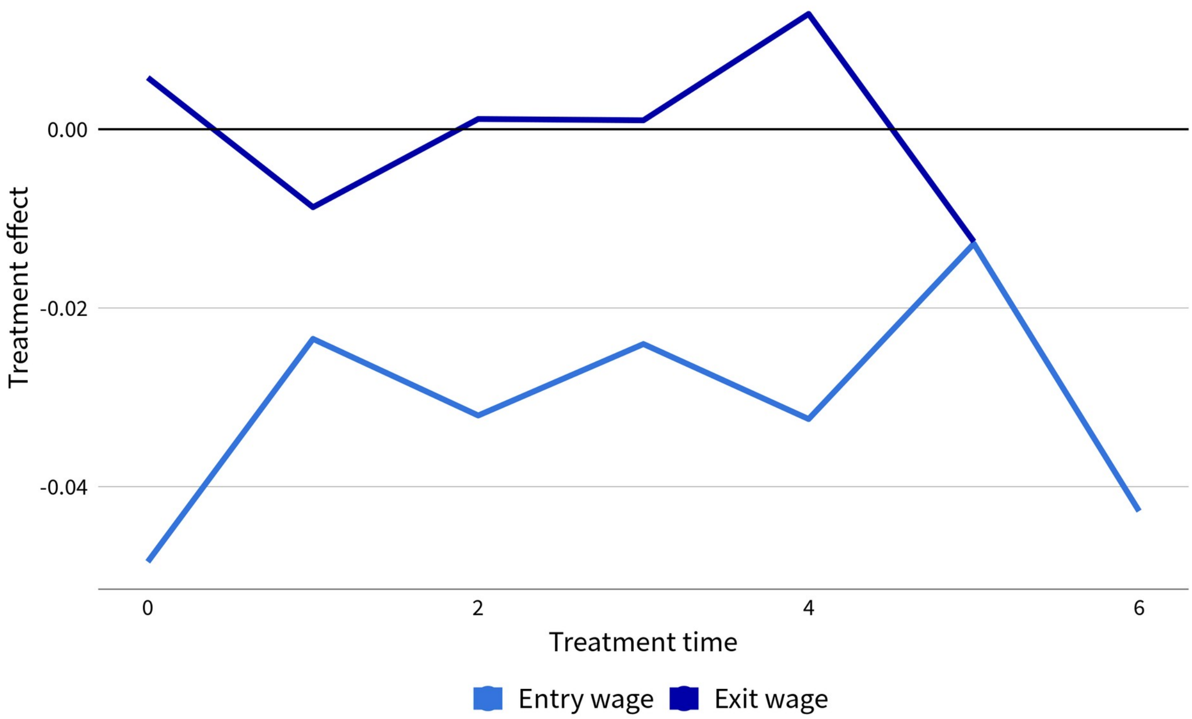

Figure 5b. Treatment effects on labor entry and exit wage rates, R&D performers